Building Resilient Engineer to Order Systems

by

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A Thesis Submitted in Fulfilment of the Requirements for

the Degree of Doctor of Philosophy of

Cardiff University

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7 Oct 2024

Acknowledgement

My sincere gratitude to my mentors,

Prof. Mohamed M. Naim for his patience, belief in my abilities, and tremendous support. His insightful feedback and constant encouragement have played a pivotal role in the completion of my Ph.D.

Prof. Jonathan Gosling for his timely and wise consultation. His profound insights and thoughtful advice have significantly enriched the quality of my work.

Dr. Xun (Paul) Wang for his invaluable guidance and support. His expertise and practical suggestions have been crucial in overcoming the challenges encountered during this research.

To the viva examiners Prof Joakim Wikner and Dr. Irina Harris, for their detailed comments and thoughtful suggestions, which have not only refined my thesis but also inspired future directions for my research.

To my family

for their selfless love and support.

Abstract:

Engineer-to-order (ETO) supply chains, common in industries such as shipbuilding and capital goods manufacturing, face unique challenges due to customization and project-based designs, leading to high uncertainty, cost overruns, and delays. This highlights the need for resilience improvement. While system dynamics (SD) archetypes are well-established for make-to-stock, make-to-order, and assemble-to-order systems, an ETO-SD model is lacking.

The thesis aims to create a resilient ETO systems archetype to improve its performance under various rework scenarios. It finds that a holistic order book controller can maintain desired lead times despite rework and disturbances. Critical sable conditions across archetypes with different rework ratios show that longer lead times negatively impact system stability. Additionally, the study quantifies the ‘Think Slow Act Fast’ theory, demonstrating that it can reduce overall lead times and production subsystem costs, with a slight increase in design subsystem costs. The research also examines how order book parameters affect system resilience, recommending optimal order book controller settings for different rework ratios, which form a 'bathtub-like' curve as rework ratios increase.

This thesis significantly advances the field by developing a comprehensive suite of ETO-SD archetypes, filling a critical gap in existing literature. It provides a deeper understanding of dynamic behaviours in ETO systems, particularly how they respond to disturbances and rework, and extends the application of SD models to ETO environments.

Practically, this research offers actionable solutions for resilience improvement in ETO industries, including effective capacity planning through system parameter selection, strategies to mitigate rework effects, and methods to minimize system dynamics variance, thereby enhancing both efficiency and effectiveness. These contributions offer practical tools and strategies directly applicable to real-world ETO environments, bridging the gap between theory and practice.

Keywords: System Dynamics; Control Theory; Stability Analysis; Frequency Analysis, Project Management, Rework

Publications

Zhou, Yuxuan, Wang, Xun, Gosling, Jonathan and Naim, Mohamed 2023. The system dynamics of engineer-to-order construction projects: past, present, and future. Journal of Construction Engineering and Management 149 (5) 10.1061/JCEMD4.COENG-12926

Zhou, Yuxuan, Wang, Xun, Naim, Mohamed M. and Gosling, Jonathan 2022. A system dynamics archetype to mitigate rework effects in engineer-to-order supply chains. International Journal of Production Economics 250, 108620. 10.1016/j.ijpe.2022.108620

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Notation

CLD	Causal loop diagram
CODP	Customer order decoupling point
CT	Control theory
ETO	Engineer to order
ETOAR	Engineer to order system archetype
ETOAR#D	Engineer to order system archetype design rework scenario
ETOAR#P	Engineer to order system archetype production rework scenario
ETOAR#PTD	Engineer to order system archetype production to design rework scenario
IOBPCS	Inventory and order-based production control system
MTO	Make to order
MTS	Make to stock
MRC	Minimal reasonable capacity
MRL	Maximum reasonable lead time
OB	Order book
PM	Project management
PSE	Parameter space exploration
RW	Rework
SD	System dynamics
STS	Ship to stock
VIOBBPCS	Variable inventory and order-book based production control system

Chapter 1 Introduction

In 2019, the COVID-19 pandemic wreaked havoc on global production and manufacturing industries, leading to widespread stoppages and a subsequent decline in the global economy. This disruption sparked an increased demand for resilient production systems that can minimise the impacts of uncertainties and demand fluctuations. While the need for resilience has been extensively researched in traditional production systems (Purvis et al. 2016; Ivanov and Sokolov 2013), the specialised design and rework activities specific to engineer-to-order (ETO) production systems lack extensive research and appropriate methodologies. Therefore, it is imperative to explore ways to enhance the resilience in an ETO system. The concept of resilience adopted here measures how effectively a system recovers from impacts and adapts to new environments (Spiegler et al. 2012).

An ETO system is defined as a production system in which the CODP is located at the design stage. This system is prevalent in industries such as shipbuilding, construction, capital goods manufacturing and other ETO type manufacturing. In these industries, product designs are customised or adapted according to specific customer requirements and products are often considered as projects due to their one-of-a-kind or first-of-a-kind nature. Simultaneously, design and production in an ETO system are not separate processes but are integrated (Naim et al. 2021) A notable characteristic of an ETO system is the absence of a finished product inventory. This is because ETO companies cannot anticipate customer requirements before receiving orders, thus leaving them without inventory buffers in the event of disruptions. These features distinguish ETO systems from other production systems, thereby increasing their complexity and vulnerability. Consequently, ETO systems encounter more uncertainties, such as rework issues (Ansari 2019), design uncertainty (Neumann et al. 2022), and delays from upstream suppliers (Park 2005). Therefore, an ETO system requires production systems that are more flexible, adaptive, and resilient than others in order to effectively manage these uncertainties while maintaining operational efficiency.

The application of system dynamics (SD) in production systems can be traced back to Towill (1982). It involves planning workflows, scheduling tasks, managing resources, and monitoring progress to ensure smooth operations. Over the last four decades, the SD methodology has been applied across a diverse range of contexts. According to the CODP categorisation (Gosling et al. 2017), production systems can be categorised into six groups, ranging from speculative make-to-stock (MTS) to highly customised ETO. SD-based research has addressed various aspects, including ship-to-stock (STS) (Wikner et al. 2017), make-to-order (MTO) (Wikner et al. 2007), and assemble-to-order (ATO) (Lin et al. 2020) systems. SD methods have contributed to the reduction of the bullwhip effect (Ponte et al. 2017), studies on ripple effects (Ivanov et al. 2016), and capacity management (Wikner et al. 2007). Despite extensive research, the application of SD in the ETO context remains underexplored, which limits the understanding of ETO system behaviour. Investigating the dynamic behaviour of ETO systems provides a clear view of how these systems' structures—that is, the combination of delays, feedback loops, and decision rules—respond to changes in demand patterns and disruptions, thus offering a comprehensive understanding of ETO systems. The outcomes of such research are beneficial for ETO system benchmarking, strategy formulation, and performance improvement in terms of both time and cost.

In summary, the lack of a quantitative ETO model, insufficient understanding of ETO SD, and gaps in extant research on improving resilience in ETO systems drive this research.

This chapter introduces the research by establishing its context, motivation, and objectives. Section 1.1 presents the background, outlining the broader context and key challenges in the domain of ETO systems. Section 1.2 highlights the research gaps identified through a background study, followed by an explanation of the motivation for this study. Section 1.3 defines the research aim and objectives, detailing how they are derived from the identified gaps. Lastly, Section 1.4 outlines the thesis structure, providing an overview of the subsequent chapters to guide the reader through the research journey.

1.1 Background

Figure 1.1 illustrates the scope of this research, depicted as the central area where the triangles meet to create an inverted triangle. Each triangle represents a distinct research topic that collectively forms the theoretical foundation of this study. The subsequent sections provide details for each of these topics, thereby providing a background of the three research fields that intersect to shape the focus of this investigation. This structured approach helps clarify the multidisciplinary nature of the study and sets the stage for a deeper exploration of how these distinct areas converge within the research framework.

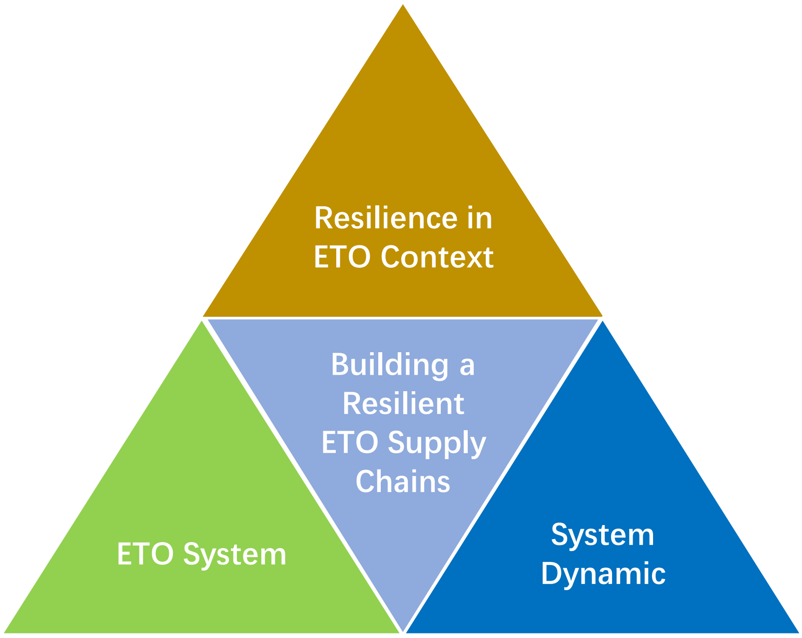

Figure 1.1 Scope of the research

1.1.1 ETO Systems

ETO systems can be defined as production systems wherein the CODP is located at or before the design stage (Naim et al. 2021). This kind of system has been widely adopted in shipbuilding (Alfnes et al. 2021), bespoke capital goods manufacturing (Birkie et al. 2017), and construction industries (Gosling et al. 2013a). The products produced by these industries are usually tailored for the customers during the designing stage and, consequently, design activities are included in the ETO system, which is a distinguishing characteristic of the ETO.

Project management (PM) plays a crucial role in ETO systems by coordinating complex and variable processes from design to production. Unlike standard production systems, ETO systems rely on a project-oriented approach to manage unique customer requirements, and design adaptations (Gosling and Naim 2009; Mello et al. 2017; Bäckstrand and Powell 2021).

This ensures alignment between customer specifications, design changes, and production, which is vital for ETO industries.

The close coupling of design with production then raises the issue of the degree of novelty of the design in satisfying customer requirements. Therefore, effort was made to further categorise ETO systems in accordance with the novelty of the design. Gosling et al. (2017) proposed a categorisation method on ETO systems in accordance with the novelty of the engineer, based on a previous study by Wikner and Rudberg (2005). The categorisation is presented below:

1. 'Research' type of ETO project: ETO project's/product's design requires research in the design stage.

    1.1 Mathematical research, 1.2 Science Research, 1.3 Engineer Research

2. 'Codes and Standards' type of ETO project: ETO project's/product's design can be developed based on the codes and standards.

    2.1 Develop Codes, 2.2 Integrated Codes, 2.3 New Design from Codes

3. 'Existing Designs' type ETO project: ETO project/product's design is created based on previous design.

    3.1 Adapted Design, 3.2 Finalised Design, 3.3 Completed Design

The lead times for 'Research' and 'Code and Standards' types of ETO project/products are usually difficult to estimate, given that products for these two may still be in the early research or experimental stage. In such ETO systems, tailored project structures are required that can readily adapt to the construction environments and local infrastructure, such as bridges (Peckens et al. 2019), tunnels (Nasirzadeh et al. 2014), and oil platforms (Engelseth et al. 2020). Hence, a pure PM view rather than a production system view may be more suitable, with management strategies that can be customised on a case-by-case basis in alignment with the unique needs of the project and environment. Therefore, this research focuses on the third type of ETO system, wherein both the design and production lead time are certain and estimable and the system is more amenable to the SD approach. Such kinds of ETO systems are widely adopted in capital goods manufacturing (Barbosa and Azevedo 2018a) and ship component manufacturing industries (Alfnes et al. 2021). Furthermore, according to Naim et al. (2021), only those that integrate design with production can be regarded as ETO systems, and this criterion is also adopted in this research.

Considering the project-orientated feature of ETO, the thesis refers to Lee et al. (2005a) to clarify the focus of the management levels. According to their research, there are four levels for PM, ranging from macro to micro: strategic aggregate planning, tactical pre-project planning, operational project execution, and post-delivery planning. This research majorly focuses on the strategic aggregated planning level, which is in alignment with the other dynamic study in the production systems field, as summarised in Table 1.1. However, the literature from the other three management levels is also reviewed to provide a comprehensive view of the operation of the ETO system, particularly in the interface between aggregate planning with the others. Therefore, the model developed is at an aggregate level.

Table 1.1 The application of SD in production planning and control systems

System Type	***Original reference***	***Typical CODP Location***	**Feedback Path**	**Feedforward Path**	***Flow***	***Main analysis technique***
MTS	(Towill 1982)	Finished stock	Inventory	Demand	Material	Laplace transform
ATO	(Lin et al. 2020)	Sub-assembly	WIP Inventory Backlog	Demand	Material	Laplace transform
MTO	(Wikner et al. 2007)	Raw materials	Order Book WIP	Demand	Material	Simulation
ETO	This thesis	Design	Order Book	Demand	Working Units	Z-domain

1.1.2 Resilience in ETO context

Resilience refers to a system's ability to recover from the impact of disruptions and disturbances (Ponomarov & Holcomb 2009). Moreover, Spiegler et al. (2012) define resilience as a system's ability to get used to change while evolving itself to a new status. Although a variety of papers study the resilience of manufacturing and production systems, there exists a paucity of literature that discusses the meaning of resilience in the context of ETO systems, with even fewer proposed methods that can measure the resilience of such systems. Therefore, this research also seeks to formulate a definition for ETO-based resilience through a literature review and, subsequently, find a suitable resilience measure index for the ETO system. Moreover, the research attempts to develop a method to improve the resilience of ETO systems and link the theoretical outputs with practical implications.

1.1.3 System Dynamics

SD modelling has been widely used in supply chain system and PM. From the supply chain perspective, SD has been successfully adopted in explaining and mitigating the bullwhip effect (Towill et al. 2007; Naim et al. 2017). In the PM field, SD has been adopted to model the project execution system, which has been used in rework management (Love et al. 1999) and ripple effect explanation (Lyneis 2012).

The control theory (CT), which originates in the engineering field, provides researchers with a set of tools for system analysis. This method was first introduced by Towill (1982) in the dynamic modelling of an inventory and order-based production control system (IOBPCS), which mathematically explained the system’s dynamic behaviour and has become the foundational archetype for various production systems (Wikner et al. 2017), although not for an ETO system. The combination of SD and the CT has deepened researchers’ understanding of inventory control (Disney et al. 2004), capacity optimisation (Wikner et al. 2007), and the bullwhip effect (Ponte et al. 2017). Compared to the application of both the SD and CT in the MTS, ATO, and MTS field, their application in the ETO field is relatively limited. This can be attributed to the dichotomous views of researchers in the PM and production system fields on the project versus the product, while ETO research merges the two perspectives regarding the design and production of a product as a unique activity (Naim et al. 2021). Hence, ETO systems include a unique activity, which is design, making them difficult to characterize through a traditional supply chain perspective that treats products as homogeneous unit.

1.2 Research Gaps

Based on the background study of relevant topics, three major research gaps are identified: the absence of a comprehensive archetype for ETO systems (Section 1.2.1), the limited exploration of dynamic performance assessment on ETO system (Section 1.2.2), and the lack of solutions for improving system resilience (Section 1.2.3). These gaps underscore the need for a deeper understanding of ETO system dynamics, which serves as the primary motivation (Section 1.2.4) for this research.

1.2.1 Research Gap One: The Absence of an ETO Archetype for Aggregated Planning

Aggregate planning refers to the strategic level of production planning, which balances capacity and demand over a medium to long-term horizon (Tiedemann et al. 2020; Brachmann and Kolisch 2021). It integrates multiple operational components, such as design, production, and production planning, into a unified framework. In the context of ETO systems, aggregate planning is crucial for managing complex, high-variability workflows that involve customized products and integrated design-production stages (Willner et al. 2016a) . By coordinating design and production department, aggregate planning enables organizations to better the capacity management, minimize delays, and enhance overall system resilience. Despite its importance, ETO systems currently lack archetypes tailored to aggregate-level planning. Such archetypes are necessary to address the complexities of ETO systems, including high variability, integrated workflows, and project-specific constraints.

An archetype is defined as a typical and general model for a specific system, which could be used as a benchmark for future study and practice (Batista et al. 2018). ETO system archetypes could benefit this research in various ways: 1) Provide an insight into the ETO system's dynamics (Willner et al. 2016); 2) help researchers understand the mechanisms underlying a dynamic phenomenon, such as bullwhip and chaos (Lin et al. 2020); 3) provide an abstract model for researchers to study the nature of the system, for testing newly developed interventions, such as information feedback (Wikner et al. 2017); 4) archetypes developed via an SD method can be easily extended or upgraded, as has happened with the IOBPCS archetypes (Towill 1982; Lin et al. 2017); 5) for ETO systems, the research at an aggregate level remains inadequate, which is because the model/archetypes developed for other production systems, such as MTS and MTO systems, ignored the differences among the products (Schoenwitz et al. 2017) and the existing models developed in the PM field merely focused on the execution of a single project (Lee et al. 2006b). An archetype can be used as a 'strategic core' to coordinate the design and production activities and estimate the capacity level of the ETO system at an aggregated level. This usage of the archetype can fill the research gap of the aggregated level planning.

Since no archetype has been developed for an ETO system, its absence can be attributed to several complex factors inherent in ETO operations. The challenges include ones listed below:

1. **Variation in the type of ETO products:** ETO systems encompass a customisable array of products, ranging from large-scale projects such as oil platforms and construction to medium-scale projects like capital goods manufacturing lines, down to smaller items like artificial limbs and specially designed machines. Despite falling under the ETO umbrella, the features and nature of these products vary significantly. This variation complicates summarising the main structure of the ETO system (Adrodegari et al. 2015).

2. **The Challenge of Transitioning from Product Focus to Process Focus in ETO Systems**

   The interdisciplinary and process-driven nature of ETO studies complicates the positioning of products within the industrial ecosystem. Unlike standard production systems, ETO systems are characterized by the uniqueness of their design, which makes them distinct from traditional production models (Jiang et al. 2019). A key challenge in ETO systems lies in shifting from a product-focused to a process-focused approach, given the high variability of products (Adrodegari et al. 2015). This process focus, supported by SD, better aligns with the dynamic and complex workflows inherent in ETO systems. This shift is crucial for managing variability and ensuring operational efficiency in ETO environments.

3. **Difficulty in design and production integration:** Additionally, modelling the design processes within the ETO system presents significant challenges that need to be addressed, including how to synchronise the flow between the design and production phases. A design blueprint may demand extensive labour for hundreds of hours, and this blueprint might require adjustments during production to meet customer requirements. The resolution of

such issues remains an area of ongoing research (Hafeez et al. 1996; Wikner and Rudberg 2005).

4. **Difficulty in comprehensively modelling aggregated level planning**: The difficulties in ETO aggregated level modelling can be summarised from three perspectives: model scope, interaction, and assumptions. From the model scope perspective, the modeler needs to deal with the trade-off between the model's conciseness and comprehensiveness (Khanzadi et al. 2018). A comprehensive model, when it is sufficiently detailed, can represent the real production system and capture the dynamic features of the system. However, a detailed model may increase the computational difficulty of the system and that would affect the model's utilisation in the decision-making process. The interaction of the model refers to how aggregate-level models simulate the interactions between departments or elements in the model. In reality, such interactions are usually complex and dynamic; however, in the model, these interactions might be oversimplified. The third difficulty in the aggregate-level model is the model assumptions. Assumptions are necessary for model simplification, but this may also decrease the fidelity of the model. Thus, when modelling an ETO system, the assumptions need to be appropriately determined and designed to ensure that the system is sufficiently real but also not too complex (Lee et al. 2006a).

These reasons collectively explain the absence of an ETO archetype. Therefore, this thesis aims to bridge this gap by facilitating the development of ETO archetypes

1.2.2 Research Gap Two: Foundational Dynamic Analysis of ETO Systems

Dynamic analysis is necessary for a profound investigation of the nature, performance, and mechanisms of a system. Since the early 1980's (Towill 1982), production SD research has contributed to the understanding of the bullwhip effect (Disney et al. 2004), inventory management (Lin et al. 2017), and chaos study (Hwarng & Xie 2008). Underpinned by the CT, researchers have a better understanding of the mechanism regarding how parameters affect the system's performance. Simultaneously, the adaptation of the CT also provides a tool kit for single, dyadic (e.g. vendor managed inventory), and whole production SD assessment, measurement, and improvement (Lin et al. 2020).

Compared to the use of SD in production system research, SD modelling in the PM field is typically utilised as a simulation tool rather than for mathematical dynamic performance analysis (Lee et al. 2005). In PM, models are often employed to explain the effects of design changes (Motawa et al. 2007) or assess the impact of revisions on project timelines (Lyneis and Ford 2007). However, no SD model in the PM field has been analysed using the CT, which limits the understanding of the system's underlying mechanisms and the influence of model parameters.

The dynamic behaviours of the ETO system, which embody both production and project characteristics, are rarely considered and analysed (Barbosa and Azevedo 2018b). This oversight can be attributed to the lack of a unified quantitative ETO model archetype and insufficient research on project dynamics analysis. This research gap has partially motivated this thesis.

1.2.3 Research Gap Three: Resilience Analysis of ETO Systems

Resilience research in the production system field is still at an incipient stage, with even less focus on ETO systems. As mentioned earlier, resilience can be defined as the ability of a system's recovery from the impact of external disturbances (Zarghami and Zwikael 2022). A production system with good resilience should always be ready for uncertainties, respond to changes swiftly, and recover from an abnormal status accurately and promptly (Spiegler et al. 2012). Traditionally, maintaining safety inventory is one way to prepare for uncertainty (Ribeiro and Barbosa-Povoa 2018). When unexpected disturbances occur, the safety inventory can help to buy more time by absorbing the impact, thereby enabling a company to seek solutions. Alternatively, a company may retain excess capacity to respond to the disturbance (Ribeiro and Barbosa-Povoa 2018). However, the cost for these strategies is relatively high. Simultaneously, without appropriate management strategies, when disturbances occur, this extra stock and capacity still cannot help the system to swiftly recover from the disturbance. Thus, to improve the overall performance of the production system in a volatile market, companies need to develop strategies with consideration of the resilience versus cost balance (Purvis et al. 2016).

Research on the resilience of ETO systems is ongoing, and it is evident that compared to more stock-based systems, ETO faces several unique challenges. The inherent design activities and frequent rework within an ETO system create an internal, as opposed to external, environment of uncertainty. Another critical challenge is determining the appropriate amount of production capacity to reserve. The ETO system does not hold any finished products in its inventory because production does not begin until a customer places an order (Gosling and Naim 2009). This feature allows the ETO system to only utilise lead time or extra capacity as the buffer for uncertainties. The challenges outlined above render greater vulnerability to the ETO system when compared to other forms and emphasise the importance of exploring ways to enhance the resilience.

1.2.4 Research Motivation

The unique characteristics of ETO systems, such as high customization, integrated design and production processes, and significant uncertainty, pose substantial challenges to operational efficiency and resilience (Mwesiumo et al. 2021; Reid et al. 2019). Despite the critical importance of these systems in industries like shipbuilding, construction, and capital goods manufacturing, there remain significant gaps in understanding and managing their dynamic behaviours. This research is motivated by the need to address these gaps and provide practical solutions to improve the resilience and performance of ETO systems.

Importance of Aggregated Planning for ETO Systems

ETO systems lack well-defined archetype for aggregated planning due to their reliance on customized processes and unique product configurations. Existing production planning models, designed for MTS or MTO systems, fail to capture the integrated nature of design and production in ETO systems. Developing tailored SD archetypes is essential for enabling better aggregated planning and providing a foundation for both academic research and industrial application.

Need for Dynamic Analysis in ETO Systems

While SD modelling has been widely applied in other production systems (Lin et al. 2017), its use in ETO environments remains limited. Understanding the dynamic interactions between design and production processes is critical for identifying factors that influence performance, such as delays, rework, and capacity constraints. This research seeks to fill this gap by conducting a foundational dynamic analysis of ETO systems, providing insights into their unique behaviours and performance drivers.

Enhancing Resilience in ETO Systems

Resilience is crucial for ETO systems to effectively respond to disruptions, such as fluctuating demand, design changes, and rework. However, resilience research in the context of ETO systems is sparse. Developing strategies to measure and improve resilience will enable organizations to mitigate risks, maintain operational stability, and enhance overall system performance. This research is driven by the need to bridge this gap and offer actionable insights for practitioners.

These motivations form the foundation for the research objectives, which aim to address these pressing challenges and provide both theoretical and practical contributions to the field.

1.3 Research Objectives

Based on the research gaps identified above, the main aim of 'establishing SD archetypes to enhance the resilience of ETO systems' emerges. This aim is divided into three research objectives, based on the three gaps identified. Figure 1.2 illustrates how the main aim emerges at the intersection of these gaps and depicts the alignment of the research questions with the identified gaps.

In summary, the first objective is to build ETO archetypes to provide a CT model which can be used as a quantitative platform for further study. The second objective is to assess the dynamic performance of the ETO archetypes. The third objective is to measure and improve the ETO archetypes' resilience from an SD perspective. The following sections provide more details on each objective.

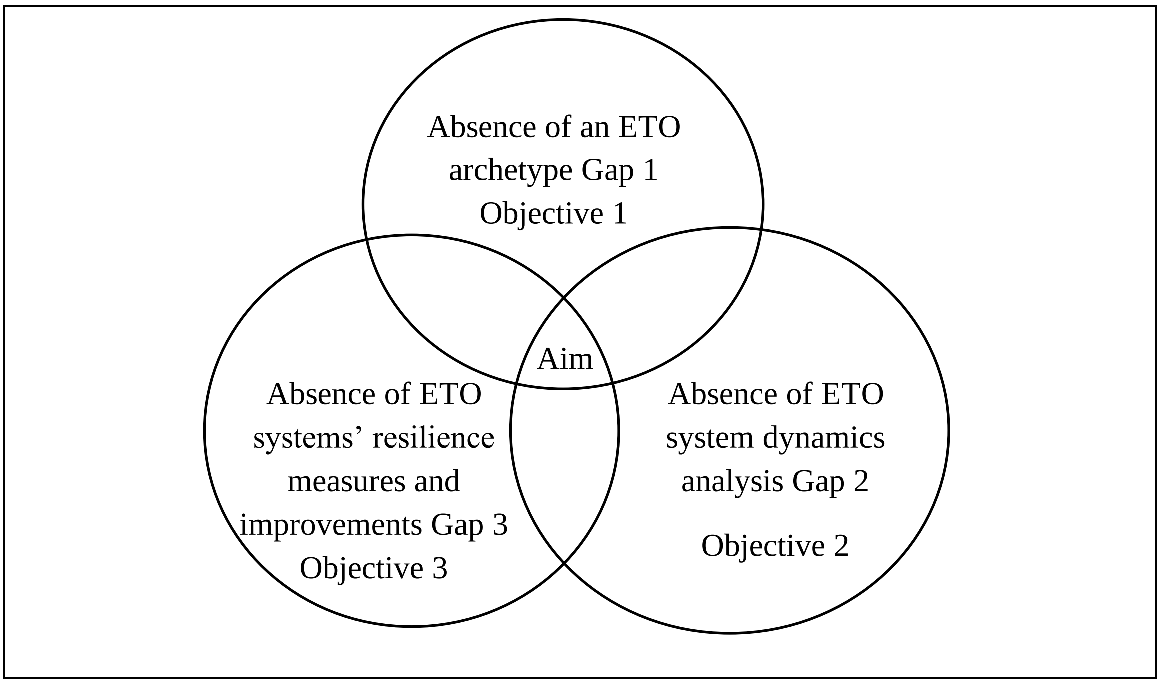

Figure 1.2 Relationship among the research's aim, gaps, and objectives

1.3.1 Objective 1

Objective 1: Build ETO archetypes to provide a CT **model which can be used as a quantitative platform for further study.**

A literature review is conducted to extract the structure, key variables, and main feedback controls of the model. Considering the multidisciplinary nature of the ETO study, pooling concepts and knowledge from both PM and ETO system becomes necessary. This objective was addressed by literature review, production system modelling, and simulation. The intended outcome was the formulation of well-developed system archetypes that can capture and reproduce the key behaviours of ETO systems. This objective can be further divided into the following three sub-objectives.

Sub-objective 1 a): Develop a causal loop diagram (CLD) of a general ETO system.

CLDs are visual representations of the causal relationship among variables. Developing a CLD model is the first step in the archetype's development. The establishment of a CLD is usually based on a literature review; hence, the key variables and the causal relationships are summarised from previous research. The developed CLD can serve as a straightforward illustration for the ETO system and help users to identify any reinforcement and/or balancing loops. The archetype is designed to represent a single company's production system, where design and production processes are seamlessly integrated.

Sub-objective 1 b); Transform the CLD into a block diagram using discrete time, z-domain notation.

This sub-objective transforms the qualitative CLD model into a quantitative CT block diagram representation formulated through difference equations. Subsequently, this model will be converted into z-transform notation, leveraging dynamic analysis tools. Unlike the CLD, the block diagram model enables researchers to apply mathematical formulas to describe the system, thereby allowing for the quantification of variables and the development of an overall mathematical transfer function equation. This facilitates cross-checking the logic with the originally developed CLD model and through SD simulation.

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1.3.2 Objective 2

Objective 2: Assess the dynamic performance of the ETO archetypes.

For this objective, a comprehensive dynamic analysis of the ETO archetypes is undertaken, which encompasses stability analysis, frequency domain analysis, and sensitivity analysis. The findings from these analyses will enhance the understanding of the newly developed ETO archetypes and illuminate the effects of various parameters on system performance across different demand patterns and environments. The insights gained from addressing objective 2 will enrich the body of knowledge by establishing a robust foundation for further selection of ‘good’ system parameters.

Sub-objective 2 a): Verification and transfer function analysis.

This sub-objective involves conducting verification and transfer function analysis of the archetypes. Before the models are analysed by other methods, researchers must guarantee the accuracy of the model. The correctness in this section refers to the logic and mathematical correctness of the model. For verification, a triangulation method has been adopted. Triangulation refers to a cross-checking technique which requires users to replicate the model's behaviours on multiple simulation platforms and cross-check the results. In this research, the model is simulated in Excel and Simulink, with a transient deterministic step change input. Only if the transient responses visualised by all simulations provide reasonably the same output, then the model is qualified to be used as a foundational archetype.

To further guarantee replicability, the transfer function cross-checking will also be used for model verification exploiting MATLAB. The derived transfer function will be used to reproduce the transient responses and cross-check the output with the simulation results. The archetypes model will be employed for further study and investigation only if the transfer function results match reasonably with the simulation. The analysis for this sub-objective is undertaken using deterministic transient responses. In addition, the initial/final value theorem is implemented based on the transfer function.

Sub-objective 2 b): Determine how the ETO archetypes perform under different frequency inputs.

Frequency domain analysis has been widely used in studies on the bullwhip effect in the production control field (Sarimveis et al. 2008); this analysis illustrates how the system's magnitude and phase changes along with the demand frequency. This method has been proved to be useful in capacity and inventory management (Lin et al. 2020). In the ETO context, frequency domain analysis can contribute to capacity management and provide an insight on how system parameters affect a system's performance under different demand frequencies.

Sub-objective 2 c): Define the critical stability boundary of the ETO archetypes.

Stability is a core requirement for a system. Without stability, the system's output will be highly fluctuating, which may dramatically increase the operational costs for the ETO company. Thus, stability analysis is necessary for the study of the archetypes, which will provide critical stability conditions for the ETO archetypes. This sub-objective aims to derive the critical stability boundary of the ETO archetypes, with consideration of the rework ratio and the lead time effect of the subsystem.

1.3.3 Objective 3

Objective 3: Measure and improve the ETO archetype's resilience from a SD **perspective**

The third research gap emphasises the importance of resilience in the ETO system. Therefore, objective three is designed to explore methods to enhance the resilience of the ETO system by optimising the parameter settings of the developed ETO archetypes. This exploration will lead to the development of practical guidance, bridging the gap between theoretical frameworks and practical application. The results from this objective will contribute to the body of knowledge by offering a methodology for resilience improvement and providing practical insights for managing ETO systems. The step change is used as an input to simulate disturbances occurring in the ETO system. It represents an abrupt and significant change, placing the system in extreme conditions to evaluate its resilience. While a step change may not fully capture the complexity of real-world disturbances, it serves as a standardized tool for testing the system's response to extreme scenarios and assessing its ability to recover from disruptions.

Sub-objective 3 a): Select a suitable resilience index for the ETO archetype.

This objective focuses on investigating the origins and development of specific resilience indices. By conducting a thorough literature review on various resilience measurement indices, a comprehensive analysis will be performed, thereby enabling these indices to be categorised into distinct groups. This categorisation will serve as a toolbox for subsequent steps in the research.

Based on the review of the resilience index, a suitable index that can be adopted for block-diagram model resilience measurement will be selected. Thereafter, this index will be adopted to measure the resilience of the system. This adaptation extends the ETO archetype's usage into resilience research and provides an effective means to test the resilience improvement strategy's effect on the ETO system.

Sub-objective 3 b): Select decision rule parameter settings to achieve the ETO archetype's best resilience.

Based on the developed archetype and selected index, this research will attempt to select 'good' parameter settings for the system to achieve its highest level of resilience. Considering that the ETO archetype transfer function modelling may yield a high-order system, this objective will primarily consider simulation-based tools to achieve this objective. The outcome of this objective can lead to the provision of managerial suggestions on how to improve resilience by changing the parameter settings in the production system decision rule.

Sub-objective 3 c): Result synthesis for a 'good' parameter selection

The results from stability analysis, bode plot analysis, and resilience analysis provide different suggestions on parameter selection because these three analyses focus on different aspects of system performance. Therefore, to offer comprehensive recommendations on tuning the production system's parameters, an analysis of the synthesis results from different chapters is conducted. The aim is to determine how to effectively establish the decision parameter(s) value and how to implement this concept in practice.

Sub-objective 3 d): Assess the ETO archetype's sensitivity to parameter uncertainty

Sensitivity analysis can be used to test how the system would react to parameter uncertainties (Towill and Mehdi 1970). In practice, physical system parameters—such as design or production delays or rework rates—may often be wrongly estimated. If so and the system is highly sensitive to parameter estimation, there may be a huge impact on the system's dynamic response. In such circumstances, sensitivity analysis can play a role in identifying which parameters the system is sensitive to by examining which factor's or parameter's change has the greatest influence on the system. With this information, the selection of a 'good' decision rule for parameter settings may be judged not merely for a specific output metric but also for how large the variance in the output is when a physical parameter varies from the expected value. Moreover, considering the ETO as a two-echelon system, it is worth observing how an individual design or production subsystem's parameter change affects the entire ETO system.

1.4 Road Map

Chapter 1: This introductory chapter provides the background of this study, explains the research gaps and motivation for this thesis. Thereafter, it presents the research objectives and questions to define the scope of this study. Moreover, Chapter 1 also provides a roadmap for the subsequent research, which can be used a guide to this thesis, with Figure 1.3 providing a visual roadmap.

Chapter 2: This chapter undertakes a literature review that is divided into three sub sections: 1) Reviewing the definition and development of ETO systems, with a particular focus on the CODP; 2) Reviewing the SD method's application in general and specifically for ETO systems; 3) reviewing the development of resilience in production. This chapter provides a foundation for this thesis. The outcome of the literature review will finally be used in model development, model analysis, and resilience study.

Chapter 3: This chapter outlines the methodology used in this thesis, which encompasses ontological and epistemological positions, research design, and research methods. This chapter also justifies why SD modelling, CT, and simulation are selected as the main methods for this research. At the same time, this chapter explains how each method will be adopted in this thesis.

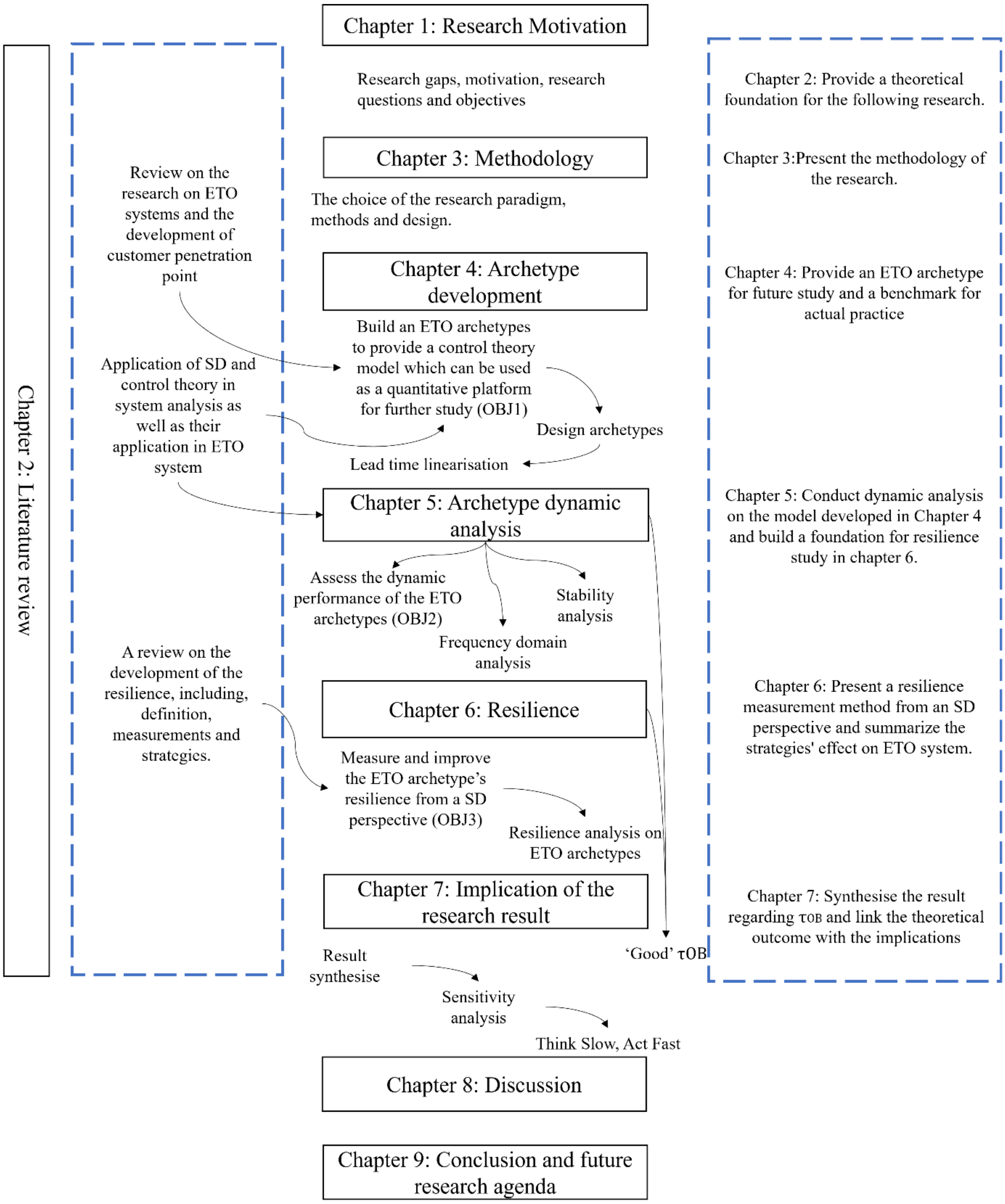

Figure 1.3 Thesis roadmap

Chapter 4: This chapter develops the ETO archetype based on the findings from Chapter 2, beginning with the CLD and then transforming to the block-diagram model, followed by its further development into transfer function models. Given the fact that ETO systems include design and production subsystems, coupled with the existence of rework, the chapter also discusses where and how the rework may occur within the ETO system and how it can be represented within the model. Next, it investigates the measure via which the controller should be set to maintaining the lead time and order book at the desired level. In this experiment, a transient response of the model under a step change input is visualised to see whether the target variable can settle down at the targeted level after a step input. Furthermore, as the lead time is a nonlinear function, a linearisation technique is adopted to aid the development of a transfer function. The outcome of this chapter is a well-developed ETO archetype family rather than any one generalisable archetype. Moreover, the models developed in this chapter are a foundation for the following research, whilst simultaneously addressing Objective 1.

Chapter 5: This chapter presents a dynamic analysis of the newly developed ETO archetype family. To guarantee the accuracy of the developed archetype, the triangulation technique is adopted to verify the model by examining whether the results from difference equation simulation (Spreadsheet), Simulink simulation, and transfer function simulation are all reasonably the same. To maintain the consistency with the previous experiments in Chapter 4, the input for all simulations is a deterministic step change input.

After the model verification, two specific techniques are utilised to analyse the archetype's dynamic performance: 1) Frequency domain analysis: This technique assesses the archetype's performance from a frequency domain perspective. A Bode plot is generated to evaluate how the system's magnitude and phase shift in response to changes in demand frequency. 2) Stability analysis: Given that this research models the system in a discrete time framework, introducing a one-unit delay results in an increase in the system dimension, thereby, complicating algebraic calculations and potentially leading to errors in the stability analysis. To address this, two methods are employed: For low-order models (where the characteristic equation's order is below four), the pure Routh-Hurwitz method is utilised, which provides accurate results. For higher-order models (where the characteristic equation's order exceeds three), a hybrid method is used to identify the stable region.

Chapter 6: This chapter discusses the meaning of resilience for an ETO system and established the integrated time and absolute error (ITAE) as the main index for resilience. To have a universal method to test the resilience performance of the ETO archetypes, the parameter space exploration (PSE) method is utilised and the model subsequently analysed is a high-order system with an eighth dimension. Therefore, the results present the change in the resilience along with the parameter setting and present a calculation of the best proportional controller value to achieve the system's best resilience under different rework ratios. The research outcomes can potentially assist the managers to create a capacity adjustment plan when the rework ratio of an ETO system is known and steady.

Chapter 7: This chapter aims to bridge the gap between research outcomes and real-world practice. This chapter comprises three subsections. Section 7.1 synthesises the research results regarding system parameter settings. Section 7.2 conducts a sensitivity analysis on the developed system with the recommended parameter settings. Finally, Section 7.3 presents an adaptation of the developed archetype in the 'Think Slow, Act Fast' philosophy.

Chapter 8: This chapter discusses all the findings and insights from the thesis; this chapter contains four sub sections, with each section focusing on one chapter.

Chapter 9: This chapter 9 provides a summary of this thesis along with a future research agenda for prospective study.

1.5 Summary

The above was an introduction to the background of this thesis as well as to how the inadequacies in the current research provided motivation for developing this project. The ETO archetype family development, SD analysis, and resilience measurement and improvement form the main structure of this thesis. At the end of this chapter, a road map is provided to demonstrate how each chapter addresses the specific research objectives.

Chapter 2 Literature Review

This chapter provides a literature review on the three core topics of this research project, namely ETO systems, SD analysis, and resilience. Both quantitative and qualitative literature is reviewed to provide a comprehensive view of the ETO system. Since quantitative studies are still at their incipient stage of exploration, research papers are collected from both qualitative and quantitative perspectives.

This review contains four major sections. In Section 2.1, there is an exploration of ETO systems, aims to provide an overview of the development of the ETO system, subsequently developing an understanding of their main structure. Section 2.2 reviews the development and application of the SD and CT in production system management. Section 2.3 reviews previous papers related to the production system resilience measurement. Section 2.4 provides an overview of the concept ‘Think Slow Act Fast’, which is believed to mitigate the impact of rework.

The outcome of this chapter is that it provides a foundation for the subsequent chapters. Sections 2.1 and 2.2 extract the main features of the ETO system, thereby providing a reference point for SD analysis. The findings from Sections 2.1 and 2.2 are used in Chapter 4 and they also contribute to Chapter 5. Section 2.3 contributes to Chapter 6 by providing a background for resilience study and measurements. Section 2.4 provides a review of the ‘Think Slow Act Fast’ philosophy, which can be used in rework effect mitigation in an ETO system.

2.1 ETO Systems

This section reviews the literature on ETO systems, providing a theoretical foundation for the subsequent research. This section also identifies key themes, including the definition of ETO, the role of the CODP, and the impact of rework and non-conformance in ETO processes. By exploring these elements, the review establishes a contextual understanding of how ETO systems operate and the challenges they face in balancing efficiency, flexibility, and resilience.

2.1.1 An Overview of the ETO System

Definition:

The ETO system can be defined in the following manner:

'*Engineer-to-order (ETO) is characterised by high levels of customisation for each product and is typically managed in a project environment, with the decoupling point at the design stage*' (Gosling et al. 2013, p. 552).

As has been previously introduced, ETO is a unique production system that does not require holding of any stock and requires customer engagement in the designing stage. Therefore, it has increasingly attracted attention from both PM and SCM fields in the last three decades (Gosling and Naim 2009). According to the definition, two core activities are included in ETO: design and production.

Design:

The ETO system is marked by its unique complexities, particularly in integrating design and production processes to meet highly specific customer requirements. However, one of the persistent challenges in ETO research lies in defining the depth of design involvement and its implications for production. Hicks et al. (2000) highlighted the difficulties in coordinating procurement and design in low-volume, highly customized products, emphasizing the interplay between tendering and production functions. Porter et al. (1999) underscored the variability in how deeply customer specifications influence the design stage, a feature that sets ETO apart from other production systems. Olhager (2003) examined ETO systems within the Order Penetration Point (OPP) framework, where the positioning of customer engagement significantly impacts operational efficiency and delivery. Hameri (1997) further noted that effective communication and configuration management are essential to manage this depth of design and ensure alignment with customer expectations. Due to the inclusion of design in the production process, ETO systems often raise confusion when compared to Design-to-Order (DTO) systems. Wikner and Rudberg (2005) explored the differences between these two systems and reviewed various perspectives on their definitions. To clarify the distinction, they proposed a new categorization method for ETO systems based on the position of the CODP. They suggest three categories of ETO systems:

Engineer-to-order type of engineer design (ETO_{ED}): This design is created based on the customer's order.

Adopted-to-order type of engineer design (ATO_{ED}): This design is adapted from a previous design.

Engineer-to-stock type of engineer design (ETS_{ED}): The design utilises an already existing design.

Gosling et al. (2017) further develop this categorisation and categorise ETO systems into the following types: 1) Research for design refers to the design required for research and development (R&D) activities. Such types of projects provide customers with a bespoke tailoring service, with a unique and first-of-a-kind design that usually requires a time-consuming and expensive formulation. 2) Codes and standards design refers to designs for integrated codes or standards. This group also includes those unique designs that use codes and standards as a starting point. Compared with the first kind of service, this group of ETO systems provide limited design services. 3) Existing design includes those projects that use existing designs, drawings, and subsystems as the starting point.

Production:

The production process in the ETO system can be regarded as a make-to-order (MTO) system, wherein no finished products are in stock, and production can only begin after the order is placed (Zhou et al. 2022). The significant difference between ETO and MTO is that the rework in ETO systems cannot be ignored. This is because, for ETO service providers who allow customers to tailor their product design, doing everything right the first time is ideal but impossible (Neumann et al. 2022; Han et al. 2013). The existence of the rework dramatically increases the complexity of the ETO system, which can be attributed to 1) rework that may occur at any stage, 2) the detection is occasionally not on time, and 3) these issues lead to new dynamic behaviour showing up in the system.

The ETO systems are mainly adopted in shipbuilding, construction, and capital goods manufacturing industries. In the shipbuilding industry, the ship itself can be regarded as a highly customised ETO product; moreover, components such as sonar systems, tank measuring, and electric power systems are also ETO products (Mello et al. 2017). Alfnes et al. (2021) conducted a study on these ship-related products and the systematic factors that create uncertainties in these production system. The research by Kristianto et al. (2015) developed a system-level configuration approach and a prototype that could improve the performance of the ship’s engine room production. In the construction industry, researchers from PM backgrounds provide a solid foundation for ETO study. However, it should be noted that not all construction can be regarded as ETO products. Only those companies that integrate design with the building process can be categorised as ETO. Ding et al. (2022) conducted a focus review on the modular medical and quarantine facilities and introduce the process and technologies adopted in the construction of these facilities. Gosling et al. (2013) explored the factors that affect the adaptability of the building and develop a CLD to demonstrate the adaptation system. In the capital goods manufacturing industry, Adrodegari et al. (2013) investigated the main weaknesses and strengths of the one-of-a-kind production system, and propose a framework for the specific purposes of the machine industry to guide the practice in multi PM planning and control.

With the increasing demand for high-performance and more innovative productions, there is an increased demand for high-value and highly customised and intelligent production systems

(Müller and Voigt 2018). This new demand challenges the traditional production system research and provides a valuable opportunity for ETO system development. ETO system practitioners also confront several challenges, which can be summarised in the following manner: 1). How to provide the appropriate design service to customers considering cost and customisation degree? 2) How to guarantee the production quality and deliver the products on time when producing a one-of-a-kind and even first-of-a-kind items. 3) How can the capacity for both design and production systems be estimated, and how can the system's flexibility and adaptability to various demands and disturbances be improved? 4) How can the downstream production system for the ETO company be managed, and how can the labour force be synchronised with the material supply? These questions that tend to arise as common difficulties in the ETO system shall be duly addressed in the thesis.

2.1.2 ETO and CODP

CODP: A new way of categorisation

One of the most important concepts that act as a distinguishing factor between different types of production system is the CODP (Gosling et al. 2017). Sharman (1984) defines the CODP as the point at which product specifications typically become frozen and as the last point at which inventory is held. For the periods before or after CODP, the company can set different targets and apply various strategies to balance the trade-off between customer service level with operation cost (Olhager 2003). For example, for the pre-CODP period, the company may use a push strategy to manage the inventory to stabilise the production rate, thereby reducing the cost entailed by production fluctuation. For the post-CODP period, the company may adopt a pull strategy; the shipment of products occurs after the customers place their order, thereby reducing the cost from the inventory and improving the utilisation of facilities. Intriguingly, the introduction of the CODP point provides a new research stream for production system management. It also provides a categorisation method for all production system, as presented in Table 2.1.

Although there are many variants of CODP such as customer order penetration point (Cannas et al. 2019) or order penetration point (Olhager 2003), but within this thesis, the terminology CODP is adopted at all places.

Table 2.1 Production system categorisation based on the CODP.

System Type	***Original reference***	***Typical CODP Location***	**Feedback Path**	**Feedforward Path**	***Flow***	***Main analysis technique***
MTS	(Towill 1982)	Finished stock	Inventory	Demand	Material	Laplace transform
ATO	(Lin et al. 2020)	Sub-assembly	WIP Inventory Backlog	Demand	Material	Laplace transform
MTO	(Wikner et al. 2007)	Raw materials	Order Book WIP	Demand	Material	Simulation
ETO	This paper	Design	Order Book	Demand	Work Unit	z-transform

Table 2.1 presents the production system categorisation based on CODP. Herein, the penetration points shift from downstream to the upper stream from top to bottom of the table, which also implies the customers’ engagement with the production system is deepened from top to bottom. MTS refers to a production system where the CODP is situated at the distribution stage and the customer is not engaged in the production system. An example of this is mass

production, which was first adopted by Henry Ford (Duguay et al. 1997). ATO refers to the production system which holds components in the inventory, and the company assembles the components after the customers' orders are placed. Typical examples for such manufacturing industries' goods are personal computers and washing machines (Ceryan et al. 2012). MTO represents a production system that produces the products after the customers' order is placed. Typical industries include personalised capital goods manufacturing and specially designed machines (Sahin & Robinson 2005). ETO, as the most unique case, is defined as a production system wherein the CODP point is situated at the design stage itself, thereby facilitating customer engagement right from the design stage and leading to customised designs with bespoke requirements—for example, in industries associated with ship building (Mello et al. 2017), special designed capital goods (Yang 2013) and construction (Naim et al. 2021).

The introduction of the CODP concept provides researchers with a new method to analyse production systems, thereby providing a valuable categorisation method for the production system study. Based on this, CODP can also be used as a positioning tool, which lets users easily locate the production system type among all categories; these benefits promote knowledge sharing and development in the production system study. From the practical perspective, CODP can assist managers in having an awareness of what kind of environment they are in and what type of production system they are managing. With this information, managers can develop suitable strategies with a particular focus on their production systems by referencing relevant research and previous experience.

As mentioned in the previous paragraphs, CODP is a valuable tool for both researchers and practitioners to position their production system and design different strategies for the pre-CODP and post-CODP period. It is important to remember that although ETO systems contain a common thread of design in their service, they belong to a diverse set of industries. Therefore, a single definition is an insufficient representation of the ETO system. Thus, the ETO system needs to be further defined to clarify the research scope of this project. To achieve that clarity, the CODP concept is a useful measure coupled with a special focus on the design.

As mentioned above, Gosling et al. (2017) introduce and summarise the typical activities in the ETO system and further classified ETO systems into three groups. This research gives us a deeper and more comprehensive understanding of ETO industries, which can benefit researchers through a refined and complete ETO category. By using the refined ETO category, Cannas et al. (2019) upgrade the CODP concept to a 2D form map, which uses engineer design processes on the y-axis and production processes on the x-axis, each point representing a kind of ETO system, with different depths in design and production. The users can position their business in this figure, thereby modifying and improving their production system management by extrapolating their experience with similar production systems. This is suggestive of managers potentially designing their management strategies depending upon both the design penetration point as well as the production penetration point. Importantly, the different combinations of design and production penetration points have different resource and capacity management requirements.

The shifting CODP

The CODP is not always situated at the same place; the CODP may shift downward when the business becomes increasingly mature (Olhager 2003). For example, if certain designs are frequently used as a primary platform for further modification or as a core component of the customers' demand, they could be packaged and modularised by the company to mitigate the cost and lead time from the design stage (Gosling et al. 2013a). According to the categorisation in the previous section, the production system changes from a 'research-to-order' type production system to a 'standard and code to order' production system. Apart from unintentionally shifting the position of CODP in the production system, the management may bring about an intentional positional change to cope with the strategies and targets for the market. For example, the company could shift the CODP point upward by introducing the ATO concept to traditional MTS production systems to provide greater freedom-of-choice and interactions with the customers (Gosling et al. 2017). On the contrary, if the company wants to improve the utilisation of the facility and reduce the number of SKU numbers, then the CODP is moved downward, which will reduce the variety of the products and, thus, reducing the hurdles in inventory management (Gosling and Naim 2009). The concept of shifting the CODP not only provides strategic foundations for the production system researchers and managers, but also provides a dynamic view to the production systems. By holding this dynamic view, the management could better adjust their strategies to adapt to the changing environment and the changes that occur within the production system.

Apart from the research that stems from the production system field, Adrodegari et al. (2013) developed a one-of-a-kind production framework to demonstrate the production process of special design machine industries (capital good products), thereby highlighting the critical role of information and communication technologies (ICTs) in ETO environments. Wang et al. (2016) designed a domain model of the service system, which could be used for facilitating computer assistance and human-centred decision-making. Bajomo et al. (2022) provides an SD model which simulates the material management system of the engineering, procurement, and construction (EPC) industry and reproduces the dynamic behaviour of material volume.

2.1.3 Non-conformance and Rework

Non-conformance is a common issue in the construction industry. It is defined as “something that has not been executed in accordance with the design, specifications, or works information contract” (Ford et al. 2023). Moreover, in some research, non-conformance can also be termed as defects or errors (Love et al. 2019). Non-conformance usually leads to cost- and time-overrun due to extra rework and rectifications. In a few extreme cases, non-conformance may finally result in project failure (Taylor and Ford 2008). Occasionally, the company can combat non-conformance via rework or simply accept its existence as a compromise on the quality, as depicted in Figure 2.1. In the ETO environment, non-conformance also exists due to the first-of-a-kind nature of ETO systems (Zhou et al. 2022). Non-conformance may appear in the design and production periods; these resulting issues usually require extra work in terms of the rectification of the errors or the defects, which are generalised as rework.

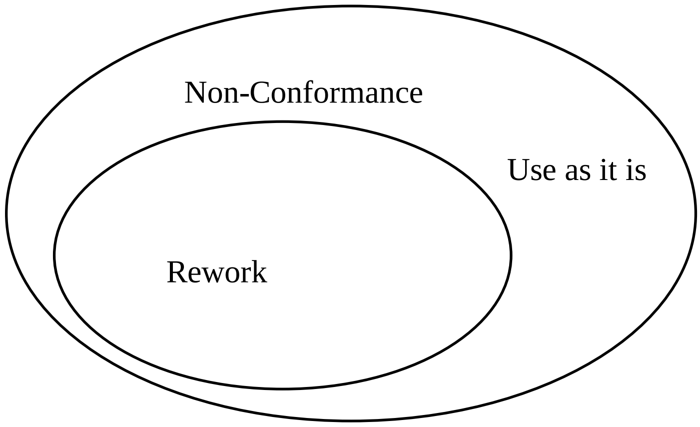

Figure 2.1: Relationship of non-conformance and rework [source: Author's own work]

Rework—which refers to the extra work that is created by errors, defects, and/or changes, has been well studied in construction field. According to the research conducted by Love et al. (2002), rework occupies 12.4% of the total contract cost, on average; however, Love and Edwards (2004) postulate the range of rework costs to be from 3% to 23% of the contract price, which makes companies suffer a huge loss in the construction industry. Such a difference in opinions could be a consequence of the varied craftmanship levels and project complexity. But it can be observed that rework occupies 13% of the total cost, on average, which may directly reduce the profit of the project. This contention has made rework reduction and rework management research a major topic of discussion within the construction industry in the last 25 years (Love et al. 1999), with the problem continuing to plague many companies.

However, in transitional production system, rework is poorly represented. The reason for this is that, typically, within the traditional production system environment, the aim is to eliminate unqualified products (Dabhilkar & Åhlström 2013), thereby minimizing waste. In contrast, in the PM scenario, rework is an inevitable issue, with researchers and practitioners reaching an agreement that doing everything right the first time in a project, particularly for a mega project, is not only impossible but also costly (Love et al. 1999). Thus, it becomes imperative to learn how to manage rework at a lower level and, subsequently, develop rework management strategies that can contribute to feasibility and cost effectiveness in PM (Love et al. 2019).

Hence, although, rework is typically considered a waste, but in the ETO environment, rework is equivalent to an inevitable necessary evil. There are several reasons for this. First, the design process usually involves multiple rounds of communication and modifications before it is sent to the production department. These changes and modifications create additional work for the design team (Strandhagen et al. 2018). Second, every new design, due to its unique nature, adds complexity and difficulty for the production department (Seth and Rastogi 2019). The aforementioned factors pose significant challenges to the attainment of the 'right first time' paradigm, thereby necessitating a proactive approach towards rework management in an ETO system (Barbosa and Azevedo 2019).

According to extant literature, rework can be divided into two groups; Design rework and production rework (Lee et al. 2006a; Park et al. 2011; Han et al. 2013). Design rework refers to the rework that is attributed to the design defects or change; however, the detection of these defects made by the customers is not always timely. In certain cases, the detection of design errors occurs in the production stage. In such circumstances, the rectification of the non-conformance requires efforts from both the design and production department, and the subsequent production may need to be postponed while awaiting the completion of the rework. According to Love et al. (1999), most of the rework can be tracked back to design defects, with the design rework being one of the largest contributors to cost and time overruns. Thus, design defects and errors, including the design changes introduced after production has begun, should be possibly controlled at the lowest level. Production rework refers to a scenario in which the production stage is riddled with defects and faults. Such problems are usually caused by the simultaneous issues of material management and poor craftmanship (Ford et al. 2023), which can be attributed to the complexity of the project (Love et al. 1999) .

The influence of non-conformance can be categorised into direct and indirect groups. Direct consequence refers to the extra cost and resources spent on rectification. To fix the errors and defects, the project manager has to schedule extra work with the implementation team and extra materials need to be purchased. If the detection of non-conformance occurs after the follow-up work, the management needs to face a demolition and rework scenario. In this case, more work needs to be spent on rectification. The indirect consequences can be summarised into the following aspects: 1) Overtime works—since the rework needs to be done as soon as possible, the managers often face difficulties related to labour shortage, and one of the common solutions to this is to ask workers to work overtime (Chritamara et al. 2002; Park 2005). However working overtime may not be entirely free of negative consequences, such as pressure on the workers, safety issues, and morale (Zhou et al. 2023), which may lower the morale for the entire project. Love (2003) developed an SD model which illustrates how the rework affects the whole system and found that the effect of the rework will eventually be exaggerated as the knock-on effect, with the consequence not always being time or cost but, occasionally, project failure as well.

To mitigate the rework in the project, the company needs to dig out the root causes of the rework, instead of focusing on the superficial. Therefore, it is essential to attend to the root causes for rework, which may be summarised in the following manner: 1) Human error—humans make errors, which usually manifest as wrong installations and wrong implementations. The engagement of the human labour in a project, particularly a construction project, is relatively high and that makes rework an inevitable issue in PM (Taofeeq et al. 2020). 2) Poor skills and craftsmanship—the poor skills of the workers can also be one of the main contributing factors towards rework. In certain companies, the percentage of fresh workers is rather high, which implies that the workers are often inexperienced and lacking training (Akkermans & Vos 2003). This could potentially lead to a high rate of non-conformance, which eventually manifests as a high rework rate. Intriguingly, the project may require some time to recruit more people for the fulfilment of the capacity and labour shortage caused by rework, thereby resulting in a vicious cycle where the recruitment leads to another batch of fresh workers (Lyneis and Ford 2007). This invariably increases the rework rates due to the formation of a cycle, or rather, a negative reinforcement loop in the project, which increases both the lead time and the costs (Lee and Peña-Mora 2007). 3) Supplier errors—this is yet another root cause for rework. The products provided by the supplier may contain quality issues or may be lacking in the standards and specifications of the project. In such cases, rework is necessary to replace the components provided by the supplier or improve the quality of products by other means to make them meet the desired standards (Barbosa and Azevedo 2018b).

As mentioned above in previous sections, in the other kinds of production system, rework is usually considered as waste and seldom considered in the production system modelling. While for an ETO system, because of its one-of-a-kind project orientation and high human engagement features, rework must not only be considered but rather be managed well through ETO system modelling in the actual practice (Love et al. 2002). Additionally, in typical ETO industries, like construction and shipbuilding, the rework analysis has diverged to pave the way for a new research direction (Papachristos et al. 2020b; Ecem Yildiz et al. 2020), which further substantiates its importance in the manufacturing and production system operations. The above reasons make rework a distinguishing feature indispensable to the ETO system.

2.2 Application of SD in the ETO Field

This section reviews the application of the SD approach in the ETO area, with a special focus on both the production system and PM fields, to comprehensively summarise the models that have been developed in this area. The reason for broadening the research scope to include PM is because, as a multi-disciplinary field, the terminology of the ETO has not been determined and unified, which results in certain researchers using different words and terms to describe the ETO system—for example, bespoke projects, highly customised products etc.

2.2.1 An Overview of SD and CT

SD was developed in the mid-1950s by Forrester (1958) and has been widely used as a simulation method in production system management and PM (Lyneis 2012; Wikner et al. 2017). By simulating the causal relationships among quantified variables, SD combines the advantages of conceptual systems thinking with mathematical formulation, providing a platform for designing solutions to problems.

SD is widely used in production system management, such as inventory control, lead time analysis, and ordering policies development (Lin et al. 2020). Multiple effective and efficient models are developed based on SD, such as the IOBPCS family (Wikner et al. 2017) which have been adopted in multiple production system but not yet for ETO systems. Adopting SD in production system design helps managers to understand the potential variability induced by internal systems structure and internal and external disturbances. Hence, SD provides management with a policy testing platform to determine stock holding, lead-time, and capacity level requirements (Wikner et al. 2017).

SD also plays a decision support role in PM, especially in construction. Compared with the production system quantity-oriented applications, most SD in PM are process-oriented (Lee 2006; Shafieezadeh et al. 2020). SD has been adopted in most project phases, covering aggregate level planning (Huang and Wang 2005), pre-construction planning (Lingard and Turner 2017), project execution (Alvanchi et al. 2011), and post-delivery (Hao et al. 2007). SD is used in national macro real estate regulation (Huang and Wang 2005), policymaking (Park et al. 2011), and execution from the management level (Lee et al. 2006), which enables SD to become a potential bridge to connect PM and production system management.

Because of SD's excellent scalability, more and more SD-based hybrid simulation modelling approaches have emerged, such as SD-Agent Based Modelling (SD-ABM) (Barbosa and Azevedo 2019; Papachristos et al. 2020b) and SD-Discrete Event Simulation (SD-DES) (Shin et al. 2014; Goh and Askar Ali 2016). Such amalgamations extend the application range of the models and improve their fidelity, which shows greater potential for their adoption in a complex system simulation and modelling.

The application of the SD in the production system has been reviewed by several authors (Lin et al. 2017; Rebs et al. 2019) whilst not much research has been undertaken on the SD approach in the ETO field. Therefore, to explore the application of SD and CT in the ETO field, the given research project adopts a review. Within this the four-step process and guidelines as proposed by Seuring and Gold (2012), namely, (1) Material collection and filtering, (2) Descriptive analysis, (3) Category selection, and (4) Material Evaluation are followed.

2.2.2 Literature Review Process

The literature review on SD and CT’s application in ETO field is composed of four steps: Material collection, Descriptive analysis, Categorisation selection and Material Evaluation. Figure 2.2 is provided to illustrates the process of the review.

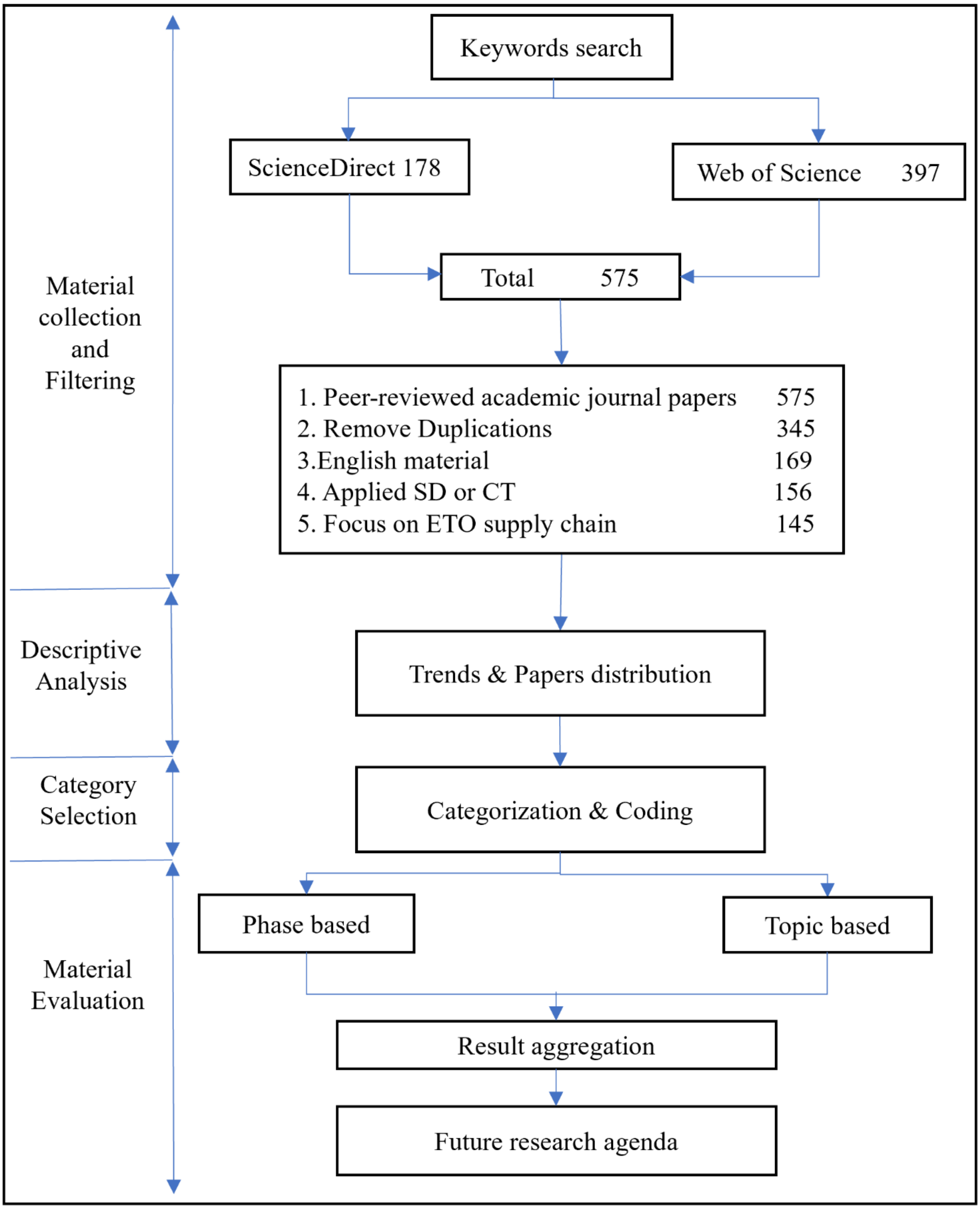

Figure 2.2 The literature review process

Material Collection: This review includes research that adopt SD and CT in modelling ETO projects, to provide insights into the status and development of these methods, thereby addressing Research Questions 1 and 2. The reason for focusing on SD and CT is that, while there have been more generic ETO system literature reviews (Gosling and Naim 2009; Cannas and Gosling 2021), there has been no review focused on those specific methods. After preliminary research, it was found that those systems-based approaches are widely used in both fields, hence potentially providing a bridge for knowledge sharing between PM and Production system Management. Although the focus of this review is placed on the quantitative SD and CT techniques, there is also research aiming for developing qualitative research adopted soft system theory and system thinking (Naim and Gosling 2022). However, such methods are beyond the scope of this study.

Given the consideration that terminology in PM and SCM might be different, the Key Word Search method adopted dealt with two mainstream academic databases "Web of Science" (WoS) and "Scopus," thereby comprehensively sampling papers across a range of journals and related disciplines. The keyword-setting process went through two iterations to collect papers precisely and comprehensively, as shown in Table 2.2, which also explains the rationale for redefining the terms of the keywords. The final keyword terms were determined and are presented in Table 2.3. Because of the limitations of character representations in the Scopus and WoS databases, four search terms combinations were utilised in Table 2.4. To narrow down the scope and focus on the SD and CT applications in ETO fields, five exclusive criteria were adopted which are listed in Figure 2.2. The first and second criteria guarantee the material's quality and readability, and the third criterion limited the scope prior to November 2023. The fourth and fifth criteria exclude papers that were irrelevant to the study. 575 papers were identified by exploiting the search terms combinations, and five filtering criteria were used to ensure adequate scope, as listed in Figure 2,2 yielding 145 articles that were then the subject of the analysis.

Table 2.2 Keyword setting process

Keywords combination	Reasons for choosing	Reasons for changing
"engineer to order" AND ("system dynamics" OR "control theor*" OR "control engineer*")	1. Narrow down the scope to ETO and SD. 2. Control theory is the mathematical foundation for SD.	1. Sample size is too small because the terminology has not been unified in ETO fields.
("construction industry" OR "construction management "OR shipbuilding OR "engineer to order") AND "supply chain" AND "system dynamics. "	1. Construction and shipbuilding belong to the ETO field. 2. Adding the Keyword "supply chain" because the research scope is limited to the supply chain management field.	1. ETO is Interdisciplinary; limited scope on the supply chain will miss the process-oriented nature of ETO products.

Table 2.3 Final version of searched keyword combinations

Application or Problems	Methods
construction sector	system dynamics
construction industry	system dynamic
shipbuilding sector	project dynamics
shipbuilding industry	control theory
engineer to order	control engineering
one of a kind	
first of a kind	

Table 2.4 Keyword combinations used for searching databases

("construction sector" OR "construction industry") AND ("system dynamic" OR "system dynamics" OR "project dynamics" OR "control engineering" OR "control theory")
("capital goods") AND ("system dynamic" OR "system dynamics" OR "project dynamics" OR "control engineering" OR "control theory")
("shipbuilding sector "OR "shipbuilding industry") AND ("system dynamic" OR "system dynamics" OR "project dynamics" OR "control engineering" OR "control theory")
("engineer to order" OR "one of a kind "OR "first of a kind") AND ("system dynamic "OR" system dynamics" OR "project dynamics" OR "control engineering" OR "control theory")

Descriptive analysis: Following the material collection, descriptive analysis was conducted to quantitatively analyse the publication trends and distribution of publications in journals, which provides readers with an up-to-date introduction to the status of knowledge development. In addition, after categorisation, the detailed descriptive analysis will be presented in section 2.2.2 to illustrate the allocation of sampled papers across each category.

Categorisation Selection: Two categorisation methods are selected for this review: Phases categorisation and topic categorisation.

(1) Phases categorisation: The phases categorisation was developed based on Gosling et al. (2016)'s work, which contains four groups, namely: Aggregating planning, Pre-project planning,

Project Execution, and Post-Delivery. Aggregating planning includes papers that study ETO from a macro level, and that group of research provides readers with analysis, understanding, or guidelines in company, organization, or market level management. The pre-project phase refers to the project preparation and mobilization stage, covering papers focusing on enhancing the project performance at the preparation stage. The project execution phase comprises papers studied at project level management. Compared with the aggregating planning phase, project execution phase research mainly focuses on individual project (product) execution (production). Post-delivery contains research focus on activities after the project is delivered, including but not limited to waste management, demolition management, and maintenance. As a complementary to the phase categorisation, papers will be categorised into two groups based on their purposes, namely, to demonstrate the structure of the system, and to demonstrate the mechanism of interventions. Finally, the categorisation result will be shown in a matrix, with phases as the horizontal axis, with model's purpose as the vertical axis.

(2) Topics Categorisation: Considering the dispersed status of current research in ETO systems, an inductive method is adopted to classify papers according to the main goal or topics. These topics were identified based on emerging themes from each paper read. Adopting the inductive approach in this paper contributes to the comprehensiveness of this review. This advantage has been recognized in the following review papers. Seuring and Gold (2012) adopted inductive methods to collect the research direction of the production system literature review. Wu et al. (2020) undertook a topic identification method in the construction management field, nine popular topics were summarized.

Material Evaluation: The collected papers will be evaluated according to the coding table in Table 2.5 and analysed by categorisation. Each article was reviewed by in-depth reading and subsequently coded by Table 2.5, which provides the description and reason for using each code to extract information from papers. To note here, the first column indicates where each code will be used and match each code to a particular categorisation or analysis.

Table 2.5 Coding table

	Code	Description	Reason for using
Descriptive analysis	ID	Identification number	Ensure all papers identified were coded
	Title	Title of the paper	Convenient for coding in spreadsheet
	Authors	Who wrote this paper	Identify any groups of papers by the same author
	Journal	Journal of final publication	Identify the distribution of the papers in different journals
	Publication Year	The year paper publication	Enable a longitudinal view of the sample to be made
	Industry	In which ETO field the paper focus.	Assess the application of SD in each ETO field.
Phase Categorisation	Phases	For which phase are models simulating.	Used for phase categorisation
	Modelling Methods	Modelling techniques used in this research	Distinguish between different modelling methods and analyse its distribution over phases
Topics Categorisation	Topic	The research focuses on which topic?	Identify the primary research direction in the current stage
	Purpose of the model	The purpose of the model, what are objectives of building this model	Evaluate the applicability of the different models across different scenarios.
	Contribution	How this research contributes to the existing ETO modelling technique:	Identify how this research contributes to the existing structure of ETO system modelling

2.2.3 Findings from the Descriptive Analysis

Figure 2.3 demonstrates the citation network of sampled papers, wherein 61 papers do not cite or are cited by other articles, 84 articles cite or are cited by at least one paper. This finding illustrates that adoption of SD in ETO field is scattered because almost a quarter of the research in the sample group is independent. However, some research direction emerges; the coloured knots in Figure 2.3 represent the cluster that the paper belongs to and are then duly labelled. These clusters are automatically generated by the Vosviewer's algorithm, which follows a five-step procedure, 1) extracting, 2) categorising 3) counting. 4) association strength calculation 5) Euclidean norm value calculation (Van Eck et al. 2008).

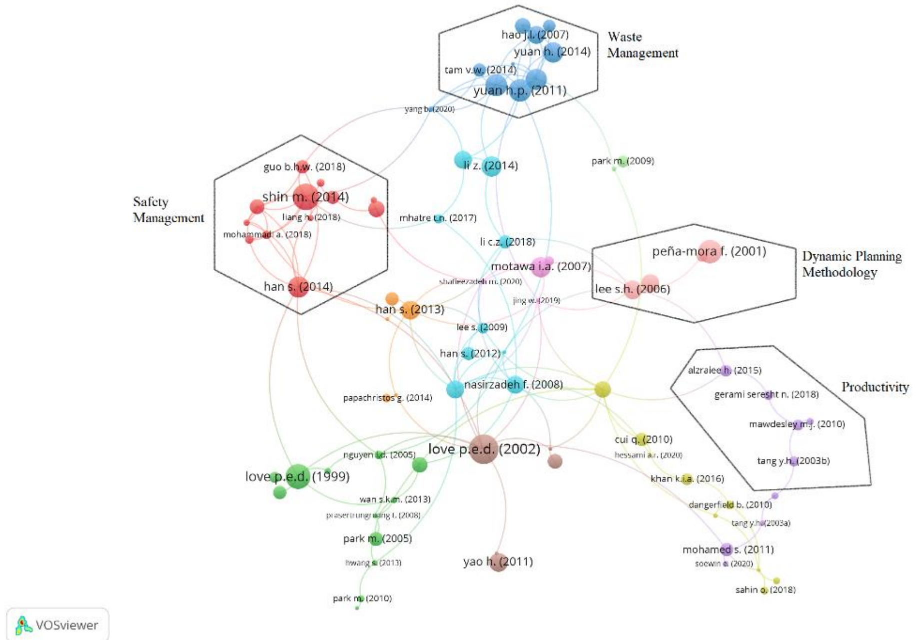

Figure 2.3 Citation network produced by Vosviewer

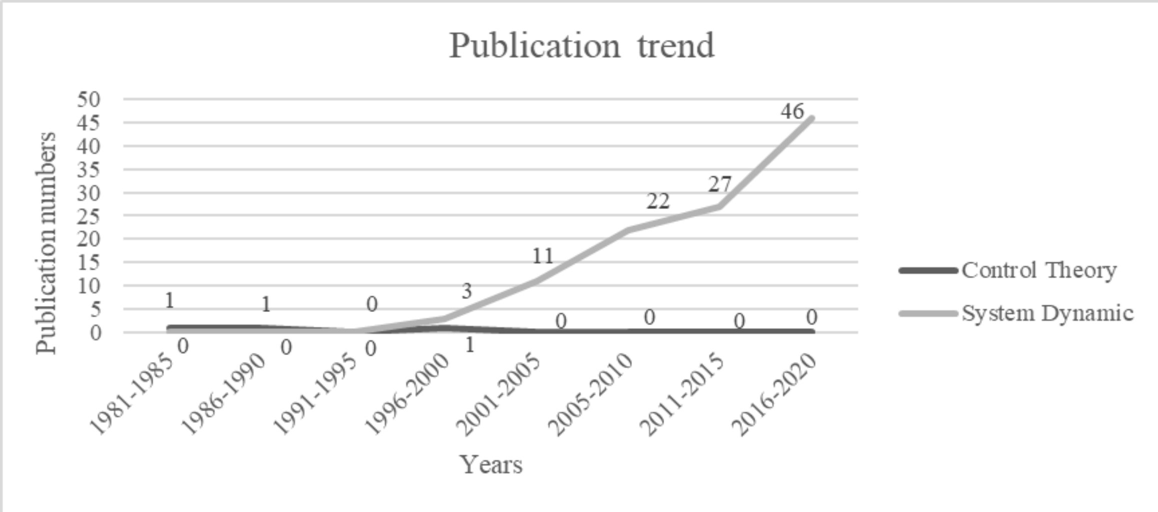

Figure 2.4 Publications trend from 1985 to 2022

Figure 2.4 shows the trend of the publications from 1985 to 2022. This paper aggregates research in a 5-year bucket, which helps readers have a clear view of the primary trend instead of fluctuations. A rising interest in applying SD simulation in ETO can be seen. However, only three papers adopt CT in research. Compared to the SD, CT can analyse the system and explain how certain phenomena happen (Lin et al. 2017). This finding suggests that most models' built-in research is simulation-orientated, and analytical research is inadequate in the current stage.

The distribution of papers across journals highlights the appropriateness of using the keywords searching method. Fifty-four different journals are identified, contributing three or more papers to the sample listed in Table 2.7. Listed journals contributing 59% of the total collection of papers is 145.

Table 2.6 Sample distribution across journals

Journal title	Number of Papers
Journal of Construction Engineering and Management	16
Construction Management and Economics	9
Automation in Construction	6
International Journal of Construction Management	5
Accident Analysis and Prevention	4
Journal of Cleaner Production	3
Journal of Management in Engineering	3
Construction Innovation	3
Engineering, Construction and Architectural Management	3
International Journal of Environmental Research and Public Health	3
Journal of Computing in Civil Engineering	3
Mathematical and Computer Modelling	3
Resources, Conservation and Recycling	3
Safety Science	3
Waste Management	3

The collected literature utilizing SD in ETO systems covers four industries: construction (94%), shipbuilding (3%), capital goods (2%), and generic ETO systems (2%). Additionally, three papers incorporate CT, distributed across construction (2 papers) and shipbuilding (1 paper). This dominance of construction journals may reflect both the widespread adoption of ETO practices in the construction sector and the maturity of SD research in this field. However, it also highlights a potential gap in exploring SD applications in other ETO-related industries, such as shipbuilding and capital goods.

Table 2.7 Sample distribution across phases

Phases	Total	Proportion
Aggregate level Planning (AP)	28	20%
Pre-Project Planning (PP)	37	26%
Project Execution (PE)	34	23%
Post-Delivery (PD)	36	25%
PP-PE	8	5%
AP-PP-PE	2	1%
Grand Total	145	100%

The papers' distribution across phases is shown in Table 2.7. The pre-project stage attracts most of the attention from researchers, which occupies 26%, followed by the post-delivery phase, which contributes 25%. 23% of papers focus on the project execution phase, and 120% focus on the aggregate level planning period.

Besides research focusing on a single-phase, 6% of papers undertake cross-phase simulation, which indicates the start of research looking at inter-phase and a more holistic view to analysing the ETO system. This novel direction provides a potential foundation for ETO archetype building.

Table 2.8 Publications distribution over methods and project stages (DES: discrete event simulation; ABM: agent-based modelling)

Row Labels	CT	SD	SD-ABM	SD-ABM-DES	SD-DES	Game theory-SD	Grand Total
Aggregate level Planning (AP)	2	26					28
Pre-Project Planning (PP)		33	1	1	1	1	37
Project Execution (PE)	2	28	1		3		34
Post-Delivery (PD)		32				4	36
PP-PE		5		2	1		8
AP-PP-PE		1			1		2
Total Number	4	125	2	3	6	5	145
Percentage	3%	86%	1%	2%	4%	3%	100%

According to Table 2.8, SD is the dominant simulation method in the papers identified, while only four papers exploit CT. It is also observed that 16 papers, almost 9%, adopt hybrid simulation techniques in ETO research. Therein, eight papers study Project Execution (PE) or PE centred cross-phase modelling, while the other four are in Pre-Project planning (PP), with the other four in post-delivery phase. The first hybrid modelling paper of the sampling group was published in 2006 and yet the application of hybrid modelling in the ETO field is still in its infancy.

2.2.4 Findings from the Categorization

In this section, papers will be categorised, summarized, and analysed. Figure 2.5 demonstrates an aggregated map to give readers an overview of the categorisation results from a macro level. Section 2.2.5-2.2.8 will dive into the categorisation and analyse the topics distribution of each group. In each section, a discussion regarding the research topic is provided (the result of topic categorisation) to give an in-depth review of each topic.

It is important to distinguish between aggregate planning and aggregate-level planning (AP). Aggregate planning is a formal process in operations management focused on production planning and capacity management. In contrast, Aggregate-level planning refers to a broad category of research and literature that focuses on high-level, strategic planning across multiple domains. Unlike detailed, operational-level planning, this approach encompasses areas such as innovation management, financial strategies (e.g., cost management and cash flow policies), market analysis (e.g., construction, shipbuilding, and capital goods manufacturing markets), supplier management, and prefabrication diffusion.

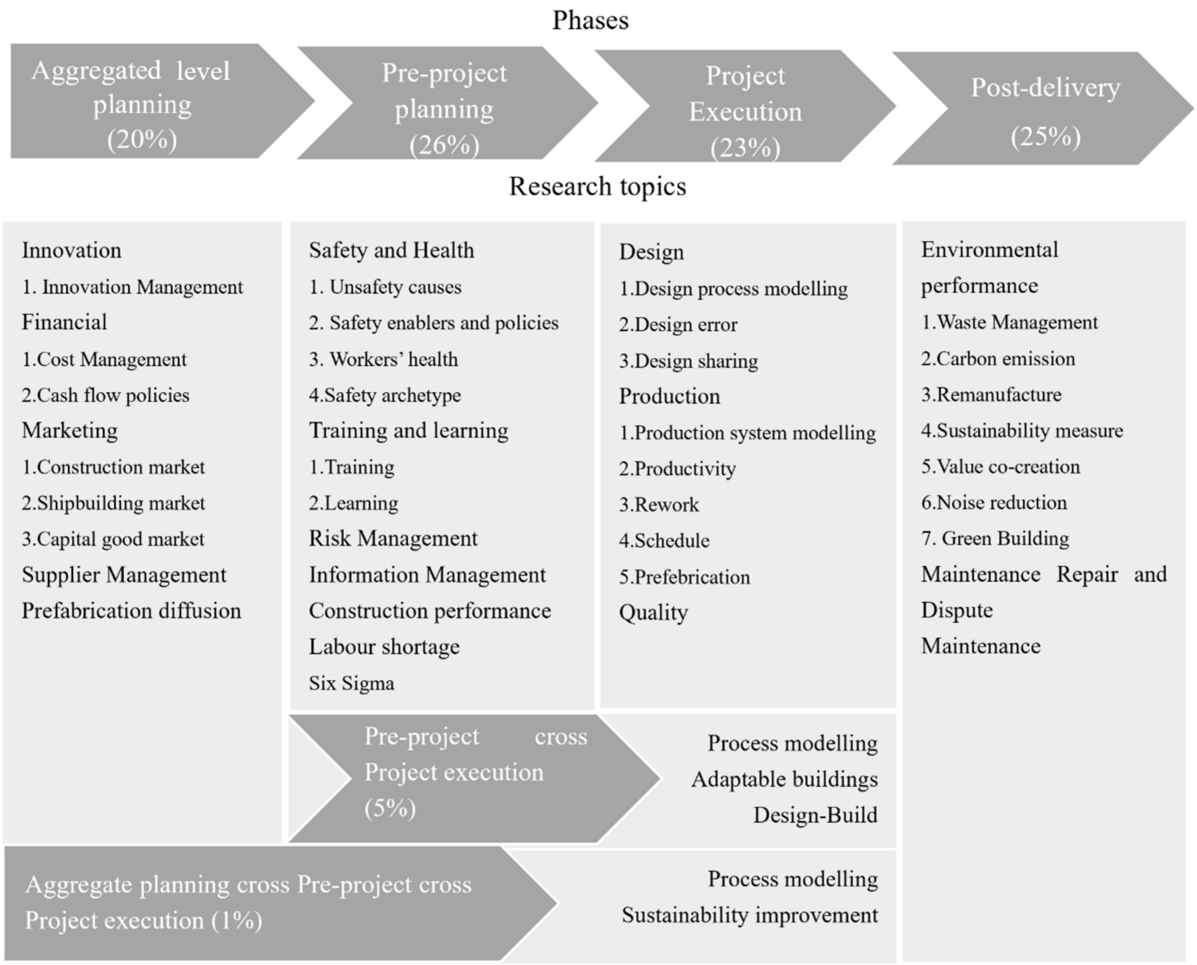

Figure 2.5 A summary of the distribution of sampled literatures

96% of the papers take a PM perspective instead of an ETO-production system view. That may be attributed to the following reasons: 1) ETO is an emerging topic in production system that has not received adequate attention, while PM, especially in construction, is a well-established field of endeavour. 2) As ETO production tends to be 'one/first of a kind,' scholars take a project perspective to study this field. 3) ETO systems require models representing both the production system and project perspectives; however, such techniques are in the infancy stage of development, and there is a lack of related modelling guidance. Although much of the PM research included in this review does not explicitly mention ETO, they do offer PM models that provide a reference base to allow simulation of the production aspect in the ETO system, thereby enriching the toolbox for ETO research and promote knowledge sharing between PM and SCM. The following analysis provides a systematic assessment of Phase-Topics categorisation in a tabular form Figure 2.5.

2.2.5 Review of the Aggregate level Planning Group

This group covers papers focusing on aggregate level planning, including innovation, finance, and marketing topics (See Table 2.9).

Research in this group holds an aggregated view and aims to improve the organization's performance by providing a better understanding of the system nature and the policies' influences. While few papers in this group investigate aggregate-level capacity management, even fewer papers study the impacts of an organizations' capacity on the tendering decision. Although capacity shortage may sometimes be overcome by outsourcing, if not addressed, such capacity limitations will directly result in lead time delays and customer service levels will decrease.

Innovation: The construction industry often confronts new and complex problems that require unique, innovative solutions (Park et al. 2004), while it is often criticized for lacking innovation (Suprun et al. 2019). SD was adopted to investigate innovation management and explore solutions to accelerate the development and diffusion of innovations.

Finance: As mentioned in the introduction section, ETO companies are often confronted with schedule and cost overrun. Four papers focus on cost management, including cost overrun causes analysis and construction financial performance investigation. The other group focuses on cash flow policies development, which utilises SD to simulate the cash flow system.

Marketing: 12 papers target the ETO market modelling and analysis, covering shipbuilding, houses, and capital goods manufacturing markets. Research in this group often holds a macro view to investigate the mechanism and structure of the market system and assesses intervention policies' impact on the market.

Others: Besides those topics mentioned above, another two topics are detected. One aims at supplier management and the other aims at the government's role in diffusing prefabrication constructions

Table 2.9 Aggregate-level planning category

Topics	Innovation	Financial	Marketing	Others	***sum***
What system has been studied	**Innovation system** Describes how project managers' attitudes, team members and organizational climate impact the innovation. (Park et al. 2004) The authors model the innovation system and highlight government incentives' importance. (Suprun et al. 2018) **Innovation transition** Modelling the innovation transition pathway (Suprun et al. 2019). Pasqualino et al.(2021) present a model to display the dynamics of innovation, inequality and inflation, within the context of Industry 4.0.	**Cost management**. This paper demonstrates the causes for cost overrun and its interrelations. (Asiedu and Ameyaw 2020) Kim et al. (2020) simulates the income and cost system of the Korean studio apartment. Lou and Guo (2020) modelled various factors' impact on the prefabrication construction Tang and Ogunlana (2003b) built an SD model to evaluate the performance of several construction projects in Malaysia from a financial perspective. Asiedu and Ameyaw (2021b) develop a model to demonstrate how cost overrun is caused and illustrate the interaction between variables.	**Construction market**. Dangerfield et al. (2010) adopted the SD illustrate the interactions among competitiveness factors. In 2013 competitiveness model was further developed and modelled the process of contracts allocation in a stylized market. (Gilkinson and Dangerfield 2013) Huang and Wang (2005) develops a model to forecast the supply sides units Choi et al. (2017) analyse the core mechanisms of brand management. Tang and Ogunlana (2003a) investigated how the market change influences the organization or companies' financial, technical, and managerial capability. Kim et al. (2021) developed a SD based profit model as a foundation for a statistical model which can be used to simulate the income and cost of studio apartments. **Shipbuilding market** Wada et al. (2018) develops a forecasting model for Ship building market. Based on this paper, Wada et al. (2022) improve the shipbuilding capacity adjustment model by developing a ship price prediction model. Kim et al. (2021b) Develop a market forecasting model which is composed of two SD model, one aims at simulating the grassroots construction market, the other demonstrate operation, maintenance, and demolition market system.	**Supplier management** Smets et al. (2013) simulate in the new product development (NPD) process, emphasized the importance of manufacturers' simultaneous control to correct NPD errors (non-conformance) and the necessity of providing training programs to the newly hired engineer. Supplier management. Bajomo et al. (2022) Present and analyse a construction material production system SD model, in Engineer procurement and Construction field. Luo et al. (2022) Analysed how additional cost of passive building is created, from a production system perspective.	**21**
What intervention has been studied	**Innovation Performance** Investigating the effect of Borrowing, Joint venture, and Training policies on Innovation performance (Ogunlana et al. 2003).	**Cash flow policies.** Cui et al. (2010) investigate the Overbilling and underbilling, Trade credit, and subcontracting policies' influence on project cash flow.	**House market** Park et al. (2010) Investigate the 831 policy's impact on Korean house market. Hwang et al. (2013) analyse the existing and suggested policies regarding the imbalance of demand, supply, and vacancy in the housing market. **Capital good market** Größler et al. (2008) demonstrates that decreasing the price or the product enhancement may lead to counter-intuitive effects on sales revenue.	**Prefabrication diffusion** Park et al. (2011) provide an insight into policies regarding prefabrication construction diffusion to the private sector. Li et al. (2022) Predict the trend of prefabrication construction diffusion.	**7**
Sum	***5***	***6***	***12***	***5***	***28***

2.2.6 Review of the Pre-project Phase

Topics in this group cover safety and health management, risk management, and training and learning management (See Table 2.10). Adoption of SD enables researchers to have a systemic view to study the problems in pre-project stage. However, two issues were identified. Most models in this group are case-orientated, there is a need for further generalization and categorisation. Second, the CLD technique demonstrates the causal relationship between variables, while some modelling examples in this topic did not clarify relations between variables as correlation or causal relationships, which may lead to misunderstanding for readers.

Safety and health: Unsafe and unhealthy behaviours damage workers' productivity in the short term and have a long-term influence on their health. This may also lead to other adverse consequences to the project implementation by knock-on effects, such as, organizational productivity decreases, non-conformance rate increases and cost overrun (Mohamed and Chinda 2011). The introduction of SD modelling contributes to this topic by providing a systematic view of the safety and health management system, which overcomes the barrier created by the project's complex implementation environment.

Training and learning: Training and learning are core activities in improving the team's performance, especially in the project preparation stage. A well-trained implementation team may benefit from the construction quality, overall project performance, and reduction of rework. In the meantime, a well-designed experience to knowledge transferring process contributes to the organization's long-term improvement. SD is utilised to investigate the causes for inefficient training and simulate the experience transfer process.

Risk Management: Risks in the project are diverse and scattered, depending on the project's diverse properties. Besides, risks' impact may be aggravated due to the complex structure and interactions in projects. SD is adopted to simulate how the risks affect the project and analyse the interactions among risks factors. SD also demonstrates its strength in determining knock-on or unintended consequence effects by providing visibility of how the original problem yields adverse impacts to the whole system, and which variables finally respond to such outcomes.

Others: Besides the above topics, there is also the miscellaneous relevance of information management, construction performance assessment, labour shortage problems and adoption, and Six-sigma.

Table 2.10 Pre-project category

	Safety & health	*Training and learning*	*Risk Management*	*Others*	*sum*
What system has been studied	**Unsafety causes:** Investigate how the production pressure affects the safety culture (Mohammadi and Tavakolan 2019) Han et al. (2014) explored the negative effect of schedule and productivity on safety performance (incident rate). Goh and Askar Ali (2016) applied SD-ABM-DES to simulate the safety performance system for an earthmoving project. **Safety enablers and policies:** Mohamed and Chinda (2011) investigate how safety enablers influence the safety culture. This paper investigates the core mechanism and the effect of how Behaviour-based safety programs improve safety (Guo et al. 2018). Woolley et al. (2020a) adopted Systems Theoretic and Accident Model and Processes (STAMP) to model safety management in construction. **Worker's health:** Lingard and Turner (2017) illustrated the determinants and their interactions of workers' health. Vitharana and Chinda (2021) adopted SD to investigate the causes of lower back pain and the interaction between key factors. Wu et al. (2016) simulate how the work-family conflict influence workers' satisfactory. Mohammadi et al. (2018) develop four safety archetypes with due consideration of delay in design, a number of sub-contractors, project cost, and supervisors' impact on the safety performance. Huang et al. (2022) developed a simulation model for Construction workers unsafe behaviour evolution. Ni et al. (2022) Demonstrate how factors affect the unsafe behaviours, with special focus on new generation construction workers. Nordin et al. (2021) To analyse the safety management system and root causes of accident	**Training** Bajracharya et al. (2000) investigate the causes and remedies for inefficient training activities in Nepal. **Learning.** This paper visualizes the concept of knowledge management capacity and simulates the evolution of such a process. (Chen and Fong 2013) Lê and Law (2009) simulate the experience transferring process in Architecture, Engineering, and Construction industry organizations.	**Risk management** Mhatre et al. (2017) established SD with the interpretive ranking process, modelling the critical factors in construction; the result suggested that the risk dimension "construction management" has a high possibility to occur. Tavakolan and Etemadinia 2017) mixed Delphi, SD, and Fuzzy logic to analyse critical risk factors and their interactions. Finally, 63 crucial risk factors were identified. By developing a risk identification feedback chart and risk flow chart. Li et al. (2017) identified investment risks in prefabrication projects. Nasirzadeh et al. (2008) developed an integrated Fuzzy-SD model to assist risk management. Purushothaman and Kumar (2022) SD is used to explore the relationship between Production system risk with the resilient capability.	**Information management:** Middleton and Golay (2008) introduced Shannon entropy into the construction project uncertainty management. Tatari et al. (2008) studied the applicability of the Construction ERP system in PM and identified the critical variables for the system development. **Construction Performance** Soewin and Chinda (2020) reveal the critical factors for construction performance maturity and its interrelation in Thailand. Sahin et al. (2018) assessed the background of off-site manufacture by SD and identified key factors to the value creation. Soewin and Chinda (2020) *utilise SD to develop a Construction Performance Index* Park (2005) developed SD to study the construction performance dynamics; this paper also demonstrated the trade-off between lead time and the cost of resource coverage.	**27**
What intervention has been studied	**Safety archetypes:** Guo et al. (2015) simulated eight safety archetypes and assessed the side effect of various safety regulations, highlighting the importance of the connection between entities in the system. Based on (Mohammadi et al. 2018), this paper place particular focus on workers, and illustrate how blaming, delay, incentives Programmed, and subcontractors' financial status affects the project safety (Mohammadi and Tavakolan 2020) Liang et al. (2018) assessed three safety management policies to deal with the trade-off between productivity and safety issues. Shin et al. (2014) assessed the effectiveness of incentives for safe behaviours and safety levels. **Lean**: Wu et al. (2019) established SD models to simulate the effect of 5 lean tools on construction safety performance.	**Learning** Ecem Yildiz et al. (2020) combined SD with the balanced scorecard and strategy maps demonstrate how selected policies affect organization's learning ability.		**Six Sigma:** Ullah et al. (2017) investigated the implementation status of six sigma in Pakistan; based on an SD simulation of how six-sigma influenced project success. **Information management** Khan et al. (2016) demonstrated vital drivers and their interrelations for absorbing cloud computing for small and medium enterprises. **Labor shortage:** Aiyetan and Dillip (2018) developed SD to model the effect and enablers of labour shortage; this paper also examines the influence of the interventions.	**10**
Sum	***19***	***4***	***5***	***9***	***37***

2.2.7 Review of the Project Execution Phase

As the core activity in both the PM and the production system management fields, this stage attracts the most attention (See Table 2.11). A potential archetype has been identified from this stage. However, according to the ETO definition, the model should comprise of both design and production systems. While there is a paucity of references (Lee et al. 2005a; Park et al. 2009) that combine design with the production system, further research could attempt to model the system by amalgamating design with production, thereby exploring the dynamic of ETO system.

Design: Design and production are often regarded as separate activities. However, the ETO system should include design activities, as the engineering process is integral to such a system (Parvan et al. 2015). Thus, design is regarded as an essential client-specific value adding activity and classify design-relevant papers in this group. SD is therefore, utilised in 1) design process simulation, 2) design error research, and 3) design sharing analysis, which demonstrates the applicability of SD in design process modelling.

Production: Production is the core activity of the project execution, which is also a determinator for schedule and cost performance. This research direction attracts quite a lot of attention from academia. SD is applied to 1) analyse the causes of poor productivity, 2) model the production process, 3) study the rework, 4) improve the schedule performance, and 5) simulate the prefabrication process. These models provide a quantified and systematic view of production control which deepens the understanding of PM. Besides, this group contains three papers that adopted CT. The introduction of optimal CT provides a set of mathematical, analytical tools in earthmoving processes, capital goods manufacturing, and ship panel manufacture schedule optimization.

Quality: One of the construction industry's primary trade-offs is between quality and cost. Shafiei et al. (2020) first adopted SD into the quality-cost trade-off analysis and proposed a model to analyse the effect of policies that are designed to decrease the cost of quality.

Dynamic Planning Methodology: Dynamic Planning Methodology (DPM) is identified as a potential candidate for ETO system archetype, which is adopted in 5 papers. This model, which is developed based on SD, simulates the construction project process. This method has been utilised in production process research, rework simulation, and design errors analysis, thereby demonstrating its applicability in the PM field.

Table 2.11 Project execution category (DEMATE: Decision-making trial and evaluation laboratory)

	Design	*Production*	*Quality*	*sum*
What system has been studied	**Design process modelling:** Chapman (1998) simulate the new staff's design process and learning curve and evaluate the risk of the change of key project personnel during the design stage. **Design errors:** The design non-conformances dynamic impact was assessed in the Dynamic Planning Methodology (**DPM**) model (Han et al. 2013). **Design sharing:** Minami et al. (2010) tested several SD-based policies and concluded that design sharing could mitigate the cost overrun problem.	**Production system modelling:** Handa et al. (1986) adopted optimal CT to optimize the earthmoving process. Peña-Mora and Li (2001) apply **DPM** in fast-tracking techniques research, and proposed methods can absorb the impact from changes. Han et al. (2012) upgraded **DPM**, enabling it can quantify and identify the non-value adding activities caused by non-conformance and changes. Alvanchi et al. (2011) developed a SD-DES model to combine the operational-level (physical activities like equipment capacity and a number of labours) with the context-level (non-physical activities, like labour skill level and organizational policies). This model is further upgraded by Alzraiee et al. (2015), with consideration of strategic-level management. Tomiyama (1985) developed a capital goods production system with a time lag and adopted optimal CT to calculate the optimality condition for this two-stage system. **Productivity:** Khanzadi et al. (2018) integrated ABM with SD to predict the value of labour productivity. Mawdesley and Al-Jibouri (2010) develop a series of equations to descript and evaluate how control, motivation, planning safety, and disruption affect productivity. Gerami Seresht and Fayek (2018a) developed a Fuzzy SD model, which can be used for predicting the productivity of the equipment-intensive project. Palikhe et al. (2019) utilised SD and fuzzy logic to identify root causes for poor productivity in Nepal. Parchami Jalal and Shoar (2019) combined SD with a decision-making trial and evaluation laboratory method distinguished several factors that most influence and influence labour productivity. **Rework:** Lee et al. (2005) introduced an enhanced **DPM** that can control the system under uncertainty and protect the system from vicious negative iterative caused by non-conformance or change. Love et al. (1999) developed several SD models to provide an insight into the causal nature of rework. Love et al. (2002) simulate how change and rework of construction impact the project management system. **Schedule:** Jalal and Shoar (2017) investigate the factors relevant to project delay and identified the most influencing factors and the most influenced factors by delay through combining SD with the (DEMATEL) method. Jing et al. (2019) evaluated Iraq's local construction project's cost level and time performance by SD. Laursen et al. (1998) adopted CT, the multi-input and multi-output (MIMO) technique, into the ship panel production system, which could be rescheduled and optimize the production sequence in real-time. **Prefabrication:** Li et al. (2018) adopted SD-DES to simulate and evaluate the effect of risk factors on the prefabrication schedule performance. Nguyen and Ogunlana (2005) utilise stock and flow diagrams and simulate the infrastructure construction process.	Shafiei et al. (2020) firstly, identified the factors affecting the cost for quality from literature and established an SD model to analyse the policies which are proposed to reduce the cost of quality Riaz et al. (2022) *Demonstrated how key factors affected the TQM implementation in construction sector.* Mohammadrezaytayebi et al. (2021) Introducing a system dynamic based model of quality estimation for construction industry subcontractors' works Bajracharya et al. (2021) To investigate why there is a recurring failure in the construction industry.	**26**
What intervention has been studied	Ko and Chung (2014) developed a lean design process that enables the process to be more pliable to the customers' needs and validate it on a SD model.	**Production system modelling** Peña-Mora et al. (2001) introduce the Dynamic Planning methodology (**DPM**) to analyse the negative effect of fast-track techniques (a technique in project management where activities are performed in parallel) and modify control policies to minimize the adverse consequence of parallel execution. Javed et al. (2018a) proposed that productivity should be perceived as a latent entity underpinned by five parts. Management should seek solutions from a systemic perspective. Shafieezadeh et al. (2020) investigated the effectiveness and robustness of change management policies, which can model the rework cycle and analyse the ripple and knock-on effect in construction. Zhou et al. (2022) Present a model demonstrate the structure of ETO and assesses the stability of such a system. Ajayi and Chinda (2022) Demonstrated a workflow model, this model is used to assess the impact from project delay variables. SD-DEMETAL is used to estimate the influence weight of each variable Ajayi and Chinda (2022b) Investigate delay-controlling parameters' impact on project schedule. Rachmawati et al. (2022) Develop a model which can forecast Work rate, and optimize the time and cost performance of a project		**8**
Sum	***4***	***26***	***4***	***34***

Table 2.12 Post-delivery category

	Environmental performance	*Others*	*sum*
What system has been studied	**Waste management:** Yang et al. (2020)adopted SD to detect the root causes of waste behaviour. Suciati et al. (2018) investigate the relationship between material waste and workers' behaviours and attitudes. Hua et al. (2022) develop a model to investigate the subsidy and environment tax's impact on C&D waste recycling. This research also studies the proper range of tax and subsidy. Yuan et al. (2022) present a stock and flow diagram illustrate how prefabrication contribute to the waste reduction in the designing stage. Liu et al. (2021) first, develop compensation model of evolutionary game for Waste management and then authors adopt SD to analyse the equilibrium point of this game Hao et al. (2007) apply SD to simulate the demolition waste chain. Yuan et al., (2011) undertake cost-analysis in a construction demolition system simulation, deepening our understanding of the impact of landfill charges on demolition waste. Ye et al. (2012) developed an evaluation system to measure the performance of construction waste management. Li Hao et al. (2008) verified the effectiveness of the on-site sorting strategy by developing SD simulation. Liu et al. (2020) simulated the construction and demolition waste recycling chain. Li et al. (2014) developed a model to quantify the impact of the adoption of prefabrication to waste reduction in China. Yuan (2012) identified major variables affecting the social performance of construction waste management; this paper also depicts the interrelation underlying the system. Ding et al. (2016) combined SD with theory of planned behaviour and investigate the effect of different construction waste management measures on environmental performance. Cheng et al. (2022) analyse how incentives and punishment affect resources utilisation of construction and demolition waste in China. **Carbon emission:** Papachristos et al. (2020) Investigating the low carbon building performance indicators' interaction by combining operation management with the SD. Du et al. (2019) Investigated the CO2 emission of construction under different economic situations Kim et al. (2013) developed a model which able to calculate the CO2 emission under all stages. Wang et al. (2022) present a game-SD model, demonstrate the low carbon practice's effect, within the prefabrication production system context **Remanufacture:** Papachristos (2014) simulated the remanufacturing process in the capital goods production system and its difficulties in practice. Mostert et al. (2022) simulate the building material flow in the future, highlight the importance of concrete recycling. **Sustainability:** SD was also applied in developing KPI for sustainability measurement (Wang et al. 2014). Liu et al. (2022) SD was used to construct and analyse the sub system of comprehensive benefit analysis of prefabricated building. Ghufran et al. (2022) present how circular economy enablers affect the sustainable development. Highlight the policy support and organizational incentive schemes are two most effective enablers. Zhang et al. (2022) Combine SD with Game theory and simulate the interaction between government, contractors, on greenhouse application this paper took wemedia (WeChat, a social application like WhatsApp and Instagram), which reflect public opinion, into consideration. **Value co-creation:** Zhang et al. (2016) study the impact of environmental force on Value co-creation in an enterprise.	**Dispute** Menassa and Peña Mora (2010) presented a model that simulates dispute resolve ladders (DRL, which is used to solve arising issues between participants), enabling participants to monitor the occurrence and resolutions of the claims and change orders. Ansari et al. (2022) use SD to predict the construction performance projects based on the reason for the claims. **Maintenance:** Prasertrungruang and Hadikusumo (2008) developed an SD model to capture the dynamic of machine downtime in the context of small or medium highway contractors. Prasertrungruang and Hadikusumo (2009) shifted their focus to the large contractors and highlighted the mitigation function of balancing cycles which is used to simulate the machine dealers' maintenance service.	**29**
What intervention has been studied	**Waste management**: Yuan et al. (2012) evaluated three environmental improving management scenarios by SD and provided decision-makers with the management level's effect on the mitigation of construction waste caused by environmental impact. Yuan and Wang (2014) apply SD in parameter adjustment to assist managers in determining the appropriate waste disposal charging fee in construction. **Noise reduction:** Yao et al. (2011) evaluated the impact of policies, tested the noise level reduction policies under different pricing strategies, considering financial, waste, and safety levels. Tam et al. (2014) simulated different policies and their effectiveness on waste management. Marzouk and Fattouh (2022) testing investment policies' effects on environment Indicators. **Green Building** Li et al. (2022b) study on Green Building Promotion Incentive Strategy Based on Evolutionary Game between Government and Construction Unit	**Dispute** Ng et al. (2007) combined dispute avoidance and resolution technique (DART) with SD simulation to present a solution to manage disputes and conflicts, which provides an insight into the nature of these challenges. This model can also be used for conflicts or dispute forecasting and serves as a testing platform for different scenarios.	**7**
Sum	***31***	**5**	***36***

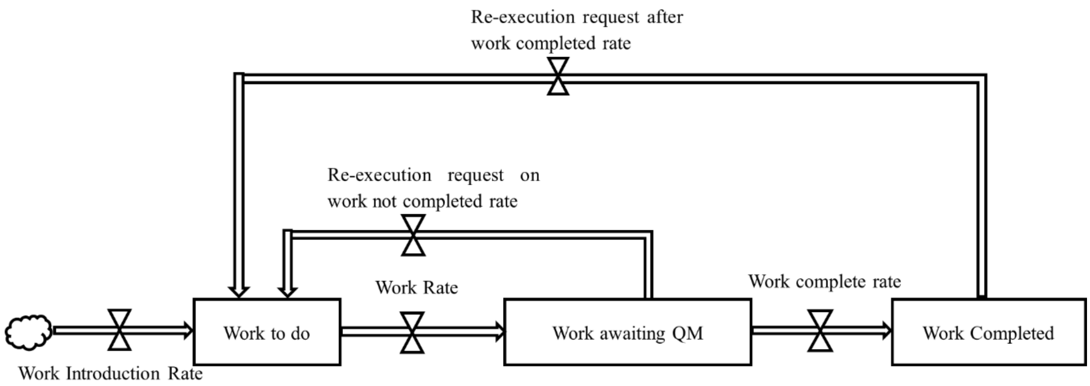

Figure 2.6 A conceptual SD model for project management (Lyneis and Ford 2007)

The main structure of DPM is illustrated in Figure 2.6. This model has been utilised in 1) cost of quality analysis (Lee et al. 2005b), 2) change management (Lee and Peña-Mora 2007), 3) fast-track technique analysis (Peña-Mora and Li 2001), 4) design error investigation (Lee et al. 2006b), and 5) non-conformance analysis (Love et al. 1999). This research further upgrades this model by adding new variables and feedback loops.

2.2.8 Review of the Post-Delivery Phase

With the gaining importance of life-cycle PM, research has been conducted in the post-delivery phase (See Table 2.12). Herein three main topics are identified: 1) Environmental performance analysis, 2) Maintenance repair and operation, and 3) Dispute solving. The post-delivery phase received more attention, not only because of the increasing demand for environmentally friendly production, but also because of the great potential for cost saving, e.g., via remanufacturing and recycling.

Environmental performance: large scale projects, such as in construction or shipbuilding, have the potential to have a negative impact on the environment if production systems do not take the following issues into consideration: construction waste management (Ye et al. 2012), demolition waste management (Yuan et al. 2011), carbon emission (Papachristos et al. 2020), and noise reduction (Yao et al. 2011). Papers aiming to analyse or improve the environmental performance of ETO projects are classified into this group, within which waste management attracts the most attention.

Others: SD is also utilised in other post-delivery activities study besides environmentally relevant research. **Maintenance** is critical for ETO products, especially for cargo ships and capital goods, which often requires regular maintenance after delivery. In addition, when the products break down, the customer may need support from the original manufacturer. Thus, post-delivery management is also crucial for ETO products. SD is applied to simulate the adverse impact of the machine breakdown and highlights the importance of equipment maintenance. **Dispute:** One of the distinguishing features of the construction industry is the high cost of resolving disputes and conflicts. SD is also adopted in this research topic to simulate the process of dispute resolution.

2.2.9 Cross-phase Research

This category includes papers that adopt SD in cross-phase research (See Table 2.13), which contribute the body of knowledge by providing aggregated, multi-level models, and demonstrating the ETO system's cross-phase behaviours.

Table 2.13 Cross-phase category

	Pre-project planning - Project execution	*Aggregate level planning – Pre-project planning – Project execution*	*Sum*
What system has been studied	**Process modelling** Lee et al. (2006b) proposed several hybrid models that can be used in whole life-cycle simulation. **DPM** was also applied to study the impact of information technology in the multi-layer system. Lee et al. (2006a) integrated **DPM** with several existing methods and implement this integrated method into a web-based system. Peña-Mora et al. (2008) bridges the gap between practice and theory by simulating the cross-level planning process in an earthmoving project. Motawa et al. (2007) adopted **DPM** in the change management field, and the authors developed a change prediction model which can combine with the original **DPM** model. Barbosa and Azevedo (2019) proposed several ETO/MTO performance determinants and developed a hybrid SD-DES-ABM model to assess the system's performance.	**Process modelling** Lee et al. (2009) further developed the **DPM** model to simulate production covering AP-PP-PE phases by integrating SD with DES. In this paper, the authors firstly introduced the Pipeline installation model.	**6**
What intervention has been studied	Wan et al. (2013b) developed an SD model to analyse the inefficiencies of the construction process in subcontractors; in the meantime, the impact of various project settings was also investigated. **Adaptable building** Gosling et al. (2013) investigated drivers for building's adoptability and identified the enablers for adaptable building. SD was utilised to illustrate the building adaptation model and rationalize the concepts. **Design-build** Park et al. (2009) presented an SD model to analyse the Korean design-build delivery system's characteristics and test previous suggestions and initiatives.	**Sustainability** Hessami et al. (2020) designed a model which simulates the revolving-fund sustainability improvement program. The model indicates that if appropriate program management and prioritization strategies were adopted, revolving funding could leverage small initial investment into a significant benefit improvement.	**4**
Sum	**8**	**2**	**10**

Pre-project planning - Project execution: Three research topics are identified, 1) Process modelling, 2) Adaptive building, and 3) Design-build delivery system, wherein process modelling occupies the most significant proportion. Papers in this group bridge the gap between production and project preparation, depicting the connections and interactions between these two stages.

Aggregate level planning – Pro-project planning – Project execution (AP-PP-PE)

Two papers are classified into this group. Dynamic planning methodology (DPM) is combined with discrete event modelling technique and simulates the AP-PP-PE process, demonstrating this cross-phase system's dynamic. Another paper adopts SD to simulate the revolving-fund sustainability improvement program. Compared with the model only focusing on a single-phase, AP-PP-PE simulation provides a macro view of the SD, improving the model's fidelity.

2.2.10 Summary of the section 2.2

The review of SD applications in ETO systems in Section 2.2 provides valuable insights into how dynamic modelling techniques have been applied to understand and manage the complexities of ETO system. SD models have demonstrated a strong capability to capture the intricate feedback loops and time delays that characterize ETO systems, such as those arising from iterative design processes, production adjustments, and resource constraints. However, a recurring theme in the literature is the lack of comprehensive frameworks that fully integrate design and production stages, which are key to the functionality of ETO systems.

One significant finding from the review is that many existing studies focus on isolated aspects of ETO systems rather than addressing the system as a whole. For example, while some studies explore waste management (Yang et al. 2020), others emphasize quality issues (Shafiei et al. 2020) or ripple effect in the production system (Lyneis and Ford 2007), often without considering how these elements interact dynamically within the broader ETO system. This gap highlights the need for holistic models that can better represent the interconnected nature of ETO workflows.

Additionally, Section 2.2 identifies a lack of attention to system behaviour under disruptions, an area that is critical for understanding and improving resilience in ETO systems. While SD models are well-suited for analysing complex SD, there is limited research on how these models can be used to evaluate system recovery and adaptability in response to external disturbances.

These findings form the foundation for the objectives of this thesis. By addressing the identified gaps, this research aims to develop SD-based archetypes that integrate the design and production stages of ETO systems, providing a more comprehensive framework for modelling their unique dynamics. Furthermore, the thesis introduces resilience as a central focus, leveraging SD models to analyse how ETO systems respond to and recover from disturbances. This integrated approach not only advances theoretical understanding but also offers practical solution for improving the performance of ETO systems.

The insights from this review serve as a crucial transition, linking the existing body of knowledge to the research objectives outlined in Chapter 1. Moreover, these reviews also provide a foundation for the model development, the outcome will be presented in chapter 4.

2.3 Production System Resilience

Resilience can be defined as ‘the behaviour of the system when facing disruption events’ (Zarghami & Zwikael 2022). In the production system management field, resilience research has received increasing attention in recent years due to the COVID-19 pandemic and the unstable political environment globally. The following paragraphs review papers which study 1) the meaning of resilience within an ETO system and 2) the measurement of resilience.

2.3.1 The Meaning of Resilience within an ETO System

The ETO resilience study aims at developing a method to measure the resilience of the ETO system and tunning the parameter settings of the system to achieve its best performance. Due to the nature of the definition of the ETO system, it has not been thoroughly studied; instead, the general production system’s resilience definition that is adopted for this research is ‘an unplanned and unanticipated event that disrupts the normal flow of goods and materials in a supply network in this study’ (Kim et al. 2015a).

With the outbreak of the COVID-19 pandemic, the global production system was heavily impacted, which resulted in wide production stoppages, transportation delays, and economic disruptions (Li et al. 2022c). Thus, an increasing number of companies and researchers realised the importance of resilience research, which possesses the potential to assist a production system from surviving disturbances and mitigating any negative influences of unexpected shocks(Christopher and Peck 2004)(Pires Ribeiro and Barbosa-Povoa 2018).

Resilience in the production system field is often used to describe the system's behaviour after the system is interrupted by a disturbance. The process often involves three stages, the readiness, responsiveness, and recovery (Spiegler et al. 2012). The detailed explanation for these three stages is explained below.

- Readiness refers to the stage before the disruption occurs. The production company usually uses extra inventory as a buffer to absorb the impact from the disturbance. Apart from the inventory, the production company also reserves a certain amount of capacity or lead time to compensate the capacity lost or the demand increase caused by the disturbance. The term redundancy usually appears along with readiness, which refers to the extra inventory or capacity of the system. Redundancy can improve the system's anti-risk ability (Wang and Ip 2009) but, simultaneously, holding a high inventory level or having a high capacity will increase the cost and the idle time for machinery, which may become a source of company waste (Purvis et al. 2016). Thus, redundancy is not a cure for the disturbance and the extra stock and capacity must be well-managed with necessary contingency measures in place (Pettit et al. 2019).

- Responsiveness describes how fast the system can react to the disturbance. From the inventory perspective, responsiveness refers to the time that the production system takes to bounce back from the disturbance events and hitting rock bottom. Such performance is often related to the lead time of the production or orders and the reaction speed of the system. A resilient production system possesses the ability to detect the disturbance swiftly and subsequently initiate the implementation of the predesigned risk mitigation plans. To improve the performance of the responsiveness stage, efforts need to be made by both the planning and the production departments. The planning department needs to make new plans to react to the events, while the production department needs to have a highly flexible manufacturing process to adopt to the changes in the production. However, an overtly swift reaction to the disturbance or the exogenous change is not always profitable. At times, reacting to the change too fast may cause other severe consequences, such as high fluctuations and frequency changes in capacity. These issues may lead to a higher operation cost, which brings forth its own challenges for the management.
- Recovery refers to a process in which the system begins bouncing back to the original level or new status (Wieland and Durach 2021). In this period, ordering policies or capacity management plays a critical role. The management needs to

make a decision regarding how much to reorder, how much capacity needs to be compensated for, how to minimise the overreaction after the disturbance, and how to prepare against the disturbance in the future (Pires Ribeiro and Barbosa-Povoa 2018). Although there is an absence of quantitative models that can support managerial decision-making, all these questions can be answered retrospectively by utilising historical data and management's experience. It is evident from the description above that the trade-off exists in each stage; apart from this, these there is another trade-off for the production system (Wikner et al. 2007). The first one is the trade-off between lead time and capacity. This trade-off implies that when designing the systems, the company has two options to improve the flexibility of the system: 1) Keep the lead time flexible, which means that a longer promised lead time will be given to the customer. In other words, the production company uses lead time as a buffer to absorb the negative influences of the disturbance. When the disturbance occurs, the company does not have extra capacity, but they can use the extra lead time to complete the production and still deliver the products to customers on time. 2.) Keep the capacity flexible, which implies that the company owns a production system wherein the capacity can be altered. In other words, the company reserves extra capacity for uncertainties and disturbances. When disturbances occur, the company can expedite the mobilisation of extra resources to do a timely delivery of products to the customers.

If the company decides to keep the delivery time flexible, which is option 1 as mentioned above, then the company may lose the competitiveness from the lead time perspective; however, the benefit would be the cost saved by maintaining a stable capacity. If the management aims to have a shorter lead time but with a flexible capacity, which is option 2, then the company has to invest more money in maintaining a high capacity and to reserve extra capacity, but the benefits would be that the capacity flexibility improves their competitiveness for delivering products within a shorter timeframe as opposed to companies that select option 1.

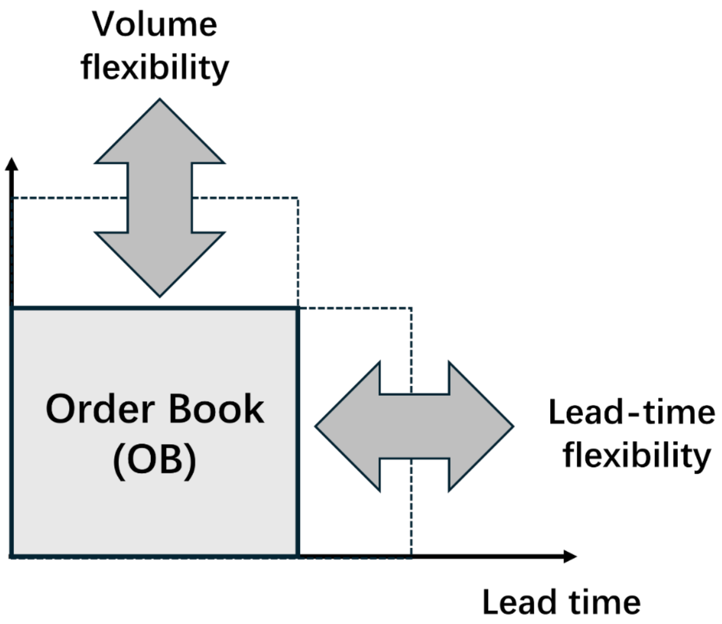

Figure 2.7 The trade-off between lead time flexibility and volume flexibility, adapted from Wikner et al. (2007).

In conclusion, improving resilience is not a single-target optimisation goal. Instead, it involves a multitarget decision-making process. The company must select an appropriate resilience improvement strategy that aligns with its vision and mission.

Furthermore, since the definition of resilience varies based on the production system's positioning, industries, and products, companies that aim to enhance their resilience must have a clear understanding of their production system's priorities and constraints. This will enable them to tailor their own resilience strategy and accordingly prepare the measures to deal with emergency events.

2.3.2 Measurement of Resilience

Resilience can be visualised by a simple curve, as depicted in Figure 2.8. The entire process is composed of three processes and each of these represents an angle of resilience: 1) Preparation stage, which refers to the period before the disruption occurs; it describes how well the system can prepare for uncertainties (Shen and Ying 2022). 2) Response stage, which refers to the period between the initiation of the disturbance and the time the system reaches its bottom; this period indicates how fast the system reacts to a disruption (Wang et al. 2021 ; Hohenstein et al. 2015). 3) Recovery stage: Refers to the period from the bottommost point of the system to the time it settles down at a new normal status (Spiegler et al. 2012); this period relates to how fast the system recovers from a disruption and settles down at the new level.

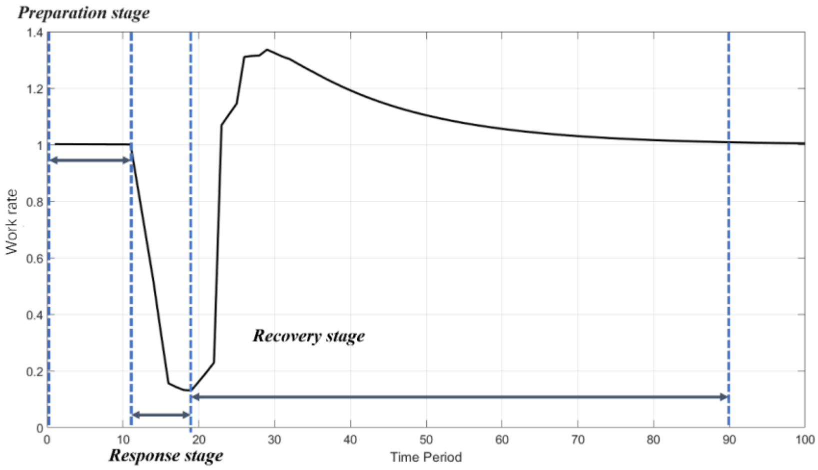

Figure 2.8 An example of a resilience curve, illustrating the work rate dynamics across the preparation, response, and recovery stages of the system during a disturbance.

The pursuit of enhancing production system resilience has become a complex undertaking with multiple objectives, primarily due to the existence of the abovementioned three distinct stages (Hohenstein et al. 2015). Previous research has uncovered several critical questions and trade-offs that must be considered (Ivanov et al. 2018). First, if a universal solution exists that can optimise the system's resilience, which stage's resilience should be prioritised (preparation stage, responding stage, or recovering stage)? Second, within the production system, there are numerous output variables that can be used to measure resilience. Which target should be prioritised—work rate resilience or lead time resilience (Munoz and Dunbar 2015)? Under what circumstances should one take precedence over the other? Lastly, what is the cost of resilience, and what are the objectives of resilience (Ribeiro and Barbosa-Povoa 2018; Pettit et al. 2019)? If resilience comes at a higher cost than production delay or stoppage, how should management navigate this trade-off? Specifically, how should they balance resilience with the high cost associated with fluctuating capacity? These questions highlight the reality that resilience may not have a single, definitive definition that is applicable to all situations and there is no one-size-fits-all solution. Therefore, this study takes a theoretically driven approach by using a whole-process resilience index to measure the system's overall resilience. While this research is not yet ready for practical application, it can provide valuable numerical evidence to guide future development and refinement. Thus, this research seeks the answers for the above questions by exploring the best setting for the production system parameters for improvement in resilience under different priorities—work rate priority and lead time priority.

To select the index to measure the resilience of the system, a review is conducted to summarise the existing resilience index, as presented in Table 2.14. Bearing in mind the need to measure the speed and accuracy of the production system to reach its new normality, it is important to focus on the index that not only quantitatively measures the entire process but does so with the desired efficiency. Therefore, for the purpose of this research, the ITAE was selected, which is a sufficient resilience measure for the modelling of production SD (Spiegler et al. 2012). As per equation (2.1), ITAE integrates the product of time and output error, and the neutral axis refers to the final steady state of the system.

Table 2.14 A summary of the resilience measurements (Han et al. 2020)

Stage	Index
Preparing stage, Readiness	Situation awareness (Rajesh 2016) Visibility (Ivanov et al. 2016) Redundance (Cabral et al. 2012)
Response stage, Responsiveness	Agility (Pettit et al. 2019) Flexibility (Rajesh 2016) Collaboration (Kim et al. 2015)
Recovery stage, Recovery	Contingency planning (Hosseini et al. 2019) Market position(Ivanov et al. 2018)
Whole period	Integrated Time Absolutely Error (Spiegler et al. 2012)

$$ITAE = \int_0^t t \times |output - Neutral\ axis| \cdot d_t. \qquad (2.1)$$

ITAE has the following advantages: 1) Integrating time with the error increases the penalty for subsequent variations from the target. 2) Capturing the performance of the entire process; the other options, such as settling time or the rise time, can only measure a specific aspect of the system. 3) It is a quantitative index which can be used on the developed ETO archetypes.

2.4 Reduce the Impact of Rework: ‘Think Slow, Act Fast’

Flyvbjerg and Gardner (2023) developed a database of over 16000 records of different projects from over 20 fields across 136 countries. According to their findings, 91.5% of these projects exceeded both their budget and schedule, while 99.5% exceeded their budget or schedule without providing the expected benefits. Based on this, the authors propose that detailed planning and design is the key to successful project execution. They suggest that those associated with design activities should take the time to plan and identify errors before any production/construction begins. In other words, ‘Think Slow, Act Fast’ (Philbin 2023).

By granting extra time to the design department, the management has to make two trade-offs. The first is the lead-time trade-off. Allocating extra time to design may assist in reducing lead-time by preventing errors from being passed on to the production system, thereby reducing delays for the whole system’s lead-time (Han et al. 2013, Li and Taylor 2014). However, adding extra time itself will increase the whole system’s lead-time. The second trade-off is related to capacity. The production department’s capacity requirements will decrease since less rework will be needed in the production system due to the decrease in undetected or post-production design changes. However, assigning extra time to the design system will reduce the time for the production system, which will make the production system maintain a higher level of capacity to speed up production. These two trade-offs highlight the significance of quantifying the ‘Think

Slow, Act Fast' philosophy. This study addresses the lead-time trade-off through a comparison between two archetypes.

2.5 Summary of Research Gaps

This chapter reviewed the papers from both SD and Resilience perspectives, summarizing their research status within the ETO context. The literature review across Sections 2.1, 2.2, and 2.3 highlights several critical gaps in the study and application of ETO systems. These gaps stem from limitations in understanding the integration of design and production processes, the lack of comprehensive modelling approaches, and the underexplored role of resilience in such systems.

Section 2.1 established the unique nature of ETO systems, where customer-specific requirements necessitate the inclusion of design activities within production workflows. While this integration distinguishes ETO systems, current studies fall short of providing structured frameworks to model and analyse this interdependence. The lack of methodologies that holistically represent both design and production phases leaves a void in addressing the operational complexities of ETO systems.

Section 2.2 reviewed the use of SD in ETO systems, emphasizing its utility in capturing feedback loops, time delays, and system-wide interactions. However, most SD applications remain fragmented, focusing on isolated elements such as inventory control or production planning, without adequately representing the dynamic interplay between design and production. Moreover, there is limited research on how SD models can incorporate iterative design processes—a key characteristic of ETO systems—to better reflect their operational realities.

Section 2.3 expanded the focus to resilience in production systems. Resilience, while recognized as a critical factor in many production environments, has not been sufficiently explored in the context of ETO systems. Existing studies lack robust metrics and modelling techniques to evaluate system performance under disruptions and assess recovery capabilities. This is particularly significant given the high degree of variability and uncertainty inherent in ETO operations.

Synthesizing these findings reveals three major gaps in the current literature: (1) the absence of holistic SD models that integrate design and production processes in ETO systems, (2) insufficient attention to ETO system's dynamic performance, and (3) the lack of methodologies to evaluate and improve the resilience of ETO systems against disruptions. These gaps underscore the need for an integrated approach that leverages SD modeming to address the dynamic complexities and resilience challenges of ETO systems. This thesis seeks to fill these gaps by developing new archetypes and frameworks that advance both theoretical understanding and practical applications.

Chapter 3 Methodology

Chapter 3 outlines the methodology of this research, covering the research philosophy and paradigm that underpin the design and methods used. This chapter lays the groundwork for the subsequent research and experiments, providing a detailed explanation of the research process.

3.1 Research Philosophy and Paradigm

A research paradigm is a framework that underpins the research and is developed from the authors' belief and understanding of the theories and practice that are prevalent in the specific research field. A research paradigm consists of three key elements: ontological position, epistemology, and research methods. Ontology refers to the researcher's belief on the nature of reality, which shapes the manner in which one observes and formulates research objectives (Saunders 2016). Epistemology deals with the assumptions of knowledge as well as what constitutes valid, acceptable, and legitimate knowledge and its communication (Burrell and Morgan 1979). The methodological position of a study is influenced by ontology and epistemology and it is the route for interpreting and developing new knowledge. The methodological position also dictates the selection of the methods, theory, and framework that researchers adopt in their research.

3.1.1 Research Philosophy and Paradigm in Production System Management

Production system management, particularly the ETO system, is a multidisciplinary field wherein both quantitative and qualitative methods are frequently used. Therefore, to design a research paradigm, a review of the philosophy traditions within production system management is presented below.

Researchers who employ positivism as their philosophy consider reality as objective and unaffected by the biases or subjective observations of the human mind. Therefore, the knowledge developed through positivistic inquiry can be generalised and adopted to a wide range of fields. Positivistic research is often quantitative and frequently employs mathematical modelling and/or system modelling, such as operations research and system dynamic modelling. A criticism for positivism is that it tends to ignore the subjective observational and nuanced differences among cases, with even less consideration for the impact of humanistic behaviour on the research objectives.

Critical realism is a philosophy that distinguishes the real world from the observable world (Fox and Do 2013). It is believed that knowledge comprehension is affected by the social and cultural contexts, while asserting that there is an underlying reality which is independent from perception. The research in this area is often qualitative or mixed and typical methods include surveys and interviews. Critical realism emphasises the understanding of the underlying mechanisms that define the phenomenon instead of merely describing superficial details.

This thesis adopts a system approach and since it is theory-driven and the reality is considered as objective, the research philosophy followed is positivism.

3.1.2 The Research Paradigm of this Thesis

Positivism is adopted as the research paradigm for this thesis, warranted by the belief that knowledge development should be based on observation and data. The focus of this study is to develop the ETO archetype and explore how to improve the resilience performance of the developed system. Therefore, developing a quantitative and mathematical model is the essence of this thesis, which is validated through a positivistic stance for conducting research. This study also conducts a literature review to quantitatively synthesise and analyse previous research studies that are aligned with the paradigm of positivism.

3.2 Research Methods and Tools

Section 3.2 introduces the research methods and tools used in this study. Mathematical modelling is chosen as the primary approach to model the ETO system, while the SD method is used to simulate the system's dynamics. The following sections, 3.2.1 and 3.2.2, provide detailed discussions on these two methods.

3.2.1 Mathematical Modelling

Mathematical modelling, specifically the control engineer approach, is the core method of this study. The CT, which originated in the engineering field, was first introduced by Towill (1982) into the study of production system management behaviour. The aim of the introduction of the CT is to describe a system via differences or differential equations and analyse the system behaviour via a set of tools, such as transfer function analysis and initial and final value theorems. The main contribution of the CT is developing insight into the mechanism of the bullwhip effect, which unfolds the mathematical relationships among parameters and provides solutions for the mitigation of work rate and inventory oscillations in the production system.

Mathematical formulations are the backbone of the system, which demonstrate the causal relationships and feedback mechanisms in a production system. The formulations could either be differential equations, which describe the system in the discrete time domain or the continuous time domain. To describe the system via mathematical formulations, the user needs to have a clear view of the causal relationships among variables; this could be achieved by logic derivation, observation, and literature-based studies.

Block diagrams, which demonstrate the relationship among variables, is a critical tool in CT. The development of the block diagram is based on the mathematical formulations of the system. The benefit of using a block diagram is that it can demonstrate the structure of the production system in a straightforward manner, which provides a holistic picture for users.

Stability reflects the core performance of the system. If the system is unstable, a tiny change in the input may cause an imbalance in the system. Disney et al. (2006) studied the stability of a production system and proposed that for a linear system, there are two kinds of statuses. One is the stable status, which implies that the system can recover from any disturbance. The other is unstable, which implies that the system cannot revert back to the stable status when a disturbance occurs. There are several methods which can be used to test the stability of the system—Routh–Hurwitz and Eigen value are two frequently used methods in CT. Eigen value analysis refers to the method that distinguishes if all Eigen values' absolute values are smaller than one. The Routh–Hurwitz method refers to the method that a stable system should meet the criteria that the elements in the first array are all positive or all negative (Lin et al. 2020).

3.2.2 Simulation: SD Approach

Simulation is a core approach in the production system analysis and optimisation. Simulation refers to the method which uses a model to reproduce the behaviour of the system in a real-world scenario. The adoption of the simulation helps researchers obtain a better understanding of system performance; moreover, it also provides researchers with a platform to test interventions to the system. Compared to experiments conducted in the actual world, which may need time and labour force, the greatest benefit of the simulation is that it costs less, as a personal computer can usually complete the job. In this research project, the adaptation of simulation is mainly through two perspectives: 1) model verification and 2) a compensatory tool for the high-order system.

Model verification is essential for the newly built model. Before conducting further testing on it, designers must ensure that the model is accurate. In such a scenario, simulation has another name—'triangulation'—which implies that the same simulation is conducted on three different platforms: 1) Excel spreadsheet, 2) MATLAB Simulink, and 3) behaviour reproduction. Based on the transfer function, the results generated by these three methods are compared. The model is believed to be valid only if the results are the same.

Simulation also plays a compensatory role in high-order system analysis. For those systems whose characteristic model exceeds four, it is difficult and occasionally impossible to derive its root. This makes it tedious to conduct analysis which is dependent upon the roots, such as stability analysis and root locus analysis etc. In such circumstances, using simulation methods is essential. By using computers to simulate a system's behaviour with different parameters, one can obtain the bigger picture of the system's performance with diverse parameters values and combinations.

3.3 Research Design

This research contains three major portions: 1) The design of ETO archetypes. 2) Dynamic analysis of the ETO archetypes. 3) ETO resilience study. Considering the unique feature of the ETO, this research begins with an overview of the ETO system's definition and applications in the industry. By extracting the common features and processes, the ETO system structure is summarised to obtain a deep understanding of the foundational mechanism and logic of the system. The outcome of this study will be an ETO archetype family which captures the main character and models the generic ETO systems. Based on the developed archetype, its dynamic behaviour—including stability analysis and frequency domain analysis—is studied. Such analysis can reveal the models' performance and enable the explanation underlying the workings of the phenomena observed in real practice from a CT perspective. The third step of this research is to measure the ETO system's resilience and seek solutions for resilience improvement. The findings from this study can benefit the production system's resilience improvement when facing disturbances or disaster. Finally, the results from all analyses were synthesised and examined from a holistic perspective to derive the 'good' parameter settings for different rework ratios. Based on these findings, a sensitivity analysis was conducted and the developed model was used to test the 'Think Slow, Act Fast' philosophy. The detailed research process is demonstrated in Figure 3.1.

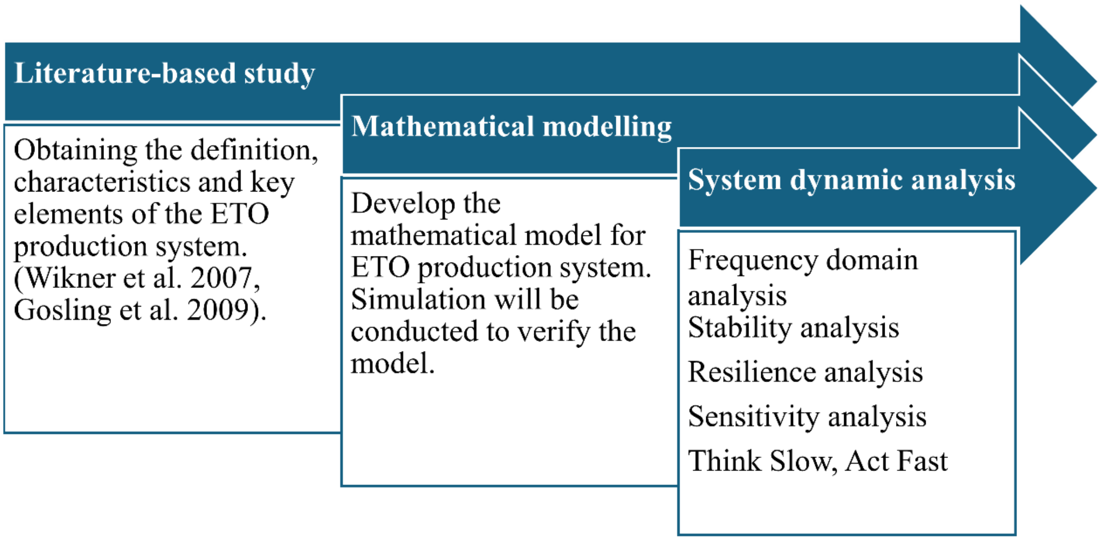

Figure 3.1 The research process for archetype development

3.3.1 The Design of the ETO Archetype

An archetype refers to a general or typical model that demonstrates the main structure of a real-world system. The benefit of studying an archetype is that it can capture the main structure of the target system while aiding researchers to analyse the system through quantitative tools. The outcome of the archetype study may enrich the knowledge for system operation and provide suggestions for the actual operational practices. The shortcoming of archetypes is that these are usually constrained by basic assumptions, which limits their fidelity. In certain circumstances the general knowledge and rules that ensue from archetypes might not be useful in real life, because the real systems are way more complex than an archetype and certain determinants for the system performance may inadvertently be ignored or hidden among assumptions. To overcome this issue, a substantial amount of research has been conducted to improve the fidelity of the system and improve the resonance of archetypes by simulating real-world systems.

However, developing an archetype is still necessary to understand the fundamental mechanism of the system; its importance has been made evident in the role it plays in explaining the phenomena of real systems, such as the bullwhip and ripple effects (Porwal et al. 2020). In addition, a well-verified and constructed archetype could be used as an ideal platform to study the effect of newly developed strategies or policies through simulations, thereby significantly adding depth to the design of real-world strategies, such as information and rework management. Another reason for simulating the strategies effect on archetypes is cost efficacy. Testing interventions in a real-life scenario is costly and carries a high risk of unexpected consequences, whereas testing newly developed policies on the archetype is safer and faster, which makes archetype an indispensable tool for decision-making and strategy design.

In this research, SD modelling methods were adopted, which have the following benefits: (1) SD modelling has been adopted in both PM and production system management fields which build a bridge for knowledge sharing between both sides. This feature is significant for ETO research due to its project-oriented nature. (2) SD models are compatible with a wide range of system analysis tools, such as transfer function analysis and stability analysis. These tools facilitate the development of insight into the system's behaviour; furthermore, it provides a foundation for system optimisation.

The adoption of SD in this study draws directly on the findings of Section 2.2, which highlights its efficacy in modelling feedback loops, time delays, and dynamic interactions in production systems. SD has proven particularly relevant to ETO systems because of its ability to integrate the design and production processes, which are inherently iterative and interdependent. Section 2.2 also underscores the underexplored potential of SD to analyse resilience, which aligns closely with the objectives of this chapter. By leveraging SD modelling techniques, this research builds on these foundational insights to develop archetypes that capture the unique dynamics of ETO systems.

The first step of the model development is the literature-based study, which aims to excavate the structure, key variables, and distinguishing features of the ETO system. Chapter 2 provides a solid foundation for this step in terms of ETO applications, development, and definitions, while the detailed research outcome regarding key variables and CLDs are presented in Chapter 4's modelling section to demonstrate the complete flow of how the model is developed. Thereafter, the CLD was transformed into a block diagram and a differential equation model was developed to crosscheck with the block diagram. The introduction of a block diagram and differential equations enable the quantification of the ETO system and provide a foundation for the further system dynamic analysis. In this thesis, the block diagram is developed in the z-domain due to its capability to effectively model pure delays. This approach is particularly advantageous for capturing the inherent time lags within ETO systems, where work packages must be completed within predefined timeframes to ensure seamless transitions between design, production, and delivery stages. By accurately representing these delays, including the time required to complete entire work packages, the model achieves higher fidelity.

To verify the accuracy of the model and to conduct an initial study on the system, simulation was performed to visualise the system’s transient response to see if it could reflect the ETO system’s behaviour. During the model development process, a key question is where and how embedded the order book controller needs to be to stabilise the targeted variable’s output at the desired level. To answer this question, simulations were conducted. To note here, this thesis does not use empirical data but relies on theoretical modelling and transient response simulations to analyse system’s performance.

Four simulation experiments were designed to evaluate the performance of two different order book controller configurations in various rework scenarios: 1) A local order book controller, situated within the production subsystem and 2) a holistic order book controller, located at a broader system level. In each configuration, two simulations are performed: one to observe the transient responses of a rework-free system following a step input and another to observe the responses of a system that includes rework. An ideal model should maintain the system’s lead time at its pre-input level. Additionally, the lead time for the ETO system should equal the sum of the lead times of the production and design subsystems. Prototypes that meet these criteria were selected to be included in the standard model.

3.3.2 ETO Archetype Dynamic Analysis

After the initial model development and simulation, the system was assessed using the tools from the CT, including transfer function analysis, initial and final value theorem (IVT and FVT), stability analysis, dynamic analysis, and sensitivity analysis. These approaches enable learning from the model that was developed in a quantitative manner, thereby providing an insight into system performance under diverse income and parameter settings. The findings and outcomes were used in the ETO system resilience study.

Model verification and transfer function analysis

The transient responses of the models due to a step-change in demand are illustrated for verification and analysis purposes.

The unit step input is a well-established approach in SD analysis, widely adopted for illustrating a system's behaviour under sudden changes (Towill et al. 2007, Wikner et al. 2017). In this research, the step change is applied as a standard input to evaluate the dynamic response of the proposed ETO archetypes. This input serves several purposes. First, it enables the measurement of key performance indicators, such as settling time and overshoot, providing insights into how the system transitions from one state to another. Second, it offers a consistent and replicable method for testing various configurations, ensuring comparability across scenarios.

One of the advantages of using step change is its simplicity and versatility. It represents a fundamental disturbance that can mimic real-world changes, such as sudden increases in demand or production delays, in a controlled and measurable way (Spiegler et al. 2012). This makes it an effective tool for identifying system characteristics and validating model logic (Nise 2015). Furthermore, by combining the step change with transfer function analysis, it is possible to cross-verify results and ensure that the modelled behaviour aligns with the expected theoretical outcomes.

In summary, the application of step changes as input provides a standardized framework for analysing the transient dynamics of the ETO archetypes, enabling systematic exploration of their behaviour under various conditions, which corresponds with the objective of this research.

The index variables selected for transient response analysis are work rate, lead time, and order book. Work rate reflects the work load of a system, which is one of the determinants of the production cost; lead time represents the time taken for all working units to be completed, which reflects the waiting time from the customer's end; order book refers to the works that still need to be completed, which in the PM field is occasionally referred to as 'work to do' (Lee et al. 2005a). These indices are key competitive indicators for an ETO system and indicate whether the system can maintain its service level to the customer at the expected level (Wikner et al. 2007). To verify that the developed archetypes are free from errors, the triangulation technique is adopted. The simulation results were crosschecked via three approaches. (1) A spreadsheet simulation was conducted via differential equations and the model was simulated with a step input. (2) A z-domain model in Simulink was developed for simulation. (3) The transfer function was derived based on the differential equations using a state space approach and a transient response was remade in MATLAB. Further research was begun only after all results were crosschecked to be the same.

The adoption of transfer function analysis in a production system has a rich history, which covers MTS (Towill et al. 1992) and ATO (Lin et al. 2020) systems analysis; moreover, it has been recognised as an effective tool for system behaviour studies. It depicts how the system will react to an input and is utilised to demonstrate the transient response of the system. The denominator of the transfer function is called the characteristic equation, which is the determinator of system performance—the stability of the system—and is determined by the roots of that equation.

Initial and final value theorems (IVT and FVT respectively) are used to derive the initial value or final value of the system. The final value is an important indicator to see if the system reaches equilibrium at the desired level, and initial value refers to the first value that the system achieves when an input is given. The reason for adopting these two approaches is the initial and final value indicate how system output changes with the given input. A well-developed model should be able to maintain the indicators at the desired level, and IVT, FVT are two approaches that can derive the final or initial value of the output. This assists in developing an insight regarding the level at which the system settles down after the step input.

Frequency domain analysis

As ETO systems are production-oriented, their production costs are highly sensitive to fluctuations in production capacity. High capacity fluctuations can lead to increased operational costs (Spiegler et al. 2012, Barbosa & Azevedo, 2019). Simultaneously, the demand in the ETO market is dynamic and often results in cost overruns in ETO systems (Abotaleb & El-adaway 2018). Therefore, understanding the system's dynamic performance under various demand patterns is imperative. This thesis adopts frequency domain analysis, a method that allows users to examine a system's dynamics under varying frequency inputs, to obtain a better understanding of the performance of various ETO archetypes.

The key variables examined in this thesis are work rate, lead time, and order book.

Work rate refers to the work rate of the production subsystem, which is a core determinant of the system's capability. In the ideal situation, the system's capability should always be above the required work rate, and if the capability falls below the work rate, then an expected delay would occur. However, when the external environment is volatile and uncertain, the required work rate will manifest a fluctuating behaviour, and these fluctuations will likely increase the on-cost production. Thus, work rate is selected as one of the target variables to understand how its dynamic behaviour is affected by the parameters. In this context, the cost specifically refers to the additional expenses caused by work rate fluctuations. Considering these costs aims to identify ways to enhance the system's resilience while simultaneously minimizing the cost associated with fluctuations.

Lead time refers to the time that the whole process requires to deliver the products/projects. The frequency analysis on lead time indicates how stable the lead time is, in a fluctuating environment. A fluctuating lead time may result in losing the customer's patience and reduction in customer service. Thus, keeping a steady lead time is critical for the companies to keep their promises to the customers.

The order book represents the volume of work awaiting completion or the length of the queue for production. It serves as a key determinant of lead time. When the system's production capacity is fixed, a larger order book typically results in longer lead times. Thus, the level of the order book is a crucial indicator for the system's efficiency. An Excessively high order book levels may compromise lead time guarantees, while excessively low levels may lead to the underutilisation of the system's capacity and cause subsequent waste.

Stability analysis

Stability is a core dynamic performance metric once the model of a system is established. If a system is unstable, a tiny change in the input may cause imbalance in the system and lead the system into endless fluctuations. In practice, it usually leads to cost and time overruns and, occasionally, chaos. The stability analysis in the discrete domain faces more difficulties than in the continuous time domain because of the nature of pure delay that is infinite dimensional (Riddalls & Bennett 2002). For a low-order system, typically lower than order four, analytical methods may be adopted. A classic analytical technique is the Routh–Hurwitz method and has been adopted in production planning and control system SD analysis by various authors, including Disney and Towill (2002), to derive the stability boundaries of a vendor-managed low-order inventory-based production control model in the z-domain. For high-order production system models with symbolic parameters, stability analysis has been limited to SD simulation modelling (Klug 2017).

The rework rate and lags are assumed to be constant for each experimental run that defines the quality control, designing and producing products, as well as the associated time taken. Thus, the focus is placed on the decision parameters of the model, which form the decision rules of the system. In this research, the decision rule is realised via a proportional operator for the order book controller, which is called τ_{OB}. The smaller the τ_{OB}, the more sensitive the system is to order book changes. Although a small τ_{OB} can lead to a prompt reaction to the order book change, it may also amplify fluctuations in the systems and, in certain cases, it may result in an unstable system (Zhou et al. 2022). To stabilise the system, τ_{OB} is useful, but the derivation of τ_{OB} is hindered by a high-order system.

In adopting the pure delay in the modelling, one of the difficulties is solving the high-order character equation. Due to the infinite nature of the pure delay (Disney and Towill 2002), a delay of one unit leads to the system's order increasing by one. Hence, in multi-echelon systems, modelling delays, as found in ETO archetypes, often exist in multiple stages, and the duration of the delay is usually greater than one. Therefore, it is critical to develop a universal stability analysis tool for the high-order systems which include symbolic parameters. The derivation of the stable condition for ETO system is organised into two parts: 1) Low-order system stability analysis and 2) high-order system stability analysis. However, it is important to note that the choice of using step responses as the primary disturbance type in this study was made to reflect sustained system changes, such as persistent demand fluctuations or resource constraints. While step responses provide insights into long-term adaptability, alternative approaches like impulse responses—which represent short-term disturbances—could complement this analysis to capture recovery dynamics. Future work could explore the combined use of step and impulse responses to present a more holistic perspective on resilience in ETO systems.

The Routh–Hurwitz method was adopted to derive the critical stable condition for low-order archetypes, the system's order of which are lower than or equal to four. According to Lin et al. (2020), to achieve stability, the first array of the Routh matrix should be all positive or all negative, and this criterion was adopted in this research. After obtaining the stable condition, a two-dimensional figure was used to visualise alongside rework as the independent variable and $1/\tau_{OB}$ as the dependent variable to illustrate which parameter settings can stabilise the system and which dangerous settings may lead the system into unstable, fluctuating situations.

To adopt the Routh–Hurwitz method for a high-order system, this method was combined with PSE (Dhanwada et al. 1999). The entire process can be divided into the following steps: 1) Derive the characteristic equation of a system. 2) Replace z with (w+1)/(w-1). 3) Extract the coefficient of w of the characteristic equation. 4) Create the Routh–Hurwitz matrix. 5) Extract the first array of the matrix. 6) Create the parameter space, with the rework ratio as the X-axis and $1/\tau_{OB}$ as the Y-axis; for both axes, the range is from 0 to 1 and the step length is set to be 0.01. 7) Test each point on the parameter space in the first array of the Hurwitz matrix to see if the array meets the criteria for stability.

Steps 6 and 7 are complimentary steps for PSE, which can reduce the difficulty in root derivation with reasonable accuracy. Although this result is not as accurate as the result of the mathematical analysis, it is sufficient for practical use. Users can reduce the step length to obtain a more accurate result if the research requires a higher accuracy. To crosscheck the result, a comparison is made between the PSE result with one delay and the analytical results.

3.3.3 The ETO Resilience Study

The resilience research can be divided into four steps. 1) PSE. 2) Best τ_{OB} derivation. 3) Transient response with best τ_{OB} setting analysis. 4) Result analysis.

PSE refers to a simulation-based method that calculates the numerical result of all possible parameter combinations. In this research, there are two parameters: rework ratio and τ_{OB}. PSE can simulate the system's transient responses with all types of parameter settings by adopting the ITAE index. This method enables the measurement of the resilience of ETO archetypes with all parameter settings. The numerical results can be used for further visualisation and analysis.

The input for the system in the PSE simulation is a unit step change. The use of such input as the primary disturbance type in this study reflects its ability to simulate sustained system changes, such as prolonged demand increases. This study specifically uses positive step changes because they provide a unified and standardized input for generating the PSE map (Thiagarajan et al. 2018). A negative step change is not used because its transient response would be a mirror image of the positive step change, yielding identical results.

By combining step change with ITAE, this study develops a systematic method for resilience measurement. Step changes act as a representative disturbance that enables a consistent assessment of how the system adapts to and stabilizes following a disruption. ITAE quantifies the overall performance by integrating two key dimensions:

- Time: Captures how quickly the system settles into a new steady state.
- Error: Reflects the extent to which the system deviates from the desired state during recovery.

The combination of these tools provides a structured approach to evaluating resilience, focusing on both dynamic response and long-term adaptability. This approach is particularly relevant for ETO systems, where disturbances often have prolonged effects and the ability to minimize both recovery time and error is critical.

With the consideration that PSE is a simulation-based algorithm which may contain errors, a triangulation was also conducted via MATLAB, Simulink, and spreadsheet simulations. The primary PSE method was conducted via MATLAB. To verify the result, 10 parameter combinations were selected from the parameter space, which is a space with rework ratio on the x-axis and τ_{OB} on the y-axis. The transient responses were then reproduced to calculate the ITAE value to crosscheck it with the PSE result. After the verification, the result was presented via a contour map, thereby providing a visual representation of the changing trends in ITAE along with the change in the rework ratio and τ_{OB}. Based on this contour map, further research on parameter optimisation can be conducted.

After obtaining the numerical result and contour map, the parameter setting which can make the system have the lowest ITAE value and which represents the highest resilience was explored. This step was undertaken to find the τ_{OB} setting that can make the system have the lowest ITAE value for each rework ratio. The reason why this research focuses on τ_{OB} is that in practice, the rework ratio is usually determined by the craftsmanship and design or production difficulties, while τ_{OB} as a reflection of the sensitivity of the system to the order book change and can be easily adjusted through managerial intervention. This study recognizes that τ_{OB} adjustments offer a practical lever for managers to influence system resilience directly. By linking τ_{OB} to real-world managerial decisions, this analysis bridges theoretical modelling with capacity management, offering insights into how managers can balance demand response speed with capacity fluctuation. Thus, in that circumstance, this research aimed to identify the best τ_{OB} for each rework ratio to achieve the best system performance.

The next step involves conducting a transient response study for the optimal τ_{OB} setting to understand how these two variables impact system performance. This step can also provide valuable insights into the balance between lead time and work rate resilience. As mentioned in the Background section, the trade-off between capacity and lead time is well-established in production planning and control. Therefore, it is crucial for management to maintain a stable capacity, which is represented by the work rate, while ensuring a promising lead time. In addition, the transient response analysis allowed for the examination of how τ_{OB} settings influence recovery behaviour under varying disturbance scenarios, highlighting the importance of adjusting operational sensitivity to improve system performance. This step also included the analysis of both recovery speed and the degree of oscillation, as these are critical metrics in resilience studies.

However, quantifying this trade-off is challenging, as different companies may assign varying weights to these targets and their strategies may also influence their decision. Therefore, this study focused on identifying the best τ_{OB} for achieving optimal lead time and work rates.

The final step for the resilience measurements is the result analysis. Based on the changing trend of the τ_{OB} against the rework ratio, the phenomenon observed from the ITAE matrix was summarised and the best τ_{OB} was compared for lead time and work rate. The aim of the result analysis was to explain the changing trend and attempt to solve or optimise the trade-off between lead time with the work rate. Simulation and comparison were adopted to clarify the role of τ_{OB} in different stage and scenarios. Additionally, this analysis included a sensitivity test to explore the robustness of the recommended τ_{OB} settings under extreme conditions, such as significant reductions in system capacity or sudden demand fluctuations. This provided deeper insights into the adaptability of the proposed τ_{OB} recommendations across diverse operational contexts. The outcome of this analysis was three maps which demonstrate the recommended τ_{OB} setting for ETO systems with diverse rework ratio; simultaneously, the result was crosschecked with the findings from the previous empirical studies to fill the gap between theory and practical.

3.3.4 Syntheses of the Results

Stability analysis, Bode plot analysis, and resilience analysis provide recommendations on archetype parameter settings from different perspectives. This introduces a new challenge: how to implement the order book concept in the ETO system. Therefore, the results from these different analyses are integrated and synthesised in Chapter 7. Based on this synthesis, a sensitivity analysis was conducted on the developed archetypes with the recommended parameter settings.

Sensitivity analysis

The focus of the sensitivity analysis was placed on rework rate and three delays—production delay, design delay, and rework scheduling delay. To comprehensively test the system's sensitivity, the system was tested under two different inputs: deterministic demand via a step change input and stochastic pattern demand.

For the determined pattern demand, the reaction of the lead time and work rate was tested against the change in delays and parameters. The change in delays and parameters was found to be 25% and 200%, respectively, and transient responses of the system were visualised to provide an insight into how peaks and transient processes look like. Thereafter, stochastic demand was used to simulate the system again and to quantify the influence of the changes.

In addition, the bullwhip ratio was utilised as an indicator to assess system performance. The Bullwhip Ratio is a widely recognized metric in supply chain dynamics, particularly in understanding how variability propagates through a system. In this study, it is used as a measure of how demand fluctuations at the customer end amplify as they move upstream in the ETO system. This amplification, commonly referred to as the bullwhip effect, is a critical factor in analysing the resilience of ETO systems under varying operational conditions. By quantifying this amplification, the bullwhip ratio provides insights into the system's ability to dampen fluctuations and maintain stability.

The choice of the bullwhip ratio as an indicator is particularly relevant for this research because ETO systems are highly sensitive to variability in demand and capacity, which directly impacts lead times, resource utilization, and overall system stability. By incorporating this metric, the analysis highlights not only how the system responds to stochastic demand but also its capacity to recover from and adapt to changes, making the bullwhip ratio a suitable and effective measure of resilience.

'Think Slow, Act Fast' in ETO

Based on the findings from the sensitivity analysis, it was realised that the duration of the design delay and production delay has different impacts on the system. At the same time, a book called 'How Big Things Get Done' (Flyvbjerg & Gardner 2023) inspired the research in this subsection. In the book, the authors proposed that a prolonged design or planning time is a safe harbour for the inspection of changes and defects, and another proposition was that project managers should 'Think Slow, Act Fast'. Although this philosophy is summarised from actual experience, there is little research that explains the underlying mechanism. Thus, for this project, the following steps were developed to quantify and study the philosophy and its benefits for ETO company management.

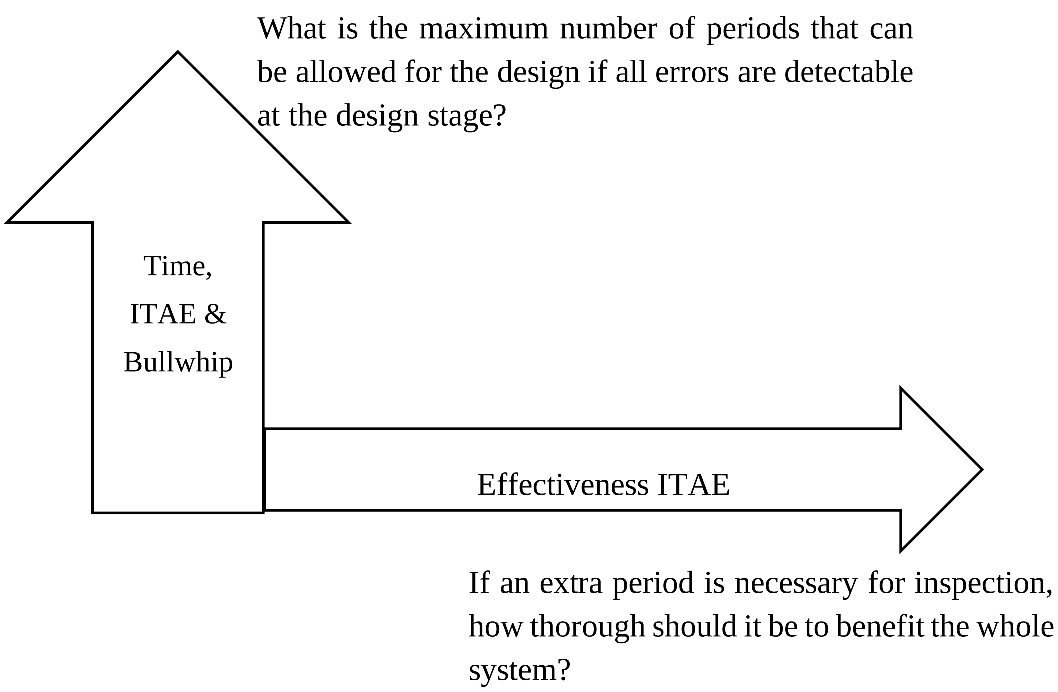

Figure 3.2 Two-dimensional experiment

Adaptation of archetypes in 'Think Slow, Act Fast' consists of two sub-experiments, as shown above, which are determined by two assumptions for the scenarios.

Experiment A: The first assumption is whether a one-period delay in the design system is worthwhile for the whole system, based on the percentage of errors detected during the design phase.

Experiment B: The second assumption is whether introducing additional periods during the design phase can prevent undetected design errors from being sent to the production system and, if so, how many periods should be allocated for this.

For both experiments, ITAE is utilised as the system performance indicator. The ITAE for lead time reflects how quickly and efficiently the system can respond to sudden changes, thereby demonstrating the system's resilience and robustness to disturbances. The detailed experiment process is provided in Section 7.3.

3.4 Summary

This chapter demonstrated the methodology of this research. Section 3.1 discussed the research philosophy and paradigm of this research. Based on the main philosophy, positivism, this research adopts mathematical modelling and simulation as its main methods, which were explained in Section 3.2. Section 3.3 introduced the research design of this thesis, which includes five steps—archetype development, system dynamic analysis, and resilience research. The next chapter presents the developed ETO archetypes.

Chapter 4 ETO Archetype Design and Modelling

4.1 ETO System Structure

To extract the structure of the ETO system, the following definition is adopted: ETO systems are dynamic, complex systems wherein the order penetration point is located at the design stage (Wikner and Rudberg 2005, Gosling et al. 2017). At the same time, products or services in such a system are fully driven by customers' orders (Gosling and Naim 2009), thereby contributing to one of the distinguishing features of ETO industries and necessitating the consideration for the simulation of the service flow within the PM field (Denicol et al. 2020).

According to the definition above, it can be concluded that the ETO system comprises two key subsystems: design and production. Considering that both design and production systems hold no stock, the production system management-orientated structure of an order-book-based MTO system (Wikner et al. 2007) is used as a reference point. These are modelled systems in which production begins only after the order arrives. To combine the two systems, the idea of the integrated design and operations management (IDOM) is borrowed (Zhang et al. 2019), which is an enterprise information system that integrates the production and design subsystems. The synthesised archetype connects the two subsystems and models the working units at an aggregate level, thereby providing the archetype with project features. The adaptation of working units rather than product quantity is to avoid potential issues caused by the one-of-a-kind feature unique to ETO. Because ETO products are usually unique, there is a tendency for the requirement of the workload being different from that for other systems. But the problem arises when bias is produced while using product quantity for modelling the system. Instead, modelling the working units flow can avoid this issue; all orders that are placed by customers will be broken down into working units so that the planning department can accordingly adjust the capacity of the design and production systems.

Apart from the two fundamental subsystems, the system incorporates a control mechanism to adjust its operational pace in response to changes in demand. Instead, a subsystem, termed the order book controller, is integrated into the ETO archetype. This controller records the volume of pending tasks and calculates its value by determining the difference between the target and actual order books. The order book controller autonomously modifies the work rate of the system and, thus, ensures that production deadlines are met. Further, lead time estimation employs Little’s Law, thereby facilitating accurate projections of process completion (Little 1961a).

In this archetype, all projects—whether single-project or multi-project—are represented uniformly in terms of the total number of working units required. Each project or set of projects is input into the model as a cumulative working unit value, which becomes the primary measure of workload and capacity. This approach ensures that the model remains scalable and consistent, regardless of the number of projects being managed. The distinction between single and multi-project environments becomes irrelevant within the scope of the model, as the focus lies entirely on the volume of working units to be processed. Future work could extend the archetype by incorporating additional subsystems to simulate delivery and further refine the connection to practical applications, enabling more detailed analysis of project-specific dynamics.

In addition, it is important to note that this archetype is a work rate decision engine and does not include the delivery process. Such decision engine concept has been adopted in the construction industry, where the SD model functions as a capacity adjustment engine integrated with other software tools (Lee et al. 2006a). And in terms of the delivery process, in practice, clients in ETO systems do not accept partial deliveries of work packages; they wait for the completion of all required packages before project delivery. Simulating this process would require introducing a subsystem to accumulate working units to the required level and then trigger delivery. However, such an approach would introduce non-linearity to the model, significantly increasing its complexity and making it difficult to analyse. For this stage of the research, the model is designed for specific use cases, focusing on foundational elements of ETO system behaviour.

After designing the main frame of the ETO system, the key elements of the ETO system are summarised in Table 4.1 by reviewing relevant papers from both the PM and production system fields. Due to the overlapping concepts and ununified terminologies in PM and production system fields, a few elements are reserved while others are deleted from the table; the main variables of the ETO systems are then summarised for further archetype development.

4.2 Key Elements

Table 4.1 Distinguishing elements of combined PM and SCM perspectives of an ETO system and synthesis results

	Elements	**Reference**	**Explanation**	**Consolidated ETO elements**
Project Management	Rework	Lyneis and Ford (2007) and Love et al. (2019) Explore the impact of rework on project dynamics.	Rework is a canonical feature in project management; such a problem is often inevitable in practice.	√
	Work-To-Do	Pena-Mora and Park (2001) and Park (2005) Study the project dynamic based on SD.	Work-To-Do is another distinguishing variable in project modelling; this variable records the overall work that has entered the system but is yet to be completed.	
	Working units	Pena-Mora and Park (2001); Lee et al. (2006) Model the working unit in their simulation.	Research in the project management field often models working units as opposed to product volume.	√
	Work rate	Lee et al. (2005) Develop a SD model which includes work rate.	Work rates directly reflect capacity.	√
Production system Management	Order rate	Towil (1982), Lin et al. (2017), and Wikner et al. (2017). Develop production system models, which include order rate.	Order rate is an essential element in production planning and control, especially in order-driven systems, which determine the production speed of the production system.	
	Lead time	Wikner et al. (2007), Lin et al. (2020), and Spiegler et al. (2012) Study the lead time dynamic of the production system	Lead time, a vital concept in SCM, directly affects both cost and revenue, which can be used as an indicator for system performance in order-based production systems.	√
	Order book	Wikner et al. (2007) Explore the adoption of Order Book control in MTO system.	One of the distinguishing variables in the MTO system is the order book, which represents the order waiting to be satisfied.	√

The key elements identified are presented in Table 4.1, with the last column presenting the variables that will be used in model development. The following are the reasons for consolidating this:

1. Rework remains a distinguishing feature of project-based production, where approaches to operational excellence have not yet fully eliminated its occurrence, as is often achieved in manufacturing production lines.

2. The work rate is retained because the model in this research emphasises working units.

3. Lead time, as a crucial indicator of system performance and a significant factor in customer satisfaction, is included as an essential variable for use as a metric in dynamic assessments.

The concept of work-to-do is merged with the order book, as both represent the work awaiting completion. The decision has been made to model the working units rather than the material flow within the system in order to circumvent potential issues arising from the diverse properties of products/projects. The use of "working units" in this research is central to capturing the dynamics of work rates, which are critical indicators for capacity management in ETO systems. This concept is closely aligned with the "work package" approach commonly employed in PM and ETO industries (Lee et al. 2005b; Han et al. 2013). Working units provide a standardized representation of progress, enabling the model to simulate the behaviour of production flows and work rates under various scenarios. Without this concept, it would be challenging to model the intricacies of ETO systems, particularly the dynamic interplay between design, production, and rework processes. In addition, the concept of an order book aligns with the 'negative inventory' and backlog in the MTS system, representing the quantity of products ordered by customers but not yet delivered (Wikner et al. 2007).

Furthermore, the order book, work rate, and lead time are selected as the principal metrics to evaluate the system’s ability to adapt to rework or changes in demand while ensuring timely product delivery. With regard to rework, the following two critical questions must be addressed: Where does non-conformance—that is unqualified products, or tasks—occur? How does the system adjust to such rework?

4.3 Rework Scenarios

In practice, rework may be caused by non-conformance and design changes. Non-conformance problems create high uncertainty, not only because they may occur at each of the design and production stages but also because the inspection of non-conformance is often not timely (Han et al. 2013). Consequently, non-conformance detected downstream may be attributed to upstream work (Love et al. 1999). Simultaneously, design changes also contribute towards a great proportion of the rework. Design changes are usually requested by clients and may occur after the production begins, which requires the company to redesign and remake the product via rework (Han et al. 2013). Thus, depending on the place where the defects or changes are detected/occur and the place where these tasks are rectified, all scenarios can be classified into the following three groups.

1. Production rework (ETOAR#P): This refers to a scenario wherein the defect or error is created in the production stage and such defects are detected in a timely manner. The rectification of such rework requires extra working units in the production system.
2. Design rework (ETOAR#D): This refers to a scenario wherein the design contains defects or errors but these are detected before the production commences. In this case, rectifying the defects or errors only requires extra working units in the design phase.
3. Delayed design rework (ETOAR#PTD): This refers to a scenario wherein the design contains a defect, but it is detected during the production stage. To rectify such cases, extra working units are required for both the design and production stages.

Based on the summarisation of rework scenarios, it was found that it is difficult to represent the rework scenarios using a single model; instead, ETO archetypes should be a suite of models which contain three basic archetypes. Table 4.2 demonstrates the definition and relevant research of these three basic models. It must be noted here that in actual practice, it is rare that rework only occurs at one stage; instead, the ETO projects often face a mixture of the basic scenarios. The reason why these scenarios are sub-divided into three basic models here is to obtain a deeper understanding of each of them and to build a solid foundation for more complex research in this regard in the future.

At the same time, design changes contribute significantly to rework. These changes, often requested by clients, may occur after production has commenced, thereby necessitating the redesign and remanufacture of the product through rework (Han et al. 2013). Consequently, scenarios are categorised into three groups based on the location where the defects or changes are detected and where the rectification tasks are performed.

Table 4.2 Definitions of the ETO archetypes

Archetype Code	Definition	Reference
ETOAR#P	The scenario wherein the rework created by production defects and can be rectified in the production phase.	(Lee et al. 2005; Barbosa and Azevedo 2018)
ETOAR#D	The scenario that reworks attribute to the design error or defects and these defects can be rectified inside the design phase.	(Khan et al. 2016; Vaagen et al. 2017)
ETOAR#PTD	The scenario, that reworks attribute to the design error or defects, but detected in the production phase, to rectify these works requires extra works in both design and production stage.	(Love and Smith 2018; Ansari 2019)

4.4 Conceptual Modelling

The abbreviations for variables are summarised and explained in Table 4.3. It is important to note that the time unit used in this study is weeks, which is a commonly used unit in the PM field. In following sections, the CLD and block diagram of the archetypes are provided, which correspond with the mathematical formulations. The main structure of archetypes is composed of three components—design system, production system, and the order book controller system—and these three systems can represent three working areas in the company, which are design area, production area, and planning area, respectively. These working areas may refer to the departments of a company; for companies that adopt foreman planning systems, each working area may include several working teams to complete the design or production for ETO products. The model that is developed in this project is an aggregate level model and the focus is on the process for each subsystem.

The orders placed by customers will first be processed by the planning department and then sent to the design department. Afterwards, the design will be transformed to the production department, wherein the products will be manufactured according to the design. The planning department plays a role in adjust the capacity of the system. Without the planning department, the design and production subsystems' work rate will be fully determined by the input of the system, which implies that the defects will not be rectified, and the target order book level cannot be maintained (Wikner et al. 2007). The order book controller has not been adopted in; It is worth noting that the model developed in this thesis can be regarded as a capacity decision engine for the system. To enable practical implementation, support from other sub-models is essential. This decision engine concept is also utilized in the Dynamic Planning Methodology (Lee et al. 2006a), which has demonstrated that integrating an SD-based decision engine with other software can lead to better decision-making, effectively addressing challenges such as customer changes or quality issues (Lee et al. 2005b).

Table 4.3 Nomenclature for the ETO archetype

Abbreviation	***Full name***	***Explanation***
ETO system		
DEM	Demand	Demand for the ETO system
OB	Order book	Order book for ETO system
LT	Lead time	The lead time of the ETO system
DELRATE	Delivery rate	Rate of qualified products, which meet the customers' requirement
Design Sub-system		
DES	Design	Abbreviation for design
DEM_{DES}	Design Demand	Demand for the design system.
$COMRATE_{DES}$	Design Completion Rate	Completion rate of the design system
OB_{DES}	Design Order Book	Order book of the design system
LT_{DES}	Design lead time	The lead time of the design system
Production Sub-system		
PROD	Production	Abbreviation for Production
DEM_{PROD}	Production Demand	Demand for the production system.
$WRATE_{PROD}$	Production work Rate	Work rate for the production system
$COMRATE_{PROD}$	Production Completion rate	Completion rate of the production system
OB_{PROD}	Production Order Book	The sum of uncompleted works (including reworks)
$RWRATE_{PROD}$	Rework rate	The number of units needing rework
LT_{PROD}	Production lead time	The lead time of the production system
Coefficients		
τ_D *(week)*	Expected Design Delay	Delay caused by designing or design adaptation
τ_P *(week)*	Expected production Delay	Delay caused by production
τ_{OB}	Time for order book adjustment	Time used for adjusting the production system's order book
RW	Rework ratio	The rework ratio of the production system

4.4.1 Model Assumptions

A general archetype that is applicable for all scenarios does not exist and it is important to realise that the model is only accurate with appropriate assumptions. Hence, the following assumptions are made for the archetypes developed for this research. Since there are three basic archetypes, the following list represents a set of common assumptions for all three models. For each basic model, specific assumptions will be added to limit the usage of these models.

Assumptions:

1. The transfer function model is linear and time-invariant.

2. The rework ratio is constant.

3. The workload for design and production can be measured by the number of working units.

4. Rectifying non-conformances requires the same number of working units as the original work.

5. Capacity is infinite. The system can respond immediately to demand changes.

6. Apart from the fundamental assumptions above, each scenario also has its special assumptions in correspondence with the specificity of the application for each of the models.

7. Little's law is used to estimate the lead time of the system.

Apart from the abovementioned common assumptions, each individual archetype has its own unique assumptions to distinguish each scenario from others. These unique assumptions are individually stated for each scenario.

8. The design and production processes within the ETO system are fully integrated and managed by a single company. This assumes that the organization oversees both the

design phase, including iterative changes and rework, and the production phase, ensuring seamless coordination and alignment between the two (Hicks et al. 2000).

9. The primary flow in the model is represented by 'working units,' where units are considered homogeneous if they require the same duration to be completed in both the design and production subsystems (Shin et al. 2014). A working unit refers to the amount of work that can be completed by a single worker or another unit, such as a group or team, within one hour. This assumption abstracts the flow of materials into working units, enabling a consistent framework to model the dependencies between the design and production phases.

10. While the model uses working units as the flowing entity, there is a fundamental distinction between the roles of design and production. Working units in the design phase represent conceptual and iterative processes, often influenced by rework and decision-making. In contrast, working units in the production phase represent tangible fabrication or assembly tasks that are typically more predictable and standardized. This assumption is specifically tailored to capture the dynamic interactions and feedback loops between these two subsystems, a key characteristic of ETO systems.

4.4.2 CLD Modelling

Based on the discussion above, the CLD was initially developed to assess the logical correctness of the mode. At an aggregate level, the model focuses on high-level trends and interactions rather than specific, detailed processes. This abstraction allows the model to capture the overall dynamics of the system while reducing complexity. Consequently, aggregate models tend to be more generic, making them applicable across a wider range of scenarios. In this research, the aggregate level approach ensures that the causal relationships and feedback loops in the SD model are logically consistent and broadly relevant to ETO systems, rather than being constrained to specific cases.

Based on the literature review in of section 2.1 and 2.3, the system should have three main subsystem, design and production construct the main structure of the ETO system (Olhager 2003, Gosling and Naim 2009, Haug 2013); and an order book control subsystem which can monitor and control the system’s work rate (Wikner et al. 2007, Barbosa and Azevedo 2019). Such structure also corresponds with the systemigram that adopted by the Alfnes et al. (2021) in a shipbuilding field. Considering the absence of inventory in both the design and production systems, the structure of the MTO system, as described by Wikner et al. (2007), was adopted to develop the initial model. Each subsystem is characterised by four basic variables: work rate, order book, completion rate, and lead time, with the flow of the system represented by working units. . Compared to previous APIOBPCS models (Lin et al. 2017), the model developed in this thesis integrates the design process with the production system, incorporates rework—a distinctive characteristic of ETO systems—into its framework, and simulates the working units flow instead of number of products.

A key distinction of this model compared to others is the flow mechanism, which specifically simulates the working units of the system. A ‘working unit’ refers to a standardised work package that necessitates a certain amount of workload and time for completion. For example, to complete a work package, one skilled worker will need to work for a specific duration. The rationale underlying the adoption of the concepts of working units is to mitigate potential biases introduced by unique products. According to the definition of an ETO system, ETO products differ from each other, thereby implying that different products require varying amounts of working units. To circumvent this variability, it is assumed that all products can be broken down into working units, thereby enabling the ETO company to estimate the required working packages when an order is placed. This concept is widely used in the PM field; however, traditional PM models typically focus on modelling a single project, with the primary aim of ensuring progress reaches 100% completion (Lee et al. 2005a; Motawa et al. 2007; Han et al. 2013). In these models, progress is treated as an accumulative process, where the output steadily increases until it reaches its maximum. In contrast, the ETO model developed in this thesis aims to ensure that all orders are completed within the required timeframe while balancing capacity and demand. The focus is not solely on individual project completion but on achieving an equilibrium where the system's capacity is optimally aligned with the overall demand.

The working units concept introduces work rate to the system, which denotes the production speed of the subsystems and reflects how many working units can be completed within a specific time unit. After a certain delay, represented by a double line on the curve arrow to denote the time needed to complete the input amount of work rate, the work rates evolve into completion rates.

The order book in this model represents the backlog of work yet to be completed. This concept is also known as work to do in construction industry (Lyneis and Ford 2007). When a new order is received and confirmed, the estimated working units are added to the order book, thereby increasing its actual size. The target order book, established by the company manager, is determined based on the product of the promised lead time and the demand. By comparing the target order book with the actual order book, the system can automatically adjust the production speed—the work rate—to ensure that products are manufactured within the promised lead time.

In this model, the lead time is conceptualised as the waiting time before the products can be delivered and is estimated using Little's Law (Little 1961). There are three types of lead times considered: those of the design system, the production system, and the entire ETO system. This estimated lead time, which may differ from the promised lead time, helps the system adjust the work rate of the subsystems to ensure that the products are completed within the lead time over the long term. The reason why lead time is included in this archetype is that time is a key indicator of the production system, especially for an ETO system, which is a pure pull system. (Lin et al. 2020). Delivering the product within the lead time is one of the determinants of customer satisfaction. (Soewin and Chinda 2022, Dallasega et al. 2019).

In developing a CLD based on the above ideas, variables at the head of an arrow represent dependent variables, while those at the tail are causative variables. The diagrams use positive (+) and negative (–) signs to indicate how the causative variables influence the dependent variables. These causal relationships form loops which are categorised into reinforcing and balancing loops. Reinforcing loops, typically marked in red, can drive the system towards instability unless controlled by external interventions or balanced by other loops; in contrast, balancing loops, depicted in blue, help maintain system stability.

Reflecting on the rework scenarios, three initial models were developed to depict different situations in which reworks occur as shown in the Table 4.2. The first scenario, labelled as the production rework scenario (ETOAR#P), addresses reworks originating from and rectified within the production subsystem, as illustrated in the block diagram below**.**

CLD for ETOAR#P

The CLD model for ETOAR#P is presented in Figure 4.1 This model addresses the scenario where rework occurs within the production subsystem. Rework in the production subsystem is prevalent within sectors such as construction, shipbuilding, infrastructure and capital goods manufacturing (Hessami et al. 2020; Ford et al. 2023). Despite longstanding recommendations to 'Do it right the first time.' Production rework may be necessitated by quality issues, poor craftsmanship, or other factors requiring workers to redo or adjust their work. Ideally, defects should be rectified as soon as they are detected. However, because defect detection is not always timely, workers may need to dismantle subsequent work and redo tasks, which is both costly and time-consuming.

The model depicted below simulates this scenario and consists of three subsystems: design, production, and order book controllers. This structure is based on the discussion in Section 4.1, which emphasizes that an ETO archetype should integrate the design and production processes (Olhager 2003). Additionally, a control subsystem is included to ensure that all tasks are completed on time (Wikner et al. 2007).

The key elements are derived from Section 4.2, and their causal relationships are based on the SD models analysed in Section 2.2.7. The basic mechanism is as follows: demand influences the order book; the gap between the target order book and the actual order book drives changes in the work rate; the work rate impacts the completion rate, which in turn affects the order book. These causal relationships are also discussed in the following references (Love et al. 1999; Peña-Mora and Li 2001; Barbosa and Azevedo 2019).

In ETOAR#P context, rework is situated within the production subsystem, production rework requires additional effort from the production team, creating feedback that connects rework with the work rate. This means that when the production team identifies a defect, they must allocate and schedule additional time to complete the rework (Park 2005; Lyneis and Ford 2007). The presence of rework creates a reinforcing loop with the completion rate and work rate, thereby necessitating a balancing mechanism. The order book controller serves this purpose. The balanced loop, highlighted in blue, demonstrates how the system compensates for the impacts of rework.

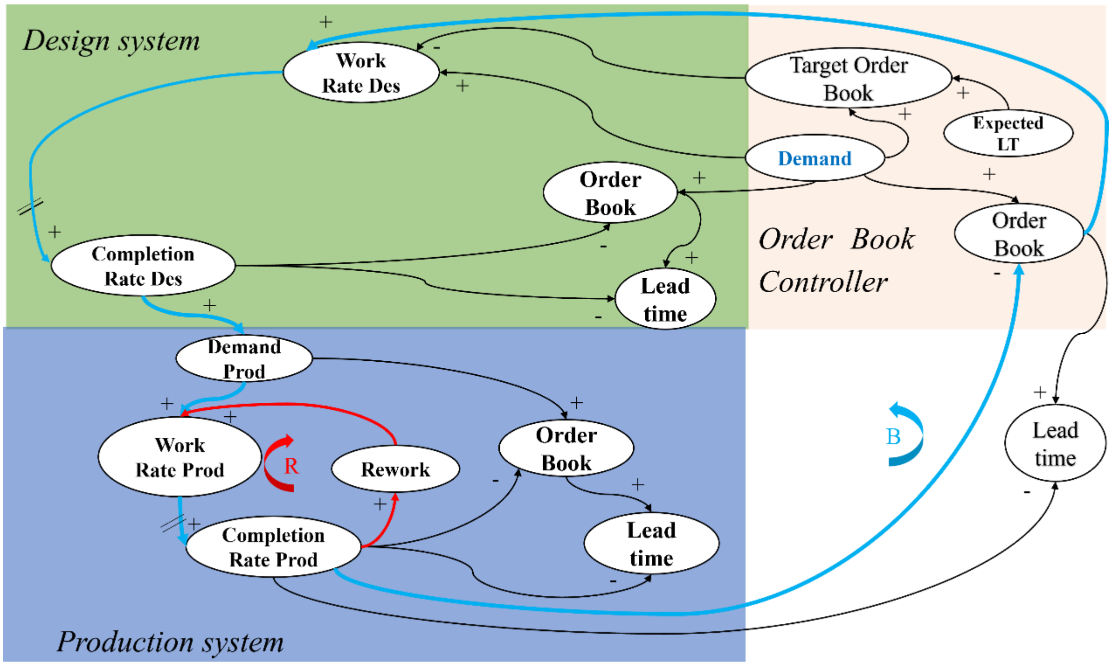

Figure 4.1 CLD for ETOAR#P

CLD for ETOAR#D

In this scenario, rework occurs within the design subsystem, which reflects changes or amendments in the design phase—a common occurrence in business due to the unique characteristics of ETO operations (Han et al. 2013). Customers and ETO companies often engage in multiple rounds of communication to refine and upgrade designs, which leads to rework within the design subsystem (Parvan et al. 2015). Consequently, feedback is drawn from the completion rate of the design system (completion rate des) to rework, and another from rework to the design system's work rate (work rate des). These arrows indicate that the design team identifies errors or receives requests for changes before transferring the design to the production system, thus necessitating additional work solely within the design subsystem.

As depicted in Figure 4.2, the red arrows form a reinforcing loop, comprising three variables: the design system's work rate, rework, and completion rate. This loop signifies that completed works containing defects require rework, and the working units designated for rework are added to the work plan for the subsequent period. However, poor workmanship in rework can generate additional rework, thereby leading to further waste in capacity and materials.

To address this issue and mitigate the effects of the reinforcing loop, a balancing loop is necessary. The balancing loops are represented by a blue line in the system and include the order book, the design system's work rate, the completion rate of the design system, the demand of the production system, the production system's work rate, and the completion work rate. This balanced loop regulates the work rates of the subsystems and compensates for any work rate gaps created by rework. This design effectively balances the vicious cycle of rework when the rework ratio is below 1.

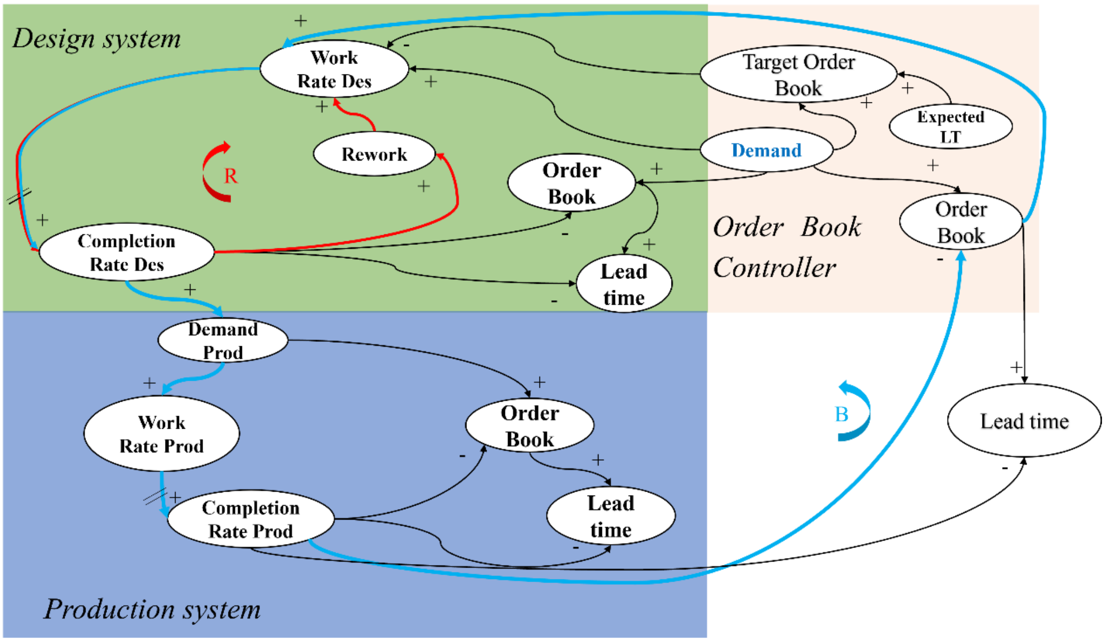

Figure 4.2 CLD for ETOAR#D

CLD for ETOAR#PTD

In addition to scenarios that solely involve design or production rework, another scenario involves production-to-design rework, as presented in Table 4.3. This scenario arises when design defects are identified or changes in design requirements are made after production has commenced (Love et al. 2002). Rectifying or adjusting for such defects necessitates collaborative rework from both the design and production departments. This type of rework is not uncommon in the ETO field and is frequently triggered by customers making late design requests or design defects (Shin et al. 2014). The cost and time required to rectify such errors or changes are typically higher and are significant contributors to cost and time overruns (Flyvbjerg and Gardner 2023). However, such issues have not been modelled using the SD approach, and their impact on dynamic performance remains unexplored.

Figure 4.3 demonstrate the CLD model of such scenario. Initially identified defects are sent to the design department, as illustrated by feedback from the production completion rate to rework and another feedback from rework to the design work rate. The main structure is the same as that of the other two models.

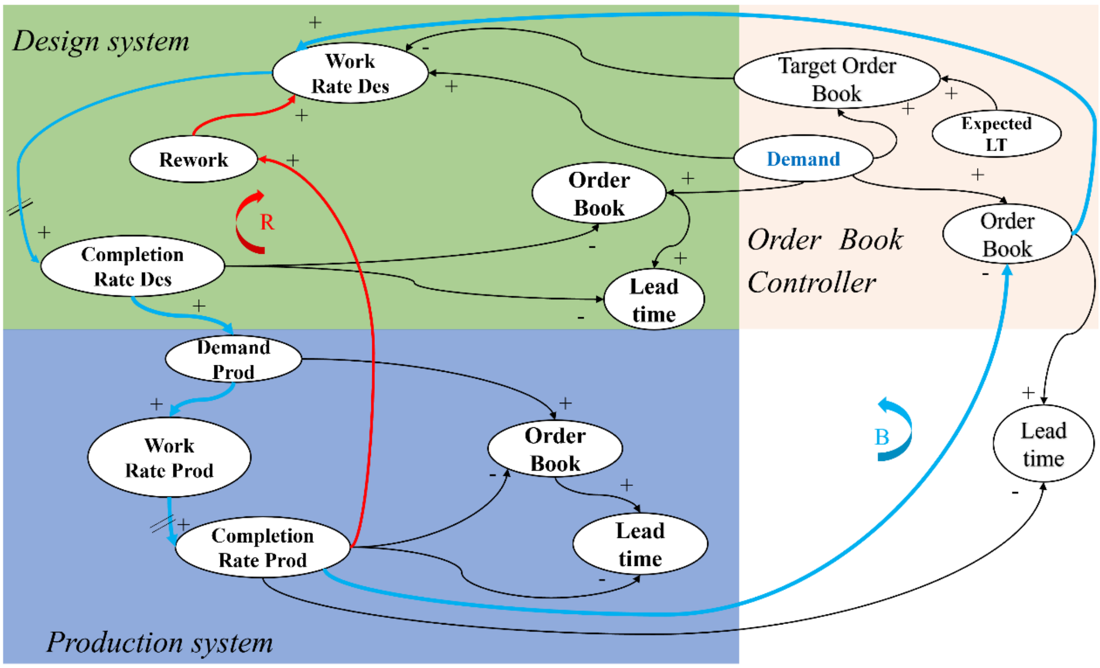

Figure 4.3 CLD for ETOAR#PTD

4.5 Mathematical Modelling

4.5.1 ETOAR#P Order Book Controller

The order book controller as a newly introduced subsystem to the ETO archetype, which brings new problems to the archetype. The concept of the order book controller was first introduced by Wikner et al. (2007) and adopts the feedback concept from inventory control to order book control. By using an order book controller, a company can adjust their work rate/capacity to maintain the desired order book level, thereby guaranteeing the lead time in the long term (Lin et al. 2017). In contrast, different from the MTO system, the ETO system is a multi-echelon system, which implies the positioning of several potential places within the system, with several combinations of such controllers. Thus, to investigate which is the best place for the order book controller, a series of preliminary studies are conducted.

ETOAR#P Experiment 1: Local order book controller

Design system

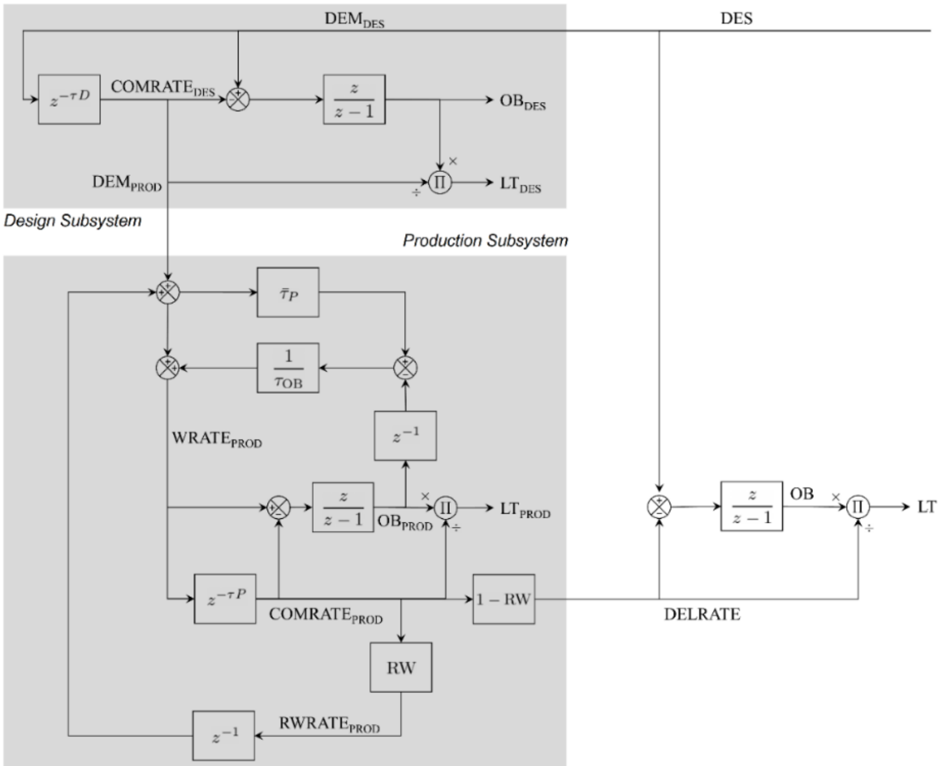

Figure 4.4 Experiment 1: A candidate ETO archetype with a local controller.

The following formulations represent the model as given in Figure 4.4. This model adopts pure delays to represent the production and design lags. Equations 4.3, 4.5, and 4.10, adopted from Wikner et al. (2007), pertain to the order book controller.

When demand, $DEM(t)$, arises, it will be sent to the design subsystem directly first, where the design activities take place.

$$DEM_{DES}(t) = DEM(t). \tag{4.1}$$

After a certain delay, the design will be completed, and the completion rate is represented by $COMRATE_{DES}(t)$:

$$COMRATE_{DES}(t) = DEM_{DES}(t - \tau_D). \tag{4.2}$$

This model utilises the order book to represent orders that are received but are not yet completed and delivered to the customer. The order book controller is installed in the production subsystem.

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t) \tag{4.3}$$

Production system

As per Assumption 4, the demand for the production system consists of demand from the upstream system and rework from the last period.

$$DEM_{PROD}(t) = COMRATE_{DES}(t) + \ RWRATE_{PROD}\ (t-1). \tag{4.4}$$

Equation (4.5) represents the local order book controller mechanism. Parameter τ_{OB} is added and set to 20. This value was selected based on multiple simulation tests and to ensure an overdamped system, thereby eliminating undesirable oscillatory behaviour that will impact capacity (Wikner et al. 2007).

$$WRATE_{PROD}(t) = DEM_{PROD}(t) + \frac{OB_{PROD}(t) - DEM_{PROD}(t) \cdot \tau_P}{\tau_{OB}}. \tag{4.5}$$

$$COMRATE_{PROD}(t) = WRATE_{PROD}(t - \tau_P). \tag{4.6}$$

Equation (4.7) illustrates how OB_{PROD} stores incomplete work units. The reason that $COMRATE_{PROD}$ is used instead of $DELRATE$ is because $DEM_{PROD}\ (t)$ includes non-conformance generated working units. Therefore, the actual incomplete working units is equal to the difference between $DEM_{PROD}(t) + RWRATE_{PROD}$ and $COMRATE_{PROD}(t)$.

$$OB_{PROD}(t) = OB_{PROD}(t-1) + DEM_{PROD}(t) - COMRATE_{PROD}(t) \tag{4.7}$$

RW represents the ratio of rework caused by non-conformance.

$$RWRATE_{PROD}(t) = COMRATE_{PROD}(t) \cdot RW. \tag{4.8}$$

$$DELRATE(t) = COMRATE_{PROD}(t) \cdot (1 - RW). \tag{4.9}$$

$$OB(t) = OB(t-1) + DEM(t) - DELRATE(t). \tag{4.10}$$

Little's Law is utilized to calculate delivery time, and its integration with a SD model has been adopted by (Wikner 2003; Lin et al. 2020).

$$LT_{DES} = \frac{OB_{DES}(t)}{COMRATE_{DES}(t)}. \tag{4.11}$$

$$LT_{PROD} = \frac{OB_{PROD}(t)}{COMRATE_{PROD}(t)}. \tag{4.12}$$

$$LT_{ETO} = \frac{OB(t)}{DELRATE(t)}. \tag{4.13}$$

Simulations are presented in the following paragraphs: the initial values and parameters settings are presented in the Table 4.4.

Table 4.4 Initial value and co-efficient value for experiment 1, with local order book controller

ETOAR#P experiment 1: Local order book controller, scenario 1					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	100	0	100	100	200
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0.0		

ETOAR#P experiment 1: Local order book controller, scenario 2					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	100	25	125	125	250
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0.2		

Experiment 1 Simulation—local controller: Scenario 1, rework ratio = 0

Given the initial and coefficient values of Table 4.4, the transient responses of the order book are depicted in Figure 4.5. It is evident that all order books are doubled. Figure 4.6 illustrates the transient performance of the system. The lead time of the design and production system, after an initial transient response, achieves the desired final steady-state value of 1 time unit each, with an overall ETO lead time of 2. Moreover, the peak value for the order book reaches 405 in period 7 and the peak value of lead time reaches 4 in period 6.

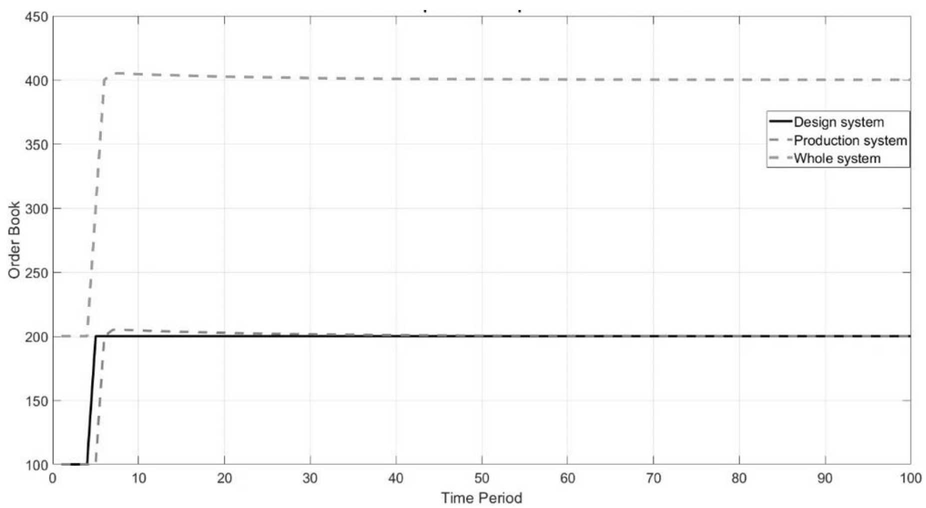

Figure 4.5 ETOAR#P experiment 1, scenario 1: Order Book transient state outputs, with local order book controller and rework ratio = 0

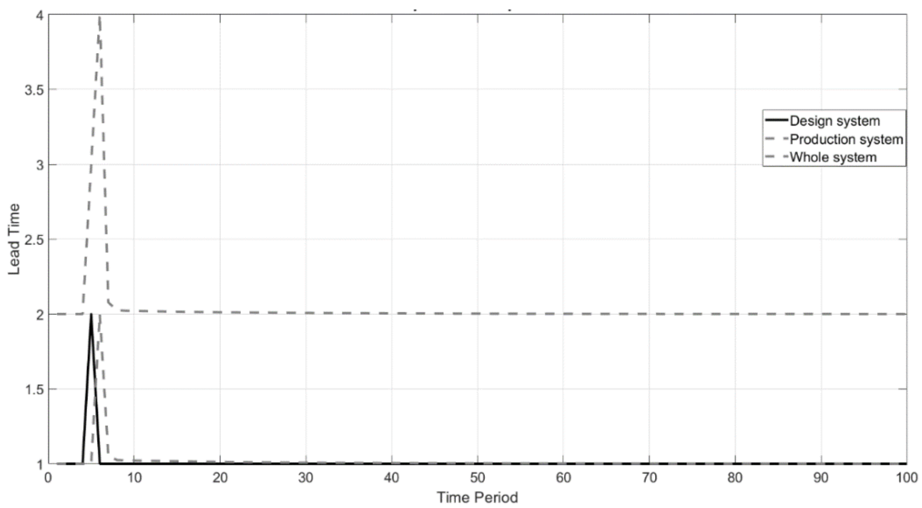

Figure 4.6 ETOAR#P experiment 1, scenario 1: Lead time transient state outputs, with local order book controller and rework ratio = 0

Experiment 1 simulation—local controller: Scenario 2, rework ratio = 0.2

To investigate the performance of the model with rework, scenario 2 was implemented. Herein, the initial values and co-efficient values are presented in Table 4.4. The initial values were adjusted to guarantee that the system is stable and balanced at an initial steady state. The initial order book is calculated as

$$OB_{PROD} = \tau_P \cdot \frac{DEM_{PROD}}{(1-RW)}. \tag{4.14}$$

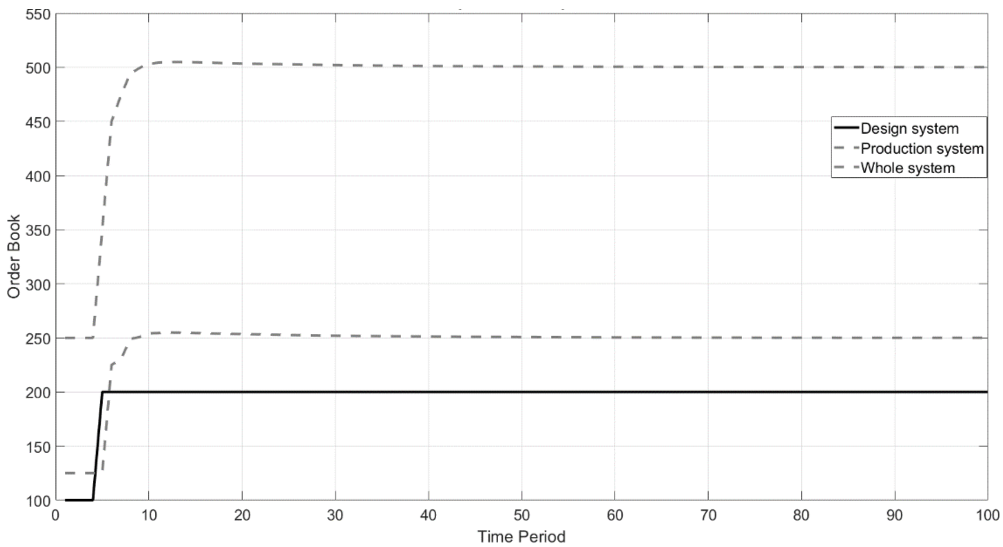

Figure 4.7 ETOAR#P experiment 1, scenario 2: Order book transient state outputs, with local order book controller and rework ratio = 0.2

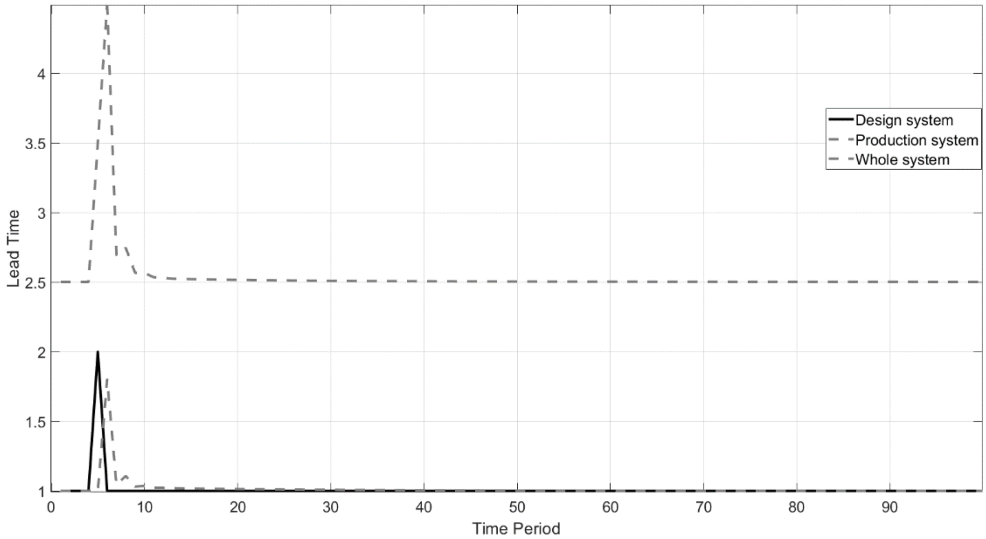

Figure 4.8 ETOAR#P experiment 1, scenario 2: Lead time transient state outputs, with local order book controller and rework ratio = 0.2

In Figure 4.7, the order book of the ETO system and production system stabilises at 500, which is 2.5 times that of new demand. The production system order book is also doubled, as calculated by equation (4.14). In the meantime, as demonstrated in Figure 4.8, the lead time of the overall system is longer than $\tau_D + \tau_P$. This problem is due to gradually increased rework until the condition for balancing the rework loop is fulfilled when $WRATE_{PROD}$ reaches DEM_{PROD} / (1-RW) = 125. Such a phenomenon was also observed in Lyneis and Ford's (2007) SD model. Moreover, in this scenario, the peak value of lead time increased by 0.5 compared to that in scenario 1, and order book peak value increased to 504, which is 100 units greater than that in scenario 1. It can be seen, the whole system's lead time is not the sum of subsystem's lead time. Which is because rework will first impact the overall system's order book before affecting the order book of the design subsystem. This time difference causes the overall system's order book to exceed the sum of the subsystems' order books. Consequently, this discrepancy results in the total lead time being longer than the sum of the individual subsystems' lead

According to the simulation above, the model developed in Experiment 1 does not automatically control the system to deliver products/projects on time and requires excess capacity to cope with a larger order book. Hence, this model was further developed and synthesised as an order book controller at the aggregate level, as given in Experiment 2.

ETOAR#P Experiment 2 holistic order book controller

Figure 4.9 demonstrates the model structure for Experiment 2. The structure in the shaded box aims at keeping the overall *OB* at the desired level by adding new working units to the ETO system. This model automatically calculates the difference between the target and actual order books and adds this value to the input demand, *DEM*.

The demand for the design system comprises the sum of the input demand and a fraction of the order-book adjustment value.

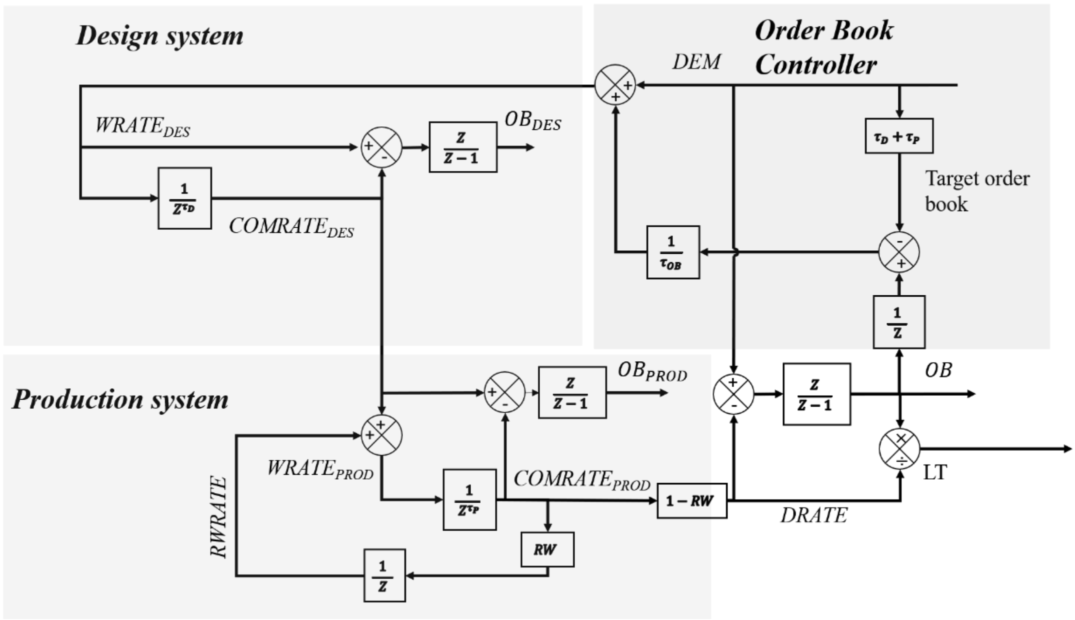

Figure 4.9 Experiment 2: A candidate ETO archetype with a holistic controller

Design system:

In order to establish the holistic order book controller, the equation (4.1) is replaced by 4.15 the rest of equations remain the same. Parameter τ_{OB} is a proportional controller that adjusts the system response time, playing a similar role as the τ_{OB} in Experiment 1, but at a whole-systems level.

$$DEM_{DES}(t) = DEM(t) + \frac{OB(t) - DEM(t) \cdot (\tau_D + \tau_P)}{\tau_{OB}}. \tag{4.15}$$

Production system

In this system, the actual and target order book difference is fed back to the design system; thus, for the production system, the work rate is equal to the sum of new demand and rework. The equation (4.5) is replaced by (4.16).

$$WRATE_{PROD}(t) = DEM_{PROD}(t). \tag{4.16}$$

Experiment 2 simulation—holistic controller: scenario 1, rework ratio = 0

Table 4.5 Initial value and co-efficient value for experiment 2, scenario 1, with whole-system order book controller and rework ratio = 0

ETOAR#P experiment 2: Holistic order book controller, scenario 1					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	100	0	100	100	200
Co-efficient value					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0.0		

ETOAR#P experiment 2: Holistic order book controller, scenario 2					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	100	25	125	100	200
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0.2		

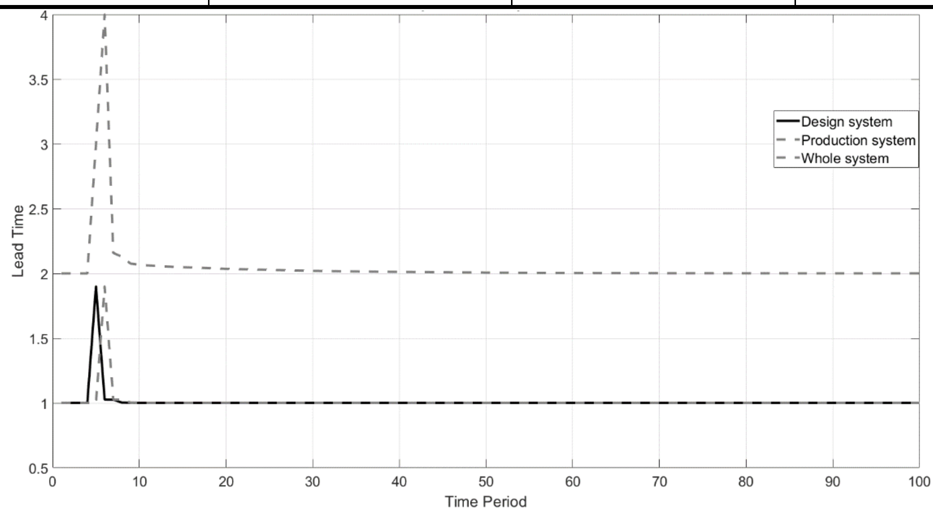

Figure 4.10 ETOAR#P experiment 2, scenario 1: Lead time transient state outputs, with whole-system order book controller and rework ratio = 0

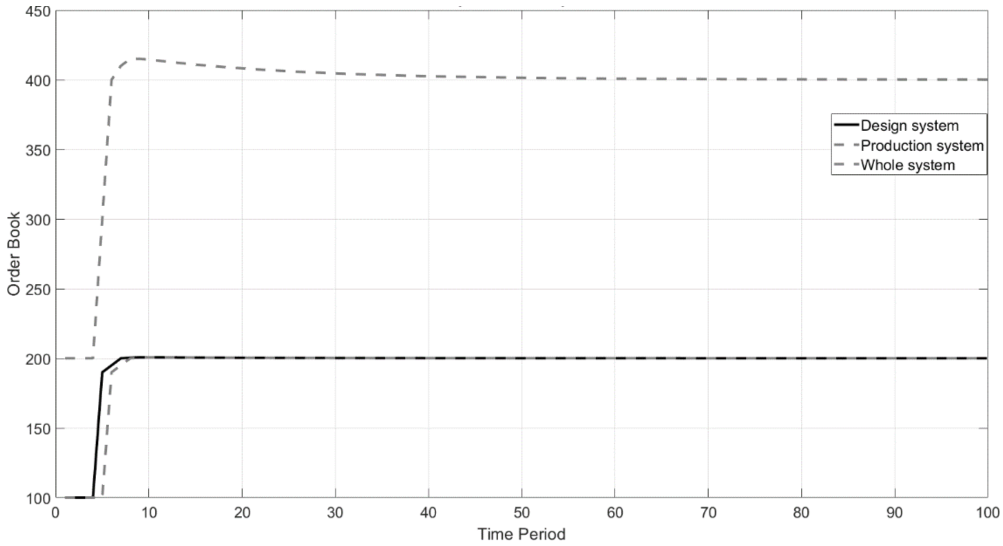

Figure 4.11 ETOAR#P experiment 2 scenario 1: Transient state outputs, with whole-system order book controller and rework ratio = 0

Scenario 1 aims to investigate the system performance without rework. Table 4.5 demonstrates the initial condition of the system. According to Figure 4.11, the lead time stabilises at 2, which refers to the on-time delivery being guaranteed in the long-term. The peak value of the order book trace slightly increased by 10 units compared to that in Figure 4.12.

Experiment 2 simulation—holistic controller: scenario 2, rework ratio = 0.2

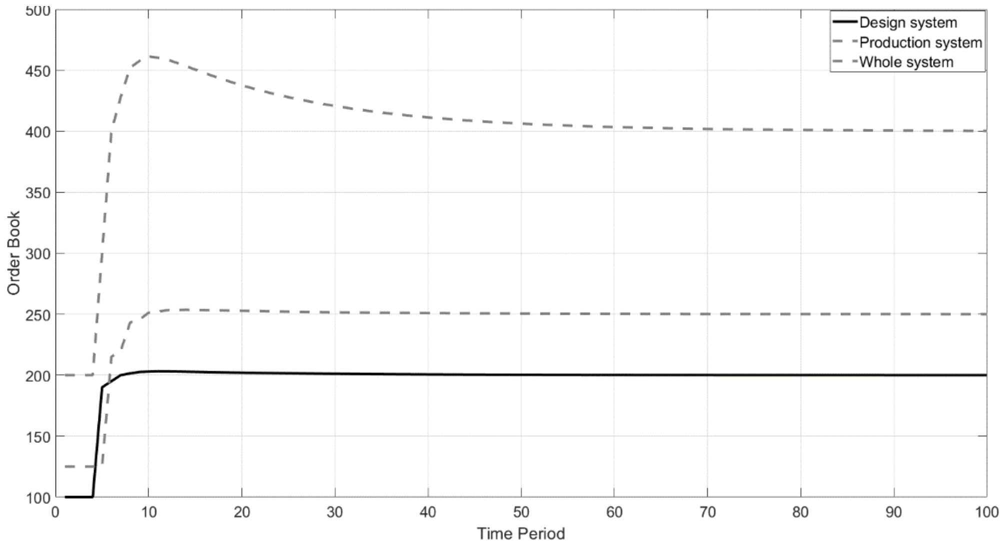

Figure 4.12 ETOAR#P experiment 2, scenario 2: Order book transient state outputs, with whole-system order book controller and rework ratio = 0.2

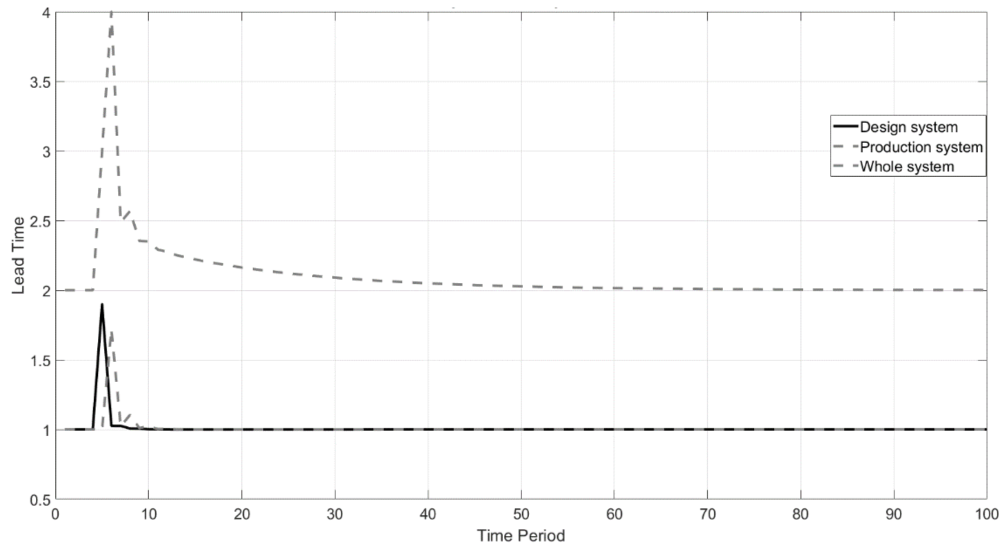

Figure 4.13 ETOAR#P experiment 2, scenario 2: Lead time transient state outputs, with whole-system order book controller and rework ratio = 0.2

Based on scenario 1, the rework ratio is adjusted to 0.2 in Table 4.6, and the simulation results obtained are depicted in Figure 4.12 and Figure 4.13.

As depicted in Figure 4.13, the lead time of the overall system begins at and returns to 2-time units, which is equal to the sum of production and design lead time, with the order book of the ETO system returning to 400, which is equal to $(\tau_P + \tau_D)\cdot DEM$ = 2 x 200 = 400. Although the drawback of this model is its longer settling time, the benefits greatly outweigh the disadvantages owing to conformance to the enhanced customer due date and reduced order book capacity requirements.

Summary

In summary, the model developed for experiment 2 is capable of maintaining lead time and order book at the desired levels in the long term. Thus, the holistic level order book controller is selected for the further development of the production rework archetype. The following paragraph demonstrates the dynamic behaviour of the work rate of the production rework ETO model.

In Figure 4.14 The dotted line demonstrates the design system's work rate; this rate refers to the design speed of the system. It is evident that the dotted line begins from 125 and jumps to 203 and then stabilises at 200. This transience demonstrates how the model adjusts the design capacity to complete the design within the required lead time. The work rate of the design subsystem is not affected by the rework while the production work rate is increased to absorb the impact of rework.

The dotted line represents the production subsystem's work rate; this rate directly determines how much workforce and resources the production requires, which comprises the main portion of the costs of the ETO products. The red dotted line jumped from 125 to 250, wherein the incremental is 125 and the extra 100 units are increased to face the demand change from 100 to 200, while the 25 units are prepared to deal with the rework. According to the simulation table, the rework ratio is 0.2, and the initial demand is 100. Intuitively, the rework should be 100 multiplied by 0.2, which equals 20; however, this calculation ignores the rework created by rework. The correct method to calculate the work rate for production should be 100/(1–0.2) = 125, demand/(1–rework ratio).

The delivery rate refers to the completed defects-free works that can be delivered in each period, consisting of the effective working package for an ETO project. It must be noted here that although the delivery rate is the output of the system, it is not the output of the ETO system. The output of the ETO system is a certain number of working packages. Thus, the lead time of the whole system is also an estimated value and is an index of the aggregated ETO system.

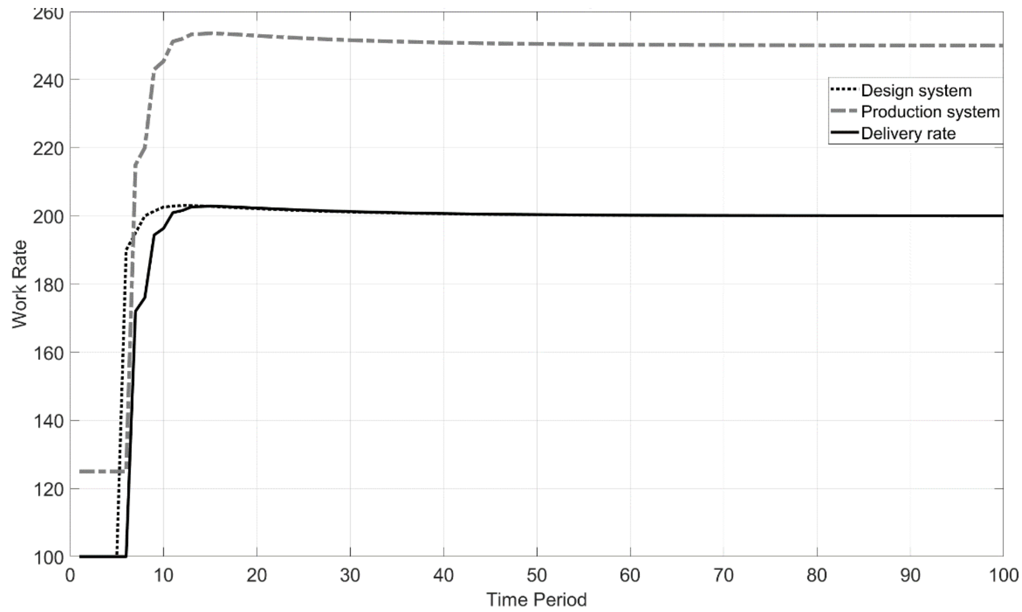

Figure 4.14 The work rate transient response of the ETOAR#P

4.5.2 ETOAR#D Order Book Controller

In this scenario, the rework may represent the design defects, which refers to the error or inappropriate design, and design change, which refers to the clients' or the manufacturers' desire to change the design to meet the production standard or customers' demand. In the ETO scenario, design rework is a frequent problem, since whilst creating the design, the clients may constantly communicate with the company to ensure that the unique design satisfies their demands, invariably resulting in several rounds of design modification.

ETOAR#D Experiment 1: Local order book controller

The following assumption was added for this model.

1. In this scenario, the defects are created and detected in the design phase, and these can be rectified within the design stage. All the defects, errors, or changes will be detected and created before the design is sent to the production systems.

2. There are no defects or errors in the production rework. For the design rework scenario, a model was firstly developed with a local order book controller. It can be seen an order book controller is in the design subsystem from Figure 4.15. The mechanism of the order book controller is to compensate for the design work rate by adding a certain portion of the variance between actual order book with the target order book. The order books for this model are local order books. Equation (4.17), (4.18) and (4.23) and (4.25) are adopted from Wikner et al. (2007)

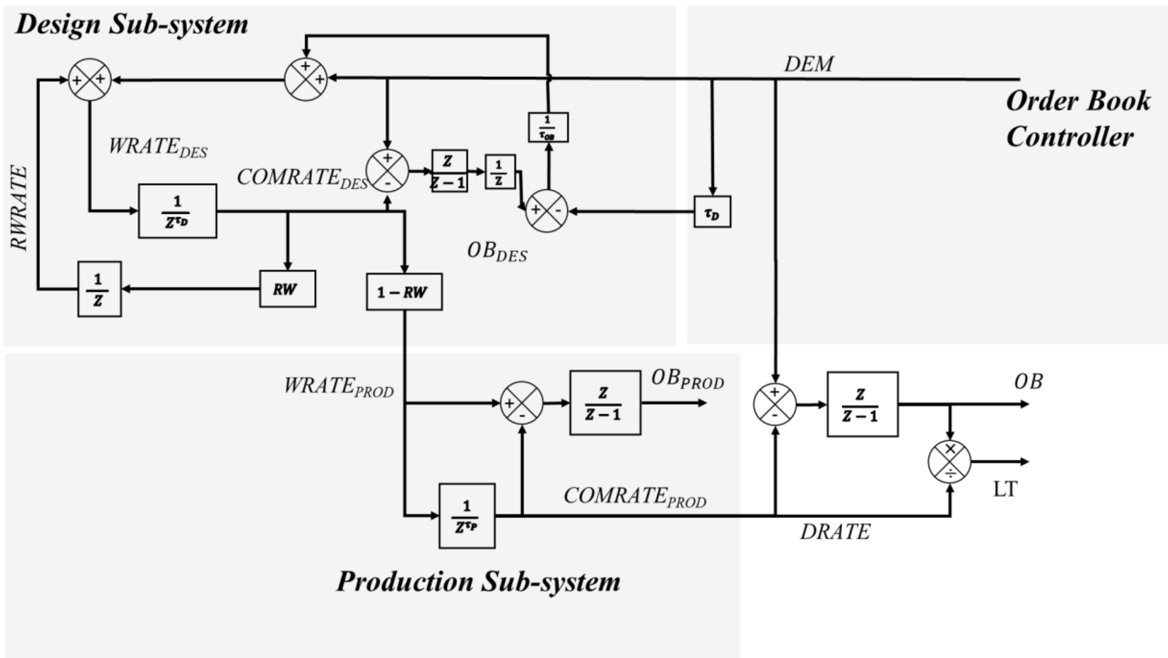

Figure 4.15 Experiment 1—a candidate ETO archetype with a local controller and design rework.

$$WRATE_{DES}(t) = DEM(t) + \frac{OB_{DES}(t) - \tau_D \cdot DEM_{DES}(t)}{\tau_{OB}} + RWRATE_{DES}(t-1). \quad (4.17)$$

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t). \quad (4.18)$$

$$COMRATE_{DES}(t) = WRATE_{DES}(t - \tau_D), \quad (4.19)$$

Where τ_D represents the delay of the design subsystem.

$RWRATE_{DES}$ refers to the rework rate of the design system:

$$RWRATE_{DES}(t) = COMRATE_{DES}(t) \cdot RW. \quad (4.20)$$

Production system

The production system's input is the completed, error-free, and change-free designs.

$$WRATE_{PROD}(t) = COMRATE_{DES}(t) \cdot (1 - RW). \quad (4.21)$$

$$COMRATE_{PROD}(t) = WRATE_{PROD}(t - \tau_P). \quad (4.22)$$

$$OB_{PROD}(t) = OB_{PROD}(t-1) + WRATE_{PROD}(t) - COMRATE_{PROD}(t) \quad (4.23)$$

The assumption of this scenario is that there is no rework in a production subsystem; thus, the $COMRATE_{PROD}(t)$ equals the delivery rate.

$$DRATE(t) = COMRATE_{PROD}(t). \quad (4.24)$$

$$OB(t) = OB(t-1) + DEM(t) - DRATE(t). \quad (4.25)$$

Little's Law is utilised to calculate the delivery time, as shown in previous sections.

To verify if the model can satisfy the performance demand, the following simulations were conducted. The simulation contains two parts: the first part is an ideal situation in which there is no rework; and the second part assumes that the rework ratio is 0.2. If the system can maintain the lead time at 2, then it is a valid model.

Simulations are presented in the following paragraphs and initial values and parameters are presented in Table 4.7.

Table 4.6 Initial value and co-efficient value for experiment 1, scenario 1, with whole-system order book controller and rework ratio = 0

ETOAR#D experiment 1: Local order book controller, scenario 1					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
125	100	0	100	100	200
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0		
ETOAR#D experiment 1: Local order book controller, scenario 2					
Initial values					
$COMRATE_{DES}$	$COMRATE_{DES}$	$COMRATE_{DES}$	$COMRATE_{DES}$	$COMRATE_{DES}$	$COMRATE_{DES}$
125	125	125	125	125	125
Co-efficient values					
τ_{OB}	τ_{OB}	τ_{OB}	τ_{OB}		
20	20	20	20		

Experiment 1 simulation—local controller: scenario 1, rework ratio = 0

Table 4.6 presents the initial values for each variable; these values are selected to keep the initial state stable. The input of the system is a step change, and the demand changes from 100 to 200 at period 4.

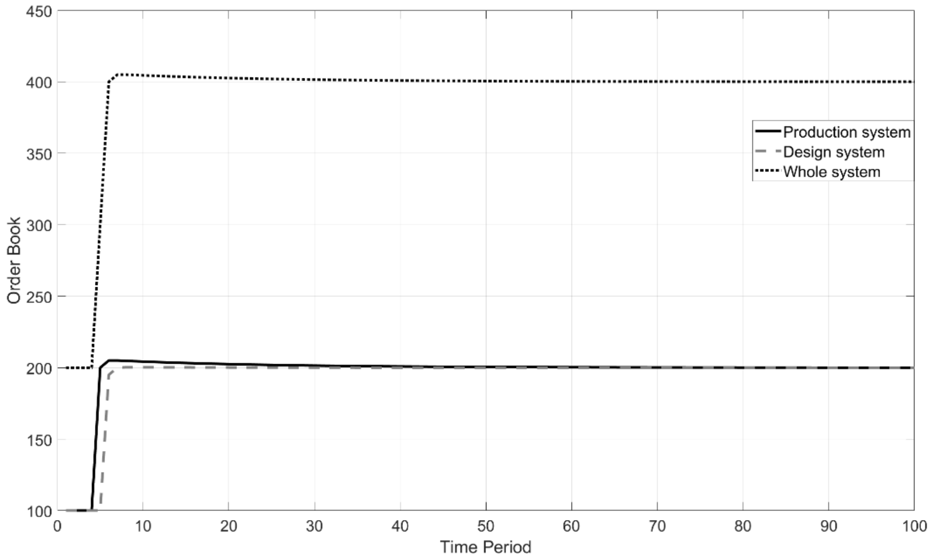

Figure 4.16 ETOAR#D experiment 1, scenario 1: Order book transient state outputs, with local order book controller and rework ratio = 0

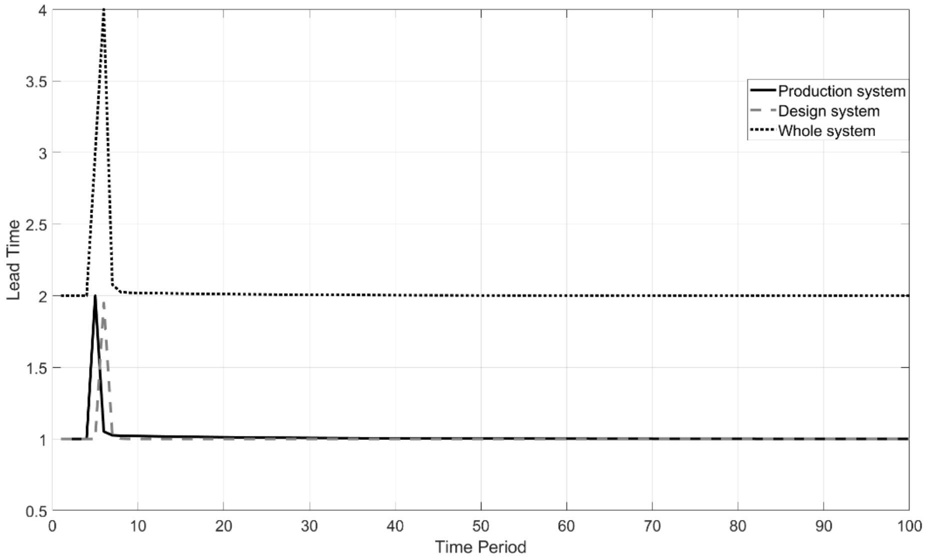

Figure 4.17 ETOAR#D experiment 1, scenario 1: Lead time transient state outputs, with local order book controller and rework ratio = 0

The simulation result is illustrated in Figures 4.16 and 4.17. The order book of an ETO system finally is finally stabilised at 400, with a slight overshoot at stage 6, and the subsystem's order book level is stabilised at 200. From the lead time perspective, the lead time of the whole ETO system stabilises at 2, which is the sum of the production and design lead time. Further, the subsystem's lead time is stabilised at 1, after an overshoot at periods 6 and 7.

According to the simulation above, the system can maintain the order book and lead time at the expected level when rework = 0; the following simulation will test how the system would perform if the rework is not 0.

Experiment 1 simulation—local controller: Scenario 2, rework ratio = 0.2

Given the initial values and parameters values tabulated above, the following simulations were conducted. In this simulation, the rework ratio was set to 0.2, which is an average rework ratio in the PM field (Love et al. 1999).

Figure 4.18 depicts the transient response of the order books of the subsystems and ETO systems. The dotted line demonstrates the whole system's order book change; the order book begins from 250 and settles down at 500. The design system's order book begins from 125 and stabilises at 250. The production subsystem's order book starts from 100 and stabilises at 200.

According to the observations above, it is concluded that the local order book controller cannot maintain the whole system and design subsystem's order book at the desired levels—400 and 200, respectively—which implies that the whole system's order book cannot be maintained by adopting a local order book controller at the system where rework occurs. To validate this conclusion, the transient response of the lead time is also checked.

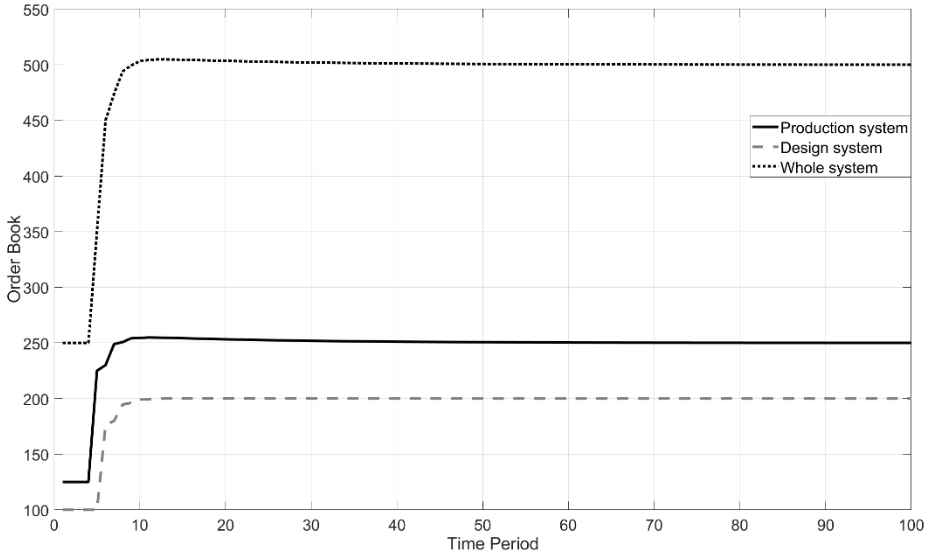

Figure 4.18 ETOAR#D experiment 1, scenario 2: Order book transient state outputs, with local order book controller and rework ratio = 0.2

Figure 4.19 depicts the transient response of the lead time of the whole system and its subsystems. Although the lead time of subsystems are finally stabilised at 1, the whole system's lead time does not revert to 2, which is the desired lead time. To solve the rework impact on the whole system's lead time, the subsystems must prepare extra buffer for the rework, and the buffer could be in the form of additional capacity or shorter lead time. Based on the above observation, it is contended that the local order book controller is unable to maintain the system's performance at the desired level; therefore, experiment 2 is conducted, which deals with the ETO archetype with the holistic-level order book controller.

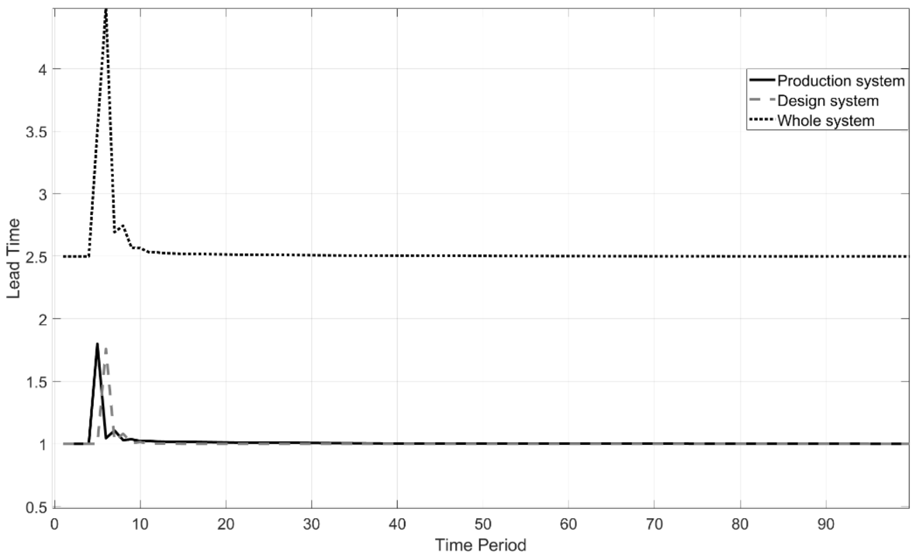

Figure 4.19 ETOAR#D experiment 1, scenario 2: Lead time transient state outputs, with local system order book controller and rework ratio = 0.2

ETOAR#D experiment 2: Holistic order book controller

Experiment 2 is designed to test if the holistic order book controller can maintain the order book and lead time at the desired levels. The block diagram of the model is illustrated in Figure 4.20. It is evident that the order book controller is moved from the design subsystem to the whole system level. Instead of using the difference between the design system's actual and target order books, the holistic order book controller uses the difference between the whole system's actual and target order book to determine the compensate work rate.

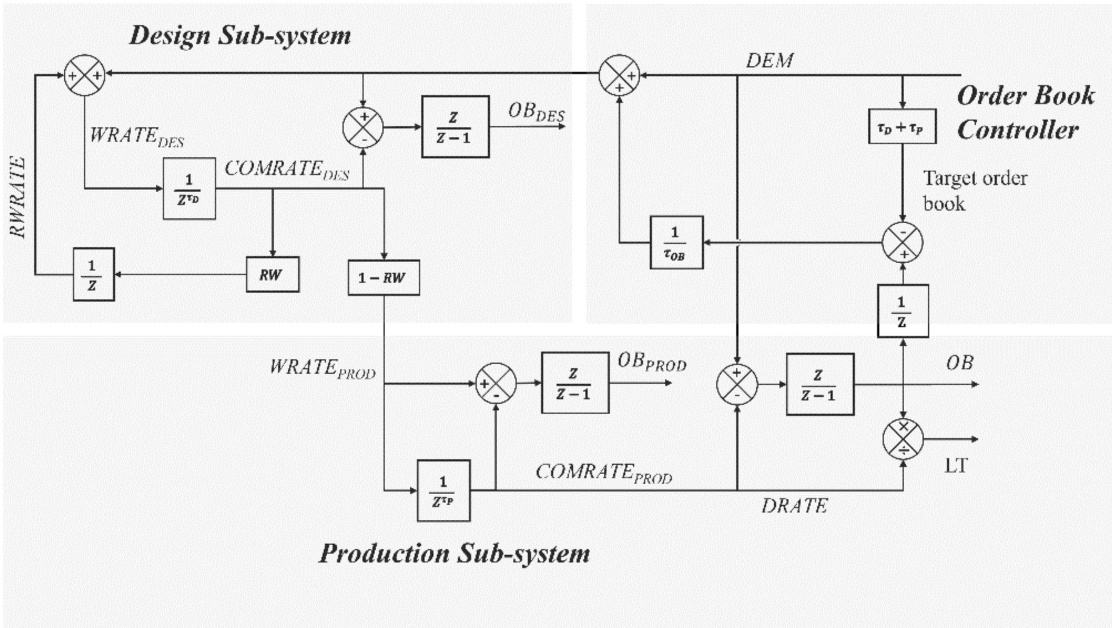

Figure 4.20 Experiment 2: A candidate ETO archetype with holistic order book controller, with design rework.

The differential equations are presented in the section below:

Design system

According to equation (4.26), the work rate of the design subsystem $WRATE_{DES}(t)$ is determined by three components, wherein the middle expression demonstrates how the models utilise the difference between the actual and target order book of the whole system to compensate for the work rate. Equation (4.17) is replaced by (4.26), to realize holistic order book controller's function.

$$WRATE_{DES}(t) = DEM(t) + \frac{OB_{DES}(t) - (\tau_P + \tau_D) * DEM_D(t)}{\tau_{OB}} + RWRATE_{DES}(t-1). \quad (4.26)$$

$RWRATE_{DES}$ refers to the rework rate of the design system

$$RWRATE_{DES}(t) = COMRATE_{DES}(t) * RW \quad (4.27)$$

Production system

The equations for the production system are the same as those for ETOAR#D experiment 1. To test the model, the following simulations are conducted, initial value and parameters settings are illustrated in the Table 4.8

Table 4.7 Initial Value and co-efficient value for experiment 1 scenario 2, with whole system level order book controller and rework ratio =0

ETOAR#D experiment 2: Holistic order book controller, scenario 1					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	100	0	100	100	200
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0		
ETOAR#D experiment 2: Holistic order book controller, scenario 2					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{DES}$	$COMRATE_{PROD}$	OB_{PROD}	OB
125	125	25	100	100	200
Co-efficient values					
τ_{ETOOB}	τ_D	τ_P	RW		
20	1	1	0.2		

Experiment 2 Simulation—holistic controller, scenario 1: rework ratio = 0

Given the initial and parameters value, as presented in Table 4.8, the experiment was conducted in MATLAB. The dotted line in Figure 4.21 demonstrates the order book of the whole system; it begins from 200, and finally stabilises at 400, with an overshoot at period 6. The order book of the design and production begins from 100 and stabilises at 200. The final level is two times of the initial level, which is the desired performance of the order book. To further assess the performance of the system, a transient response to the lead time was created.

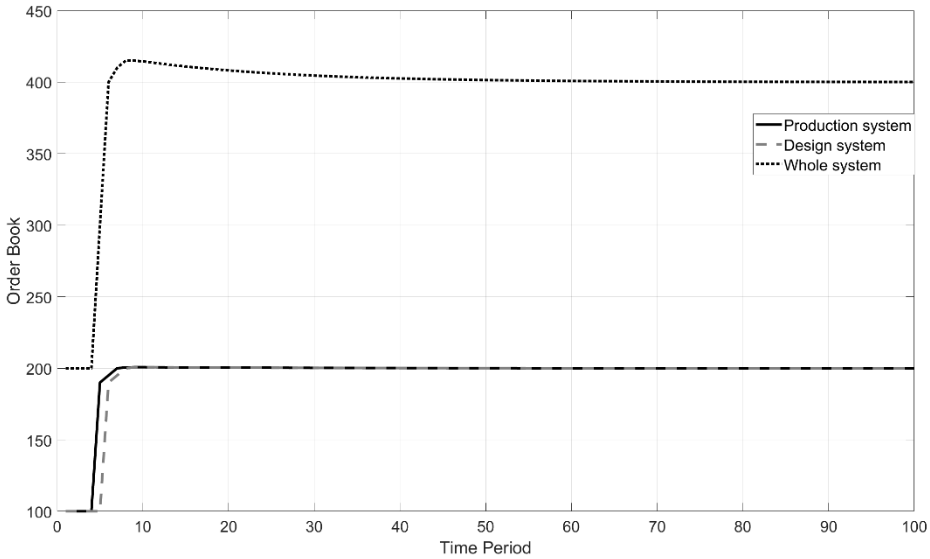

Figure 4.21 ETOAR#D experiment 2, scenario 1: Order book transient state outputs, with whole-system order book controller and rework ratio = 0

Figure 4.22 depicts the lead time transient response of subsystems and the whole system. The red dashed line indicates the lead time of the whole system. The lead time begins from 2 and stabilises at 2 after the step input, with a peak value of 4. The design system’s and production system’s lead time begin from 1 and stabilises at 1. The difference between design and production systems is the design subsystem’s lead time reaction to the step change one period faster.

These two simulations are conducted under the assumption that there is no rework, and the results reveal that the holistic order book controller can make the system maintain the order book and lead time level at the desired level with the step change input. To test the model's performance with rework, the following simulations were conducted.

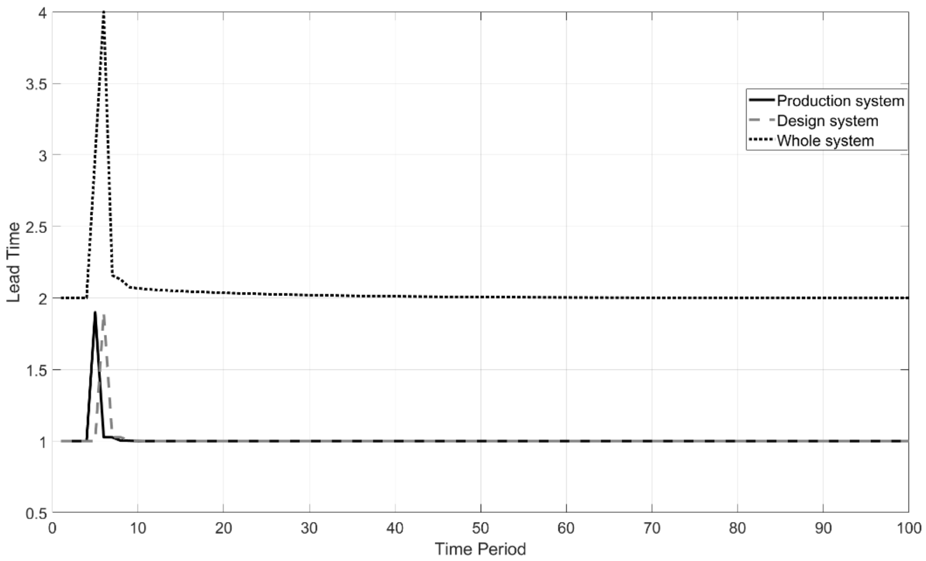

Figure 4.22 ETOAR#D experiment 2, scenario 1: Lead time transient state outputs, with whole-system order book controller and rework ratio = 0

Experiment 2 simulation—holistic controller, scenario 2: rework ratio = 0.2

Table 4.11 demonstrates the initial value setting and parameter setting for the design rework scenario. The initial values of $COMRATE_{DES}$, OB_{DES}, and $COMRATE_{PROD}$ are adjusted to stabilise the system.

Figure 4.23 demonstrates the order book change of systems; the whole system's order book finally stabilises at the 400 level with a big overshoot at period 10. The design system' order book stabilises at 250 and the incremental is caused by the extra working units for the rework. The production system's order book stabilises at 200.

It is evident that the whole system's order book stabilises at 400, which is the desired level; in contrast, the design subsystems order book stabilises at 250, which implies that the rework in the design system prolongs the queue in the design subsystem.

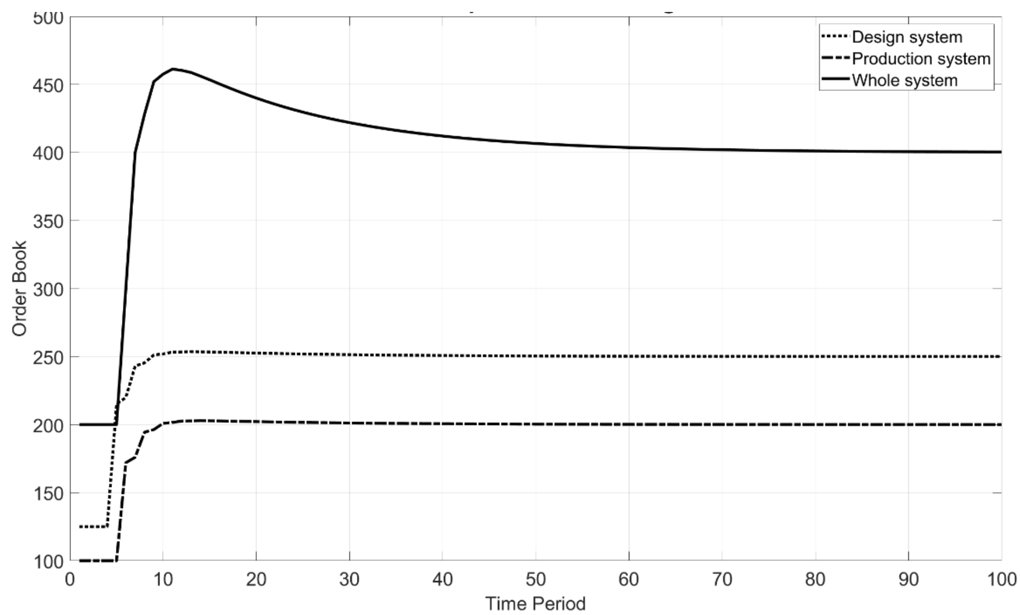

Figure 4.23 ETOAR#D experiment 2 scenario 2: Order book transient state outputs, with whole-system order book controller and rework ratio = 0.2

From the lead time of the system demonstrated in Figure 4.24, it is evident that the black straight line stabilises at 2, after a peak occurs at 6; this implies that from the whole system's perspective, the lead time performance can meet the requirement. Further, the design and production subsystem's lead time transient responses stabilise at 1, which implies that these two subsystems can maintain the lead time at one, with the existence of the rework. However, according to Figure 4.23, the order book of the design subsystem is 50 units higher than the order book level without the rework, which implies that the design system work rate must be higher than the rework-free scenarios. Thus, the transient responses of work rates were visualised to see how rework affects work rate/capacity of the systems.

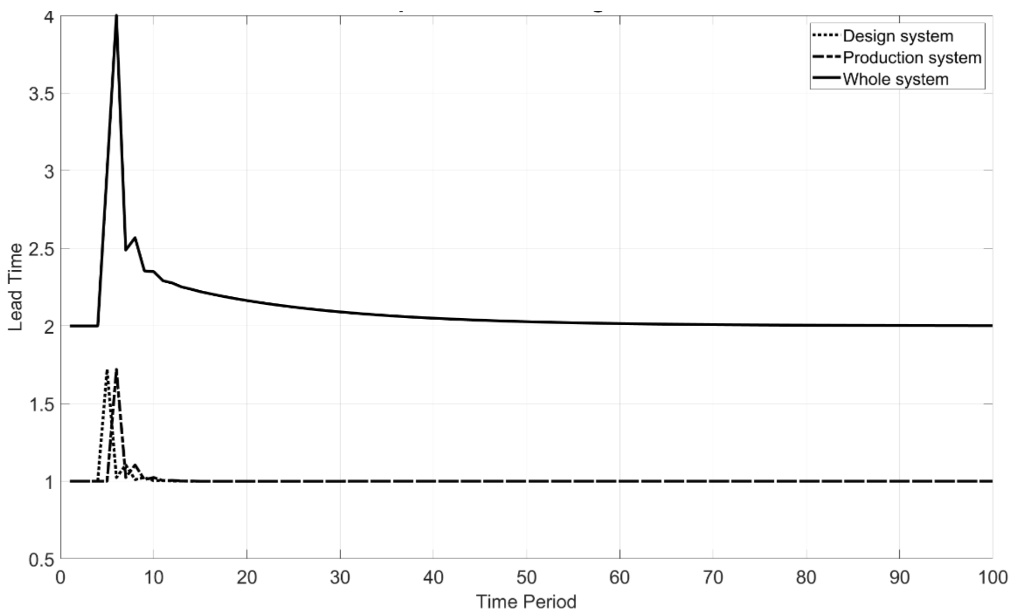

Figure 4.24 ETOAR#D experiment 2, scenario 2: Lead time transient state outputs, with whole-system order book controller and rework ratio = 0.2

The work rate of the system reflects the capacity of the system, and according to Figure 4.25, the order book controller changes the delivery rate to 200, which is the same as the new demand after the step change. This value implies that the system's output can adapt to the demand change. The production system's work rate is also 200, while the design system's level stabilised at 250. The increment 50 is the extra capacity that the design system reserves for the rework; this value can be calculated as 200/0.8-200 = 50.

This change represents that the holistic order book controller reserves an extra portion capacity for the design subsystem to cover the extra work caused by rework.

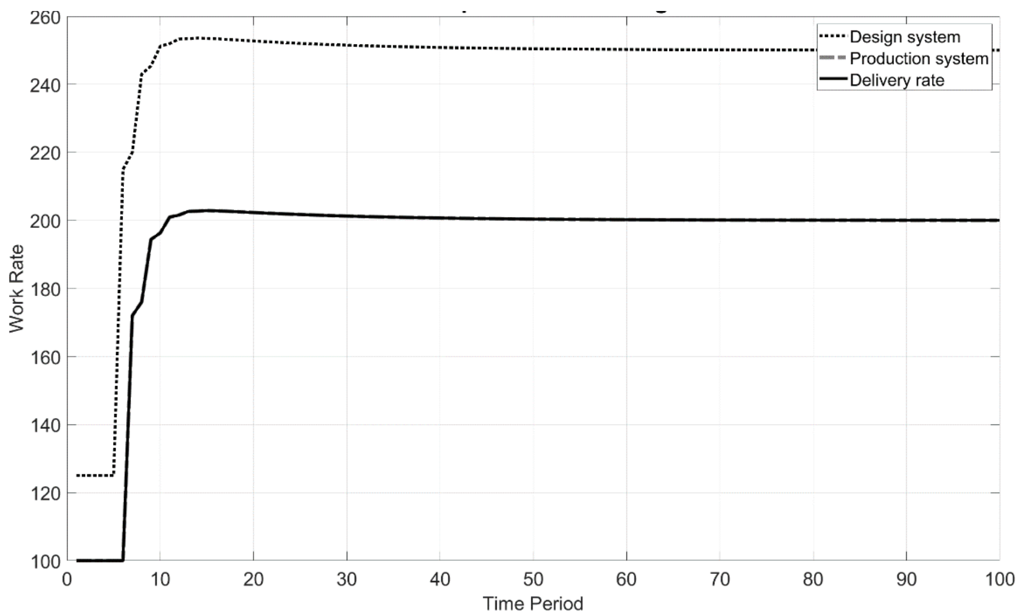

Figure 4.25 ETOAR#D experiment 2, scenario 2: work rate transient state outputs, with whole-system order book controller and rework ratio = 0.2

Summary

This subsection focuses on developing an archetype to model the ETO system with design rework. Two prototypes are developed, one with local order book controller and the other with the holistic level order book controller.

According to the simulations, both controllers can maintain the system's lead time at the desired level after a step change in demand. However, when rework exists in the design subsystem, only holistic order book controller can maintain the system's lead time at the desired level. The mechanism underlying this is that the holistic order book controller reserves extra capacity for the design system, so that the extra work caused by rework can be covered and the lead time can be guaranteed. Thus, the selected model includes the holistic order book controller as the ETO archetype for the design rework scenario and is called ETOAR#D.

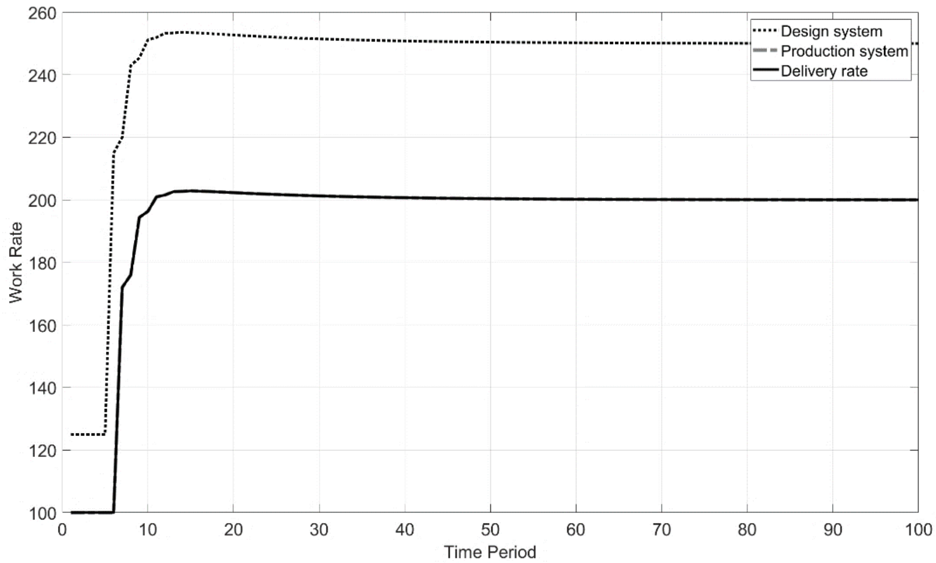

Figure 4.26 The work rate transient response of the ETOAR#D

Figure 4.26 demonstrates the work rates of design, production subsystems, and the delivery rate of the whole ETOAR#D system. The parameter settings and initial values are presented in Table 4.11

4.5.3 ETOAR#PTD Order Book Controller

In this scenario, the design defects/changes are detected or occur after the production begins, thereby requiring rework in the design first and then in production. For example, in certain cases, during the design stage, engineers may find that because of the mechanical techniques, the design cannot be realised or that, occasionally, the completed products include design defects which do not meet the clients' requirements. This kind of scenario often requires design change or redesign, and the consequences are often severer than those in other scenarios, with demolishing and redoing the work being required in certain extreme cases. Thus, it is essential to analyse the system performance in such scenarios.

To develop the production to design rework archetype, two prototypes were created: one is the system that contains the order book controller, wherein the controller is located at the level of the subsystem. The other prototype is the holistic order book controller, where the controller is located at the whole-system level. The following figure depicts the mathematical representation of the system.

ETOAR#PTD experiment 2: Dual local order book controller

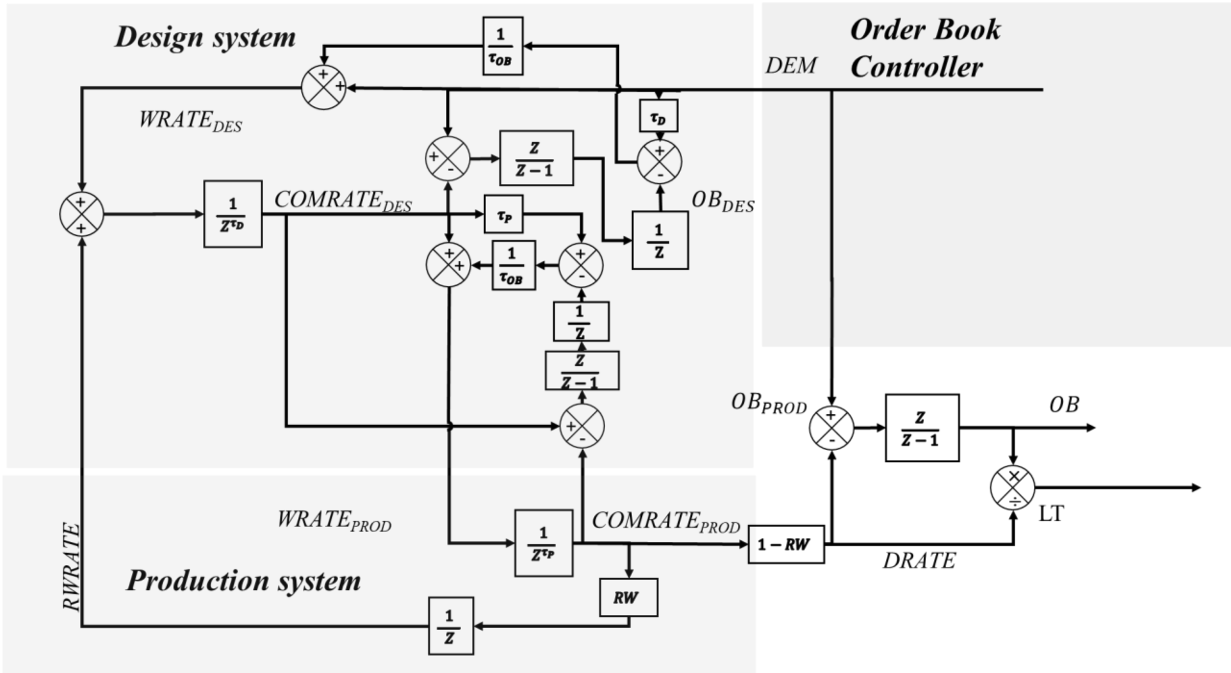

Figure 4.27 Experiment 1, a candidate ETO archetype with dual local controller and production to design rework.

DEM_{DES} also includes $RWRATE_{PROD}$, while this $RWRATE_{PROD}$ comes from the production system; this represents the defects detected in the production stage and those that require design change or redesign.

$$DEM_{DES}(t) = DEM(t) + \ RWRATE_{PROD}\ (t-1). \quad (4.28)$$

Equation (4.29) depicts the design subsystem using the difference between the subsystem's actual order book with the target order book to compensate for the work rate and cover the extra work required for redesigning. The target is set to the product of demand of the subsystem, with a delay in the subsystem. The dual order book Equation (4.29), (4.31) (4.33) and (4.35) is inspired by Wikner et al. (2007),

$$WRATE_{DES} \; = \; DEM_{DES}(t) + \frac{OB_{DES}(t) - DEM_{DES}(t) \cdot \tau_D}{\tau_{OB}}. \tag{4.29}$$

$$COMRATE_{DES}(t) = WRATE_{DES}(t - \tau_D). \tag{4.30}$$

OB_{DES} represents the order book of the design subsystem, and this variable (OB_{DES}) represents the actual order book of the design system.

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t). \tag{4.31}$$

Production system

As per Assumption 4, the demand for production system consists of demand from the upstream system. Due to the rework caused by the design subsystem, all rework will be directly sent back to the design system.

$$DEM_{PROD}(t) = COMRATE_{DES}(t). \tag{4.32}$$

Equation (4.57) represents the production subsystem's local order book controller mechanism. Parameter τ_{OB} is added and set to 20. This value was selected based on multiple simulation tests and selected to ensure an overdamped system, thereby eliminating undesirable oscillatory behaviour that will likely impact capacity (Wikner et al. 2007).

$$WRATE_{PROD}(t) = DEM_{PROD}(t) + \frac{OB_{PROD}(t) - DEM_{PROD}(t) \cdot \tau_P}{\tau_{OB}}. \tag{4.33}$$

$$COMRATE_{PROD}(t) = WRATE_{PROD}(t - \tau_P). \tag{4.34}$$

Equation (4.59) illustrates how OB_{PROD} stores incomplete work units. $COMRATE_{PROD}$ is used instead of $DELRATE$ because $DEM_{PROD}\,(t)$ includes non-conformance generated working units. Therefore, the actual incomplete working units is equal to the difference between $DEM_{PROD}\ (t) + RWRATE_{PROD}$ and $COMRATE_{PROD}(t)$.

$$OB_{PROD}(t) = OB_{PROD}(t-1) + \ DEM_{PROD}\ (t) - COMRATE_{PROD}(t) \qquad (4.35)$$

RW represents the ratio of rework caused by design error, or design changes.

$$RWRATE_{PROD}(t) = COMRATE_{PROD}(t) \cdot RW. \qquad (4.36)$$

1-RW represents qualified works.

$$DELRATE(t) = \ COMRATE_{PROD}(t) \cdot (1 - RW). \qquad (4.37)$$

$$OB(t) = OB(t-1) + DEM(t) - DELRATE(t). \qquad (4.38)$$

Little's Law is utilised to calculate the delivery time, as shown in previous sections.

The initial and parameter values are presented in Table 4.9

Table 4.8 Initial value and co-efficient value for experiment 1, scenario 1, with whole-system order book controller and rework ratio =0

ETOAR#PTD experiment 1: Local order book controller, scenario 1					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{DES}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	100	0	100	100	200
Co-efficient values					
τ_{ETOOB}	τ_D	τ_P	RW		
20	1	1	0		
ETOAR#PTD experiment 1: Local order book controller, scenario 2					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{DES}$	$COMRATE_{PROD}$	OB_{PROD}	OB
125	125	25	125	125	275
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	25		

Experiment 1 simulation—local controller scenario 1: Rework ratio = 0

Figure 4.28 demonstrates the transient responses of order books, with the demand step change input; the rework ratio for this simulation is 0. Parameter settings are presented in Table 4.9. The dot line represents the whole system's order book, which ranges from 200 to 400. The order book of subsystems ranges from 100 to 200. This change in the order books is as expected.

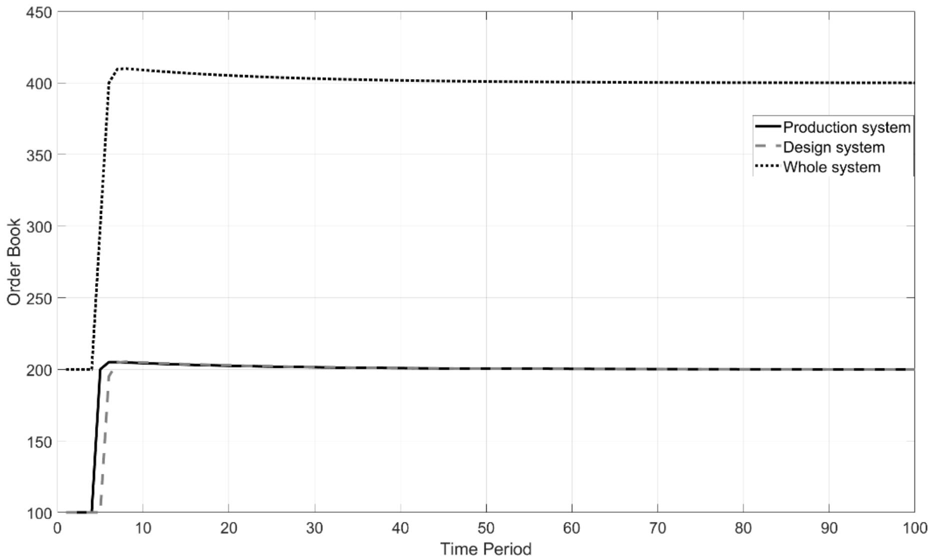

Figure 4.28 ETOAR#PTD experiment 1, scenario 1: Order book transient state outputs, with dual local order book controllers and rework ratio = 0

Figure 4.29 demonstrates the lead time performance of prototype 1. When rework = 0, the lead time of the whole system begins from 2 and stabilises at 2, with a peak at period 7. The subsystem's lead times are also stabilised at the desired level, which is 1. The design system's peak occurs at 6 and the production system's lead time peak occurs at 7.

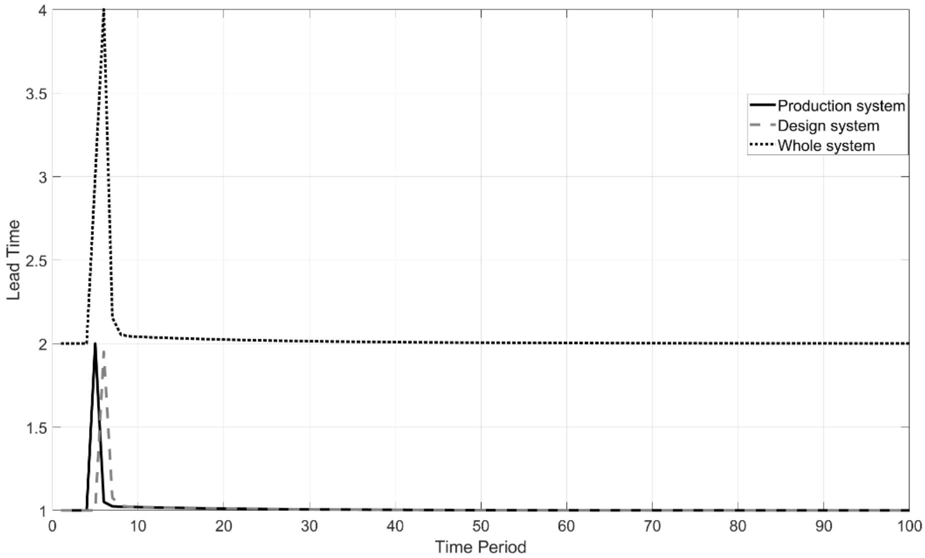

Figure 4.29 ETOAR#PTD experiment 1, scenario 1: Lead time transient state outputs, with dual local order book controllers and rework ratio = 0

The simulation above indicates that prototype 1 can automatically adjust the system capacity to absorb the impact of the demand change when there is no rework. The following subsection assesses the performance of the system when rework exists.

Experiment 1 simulation—local controller scenario 2: Rework ratio = 0.2

Given the initial and parameter values in Table 4.9, the following simulations were conducted. Figure 4.30 demonstrates the order book transient responses of the whole system. The curve begins from 275 and jumps to 550. The subsystem's order books begin from 125 and are finally stabilised at 250. According to these numbers, it is evident that the whole system and subsystems maintain a high order book level because of the existence of the rework, which also implies that the completion of the production on time requires the system to maintain a higher capacity.

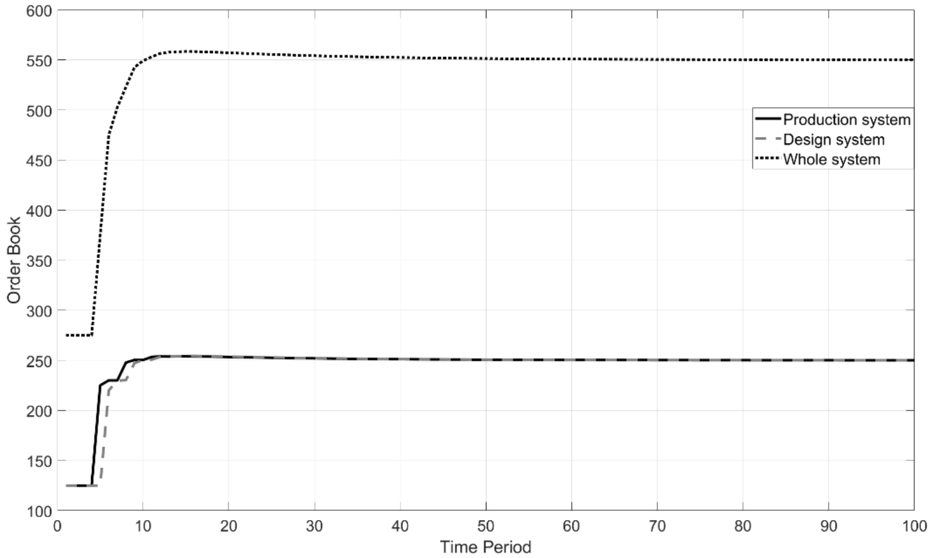

Figure 4.30 ETOAR#PTD experiment 1, scenario 2—order book transient state outputs, with dual local order book controllers and rework ratio = 0.2

Figure 4.31 illustrates the lead time performance of the dual local order book controller prototype. The dot line represents the whole system's estimated lead time, which begins from 2.75 and stabilises at 2.75. The required lead time is 2, which implies that the system cannot maintain the lead time at the desired level. The subsystems' lead time level stabilises at 1, which implies that the design and production subsystem complete their work on time. It is evident that the sum of the subsystem's lead time does not equal to the whole system's lead time, the reason is explained in the section 4.4.2 Experiment

1 scenario 2. While subsystems can complete their work on time, the entire ETO system requires both subsystems to work faster to compensate the delay created by the rework.

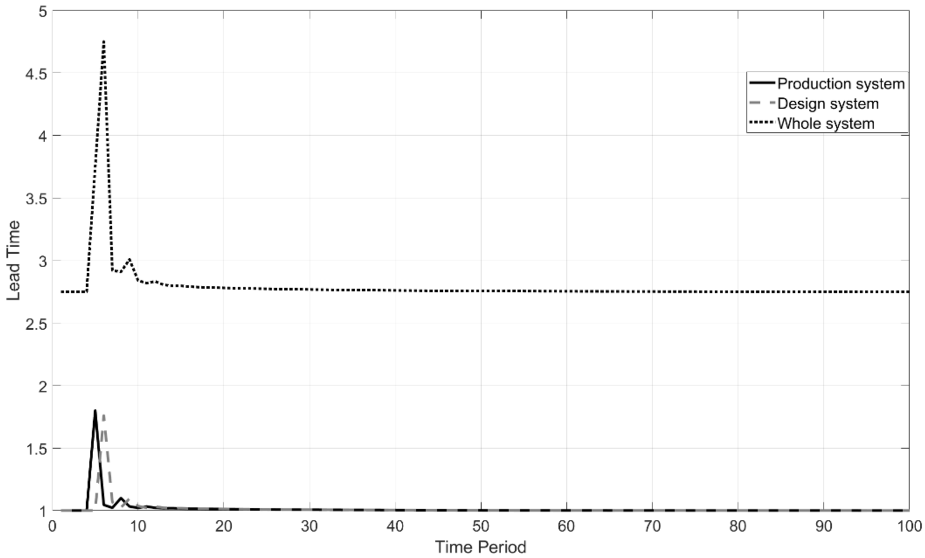

Figure 4.31 ETOAR#PTD experiment 1, scenario 2: Lead time transient state outputs, with dual local order book controller and rework ratio = 0.2

ETOAR#PTD experiment 2: The ETO model with a holistic order book controller

In this subsection, the model for prototype 2 was upgraded to the holistic-level order book controller prototype. The main difference is that the order book controller is installed at the holistic system level, and the whole system's order book is used to calculate how much capacity should be added to the system. Figure 4.32 demonstrates the block diagram of this prototype.

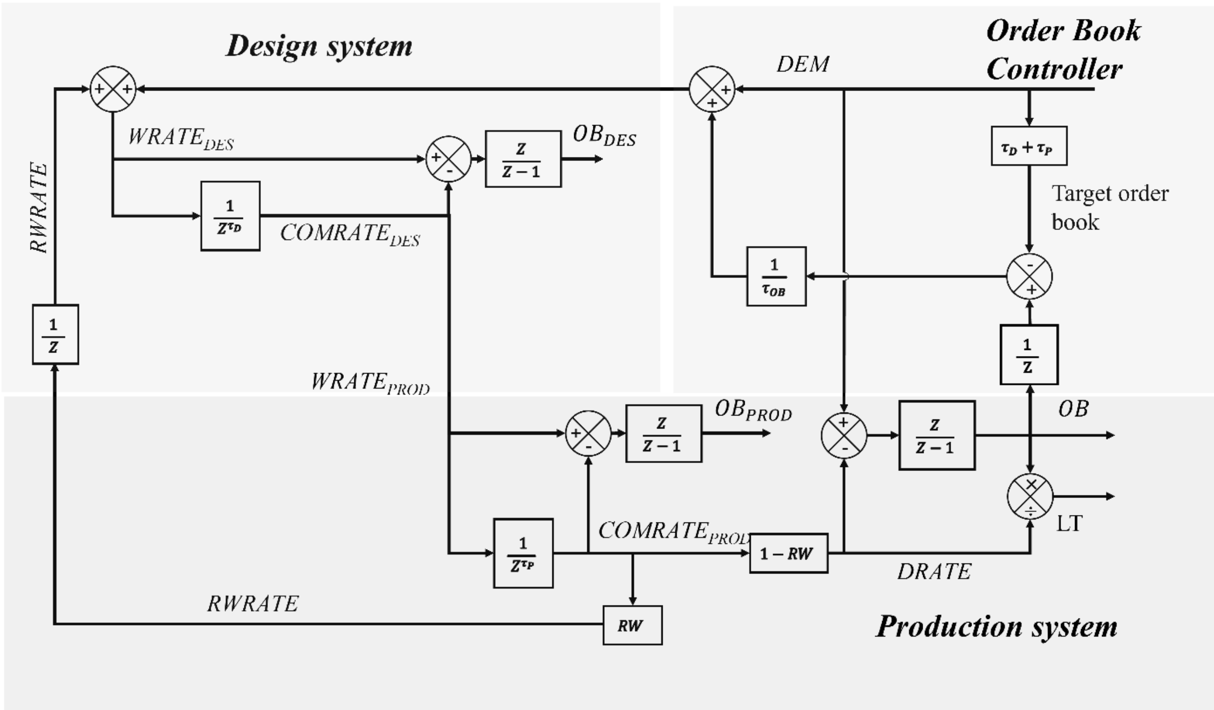

Figure 4.32 Experiment 2, a candidate ETO archetype with holistic order book controller and production to design rework.

The local order book controllers were removed, and a holistic order book controller was added to the system.

Design system

It is observed that the rework goes back to the system, which is represented by $RWRATE$. Equation (4.39) demonstrates how the order book controller increases the work rate of the system. $OB(t)$ represents the actual order book and $DEM(t) \cdot (\tau_P + \tau_D)$ represents the target order book of the whole system. The difference between these two values is divided by τ_{OB}—the proportional controller—and the division is added to the work rate for the design system $WRATE_{DES}(t)$. When the target order book is higher, it implies that the system can reduce the capacity to save the cost for production; if the actual order book is higher, then it indicates that the system needs to boost the production speed. Equation (4.39), (4.41) (4.44) and (4.49) are adopted from (Wikner et al, 2007)

$$WRATE_{DES}(t) = DEM(t) + \frac{OB(t) - DEM(t)\ *(\tau_P + \tau_D)}{\tau_{OB}} + RWRATE\,(t-1). \quad (4.39)$$

$$COMRATE_{DES}(t) = WRATE_{DES}(t - \tau_D). \quad (4.40)$$

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t). \quad (4.41)$$

Production system

It is evident that the RWRATE is a portion of the COMRATE, which indicates that a certain proportion of the completed work is not fulfilled by the criteria and the task requires rework to rectify.

$$WRATE_{PROD}(t) = COMRATE_{DES}(t). \quad (4.42)$$

$$COMRATE_{PROD}(t) = WRATE_{PROD}(t - \tau_P). \quad (4.43)$$

$$OB_{PROD}(t) = OB_{PROD}(t-1) + \ DEM_{PROD}\,(t) - COMRATE_{PROD}(t). \quad (4.44)$$

RWRATE refers the production to design rework.

$$RWRATE_{PROD}(t) = COMRATE_{PROD}(t) * RW. \quad (4.45)$$

DRATE refers to the conformant works that can be delivered to the clients.

$$DRATE(t) = \ COMRATE_{PROD}(t) * (1 - RW). \quad (4.46)$$

$$OB(t) = OB(t-1) + DEM(t) - DELRATE(t). \quad (4.47)$$

Little’s Law is utilised to calculate the delivery time, as shown in previous sections.

To test the performance of the system, following simulations are conducted. Initial value and parameters settings are demonstration in Table 4.10.

Table 4.9 Initial value and co-efficient value for experiment 2, scenario 1, with whole-system order book controller and rework ratio = 0

ETOAR#PTD experiment 2: Holistic order book controller, scenario 1					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{DES}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	125	0	100	100	200
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0		
ETOAR#PTD experiment 2: Holistic order book controller, scenario 2					
Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	125	25	125	125	200
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0.2		

Experiment 2 Simulation-holistic controller—Scenario 1: Rework ratio = 0

Table 4.10 demonstrates the parameter and initial value settings. The first simulation is conducted with the assumption that there is no rework in the system to see if the system can maintain the system’s order book at the desired level, as shown in Figure 4.33. The red line presents the entire system's order book. It is evident that the transient response began from 200 and stabilised at 400, with the peak value at 415. The subsystem's order book began from 100 and stabilised at 200. The result reveals that, with the given input, the system is able to maintain the system's order book at the desired level and maintain the stability of the system.

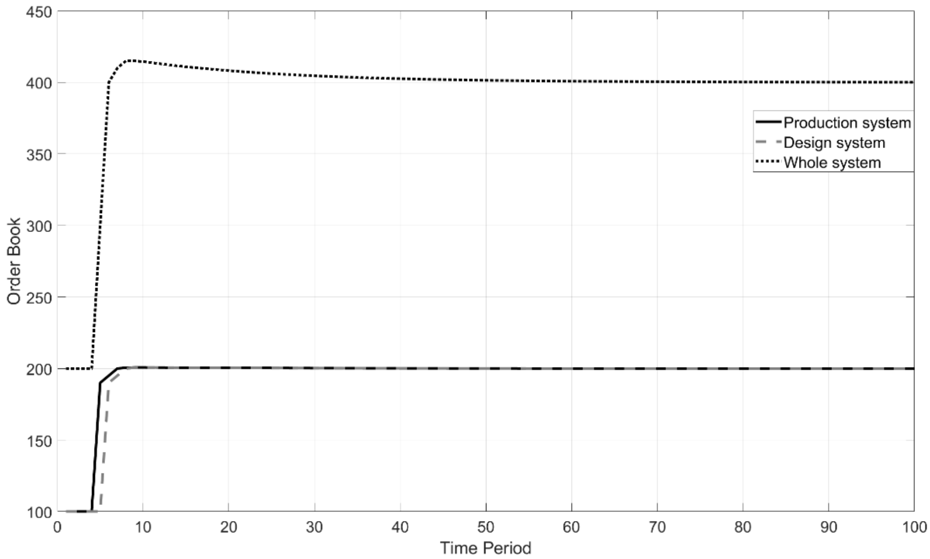

Figure 4.33 ETOAR#PTD experiment 2, scenario1: Order book transient state outputs, with whole-system order book controller and rework ratio = 0

The simulation result of the lead time performance is presented in Figure 4.34. It is evident that the lead time of the whole system begins from 2, and after an overshoot at period 7, it finally stabilises at 2; this is the promised lead time to the customer. The subsystem's lead time begins from 1 and finally stabilises at 1 after an overshoot at periods 6 and 7. From the lead time perspective, prototype 2 satisfied the demand for the archetype when there was no rework in the system. To further verify the model, a simulation with existing rework was conducted.

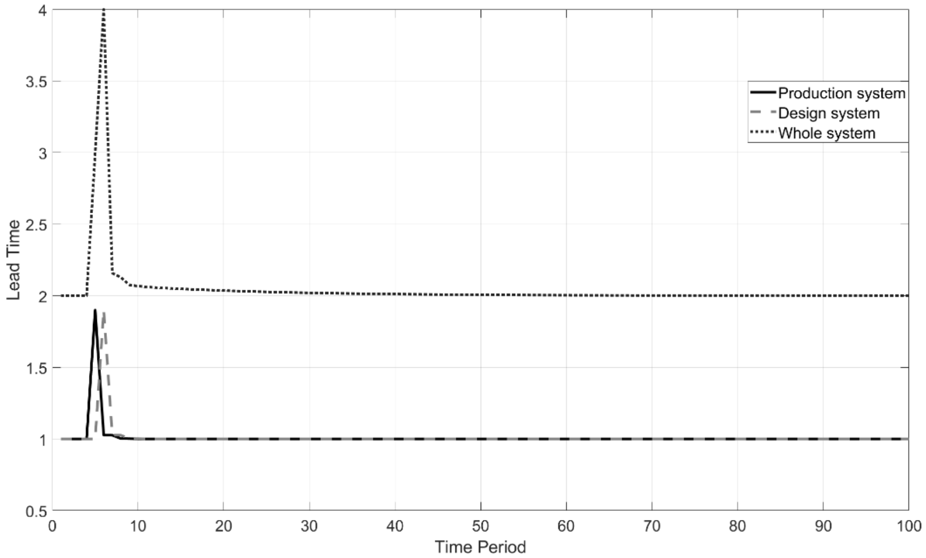

Figure 4.34 ETOAR#PTD experiment 2, scenario1 Lead time transient state outputs, with whole-system order book controller and rework ratio = 0

Experiment 2 Simulation-local controller—Scenario 2: Rework ratio = 0.2

This simulation is designed to verify the system's performance when rework exists in the system. A value of 0.2 is assigned to the rework ratio to align with the previous simulations. Table 4.10 demonstrates the parameter and initial value setting for the simulation.

Given the initial and parameter values above, the following simulations were conducted.

Figure 4.35 demonstrates the order books' transient responses. The whole-system order book stabilises at 400 but consumes more time. The production and design system's order book stabilises at a new level of 250, which can be attributed to the delayed design rework led by the extra working units in both design and production. From this figure, it is evident that the system maintains the whole-system order book at 400. But the subsystems' order book is stabilised at 250 after the demand step change. The increment of the order book indicates that the subsystem has a longer queue, which implies that to complete these works on time, the subsystems must reserve a higher capacity.

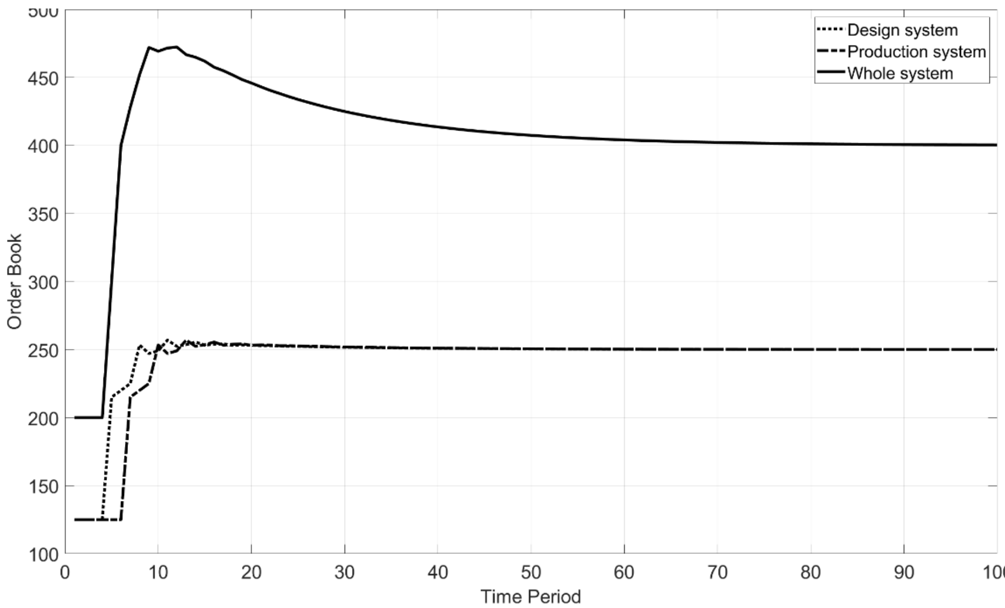

Figure 4.35 ETOAR#PTD experiment 2, scenario 2: Order book transient state outputs, with whole-system order book controller and rework ratio = 0.2

Figure 4.36 illustrates the lead time performance of the whole system; the black straight line represents the lead time of the whole system. After the demand step change, the lead time increased to 4 and gradually stabilised at 2 again; hence, 2 is the desired lead time of this simulation. While during the stabilising process, there were a few fluctuations, the subsystem's lead time began from 1 and finally stabilised at 1, with the peak lead time being 1.75.

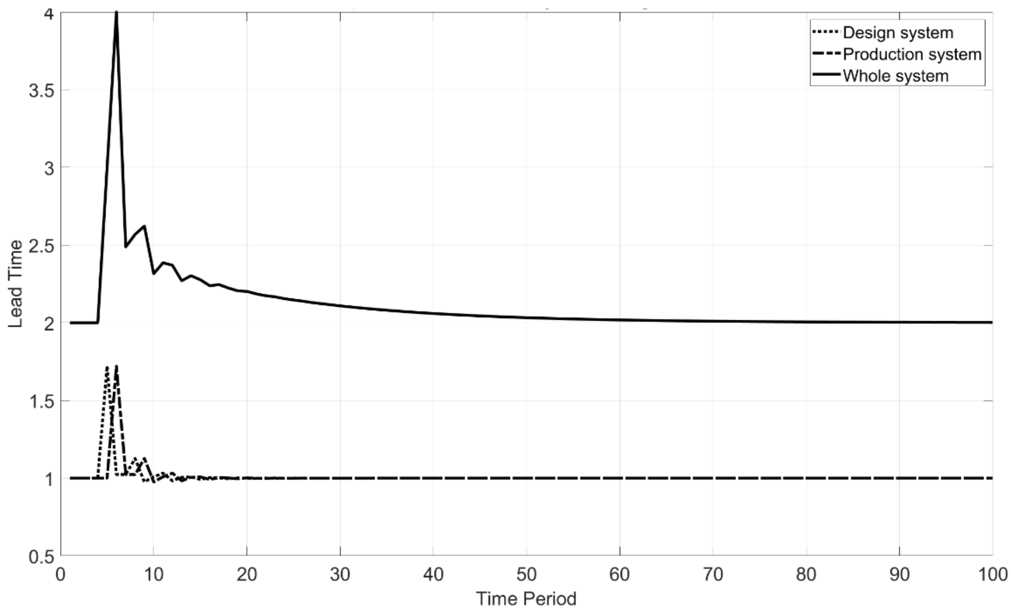

Figure 4.36 ETOAR#PTD experiment 2, scenario 2: Lead time transient state outputs, with whole-system order book controller and rework ratio = 0.2

According to the simulation above, it was concluded that the holistic order book controller can maintain the system's order book and lead time at the promised level. This implies that the holistic order book controller should be used as the controller for the production to design rework scenario; thus, prototype 2 was selected as the archetype and called ETOAR#PTD.

To develop an insight into the system's work rate, the transient response of the work rates is presented in Figure 4.37. It is evident that the delivery rate of the system stabilised at the 200 level, while both the production and design system's work rates stabilised at 250, after the demand step change. This change implies that the holistic order book controller increases the work rate of design and production subsystems to accelerate the speed of the entire process. This also explains why the order book of subsystems is prolonged, while lead times can still be maintained at 1. Simultaneously, compared to the other rework scenarios, ETOAR#PTD (archetype with holistic controller) takes more time to stabilise and there is fluctuation between period 10 and 20. This indicates that the production-to-design rework, or the delayed detected design defect/changes, are more severe than their other rework types. This is because to rectify/make these defects/change requires rework in both the design and production systems.

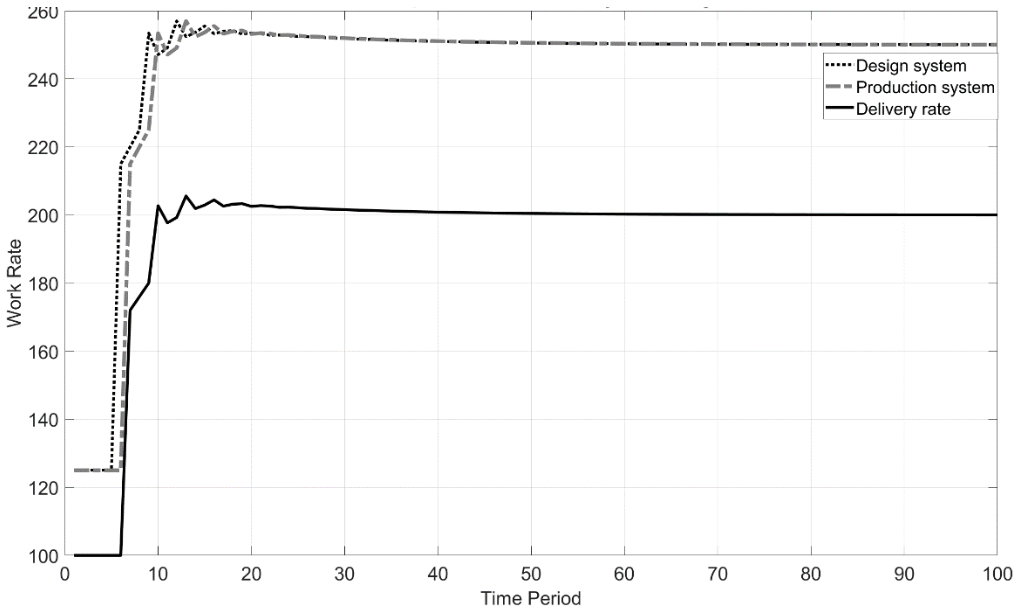

Figure 4.37 The work rate transient response of ETOAR#PTD

Summary

Two prototypes were created in this subsection—dual local order book controller and holistic order book controller. These two prototypes differ from each other with regard to the location of the order book controller. According to the simulation that was conducted, the prototype with holistic order book controller can maintain the system lead time at the promised level and the order book of the whole system can be maintained at twice the demand, irrespective of whether rework exists.

Thus, the prototype with holistic order book controller is selected as the archetype and named ETOAR#PTD.

4.5.4 Modelling Summary

Section 4.4 aims to model the ETO systems via a CLD and block diagram in the z-domain. The development of the models is done while keeping the following questions in mind: 1) How can different types of reworks be modelled in the ETO system? 2) Where can the order book controller be installed to maintain the system's lead time and order book at the desired level?

For the first question, one may realise that it is difficult to develop a single archetype that covers all types of reworks. Therefore, rework can be categorised into three types and determined to create one archetype for each rework scenario. Three archetypes form an archetype family, which represent three basic scenarios of an ETO system.

For the second question, a set of experiments is designed to test where and how to adopt the order book controller to the system. In practice, this controller represents the decision rules for capacity management, which is a key structure of the system. To achieve this aim, two experiments were designed for each scenario and each experiment contains two sets of simulations. Only the model which can maintain the lead time and order book level at the desired level can be selected as the archetype. The results of the experiments are summarised in Table 4.16. In summary, for all three models, only holistic order book controller can maintain lead time at the promised level, and local controllers can only main the subsystem's lead time at its promised level. Therefore, prototypes were selected with the holistic order book controller as the archetypes and from the ETO archetype family. This archetype family extends the application of the order book controller developed by Wikner et al. (2007) to the ETO context. It is designed to automatically adjust the system's work rate while considering rework.

Table 4.10 A summary of the developed archetypes

	Local order book controller in design system	**Local order book controller in Production system**	**Dual local order book controllers**	**Holistic order book controller**
Scenario 1 **Production rework**	Can not maintain lead time at desired level when rework exists			Yes ETOAR#P
Scenario 2 **Design rework**		Can not maintain lead time at desired level when rework exists		Yes ETOAR#D
Scenario 3 **Production to design rework**			Can not maintain lead time at desired level when rework exists	Yes ETOAR#PTD

The following subsections aim to linearise the non-linearity of this model in order to derive the transfer function of the lead time, which will be helpful in the prospective dynamic analysis sections.

4.6 Lead Time Linearisation

The main structure of the archetype is developed in Section 4.4 and provides a foundation for the mathematical analysis. However, there is a non-linearity in the model which obstructs the adoption of the transfer function, which is lead time.

In this research, lead time is calculated using Little's law (Little 1961), as given in equation (4.48). Herein, it is evident that the order book and delivery rate together determines the lead time. The division of the expression creates the only non-linearity to this model, and the expression for the lead time can be written as

$$Lead\ time, LT = \frac{OB(t)}{DRATE(t)}. \tag{4.48}$$

Taylor series expansion is selected to linearise the lead time (Lin et al. 2020), which can be written as

$$LT^{*} - (\tau_D + \tau_P) = \frac{\partial LT}{\partial OB}(OB^{*} - OB) + \frac{\partial LT}{\partial DRATE}(DRATE^{*} - DRATE). \tag{4.49}$$

Considering that the final value for the DRATE(t) is DEM and the final value for OB is $(\tau_D + \tau_P) \cdot DEM$, then the partial derivation at the resting point can be derived.

$$\frac{\partial LT}{\partial OB} = \frac{1}{DRATE} = \frac{1}{DEM}. \tag{4.50}$$

$$\frac{\partial LT}{\partial DRATE} = -\frac{OB}{DRATE^2} = -\frac{(\tau_D + \tau_P) \cdot DEM}{DEM^2}. \tag{4.51}$$

If (4.50) and (4.51) are taken into (4.49), after reorganisation, (4.52) can be obtained:

$$LT = \frac{OB - (\tau_D + \tau_P) \cdot DRATE}{DEM} + (\tau_D + \tau_P). \tag{4.52}$$

It is evident from equation (4.52) that DEM at the resting point will be a constant, thereby making LT a linear expression. As presented in Section 4.5, the ETO archetype family includes three archetypes, while the algorithms for lead time estimation are the same and the final state for the lead times and order books are all the same. Thus equation (4.52) is the expression for lead time for all ETO archetypes.

To verify the accuracy of the linearised lead time, the following comparison simulations were conducted. These simulations aim to test the accuracy of the linearised lead time. There will be two simulations for each model. One is a simulation with step change input, the other one is a simulation with the cyclical fluctuations. The latter one is much closer to the reality because the demand pattern in the market usually manifests fluctuations.

The following sections present a comparison of Littles' law lead time with the linearised lead time under step change demand and cyclical demand pattern. The aim of these simulations is to test how accurate the linearisation is and what the limitations of this method are.

4.6.1 ETOAR#P Result Comparison

This section presents the comparison of linearised lead time with the estimated lead time for the ETOAR#P archetype. The initial value and parameter settings are presented in Table 4.11. To maintain the consistency, the settings are the same as the settings in the modelling section.

Table 4.11 Simulation configuration

Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	125	25	125	125	200
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW		
20	1	1	0.2		

Step input rework = 0

Figure 4.38 depicts the lead time and linearised lead time's transient response with the step change input. The demand changed from 100 to 200. For the first six periods, the linearised lead time are same with the estimated lead time, while from period 7 onward, the errors appear. Finally, both lead times become stable at 2, which is the desired level for lead time. One of the limitations of adopting the Taylor expansion linearisation is that it is only accurate around the resting point and that the accuracy will decrease with the increase in the distance between the linearised and resting points.

According to Figure 4.38, when rework = 0, the linearised lead time can capture the changing trend of the estimated lead time and the accuracy is acceptable.

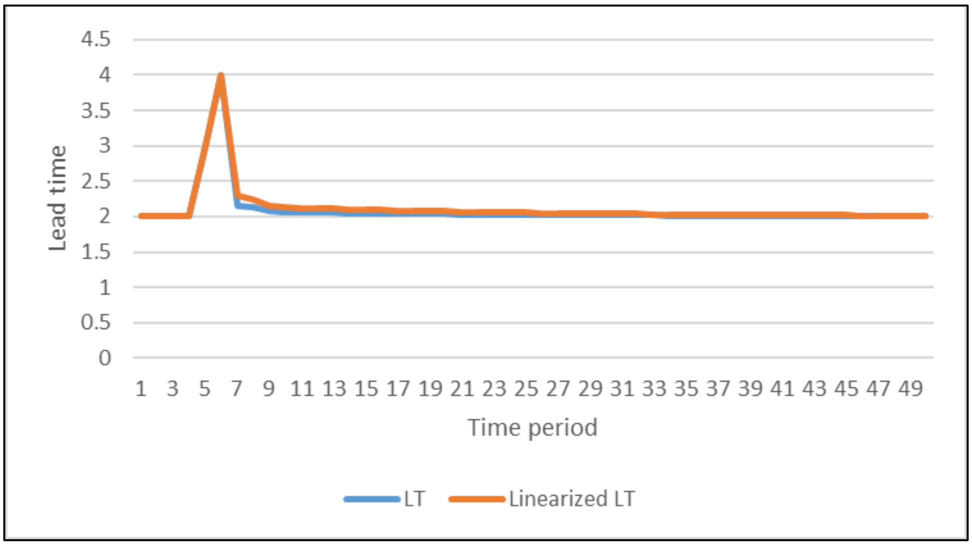

Figure 4.38 A comparison between linearised lead time with the estimated lead time (week), when rework = 0, step input, ETOAR#P

Step input rework = 0.2

However, if the rework exists, the accuracy of the linearised lead time would decrease, as depicted in Figure 4.39. The simulation below demonstrates the lead time transient responses when rework = 0.2. It is evident that the linearised lead time has a higher value than the estimated lead time start from period 7, which implies that when rework exists, the linearised lead time is only accurate within the first three periods (the first four periods represent the initial stage, thus 7 – 4 = 3 periods).

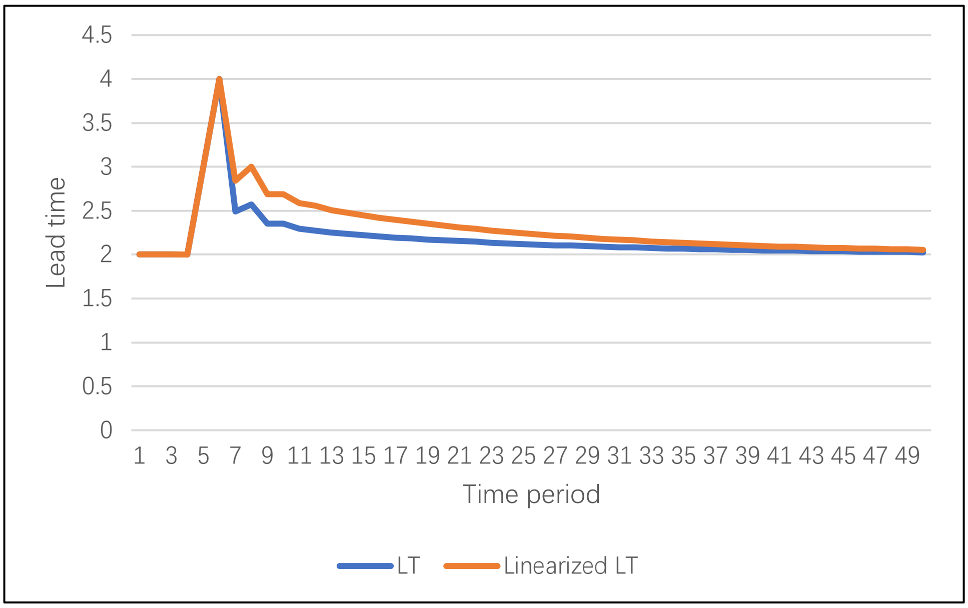

Figure 4.39 A comparison between linearised lead time with the estimated lead time (week), when rework = 0.2, step input, ETOAR#P

Frequency response

Figure 4.40 demonstrates the linearised lead time's performance under the cyclical demand pattern. Note here the cyclical demand pattern is a sine wave with 10 as the amplitude and 52 weeks as the cycle time. The cycle time is assumed to be a year, and the time unit of the system is a week. The level is set to be 100. The equation (4.53) demonstrates the input expression.

$$Demand(t) = 10 * Sine\left(\frac{2\pi}{52} * t\right) + 100. \tag{4.53}$$

According to Figure 4.40, the linearised lead time almost overlaps with the estimated lead time, although there is a slight difference at the top and bottom of the curves. This observation means that the linearised lead time can represent the lead time when the input is cyclical demand.

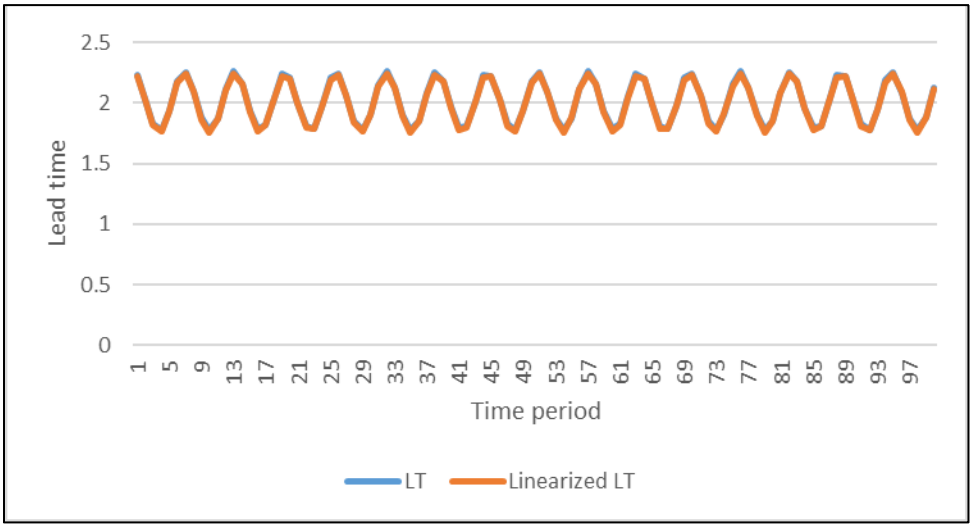

Figure 4.40 A comparison between the linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0, frequent input, ETOAR#P.

Figure 4.41 below demonstrates the linearised lead time and estimated lead times' transient responses when rework = 0.2. It can be observed that the error at the top and bottom of the curve becomes larger, but the accuracy remains acceptable.

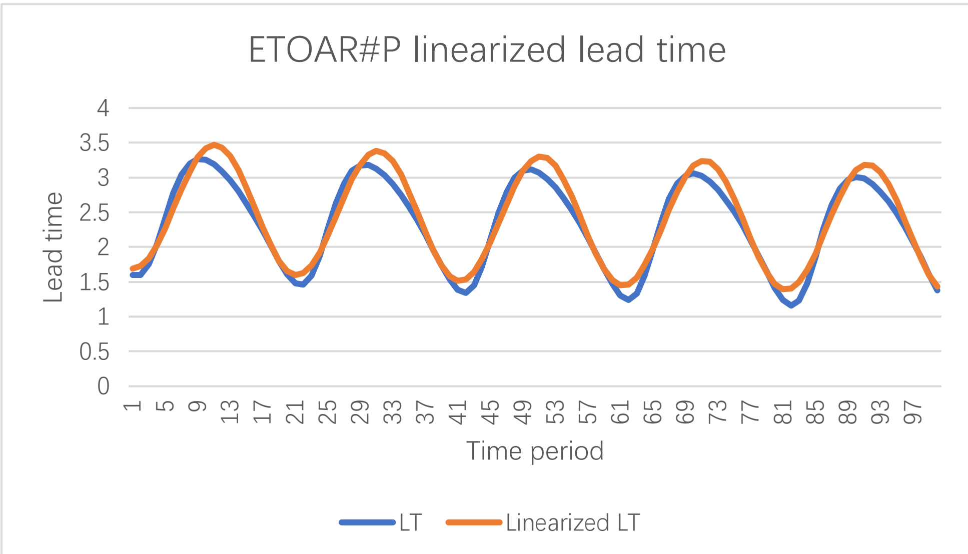

Figure 4.41 A comparison between linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0.2, frequent input, ETOAR#P.

4.6.2 ETPAR#D Result Comparison

The co-efficient values and initial values for the simulation are demonstrated in the Table 4.13.

Table 4.12 Simulation configuration

Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{DES}$	$COMRATE_{PROD}$	OB_{PROD}	OB
125	125	25	100	100	200

Co-efficient values			
τ_{OB}	τ_D	τ_P	RW
20	1	1	0.2

Step input

The transient response of the linearised lead time and estimated lead time are illustrated in Figure 4.42. It is evident in first six stages that the linearised lead time is the same as the estimated lead time, while from period 7 onward, the variance appears until both curves are stabilised at 2, which is the desired lead time level. It is evident from the figure that for the ETO model with demand step change input, the linearisation can represent the lead time, particularly within the first seven periods. Thereafter, the accuracy of the linearisation decreases.

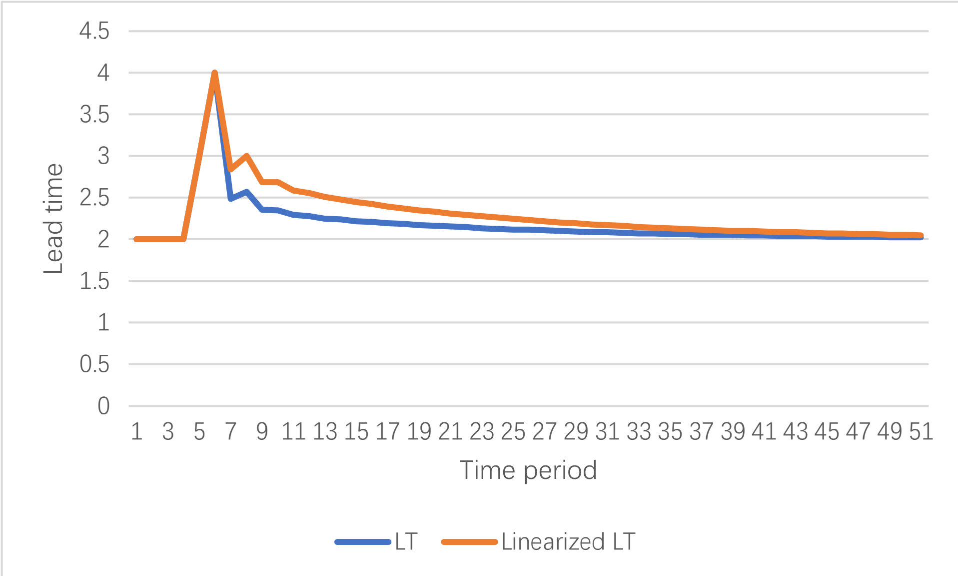

Figure 4.42 A comparison between linearised lead time with the estimated lead time (week), when rework = 0, step input, ETOAR#D.

Figure 4.43 demonstrates the transient responses of both linearised lead time and estimated lead time when rework = 0.2. It is evident that the variance between the two lead times is increased, and the linearised lead time exhibits a higher value than the estimated lead time starting from period 7. This implies that when rework exists in the system, the linearised lead time can only be used in calculating the initial periods' lead time.

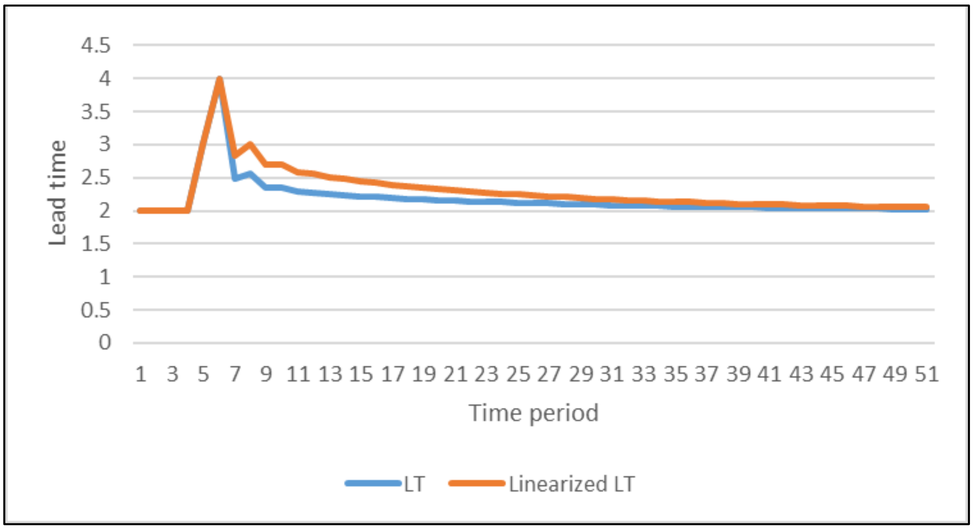

Figure 4.43 A comparison between linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0.2, step input, ETOAR#D.

Frequency response

The transient responses of estimated lead time and linearised lead time under cyclical demand are demonstrated in Figures 4.44 and 4.45. The demand is the same with the demand in previous section, as presented in the equation above. It is evident that these two lead times overlap with each other, with slight differences at the top and the bottom of the curve. This indicates that, when the input to the system is the cyclical demand and the amplitude is 10, the linearisation lead time can represent the lead time.

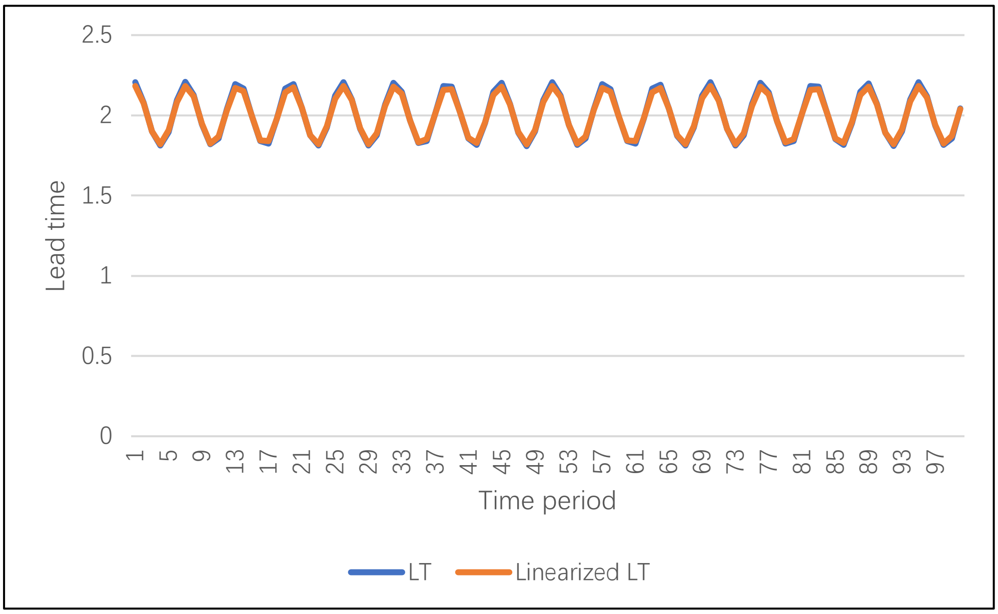

Figure 4.44 A comparison between linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0, frequent input, ETOAR#D.

When rework = 0.2, the simulation with cyclical demand input did not demonstrate a significant variance between two lead times.

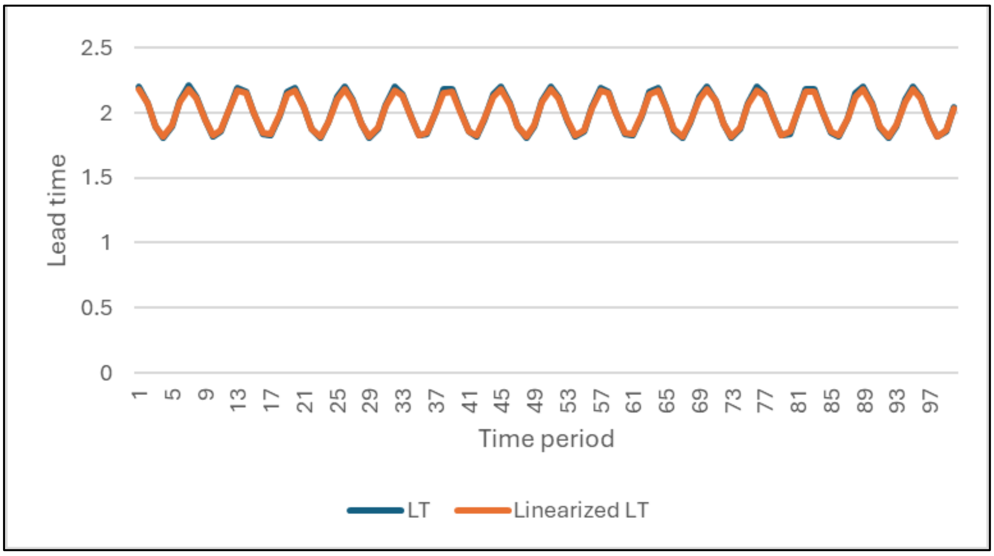

Figure 4.45 A comparison between linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0.2, frequent input, ETOAR#D.

4.6.3 ETOAR#PTD Result Comparison

The following simulation is conducted to test the linearisation lead time of the ETOAR#PTD model. Given the initial and parameter setting in Table 4.13, two simulations were conducted.

Table 4.13 Simulation configuration

Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	125	25	125	125	200

Co-efficient values			
τ_{ETOOB}	τ_D	τ_P	RW
20	1	1	0

Step input

The first simulation is conducted with a step change input; specifically, the demand begins from 100 and jumps to 200 within one period. Such a demand represents an extreme market environment wherein the demand changes dramatically, which is an ideal tool to test the system's performance under stochastic changes in demand.

Figure 4.46 presents the lead time transient responses of both the linearised and estimated lead times. In the initial stages when demand change occurs, the linearised lead time overlaps with the lead time; beginning from stage 7, the errors are detected until period 7, where the errors become trivial. This figure indicates that the linearised lead time is able to represent ETOAR#PTD's lead time, particularly for the lead time in the initial stages. While with time, the accuracy of the lead time will decrease, but the final value is the same with estimated lead time.

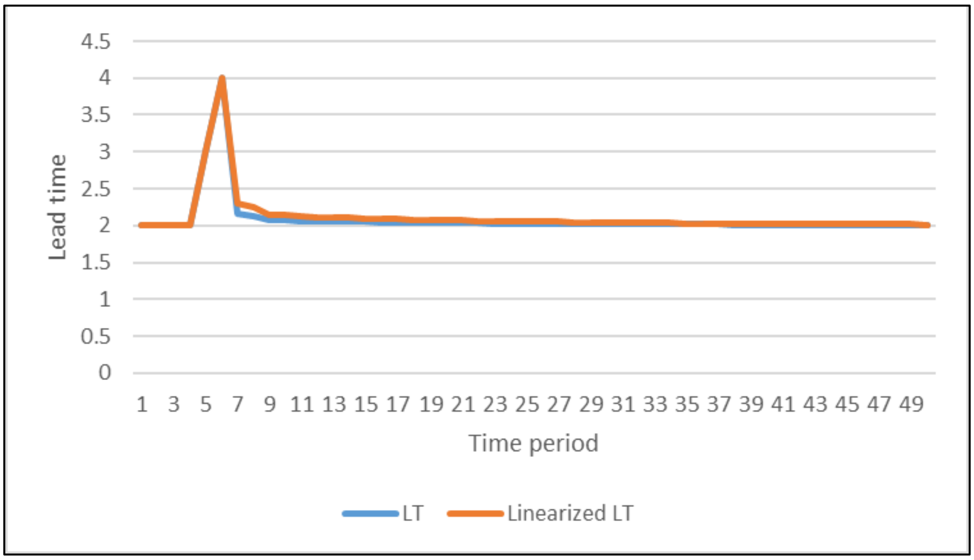

Figure 4.46 A comparison between linearised lead time with the estimated lead time (week), when rework = 0, step input, ETOAR#PTD.

However, when rework exists in the ETOAR#PTD archetype, the result is different. Figure 4.47 demonstrates the simulation result for both lead times when rework = 0.2. It is evident that there is a significant error between estimated lead time with the linearised lead time after period 7. Figure 4.47 depicts that for the ETOAR#PTD scenario, the linearised lead time can only represent the lead time for the first three periods.

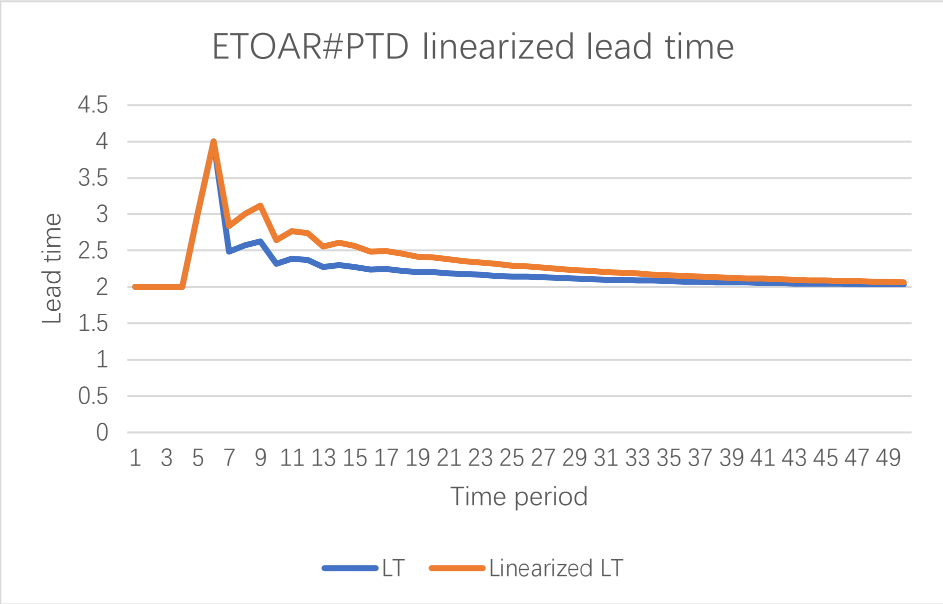

Figure 4.47 A comparison between linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0.2, step input, ETOAR#PTD.

Frequent input

Figure 4.48 illustrates the linearised lead time's transient response against the estimated lead time. The cyclical demand is the same as the demand in the previous section, as shown in equation above. According to Figure 4.48, the linearised lead time overlaps with the estimated lead time, except at the top and bottom values, where the errors at the top and bottom are relatively small. This observation implies that the linearised lead time expression can represent the estimated lead time when the demand pattern is cyclical. However, when upon creating the demand sequence, it was assumed that the amplitude is 10, which is rather small. The question that then arises is whether the result would stay the same if the amplitude became bigger. To answer this question, the following simulations were generated.

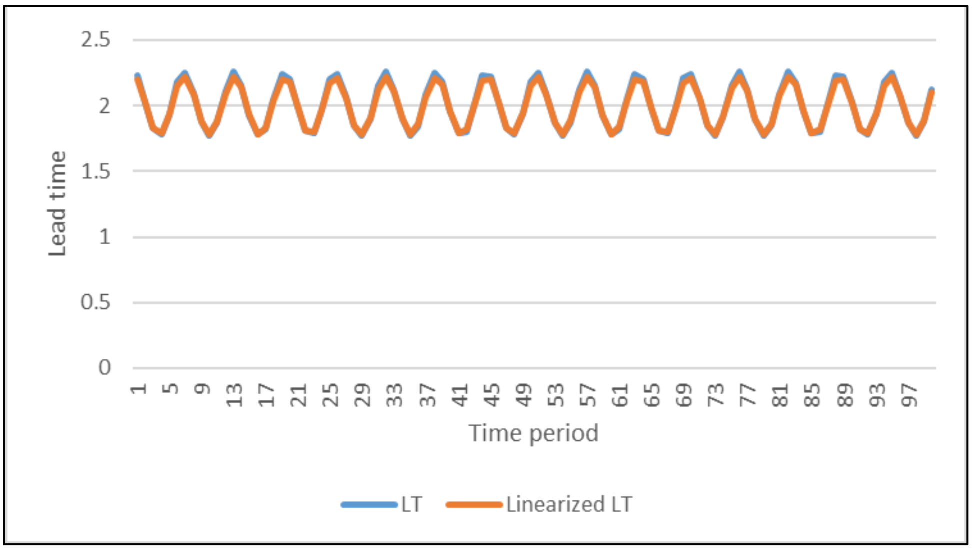

Figure 4.48 A comparison between linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0, frequent input, ETOAR#PTD.

As depicted in Figure 4.49, the rework has an insignificant influence on linearised lead time accuracy for the ETOAR#PTD archetype under cyclical demand pattern.

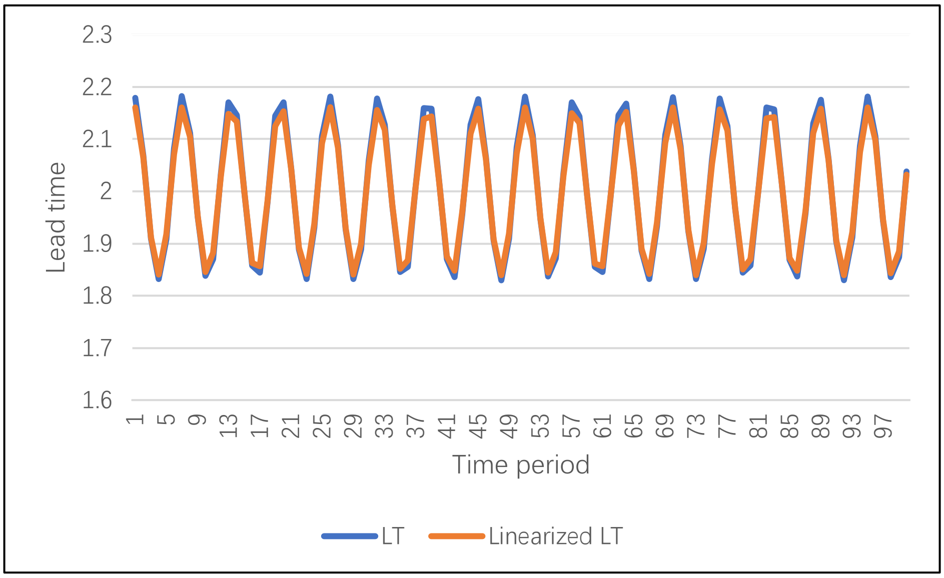

Figure 4.49 A comparison between linearised lead time with the estimated lead time (week) under cyclical demand, when rework = 0.2, frequent input, ETOAR#PTD.

High amplitude input

In this subsection, two simulations were conducted with two different amplitudes. The first simulation was conducted with a demand sequence that has an amplitude of 50. It is evident from Figure 4.50 that the difference between the linearised lead time with estimated lead time is greater—there is a significant difference between the top and bottom values.

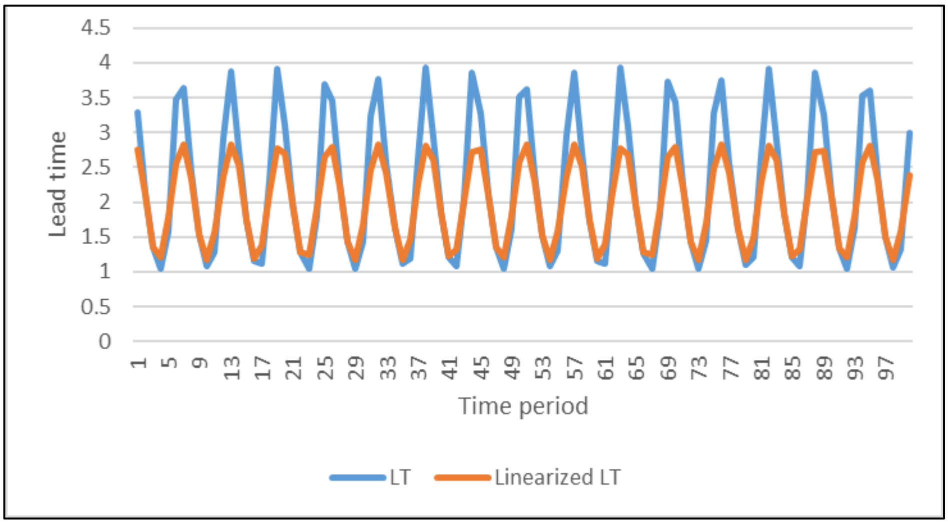

Figure 4.50 A comparison between linearised lead time with the estimated lead time (week), under cyclical demand, when rework = 0.2 and amplitude = 50, high amplitude input.

To further verify this finding, the amplitude was increased from 50 to 100, and the simulation was conducted as presented in Figure 4.51. It was found that the difference between the top and bottom values became even greater, and the linearised lead time can barely account for the estimated lead time.

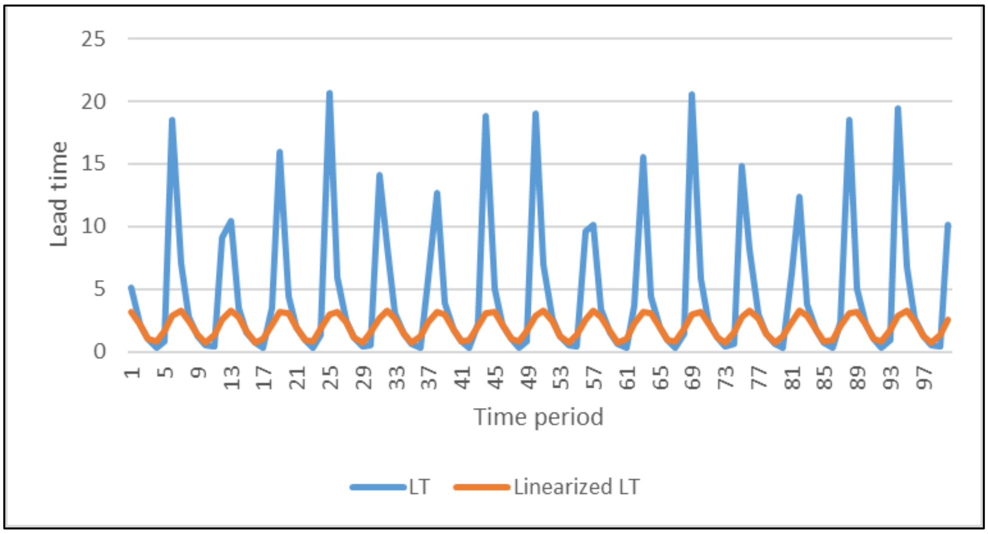

Figure 4.51 A comparison between linearised lead time with the estimated lead time (week), under cyclical demand, when rework = 0.2 and amplitude = 100, high amplitude input.

4.6.4 Lead Time Linearisation Summary

At the same time, it is found that the linearised lead time's accuracy is affected by the rework ratio and amplitude of the demand. For the step change input when there is no rework in the system, the linearised lead time accuracy is satisfactory, while when rework increases, the error of the linearised lead time will increase. The usage of linearised lead time to represent the lead time would depend upon the requirement for the accuracy. For the cyclical input, the linearised lead time's accuracy is sensitive to the amplitude of the demand pattern; specifically, when the amplitude is high, the accuracy of the linearised lead time is low. Moreover, the error will increase along with increases in the amplitude. When it comes to the model simulation, when the demand's fluctuation is severe, the accuracy of the linearised lead time will deteriorate, which implies that for the simulations with a high fluctuating demand pattern, the linearised lead time should not be utilised in lead time analysis.

4.7 Summary

This chapter outlined the development process of the ETO archetype, beginning with a literature-based exploration of the key variables, structures, and features of the ETO system, followed by the design of the archetype itself. To better evaluate the newly introduced order book controllers' mechanism, a preliminary study was conducted to determine the optimal placement of the controller, thereby ensuring that the system can stabilise the lead time and output rate (delivery rate) at the designated level. Subsequently, three archetypes are presented, each depicted through both block diagrams and mathematical formulations. Simulation methods were employed to assess performance. Additionally, lead time linearisation was performed to prepare the model for subsequent chapters.

In the following chapter, the system is analysed using a suite of dynamic analysis tools derived from CT. Such analysis not only deepens the understanding of the developed model but also identifies the unstable regions within the system.

Chapter 5 Dynamic Analysis of the ETO Archetype Family

This chapter places the focus on the dynamic analysis of the ETO archetypes which were developed in Chapter 4. Section 5.1 illustrates the findings from transfer function analysis, which includes the transfer function for all archetypes, and FVT and IVT analysis. Section 5.2 presents the findings from the frequency analysis. Section 5.3 demonstrates the critical stability for all archetypes.

5.1 Transfer Function

ETOAR#P production rework scenario

The transfer functions of the ETO archetype with production rework (ETOAR#P) are demonstrated below.

The delivery rate transfer function is given below:

$$\frac{DR(z)}{Dem(z)} = \frac{\begin{array}{c}(z^2(t_D - \mathrm{RW}t_D - t_{\mathrm{OB}} + \mathrm{RW}t_{\mathrm{OB}} + t_P - \mathrm{RW}t_P) + \\ z(-1 + \mathrm{RW} - t_D + \mathrm{RW}t_D + t_{\mathrm{OB}} - \mathrm{RW}t_{\mathrm{OB}} - t_P + \mathrm{RW}t_P))\end{array}}{-z + \mathrm{RW}z - \mathrm{RW}z^{t_D}t_{\mathrm{OB}} + \mathrm{RW}z^{1+t_D}t_{\mathrm{OB}} + z^{1+t_D+t_P}t_{\mathrm{OB}} - z^{2+t_D+t_P}t_{\mathrm{OB}}} \quad (5.1)$$

The work rate transfer function is given below:

$$\frac{WR(z)}{Dem(z)} = \frac{z + zt_D - z^2t_D - zt_{\mathrm{OB}} + z^2t_{\mathrm{OB}} + zt_P - z^2t_P}{\begin{array}{c}z - \mathrm{RW}z + \mathrm{RW}z^{t_D}t_{\mathrm{OB}} - \mathrm{RW}z^{1+t_D}t_{\mathrm{OB}} \\ -z^{1+t_D+t_P}t_{\mathrm{OB}} + z^{2+t_D+t_P}t_{\mathrm{OB}}\end{array}}. \quad (5.2)$$

The order book transfer function is given below:

$$\frac{OB(z)}{Dem(z)} = \frac{\begin{matrix}(z^2t_D - \mathrm{RW}z^2t_D - z^2t_{\mathrm{OB}} + \mathrm{RW}z^2t_{\mathrm{OB}} \\ -\mathrm{RW}z^{1+t_D}t_{\mathrm{OB}} + z^{2+t_D+t_P}t_{\mathrm{OB}} + z^2t_P - \mathrm{RW}z^2t_P)\end{matrix}}{\begin{matrix}z - \mathrm{RW}z + \mathrm{RW}z^{t_D}t_{\mathrm{OB}} - \mathrm{RW}z^{1+t_D}t_{\mathrm{OB}} - \\ z^{1+t_D+t_P}t_{\mathrm{OB}} + z^{2+t_D+t_P}t_{\mathrm{OB}}\end{matrix}}. \qquad (5.3)$$

The lead time transfer function is derived based on the linearised lead time, and the derivation process has been presented in Section 4. According to the findings from Section 4, the accuracy of the linearised lead time decreases along with the increases in rework; thus, this transfer function can only be used when the rework ratio is small. For the model with a high rework ratio, Little's Law lead time is recommended.

$$\frac{LT(z)}{Dem(z)} = -\frac{\begin{matrix}z((-1+\mathrm{RW})(-1+z)t_D^2 - (-1+\mathrm{RW})(-1+z)t_D(-1+t_{\mathrm{OB}}-2t_P) + \\ (-1+\mathrm{RW})(-1+z)t_P(1+t_P) + t_{\mathrm{OB}}(z - \mathrm{RW}z + \mathrm{RW}z^{t_D} - z^{1+t_D+t_P} + \\ (-1+\mathrm{RW}+z-\mathrm{RW}z)t_P))\end{matrix}}{z - \mathrm{RW}z + \mathrm{RW}z^{t_D}t_{\mathrm{OB}} - \mathrm{RW}z^{1+t_D}t_{\mathrm{OB}} - z^{1+t_D+t_P}t_{\mathrm{OB}} + z^{2+t_D+t_P}t_{\mathrm{OB}}}. \quad (5.4)$$

Initial value and final value theorem

To crosscheck the accuracy of the transfer function, the initial and final value theorems (IVT and FVT) were implemented. The definitions of the IVT and FVT are presented as follows (Nise 2015):

- IVT: The Initial Value Theorem states that the initial value of a discrete-time signal can be determined directly from its Z-transform. It provides the value of the signal at the first-time step, reflecting the system's response at the start without needing to compute the entire time-domain signal.

- FVT: The Final Value Theorem states that the steady-state or long-term behaviour of a discrete-time signal can be determined directly from its Z-transform. It describes the value that the signal approaches as time progresses to infinity, provided the system reaches a steady state and certain stability conditions are met.

In this test, the design and production delay were assumed to be 1; thus the total delay of the ETO process is 2, and the rework ratio is 0.2. According to Truxal (1958), FVT and IVT can be calculated in the following manner. To note here, the input signal for initial/final value derivation is DEM(z) = $\frac{z}{z-1}$, which represents a unit step. For this input signal, DEM (0)=1.

DR refers to the deliver rate; the first formula represents the initial value of the deliver rate, which is the first value of system output after the step input. Given the input signal DEM(z) = $\frac{z}{z-1}$**,** which represents a unit step and has a value of 1 at stage 0 (DEM(0) = 1). The application of the Initial Value Theorem (IVT) to $\frac{DR(z)}{Dem(z)}$ results in an initial value of 1. This means that when a unit step input is applied, the delivery rate starts at a value of 1. The second formula is the final value of the system; 1 represents that at the final stage, the deliver rate equals to the demand rate.

$$\lim_{z\to\infty}\left(\frac{DR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \qquad \lim_{z\to 1}\left(\frac{DR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \tag{5.5}$$

WR refers to the working rate, which is different from the delivery rate, which represents the output of the whole system, whereas WR represents the output of the production subsystem. At the same time, it is also a crucial variable which is linked to system capacity.

$$\lim_{z\to\infty}\left(\frac{WR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)=1 \qquad \lim_{z\to 1}\left(\frac{WR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)=1. \tag{5.6}$$

OB refers to the order book and this variable represents the number of working units that are remaining in the queue. The initial value is one, which implies that when the step input is given, the system's order book remains at 1. FVT is 2, which implies that the system's order book will finally reach 2 after the demand shock.

$$\lim_{z\to\infty}\left(\frac{OB(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)=1 \qquad \lim_{z\to 1}\left(\frac{OB(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)=2. \tag{5.7}$$

LT refers to the lead time of the system. It is important to note that the transfer function for LT is derived based on the linearized lead time expression and does not include($t_D + t_P$), As a result, both the Initial Value Theorem (IVT) and Final Value Theorem (FVT) yield 0, indicating that when an input signal is applied to the system, the lead time does not change immediately and remains at $(t_D + t_P)$.

$$\lim_{z\to\infty}\left(\frac{LT(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)=0 \qquad \lim_{z\to 1}\left(\frac{LT(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)=0. \tag{5.8}$$

ETOAR#D design rework scenario.

The order book transfer function is given below:

$$\frac{OB(z)}{Dem(z)}=\frac{\begin{gathered}z^2t_D-\mathrm{RW}z^2t_D-z^2t_{\mathrm{OB}}+\mathrm{RW}z^2t_{\mathrm{OB}}-\mathrm{RW}z^{1+t_P}t_{\mathrm{OB}}\\+z^{2+t_D+t_P}t_{\mathrm{OB}}+z^2t_P-\mathrm{RW}z^2t_P\end{gathered}}{z-\mathrm{RW}z+\mathrm{RW}z^{t_P}t_{\mathrm{OB}}-\mathrm{RW}z^{1+t_P}t_{\mathrm{OB}}-z^{1+t_D+t_P}t_{\mathrm{OB}}+z^{2+t_D+t_P}t_{\mathrm{OB}}} \tag{5.9}$$

The work rate transfer function is given below:

$$\frac{WR(z)}{Dem(z)} = \frac{\begin{array}{c}-z+\mathrm{RW}z-zt_D+\mathrm{RW}zt_D+z^2t_D-\mathrm{RW}z^2t_D+zt_{\mathrm{OB}}-\mathrm{RW}zt_{\mathrm{OB}}-z^2t_{\mathrm{OB}}+\\ \mathrm{RW}z^2t_{\mathrm{OB}}-zt_P+\mathrm{RW}zt_P+z^2t_P-\mathrm{RW}z^2t_P\end{array}}{-z+\mathrm{RW}z-\mathrm{RW}z^{t_P}t_{\mathrm{OB}}+\mathrm{RW}z^{1+t_P}t_{\mathrm{OB}}+z^{1+t_D+t_P}t_{\mathrm{OB}}-z^{2+t_D+t_P}t_{\mathrm{OB}}}. \quad (5.10)$$

The lead time transfer function is given below:

$$\frac{LT(z)}{DEM(z)} = \frac{\begin{array}{c}-((z((-1+\mathrm{RW})(-1+z)t_D^2-(-1+\mathrm{RW})(-1+z)t_D(-1+t_{\mathrm{OB}}-2t_P)+\\ (-1+\mathrm{RW})(-1+z)t_P(1+t_P)+t_{\mathrm{OB}}(z-\mathrm{RW}z+\mathrm{RW}z^{t_P}-z^{1+t_D+t_P}+\\ (-1+\mathrm{RW}+z-\mathrm{RW}z)t_P)))\end{array}}{z-\mathrm{RW}z+\mathrm{RW}z^{t_P}t_{\mathrm{OB}}-\mathrm{RW}z^{1+t_P}t_{\mathrm{OB}}-z^{1+t_D+t_P}t_{\mathrm{OB}}+z^{2+t_D+t_P}t_{\mathrm{OB}}}. \quad (5.11)$$

The delivery rate transfer function is given below:

$$\frac{DR(z)}{DEM(z)} = -\frac{(-1+\mathrm{RW})z(-1+(-1+z)t_D-(-1+z)t_{\mathrm{OB}}-t_P+zt_P)}{(-1+\mathrm{RW})z+(-1+z)z^{t_P}(\mathrm{RW}-z^{1+t_D})t_{\mathrm{OB}}}. \quad (5.12)$$

The calculation for initial and final value theorem is as per Truxal (1958). According to equations (5.9), (5.10), (5.11), and (5.12), following a unit step input of the form $\left(\frac{z}{z-1}\right)$, equations (5.13), (5.14), and (5.15) can be obtained.

DR refers to delivery rate.

$$\lim_{z\to\infty}\left(\frac{DR(z)}{DEM(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \qquad \lim_{z\to 1}\left(\frac{DR(z)}{DEM(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1. \quad (5.13)$$

It is evident that the final value of the work rate is $\frac{1}{(1-RW)}$, which implies that the production subsystem's work rate stabilises at $\frac{1}{(1-RW)}$. The extra working capacity is prepared to offset the impact of rework.

$$\lim_{z\to\infty}\left(\frac{WR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \qquad \lim_{z\to 1}\left(\frac{WR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = \frac{1}{1-RW}. \quad (5.14)$$

It is evident that the final value increases to 2, which implies that the step change in the demand doubled the order book level of the system.

$$\lim_{z\to\infty}\left(\frac{OB(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \qquad \lim_{z\to 1}\left(\frac{OB(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 2. \quad (5.15)$$

For DR, WR, and OB, the system's initial value is 1, which indicates that the first increment of delivery is one time that of demand. The final value for (5.14) is dependent on RW, which means that if RW is greater than 0, it will lead to an offset of the desired level. The final value of (5.15) is 2, which implies that the output is equal to the sum of designing delay and production delay. This result corresponds with the simulation result in Chapter 4, Figure 4.17, wherein the sum of τ_D and τ_P is 2. Taking scaling into account, it is evident from Figure 4.16 that the first change in output value is +100 and the final value steady state change in output is +200.

$$\lim_{z\to\infty}\left(\frac{LT(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 0 \qquad \lim_{z\to 1}\left(\frac{LT(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 0. \qquad (5.16)$$

Equation (5.16) demonstrates the IVT and FVT of the lead time of archetype 2.

ETOAR#PTD Delayed Design Rework Scenario

The order book transfer function is given below:

$$\frac{OB(z)}{Dem(z)} = \frac{\begin{array}{c} z^2 t_D - \mathrm{RW}z^2 t_D - \mathrm{RW}z t_{\mathrm{OB}} - z^2 t_{\mathrm{OB}} \\ +\mathrm{RW}z^2 t_{\mathrm{OB}} + z^{2+t_D+t_P} t_{\mathrm{OB}} + z^2 t_P - \mathrm{RW}z^2 t_P \end{array}}{z - \mathrm{RW}z + \mathrm{RW}t_{\mathrm{OB}} - \mathrm{RW}z t_{\mathrm{OB}} - z^{1+t_D+t_P} t_{\mathrm{OB}} + z^{2+t_D+t_P} t_{\mathrm{OB}}}. \qquad (5.17)$$

The deliver rate transfer function is given below:

$$\frac{DR(z)}{Dem(z)} =$$

$$\frac{\begin{gathered}z^2 t_D - \mathrm{RW} z^2 t_D - \mathrm{RW} z t_{\mathrm{OB}} - z^2 t_{\mathrm{OB}} \\ + \mathrm{RW} z^2 t_{\mathrm{OB}} + z^{2+t_D+t_P} t_{\mathrm{OB}} + z^2 t_P - \mathrm{RW} z^2 t_P\end{gathered}}{z - \mathrm{RW} z + \mathrm{RW} t_{\mathrm{OB}} - \mathrm{RW} z t_{\mathrm{OB}} - z^{1+t_D+t_P} t_{\mathrm{OB}} + z^{2+t_D+t_P} t_{\mathrm{OB}}}. \tag{5.18}$$

The lead time transfer function is given below:

$$\frac{LT(z)}{Dem(z)} =$$

$$\frac{\begin{gathered}-((z((-1+\mathrm{RW})(-1+z)t_D^2 - (-1+\mathrm{RW})(-1+z)t_D(-1+t_{\mathrm{OB}}-2t_P) + \\ (-1+\mathrm{RW})(-1+z)t_P(1+t_P) + t_{\mathrm{OB}}(\mathrm{RW}+z-\mathrm{RW}z - z^{1+t_D+t_P} + \\ (-1+\mathrm{RW}+z-\mathrm{RW}z)t_P)))\end{gathered}}{z - \mathrm{RW} z + \mathrm{RW} t_{\mathrm{OB}} - \mathrm{RW} z t_{\mathrm{OB}} - z^{1+t_D+t_P} t_{\mathrm{OB}} + z^{2+t_D+t_P} t_{\mathrm{OB}}}. \tag{5.19}$$

The work rate transfer function is given below:

$$\frac{WR(z)}{Dem(z)} =$$

$$\frac{z + z t_D - z^2 t_D - z t_{\mathrm{OB}} + z^2 t_{\mathrm{OB}} + z t_P - z^2 t_P}{z - \mathrm{RW} z + \mathrm{RW} t_{\mathrm{OB}} - \mathrm{RW} z t_{\mathrm{OB}} - z^{1+t_D+t_P} t_{\mathrm{OB}} + z^{2+t_D+t_P} t_{\mathrm{OB}}}. \tag{5.20}$$

Initial value and final value theorem

Deliver rate IVT and FVT

$$\lim_{z\to\infty}\left(\frac{DR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \qquad \lim_{z\to 1}\left(\frac{DR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \tag{5.21}$$

Equation (5.21) demonstrated the work rate’s IVT and FVT. Note here that the final value of the work rate is determined by the rework because the system needs to increase the work rate to cover the extra working units created by the rework.

$$\lim_{z\to\infty}\left(\frac{WR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = 1 \qquad \lim_{z\to 1}\left(\frac{WR(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right) = \frac{1}{1-RW}. \tag{5.22}$$

OB refers to the order book. This variable represents the number of working units that are left in the queue. The initial value is one, which implies that when the step input is given, the system's order book remains at 1. FVT is 2, which implies that the system's order book will finally reach 2 after the demand shock.

$$\lim_{z\to\infty}\left(\frac{OB(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)= 1 \qquad \lim_{z\to 1}\left(\frac{OB(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)= 2. \quad (5.23)$$

LT refers to the lead time of the system. Note here that the transfer function for LT is derived based on the linearised lead time expression and does not include the content part $(t_D + t_P)$; thus, both IVT and FVT values are 0, which implies that the system is able to maintain the lead time in the long-term.

$$\lim_{z\to\infty}\left(\frac{LT(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)= 0 \qquad \lim_{z\to 1}\left(\frac{LT(z)}{Dem(z)}\cdot\frac{z}{z-1}\cdot\frac{z-1}{z}\right)= 0. \quad (5.24)$$

Triangulation:

The accuracy of the transfer function is ensured through triangulation. This process involves comparing the results of the spreadsheet model, the Simulink model, and the model reproduced using the transfer function. The transfer function is only validated if all three models yield identical results. Furthermore, the initial and final values derived from these comparisons are crosschecked with the results presented in Chapter 4.

In Chapter 4, it is evident that the total system lead time for all archetypes begins at 2 and returns to 2, equivalent to $\tau_D + \tau_P$, as illustrated in Figures 4.13, 4.24, and 4.36. Following the demand step change, the order book doubles, as depicted in Figures 4.12, 4.23, and 4.35. The initial and final values of the work rate remain consistent, as shown in Figures 4.14, 4.26, and 4.37. For ETOAR#P and ETOAR#PTD, the production system's work rate is $\frac{1}{1-RW}$, while for the design system, the work rate of production system is 1.

5.2 Frequency Domain Analysis

The ETO model developed in the chapter 4 has two parameters, τ_{OB} and RW. τ_{OB} needs to be set based on the management decision. This parameter represents the sensitivity of the company to the order book change and determines the changing speed or slowness of the work rate. In the meantime, RW represents the rework ratio of the production or design, which also reflects the conformance rate of the ETO production. Such the ratio barely changes, it is usually determined by craftsmanship, the complexity, and level of difficulty in the production of the ETO products.

To have an insight into how the τ_{OB} and RW affect the system's dynamic performance, two experiments are designed for each scenario: one experiment aims to determine how τ_{OB} affects the system's reaction to different frequencies; the other one aims to study how RW ratio affects the system's behaviour. The common coefficients value is set as presented in Table 5.1:

Table 5.1 Initial value for the Bode plot analysis

Co-efficient values			
Experiment one τ_{OB} oriented		*Experiment two* RW oriented	
τ_{OB}	RW	τ_{OB}	RW
0, 2,20,40,80,160,200	0.5	*20*	*0,0.2,0.5,0.8*

To control the variable, when the τ_{OB} is focused on, the RW is set as 0.5, and when focus is given to the RW, τ_{OB} will be set as 20. These two values are selected based on the experience from previous experiments in Chapter 4. A system with such settings undergoes milder fluctuations.

In addition, according to previous literature, the demand fluctuation cycle in the ETO industries has a strong correlation with the global economy cycle (Wigren & Wilhelmsson 2007, Wada et al. 2018). Based on this, the research estimates the demand frequency of the ETO industry as 7 years or 364 weeks (Wang and Xiao 2023). Since this estimation is roughly calculated based on the global economy cycle, and the demand cycle for different ETO products may vary, this section visualises and summarises the ETO system's performance across all demand frequencies. The red box highlights the most possible demand frequency of the ETO system (demand cycle: 7 years, 364 Weeks, 0.01725 rad/week, $\log_{10}(0.01725) = -1.7632$; thus, the red box highlights the frequency from 0.01 to 0.02 rad/week).

Due to the similarity of the Bode plots across the three scenarios, this section presents only the Bode plots of ETOAR#P to illustrate the research procedure. The remaining plots are provided in the Appendix.

5.2.1 ETOAR#P Production Rework

Work rate

The Bode plot in Figure 5.1 demonstrates the frequency response of the ETOAR#P: the production rework scenario, wherein the rework happens and can be rectified in the production stage. The magnitude chart illustrates how the output of the system reacts to the diverse demand cycle frequencies. When the demand frequency is below 0.02 rad/weeks (314 weeks), the magnitude is approximately 6 dB and, according to the transformation formula (5.39), it can be calculated that the output's amplitude is approximately two times of the input. Between 0.02 and 0.04 rad/week (314 to 157 weeks), the curve increases along with the increase in the frequency. When demand frequency is higher than 0.1 rad/week (62.8 weeks) but lower than 0.5 rad/week (12.56 weeks), all magnitude curves begin to fall, and the system with the smallest stable τ_{OB} value has the lowest magnitude.

When $\tau_{OB} = 2$, the system is unstable, as per the analysis of Section 5.3, and the magnitude curve is much higher than the others when demand frequency is higher than 0.02 rad/week (314 weeks).

The chart below the magnitude chart is the phase chart, which illustrates the phase change between the input and output signal. It can be observed that, in the red box, the magnitude curves of all τ_{OB} settings are located at 6dB. This indicates that for ETOAR#P, the value of τ_{OB} has a minor influence on the fluctuation of production capacity.

$$Magnitude = 20 * Log_{10}\left(\frac{Output}{Input}\right). \qquad (5.39)$$

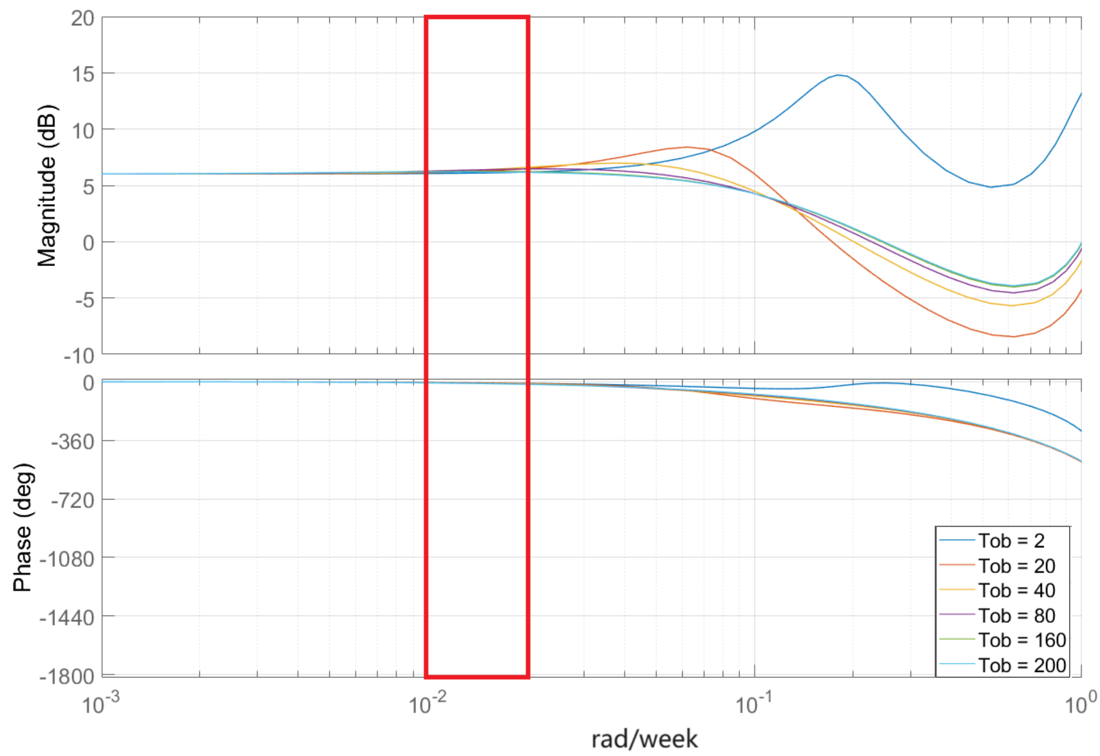

Figure 5.1 Bode plot for the ETOAR#P τ_{OB} orientated for RW = 0.5

The Bode plot in Figure 5.2 demonstrates how the system's dynamic performance changed along with the change of the rework ratio (RW). The red box in the diagram displays the magnitude curves corresponding to the ETO demand frequencies. As shown within the red box, the higher the rework ratio, the higher the magnitude curves. This indicates that rework negatively influences the system's fluctuation.

Apart from the observations from the red box, the following changes were observed: in the low frequency area where the frequency is lower than 0.1 rad/week (62.8 weeks), with the increases in the rework ratio, the system was increasingly fluctuating; when RW increased, the system fluctuated even more. In the moderate frequency area, where the frequency is between 0.1 and 1 rad/week, a greater RW ratio may play a role to smooth the output. It is evident that RW = 0.8 falls to the bottom of the plot, which implies that in that circumstance, the output's fluctuation is smaller than the input and the fluctuation ratio between the output with input is also smaller than the situation when RW is smaller than 0.8.

Moreover, it is observed that peaks appear in the magnitude curves when demand frequency is between 0.04 and 0.07 rad/week (apart from the unstable parameter when τ_{OB} = 2). This suggests that the ETO company should avoid such demand patterns, because such frequency will cause fluctuation in the work rate.

RW has a small influence on the system's performance from the phase's perspective. The trend for the phase plot is decreasing, which implies that the delay of the output and input waveform is enlarged by the frequency increase.

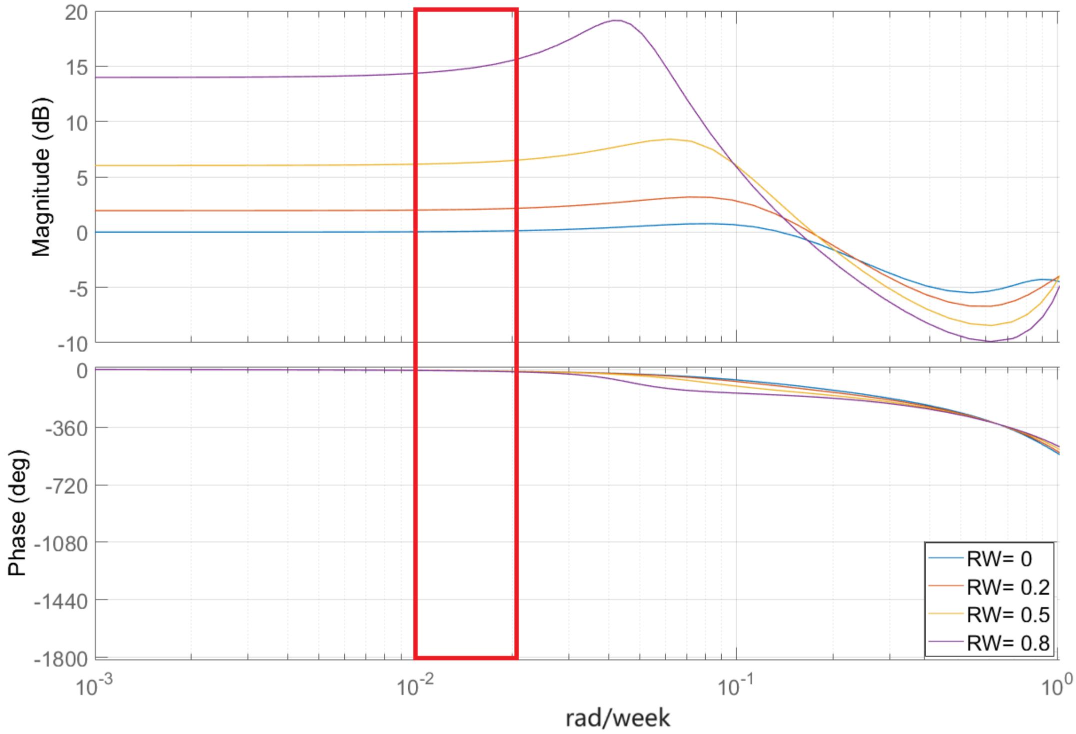

Figure 5.2 Bode plot for the ETOAR#P rework orientated for $\tau_{OB} = 20$.

Order book

Figure 5.3 demonstrates the Bode plot of the ETOAR#P's order book. In the red box, it is evident that with the increase in the rework ratio, the order book's amplitude increases slightly, which indicates that the increase in the rework ratio has a negative effect on the fluctuation of the order book of ETOAR#P. Moreover, there is a gap around 1.6 rad/week (4 weeks). This gap implies that this system is a Notch filter, which can reject one specific frequency. In practice, this implies that when the demand fluctuation frequency is 1.6 rad/ week, the order book fluctuation will be approaching 0. To validate this finding, an experiment is conducted, as depicted in Figure 5.4

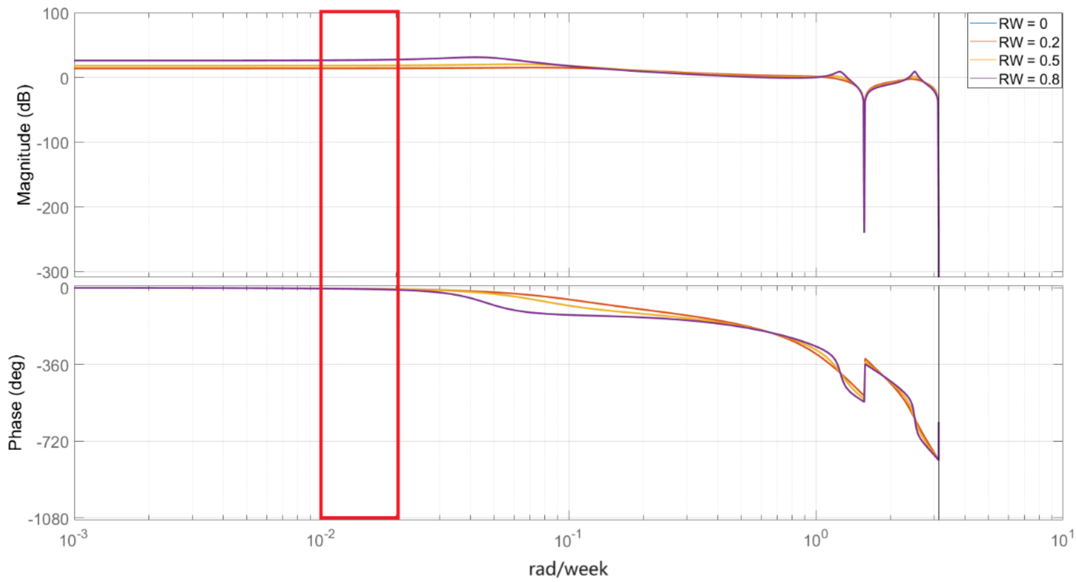

Figure 5.3 Bode plot for the ETOAR#P rework orientated for $\tau_{OB} = 20$

According to Figure 5.3, when demand frequency is 1.6 rad/week, the order book level will become a straight line, which indicates that, under such frequency, the systems order book would not fluctuate along with the change of the demand.

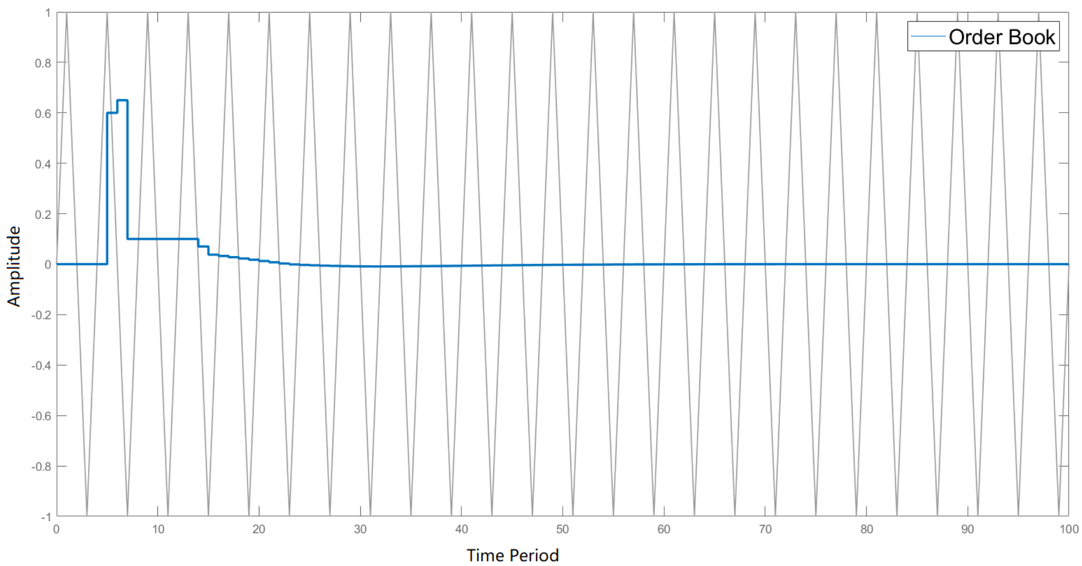

Figure 5.4 Amplitude of the order book with cyclical input; demand frequency = 1.6 rad/week; one cycle is four-time units.

Figure 5.5 demonstrates how τ_{OB} affects the frequency responses of the order book of the ETOAR#P system. In the red box, the influence of the τ_{OB} to the magnitude curve is trivial. When τ_{OB} = 2, the amplitude of the orderbook is higher than the others. This indicates that τ_{OB} = 2 exaggerates the fluctuation of the system. From the phases plot, it is evident that when τ_{OB} = 2, the phases shift is larger than the other configuration. When the frequency is 1.6 rad/week, the phases curve of τ_{OB} = 2 and τ_{OB} = 200 demonstrate larger shifts.

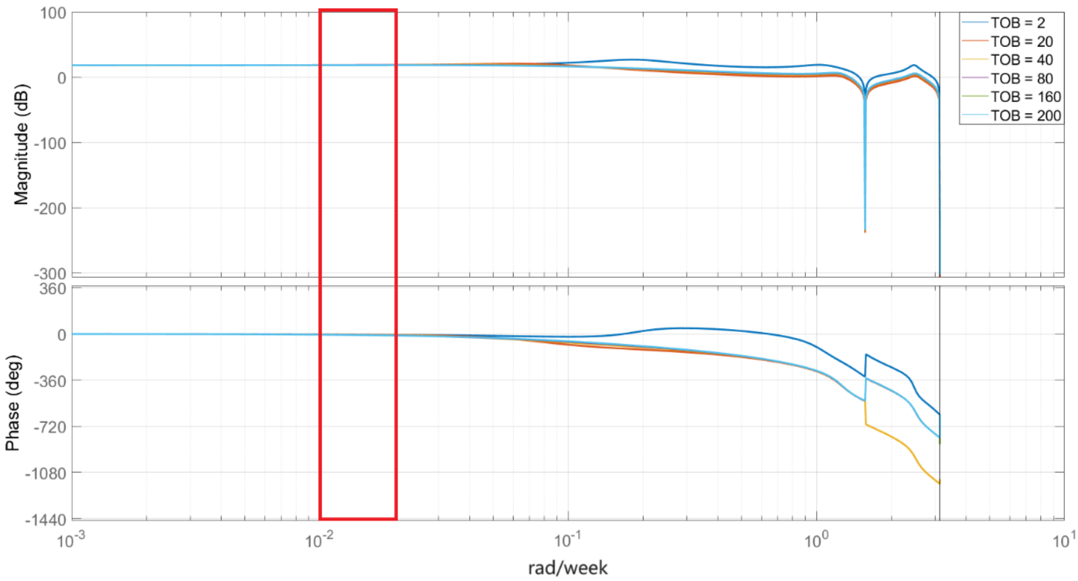

Figure 5.5 Bode plot for ETOAR#P rework orientated for τ_{OB} = 0.5

Lead time

Figures 5.6 and 5.7 demonstrate how rework and τ_{OB} affect the lead time's performance under a cyclical demand input. According to Figure 5.6, in the red box, the magnitude curves increase as the frequency increases, and the higher the rework ratio, the higher the magnitude. This can be interpretated as that the rework ratio has a negative impact on the fluctuation of the lead time.

Apart from the observation from the red box, the following observations are made: When the demand frequency is low, the magnitude of the lead time increases with the increase in the rework ratio. In the high frequency area, the magnitude curve begins to fluctuate and the fluctuation increases with the increases in the rework ratio.

According to the phase plot, the increase in rework ratio from 0 to 0.5 does not affect the phase shift too much, and the phase shift decreases with increasing input frequency. However, when rework = 0.8, the systems' phase curve begins at a lower level and decreases with increasing frequency.

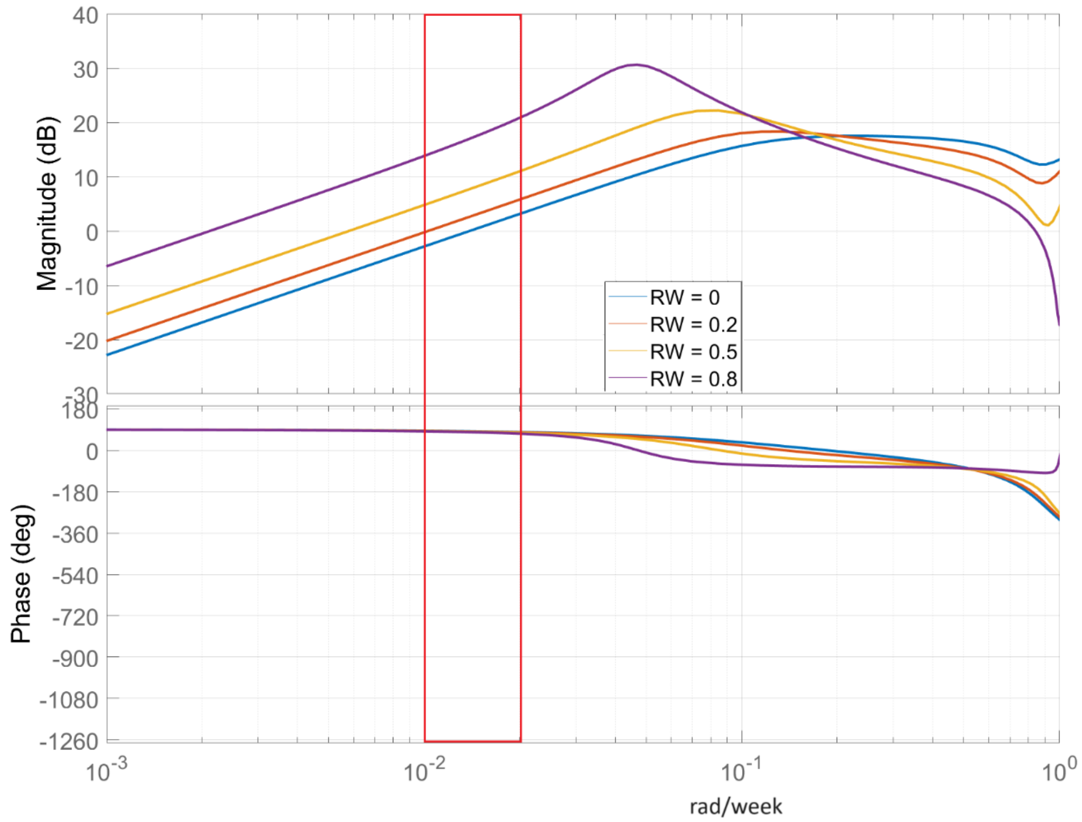

Figure 5.6 Lead time Bode plot of the ETOAR#P rework orientated for $\tau_{OB} = 20$

Figure 5.7 demonstrates the influence of τ_{OB} to the system's lead time performance. When the frequency is below 0.03 rad/week, which covers the frequency highlighted by the red box, the magnitude curve shifts up with the increase in τ_{OB}, which indicates that a smaller τ_{OB} can smoothen the fluctuation of the system's output when the input frequency is below 0.03 rad/week. When the frequency is above 0.1 rad/week, fluctuation appears and the curves with smaller τ_{OB} have a smaller magnitude. In practice, this implies that when the demand frequency is low, the system should select a smaller τ_{OB} to reduce the fluctuation. When demand frequency is high, the system should select a larger τ_{OB}, thereby reducing the fluctuation of the output.

According to the phase plot, the phase value remains at 90 degrees, thereby suggesting that the output phase is 90 degrees ahead of the input signal. As the demand frequency increases, the phase gradually decreases. Based on the phase differences, the delayed or advanced time can be calculated using equation (5.40) from Nise (2015). When the phase difference is 90 degrees and the frequency is 0.02 rad/week, the time difference is 78.5 weeks. This implies that the peak of the lead time will occur 78.5 weeks ahead of the input signal's peak.

$$\Delta t = \frac{Phase\ different\ (degree)}{360° \cdot frequency\ (Hz)}. \tag{5.40}$$

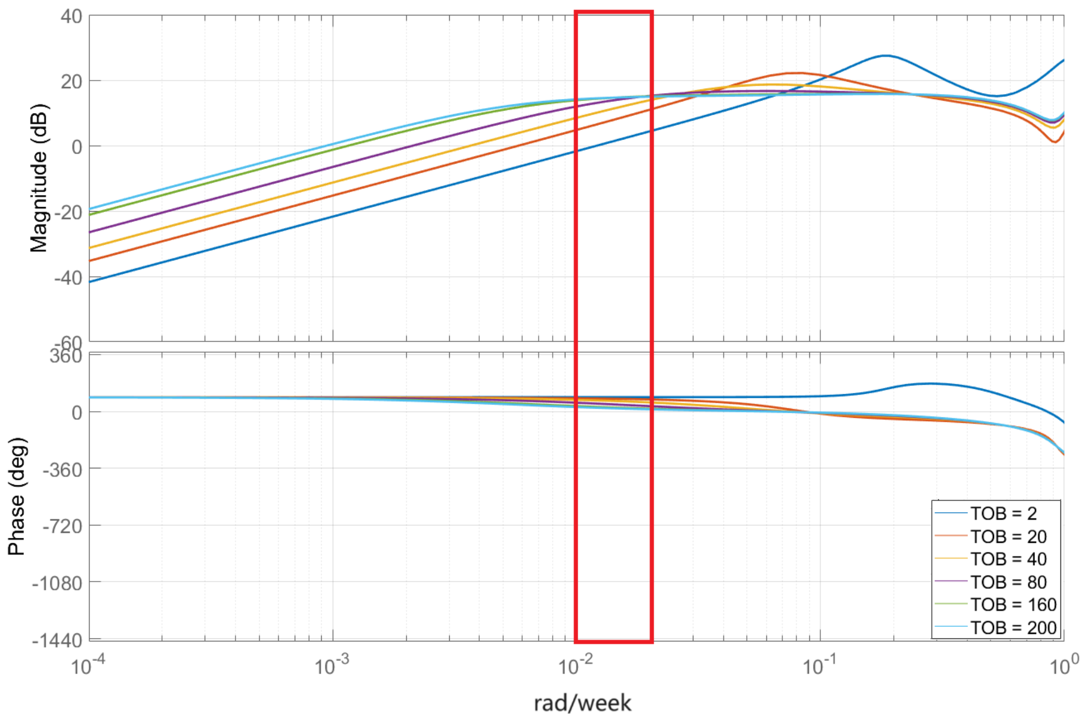

Figure 5.7 Lead time Bode plot of the ETOAR#P rework orientated for τ_{OB} = 0.5

5.2.2 Result Analysis

In this subsection, the effect of rework and τ_{OB} to different ETO archetypes are analysed. Tables 5.2–5.13 demonstrate the findings from the Bode plot across different frequency zones. The red box frequency zone covers the ETO demand frequencies to illustrate the changing trend of the magnitude across the various frequencies. To narrow down the scope, a detailed analysis of the ETO system under all the possible demand frequencies (0.01–0.02 rad/week) is provided in Tables 5.5, 5.9, and 5.13. Based on this, the minimal reasonable capacity (MRC) and the maximum reasonable lead time (MRL) for the ETO systems under different rework scenarios are derived to link the frequency domain analysis with actual practice

- Minimal Reasonable Capacity (MRC) is the smallest level of capacity a system needs to operate effectively while covering peak demand and accounting for dynamic variability. It ensures the system meets performance requirements without excessive waste, balancing efficiency with resilience to fluctuations (Lin et al. 2020).

- Maximum Reasonable Lead Time (MRL) refers to the maximum allowable lead time, determined by estimating and accounting for the amplification of lead time fluctuations within a system. By calculating the theoretical maximum lead time, MRL ensures that project delivery stays within acceptable limits, preventing delays that could disappoint customers and aligning with SD predictions (Lin et al. 2020) .

ETOAR#P

Table 5.2 ETOAR#P work rate magnitude summary

Frequency Zone	Low (rad/ week)	**Medium (rad /week)**	High (rad / week)
Frequency	Lower than 10^{-2}	10^{-2} to 10^{0}	Higher than 1
Cycle	628 weeks	Between 628 weeks to 6.28 weeks	Less than 6.28 week
Trend	Start from 8dB and maintain at 8dB	The magnitude increases at first and then decreases.	The curve fluctuated.
τ_{OB} effect	Insignificant	Before 10^{-1}: The system with a larger τ_{OB} has a higher magnitude. After the 10^{-1}: The system with larger the τOB has a lower magnitude.	The system with larger τ_{OB} has a lower magnitude.
RW effect	For various rework ratios, the starting level of the magnitude are various. The more the rework, the higher the level will be, which means the magnitude of the work rate will be exaggerated by the rework.	The systems with higher rework ratio increase faster, and the peaks are higher. While after 10^{-1} rad/s all magnitude curves start to decrease, and the systems with higher rework ratio, has a lower-level magnitude.	The higher the rework ratio, the higher the fluctuations of magnitude curve are.

Table 5.3 ETOAR#P order book magnitude summary

Frequency Zone	Low	Medium	High
Frequency	Lower than 10^{-2}	10^{-2} to 10^{0}	Higher than 1
Cycle	628 weeks	Between 628 weeks to 6.28 weeks	Less than 6.28 week
Trend	Start from 18dB, and maintain this level until 10^{-2}	From $10^{-2,}$ the magnitude curve decreases slightly, and the curve reach 0dB when frequency is 10^{0}	In the high frequency area, a sharp valley appears at $10^{0.1}$, which means at that frequency this system can filter the frequency. When frequency keep increasing, the magnitude goes back to the 0 dB.
τ_{OB} effect	Insignificant	The higher the τ_{OB}, the higher the magnitude curve is.	The higher the τ_{OB}, the higher the magnitude curve is.
RW effect	The higher the rework ratio is, the higher the magnitude curve is. Which means, the rework can increase the magnitude of the order book	When frequency is lower than $10^{-1,}$ the higher the rework ratio, the higher the magnitude curve is. When frequency is above 10^{-1} the magnitude curves overlap each other, which indicate that the rework ratio has insignificant influence on the magnitude.	insignificant

Table 5.4 ETOAR#P lead time magnitude summary

Frequency Zone	Low	Medium	High
Frequency	10^{-4} to 10^{-2}	10^{-2} to 10^{-1}	>10-1
Trend	The magnitude curve increases from the starting point.	The magnitude curve keeps increasing until they reach the peaks and start to decrease.	Fluctuation appears in the high frequency domain.
τ_{OB} effect	The higher the τ_{OB} is, the higher the magnitude curve is. However, the unstable parameter setting has a smaller magnitude.	The systems with lower τ_{OB} increase faster. When τ_{OB} = 20 or 40, a peak appears on their magnitude curves.	Fluctuations, while the systems with small τ_{OB} value have a smaller magnitude.
RW effect	The higher the rework ratios, the higher the magnitude.	Magnitude curves reach its' peak, afterwards, curves start to decreases,	The higher the rework is the smaller the magnitudes are.

For ETOAR#P, the rework ratio significantly impacts both the work rate and the magnitude of lead time, while it has a minor effect on the magnitude of the order book. Additionally, all these influences are negative; higher rework ratios lead to greater magnitudes in these metrics.

Based in the above analysis, the influence of rework on the system's influence is summarised in the Table 5.5. This table contains three main columns—work rate, lead time under 0.01 rad/week frequency, and lead time under 0.02 rad/week frequency. Under each major column, there are two sub-columns, one presents the magnitude and the other presents the ratio between lead time/work rate amplification with demand amplification. The ratio is derived from equation (5.39). The MRC and MRL of the ETOAR#P can be derived from Table 5.5. MRC represents the MRC the system should maintain to cover the fluctuation of the work rate. This value corresponds to the peak of the work rate in the frequency response, thereby indicating the minimal capacity required for the production system. Maintaining production capacity at this level ensures that demand peaks are covered while avoiding the waste associated with maintaining an excessively high capacity. MRL represents the peak lead time value when demand fluctuates. In practice, it can serve as a reference when proposing lead times for ETO products, thereby ensuring that the proposed lead time is achievable and prevents lead time overruns (Lin et al. 2020).

Table 5.5 The MRC and MRL of ETOAR#P, derived from the Bode plot. Assumption: demand level = 100 working units per week; amplification = 10 working units per week

	Work rate 0.01-0.02 rad/week			Lead time 0.01 rad/week			Lead time 0.02 rad/week		
RW	Magnitude (dB)	$\frac{Work\ Rate}{Demand}$	MRC	Magnitude (dB)	$\frac{Lead\ time}{Demand}$	MRL	Magnitude (dB)	$\frac{Lead\ time}{Demand}$	MRL
0	0	1.0	200	-3.0	0.7	8.7	3.2	1.4	9.4
0.2	2	1.3	230	0.0	1.0	9	5.8	2.0	10
0.5	6	2.0	300	5.0	1.8	9.8	11.0	3.5	11.5
0.8	14	5.0	600	14.0	5.0	13	21.0	11.2	19.2

From the τ_{OB} perspective, when the demand frequency is between 0.01 and 0.02 rad/week (ETO demand frequency), it has insignificant influence on the work rate and the order book. For the lead time, the smaller the τ_{OB}, the smaller the magnitude.

ETOAR#D

For the ETOAR#D system, the rework ratio has insignificant influence on the work rate, moderate influence on the order book magnitude, and significant influence on the lead time magnitude. Moreover, for both order book and lead time magnitude, the larger the rework ratio, the higher the magnitude, as presented in Table 5.9.

Table 5.6 ETOAR#D Work rate magnitude summary

Frequency Zone	Low	Medium	High
Frequency	Lower than 10^{-2}	10^{-2} to 10^{0}	Higher than 1
Week	628 weeks	Between 628 weeks to 6.28 weeks	Less than 6.28 week
Trend	Start from 0dB and maintain at 0dB	The magnitude increases at first and then decreases.	The curve fluctuated.
τ_{OB} effect	Insignificant	Before $10^{-0.9}$: The system with larger the τ_{OB} has a higher magnitude. After the 10^{-1}: The system with larger the τ_{OB} has a lower magnitude.	The system with larger τ_{OB} has a lower magnitude.
RW effect	All curves start from 0 dB, and maintain at 0dB	The magnitude curves with higher rework ratio increase faster, and the peaks are higher. While after 10^{-1} rad/s all magnitude curves start to decrease, and the systems with higher rework ratio, has a lower-level magnitude.	The higher the rework ratio, the higher the fluctuations of magnitude curve are.

Table 5.7 ETOAR#D Order book magnitude summary

Frequency Zone	Low	Medium	High
Frequency	Lower than 10^{-2}	10^{-2} to 10^{0}	Higher than 1
Cycle	628 weeks	Between 628 weeks to 6.28 weeks	Less than 6.28 week
Trend	Start from 18dB, and maintain this level until 10^{-3} , afterwards, all curves start to increase.	From $10^{-2,}$ the magnitude curve keeps increasing. When frequency increases to 10^{-1}, all	In the high frequency area, a sharp valley appears at $10^{0.1,}$ which means at that frequency this system can filter the frequency. When frequency keep increasing, the magnitude goes back to the 0 dB.
τOB effect	The curves with higher τOB increases faster	The higher the τ_{OB}, the higher the magnitude curve is.	insignificant
RW effect	The higher the rework ratio is, the higher the magnitude curve is. Which means, the rework can increase the magnitude of the order book	When frequency is lower than $10^{-1.6,}$ the higher the rework ratio, the higher the magnitude curve is. When frequency is above $10^{-1.3}$ and lower than $10^{-0.6}$ The higher the rework ratio is, the smaller the magnitude is.	Fluctuation

Table 5.8 ETOAR#D lead time magnitude summary

Frequency Zone	Low	Medium	High
Frequency	Lower than 10^{-2}	10^{-2} to 10^{0}	Higher than 1
Cycle	628 weeks	Between 628 weeks to 6.28 weeks	Less than 6.28 week
Trend	The magnitude curve increases from the starting point.	The magnitude curve keeps increasing until they reach the peaks and start to decrease.	Fluctuation appears in the high frequency domain.
τOB effect	The higher the τ_{OB} is, the higher the magnitude curve is. However, the unstable parameter setting has a smaller magnitude.	The systems with lower τ_{OB} has a lower magnitude. When τ_{OB} =2, 20 or 40, a peak appears on their magnitude curves.	Fluctuations, while the systems with small τ_{OB} value have a smaller magnitude.
RW effect	The higher the rework ratios, the higher the magnitude.	Magnitude curves reach its' peak, afterwards, curves start to decreases. When frequency is above $10^{0.9}$, the larger the rework ratios are the smaller the magnitude is	The higher the rework is the smaller the magnitudes are.

Table 5.9 The MRC and MRL of ETOAR#D, derived from the Bode plot. Assumption: demand level = 100 working units per week; amplification = 10 working units per week

	Work rate 0.01-0.02 rad/week			Lead time 0.01 rad/week			Lead time 0.02 rad/week		
RW	Magnitude (dB)	$\frac{Work\ Rate}{Demand}$	MRC	RW	Magnitude (dB)	$\frac{Work\ Ra}{Deman}$	MRC	RW	Magnitude (dB)
0	0	1.0	200	0	0	1.0	200	0	0
0.2	0.1	1.0	200	0.2	0.1	1.0	200	0.2	0.1
0.5	0.2	1.0	200	0.5	0.2	1.0	200	0.5	0.2
0.8	0.7	1.1	210	0.8	0.7	1.1	210	0.8	0.7

From the τ_{OB} perspective, it has insignificant influence on the work rate magnitude and moderate influence on the order book and lead time. For both variables, the smaller the τ_{OB}, the smaller the magnitude, the smaller the fluctuation.

ETOAR#PTD

For the ETOAR#PTD model, the rework ratio influences all targeted variables, and the larger the rework ratio, the greater the magnitude the greater the fluctuation. It is evident the rework has a negative influence on the ETOAR#PTD model. Table 5.13

summarises the observation from the Bode plot and yields the MRL and MRC of the system under various rework ratios.

Table 5.10 ETOAR#PTD work rate magnitude summary.

Frequency Zone	Low	Medium	High
Frequency	Lower than 10^{-2}	10^{-2} to 10^{0}	Higher than 1
Cycle	628 weeks	Between 628 weeks to 6.28 weeks	Less than 6.28 week
Trend	Start from 8dB and maintain at 8dB	The magnitude increases at first and then decreases.	The curve fluctuated.
τ_{OB} effect	Insignificant	Before $10^{-0.9}$: The system with larger the τ_{OB} has a smaller magnitude. After the $10^{-0.9}$: The system with larger the τ_{OB} has a higher magnitude.	The system with larger τ_{OB} has a higher magnitude.
RW effect	The higher the rework ratios, the higher the starting point.	The magnitude curves with higher rework ratio increase faster, and the peaks are higher. While after 10^{-1} rad/s all magnitude curves start to decrease, and the systems with higher rework ratio, has a lower-level magnitude.	The higher the rework ratio, the higher the fluctuations of magnitude curve are.

Table 5.11 ETOAR#PTD order book magnitude summary

Frequency Zone	Low	Medium	High
Frequency	Lower than 10^{-2}	10^{-2} to 10^{0}	Higher than 1
Cycle	628 weeks	Between 628 weeks to 6.28 weeks	Less than 6.28 week
Trend	Start from 18dB, and maintain this level until 10^{-3} , afterwards, all curves start to increase.	From $10^{-2,}$ the magnitude curve keeps increasing. When frequency increases to 10^{-1}, all curves start to decrease.	All curves start to fluctuate
τOB effect	The curves with higher τ_{OB} increases faster	The higher the τ_{OB}, the higher the magnitude curve is.	insignificant
RW effect	Curves with higher rework ratio increases faster	When frequency is lower than $10^{-1,}$ the higher the rework ratio, the higher the magnitude curve is. When frequency is above 10^{-1} and lower than $10^{-0.4}$ The higher the rework ratio is, the smaller the magnitude is.	Fluctuation

Table 5.12 ETOAR#PTD lead time magnitude summary

Frequency Zone	Low	Medium	High
Frequency	10^{-4} to 10^{-2}	10^{-2} to 10^{0}	$>10^{0}$
Trend	The higher the τOB is, the higher the magnitude is.	The magnitude curve decreasing until $10^{0.6}$	Fluctuation appears in the high frequency domain.
τOB effect	The higher the τ_{OB}, the higher the magnitude curve is. And the unstable parameter setting has a smaller magnitude.	The systems with lower τ_{OB} have a lower magnitude until$10^{-0.9}$, afterwards, the smaller the τ_{OB}, the smaller the magnitude	Fluctuations, while the systems with small τ_{OB} value have a smaller magnitude.
RW effect	The higher the rework ratios, the higher the magnitude.	Magnitude curves reach its' peak, afterwards, curves start to decreases. When frequency is above $10^{-1.1}$, the larger the rework ratios are the smaller the magnitude is	The higher the rework is the smaller the magnitudes are, but the magnitude curve have more fluctuation

Table 5.13 MRC and MRL of ETOAR#PTD, derived from the Bode plot. Assumption: demand level = 100 working units per week; amplification = 10 working units per week

	Work rate 0.01-0.02 rad/week			Lead time 0.01 rad/week			Lead time 0.02 rad/week		
RW	Magnitude (dB)	$\frac{Work\ Rate}{Demand}$	MRC	RW	Magnitude (dB)	$\frac{Work\ Ra}{Deman}$	MRC	RW	Magnitude (dB)
0	0	1.0	200	0	0	1.0	200	0	0
0.2	2	1.3	230	0.2	2	1.3	230	0.2	2
0.5	6.2	2.0	300	0.5	6.2	2.0	300	0.5	6.2
0.8	14.6	5.4	640	0.8	14.6	5.4	640	0.8	14.6

From the τ_{OB} perspective, it has insignificant influence on work rate magnitude in the ETO demand frequency zone. However, for the order book and lead time, the smaller the τ_{OB}, the smaller the magnitude.

5.2.3 Summary of Section 5.2

Section 5.2 analyses the system's performance under various frequencies and summarises how different parameter settings affect performance across different systems under varying demand frequencies. Special focus is given to the rework ratio and the τ_{OB} ratio, which are the only two parameters in the ETO archetypes.

In the ETO demand frequency zone, rework provides no benefits and exacerbates fluctuations in all target variables across the three archetypes. The influence of τ_{OB} is summarised in Table 5.2-5.13. Additionally, based on the Bode plots, the MRC and MRL for all archetypes are derived and summarised in Tables 5.9 and 5.13. In the next section, the stability of the system is analysed. Moreover, to reduce the fluctuation in the system, the magnitude curve should be avoided. Based on the result above, it is found that 0.04–0.07 rad/week (89.7–157 weeks) is the domain where the major portion of the magnitude peak appears. This suggests that this demand frequency zone should be avoided in the production system.

From the phase plot perspective, for ETOAR#P and ETOAR#D, apart from the lead time responses, which begin to decrease from 90 degrees, the phase curves of the other variables all begin from 0 degrees and decrease with increasing frequency. For the ETOAR#PTD archetype, the lead time phase plot begins from 180 degrees and starts decreasing with increasing frequency. The phase chart illustrates the ability of the production system to catch up with the external demand pattern. According to the result above, it can be concluded that, with the increase in the frequency, the system’s output requires more time to catch up to market change.

5.3 Stability Analysis

This subsection focuses on conducting a stability analysis of the ETO archetype. Specifically, terms such as "system," "archetype," and "model" mentioned in this subsection all refer to the archetype developed in this thesis.

A stability analysis aims to test the stability of the developed model. A stability analysis for the ETO archetype can yield the critical stable condition of the system, which indicates what kind of parameter settings may set models in a dangerous position. The consequence of the unstable parameter settings is that a tiny change in the input will lead to a non-convergent output of the model and the archetype system is not able to maintain the output at the designated level. For example, for a production system, when the system is unstable, a small change on the demand side will lead to an exacerbated fluctuation in the inventory. The consequence of such behaviour will be reflected in a huge increase on the inventory cost and a decrease in the customer service level.

The definition for stability adopted in this research is bounded input bounded output (BIBO). This implies that for each bounded input, there will be a bounded output. Based on this definition, the Routh–Hurwitz method is selected to be the main method for stability analysis.

The stability of the system is determined by the characteristic equation (Disney & Towill 2002). On the other hand, when the order of this equation becomes too high (exceeds 4), it is difficult to derive the roots manually, which becomes a barrier for the analytical result derivation, particularly for the systems containing symbolic parameters (Disney et al. 2006). The systems which contain symbolic parameters enable researchers to study the effect of one specific parameter on the entire system. Although deriving the expression for the roots of characteristic equations of orders exceeding four is often complex and time-consuming, even with the aid of computer software, this section divides the analysis into two distinct parts: 1) Low-order system stability analysis, and 2) high-order system stability analysis.

For the low-order system, original Routh–Hurwitz method is adopted. The Routh–Hurwitz method provides a stable condition for the system, which is that the first array of Routh Matrix must be all positive or all negative (Lin et al. 2020). This criterion can provide an analytical result for the stability analysis. The derived expression of the characteristic roots can be visualised on a map, with RW and τ_{OB} as the X and Y axes, respectively, that enable the stability condition to be visualised in the plot. To guarantee the accuracy of the result, the Eigen value is used to verify the numerical result of the critical stable condition.

For the high-order system, a hybrid method which combines PSE and Routh–Hurwitz is designed, to derive the critical stable condition of the system. The introduction of PSE enables this research to analyse the critical stable condition of high-order system with symbolic parameters.

Considering the fact that PSE is a simulation-based method, a verification is necessary. After the stable condition is derived, transient responses of both stable and unstable parameter settings will be visualised to cross-check the result.

5.3.1 Low-order System Stability Analysis

In this section, the delay of the design and production are assumed as 1, which makes the system's order below 4. All three models in the archetype family are analysed.

ETOAR#P Production Rework Transfer Function

Equation 5.25 demonstrates the transfer function of the ETOAR#P; the rework ratio and proportional controller values are represented by RW and τ_{OB}, respectively.

$$\frac{OB(z)}{DEM(z)} = \frac{2z - 2RWz - \tau_{OB}z + \tau_{OB}z^3}{1 - RW + RWt_{OB} - RWt_{OB}z - t_{OB}z^2 + t_{OB}z^3}. \tag{5.25}$$

The matrix below demonstrates the Routh–Hurwitz matrix of the ETOAR#P, as presented below.

$$\begin{array}{c} w^3 \\ w^2 \\ w^1 \\ w^0 \end{array} \left| \begin{array}{cc} 1 - RW & 3(1 - RW) + 4\tau_{OB} + 4RW\tau_{OB} \\ -3(1 - RW) + 2\tau_{OB} - 2RW\tau_{OB}) & RW - 1 + 2\tau_{OB}(1 - RW) \\ \dfrac{8((RW - 1) - (1 - 2RW)\tau_{OB} + (1 + RW)\tau_{OB}{}^2)}{2\tau_{OB} - 3} & 0 \\ (1 - RW)(2\tau_{OB} - 1) & \end{array} \right|. \tag{5.26}$$

The first element of the first array is 1-RW and considering RW is less than 1, 1-RW is a positive value. Thus, according to the Routh criteria, to maintain the stability of the system, the other elements of the first array must be positive as well. Thus, equation (5.27) is obtained after reorganisation.

$$\begin{cases} -3(1-RW)+2\tau_{OB}-2RW\tau_{OB})>0 \\ and \\ \dfrac{8((RW-1)-(1-2RW)\tau_{OB}+(1+RW)\tau_{OB}{}^{2})}{2\tau_{OB}-3}>0. \end{cases} \tag{5.27}$$

After simplification,

$$\begin{cases} \tau_{OB} > 1.5 \\ and \\ \tau_{OB} > \dfrac{(1-2RW)+\sqrt{5+4RW})}{2(1+RW)} \end{cases}. \tag{5.28}$$

Surprisingly, when RW = 0, the value for τ_{OB} should be greater than 1.618, which is the golden ratio. This result is also found in Disney et al. (2006).

ETOAR#D internal design rework transfer function

The transfer function of the ETOAR#D is derived by using the state-space representation. It is evident that the formula is that same as equation (5.29).

$$\frac{OB(z)}{DEM(z)}=\frac{2z-2RWz-\tau_{OB}z+z^{3}\tau_{OB}}{1-RW+RW\tau_{OB}-RW\tau_{OB}z-\tau_{OB}z^{2}+\tau_{OB}z^{3}} \tag{5.29}$$

Equation (5.30) demonstrates the Routh–Hurwitz matrix of the ETOAR#D, as shown below:

$$\begin{array}{c|cc|} W^{3} & RW-1 & 3(-1+RW)-4(1+RW)\tau_{OB} \\ W^{2} & (-1+RW)(-3+2\tau_{OB}) & (-1+RW)(-1+2\tau_{OB}) \\ W^{1} & -\dfrac{8(-1+RW-(1+2RW)\tau_{OB}+(1+RW)\tau_{OB}^{2})}{-3+2\tau_{OB}} & 0 \\ W^{0} & (-1+RW)(-1+2\tau_{OB}) & \end{array}. \tag{5.30}$$

The RW-1 element in the first array determines that all elements should be negative, because an assumption is made that the rework ratio cannot be larger than 1. Thus, after reorganizing, the first array is obtained in the following manner:

$$\begin{cases} (-1+RW)(-3+2\tau_{OB}) < 0 \\ and \\ -\dfrac{8(-1+RW-(1+2RW)\tau_{OB}+(1+RW)\tau_{OB}^2)}{-3+2\tau_{OB}} < 0 \end{cases}. \tag{5.31}$$

After reorganizing,

$$\begin{cases} \tau_{OB} \; > \; 1.5 \\ and \\ \tau_{OB} > \dfrac{(1-2RW)+\sqrt{5+4RW)}}{2(1+RW)} \end{cases}. \tag{5.32}$$

ETOAR#PTD External design rework transfer function

The transfer function of ETOAR#PTD can be written in the following manner:

$$\frac{OB(z)}{DEM(z)} = \frac{-\mathrm{RW}\tau_{\mathrm{OB}}\,\mathrm{z}+2\,\mathrm{z}^2-2\,\mathrm{RW}\,\mathrm{z}^2-\tau_{\mathrm{OB}}\mathrm{z}^2+\mathrm{RW}\tau_{\mathrm{OB}}\,\mathrm{z}^2+\tau_{\mathrm{OB}}\mathrm{z}^4}{\mathrm{RW}\tau_{\mathrm{OB}}+\mathrm{z}-\mathrm{RW}\,\mathrm{z}-\mathrm{RW}\tau_{\mathrm{OB}}\,\mathrm{z}-\tau_{\mathrm{OB}}\mathrm{z}^2+\tau_{\mathrm{OB}}\mathrm{z}^4}. \tag{5.33}$$

Based on the characteristic equation, the Routh–Hurwitz matrix (5.34) can be derived, as shown below.

$$\begin{array}{c} W^4 \\ W^3 \\ W^2 \\ \\ W^1 \\ \\ W^0 \end{array} \begin{vmatrix} 1-\mathrm{RW} & 6(1+\mathrm{RW})\tau_{\mathrm{OB}} & -2(-1+\mathrm{RW})(1+3\tau_{\mathrm{OB}}) \\ -2(-1+\mathrm{RW})(-1+\tau_{\mathrm{OB}}) & -2(-1+\mathrm{RW})(1+3\tau_{\mathrm{OB}}) & 0 \\ \dfrac{\begin{array}{c}-1+\mathrm{RW}-3(3+\mathrm{RW})\tau_{\mathrm{OB}}+ \\ 6(1+\mathrm{RW})\tau_{\mathrm{OB}}^2\end{array}}{-1+\tau_{\mathrm{OB}}} & -2(-1+\mathrm{RW})(-1+\tau_{\mathrm{OB}}) & 0 \\ -\dfrac{2(1+3\tau_{\mathrm{OB}})\begin{pmatrix}(-1+\mathrm{RW})^2 \\ -3(-3+2\mathrm{RW}+\mathrm{RW}^2)\tau_{\mathrm{OB}} \\ +6(-1+\mathrm{RW}^2)\tau_{\mathrm{OB}}^2\end{pmatrix}}{-1+\tau_{\mathrm{OB}}} & 0 & 0 \\ -2(-1+\mathrm{RW})(-1+\tau_{\mathrm{OB}}) & 0 & 0 \end{vmatrix}. \tag{5.34}$$

The first element of the first array, 1-RW, is greater than 0; hence, according to the Routh stable condition, the value of RW and τ_{OB} must lead to the other elements in the array to become positive. Therefore, the formulations group in equation (5.35) can be obtained. It is evident that the order of the ETOAR#PTD's characteristic equations are one order higher than ETOAR#P and ETOAR#D, and it results in a much more complex formula expression for τ_{OB}. The derivation process is also much more difficult because of the existence of the fourth-order formula.

$$\begin{cases} \tau_{OB} > 1 \\ and \\ \tau_{OB} > \dfrac{9 + 3\mathrm{RW} + \sqrt{3}\sqrt{35 + 18\mathrm{RW} - 5\mathrm{RW}^2}}{12(1 + \mathrm{RW})} \\ and \\ \tau_{OB} > \dfrac{-9 + 6\mathrm{RW} + 3\mathrm{RW}^2 - \sqrt{3}\sqrt{35 - 52RW - 6RW^2 + 28RW^3 - 5RW^4}}{12(-1 + \mathrm{RW}^2)}. \end{cases} \quad (5.35)$$

Summary for all three archetypes

Figure 5.8 demonstrates the stability boundary of all three scenarios. Each point represents a pair of parameters settings; the X axis represents the rework ratio and the Y-axis represents the1/ τ_{OB} value. There are two lines in the figure; the straight line represents the ETOAR#PTD archetype; the other dotted line refers to the critical boundary of ETOAR#D and ETOAR#P.

The area above the line is the non-stable parameter configurations and the space below is the stable settings. Because ETOAR#P and ETOAR#D share the same characteristic equation, these two scenarios have the same stability boundary represented by the dotted line in Figure 5.8, while the stability boundary of ETOAR#PTD is illustrated by the solid line. For all three scenarios, the $1/\tau_{OB}$ value increases with an increase in RW to ensure system stability. Another important finding is through the area of the stable region (within which the system is stable). The stable area of ETOAR#PTD is more reduced than the area of ETOAR#P and ETOAR#D, thereby suggesting higher difficulty in maintaining stable operations when design–production rework is common.

To verify the accuracy of the model, five points are selected to visualise the transient responses of the system with corresponding parameter settings, out of which three are for the ETOAR#PTD.

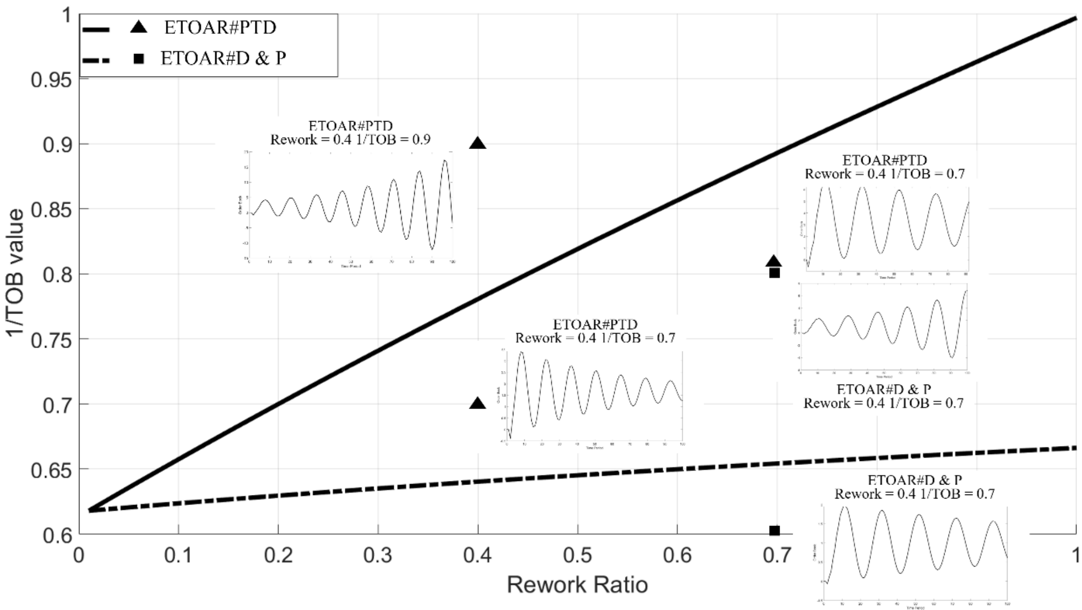

Figure 5.8 Stability boundary of production rework, design rework, and delayed design rework scenarios.

5.3.2 High-order System Stability Analysis

For the high-order system (above 8th order) stability analysis, the hybrid Routh–Hurwitz and PSE method is adopted. This helps to investigate the high-order system's stability boundary to derive the critical stable condition. Note here that in order to simplify the formula of the transfer function, $1/\tau_{OB}$ is represented by a. The experiments follow in the steps given below:

Assign different values to τ_D and τ_P and reorganise the transfer function. Then, the Routh-Hurwitz matrix is derived, and the first array of the matrix is tested via a simulation to determine if the elements are all positive or all negative under different RW and τ_{OB} combinations. Finally, the result is visualised in a figure, with rework on the X-axis and $1/\tau_{OB}$ on the Y-axis. To guarantee the accuracy of the result, the low order system's stability is also examined using this method. Further, to improve the reliability of the hybrid methods, the result will also be crosschecked using the results derived from the analytical method in 5.2.1.

ETOAR#P production rework

$$\frac{OB(z)}{DEM(z)} = \frac{(-1 + a + a\tau_D + a\tau_P)z + (1 - a\tau_D - a\tau_P)z^2}{z^{2+\tau_D+\tau_P} - z^{1+\tau_D+\tau_P} - \mathrm{RW}z^{1+\tau_D} + \mathrm{RW}z^{\tau_D} - a(RW - 1)z}. \quad (5.36)$$

Figure 5.9 demonstrates the stability boundary of the ETOAR#P, with the delay of various subsystem ranging from 1 to 4. The upper areas are the unstable region and the white area is the stable region. Y-axis refers to the Tob value and X-axis represents the rework ratio.

In this figure, each point represents a combination of rework ratio and $1/\tau_{OB}$ value. It is evident that, when the delay is equal to one, with an increase in the rework ratio, the $1/\tau_{OB}$ needs to be increased to stabilise the system. For systems with other delay times, the $1/\tau_{OB}$ value needs to be decreased to maintain the stability of the system.

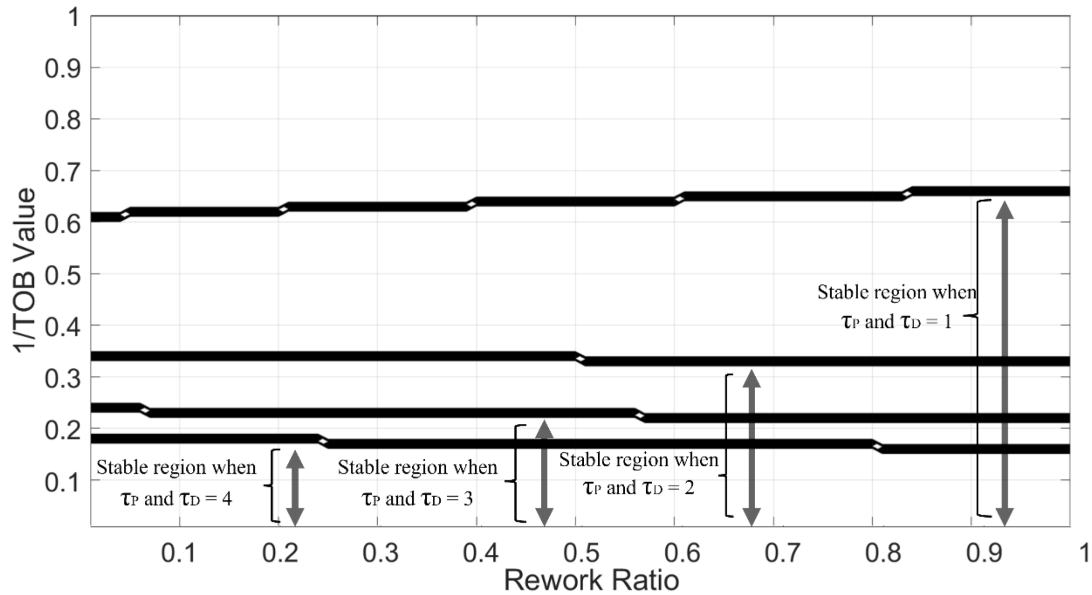

Figure 5.9 Stability of the ETOAR#P using the PSE method

ETOAR#D Internal Design Rework

$$\frac{OB(z)}{DEM(z)} = \frac{-9 + 9\mathrm{RW} + t_{\mathrm{OB}} - \mathrm{RW}t_{\mathrm{OB}} + z(8 - 8\mathrm{RW} - t_{\mathrm{OB}} + \mathrm{RW}t_{\mathrm{OB}})}{-1 + \mathrm{RW} - \mathrm{RW}z^3 t_{\mathrm{OB}} + \mathrm{RW}z^4 t_{\mathrm{OB}} + z^8 t_{\mathrm{OB}} - z^9 t_{\mathrm{OB}}}. \quad (5.37)$$

Equation (5.37) is the transfer function of the ETOAR#D. The denominator is the same as that in equation (5.36), which can be interpreted as that the main characteristics of ETOAR#D and P are the same. The experiment result presented in Figure 5.10 also proves this finding.

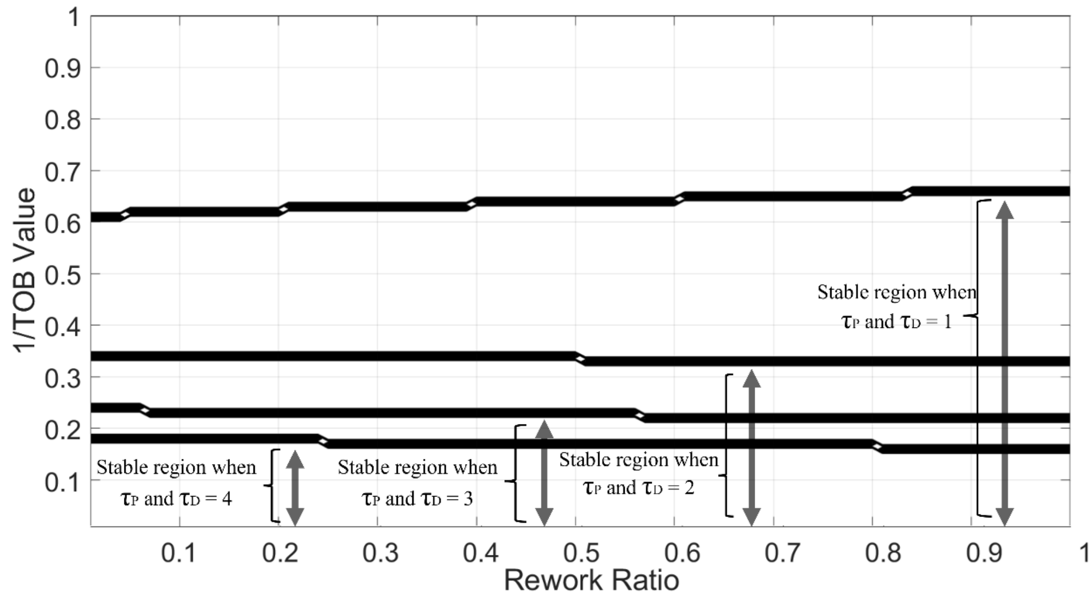

Figure 5.10 Stability of the ETOAR#D using the PSE method

ETOAR#PTD external design rework

$$\frac{OB(z)}{DEM(z)} = \frac{z(-9+9\mathrm{RW}+t_{\mathrm{OB}}-\mathrm{RW}t_{\mathrm{OB}})+z^2(8-8\mathrm{RW}-t_{\mathrm{OB}}+\mathrm{RW}t_{\mathrm{OB}})}{-\mathrm{RW}t_{\mathrm{OB}}+z^9t_{\mathrm{OB}}-z^{10}t_{\mathrm{OB}}+(-1+\mathrm{RW}+\mathrm{RW}t_{\mathrm{OB}})z}. \quad (5.38)$$

Figure 5.11 demonstrates the stability boundary of the ETOAR#PTD. The changing trend of τ_{OB} in the ETOAR#PTD is different from that of the former two archetypes. This implies that with the increase in the rework ratio, τ_{OB} should be increased to stabilise the system.

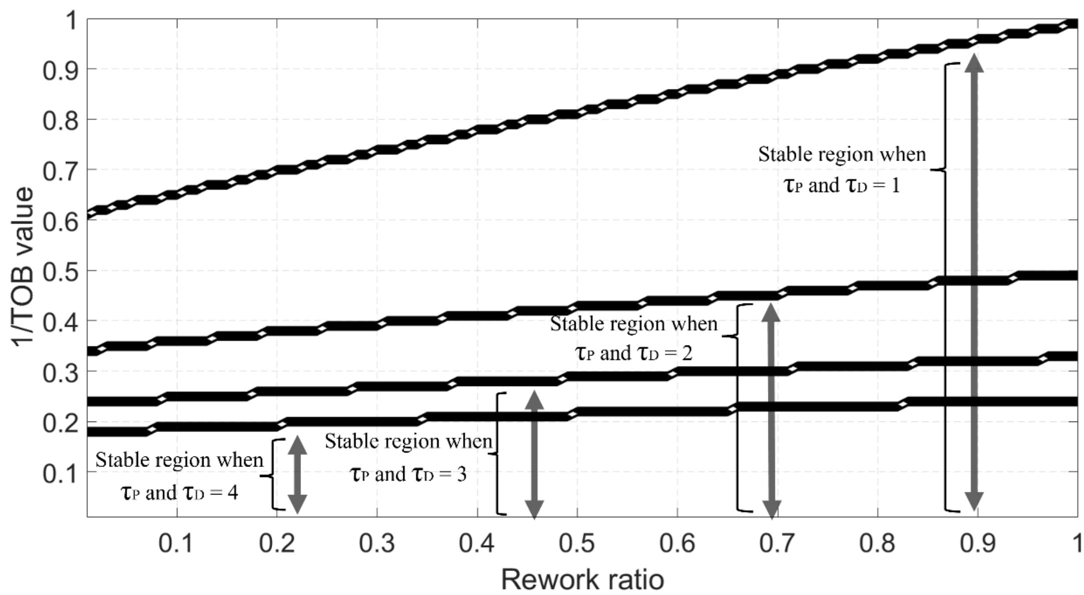

Figure 5.11 Stability of the ETOAR#PTD using the PSE method.

5.3.3 A Summary of the Stability Analysis

This subsection investigates the stability region for ETO archetypes with various rework types and various parameter settings.

For the ETOAR#P and ETOAR#D archetypes, the stable region shrinks with the increase in production or delay in the design subsystem, which indicates that the duration of the delay in the subsystem has a negative effect on the system's stability control. Moreover, an interesting observation is that when the delay in the subsystem equals 1, the critical τ_{OB} for stability increases with the increase in the rework ratio. When the delays are above 1, the critical τ_{OB} value decreases with the increase in the rework ratio. For the ETOAR#PTD archetype, the delay in the subsystem has a negative effect on the system's stability and the critical τ_{OB} value decreases with the increase in the delay.

Combining these two observations, the following conclusion can be made: the effect of the rework ratio on the stability analysis depends on the subsystem's delay and also on the type of rework. Further, the duration of the delay in the subsystems has a negative effect on the system's stability.

5.4 Summary

Section 5 presents the findings from the frequency domain analysis and stability analysis. The frequency analysis examines the work rate, order book, and lead time of all three ETO archetypes. The Bode plots are illustrated, with special focus on the 0.01 rad/week to 0.02 rad/week range, which corresponds to the frequency range of ETO product demand. Based on this, MRC and MRL are provided, which can serve as references for capacity planning and project lead time estimation.

The stability analysis offers an in-depth investigation into how τOB, rework, and lead time affect the system's stability. The findings suggest that the influences of rework and τOB differ among the ETO archetypes, with the critical conditions for all three archetypes are highlighted in Figures 5.9, 5.10, and 5.11.

This section provides a comprehensive examination of the developed ETO system archetypes, thereby providing a fundamental understanding of their performance. In the next section, the focus shifts to resilience performance, exploring how to improve system resilience by tuning system parameters.

Chapter 6 ETO Resilience

This chapter focuses on analysing the resilience of the ETO system, from a quantitative perspective. The first step taken is to provide an overview of the general meaning of resilience and discuss its specific significance in the ETO context. Subsequently, suitable resilience measurements are explored for the ETO system, developed via the CT, which forms the core of this chapter. Further discussion and analysis are built upon this foundation. Finally, the theoretical outcome is linked with practical application, and managerial suggestions are provided to improve ETO operations.

6.1 PSE Contour Map

This section presents visual representations of the ITAE contour map for three distinct archetypes are provided. These maps illustrate how work rate and lead time resilience are affected by different parameter settings. For each archetype, there are two contour maps, which represent lead time resilience and work rate resilience separately. ITAE was adopted for both work rate and lead time resilience measurement. Figures 6.2–6.7 demonstrate the work rate ITAE value under different rework ratios and τ_{OB} values. Every point represents one ITAE value, which represents the system's performance under a pair of RW and τ_{OB}.

6.1.1 Contour Map

In this section, contour maps of the ITAE values under various parameter settings are presented. According to equation 6.1, the neutral axis needs to be pre-decided for the ITAE. For the lead time resilience, the neutral axis will always be the sum of design and production delay because the ETO archetype is expected to maintain the lead time at that level. For the work rate contour map, the neutral axis will be different due to the rework existing in different phases of the ETO system. Thus, the neutral axis will be explained for every scenario. The following sections present the contour maps for all scenarios, and a summary of findings is provided at the end of this subsection. To assess the system's resilience, a positive demand step change is used as a standardized disturbance, which aligns with the previous resilience study on SD model (Spiegler et al. 2012). This approach focuses on the system's ability to recover under challenging conditions, such as increased demand, which strain capacity and rework mechanisms. Negative step changes will create a mirror image as the positive one, therefore the result will be identical. Additionally, a standardized positive step change ensures consistency and comparability across scenarios, aligning with the research aim. Future research could explore negative demand shocks to further enrich the understanding of ETO system resilience.

$$ITAE = \int_0^t t \times |output - Neutral\ axis| \cdot d_t. \qquad (6.1)$$

ETOAR#P production rework

For ETOAR#P, this research uses the $\frac{Demand\ rate}{1-RW}$ as the neutral axis, which is because the rework occurs in the production subsystem, and the production subsystem needs to reserve extra capacity to off-balance the impact of the rework. Thus, the work rate is expected to reach that level.

Figure 6.1 demonstrates the ITAE contour map of the ETOAR#P. It is evident that when τ_{OB} is fixed, the increase in the rework ratio will lead to an increase in the ITAE, which is accelerating. The density of the contour line in the white area can prove this point. When the rework ratio is fixed, the ITAE value first decreases and then increases, which implies that there is a smallest ITAE value for each rework rate.

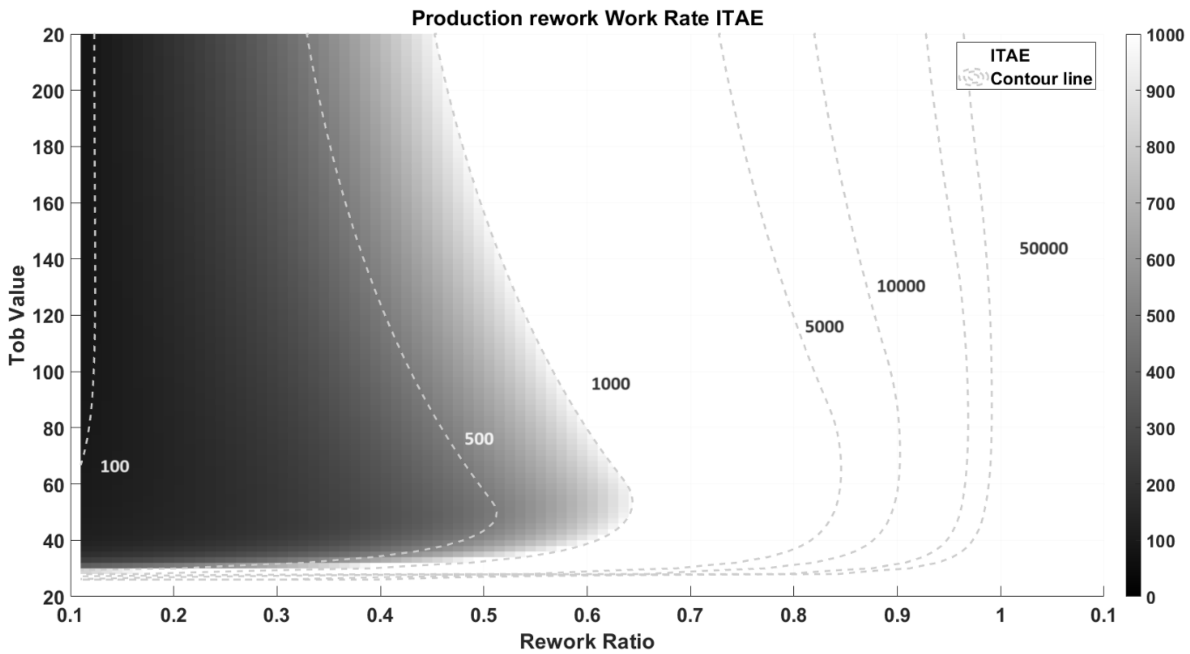

Figure 6.1 The contour map of ETOAR#P work rate

Figure 6.2 illustrates the lead time ITAE of the ETOAR#P; the increase in the rework will lead to the increase in the ITAE, but the acceleration is not obvious. For each rework ratio, there is a τ_{OB} value that can make the system reach its lowest ITAE.

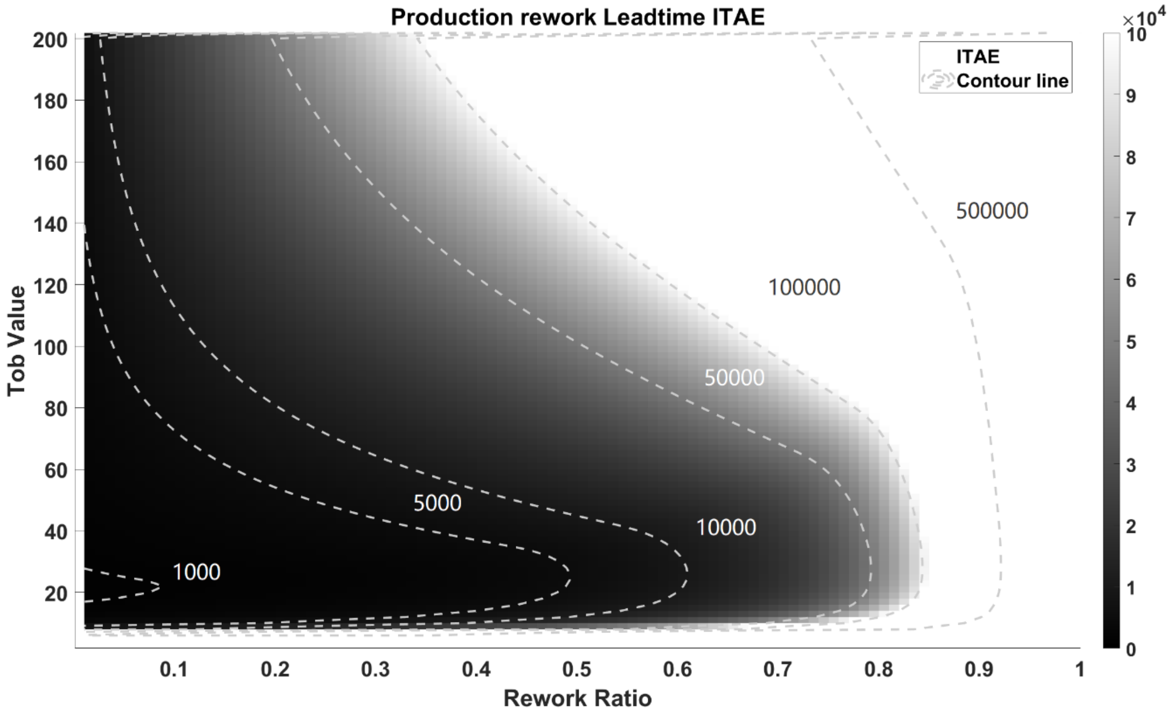

Figure 6.2 The contour map of ETOAR#P lead time

ETOAR#D design rework

For the ETOAR#D, the neutral axis is set to the demand rate, which is because the rework occurring in the design system would not affect the work rate of the production subsystem, and work rate is expected to settle at the level which is the same as the demand rate.

In Figure 6.3, a contour map indicates the work rate resilience of the ETOAR#D. As rework increases, the ITAE value also increases, thereby indicating a decline in the system's resilience. On the other hand, when rework is fixed, the ITAE experienced initially decreases and then increases as the τ_{OB} increases. This shows that there exists a τ_{OB} for every rework ratio that can help the system achieve its highest resilience. The same phenomena are observed in Figure 6.4, which represents the lead time.

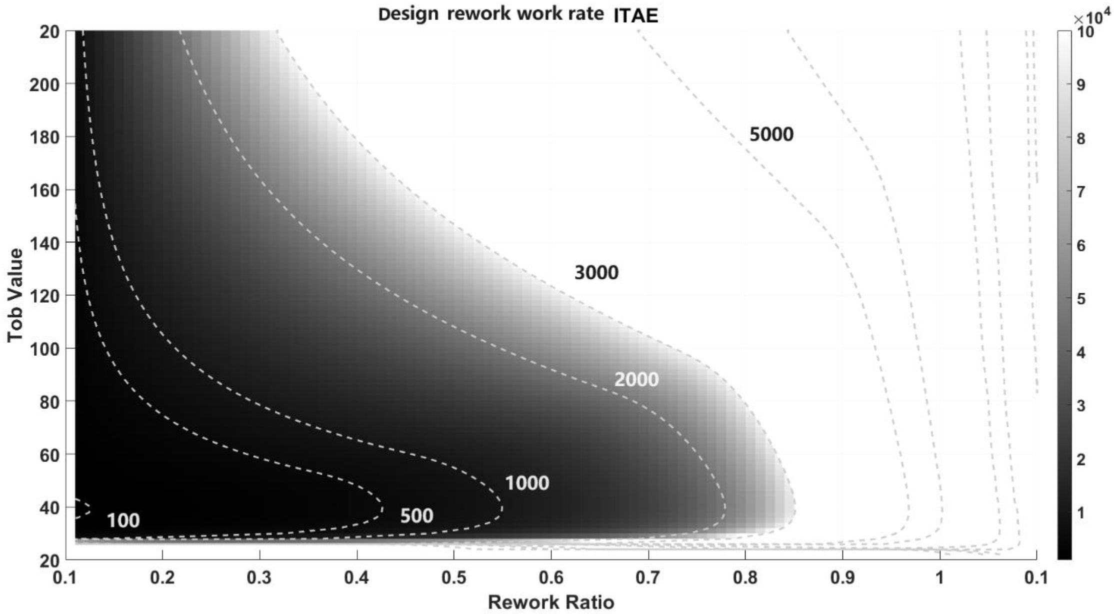

Figure 6.3 The contour map of the ETOAR#D work rate

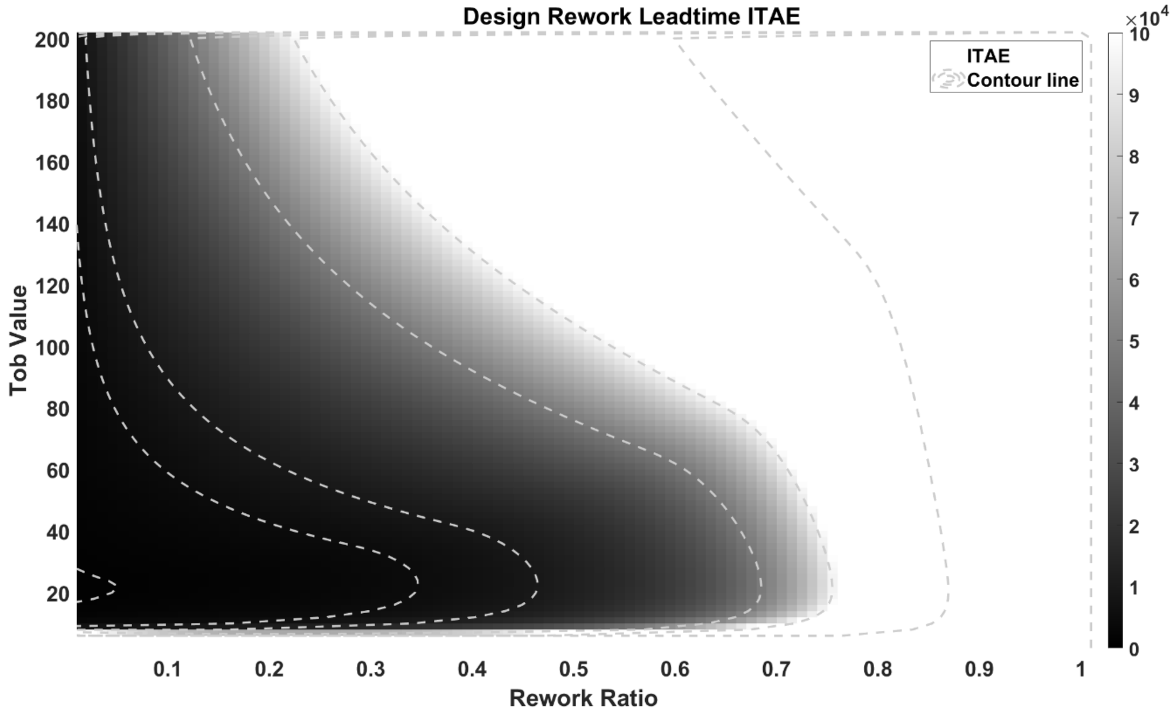

Figure 6.4 The contour map of the ETOAR#D lead time

ETOAR#PTD delayed design rework

The neutral axis for the ITAE of ETOAR#PTD is set to $\frac{Demand\ rate}{1-RW}$ because the production system's work rate is expected to reach a higher level to cover the loss that may occur during rework. Figure 6.5 illustrates the changing trend of work rate resilience of the ETOAR#PTD archetype, and Figure 6.6 represents the changing trend of lead time resilience. The same pattern was observed in the other two archetypes.

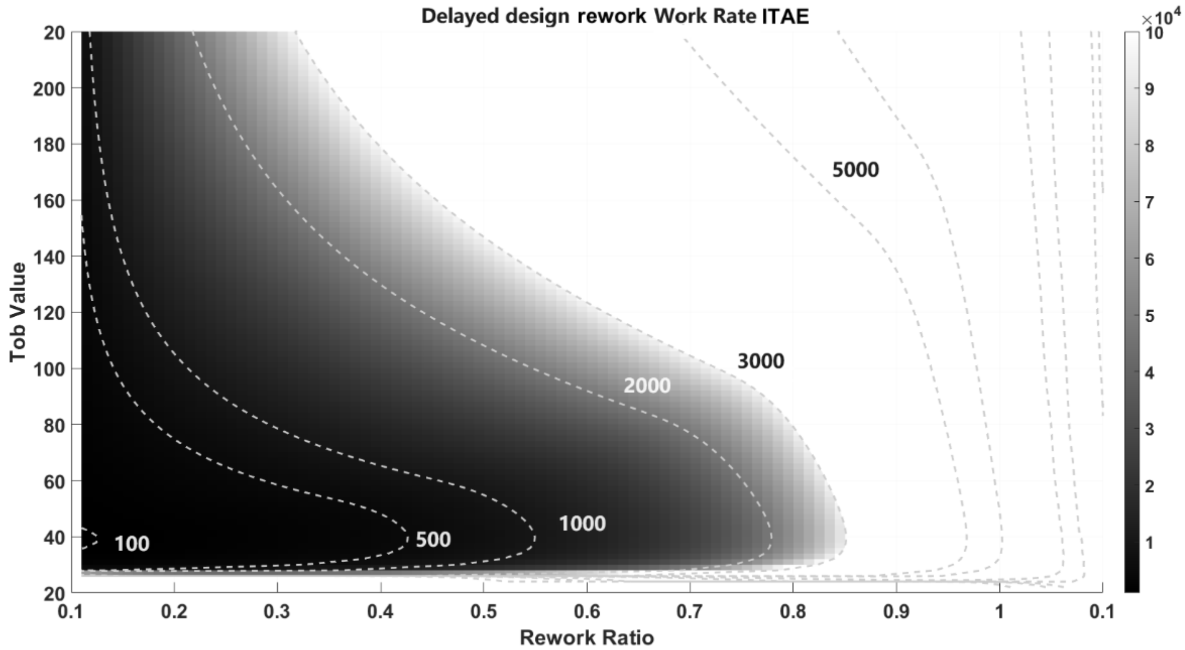

Figure 6.5 The contour map of ETOAR#PTD work rate

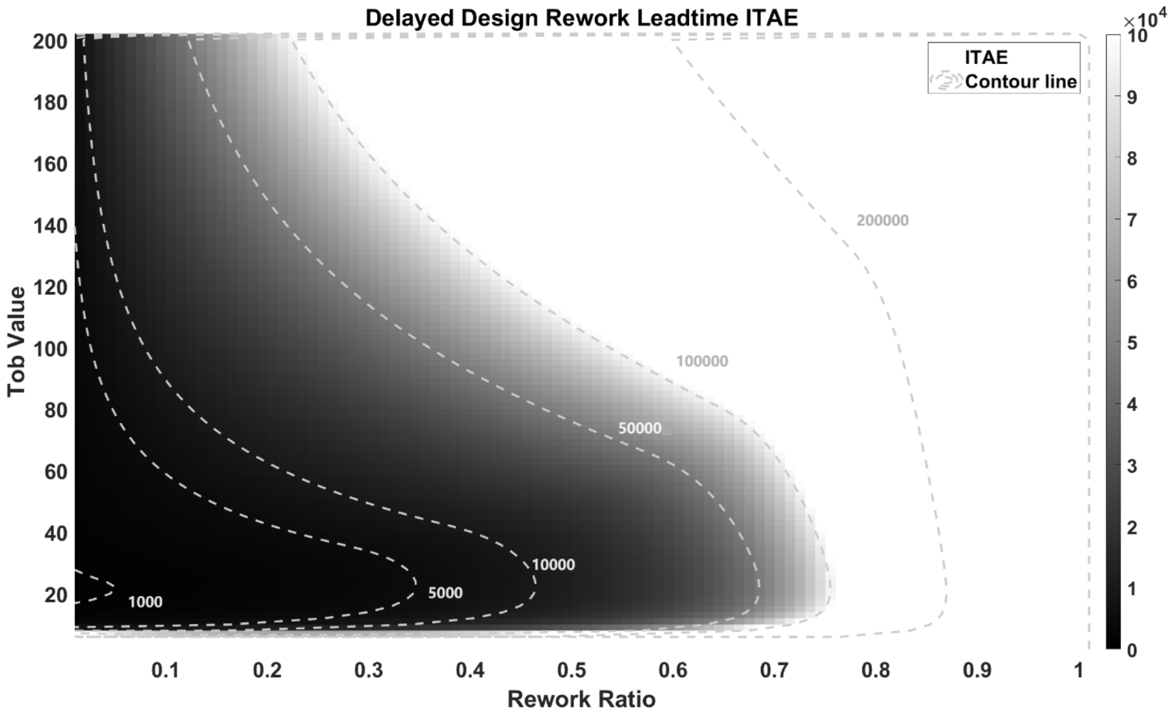

Figure 6.6 The contour map of ETOAR#PTD lead time.

Below is a summary of the findings based on Figures 6.1–6.6.

6.1.2 Exploration of the Transient Responses

The figures for all archetypes, for both work rate and lead time, are 2D versions of the ITAE surface. In contrast, if the figure is created in a 3D dimension, the ITAE values form a paraboloid surface. This finding provides a general understanding of how rework ratio and τ_{OB} affect the resilience performance of the system. In general, the ITAE will decrease with the increase in τ_{OB} at the initial stage, and then begin going up with further increases in τ_{OB}. From this observation, it may be evident that there are at least two driving forces for the ITAE, and it is the process of one force taking over the other that leads to such a phenomenon. To further investigate this aspect, this research visualised the transient responses with various parameter settings under a demand shock. According to the contour maps above, these three archetypes' contour maps demonstrated similar patterns, thereby indicating that τ_{OB} and the effect of the rework ratio on the different archetypes are similar. Therefore, the transient response of work rate and lead time on ETOAR#D were visualised, which are representative of ETO archetype families. The findings from transient responses are discussed below:

Lead time transient responses

Figure 6.7 demonstrates the transient responses of the ETOAR#D, with different τ_{OB} values and a rework ratio that is fixed at 0.6. The black arrow demonstrates the τ_{OB} value changing trend. When τ_{OB} is small, which implies that the system is sensitive to the order book changes, the lead time transient responses react to the demand shock quickly but with dramatic fluctuations. When τ_{OB} becomes larger, the fluctuations become milder until they disappear; however, it takes a longer time for the lead time to settle down at the desired level.

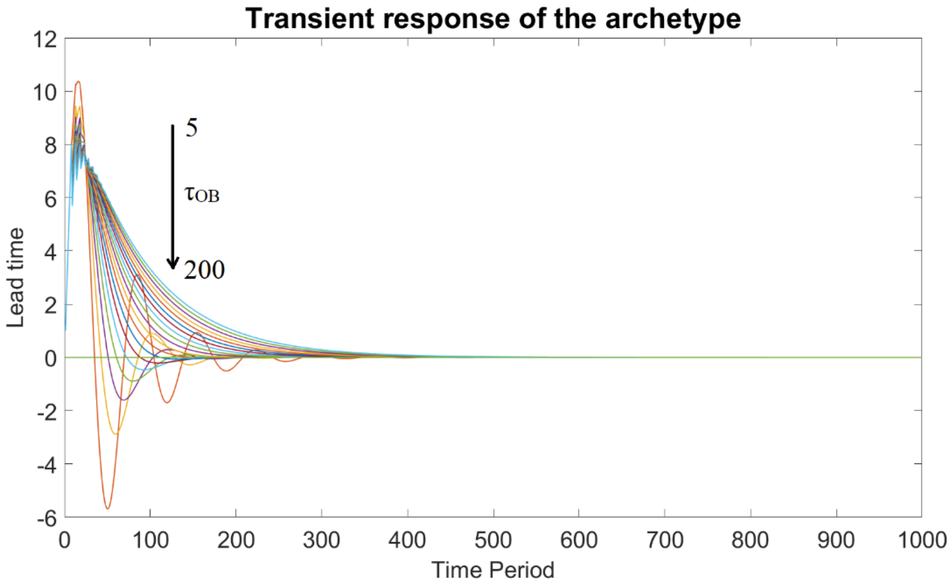

Figure 6.7 The lead time transient response of the ETOAR#D; rework ratio = 0.6; τ_{OB} ranges from 5 to 200.

Figure 6.8 visualises the transient responses of the lead time; the τ_{OB} value is fixed at 20, and the rework ratio ranges from 0 to 0.99. According to this figure, it can be concluded that the rework increases will exaggerate the lead time fluctuation.

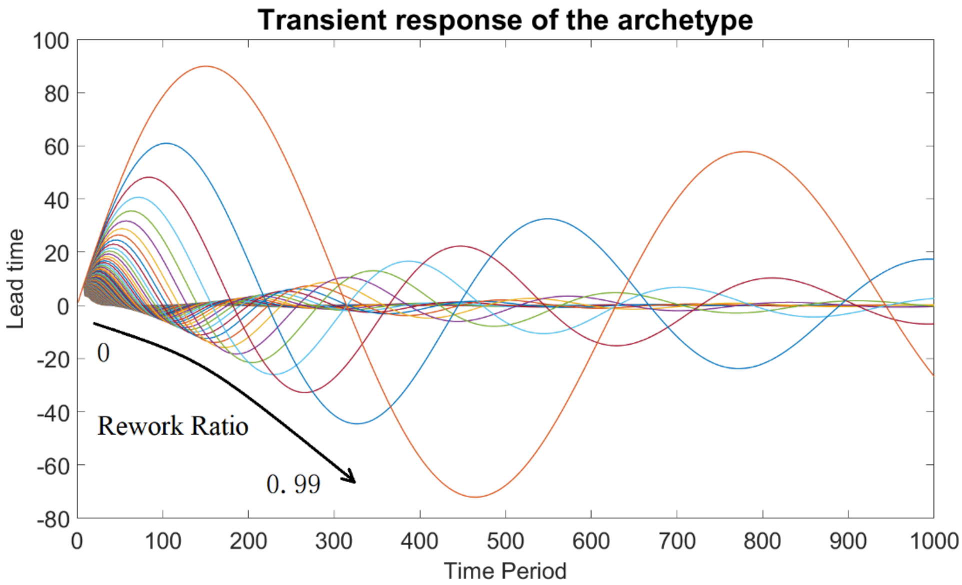

Figure 6.8 The lead time transient response of the ETOAR#D; τOB = 20; the rework ratio ranges from 0 to 0.99.

Figure 6.9 presents the work rate transient response of the ETOAR#D. The rework ratio is set to 0.6 and the τ_{OB} values range from 5 to 100. This figure indicates that when τ_{OB} is small, the system reacts strongly to the demand shock but with huge fluctuations. With an increase in the τ_{OB} value, the fluctuations become smoother, while it takes longer for the transient response to settle down at the desired level.

Work rate transient responses

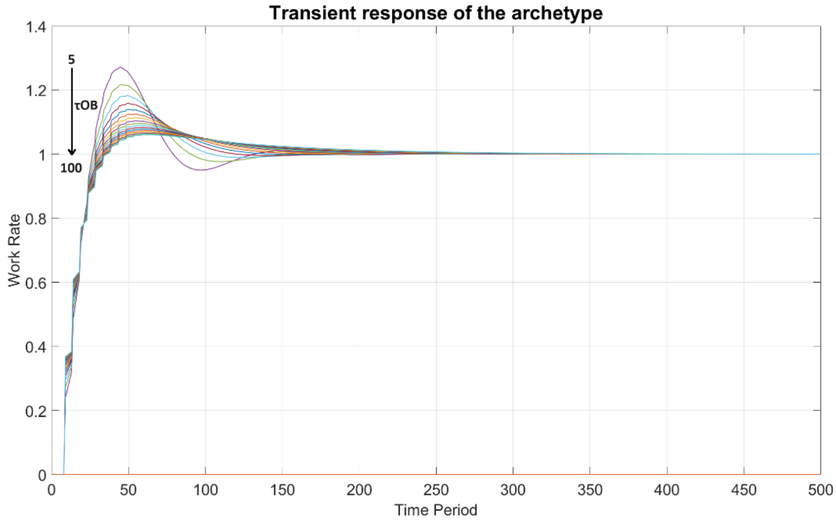

Figure 6.9 The work transient response of the ETOAR#D, rework ratio = 0.6, τ_{OB} ranges from 5 to 200.

Figure 6.10 demonstrates how the rework ratio affects the transient response behaviour. According to this figure, the increasing rework ratio exaggerates the fluctuation of the work rate transient responses.

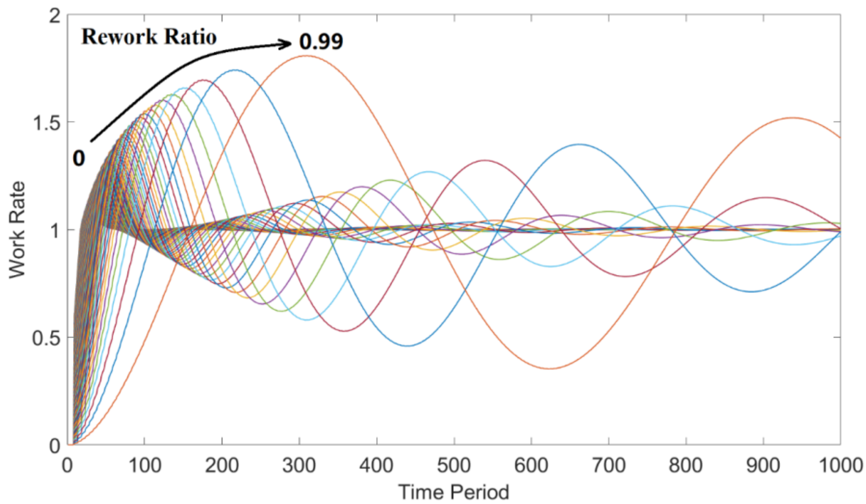

Figure 6.10 The work rate transient response of the ETOAR#D; τ_{OB} = 20; the rework ratio ranges from 0 to 0.99.

6.1.3 Summary of Findings

1. The white area at the bottom of the figure

Upon examining the lower portion of the contour maps, one makes an interesting observation. A white region was spotted beneath the black area, with tightly spaced contour lines indicating a rapid increase. This white area reflects the ITAE value for small τ_{OB} values and as the amount of rework increases, the white region expands. The parameter settings of this white area are in alignment with the stability analysis in Section 5.1. In the contour map, the white area represents the system with ITAE value higher than 10000, thereby indicating a system with a dramatic fluctuated output. Upon closer inspection of the numerical data for this region, it was discovered that the values were significantly elevated to 10^41. However, it is worth noting that the peak value of 10^41 is not the actual ITAE value, as this is limited by the simulation period. If there were no such limitations, the ITAE value would be infinite.

Figures 6.1–6.6 indicate that there is a slow and then fast horizontal changing trend of the ITAE due to the distribution of the contour showing sparseness and then density. This suggests that an increase in rework will lead to an increase in ITAE when τ_{OB} is fixed, which corresponds with the finding from the transient responses, as depicted in Figures 6.7–6.10.

2. The role of τ_{OB} and rework

After analysing the transient responses, it can be concluded that the τ_{OB} (the proportional controller parameter) and rework ratio play a significant role. The findings indicate that when τ_{OB} is small, both lead time and work rate transient responses tend to fluctuate more. However, as τ_{OB} increases, these responses become milder. On the other hand, when τ_{OB} is large, settling down takes a longer time. In extreme cases, when τ_{OB} becomes too large, the system becomes insensitive to the order book's deviation and results in excessive time being spent on settling down. Therefore, it can be deduced that the optimal τ_{OB} exists for each rework ratio.

Similarly, the rework ratio also affects the lead time and work rate transient response. As the rework ratio increases, the system tends to fluctuate more, which can be considered to have a negative effect on the rework ratio.

However, there are limitations to the experiment in this section. It provides only limited information regarding how each pair of rework ratio and τ_{OB} determines the transient response. Additionally, it does not provide exact information about which pairing can provide the company the best-performing system. Furthermore, after comparing different archetypes' contour maps, it was found that it is difficult to summarise and gain insight from the graph. Therefore, after presenting the ITAE contour maps of all the archetypes, the research delves into the examination of the effect of τ_{OB} value on performance resilience and how to translate the theoretical results into practical guidance.

6.2 Proportional Controller's Role in Resilience Improvement

After analysing the findings from the previous section, further studies were conducted to investigate the impact of τ_{OB} on the system's performance. The goal of this section is to determine the resilient setting for the system and identify the 'good' τ_{OB} for each rework ratio. In this section, the analysis is conducted from two scopes: a wider scope that focuses on the changing trend of the 'good' τ_{OB}, and a narrow-down scope that examines how τ_{OB} affects the system's behaviour

6.2.1 A Wider Scope

For each archetype, two comparison figures are provided: one illustrating the transient responses of lead time and the other showing the transient responses of work rate. Each figure contains two curves—one representing the best τ_{OB} value for lead time resilience, and the other for work rate resilience. This side-by-side comparison highlights the differences between the optimal τ_{OB} values for these two objectives, providing insights into the inherent trade-offs between lead time and work rate resilience.

The determination of the 'best τ_{OB} ' values depends on the specific resilience objective—whether prioritizing lead time or work rate. These values are not universally optimal but are tailored to the dynamic characteristics of the modelled ETO archetypes under the given conditions. The selection process focuses on the archetype's ability to minimize disruptions and stabilize system performance, ensuring that the chosen parameters align with the operational focus.

For lead time resilience, the best τ_{OB} minimizes fluctuations in delivery timelines, thereby enhancing reliability and customer satisfaction. On the other hand, the best τ_{OB} for work rate resilience emphasizes maintaining a steady resource flow and efficient workload distribution. This comparison underscores the trade-offs inherent in ETO systems, where improving one objective may have implications for the other. While the recommended τ_{OB} values are specific to the modelled scenarios, they establish a framework that can be adapted and refined for different real-world ETO environments, enhancing their relevance and practical utility.

ETOAR#D production rework

One observes the distinct work rate transient responses in Figure 6.12 corresponding to the optimal work rate τ_{OB} value setting and the optimal lead time τ_{OB} value setting. Conversely, Figure 6.12 showcases the lead time transient responses for both best work rate and lead time resilience setting. It is crucial to clarify that the work rate mentioned pertains to the production system's capacity. To prevent any ambiguity between work rate transient response and the best τ_{OB} for work rate, one may refer to the best τ_{OB} for work rate as the best τ_{OB} for capacity.

In Figure 6.11, the grey line demonstrates the value for the best τ_{OB} for the work rate, which is a bathtub curve; this implies that when the rework ratio is extremely small and extremely big, the best τ_{OB} are comparatively higher. The black line represents the best τ_{OB} for the lead time and the whole line is below the grey line, which implies that lead time resilience requires a smaller τ_{OB} to achieve its best resilience. To further investigate this finding, both capacity and lead transient response were generated with both best work rate and lead time configuration.

From figure 6.12, the lead time transient responses were compared for the optimal τ_{OB} for capacity resilience and lead time resilience. Horizontally speaking, with the increase in rework, the transient responses became increasingly fluctuating, which implies that the rework ratio exaggerated the fluctuation of the lead time transient responses. This phenomenon is observed in both Figures 6.11 and 6.12. Vertically speaking, to achieve a better capacity resilience, systems always require a greater τ_{OB} to stabilise the capacity fluctuation, particularly for the initial and final periods. This indicates that to achieve capacity resilience, the system should be adjusted to be less sensitive to the change in the order book.

To deepen understanding of the above observations, several experiments were conducted to investigate what causes the bathtub curve, and why work rate requires a higher τ_{OB}. Generally, it is because the capacity requires a slower speed to adjust to the required level. For the detailed study, the entire process was separated into three periods to analyse how the bathtub curve is formed.

As already mentioned in Chapter 4, the work rate is composed of two parts: 1) Demand input; 2) the order book controller compensation; this is shown below:

$$WRATE_{DES} = DEM_{DES}(t) + \frac{OB_{DES}(t) - DEM_{DES}(t) \cdot \tau_D}{\tau_{OB}}. \tag{6.2}$$

When rework does not exist or is very minor (between 0 and 0.2), the ideal situation would be that after the demand change, the work rate changes to the new demand rate immediately, thereby ensuring that the ITAE value would be zero. For this period, the main contributor to the ITAE error is the error created in the initial stage of the transient responses. Specifically, it is because the existence of the order book controller slows down the reaction of the work rate, which leads to increases in ITAE errors.

In the moderate rework area, as the rework ratio increases, the system must quickly adjust its work rate to manage the additional rework generated by rising demand. However, the inherent delays caused by rework itself also slow down the system's response to changes in demand. Therefore, it becomes necessary to enhance the system's capacity more rapidly. This implies setting a smaller τ_{OB} for the proportional controller to allow swift changes in the work rate. Consequently, in systems with a moderate rework ratio (0.2–0.7), the primary contributor to the ITAE is the slow settling time.

In the high rework ratio area (0.2–0.99), research experience from the horizontal study indicates that increased rework amplifies system fluctuations. Therefore, in this region,

τ_{OB} should be adjusted to be smoother to help stabilise the system's fluctuations. The transient response analysis supports this adjustment.

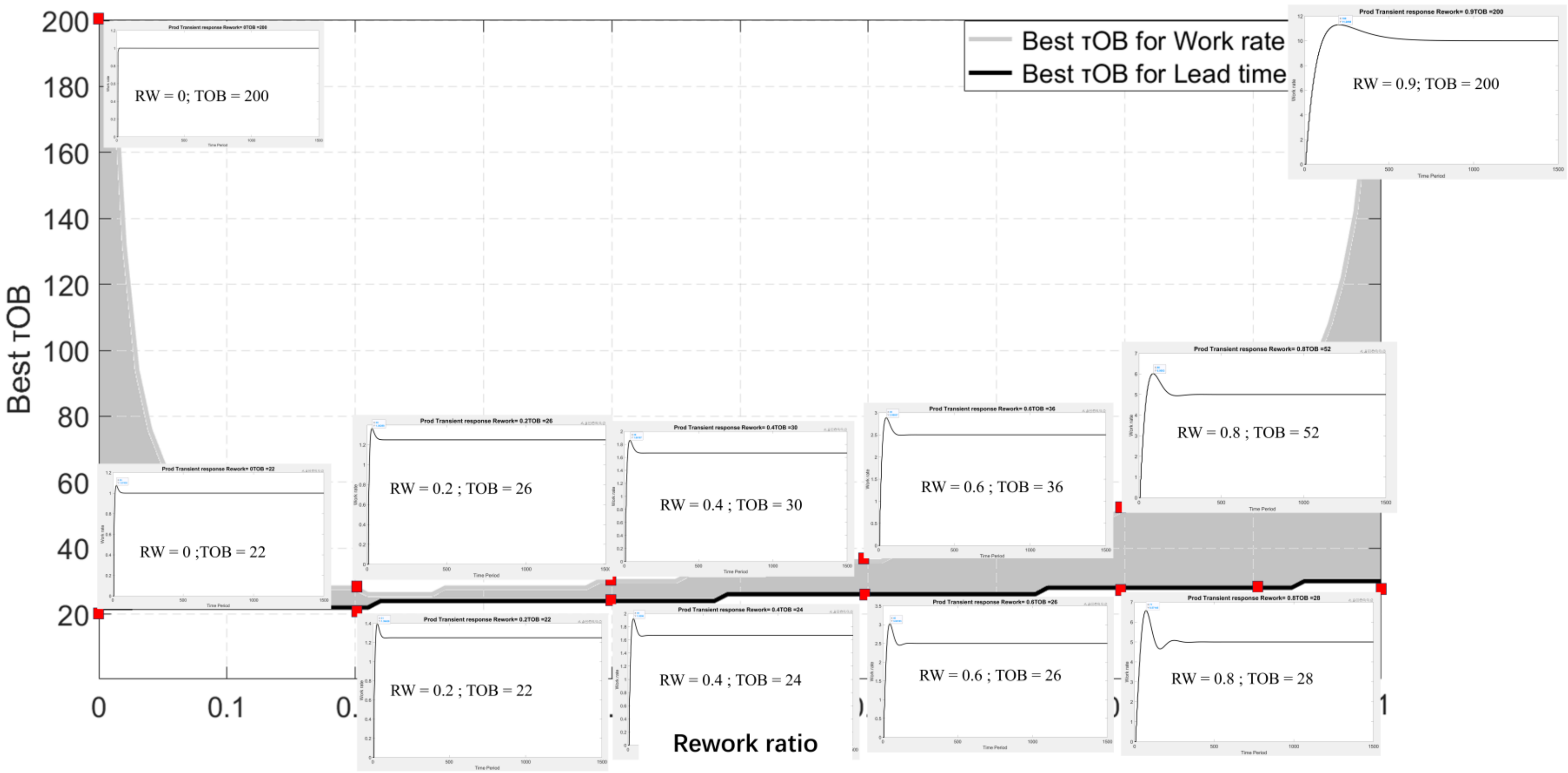

Figure 6.11 The 'good' τ_{OB} value for different rework ratios for each variable of interest, with work rate transient response, ETOAR#P. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the work rate, while the X-axis represents the time period.

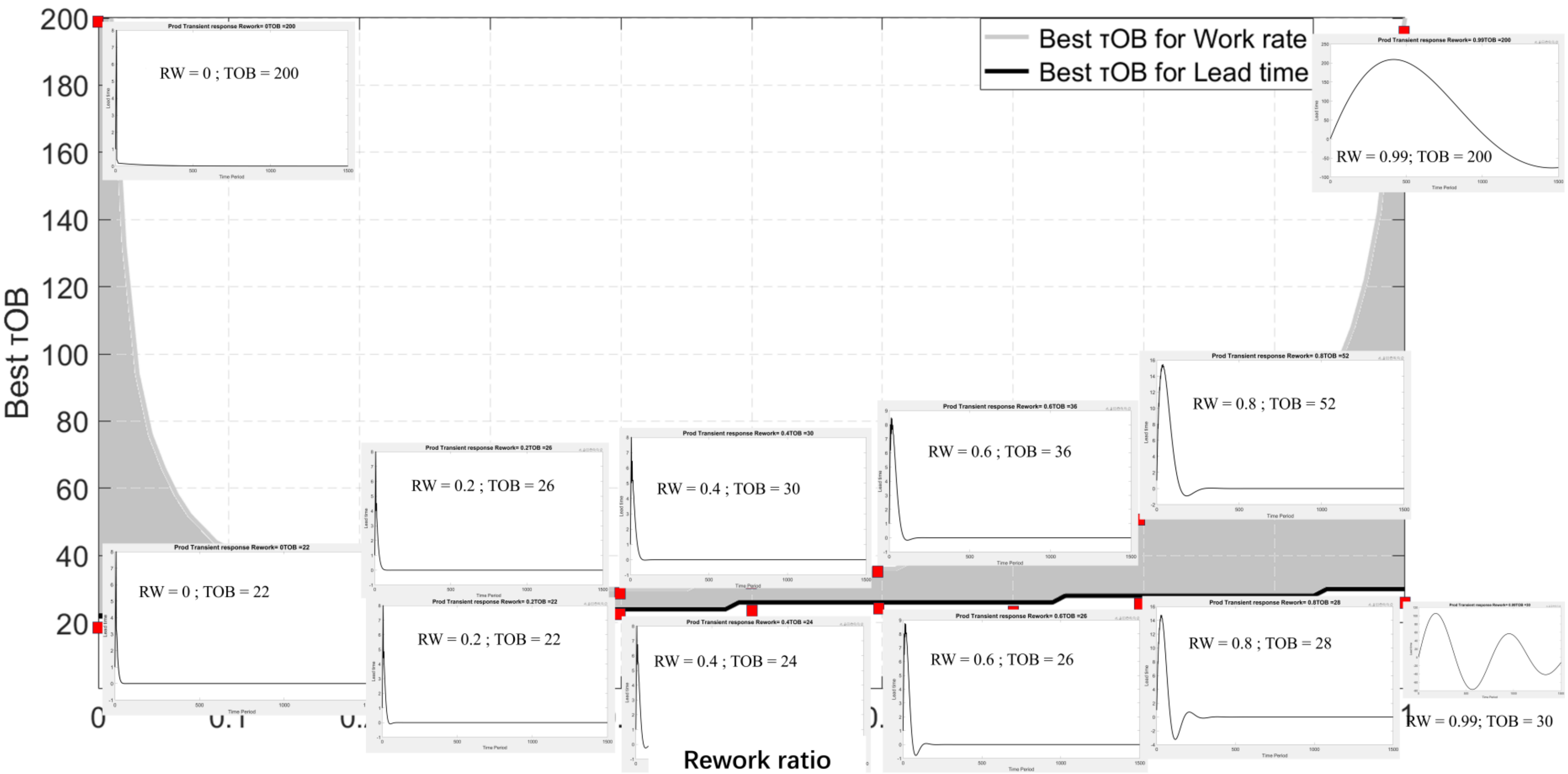

Figure 6.12 The 'good' τ_{OB} value for different rework ratios for each variable of interest, with lead time transient response, ETOAR#P. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the lead time, while the X-axis represents the time period.

The transient responses of lead times illustrate how the system adapts to increases in rework. From a horizontal perspective, as the rework ratio rises, fluctuations are exaggerated. Consequently, it is observed that the black line—which represents the optimal τ_{OB}—moves upwards slightly. This suggests that τ_{OB} plays a more significant role in smoothing out fluctuations.

Vertically speaking, it is evident that the optimal τ_{OB} for the work rate is greater than the τ_{OB} for achieving the best lead time resilience. The transient responses indicate that the system using τ_{OB} optimised for capacity resilience reacts more slowly to demand shocks. In practical terms, this slower response implies that lead times become unstable and fail to meet promised targets for longer periods. Such issues could lead to a decline in customer service levels.

ETOAR#D design rework

Figures 6.13 and 6.14 demonstrate the work rate with τ_{OB} settings optimised for both work rate resilience and lead time resilience. Although the waveform of the curve resembles that in ETOAR#P, the fundamental difference between ETOAR#D and ETOAR#P lies in the neutral axis. In ETOAR#P, rework occurs during the design stage, requiring additional work units in the design subsystem. Consequently, the final value for the work rate of the production subsystem is set at 1, instead of 1/(1-RW). However, for ETOAR#D, the rework occurs in the design stage and the work rate of the production subsystem is not affected; thus, the neutral axis of ETOAR#D is set at 1.

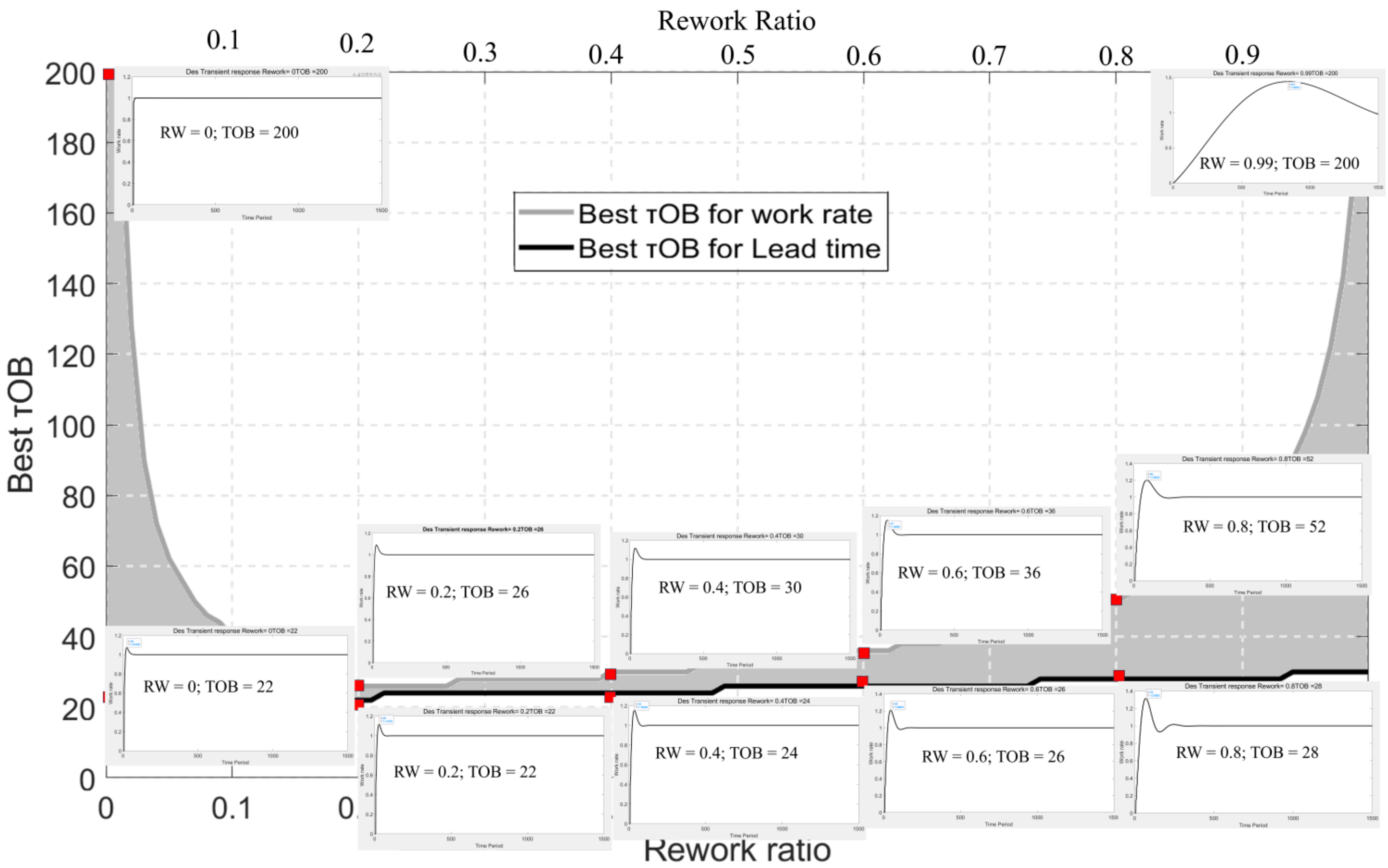

Figure 6.13 The 'good' τ_{OB} value for different rework ratios for each variable of interest, with work rate transient response, ETOAR#D. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the work rate, while the X-axis represents the time period.

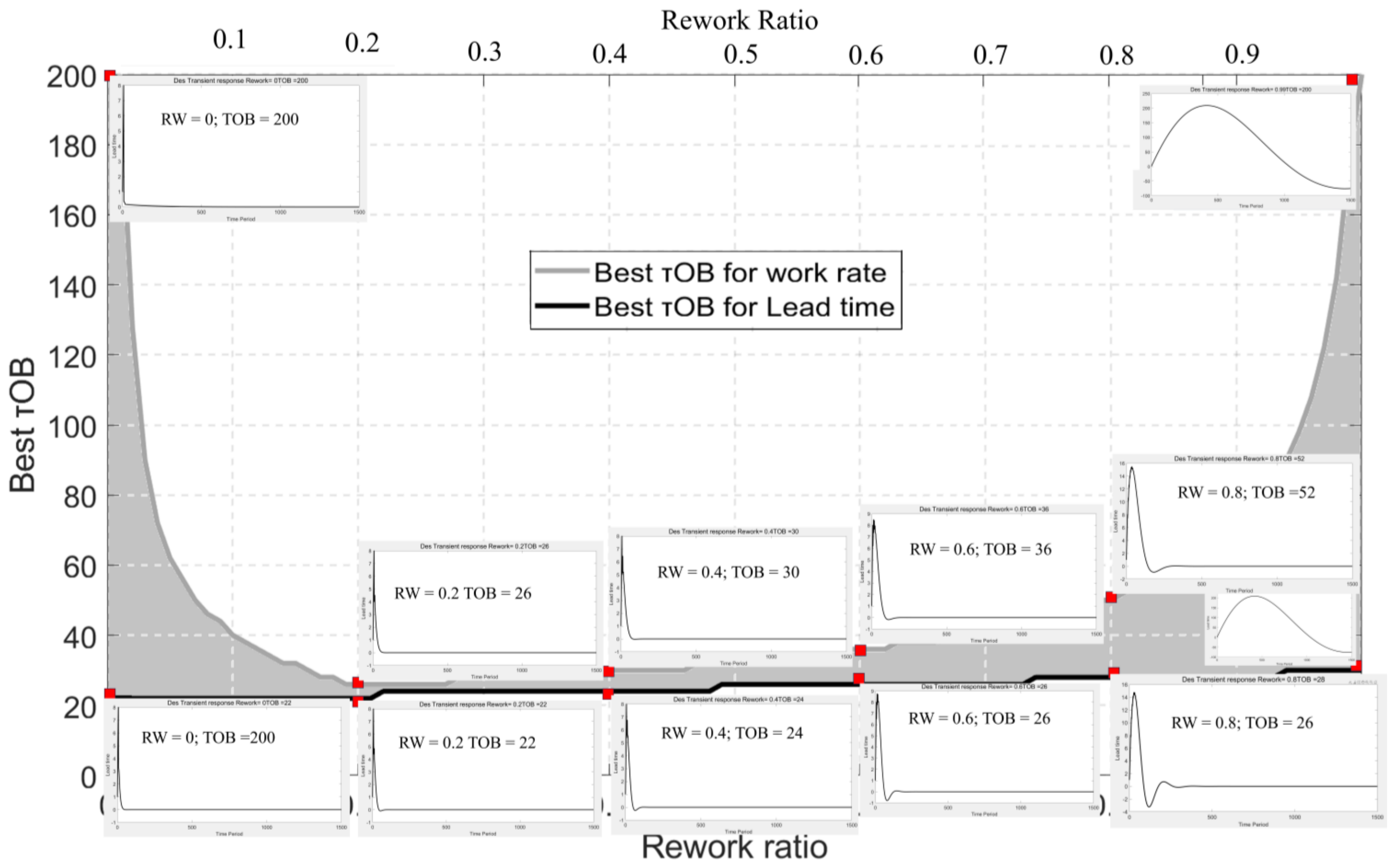

Figure 6.14 The 'good' τ_{OB} value for different rework ratios for each variable of interest, with work rate transient response, ETOAR#D. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the lead time, while the X-axis represents the time period.

It can be observed that the figures for ETOAR#D and ETOAR#P are similar. After multiple checks, the possibility of bias and error was eliminated and what was discovered was that the root cause of the similarity between both systems is sharing the same characteristic equation, which results in almost identical system performances. Moreover, from the perspective of the whole system, regardless of whether rework occurs in the design or production subsystem, as long as it is detected promptly, the negative impacts are the same. This observation naturally piques one's curiosity about the performance of ETOAR#PTD, where rework occurs in the design system but is detected in the production system.

ETOAR#PTD delayed design rework

According to Figure 6.15, the optimal τ_{OB} value and the rework ratio exhibit a convex relationship. Specifically, when the rework ratio ranges between 0-0.1 and 0.7-1, the best τ_{OB} spans from 40 to 200. Conversely, when the rework ratio is between 0.1 and 0.7, the τ_{OB} value should be less than 40. Additionally, the best τ_{OB} for work rate is consistently above the best τ_{OB} for lead time. This suggests that, compared to lead time, maintaining the work rate requires a slower system response to demand changes. In particular, when the rework ratio is below 0.1 or above 0.7, a slow response is necessary to maintain work rate resilience.

From the lead time perspective, the best τ_{OB} is depicted by the black line. Compared to ETOAR#P and ETOAR#D, the black line for ETOAR#PTD shows a minor decreasing trend. Although the decrease is slight, it contrasts with the increasing trend observed in the other two ETOAR archetypes. This indicates that the presence of rework leads to exaggerated fluctuations and, thus, necessitates a smaller τ_{OB} to accelerate the system's reaction speed. Such findings suggest that for delayed design rework, a rapid reaction is crucial, particularly when the design may have a high rework ratio.

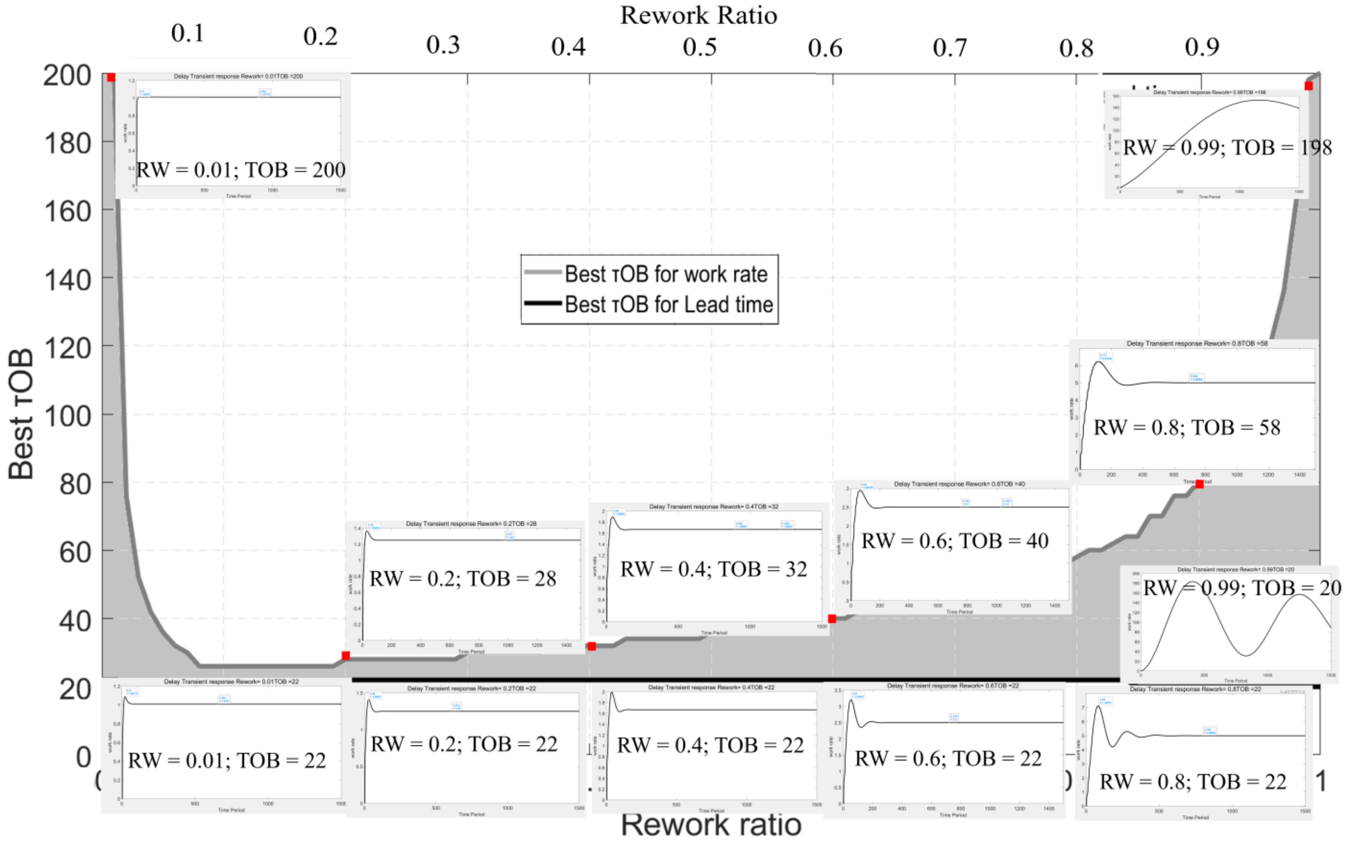

Figure 6.15 The 'good' τ_{OB} value for different rework ratios for each variable of interest, with work rate transient response, ETOAR#PTD. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the work rate, while the X-axis represents the time period.

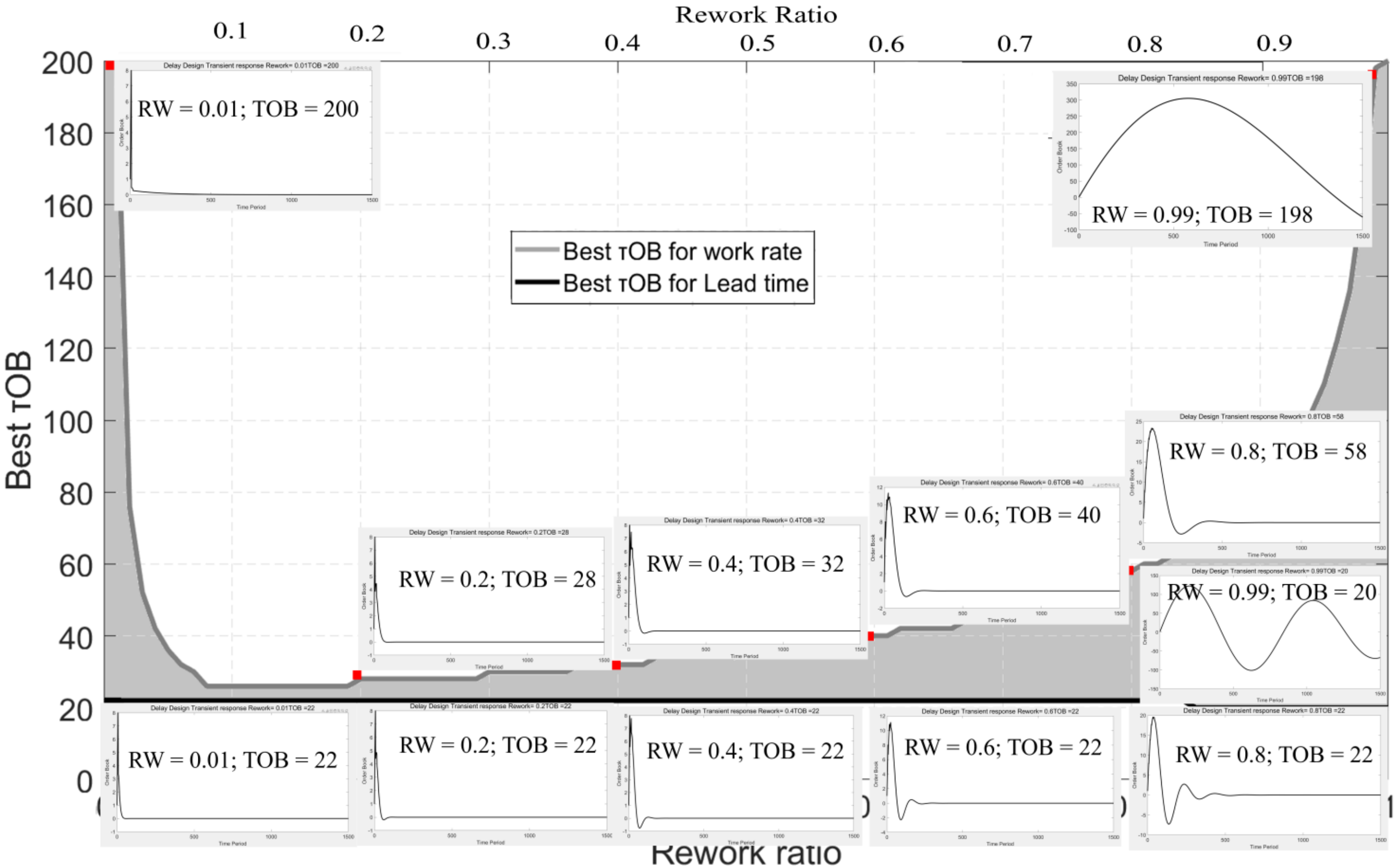

Figure 6.16 The 'good' τ_{OB} value for different rework ratios for each variable of interest, with lead time transient response, ETOAR#PTD. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the lead time, while the X-axis represents the time period.

6.2.2 A Narrowed-Down Scope

While Figures 6.11–6.16 cover a scope that is rather broad, which hinders the extraction of information, this subsection places a special focus on ETOAR#D, which can represent the ETOAR family because of the similarity it shares with the other archetypes. The following analysis were segmented based on the value of the rework ratio into three groups: minor rework ratio (0–0.2), moderate rework ratio (0.2–0.7), and major rework ratio (0.7–0.99). Concurrently, it was observed that the trend in capacity resilience τ_{OB} could be divided into two periods: a τ_{OB} decreasing period (RW 0–0.2) and a τ_{OB} increasing period (RW 0.2–0.99). The subsequent analysis is based on this categorisation.

In scenarios where the rework ratio is minor, the τ_{OB} value for capacity resilience decreases. An analysis of the transient response revealed that the peak τ_{OB} value in the minor rework area is attributed to the presence of the order book controller. In this domain, when a demand shock occurs, the work rate is immediately raised to meet the demand level. However, the order book controller serves to smooth the work rate, as detailed in Equations 4.15, 4.26, and 4.44, thus slowing down the system's adjustment to the work rate. This observation is supported by Figure 6.17 below, where a comparison of three transient responses with the same rework ratio but different τ_{OB} values reveals that a smaller τ_{OB} significantly slows down the response of the work rate.

Conversely, when τ_{OB} is set at 200—indicating minimal connection of the order book controller with the system—the transient response escalates rapidly.

From these findings, it can be concluded that when the rework ratio is relatively small, the ITAE error is primarily contributed by the initial error. However, as the rework ratio increases, the dominant source of error transitions from the initial error to the settling error, particularly for the ITAE index, which penalises slow responses with time. Therefore, the best τ_{OB} for work rate decreases until it reaches 0.2, a reduction that can be interpreted as a necessary shift in focus from initial error to settling error as the rework ratio increases. In addition, τ_{OB} acts as an accelerator for the system to minimise the error caused by slow settling.

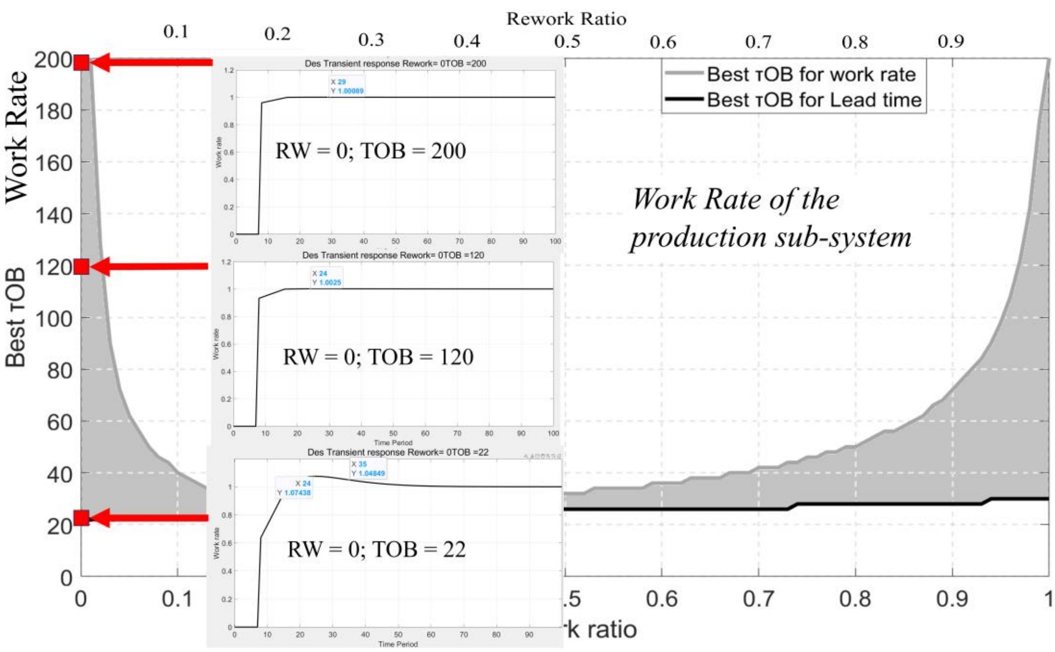

Figure 6.17 Transient responses for the τ_{OB} comparison in the low rework domain. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the work rate, while the X-axis represents the time period.

In the moderate rework ratio area, the transient responses, as demonstrated in the figure below, indicate that τ_{OB} values begin to increase. This trend is primarily driven by the further increases in the rework rate, which prolong the system's settling time, thereby necessitating a smaller τ_{OB} to accelerate the system's response. Simultaneously, the fluctuation in the work rate is exacerbated by both the increased rework ratio and the rapid response to demand changes. These dual factors—settling time and fluctuation—require τOB adjustments in opposite directions; this results in τ_{OB} values in the range of 0.2–0.7 remaining at a lower level without dramatic increases or decreases.

According to the transient responses depicted in the figure, it is evident that if τ_{OB} is too large, the system's transient response becomes smoother but takes a longer time to settle. Conversely, with a relatively small τ_{OB} (set to achieve resilient lead time), the peak of the transient response is rather pronounced. When τ_{OB} is set at the grey line, the transient response exhibits a lower peak than that for lead time resilience; however, this settles faster than when τ_{OB} is set at 120. In this context, τ_{OB} serves to balance the ITAE error from settling time with the error due to fluctuation.

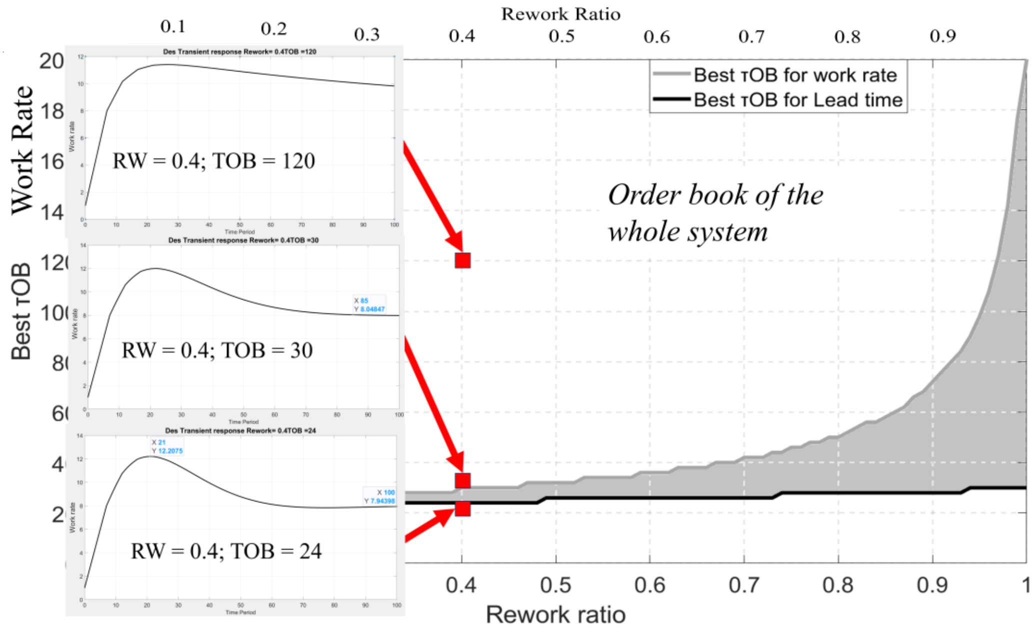

Figure 6.18 Transient responses for the τ_{OB} comparison in a moderate rework domain. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the work rate, while the X-axis represents the time period.

In the high rework domain, the optimal τ_{OB} value for the work rate soars to the upper limits of the figure. This increase is primarily caused by fluctuations becoming the predominant contributor to the ITAE error, overtaking the settling time. As the rework ratio further increases, the fluctuation of the transient responses becomes more pronounced. Although the settling time error also escalates with the increase in rework ratio, its progression is slower than that of the fluctuations. Thus, the impact of the rework ratio not only intensifies the magnitude of the fluctuations but also prolongs their duration. Such effects severely impair the system's performance from a resilience perspective and necessitate a different role for τ_{OB} compared to other scenarios. In this domain, τ_{OB} must act as a smoother to mitigate the system's dramatic fluctuations, albeit at the cost of a slow initial reaction and prolonged settling time. Compared to other types of errors, fluctuations exert a long-term and high-intensity impact on the system; if not adequately addressed, this may lead to severe cost overruns. As illustrated in Figure 6.19, on the right-hand side, τ_{OB} is set at 200, which represents the upper boundary of the figure, and the transient response demonstrates that τ_{OB} effectively smooths the fluctuations.

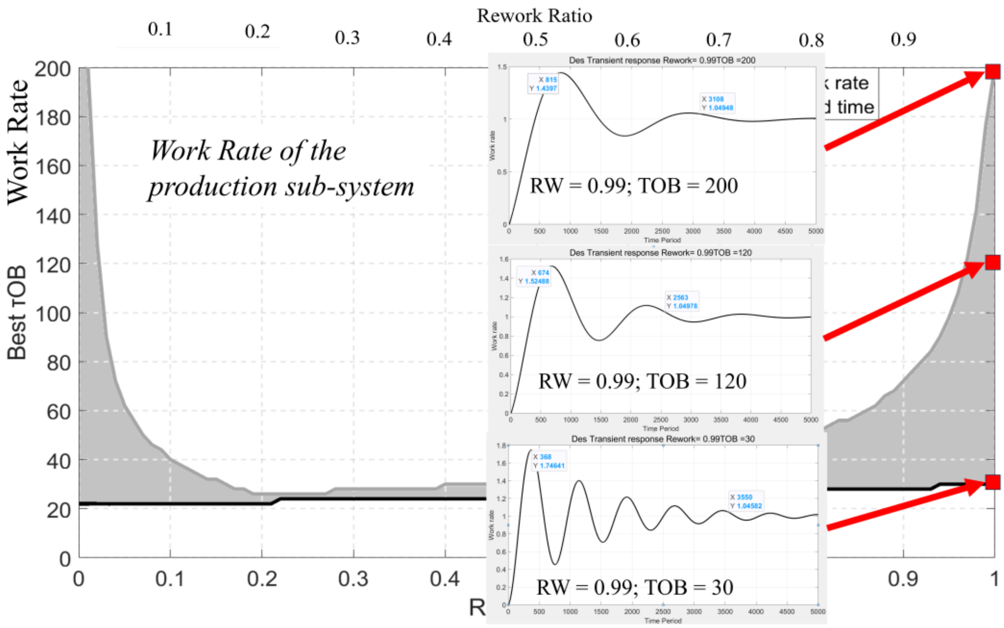

Figure 6.19 Transient responses for the τ_{OB} comparison in a high rework domain. Note: The small figures illustrate the transient response of the system under varying RW and TOB values. For the transient response figures, the Y-axis represents the work rate, while the X-axis represents the time period.

In addition to work rate resilience, this analysis also seeks to highlight how τ_{OB} for optimal lead time resilience changes in response to variations in the rework ratio. Cross-comparing these three scenarios reveals that the best τ_{OB} value for lead time resilience remains relatively consistent across all scenarios, typically maintaining around 20–22, irrespective of changes in the rework ratio. The primary distinction in the delayed design rework scenario compared to the other two scenarios is that the best τ_{OB} for lead time slightly decreases as the rework ratio increases, whereas in the other two scenarios, τ_{OB} increases with increasing rework ratios.

For ETOAR#P, the increase in τ_{OB} is attributed to the augmentation in fluctuation caused by increased rework ratios, thereby necessitating a less sensitive response to demand shocks. Conversely, for ETOAR#PTD, as the rework ratio increases, the lead time's settling time is prolonged. Although fluctuations are also present, their impact is less significant compared to the errors introduced by the extended settling time.

6.3 Analysis of Results

Based on the result obtained from the previous sections, the findings are summarised in Table 6.1.

In the minor rework domain (0–0.2 rework ratio), τ_{OB} should be set close to the optimal setting for lead time resilience. This is because when the rework is relatively minor, the primary error contributing to the ITAE is the initial error of the work rate, with fluctuation errors being even smaller. Therefore, in this stage, the best τ_{OB} value should be set close to that for lead time resilience, albeit with a slight compromise on work rate fluctuation. This setting enables the management to keep the system as responsive as possible, thereby enabling a relatively rapid response to demand shocks.

In the moderate rework ratio domain, the τ_{OB} setting should be closer to the work rate in line to minimise fluctuation as much as possible. Notably, numerical results indicate that, in this scenario, the optimal τ_{OB} for work rate resilience and lead time resilience are relatively close. Consequently, management can select a τ_{OB} value that strikes a balance between lead time and work rate resilience.

Table 6.1 A summarisation for the phenomena observed from the experiment.

RW	***Minor 0 - 0.2***	***Moderate 0.2-0.6***	***High 0.6-0.99***
Trend	Decrease	Increase	
Error	Initial error -> Settling error	Settling error -> Fluctuation	
τ_{OB} **Role**	Accelerate the system's reaction speed, to reduce the settling error, with the cost of the fluctuation and negative compensation.	Slow down the system's reaction to the change, due to the rework increase the system's fluctuation exaggerated. τ_{OB} need to be increased to smoothen the system, thereby reduce the fluctuation, but with cost of settling time be prolonged.	
Suggestion	τ_{OB} should be set to close to best Lead time resilience performance, quick response can make the lead time quickly settle down, and the initial error of work rate is minor.	τ_{OB} should be set in the grey area, between best lead time and work rate. Management needs to choose between lead time resilience with work rate resilience	τ_{OB} should be set to achieve best work rate resilience, to eliminate the great fluctuations.

For systems with a rework ratio above 0.6, sacrifices must be made in terms of lead time. In such cases, the presence of high rework results in a fluctuating work rate transient response, which implies high costs associated with demand shock responses. This situation is particularly costly for companies, as more time, resources, and money must be expended on capacity changes; moreover, lead times are also extended due to increased rework ratios. Therefore, it is recommended that management set τ_{OB} close to the work rate resilience line. Although this setting may prolong the system's settling time and the promised lead time, it can help stabilise the system. Additionally, given that a high rework ratio typically signifies greater complexity and difficulty, companies should offer a more conservative lead time estimate (maximal reasonable lead time) to customers, advising them that the project or ETO product may require more time than initially expected.

One common feature across all three archetypes is the differing values of best τ_{OB} for lead time and work rate resilience. To illustrate this, Table 6.2 summarises the advantages and disadvantages of prioritizing the resilience of different variables.

The primary choice involves prioritising work rate and focusing on maximising capacity resilience. The advantages of this approach include the ability of the capacity to reach the desired state quickly and accurately with minimal cost incurred by fluctuations. This enables the company to adapt to demand shocks swiftly and accurately. Additionally, by employing the concept of MRC, which should cover the peak of the work rate, it is ensured that all planned working units can be completed within the allotted time. Prioritising work rate implies that the MRC value can be smaller, thereby allowing the system to save costs associated with maintaining high-level capacity. Moreover, compared to prioritising lead time resilience, focusing on work rate can also reduce the fluctuation of the transient response, benefiting on-cost savings in production. This is particularly crucial for high-rework ETO systems, where fluctuations are significant and this necessitated system smoothing to reduce the costs associated with these fluctuations. However, the disadvantages are also clear; by setting τ_{OB} to a larger value, the system becomes less sensitive to demand changes and responses become slower. This slow response can extend lead times beyond the designed level, often resulting in time overruns, which diminishes customer trust and service levels.

Conversely, prioritising lead time resilience offers significant benefits: First, the system's lead time can reach and stabilise at the desired level more quickly, thereby minimising the negative impact of time overruns. Furthermore, the maximal reasonable lead time will be less than that under a work rate prioritising strategy, thereby allowing the company to promise shorter lead times to customers and, thus, gaining a competitive edge in the market.

Table 6.2 Pros and cons of prioritising work rate and lead time resilience

'Good' τ_{OB}	**Pros**	**Cons**
Prioritising work rate resilience	• Work rate of production system has some overshoot but has a quicker settling time. • Minimum Reasonable Capacity is lower. • Less fluctuation for production system's work rate • Minimises production on-costs	• Lead time takes longer to recover to the promised level.
Prioritising lead time resilience	• Lead time recovers faster. • Maximum Reasonable Lead time smaller than τ_{OB} for best work rate	• High production system work rate variability leads to higher production on-cost. • Peak value of the work rate higher than best work rate τ_{OB} the Minimum Reasonable Capacity is higher

6.4 How to Select ‘Good’ τ_{OB} for Resilience Enhancement

This subsection aims to connect theoretical outcomes with practical implementation. Within ETO systems, no single parameter setting can simultaneously maximise lead time resilience and delivery rate resilience. Lead time resilience enables the system to settle at the target lead time swiftly and accurately, which in practical terms implies maintaining promised lead times at their maximum during demand shocks. Conversely, capacity rate resilience ensures that the system’s work rate can smoothly and swiftly transition to a new stage; this typically prioritises production capacity, aiming to ensure that capacity transitions smoothly from the original level to the new level without significant changes or oscillations. While demand shocks can be either positive or negative, a negative demand shock is not explicitly addressed here because its transient response would be a mirror image of a positive shock, leading to similar system behaviour and conclusions.

These two types of resilience represent distinct strategies. The former embodies an agile strategy that prioritises customer service level with less consideration for capacity fluctuation. This system reacts quickly to changes but at the cost of frequent adjustments. The latter strategy is more conventional, featuring a milder reaction to market changes. The choice between these strategies should be guided by the market position, the long-term strategy of the company, and the rework rate.

The strategies are summarised and explained in Figures 6.20, 6.21, and 6.22.

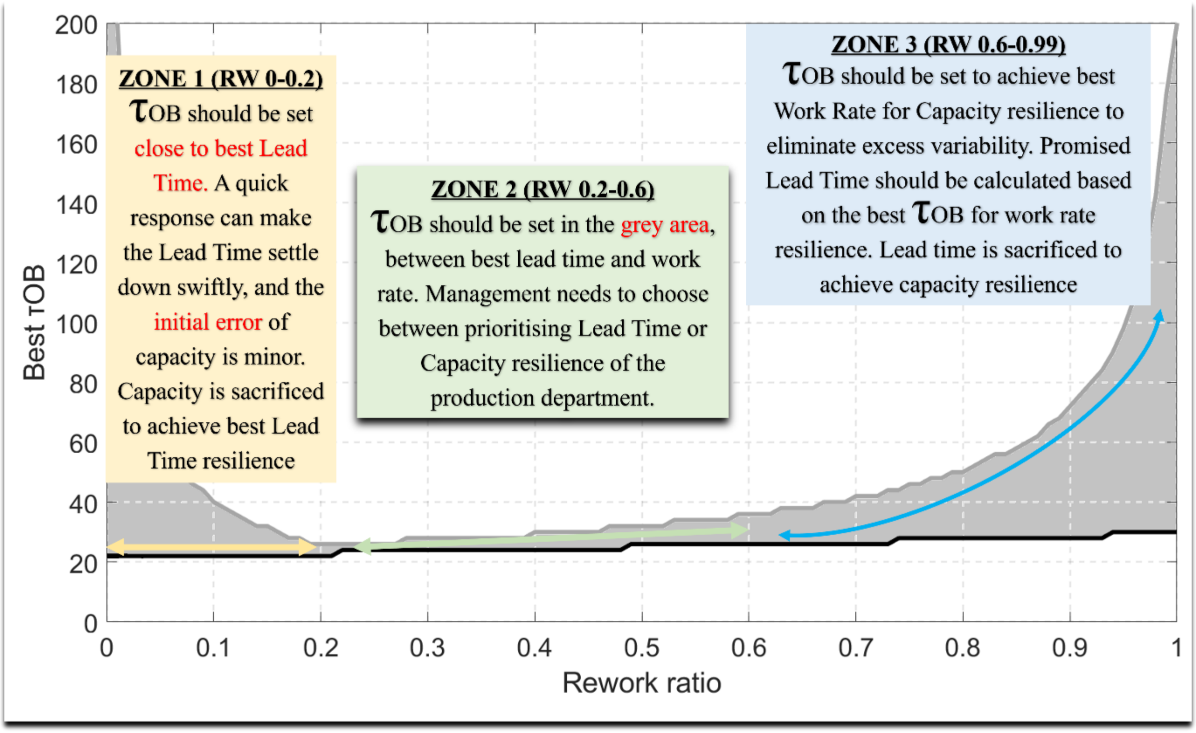

Figure 6.20 Matching theoretical results with management strategies in ETOAR#D.

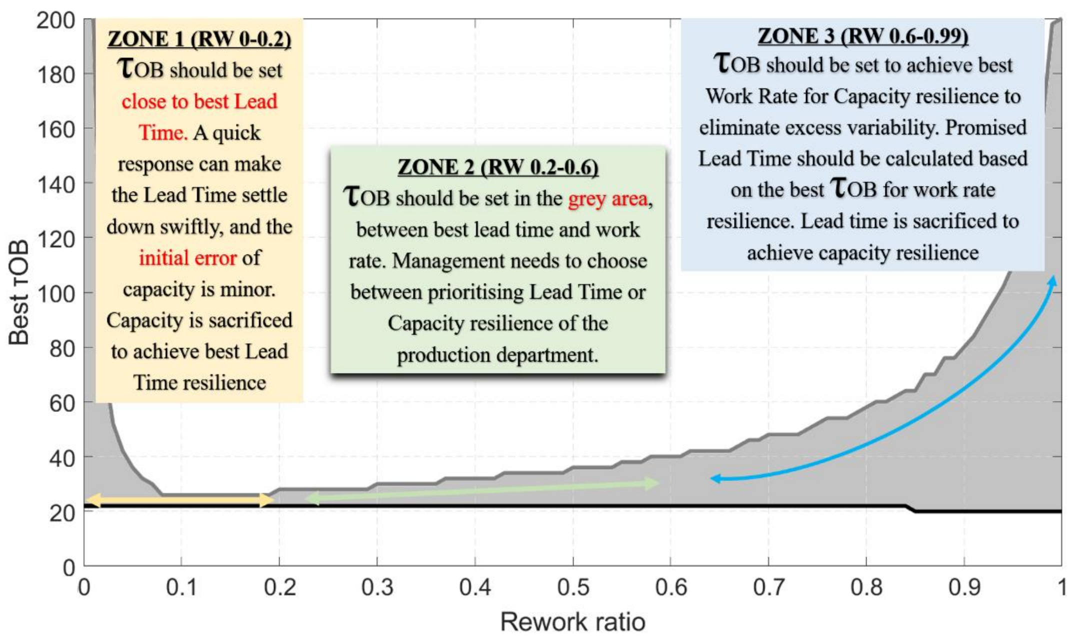

Figure 6.21 Matching theoretical results with management strategies in ETOAR#P.

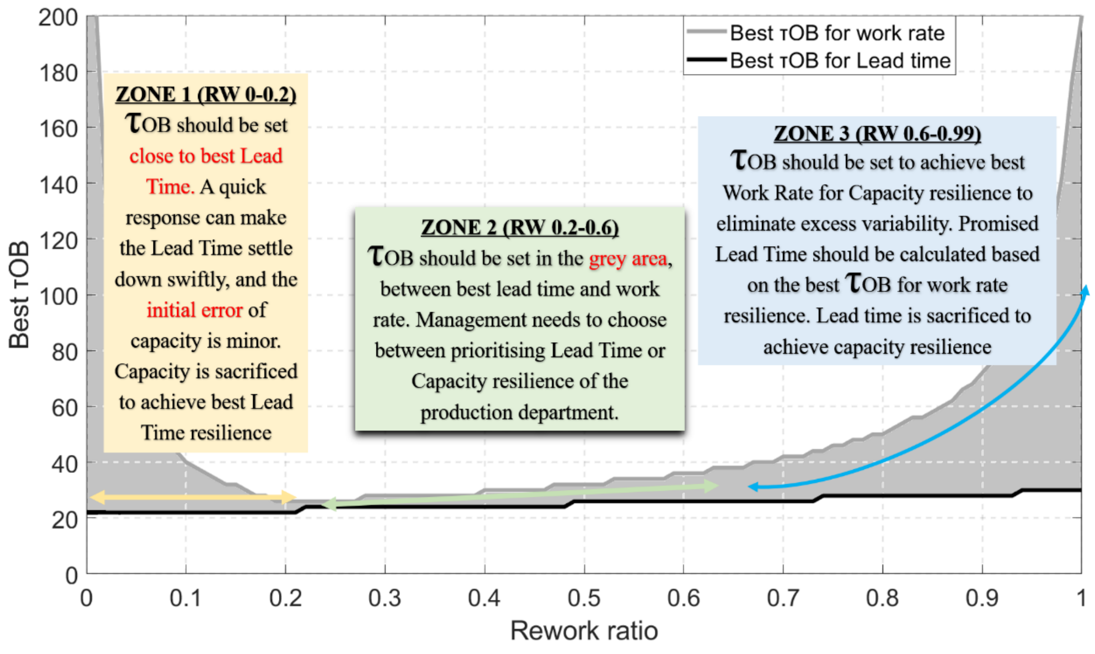

Figure 6.22 Matching theoretical results with management strategies ETOAR#PTD.

Figures 6.21, 6.22, and 6.23 illustrate the effects of rework on the resilience strategy adjustments across the three ETO archetypes, respectively. It is observed that the main trends in τ_{OB} changes are similar across all scenarios, thereby indicating that the impact of the rework ratio is consistent regardless of the location of the rework. This suggests that ETO systems are sensitive to the rework ratio but relatively insensitive to the specific site of rework. Based on these observations, and informed by the data in Table 6.3, the following recommendations are proposed:

Low rework ETO products/projects: Companies should prioritise lead time because the cost associated with capacity fluctuation is minor and justifiable in exchange for higher lead time resilience. This implies that companies should remain responsive to market changes and adjust production capacities accordingly.

Moderate rework area: The requirements for lead time resilience and work rate resilience are closely matched, thereby suggesting that strategies could favour either lead time resilience or delivery rate resilience. In this scenario, the τ_{OB} value should be approximately 20.

High rework rate products or projects: Priority should be given to delivery rate resilience, even at the expense of lead time. In such cases, capacity adjustments should not directly follow market changes. The high rework ratio leads to significant capacity fluctuations, potentially causing cost overruns; thus, τ_{OB} should be minimised to smooth these fluctuations.

6.5 Summary

This chapter focuses on improving resilience within ETO systems. The discussion began by defining resilience in the context of the ETO system as 'the behaviour of the system when facing disruption events'. Following the establishment of this definition, a literature review was conducted to examine existing resilience indices, summarising their advantages and disadvantages. A notable limitation identified in these indices was their focus on single-period performance, which may not fully capture the system's resilience over time.

To address this issue, this study adopts the ITAE as the primary index for measuring resilience, based on recommendations from prior literature (Spiegler et al. 2012). Utilising the PSE technique, this chapter visualises the changing trends of ITAE in relation to variations in the rework ratio and τ_{OB}. Additionally, the optimal τ_{OB} values for different rework ratios are identified and visualised. The choice of focusing on τ_{OB} is motivated by its nature as a manageable parameter, unlike the rework ratio, which is typically fixed.

The subsequent sections of this chapter present these findings through several tables that compare the optimal τ_{OB} values across different scenarios. The final subsection will analyse these results and link the theoretical findings to practical managerial implementations. This approach not only provides a comprehensive understanding of how resilience can be measured and enhanced in ETO systems but also bridges the gap between theoretical research and practical applications.

Chapter 7 Implications and Sensitivity Analysis

This chapter aims to synthesise the research outcomes regarding τ_{OB} and explore the practical implications of the order book controller. In Sections 5.2 and 5.3, frequency domain analysis was conducted and critical stable conditions were derived, thereby providing insights into how τ_{OB} affects system performance. In Chapter 6, the resilience of the ETO archetype was studied, with the recommended τ_{OB} values illustrated in Section 6.4. However, the recommended τ_{OB} values from different analyses vary. For example, stability analysis suggests that τ_{OB} should be above 6.25 ($\frac{1}{\tau_{OB}}$ should be greater than 0.16), while the Bode plot analysis suggests that the larger the τ_{OB}, the smaller the magnitude of work rate. In addition, the research in the resilience analysis suggests that the τ_{OB} need to be adjusted according to the rework ratio of the system. To correlate this finding with a practical application, effort needs to be made to synthesise the result with consideration of the reality of an ETO system. Therefore, this chapter aims to conduct a comprehensive study on τ_{OB}. Section 7.1 synthesises the result related to τ_{OB} and explores the usage τ_{OB} into the capacity management field. Section 7.2 conducts a sensitivity analysis to investigate the sensitivity of the system with recommended τ_{OB} to parameter changes, which push the model closer to reality. Section 7.3 implicates the developed model in validating the 'Think Slow Act Fast' principle in the ETO field, which is followed by a summary of the chapter in Section 7.4.

7.1 Value Determination for τ_{OB}

Chapters 5 and 6 examine the effect of τ_{OB} values from different perspectives and offer various recommendations for setting these values. This subsection aims to synthesise the findings from Chapters 5 and 6 and provide theoretical guidance on determining a 'good' τ_{OB} value. Given that the lead times of the subsystems in ETO archetypes can influence critical stable conditions and resilience performance, the lead times of subsystems are assumed to be four time units.

7.1.1 Result Synthesis

Figure 7.1 demonstrates the suggested τ_{OB} from different perspectives. The dotted and black lines represent the recommended τ_{OB} from the resilience research; the grey dotted line refers to the stability boundary for the τ_{OB}; the red dotted and blue dotted lines represent the suggested τ_{OB} from the Bode plot analysis.

It is evident that the suggested τ_{OB} from resilience analysis is within the stability boundary, while the suggested τ_{OB} from the Bode plot analysis is located in the unstable zone. Simultaneously, it is observed that, in the Bode plot analysis, lead time and work rate have very different requirements that the τ_{OB} value, which made the selection of τ_{OB} more difficult. Therefore, a synthesis analysis is conducted in this chapter; the following paragraphs summarise the τ_{OB} relevant findings in this thesis and provide a synthesised result on τ_{OB} value determination. Note here that, the red and blue dots are derived based on Bode plots whose rework ratio corresponds with the value of its x-axis.

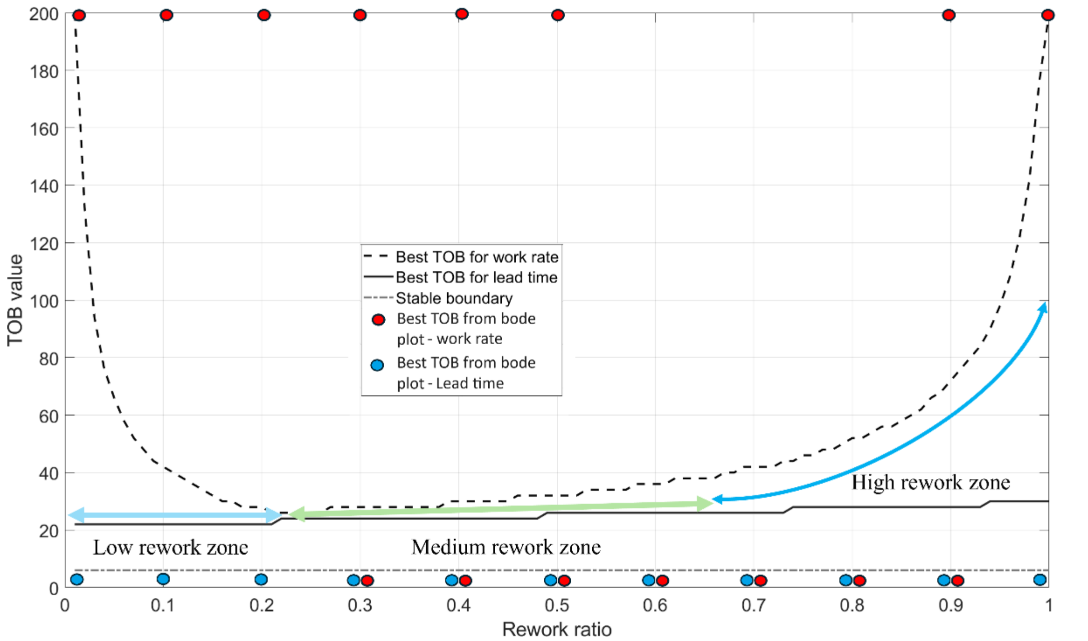

Figure 7.1 'Good' τ_{OB} summarisation from different perspectives.

Based on the synthesised results presented in Figure 7.1, the τ_{OB} value should meet the following criteria:

1. **Stability analysis:** τ_{OB} should be greater than 6.25. Although the findings from the Bode plot suggest that τ_{OB} should be as small as possible when the frequency is between 0.01 and 0.02 rad/week (lead time perspective and represented by the blue dot in Figure 7.1), the system's stability must always be maintained to avoid non-convergent fluctuation. This implies τ_{OB} should always be greater than 6.25 to ensure system stability. Otherwise the excessive fluctuation will dramatically increase the operational cost of the production system (Spiegler et al. 2012) and result in a fluctuated product lead time, which may decrease the customer service

quality.

2. **Resilience analysis:** The τ_{OB} value should be selected from the area between the black dotted line and the straight line. The τ_{OB} values in this area enable the system to achieve its highest resilience. For low or moderate rework ratio production systems, τ_{OB} should be set close to the straight line. For high rework ratio production systems, τ_{OB} should be set close to the dotted line to eliminate fluctuations caused by rework. A more detailed discussion can be found in Section 6.4.

3. **Bode plot analysis:** When the demand pattern has an explicit cycle and fluctuation, the Bode plot analysis suggests that, in the typical ETO demand frequency domain, the τ_{OB} value needs to be as small as possible to achieve lead time resilience. For work rate resilience, although when $\tau_{OB} = 200$, the magnitude is the smallest, the influence of the τ_{OB} value is insignificant, as stated in Section 5.2.2. Therefore, from the Bode plot perspective, the smaller the τ_{OB}, the smaller the lead time fluctuation, and the better the system performance.

In addition, with respect to the demand frequency, according to the study in Chapter 5.2, the frequency 0.04–0.07 rad/week (89.7–157 weeks) should always be avoided. The reason for this is that work rate's magnitude plot demonstrates a peak in this frequency domain. The consequence would be a highly fluctuating capacity.

4. Result synthesis: The stability of a production system is essential, thereby necessitating that τ_{OB} always exceeds 6.25. Resilience analysis provides varied recommendations compared to Bode plot analysis. Resilience analysis suggests adjustments in the τ_{OB} value indicated by three arrows across different rework zones. Conversely, Bode plot analysis indicates minimising τ_{OB} for typical ETO demand frequencies. The discrepancy between these analyses arises from their distinct system inputs: deterministic step input for resilience analysis and frequency input for Bode plot analysis. Consequently, it is concluded that for demand exhibiting a strong cyclical pattern within the ETO frequency range, Bode plot recommendations should prevail. Here, τ_{OB} should be minimised while remaining above the stability of the system. Conversely, if demand lacks a cyclical pattern, resilience analysis recommends setting τ_{OB} to 20 for rework below 0.6, thereby increasing proportionally with higher rework ratios, as depicted in Figure 7.1.

7.1.2 The Implication of τ_{OB}: Aggregate Planning and MRL/MRC

The order book controller represents the capacity decision rules of the ETO company. Its control is implemented by adjusting the system's work rate based on a proportion (denoted by τ_{OB}) of the difference between the target and actual order book levels. This method determines the capacity level without relying on historical data.

The ETO system faces two main issues: fluctuations that may increase production costs and inadequate consideration of the ripple effects of rework, such as additional fluctuations and rework-generated rework. The introduction of the holistic-level order book controller provides a decision rule for adjusting work rates, with a comprehensive consideration of rework and the system's dynamics. Additionally, by incorporating the MRL and MRC into the system analysis, the capacity requirements of the production system can be better estimated at an aggregated level.

Aggregate planning for the ETO system remains an underexplored area in academia. By using the 'good' τ_{OB} value derived from the archetype, both the MRL and MRC can be determined. MRL indicates the time that an ETO company takes to complete a project or product, which can be used as a reference during customer negotiations. MRC refers to the minimum reasonable capacity that the ETO company should maintain. The production capacity must always cover the peak work rate to ensure that lead times are met. However, maintaining an excessively high capacity can be costly for the company. To balance this, the capacity should be set to the MRC level, which can just cover the peak work rate and reduce capacity waste (Lin et al. 2020).

In practice, the rework type is often unknown before manufacturing/constructing begins, but the rework ratio can be estimated based on the experience and complexity of the products/projects. Thus, capacity planning should consider all possible rework scenarios, thereby ensuring that the project is completed within the MRL, even under the most challenging conditions. Table 7.1 summarises the MRC and MRL for all archetypes and suggests capacity and lead times for the overall ETO system.

Table 7.1 MRC and MRL of the ETO system with rework ratio = 0.2, and ‘good’ τ_{OB}

	ETOAR#P	ETOAR#D	ETOAR#PTD
MRC	230	230	230
Minimum Capacity	230		
MRL	9.0	9.0	31.7
Maximum Lead Time	31.7		

7.2 Sensitivity Analysis

Section 7.1 synthesises the findings regarding the ‘good’ τ_{OB} and provides suggestions on capacity management and lead time estimation. However, in practice, the system’s parameters or subsystem delays are often not precise, which raises concerns regarding the reliability of the decision rules and system performance. Therefore, in section 7.2, sensitivity analysis is adopted to study the influence of factors on the output or the performance index of the developed model, under a ‘good’ τ_{OB}. This can help to effectively investigate how sensitive the output is to the changes in parameters or variables. The adoption of sensitivity analysis can also help users to detect how uncertainty may affect the output or the performance of the system; the analysis result can be beneficial to the system robustness, improvement, and upgradation. For practitioners, this method can support detection of the weak point of the whole system, thereby improving the resilience and robustness of the production system.

Returning to the ETO archetype, there are vital assumptions which form the foundation of the model, which are (a) the lead time for the design and production is a known constant; (b) rework scheduling time is 1, and (c) τ_{OB} is determined by the management. It should be noted that in practice, the first two assumptions may not be known or achievable. Therefore, in this section, a sensitivity analysis is conducted to investigate how system output and performance will be influenced by the change in the lead time and changes in the rework inspection times; the τ_{OB} is set to 20, which is recommended in Section 7.1.

The process for the analysis is described below:

1. Sensitivity analysis on the lead time change.

The lead time for the design and production subsystem is a determined value in the archetype. While in the operation, particularly in the environment that includes high uncertainties such as ETO, the lead time may be influenced by various factors. In particular, design lead time, unlike production, is even more uncertain because the customer may request for design changes at any time. Thus, in such circumstances, sensitivity analysis is conducted on both design and production lead time for all three archetypes. The analysis comprises two parts—the first part is determined input, which is a step change; the second part is stochastic input, which is a vector containing a random demand.

2. Sensitivity analysis on the rework scheduling time change.

Rework scheduling time refers to the time used to detect the rework and schedule the extra working units for reworking. Thus, to test how sensitive the system is to such delay, an analysis is conducted on this. Unlike the sensitivity analysis on the lead time, which has been the study of several papers, sensitivity analysis on rework scheduling time remains unexplored. This analysis includes two parts, stochastic demand and determined demand, thereby having a comprehensive understanding of the system's performance.

The research outcomes for ETOAR#D and ETOAR#PTD are presented in the appendix, and this section only presents the research outcome of ETOAR#P. The findings are summarised in Section 7.2.4.

7.2.1 Sensitivity Analysis on the Subsystems' Lead Time Change

ETOAR#P Production Rework

Table 7.2 is the configuration of the system's initial status and parameter setting. To investigate the influence of the single lead time on the system's output, one variable for each time is controlled. Two experiments are included in this section: (a) determined demand scenarios, wherein the input is a step input from 0 to 1.2, and (b) stochastic demand scenarios, wherein the input is a vector formed by random numbers. These two experiments test the sensitivity of the system under different environments, such as 25% baseline and 200% baseline. Such a design can estimate how the system would perform when the subsystem's lead time is mis-estimated.

Table 7.2 The initial value and parameter setting for the ETOAR#P lead time sensitivity analysis.

Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	400	25	125	500	800

Co-efficient values				
τ_{OB}	τ_D	τ_P	RW	RW scheduling time
20	1(25%) 4(Baseline) 8(200%)	1(25%) 4(Baseline) 8(200%)	0.2	1

Deterministic demand analysis

The Figure 7.2 depicts the sensitivity of the system to the step input. In general, the greater the lead time, the longer the system takes to settle down and the higher the peak of the delivery rate. The blue line—which indicates that the design lead time is shorter than the expectation—reacts faster to the demand change and the form of the wave is smooth. The yellow line demonstrates that the lead time is longer than the expectation, takes a longer time to reach the demand level, and also has an overshoot. It can be concluded that the longer the lead time, the more fluctuating the curve will be and the order-book controller can stabilise the system, even if the lead time estimation occurs. Compared with design and production lead time misestimation, the latter situation creates a longer time for the system to reach its peak. This phenomenon can be interpreted as, if the misestimate occurs at the lower echelon of the ETO production, it may create a longer time for the system to absorb the negative effect.

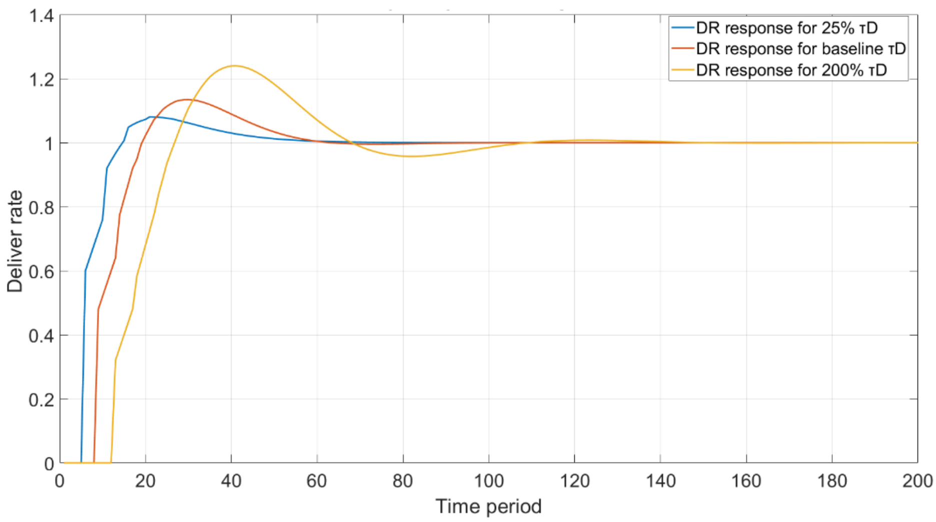

Figure 7.2 Sensitivity analysis of ETOAR#P's deliver rate to the design lead time, with a determined demand.

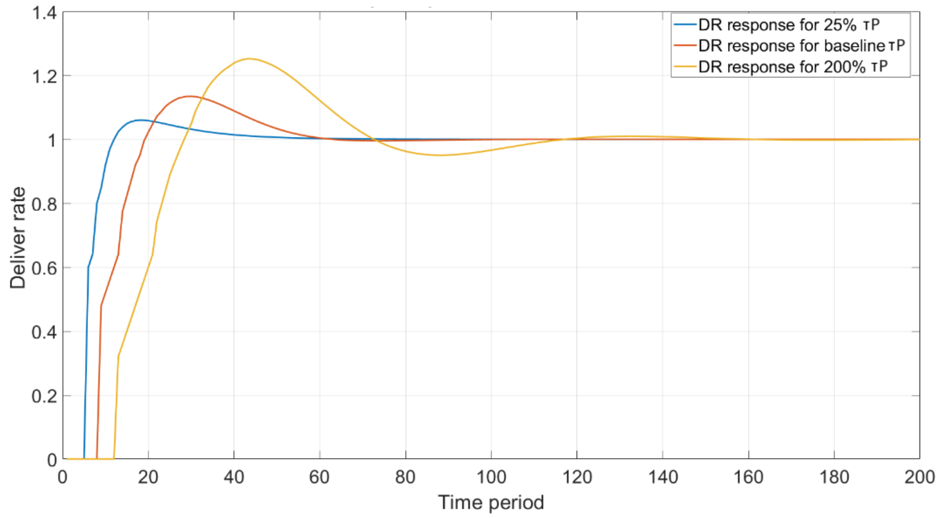

Figure 7.3 Sensitivity analysis of ETOAR#P's deliver rate to the production Lead time, with a determined demand.

Stochastic demand analysis

In order to test the system sensitivity to the design and production lead time, the experiment is conducted under stochastic demand. To control the variable of experiments, the same demand vector is used to separately test the design and production systems. There are two phenomena witnessed in both plots: (a) The bullwhip changing trend in lead time is affected by the τ_{OB}, and (b) the reaction of the output rate is delayed by the prolonged lead time. This aspect is easy to understand, because the prolonged lead time leads to a prolonged whole-system lead time. Therefore, to further investigate the first observation, the bullwhip effect is calculated. These simulations are depicted in Figures 7.4 and 7.5

According to (Towill et al. 2007), the bullwhip can be calculated in the following manner:

$$Bullwhip = \frac{Output\ Variance}{Demand\ variance}. \tag{7.1}$$

The bullwhip ratios for all three scenarios are summarised in Table 7.3:

Table 7.3 Bullwhip ratio for each scenario

Experiment	Bullwhip
Design lead time sensitivity analysis	
-50% design delay: (total lead time: 5)	0.2596271
Baseline design delay:(total lead time: 8)	0.2587154
+50% design delay:(total lead time: 12)	0.2645415
Production lead time sensitivity analysis	
-50% production delay	0.2572314
Baseline production delay	0.2587154
+50% production delay	0.2551646

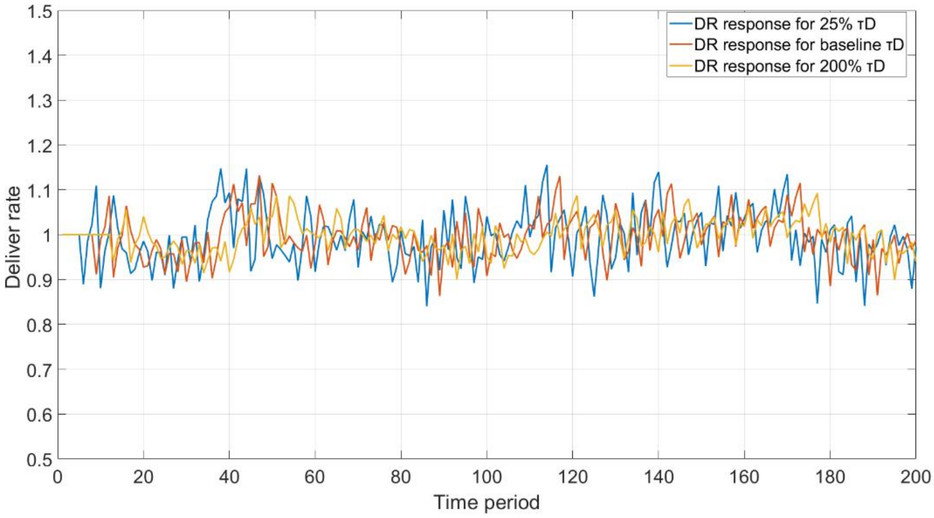

Figure 7.4 Sensitivity analysis of ETOAR#P's deliver rate to the design Lead time, with stochastic demand

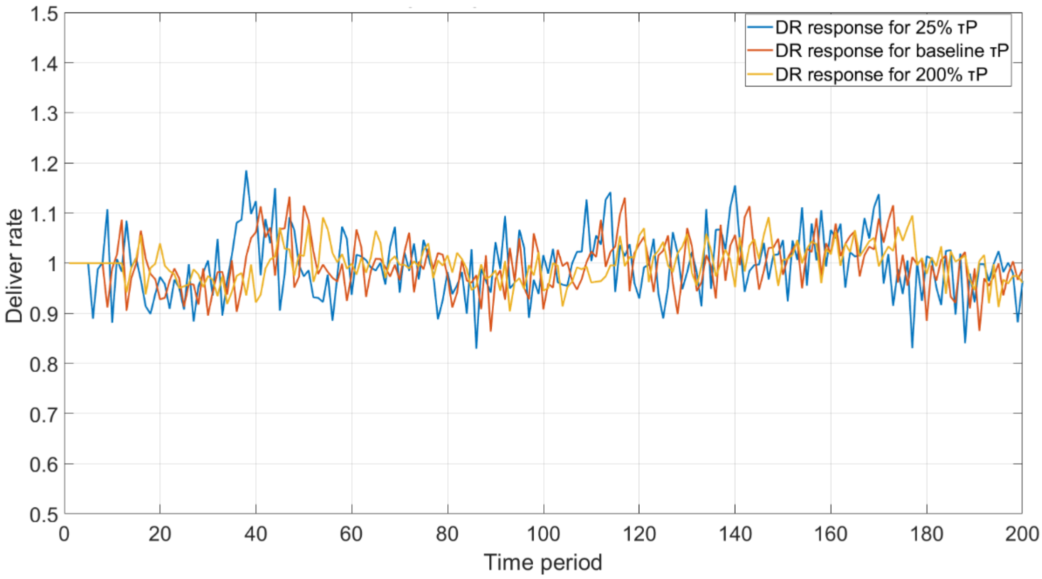

Figure 7.5 Sensitivity analysis of ETOAR#P's deliver rate to the production Lead time, with stochastic demand

To further analyse this result, more experiments are conducted for a detailed investigation into how ETOAR#P reacts to the changes in design lead time. In this experiment, the design delay is set as 1, 2, 4, 6, 8, 10,12, 14, 16, thereby providing an overview on how the bullwhip ratio is affected by the changes in lead time. It is worthwhile to note here that although the design lead time changes, the total expected lead time for the entire system is assumed to be 8 and this setting is for the control variable consideration. Moreover, the result for when the rework is assigned as 0.2 is depicted in Figure 7.6.

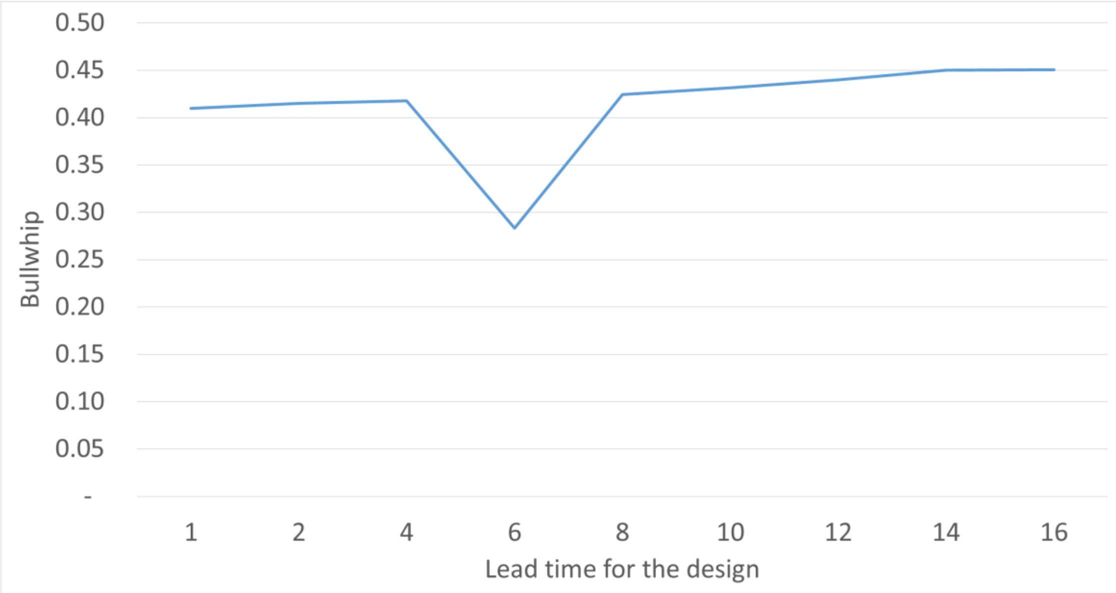

Figure 7.6 Sensitivity analysis of the ETOAR#P on the bullwhip effect.

It is evident that with the increase in the design lead time, the bullwhip ratio for the ETOAR#P has an increasing trend but with several fluctuations. The fluctuations occur when design delay equals 4, 14, and 16 weeks.

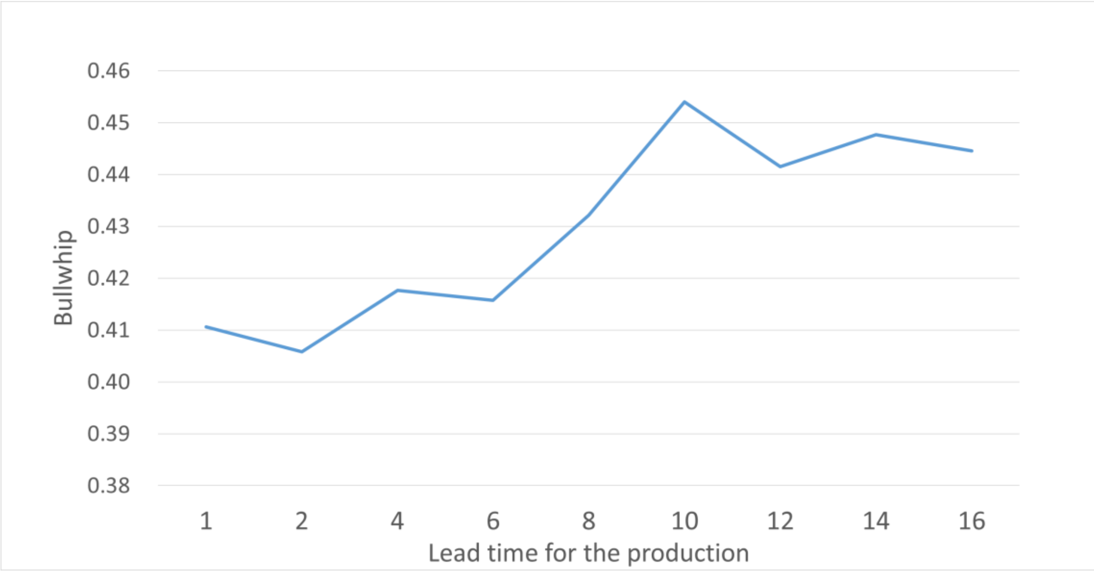

Figure 7.7 Sensitivity analysis of the ETOAR#P bullwhip effect.

According to the Figure 7.7, the increase of the production subsystem led to increase and fluctuation of the bullwhip ratio.

7.2.2 Sensitivity Analysis on the Rework Scheduling Time

Apart from the sensitivity analysis to the design and production lead time, analysis on the scheduling time for the rework is also conducted. In the practical situation, this variable represents how long it takes to schedule the extra working units for rework to the workers. In the origin model, it is assumed that it only takes one period to detect and schedule the extra working units for the worker team. The following paragraph demonstrates the findings from the ETOAR#P. The simulation's initial value and parameter value are presented in Table 7.4. The simulation results are depicted in Figures 7.8 and 7.9.

Table 7.4 The initial value and parameter setting for the ETOAR#P rework scheduling time sensitivity analysis

Initial values					
COMRATE DES	OBDES	RWRATEP ROD	COMRAT EPROD	OBPRO D	OB
100	400	25	125	500	800

Co-efficient values				
τ_{OB}	τ_D	τ_P	RW	RW scheduling time
20	4	4	0.2	1(Baseline) 2 (200%) 4 (400%) 8 (800%)

ETOAR#P Production rework

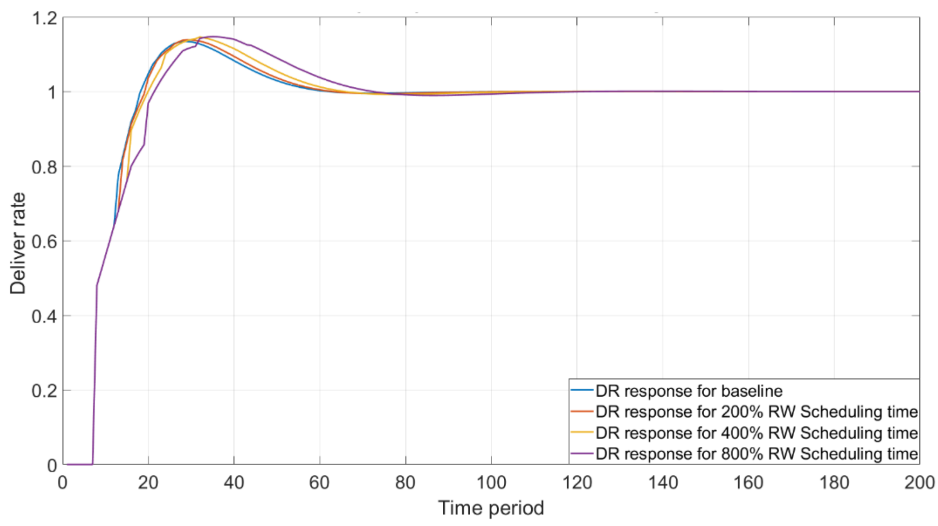

Figure 7.8 ETOAR#P delivery rate transient response with determined demand

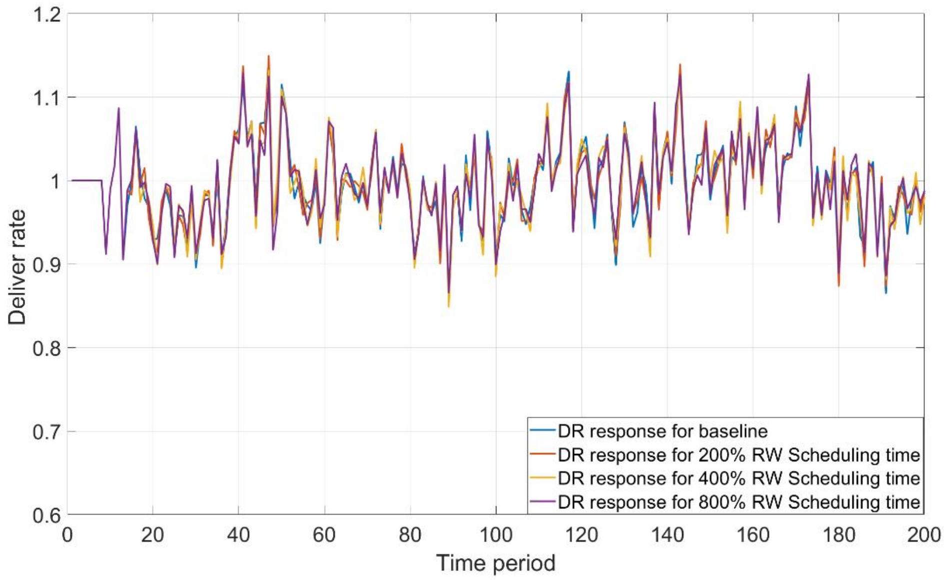

Figure 7.9 ETOAR#P delivery rate transient response with stochastic demand

7.2.3 Sensitivity Analysis of Different Rework Types

This subsection focuses on comparing how different types of reworks affect the system's work rate. In this section, several simulations are conducted to investigate how work rate of each scenario changes along with the rework. The simulation result is summarised in Table 7.5.

For the ETOAR#P scenario, with the increase in the rework ratio, the workload of the production subsystem increases, while the design subsystem's workload is maintained at the original level. For the ETOAE#D scenario, the design subsystem's workload increases with the rework ratio, while for the production subsystem, the workload is maintained at 100%. For the ETOAR#PTD, it is evident that the workload of both the design and production subsystems' increases. According to the table below, a conclusion can be made that ETOAR#PTD is much more harmful than the other scenario, because both design and production systems need to do more work to cover the impact caused by the rework.

Table 7.5 The workload of subsystems for each archetype, $\tau_{OB} = 20$.

Rework ratio	ETOAR#P		ETOAR#D		ETOAR#PTD	
	Design Sub-system Work rate	Production Sub-system Work rate	Design Sub-system Work rate	Production Sub-system Work rate	Design Sub-system Work rate	Production Sub-system Work rate
0	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
0.1	100.00%	111.11%	111.36%	100.00%	111.36%	111.11%
0.2	100.00%	125.28%	125.28%	100.00%	125.28%	111.11%
0.3	100.00%	142.86%	143.17%	100.00%	143.17%	142.86%
0.4	100.00%	166.67%	167.04%	100.00%	167.04%	166.67%
0.5	100.00%	200.00%	200.44%	100.00%	200.44%	200.00%
0.6	100.00%	250.00%	250.56%	100.00%	250.56%	250.00%
0.7	100.00%	333.33%	334.07%	100.00%	334.07%	333.33%
0.8	100.00%	500.00%	501.11%	100.00%	501.11%	500.00%
0.9	100.00%	999.78%	1001.97%	100.00%	1001.97%	999.78%

7.2.4 Summary for Section 7.2

Sensitivity to the subsystem's lead time change.

The findings from Section 7.2.1 can be concluded in the following manner: for all three rework scenarios, the work rate of the system is sensitive to the lead times of both design and production subsystems. The longer the subsystems' lead time, the higher the peak value of work rate, and the longer the settling time of the work rate transient responses. This finding suggests that a prolonged lead time for a subsystem has a negative impact on the work rate of the system, which requires the system to maintain a higher capacity.

The experiments with stochastic demand input suggest that all three types of the bullwhip effect of all three archetypes are sensitive to the changes in the subsystem's lead time, while the changing trend of the bullwhip effect with subsystems' lead time fluctuate. The following paragraph demonstrates the sensitive analysis process of the ETOAR#P archetype; the research findings of the other two archetypes are demonstrated in Appendix.

Sensitivity to the rework inspection time

According to the experiments for all three archetypes, it was found that rework scheduling time may affect settling time for the transient responses; however, it has an insignificant effect from other perspectives, such as peak value or fluctuation. All curves have the same peak value and begin responding simultaneously. In terms of the stochastic demand experiments, all four curves overlap with the others; the difference between them is so small that it can be ignored.

However, comparing this result with that of the previous literature reveals an contrasting result (Han et al. 2014). This reason can be attributed to the model development assumptions. There is an assumption that the flow in the model is working units. The reason for this assumption is to avoid the potential problem which may rise due to the different design and configuration for the products and, hence, all projects will be broken down into homogeneous working units. Thus, the findings in this context can be summarised in the following manner: the rework scheduling time only affects the systems' settling time and has no effect on the performance of other variables.

Sensitivity to the rework type

According to Table 7.5, the work rates of the production and design subsystems are significantly affected by the rework type and rework ratio. The work rate of the design subsystem for ETOAR#D and ETOAR#PTD increases with the rework ratio. However, for ETOAR#P, there is no design rework; thus, the design subsystem's work rate does not increase. From the production subsystem perspective, the work rates for ETOAR#P and ETOAR#PTD increase with the rework ratio. Notably, ETOAR#PTD is the most detrimental rework scenario, requiring additional work units in both the design and production subsystems. This finding is supported by Section 5.2.2, which indicates that when demand fluctuates, ETOAR#PTD's MLR time is significantly longer than that of other scenarios.

In reality, production rework is often more costly than design rework due to material usage and labour force engagement (Lyneis and Ford 2007). Additionally, once production begins, the project faces more uncertainties, thereby increasing the risks (Han et al. 2014). Therefore, minimizing rework in production is crucial, particularly in preventing ETOAR#PTD type rework. One solution to prevent ETOAR#PTD and reduce production rework is the 'Think Slow, Act Fast' approach proposed by

Flyvbjerg and Gardner (2023). In the next section (7.3), the adaptation of this philosophy in the ETO field is discussed.

7.3 Think Slow, Act Fast

Understanding the severe impact of ETOAR#PTD type of rework, a philosophy of ‘Think Slow, Act Fast’ has been proposed. The philosophy emphasises the importance of spending more time on design and detailed planning prior to the initiation of action. By doing so, the likelihood of going over budget or exceeding the timeline can be reduced (Flyvbjerg and Gardner 2023). Although this philosophy is embedded within practice, there is little research that explains the underlying mechanisms from an SD perspective. The given research utilises the SD method to investigate this philosophy from a quantitative perspective.

Section 7.3 discusses how different types of design rework affect the lead-time of an ETO system, and how a strategy based on the ‘Think Slow, Act Fast’ philosophy improves the system’s performance. The research outcome is presented in two subsections. Section 7.3.1 explains the experiment process, followed by Section 7.3.2, which presents the newly developed models: one simulates the scenario in which extra time is given to the design process, and the other one simulates the scenario in which ETOAR#D and ETOAR#PTD types of reworks exist simultaneously. Section 7.3.3 presents the influence of the adaptation of ‘Think Slow, Act Fast’ principle for the dynamic process of the ETO system.

7.3.1 Experiment Process

Experiment A assumed that dedicating more time to the design subsystem could decrease the number of undetected reworks by a certain percentage. In this study, the aim is to determine the optimal level of inspection required to enhance the system's performance in terms of lead time. Specifically, for ETOAR#PTD, 100% of design errors go undetected in the design stage, while for ETOAR#U, the RW-U percentage is detected in the design stage. The question for which an answer is sought is what proportion of the design error the inspection should discover in the design stage to improve the system's lead time performance. For this, a matrix is used to illustrate the required effectiveness of the inspection.

Figure 7.10 portrays the experiment's process. The first step is to calculate the ITAE value for each RW ratio and each U for ETOAR#D+1. Concurrently, the ITAE value vectors for all RW ratios are calculated. The second step is to determine the ratio of ITAE between ETOAR#D+1 and ETOAR#PTD. ETOAR#D+1 is a matrix where, for each column, each element is divided by the ITAE value of ETOAR#PTD with the same rework ratio. After obtaining the matrix, the values that are smaller than 100% are marked, and the minimum effectiveness required for inspection is demonstrated. Experiment A involves testing a new model that includes a ratio that indicates the number of defective working units sent to the production department. By introducing an additional inspection period, the number of errors sent to the production system can decrease, but a few may still make their way downstream.

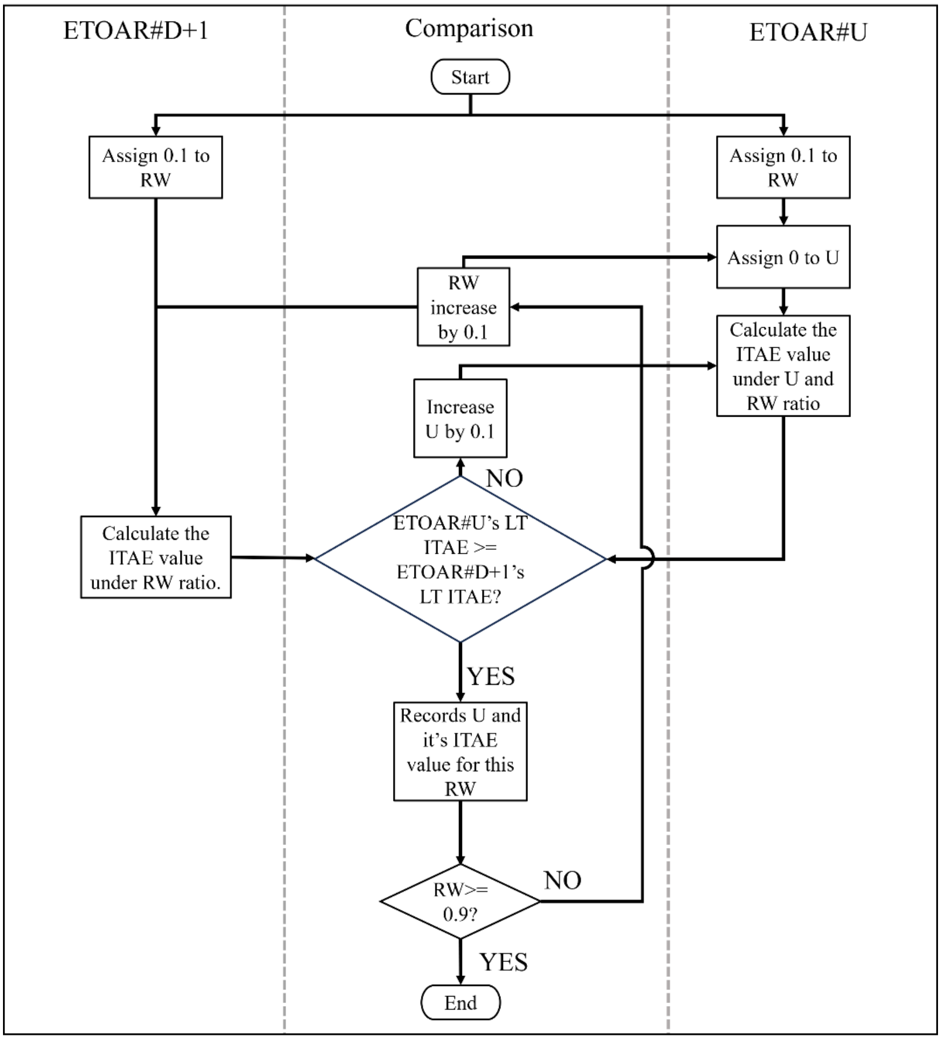

Figure 7.10 Research process for experiment A

The goal of experiment B is to determine if introducing an inspection in the design system can identify all design errors and ensure all necessary changes are made, then how many extra times period can be used for inspection?

The process for experiment B is depicted in Figure 7.11. The first step involves calculating the ITAE value for ETOAR#D+X with various RW as well as calculating the ITAE value for ETOAR#PTD under different RW ratios. The second step involves comparing the ETOAR#D+X ITAE value with ETOAR#PTD. Starting with X = 1, increase X by one unit each time until ETOAR#D+X's lead time ITAE value is smaller than that of ETOAR#PTD. Record this value of X. If the value is not smaller, record X-1 and start over with a different RW ratio. This approach will help identify the maximum amount of extra time that can be allocated to the design subsystem from a time perspective.

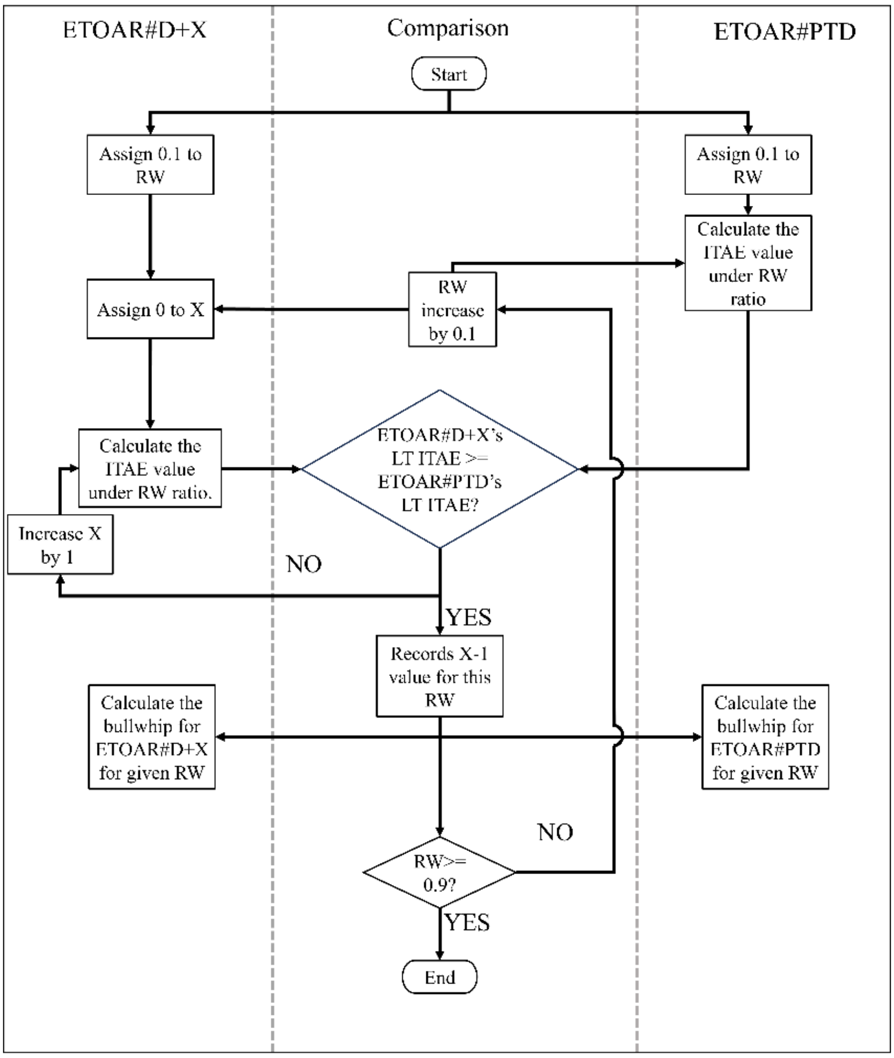

Figure 7.11 Research process for Experiment B

7.3.2 Archetype Development of ETOAR#D+X and ETOAR#U

ETOAR#D+X

The archetypes are developed in the z-domain to align with previous studies (Zhou et al. 2022). Both models will be presented in both block diagram and mathematical forms. Figures 7.10 and 7.11 demonstrate the block diagram of the ETOAR#D+X and ETOAR#PTD, respectively, which are composed of three subsystems and one rework loop.

Figure 7.10 demonstrates the block diagram of the ETOAR#D+X archetype, which contains three subsystems: Design subsystem, production subsystem, and order book controller. DEM_{DES} for the design system is composed of three parts: external demand, compensation value from order book controller, and rework. Equation 7.2, adopted from Wikner et al. (2007), is used to calculate the compensation value for the work rate.

$$WRATE_{DES}(t) = DEM(t) + \frac{OB\,(t) - DEM\,(t) \cdot (\tau_P + \tau_D)}{\tau_{OB}} + RWRATE_{DES}(t-1). \tag{7.2}$$

A pure delay τ_D is used to represent the design time, while X refers to the extra time window given to the design error inspection, detection, and changes.

$$COMRATE_{DES}(t) = WRATE_{DES}(t - \tau_D - X). \tag{7.3}$$

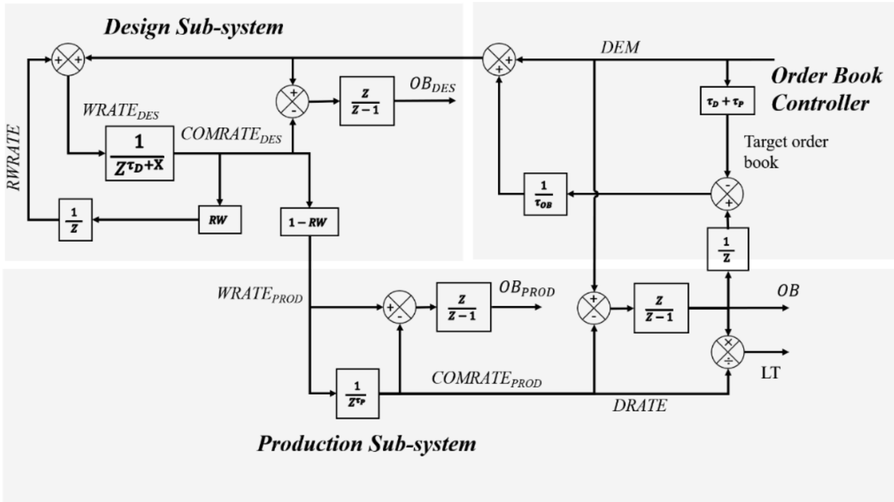

Figure 7.12 The block diagram of ETOAR#D+X

The order book is a record of all orders that have been placed but are yet to be completed. The meaning of the order book differs across various industries. In this research, it is defined as the total number of working units that are required to complete all orders in the queue. In the PM field, this variable is also known as 'work to do' (Lee et al. 2005a). Equation 7.4, 7.8 and 7.10 is adopted from (Wikner et al. 2007) to calculate the order book, for period t.

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t) \tag{7.4}$$

It is assumed that rework is a proportion of $COMRATE_{DES}(t)$ and can be represented by Equation (7.5). In practice, the rework ratio, RW, can be calculated through statistical analysis.

$$RWRATE_{DES}(t) = COMRATE_{DES}(t) \cdot RW. \tag{7.5}$$

A design is sent to the production department after the inspection and design change waiting window. $WRATE_{PROD}(t)$ refers to the work that needs to be done by the production subsystem, which is a proportion of the $COMRATE_{DES}(t)$.

$$WRATE_{PROD}(t) = COMRATE_{DES}(t) \cdot (1 - RW) \tag{7.6}$$

τ_P is a pure delay, which represents the production time.

$$COMRATE_{PROD}(t) = WRATE_{PROD}(t - \tau_P). \tag{7.7}$$

$$OB_{PROD}(t) = OB_{PROD}(t-1) + WRATE_{PROD}(t) - COMRATE_{PROD}(t) \tag{7.8}$$

or the ETOAR#D system, it is assumed that there are no production defects, thus formulating equation 7.9.

$$DELRATE(t) = COMRATE_{PROD}(t). \tag{7.9}$$

Equation 7.10 presents the order book of the whole system over time.

$$OB(t) = OB(t-1) + DEM(t) - DELRATE(t). \tag{7.10}$$

Little's Law (Little 1961) is adopted to calculate the lead-time of whole system, as shown in 4.11, 4.12 and 4.13.

The order book controller is responsible for making decisions based on the target order book, which represents the production target set by the company. This model assumes that the target is based on the company's promised lead-time, $\tau_D + \tau_P$, to customers and the demand for each period. The target order book is the product of $\tau_D + \tau_P$ and demand. To ensure that orders can be fulfilled on time, the company needs to adjust its production speed, which is reflected by the work rates, $WRATE_{PROD}$, in the model. This order book controller is realised by equations (7.2) and (7.10). This structure enables the establishment of the capacity decision rule for the model.

ETOAR#U

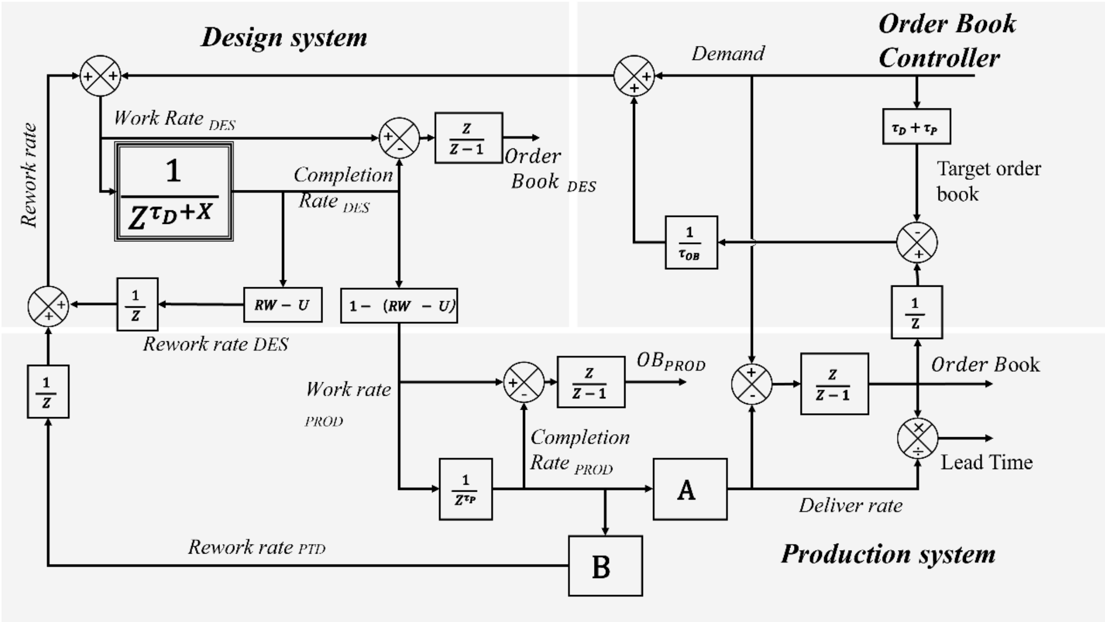

Figure 7.13 The block-diagram for ETOAR#U

In reality, projects are a mixture of ETOAR#PTD and ETOAR#D. Therefore, these two models were combined to create a consistent model in the z-domain, which will be presented in the form of both a block diagram and mathematical expressions. This amalgamation will provide a foundation for further investigation into the ‘Think Slow, Act Fast’ philosophy. Hence, another parameter, U, was introduced, which represents the number of undetected design errors or changes that are remaining and sent to the production system in the ETOAR#D design rework scenario. Figure 7.11 demonstrates the block diagram of the newly developed model, which is composed of three subsystems and one rework loop.

Design system

DEM_{DES} for design system comprises three parts—external demand, compensation value from order book controller, and rework. Equation (7.12), (7.16), (7.20) and (7.22), adopted from Wikner et al. (2007), demonstrates the mechanism of the order book controller.

$$DEM_{DES}(t) = DEM(t) + \frac{OB(t) - DEM(t) \cdot (\tau_D + \tau_P)}{\tau_{OB}} + RWRATE\,(t) \qquad (7.12)$$

The summation of pure design rework and 'production to design' rework is $RWRATE\,(t)$, which indicates the total number of working units required for errors and changes.

$$RWRATE\,(t) = RWRATE_{DES}(t) + RWRATE_{PTD}(t). \qquad (7.13)$$

The finished works in this system are divided into two parts—designs that are ready for production and those that go into rework. The rework represents the detected design errors and changes that occur before the production stage. The RW-U parameter is the proportion of detected rework in the design system. RW represents the total rework caused by errors or changes, and U refers to the undetected errors or changes.

$$RWRATE_{DES}(t) = COMRATE_{DES}(t) * (RW - U). \qquad (7.14)$$

$$COMRATE_{DES}(t) = DEM_{DES}(t - \tau_D). \qquad (7.15)$$

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t). \qquad (7.16)$$

Production system

Production begins after the design is completed, and τ_P represents the production lead time. Parameter $(1-(RW-U))$ indicates the designs that are sent to the production system and still contain undetected errors or defects.

$$DEM_{PROD}(t) = COMRATE_{DES}(t) * \big(1-(RW-U)\big). \tag{7.17}$$

$$COMRATE_{PROD}(t) = DEM_{PROD}(t-\tau_P). \tag{7.18}$$

$$RWRATE_{PTD}(t) = COMRATE_{PROD}(t) \cdot B. \tag{7.19}$$

B represents the portion of design error that is spotted in the production stage. The value of B will be derived in the following paragraphs:

$$OB_{PROD}(t) = OB_{PROD}(t-1) + DEM_{PROD}(t) - COMRATE_{PROD}(t). \tag{7.20}$$

A represents the qualified working package, and the expression of *A* is presented in the following paragraphs.

$$DELRATE(t) = COMRATE_{PROD}(t) \cdot A \tag{7.21}$$

$$OB(t) = OB(t-1) + DEM(t) - DELRATE(t) \tag{7.22}$$

Little's Law was adopted to estimate the lead time of the whole system, as shown in 4.11, 4.12 and 4.13.

In the context of production systems, the simulation of production lead time as a pure delay $\frac{1}{Z^{\tau P}}$ is a widely adopted practice. The input for such systems is often represented by $DEM_{PROD}(t)$, which in turn is a function of $COMRATE_{DES}(t)$. However, it is worth noting that $DEM_{PROD}(t)$ may still contain design defects and changes. Therefore, the production system plays a critical role in detecting such defects and changes through rework. Block A in the production system of Figure 7.12 illustrates the process of qualifying the working packages, while block B represents the rework caused by design errors or changes that occur after production begins. By making the assumption that all design errors and changes will be detected in the production system, it is possible to derive the expression for blocks A and B.

Given that

$$RW = (RW - U) + \big(1 - (RW - u)\big) \cdot B, \tag{7.24}$$

then

$$B = \frac{U}{1 - (RW - u)} \tag{7.25}$$

For block A, the delivery rate must equal Demand*(1-RW); thus,

$$\big(1 - (RW - U)\big) * A = 1 - RW. \tag{7.26}$$

Then,

$$A = \frac{1 - RW}{1 - (RW - U)}. \tag{7.27}$$

Order book controller

The order book controller is responsible for making decisions based on the target order book, which represents the production target set by the company. This model assumes that the target is based on the company's promised lead time $(\tau D + \tau P)$ to customers and the demand for each period. The target order book is determined by multiplying $(\tau D + \tau P)$ with demand. The actual order book, which is also known as work to do in PM, represents the amount of work that remains to be completed. Due to capacity constraints, order books take a certain amount of time to complete. To ensure that orders can be fulfilled on time, the company needs to adjust its production speed, which is reflected by work rates. This structure enables the establishment of the capacity decision rule for the model. Lead time, which is a crucial indicator of a company's performance, is estimated using Little's Law, as presented in equation (7.23).

7.3.3 Model Simulation

The lead time of the model is linearised via Taylor expansion, as presented in Section 5. The transfer function is derived as presented in equation (7.28).

$$TF(LT) = \frac{LT(z)}{DEM(z)} = \frac{\begin{array}{c} z^{11} + (\mathrm{U} - \mathrm{RW})z^5 + (-72a\mathrm{RW} + 72a + 9\mathrm{RW} - 9)z^2 + \\ (72a\mathrm{RW} - 72a - \mathrm{U} - 8\mathrm{RW} + 8)z \end{array}}{\begin{array}{c} z^{11} - z^{10} + (\mathrm{U} - \mathrm{RW})z^5 + (\mathrm{RW} - \mathrm{U})\, z^4 + \\ (a - a\mathrm{RW} - \mathrm{U})z + \mathrm{U} \end{array}}. \quad (7.28)$$

Note: $a = 1/\tau_{\mathrm{OB}}$

To verify and comprehend the newly developed models, a simulation is performed on lead-time, LT_{ETO}, for both models. The simulations in this section enable us to visualise the systems' dynamic behaviours. The parameter setting of this research, which is presented in Tables 7.6, are determined based on previous research (Zhou et al. 2022). The initial values for simulations for the two models differ to ensure steady-state initial conditions.

Table 7.6 Simulation parameter settings for both ETOAR#D+X and ETOAR#PTD

ETOAR#D+X				
Initial values				
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{DES}$	OB_{PROD}	OB
250	1000	150	400	800
Parameter setting				
$1/\tau_{OB}$	τ_D	τ_P	RW	X
1/26	4	4	0.6	1
ETOAR#PTD				
Initial values				
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PTD}$	OB_{PROD}	OB
250	1000	150	1000	800
Parameter setting				
$1/\tau_{OB}$	τ_D	τ_P	RW	
1/26	4	4	0.6	

In Figure 7.12, the lead-time transient response of both models to a step change input can be seen. This aids in observing the system's performance after a demand shock, as recommended by Towill et al. (2007). Both systems' lead times eventually stabilise at eight-time units, which is the desired lead-time for the archetypes. This indicates that the model can maintain the lead-time at the desired level in the long term although only after an increase during the transient period. After comparing the transient response of the two systems, it can be observed that even though ETOAR#D+1 has a higher peak value in its lead time than ETOAR#PTD, it settles down faster from 65 to 120 periods, ETOAR#PTD has a lower lead time due to its greater variance. These two findings reveal that providing extra time to the design system, represented by X = 1, can help speed up the settling time for the lead time and reduce the variance of lead time, but it may result in a higher peak value. This supports the idea of a trade off in the lead time that was mentioned in Chapter 2. Based on this finding, an experiment was conducted in Section 4 to see how much extra time, X, is beneficial for the inspection of design defects and consequent changes.

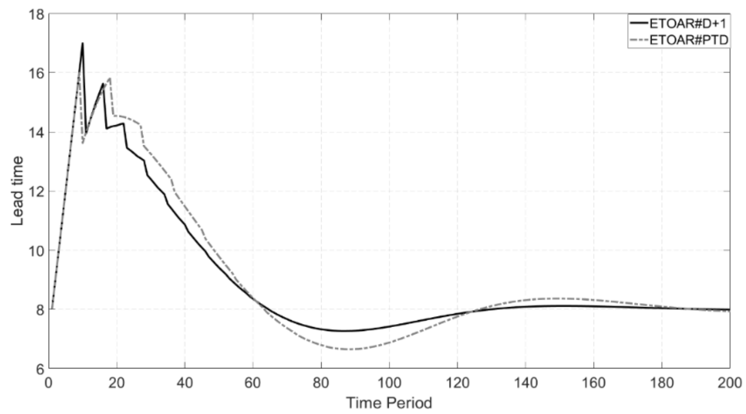

Figure 7.14 The transient response for both models

7.3.4 Findings from Experiment A

The limitation of experiment A is that it assumes that the handover of the rework is all or zero. This assumption limited the adoption of the model and has limited the adaptation of this finding. Thus, model ETOAR#U was developed, which is a model that combines ETOAR#D with ETOAR#PTD, with one extra delay in the design subsystem which represents the extra time given to the inspection or design freezing time; U represents undetected rework, and RW represents the actual amount of rework.

Table 7.7 ITAE percentage for Experiment A

U \ RW	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	120.3%	98.7%	84.4%	73.9%	66.5%	60.2%	52.2%	49.8%	51.6%
	24	24	25	26	25	25	26	26	26
0.1	100.0%	121.4%	102.9%	89.3%	79.1%	70.6%	61.0%	57.7%	59.0%
	24	24	26	25	26	24	26	26	26
0.2		100.0%	123.0%	105.7%	92.9%	82.3%	70.7%	66.2%	66.8%
		24	25	25	26	26	26	26	26
0.3			100.0%	123.6%	108.0%	95.0%	80.9%	75.4%	74.9%
			24	25	25	26	26	26	26
0.4				100.0%	123.9%	108.6%	92.0%	85.3%	83.4%
				23	25	24	26	26	26
0.5					100.0%	123.1%	103.8%	95.9%	92.3%
					23	25	24	26	26
0.6						100.0%	116.5%	107.1%	101.4%
						24	25	25	25
0.7							100.0%	118.9%	110.7%
							25	24	24
0.8								100.0%	120.2%
								24	22
0.9									100.0%
									18

Table 7.7 is the result from experiment A, which displays the ITAE ratio between ETOAR#U and ETOAR#PTD as a percentage. The cells highlighted in grey indicate the values that are less than 100%, thereby indicating that ETOAR#U outperforms ETOAR#PTD with the given parameters. A bold line is included in the table to signify the minimum effectiveness of the inspection. If the inspection cannot lower U to the boundary level, then additional time should not be allocated to the design stage. For example, if the system's RW is 0.5, the undetected errors must be reduced to 0.2 with the extra time allotted to the design stage. If not, no additional time should be given. The second row for each rework ratio represents the best τ_{OB} value, which guarantees that both models are compared with its best performance.

7.3.5 Findings from Experiment B

The purpose of this section is to present the experiments and the findings regarding how the maximum permitted time for ‘Thinking Slow’ at the design stage was derived to include inspection and change. The basic assumption of the experiment is that dedicating more time to the design process for inspection and design change can eliminate any undetected design defects before reaching the production stage.

The findings suggest that the system does not require additional time for the design subsystem when RW = 0.1. However, for RW ranging from 0.2 to 0.5, allocating one extra time unit for the design stage is recommended. When RW ranges from 0.6 to 0.9, one or two extra time units can be allocated; the exact amount of extra time that should be given to the design stage would depend on the effectiveness of inspection and requirement of the bullwhip ratio. The highlighted value suggests that allocating extra time for design inspection or waiting for design change is unnecessary. Otherwise, the lead-time ITAE for adding X time units to design will be higher than the lead-time ITAE of ETOAR#PTD; thus, the maximal allowed inspection/waiting time is the second largest value for X.

It is evident from Table 7.8 that the bullwhip value decreases with an increase in the RW ratio for the ETOAR#D+X scenarios, while for the ETOAR#PTD, the increase in RW ratio leads to an increase in the bullwhip effect. At the same time, all bullwhip values of ETOAR#D+X are smaller than ETOAR#PTD, which suggests that the ETOAR#D+X model’s production department faces a smaller oscillation. However, the influence of X on the bullwhip is indeterminate. For example, when RW = 0.7, the increasing X values create the following bullwhip ratio: 0.092, 0.097, 0.077, 0.081. As the value of X increases, the change in the bullwhip effect is not a straightforward progression from increase to decrease but rather exhibits a fluctuating pattern (Gaalman et al. 2022).

Table 7.8 Result summary of Experiment B from the simulation.

RW ratio	X: Extra time	Lead-time ITAE (Step input)		Production Bullwhip (Stochastic)	
		ETOAR#D+X	ETOAR#PTD	ETOAR#D+X	ETOAR#PTD
0.1	0	1164	1406	0.373	0.463
	1	1692		0.371	
0.2	0	1496	2380	0.312	0.497
	1	2348		0.311	
	2	3547		0.294	
0.3	0	2175	4076	0.267	0.532
	1	3442		0.266	
	2	5206		0.244	
0.4	0	3339	7200	0.224	0.590
	1	5324		0.224	
	2	8066		0.199	
0.5	0	5473	13380	0.181	0.680
	1	8899		0.184	
	2	13642		0.157	
0.6	0	10034	27307	0.132	0.782
	1	16431		0.136	
	2	25027		0.112	
	3	36652		0.113	
0.7	0	21573	67765	0.092	0.838
	1	35616		0.097	
	2	54405		0.077	
	3	79837		0.081	
0.8	0	62395	206231	0.054	1.195
	1	103515		0.060	
	2	160094		0.047	
	3	232589		0.053	
0.9	0	365768	1161779	0.026	2.972
	1	611410		0.033	
	2	927740		0.027	
	3	1269755		0.028	

Design workload is the integration of work rates of all simulation periods, and production workload is the integration of work rates of all simulation periods. These two values represent how much work the entire ETO system completes within the simulation time. Each cell of the table represents the total amount of work that was done, with the given rework ratio and the extra time X. Based on this, the ETOAR#D+X's design workload and ETOAR#PTD's design workload within the rework free system is compared. The rework free system refers to the archetype without rework, which is a special scenario for both ETOAR#D+X and ETOAR#PTD. The workload for subsystems is demonstrated in the 'workload' column and the ratio is the division between values in each cell over the benchmark 179800, which is the workload for the rework free model. The grey rows represent the scenario where no extra time is given to the ETOAR#D+X, which is an ideal situation that all design rework can be detected in the design subsystem. The reason for including it in the table is to provide a comparison to see how X, the extra time, affects the workload of ETOAR#D+X. At the same time, this table also demonstrates how this experiment is conducted; X is tested from 0 to the value that the lead time ITAE value of ETOAR#D+X is greater than ETOAR#PTD, which is demonstrated in Table 7.9.

From the workload perspective, there are two findings that can be derived from Table 7.9—how rework affects the total design workload and how extra time affects the production workload.

The first finding is the production workload of ETOAR#PTD that keeps increasing with the value of rework ratio, while the ETOAR#D+X can maintain the production workload at the same level as the benchmark. Another finding is that the extra workload given to the design subsystem has a negative impact as it can indirectly increase the benchmark of the design subsystem. For example, when the rework ratio = 0.3, the ratio between ETOAR#D+X's design workload with the benchmark increases with prolonged X. This observation implies that the prolonged lead time may increase the schedule pressure of the design subsystem. However, the incremental of the design workload is relatively small compared to the extra workload to the production system. Thus, it is wise to spend more time and make more efforts on the design subsystem to prevent any defect of the production subsystem.

Table 7.9 Results from experiment B and a workload orientated summary from the simulation.

RW ratio	**X: Extra time**	**Workload**				**Percentage**			
		ETOAR#D + X		ETOAR#PTD		ETOAR#D + X		ETOAR#PTD	
		Design workload	Production workload	Design workload	Production workload	Design workload	Production workload	Design workload	Production workload
0	0	179800	179800	179800	179800	100%	100.00%	100%	100%
0.1	0	200222.2	179800	200222.2	199777.8	111.36%	100.00%	111.36%	111.11%
	1	200333.3	179800	200222.2	199777.8	111.42%	100.00%	111.36%	111.11%
0.2	0	225250	179800	225250	224750	125.28%	100.00%	125.28%	111.11%
	1	225375	179800	225250	224750	125.35%	100.00%	125.28%	125.00%
	2	225500	179800	225250	224750	125.42%	100.00%	125.28%	125.00%
0.3	0	257428.6	179800	257428.6	256857.1	143.17%	100.00%	143.17%	142.86%
	1	257571.4	179800	257428.6	256857.1	143.25%	100.00%	143.17%	142.86%
	2	257714.3	179800	257428.6	256857.1	143.33%	100.00%	143.17%	142.86%
0.4	0	300333.3	179800	300333.3	299666.7	167.04%	100.00%	167.04%	166.67%
	1	300500	179800	300333.3	299666.7	167.13%	100.00%	167.04%	166.67%
	2	300666.7	179800	300333.3	299666.7	167.22%	100.00%	167.04%	166.67%
0.5	0	360400	179800	360400	359600	200.44%	100.00%	200.44%	200.00%
	1	360600	179800	360400	359600	200.56%	100.00%	200.44%	200.00%
	2	360800	179800	360400	359600	200.67%	100.00%	200.44%	200.00%
0.6	0	450500	179800	450500	449500	250.56%	100.00%	250.56%	250.00%
	1	450750	179800	450500	449500	250.70%	100.00%	250.56%	250.00%
	2	451000	179800	450500	449500	250.83%	100.00%	250.56%	250.00%
	3	450930.8	179800	450500	449500	250.80%	100.00%	250.56%	250.00%
0.7	0	600666.7	179800	600666.7	599333.3	334.07%	100.00%	334.07%	333.33%
	1	601000	179800	600666.7	599333.3	334.26%	100.00%	334.07%	333.33%
	2	601333.3	179800	600666.7	599333.3	334.45%	100.00%	334.07%	333.33%
	3	601666.7	179800	600666.7	599333.3	334.63%	100.00%	334.07%	333.33%
0.8	0	901000	179800	901003.5	899003.2	501.11%	100.00%	501.11%	500.00%
	1	901499.9	179800	901003.5	899003.2	501.39%	100.00%	501.11%	500.00%
	2	902000.6	179800	901003.5	899003.2	501.67%	100.00%	501.11%	500.00%
	3	902498.9	179800	901003.5	899003.2	501.95%	100.00%	501.11%	500.00%
0.9	0	1802017	179800	1801534	1797608	1002.23%	100.00%	1001.97%	999.78%
	1	1802119	179800	1801534	1797608	1002.29%	100.00%	1001.97%	999.78%
	2	1804169	179800	1801534	1797608	1003.43%	100.00%	1001.97%	999.78%
	3	1804441	179800	1801534	1797608	1003.58%	100.00%	1001.97%	999.78%

7.3.6 Summary for Section 7.3

This section investigates the ‘Think Slow, Act Fast’ theory from a system dynamic perspective. Two experiments were conducted—one studied how many extra times should be assigned to the design subsystem, the other one studied how effective the inspection should be to guarantee that the lead time performance is better than ETOAR#PTD. These two experiments take two differing assumptions; the first one is to assume that extra time can prevent all design rework from being handed over to the production, while the other one investigates how effective the inspection should be to save more time for the entire ETO project. The finding of the experiment can be used as a qualitative sensemaking tool for the 'Think Slow, Act Fast' theory. At this stage, the experiments are conducted using a theoretical framework and simulated scenarios rather than real-world data. The parameters and assumptions used in the models are derived from established literature and SD principles to explore the behaviour of the 'Think Slow, Act Fast' theory. While the findings provide valuable qualitative insights, the integration of empirical data to calibrate and validate these models remains a future step. Incorporating real-world data, such as design and production timelines or inspection efficiency metrics from actual ETO projects, would enhance the applicability and precision of these findings in practical contexts.

7.4 Summary

This chapter aims to explore the implications of τ_{OB} by synthesising the research outcomes from Chapters 4, 5, and 6 in Section 7.1. The findings suggest a theoretical τ_{OB} for the ETO system, representing a 'good' value that combines system stability, frequency performance, and resilience. Based on these synthesised findings, Section 7.2 conducts a sensitivity analysis, considering the lead time uncertainties of subsystems and the uncertainty of rework inspection time. This analysis examines the ETO system's performance with the suggested τ_{OB} value in an uncertain environment. Section 7.3 investigates the adaptation of the 'Think Slow, Act Fast' philosophy within the ETO system, highlighting the benefits and limitations of allocating more time to the design stage. In the next chapter, the system's performance from a resilience perspective will be studied.

Chapter 8 Discussion

This chapter summarises the insights and knowledge gained from this research. In general, Chapter 2 reviews the existing literature studies on ETO systems, summarizing the general production system, CODP concept, and existing SD-ETO models found in the literature. Finally, it provides a review of the research on the resilience of relevant production systems. Chapter 4 developed the ETO archetype, with CT and SD modelling being the main methods employed. To investigate the dynamic performance and stability of the system, a series of studies were conducted. In Chapter 6, the resilience of the system was assessed by the ITAE index, and guidance on resilience improvement were provided. Chapter 7 synthesised the result regarding the τ_{OB} from previous sections and conducted a sensitivity analysis which analyses the model from a more practical perspective.

In this chapter, the findings from previous chapters are summarised under each objective, and a discussion is presented based on the summarised findings. Section 8.1 illustrates the insights from **Objective 1: Build ETO archetypes to provide a** CT **model which can be used as a quantitative platform for further study.** Section 8.2 presents the insights from **Objective 2: Assess the dynamic performance of the ETO archetypes.** Section 8.3 demonstrates the insights from **Objective 3: Measure and improve the ETO archetype's resilience from an SD perspective.** Section 8.4 discusses the implications of the research outcomes. Figure 8.1 provides an overview of the outcomes from each research objective; the figure also includes the conclusion and future research agenda to illustrate the complete picture of the research outcome, but these two sections will be presented in the next chapter.

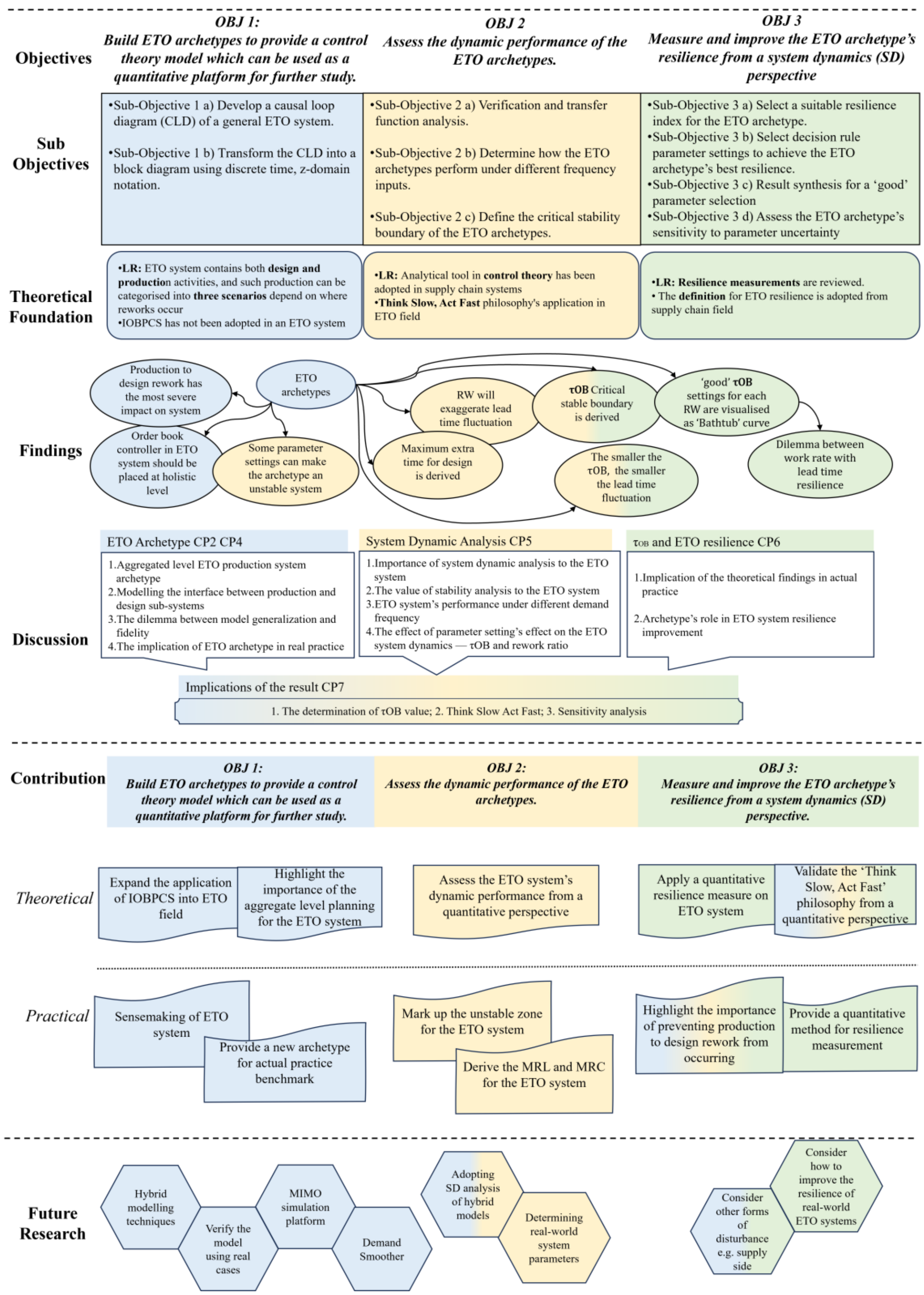

Figure 8.1 Summary of research insights and contribution of this thesis. [Blue represents objective one, yellow represents objective two, and green represents objective three.]

8.1 Insights from the Development of the ETO Archetype

This section summarises the insights gained from the development of the ETO archetype. Findings are presented, followed by a discussion based on these results.

8.1.1 Summary of Findings

ETO archetype

In Chapter 4, three ETO archetypes were developed and each represented one rework scenario. The key elements and the main structure of the archetype were collected and developed based on previous literature(Lee et al. 2005b; Gosling and Naim 2009). The archetype developed in this research can represent the integrated design and production process of the general ETO system with the consideration of the rework. These fill the gap in the ETO aggregated level planning research by providing three ETO archetypes which represent three basic rework scenarios of an ETO system.

Production-to-design rework is most harmful

Among the developed archetypes, production-to-design rework (ETOAR#PTD) is identified as the most detrimental scenario for an ETO system. ETOAR#PTD occurs when design defects or changes are identified or made during the production stage, thereby necessitating additional effort from both the design and production teams. This scenario has two major effects.

First, it requires additional work from both subsystems, as depicted in Table 7.10. Moreover, in actual practice, to complete these rectifications, extra materials and labour are needed, inevitably leading to increased budget and time requirements.

Second, ETOAR#PTD rework can significantly extend the lead time for the ETO system, as illustrated in Table 5.13, and this results in an increase in the MRL. This issue not only impacts the lead time performance of ETO projects but also complicates the estimation of lead times during the planning stage.

The position of the order book controller

During the model development period, one of the difficulties is to determine the position of the order-book controller of the ETO archetype. The order book controller represents the capacity decision rules of the ETO company; in turn, different positions of the order book controller impacts where decisions are made and who makes them. In this section, a set of simulations are conducted to examine what type of order book can maintain the system's desired performance even when rework exists.

After the investigation, it was found that irrespective of the type of rework scenario, as long as rework exists, the order book must be placed at the holistic system level to maintain the performance of the system. In other words, irrespective of which level the rework occurs at, its effect should be taken into consideration by the whole-process manager (production system perspective) or whole-project manager (project perspective). This is because the effect of the rework will not only affect the subsystem where it happens but will also create an indirect effect on the other subsystems and the entire ETO process. It is inadequate to absorb the effect of the rework by only adjusting one subsystem's production; the plan for each subsection needs to be adjusted accordingly.

Thus, based on this finding, three prototypes with holistic order book controller were selected as the ETO archetypes. These three archetypes form an ETO archetype family, which contains three typical rework scenarios in the ETO environment.

8.1.2 Discussion

Aggregate-level ETO system archetype

Compared with the other kinds of production systems (e.g., MTS (Towill 1982), MTO (Wikner et al. 2007), and ATO (Lin et al. 2020), the ETO community has not yet developed a recognised SD archetype to model and benchmark against. At the same time, IOBPCS concepts have been adopted in the other type of supply chains/production systems, which contributes to the understanding of the bullwhip effect and the estimation of capacity (Lin et al. 2017). This thesis focuses on the development of the ETO system archetype and enhances the IOBPCS family by providing an order-based control system in an ETO environment, as presented in Table 1.1. Additionally, research in aggregated level planning for the ETO system is still in its early stages. Most models developed within the ETO environment focus on single project modelling (Jiang & Xi 2019, Barbosa & Azevedo 2019). The archetype developed in this research constructs a model from the aggregated level, thereby providing a new scope for ETO system research.

However, archetype research also has limitations: 1) An archetype only represents the general scenario of a system. Hence, for a specific industry or project, researchers still need to modify and adjust the model to correspond to real-world scenarios (Shafiei et al. 2020). 2) SD as a top-down simulation technique is weak in capturing disaggregate detail (Ding et al. 2016a).

Even though SD archetypes have a few weaknesses, given its advantages, there is still value in developing a general model; the disaggregate modelling weaknesses may be addressed by hybrid modelling, such as agent-based SD and discrete-event SD modelling. In terms of the disadvantages being too general, it is recommended that the development of any kind of model include both practice and theory. The adoption of the ETO archetype in practice must benefit the verification of the archetype and provide an opportunity for the archetype/practice benchmarking.

Modelling the interface between production and design subsystems

During the model development stage, one of the challenges is modelling the interface between the design and production subsystems (Shin et al. 2014). The outputs of these two subsystems differ: the design subsystem produces engineering drawings, while the production subsystem produces the final product or project. This thesis used working units flow to simulate the archetype, thus maintaining system linearity and unified flows.

This approach treats the entire ETO system as an integrated system and enables researchers to understand the system's behaviour from an aggregate perspective.

However, the archetypes based on the flow of working units overlook the coordination between the design and production subsystems, thereby reducing the fidelity of the developed model. To improve model fidelity, it is crucial to find a better way to simulate the interface between subsystems. This simulation should represent the process of handing over blueprints to the production subsystem and how the production system transforms the design into a production plan and initiates production. Improving this aspect would enhance the model's realism by considering the unique activities at the interface between the production and design systems. It would also enable the model to simulate more realistic scenarios, such as stoppages caused by design changes or contract cancellations due to unsatisfactory designs.

The dilemma between model generalisation and fidelity

The archetypes developed in this thesis model a general ETO system, capturing the main features of such systems. The development of these archetypes references previous models developed for construction and shipbuilding (Lee et al. 2006a; Mello et al. 2017). Compared to earlier models, this newly developed model is more generalised based on the definition of the ETO system. However, it lacks the specificity of models developed for particular industries, thereby raising a dilemma: how to balance generalisation with specificity in an ETO system that can be adopted across different industries and produce various products?

To address this dilemma, the aim of the model development must be carefully reviewed and considered. In this thesis, the primary aim is to develop ETO archetypes that provide a foundation for studying the dynamic behaviour of the ETO system. Therefore, the model must be a general one to accurately represent and analyse the dynamic performance of the general ETO system. However, if the aim is to study the system behaviour of a specific industry or to adopt a model for a particular production process, the model must be tailored to the real system to effectively support understanding and provide optimisation.

The model developed in this thesis can serve as a fundamental model for studying ETO systems and can be directly used for general ETO system behaviour studies. For specific system studies, this model can serve as a theoretical benchmark and provide users with general knowledge regarding the ETO system. With the ongoing research in the specific system, the knowledge of this model can provide feedback to ETO archetype studies (Gosling et al. 2015).

The implications of the ETO archetype in real practice

The ETO archetype developed in this research can be used as a tool to link the theoretical outcomes to the practical guidance design; its usage can be summarised from the following perspectives: 1) Providing suggestions on aggregated level capacity management and assisting management with the estimation of the extra capacity to offset the impact of rework (Section 7.1.3) (Zhou et al., 2022). 2) Providing a platform for researchers and practitioners to design and test managerial interventions via simulation (Pena-Mora and Park 2001). 3) Estimating the aggregated level lead time/delivery time based on Little's Law (Wikner et al. 2007) (Section 7.1.3). 4) Building a bridge to promote knowledge exchange between PM and SCM. 5) Providing a solid quantitative foundation for further dynamic studies to gain deeper insight into production dynamic behaviour (Spiegler et al. 2012), which can be referenced in the designing of management policies.

8.2 Insights from the Dynamic Performance Assessment

This section summarises the insights gained from the dynamic performance assessment. Findings are presented, followed by a discussion based on these results.

8.2.1 Summary of Findings

The stability boundary of the system

In section 5.3, the stability boundary for all three archetypes is visualised, noting that the boundary refers to the value selection of τ_{OB}. The observation revealed that for the design and production rework archetypes, with an increase in the rework ratio, a smaller τ_{OB} value increases stability. In contrast, for the delayed design rework scenario, a smaller τ_{OB} value decreases stability. Paying attention to this phenomenon by further comparison and investigation, it was found that the delayed design rework loop smoothens the production system. After the analytical results, for the higher-order system, the PSE method was adopted to determine the stability boundary of the archetypes. Taking the tenth order system as an example, the system's boundary was derived via both Routh–Hurwitz and PSE. The visualisation methods adopted in this analysis and the trend change were found to be the same as the analytical methods used for the low-order system.

This leads to the insight that the stability analysis provides a critical stable condition for all the models and illustrates the changing trend of the stability condition along with rework changes. Considering the τ_{OB} for the sensitivity and order-book adjustment speed, the research outcome provides guidance on how fast the system should react to a demand change to adjust capacity for the design or the production. Simultaneously, for a resilient system, stability is a basic requirement, as an unstable system cannot maintain the system at the required level.

Frequency domain analysis

The exploitation of frequency response analysis provided insights into how the magnitude and phase of the system's output change with demand frequency. It was found that the order book controller's parameter τ_{OB}, rework type, and rework ratio can significantly influence the magnitude of the ETO system's output. Specifically, ETO products' demand cycle is deeply affected by the economic cycle. The cycle lasts approximately 5–10 years (Wigren and Wilhelmsson 2007, Wada et al. 2018), and it's frequency is between 0.01rad/week to 0.02rad/week (628–314 weeks). In this frequency domain, a smaller τ_{OB} results in a smaller lead time magnitude, while a higher rework ratio leads to a higher lead time magnitude.

From the perspective of rework type, ETOAR#PTD is identified as the most unwanted scenario, which is because it not only requires extra work in both design and production systems but it also exaggerate the fluctuations of the work rate of the system, which lead to consequences of ETOAR#PTD that are consistently more severe than those of other rework types.

8.2.2 Discussion

Importance of SD analysis to the ETO system

The dynamic analysis of ETO systems is rather rare in the field of system analysis, which can be attributed to the lack of a unified ETO archetype and the disregard for dynamic performance in the ETO industries. Dynamic analysis of production systems has been widely used in other types of industries, such as ATO and MTO systems (Wikner et al. 2007, Lin et al. 2020). This not only provides a significant understanding of system behaviours, such as the bullwhip and ripple effects, but also enables users to adjust systems to improve their performance and resilience when disturbances occur.

Based on previous experience, the adoption of dynamic analysis in the ETO sector is necessary for two main reasons: cost and time. From a cost perspective, a fluctuating production plan requires frequent changes in system capacity to meet demand, thereby resulting in additional costs for hiring and firing staff and buying or selling machinery. If a company chooses to maintain high capacity to cover fluctuations, it will face wastage from idle machinery. Therefore, a smooth and stable production plan is essential, and these requirements can be met through a dynamic analysis.

From a time perspective, schedule overruns are a common issue in PM. These overruns can be attributed to rework, disturbances, and inadequate productivity. ETO companies face an additional challenge of fluctuating demand. To overcome these challenges and mitigate the effects of rework or disturbances, production companies need a dynamic analysis to understand the mechanisms of their production systems and adjust the promised lead time to customers and decision rules related to capacity. This approach allows for proposing realistic lead times during the planning stage and reduces the likelihood of time overruns.

In this research, two methods are adopted: stability analysis and frequency domain analysis. These analyses investigate the system's dynamic performance from a quantitative perspective. The discussions derived from these analyses are presented below.

Stability analysis—critically stable condition

The outcome of the stability analysis is the identification of the critical stable condition for all archetypes under various rework ratios. This stable condition indicates the smallest τ_{OB} value that ETO archetypes can adopt. If the τ_{OB} value is smaller than this critical condition, the system's output may exhibit non-convergent behaviour.

τ_{OB} represents how the system compensates for the work rate of the whole system, which is related to the production planning decision rules. When τ_{OB} is small, the system's work rate changes rapidly with demand, thereby implying that the system's capacity also changes frequently to keep up with fluctuations in demand and the order book. Conversely, when τ_{OB} is large, the system's capacity does not change as quickly with demand, sacrificing lead time but providing a smoother trend for the system and maintaining the bullwhip effect at a lower level. Having a τ_{OB} value that ensures system stability can prevent dramatic fluctuations in capacity or lead time.

However, there is evidence that when demand is cyclical, the τ_{OB} value can be set to a smaller value to align with market demand changes without causing dramatic fluctuation. This phenomenon occurs because fluctuations in demand offset fluctuations in the outcome, thereby preventing variables from reaching infinite values. Therefore, even when demand patterns exhibit cyclical features, the τ_{OB} value should always be set to meet the stable criteria.

Stability analysis—the PSE method

The methods presented in Chapter 5 can be applied to stability analysis of other discrete high-order systems. The developed archetype is a two-echelon discrete-time model, which implies that the system's order increases with the extent of the pure delay. The initial configuration set the delay for both the design and production systems at 1, thereby yielding in a total system order of 4. However, when analysing system stability, the order of the system dictates the complexity of deriving stability boundaries. When the system's order exceeds 4, the derivation process becomes more challenging and time-consuming. For a system like the ETO archetype, which contains symbolic elements, solving the characteristic equation becomes exceedingly difficult.

To enhance efficiency, two distinct methods were utilised for analysing low and high order systems. For low-order systems, the Routh-Hurwitz criterion was employed, which involves the derivation of the first row of the Routh matrix and calculating conditions that ensure all elements are either all positive or all negative. For high-order systems, methods based on PSE and Routh–Hurwitz simulations were used to cross-verify experimental results, which specified the stable boundaries of the ETO system.

The advantage of adopting the PSE-Routh Hurwitz method is that it avoids solving high-order symbolic characteristic equations and provides visual results that can directly inform system parameter adjustments. However, the accuracy of this method heavily relies on the step length used in the simulation; if the step length is too large, the precision of the results can be significantly compromised.

ETOAR#PTD has a wider selection range for τ_{OB} value.

One surprising finding from the research is that Figure 5.8-5.11 highlights that ETOAR#PTD maintains system stability with a smaller τ_{OB} compared to other scenarios, suggesting that it can achieve faster response times to demand changes while still preserving stability. This observation contrasts with previous research (Flyvbjerg & Gardner, 2023), which indicates that ETOAR#PTD generally introduces more significant challenges than the other rework types. This discrepancy invites a closer look at why ETOAR#PTD appears more advantageous from a dynamic stability perspective.

The explanation lies in the feedback loop that connects the production and design subsystems. This feedback serves as a damping mechanism, slowing down the system's response and thus enhancing stability (Nise, 2015). While ETOAR#PTD may typically be more challenging, the feedback structure between production and design shows that adding feedback loops with proper parameter settings can contribute positively to system stability, and this finding align with the previous research (Naim et al. 2017, Wikner et al. 2007).

In practice, such feedback loops might represent structured communication channels, iterative review processes, or quality checkpoints, which can act as stabilizing forces. Examples include regular cross-functional meetings, real-time data-sharing platforms, or integrated metrics that provide timely insights between production and design teams. This research suggests, these practical feedback mechanisms not only improve efficiency and project performance, but also help mitigate fluctuations (Shen and Ying 2022 ,Lee et al. 2006). Such finding echoes strategies used to reduce the bullwhip effect in supply chains (J. D. Sterman & Dogan, 2015). By implementing feedback channels that facilitate early and effective communication between subsystems, designers can create a more responsive and stable system overall.

The performance of the ETO system under different demand frequencies

The research outcome presented in Chapter 5.2 presents Bode plot figures that demonstrate the system's magnitude under different frequencies. Magnitude is crucial for the ETO system because higher magnitudes indicate greater system fluctuations, which are typically undesirable for production-oriented companies. When the magnitude is high, the company needs to dramatically adjust system capacity by hiring or laying off labour as well as by purchasing or selling machinery. According to the concept of MRC, companies may maintain higher capacity to manage these fluctuations; however, this often results in underutilised machinery for a major proportion of the time. From the MRL perspective, such systems tend to have more fluctuating lead times and a higher likelihood of exceeding planned delivery times. Therefore, this section provides a discussion on the effects of τ_{OB} and rework ratio on the ETO system.

The effect of the parameter settings on the ETO SD—τ_{OB}

In Section 5.2, the effect of τ_{OB} is investigated using Bode plots. In the 0.01–0.02 rad/week frequency domain, the influence of τ_{OB} on different variables of various ETO archetypes is summarised in Table 8.2. It is evident from this table that, from a work rate perspective, τ_{OB} does not have a strong influence on all three archetypes. From the order book perspective, except for the ETOAR#P archetype, a smaller τ_{OB} results in smaller fluctuations. For lead time, a smaller τ_{OB} leads to milder fluctuations across all archetypes.

Table 8.1 τ_{OB} influence on the variables of various ETO archetypes (0.01 to 0.02 rad/week 628314 weeks).

	ETOAR#P	ETOAR#D	ETOAR#PTD
Work Rate	Insignificant	Insignificant	Insignificant
Order book	Insignificant	The smaller the better	The smaller the better
Lead time	The smaller the better	The smaller the better	The smaller the better

From the frequency domain analysis perspective, τ_{OB} should be always set to a smaller value. This adjustment helps ensure that the production system minimises the peak magnitude. While this conclusion conflicts with the result from the stability analysis, such conflicts are attributed to the different demand pattern; the detailed discussion will be presented in Section 8.4.

The effect of parameter settings on the ETO SD—rework ratio

According to the rework Bode plot, the rework ratio has a significant impact on the magnitude ratio of all outputs in all scenarios. It can be concluded that rework has no positive impact on the ETO system, thereby suggesting that previous research has underestimated its effects. Previous research only considers the direct working units and the ripple effect, such as schedule delays, overtime, and worker fatigue (Lyneis and Ford 2007). The outcome from the Bode plot suggests that the system's dynamics must also be considered when mitigating the effects of rework. This implies that, in addition to addressing the immediate consequences of rework, managers should account for how these changes impact the overall system behaviour over time. Moreover, rework can introduce dynamic behaviour into the system; therefore, managers need to consider these dynamics when planning capacity and estimating lead times. To calculate the necessary capacity and possible lead time, MRL and MRC can be adopted. As depicted in Tables 5.5, 5.9, and 5.13, MRC capacity can cover the direct working units created by non-conformance as well as the indirect effects caused by the system's dynamics.

8.3 Insight from the ETO Resilience Measurement

This section summarises the insights gained from the ETO resilience measurement. Findings are presented, followed by a discussion based on these results.

8.3.1 Summary of Findings

'Good' τ_{OB} for different rework ratio, bathtub curve

One of findings from resilience research is the bathtub curve of the work rate resilient τ_{OB} value-changing trend. According to Figures 6.17, 6.18, 6.19, for all three scenarios, the changing trend of the τ_{OB} along with the rework ratio displays a bathtub curve. In other words, in the low rework ratio area, the τ_{OB} value is comparatively high, and when the rework ratio is moderate, the τ_{OB} value is low and flat; in contrast when the rework ratio becomes higher, the τ_{OB} increases and reaches the upper boundary. To develop a better understanding of this, the transient response of the system was investigated to reveal three driving forces that determine the ITAE value. With the increases in the rework ratio, the contributors to the dominant error change. These driving forces are 1) Initial error, 2) settling error, and 3) fluctuation error. This finding is summarised and explained in Tables 6.1 and 6.2.

Lead time and work rate dilemma

A trade-off between work rate and lead time resilience is discovered in this research, and such a trade-off was also found for the MTO system (Wikner et al. 2007). In this study, it was proposed that in a fluctuating market, if the company wants to complete a project within the promised lead time, then the work rate must be as flexible as possible. From another perspective, if the company wants to have a stable, or non-fluctuated work rate to reduce the production cost, then the lead time should be more flexible, which implies that the delivery of the product/project might be delayed. To achieve different resilience goals, there is a different requirement for τ_{OB}.

8.3.2 Discussion

Implication of the theoretical findings in practice

Based on the findings and analysis above, a general analysis was conducted to link the theoretical contribution to the real practice, as presented in Table 6.23. The table summarises how the different period errors affect the ITAE value, and managerial suggestions were proposed for prioritising the variable based on different rework zones.

Further, the research provides suggestions for various rework ratio levels to improve resilience performance with consideration of the trade-off between lead time and work rate. The findings depicted in Figure 6.23 can assist in adjusting the capacity management strategies for products in different stages of the lifecycle. To be specific, the rework will reduce because of the increase in the workers' familiarity with production process (Love et al. 1999) and the production system's increased maturity (Aitken et al. 2003). Thus, management needs to adjust the 'sensitivity' to the changes in the order book to achieve the highest resilience performance of the production system at different stages of the product lifecycle. In addition, products/projects in different industries have different rework ratios because of diverse complexities and operational uncertainties. The findings can be used to improve ETO system resilience, for varying levels of rework, by selecting the 'good' τ_{OB} value (Love et al. 2019) without a change in the structure of the production system.

The archetype's role in the improvement of ETO system resilience

The ETO model developed in this research can provide quantitative suggestions on parameter tuning and help make sense of the dynamic behaviour of the ETO system. However, to comprehensively improve the resilience of the ETO system, a systematic approach involving strategy design, structural adjustment, and crisis management is required (Sáenz & Revilla 2014). It is true that an archetype's insights alone are not sufficient for enhancing the overall system's resilience. Nonetheless, a well-developed archetype can provide a valuable platform for sensemaking and simulation.

From a sensemaking perspective, an archetype offers a clear illustration of the production system structure, thereby enabling management to gain a systematic understanding of the system's fundamental mechanisms. For simulation purposes, the archetype can be used to test newly designed resilience strategies, providing an overview of their impact and identifying potential risks or unexpected negative effects.

In summary, while an archetype alone is not sufficient to improve system resilience, its value is significant. To maximise the utility of the archetype, continuous upgrading and case-by-case adjustments are necessary, which requires effort from both modellers and practitioners.

8.4 Implications

The determination of the τ_{OB} value and its implications

Section 7.1 synthesises the experimental results from previous chapters and illustrates them in Figure 7.1, followed by a recommendation on the τ_{OB} value setting. The recommended τ_{OB} value varies according to the rework ratio and demand frequency, but it should always be greater than 6.25 to maintain system stability. The τ_{OB} value represents the system's compensation to the work rate in each period, which is based on the difference between the actual and the real order book. It reflects how the production plan is formulated for each period and determines the required capacity, represented by MRC. Additionally, based on the τ_{OB} value, the MRL can also be derived and should be referred to when deciding on the promised lead time for a product or project.

Sensitivity analysis

A simulation approach is used for the sensitivity analysis in Section 7.2. By employing this approach, the system's sensitivity-to-design lead time, production lead time, rework ratio, and rework rescheduling time was tested. The insights from the sensitivity analysis can be summarised in the following manner:

1. Regardless of the accuracy of the design or production lead time estimates, the final state for output, delivery rate, and lead time will always stabilise at the designed level.
2. Changes in the subsystem's lead time affect the settling time and peak value of the work rate, thereby implying that variations in subsystem lead times can lead to increases in both the production subsystem's capacity and the overall system's lead time.
3. An increase in the rework ratio provides no benefits to the system and results in a more dynamic and unstable system.
4. The ETOAR#PTD type of rework is the most destructive, as it increases the workload for both the design and production subsystems.

The sensitivity analysis reveals that subsystem lead time negatively influences both the overall system's lead time and capacity. Therefore, maintaining subsystem lead times at the designed level is crucial. Another important insight is that ETOAR#PTD should always be avoided. One strategy to mitigate this is to adopt a 'Think Slow, Act Fast' approach in production. Consequently, Section 7.3 conducts several experiments on this strategy and the discussion is presented below.

Think Slow, Act Fast

The 'Think Slow, Act Fast' philosophy provides a structured lens to examine the relationship between the design and production phases in complex systems. This study revealed nuanced impacts of allocating additional design time, showing that design changes or errors detected during the production stage are far more detrimental than allocating additional time for design inspections or waiting for customers to finalize the design. These findings challenge the intuitive simplicity often associated with this concept, emphasizing the critical importance of thorough preparation in the design phase.

Section 7.3 delves into the 'Think Slow, Act Fast' philosophy, applying it within a SD framework to the ETO system. Through the development and analysis of two distinct SD models, ETOAR#D+X and ETOAR#PTD, the impact of additional design time (denoted as '+X') was examined on the ETO system's lead time. The findings reveal a direct correlation between the rework ratio and the feasibility of allocating extra design time. Notably, the ETOAR#D+X model demonstrates a decrease in the bullwhip effect within the system, contrasting with the ETOAR#PTD scenario in which rework amplifies this effect. This distinction is critical, as it emphasises the benefit of addressing design issues before production initiation.

Aligning with the principles outlined in the book entitled 'How Big Things Get Done' (Flyvbjerg and Gardner 2023), the study echoes the segmentation of PM into the 'Planning' and 'Delivery' phases. This segmentation resonates with the 'Design System' and 'Production System' in an ETO context, thereby reinforcing the concept that thorough planning (or design for production) is crucial for efficient delivery (or production). The given research supports the book's advocacy for comprehensive planning, emphasising the importance of cross-departmental collaboration and early-stage prototyping and modelling.

Practically, the findings advocate for the implementation of a design inspection and a 'design freeze' window, which has been proved effective in reducing the uncertainty in the production system in previous research (Ford and Sobek 2005). This approach not only aids in minimising the transfer of defects to the production phase but also contributes to reducing fluctuations in the production system's work rate and capacity requirements. By comparing the ETOAR#D+X and ETOAR#PTD models across various rework ratios (RW) and extra time allocations (X), it is consistently observed that the former yield more favourable outcomes in terms of the system's lead time. Additionally, allocating enhanced resources to the design department and empowering the inspection and design team leaders with greater decision-making authority can further mitigate risks associated with design defects.

8.5 Summary

In summary, this research developed a ETO archetype family by referencing the IOBPCS archetype (Towill 1982) and the order book-based control policy from the MTO archetype (which is also known as the variable order book based production control system (VOBBPCS)) (Wikner et al. 2007). The ETO archetype family developed in this research completes the production system archetype family, as shown in the Table 1.1, which indicates that dynamic analysis can be applied in ETO field. Chapter 5 illustrates the dynamic analysis result of the ETO archetype family, which includes stability boundary and Bode plot of the archetype. The result is further used to derive the ETO system's MRL and MRC (Lin et al. 2020). Thereafter, the archetype family is used for the system's resilience measure and improvement, and the results leads to the derivation of the 'good' τ_{OB} for different rework ratio. This method has been adapted from the resilience analysis reference the method developed by Spiegler et al. (2012) and extends the original method into the high-order discrete system field. In Chapter 7, a synthesised analysis on the order book controller's parameter is conducted, which provides suggestions on the τ_{OB} value setting in a real scenario. Finally, the ETO archetype family is adopted in validating the 'Think Slow, Act Fast' philosophy (Flyvbjerg and Gardner 2023); this archetype also contributes to deriving the best ‘Thinking’ time for the ETO system.

In the next chapter, the contribution of each research objective is discussed. Moreover, based on the discussion and insights from this chapter, the future research agenda is presented.

Chapter 9 Conclusion and Future Research Agenda

This chapter retrospectively relates the research with the initial objectives. It concludes by detailing the theoretical and practical contributions of the research. The theoretical contributions are outlined for all three main objectives. For each main objective, there are several sub-objectives, and an explanation is provided for how each sub-objective contributes to the main objectives and overall contributions. From a practical perspective, the main contributions are identified for each objective. Additionally, this chapter outlines the limitations encountered during the study and proposes a future research agenda. The main contribution points and future research agenda are depicted in Figure 8.1.

9.1 Theoretical Contributions

This research provides three main contributions that align with the overarching aim of enhancing the understanding and management of ETO dynamics and resilience. First, it introduces an archetype framework that captures the key characteristics and feedback loops in ETO systems, offering a foundational tool for system analysis (9.1.1). Second, the research presents a dynamic analysis of interactions within these systems, revealing critical trade-offs between lead time and work rate resilience (9.1.2). Finally, it focuses on resilience, providing solutions for resilience improvement through better parameter settings (9.1.3). Together, these contributions advance both the theoretical understanding of ETO systems and practical approaches for improving operational performance. The theoretical contributions from each research objective are presented in Section 9.1.

9.1.1 The Contribution from Addressing Research Objective 1

Objective 1: Build ETO archetypes to provide a CT **model which can be used as a quantitative platform for further research.**

The main contribution can be summarised into two aspects: (1) Contribution 1—expand the application of IOBPCS into the ETO field. (2) Contribution 2—highlight the importance of aggregate-level planning for an ETO system. In the following paragraphs, the details of the contributions are provided.

Contribution 1: Expanding the application of IOBPCS into ETO field.

The IOBPCS archetype has been widely adopted in MTS, ATO, and MTO systems. Its order book and feedback loops simulate decision-making processes within production systems, thereby enabling users to reproduce the dynamic behaviour of these systems at an aggregate level. This approach explains the mechanisms underlying the bullwhip effect from a systemic and quantitative perspective and providing dynamic control solutions for management (Ponte et al. 2017, Disney et al. 2004). However, the IOBPCS has not yet been applied to ETO systems, where dynamic behaviour is seldom investigated. Thus, this research aimed to build ETO archetypes to provide a CT model which can be used as a quantitative platform for further research.

In this research, an ETO archetype family is developed which encompasses three archetypes that represent different rework scenarios within an ETO system. The primary structure of these archetypes includes two subsystems: design and production. These correspond to the major activities in the ETO system—design activities tailored to customer requirements and production activities that actualise these designs into products or projects. An order book controller at the holistic level of the archetype ensures system performance stabilises at the desired level, even with rework.

The newly developed archetype references the modelling techniques and control loops of the IOBPCS archetype, thereby providing a quantitative platform for a dynamic analysis of ETO systems. Unlike the IOBPCS archetype, the ETO archetype family incorporates rework, thereby offering insights into how this unique activity affects dynamic of the system. Additionally, the new archetype family simulates working units as a flow rather than as a quantity of products, thereby making the model applicable to production-oriented systems, such as ETO or MTO.

Furthermore, due to similarities in modelling techniques, the analytical methods used for the IOBPCS archetype, such as stability and frequency domain analysis, can be easily applied to the ETO archetype family. This expands the application areas for these analytical methods.

In summary, this research extends the application of the IOBPCS archetype to the ETO field, thereby completing the IOBPCS family by introducing an ETO archetype family. This enables a quantitative analysis of ETO systems. The introduction of elements like rework and working units presents new questions for system analysis, but also allows methods and knowledge developed for the IOBPCS model to be applied to new topics.

Contribution 2: Highlight the importance of aggregate-level planning for an ETO system.

According to the previous literature (Cannas and Gosling 2021, Zhou et al. 2023), there are not many quantitative studies in the ETO field , with even fewer focus on the model-based aggregated level planning. In the PM field, there are a few studies that focus on model development for project execution (Lee et al. 2006c, Han et al. 2013). The models developed in this research are single project/product focused and neglect aggregated level planning. For an ETO system, an aggregated level planning system is necessary because an ETO system usually needs to be able to handle scenarios wherein several ETO products are being produced simultaneously. This implies that when management makes decisions regarding capacity planning or lead time estimation, they need to take all ongoing projects/productions into consideration. Therefore, an aggregate level planning system is necessary for the ETO system.

The archetype family developed in this thesis models an ETO system on an aggregated level with the consideration of rework creating extra working load. The input of the system is the total amount of working units in a certain timeframe, which is weak in the model. All the unfinished works will be 'stored' in the order book, and the order book controller will adjust the working rate of the whole system to guarantee that production can be finished on time. Simultaneously, rework is also considered in this model; the rework loop simulates the rework's effect on the system. The effect of the rework not only includes the direct working units created by the rework but also the extra work caused by the errors made during the reworking.

In summary, the archetype family developed in this research simulate an ETO system on an aggregated level, with consideration of rework and its side effects, which can reflect the production system's behaviours. Combining this with the MRL/MRC concept makes this family suitable for use in capacity management. By considering the dynamic behaviour of the system, the capacity estimation can be more accurate and the waste can be reduced.

How sub-objectives contribute to the main objective:

The initial modelling step aims to: Sub-objective 1 a)—develop a CLD of a general ETO system. The contribution of this to answering research objective 1a (OBJ 1a) is significant, as it distils crucial elements and structures for general ETO systems, and the models developed depict three fundamental scenarios for an ETO system. However, since the CLD provides limited quantitative evidence and insight, the position of the order book controller cannot be definitively determined at this stage of research. Sub-objective 1 b)—Transform the CLD into a block diagram using discrete time, z-domain notation. The sub-objective aims to transform the model into a block-diagram model, thereby allowing for the application of more quantitative tools to the developed model.

Based on the developed CLD, the model was transformed into a block-diagram format, and several simulations were conducted to determine where the order book controller should be placed. It was found that for production-oriented systems, the order book controller is necessary to regulate the system's output and only a holistic controller can maintain the system at the desired performance level in the presence of rework. Local order book controllers fail to sustain overall system output or lead time in the long-term. Furthermore, given the challenges associated with non-linearity calculations, Little's Law for lead time was linearised. This adaptation contributed to the model by enabling the derivation of a linear transfer function for lead time, thereby enabling control engineering tools to be effectively applied to the ETO system. The outcome subjective 1 b) is an ETO archetype family based on the linearised CT, which enables the subsequent dynamic analysis to be utilised for an ETO system.

9.1.2 The Contribution from Addressing Research Objective 2

Objective 2: Assess the dynamic performance of the ETO archetypes.

Contribution 1: Assess the ETO system's dynamic performance from a quantitative perspective.

Due to the absence of the ETO archetype family, the dynamic behaviour of the ETO system remains unrevealed. The importance of the dynamic behaviour study has not been well recognised in the ETO field, but its manifestation has been observed. In a typical ETO field, such as construction and shipbuilding industries, time and budget overruns are a common problem. According to Lyneis and Ford (2007), apart from external factors, the ripple effect and knock-on effect caused by rework may lead to cost and time overruns. Simultaneously, this aspect is also supported by Flyvbjerg and Gardner (2023), who indicated that for a complex system, a tiny change—such as a defect in design—can trigger a chain effect which finally leads to a huge time or cost overrun. The chain effect, ripple effect, and knock-on effect depicts how the system reacts to the change, and the process of reaction constitutes the dynamic behaviour of the system. Therefore, in order to understand and improve the dynamic performance of the system as well as to reduce the time and budget overruns, the system's dynamic performance analysis is necessary.

Chapter 5 provides a holistic analysis of stability analysis and frequency domain analysis. The stability analysis reveals a dangerous parameter setting, which may lead to an unstable system. For the ETO archetypes, an unstable parameter setting may lead to a non-convergent fluctuation, and the fluctuation will result in a fluctuated production capacity. This issue will finally lead to increases in cost due to the frequent buying and selling of machines or hiring and firing in the labour force.

The frequency domain analysis investigates the system's performance under a variety of demand frequencies. This research focuses on magnitude of the output and the phase difference between output with input. The research outcome given in section 5.2 sheds light on how the parameters affect the system's behaviour and provides recommendations on parameter settings.

In conclusion, in Chapter 5, several dynamic performance investigations were conducted based on the transfer function derived in Section 5.1. These analyses provided a profound understanding of the archetype's properties and enhanced knowledge of how various parameters impact the system's performance. In the following sections, the contribution of each sub-objectives is presented.

How sub-objectives contribute to the main objective.

Sub-Objective 2 a) is the verification and transfer function analysis serving as a critical step for ensuring the reliability of the archetype. An incorrect archetype or one that contains even trivial errors could lead to misleading experimental results, which is particularly problematic for a model intended for further investigation and research. In Chapter 5, the verification involved simulations on different software platforms and simulation on transfer functions. Only if the results are all the same, further analysis can be conducted.

After the verification, the research focuses on sub-objective 2 b)—determine how the ETO archetypes perform under different frequency inputs. For th**e** frequency domain analysis, Bode plots were utilised to examine the system's magnitude and phase delay under varying demand frequencies. These plots provide insights into how rework and τ_{OB} affect the system's magnitude and phase delay under various demand frequencies. The contribution of this sub-objective is that it provides recommendations on parameter settings from a frequency domain analysis perspective and helps in the derivation of the MRC/MRL for the ETO system.

Sub-objective 2 c) aims to define the critical stability boundary of the ETO archetypes**.** The contributions of this sub-research question are significant and can be summarised in the following points:

Hybrid method for stability analysis: The hybrid Routh-Hurwitz-PSE method provides a robust approach for the stability analysis of discrete high-order time systems with symbolic elements. Given that the order of a discrete-time system is influenced by delay, systems often exceed the fourth order, which complicates solving the characteristic equations with symbols. The hybrid method combines the benefits of analytical methods with simulation techniques. A key advantage of this method is the adjustable accuracy, which can be fine-tuned by setting the length of the simulation step.

Critical stability boundary: The derived critical stability boundary illustrates how the rework ratio impacts the system's stability. The findings also indicate that the duration of delay within the system negatively affects stability, thereby highlighting areas that require attention for improving system design and operation.

These insights contribute to a deeper understanding of the dynamic behaviour of higher-order systems and provide practical guidelines for managing the inherent complexities associated with delays and rework processes.

9.1.3 The Contribution from Addressing Research Objective 3

Objective 3: Measure and improve the ETO archetype's resilience from a SD perspective.

Contribution 1: Application of a quantitative resilience measure on an ETO system

The resilience of the ETO system remains in its initial stages of study and is particularly evident after the increased interest in the resilience of production systems post-COVID-19. Despite this growing interest, the unique combination of production system and PM aspects within ETO systems has not been extensively explored before. Resilience is particularly vital for an ETO system due to its complex network and structure, coupled with higher levels of uncertainty compared to other production system types. Therefore, the third objective aims to measure and improve the ETO archetype's resilience from an SD perspective.

In this research, resilience measurements from both the production system and PM fields were reviewed. A quantitative measurement applicable to the ETO archetypes developed in this thesis was selected. Multiple experiments were conducted to visualise changes in resilience in response to parameter changes within the system. Based on the visualised figures, the ‘good’ τ_{OB} is picked up for each rework ratio, and the dilemma between capacity and lead time resilience is observed and analysed. The finding and recommendations are presented in section 6.3. The work rate’s ‘good’ τ_{OB} demonstrates a ‘bathtub’-like curve along with the increase in rework, while the lead time’s ‘good’ τ_{OB} is maintained at a level between 20 and 25. To overcome this different requirement for τ_{OB}, this research investigates the transient responses of both lead time and work rate, with its own ‘good’ τ_{OB} value. The main ITAE error contributors are identified and summarised, based on which the recommended τ_{OB} value is derived and illustrated in Figure 6.20.

However, according to the research outcome of objective 2, the stability analysis and Bode plot analysis also have their own requirements for a ‘good’ τ_{OB}. Therefore, a synthesised analysis is conducted. To select the most appropriate τ_{OB} which can maintain the system’s stability, it is important to improve the system’s performance under different demand patterns and create a system with high resilience. The synthesised analysis provides a comprehensive recommendation on τ_{OB} from three perspectives, which integrated all the findings from this thesis.

In summary, this objective contributes to the body of knowledge by adapting ITAE to the ETO archetype family and summarising the ‘good’ τ_{OB} for each rework ratio, which can improve the system’s performance in general.

Contribution 2: Validate the 'Think Slow, Act Fast' philosophy from a quantitative perspective.

'Think Slow, Act Fast' is a philosophy that is widely accepted in the PM field. 'Think Slow' refers to the scenario wherein management spend more time and effort in making a good and detailed design/plan for project and occasionally it also implies that the PM reserves a longer window for the customer to freeze their design. 'Act Fast' can be understood from two perspectives: one is that the production or the construction should be finished as soon as possible to prevent any uncertainty; the other is that 'Think Slow' can result in a shorter overall project time. This philosophy demonstrates its adaptability in the ETO field of improving the overall performance of the system, including resilience. Therefore, this research attempts to validate this philosophy from a quantitative perspective and to adopt it in an ETO system.

The 'Think Slow, Act Fast' philosophy is investigated based on the developed archetype and the measurements adopted in the resilience research, and the findings suggest that such a philosophy can be used in an ETO environment, and the maximum time that can be allocated to the 'thinking' is derived.

The contribution of this study is that it quantifies the benefit of 'Think Slow', and manifests how 'Fast' the 'Act' can be. In turn, this proves the accuracy of this philosophy from an SD perspective and validates the effectiveness of this philosophy in the ETO field.

How sub-objectives contribute to the main objective.

The following paragraphs illustrate how sub-objectives contribute to the main objective. To measure the resilience of the system, a quantitative measurement is necessary; therefore, sub-objective 3 a) aimed to select a suitable resilience index for the ETO archetype. Table 6.1 summarises the result from a literature review, which categorises resilience measurements into three groups, with each group representing a phase of the resilience process. The ITAE was selected as the primary resilience index for this research because it can measure the system's resilience from a whole-process perspective.

Based on the selected index, sub-objective 3 b) focuses on selecting decision rule parameter settings to achieve the ETO archetype's best resilience. This study utilised simulation to assess the ITAE values across various combinations of rework ratios and τ_{OB} (order book time constant), thereby selecting the combination that yielded the lowest ITAE. For each archetype, two sets of parameter settings were identified to achieve the highest system resilience—one set for delivery rate resilience and another for lead time resilience. A comparison of these sets revealed differing requirements for each type of resilience, thereby highlighting a trade-off between them.

To address the identified trade-off, an in-depth analysis of the system's transient responses was conducted, culminating in the development of Figure 6.20. This figure provides recommended strategies for managing systems with different rework ratios, offering a practical approach to navigating the complexities associated with balancing resilience factors.

However, from a resilience perspective, the ‘good’ τ_{OB} is derived according to the stability and frequency domain analyses, both of which also have a requirement for τ_{OB}. Therefore, sub-objective 3 c)—result synthesis on ‘good’ τ_{OB} research—is designed to synthesise all result relevant to τ_{OB}. Chapter 7.1 synthesises the results of the stability analysis, Bode plot analysis, and resilience analysis in Figure 7.1. Based on this figure, three guidelines are provided for selecting the value of τ_{OB}. The synthesised results summarise the findings from previous analyses organically and provide insights into determining capacity at an aggregated level while considering rework and demand fluctuations. The contribution of this objective is its attempt to relate theoretical results with practical recommendations, considering all previous findings. It provides an overview of how to comprehensively enhance the dynamic performance of the production system.

Finally, sub-objective 3 d) is designed to assess the ETO archetype’s sensitivity to parameter uncertainty. The sensitivity analysis conducted in Chapter 7.2 and investigates how sensitive the systems are to changes in parameters and delays. The contributions of this analysis can be summarised in the following manner:

Impact of prolonged delay in subsystems: An increase in the delay within subsystems leads to higher peaks in the transient responses and a longer time required for the system to stabilise at a new normal state. This finding enhances the understanding of how delays in subsystems influence the overall system's output. By identifying the effects of delay, strategies can be developed to mitigate these impacts, potentially improving system stability and responsiveness.

Sensitivity of the bullwhip ratio to delay: The bullwhip ratio is highly sensitive to the delay changes within the subsystems. The trend observed is either an increase or a fluctuating increase in the bullwhip ratio, thereby indicating that longer delays correlate with higher bullwhip ratios. This insight is significant as it contributes to the understanding of how subsystem delays affect the system's bullwhip ratio. It addresses a gap in the research on the bullwhip effect within the ETO system field and provides a foundation for future strategies to reduce inefficiencies caused by delay-induced variability.

9.1.4 Summary of Theoretical Contribution

This research contributes to the existing body of knowledge, first, by providing an ETO archetype family which is composed of three basic rework scenarios that compensate the application of SD in the production systems family. Second, by adopting dynamic analysis techniques for the developed archetypes, it provides readers with a better understanding to the ETO system. Finally, the research regarding the ETO system resilience fills the blank in this field and provides a quantitative method to improve the system's performance from the resilience perspective.

9.2 Contribution to Practice

The practical contributions from each research objective are presented in Section 9.2. The practical implications and recommendations presented in this research are grounded in the theoretical model developed to explore the dynamics of ETO systems. While the model has not been validated through real-world cases or interviews, it is built on well-established principles of SD and supported by insights from the existing literature. This provides a solid foundation for identifying key system behaviours, such as rework impact, capacity fluctuations, and lead time resilience.

These recommendations serve as a conceptual framework to guide industry practitioners in better understanding and addressing operational challenges. It is acknowledged that the absence of empirical validation represents a limitation. Future research could involve validating the model through real-world data, case studies, or industry collaborations to further enhance its applicability and refine the recommendations. Despite this limitation, the theoretical contributions of this research provide valuable tools for sensemaking and system study in the context of ETO systems.

9.2.1 Practical Implications from Addressing Research Objective 1

For industry practitioners, this research offers three ETO archetypes that can facilitate a better understanding of the system and enable benchmarking with actual practices.

Enable benchmarking' refers to providing industry practitioners with a framework to compare their existing practices against the modelled ETO archetypes. By using these archetypes, practitioners can identify gaps in their current systems, evaluate performance metrics such as lead time and work rate resilience, and assess how closely their operations align with the theoretical benchmarks provided by the archetypes (Lin et al. 2020). This comparison allows them to pinpoint areas for improvement to enhance their operational efficiency and resilience. The detailed contributions of this research are detailed below:

Sensemaking of an ETO system:

The models developed in this research serve as tools for sensemaking and understanding the dynamics of ETO systems. They abstract ETO activities and simplify them using carefully defined assumptions to focus on key interactions and behaviours. These assumptions, such as idealized lead times, rework mechanisms, and capacity constraints, make the models computationally feasible and conceptually clear. This simplification enables the framework to effectively explain phenomena observed in practice, such as capacity fluctuations, bullwhip effects, and cost or time overruns. Despite the abstraction, the models provide valuable insights into SD and serve as a solid foundation for further development and integration with real-world complexities.

Highlight the importance of a holistic order book controller:

The findings from Chapter 4 suggest that the order book controller is crucial in maintaining system performance, even in the presence of rework. This research indicates that the effects of rework in the production system should be considered at a holistic system level, thus requiring adjustments in both upstream and downstream processes to fully mitigate the impacts of rework.

Provide a simulation platform:

In practical scenarios, experimenting with policies or strategies for real projects is often unfeasible due to the high demands on labour and capital as well as the risks associated with potential failures. However, strategy design and testing are essential for managers to ensure the effectiveness of their approaches. In this context, the archetype can function as a strategic experiment platform. Testing strategies through simulation is typically swift and cost-effective and allows managers to gain a comprehensive understanding of the production system without the high risks associated with direct implementation.

These contributions emphasise the practical utility of the ETO archetypes developed in this research, providing industry practitioners with valuable tools to enhance decision-making and strategic planning for ETO systems.

A Decision-Making Framework for Capacity and Production Planning

The SD based archetype developed in this research provides a foundation for a decision-making framework that supports capacity and production planning in ETO systems.

SD-based engines have been successfully deployed in production planning by connecting SD models with other tools and software to improve decision-making (e.g., (Lee et al. 2005a; Lee et al. 2006a; Han et al. 2013)). These engines facilitate resource allocation and scheduling by integrating real-time data and predictions, demonstrating the practicality of SD models in complex environments. Similarly, the SD model presented here has the potential to serve as a decision-making engine for ETO systems, enabling organizations to incorporate dynamic insights into their production planning processes.

This archetype's ability to estimate work rates and working packages can enhance Sales and operations planning (S&OP) processes by providing a clear understanding of capacity bottlenecks and dynamic trade-offs (Furlan de Assis et al. 2023). Additionally, its outputs can feed into Integrated-Material Requirements Planning systems (Velasco Acosta et al. 2020), enabling more precise material procurement and inventory planning. By bridging aggregate-level planning with operational decision-making.

The archetypes can support: 1. Dynamic adjustment of system capacity and associated resources, accounting for fluctuations and variability within the system. 2. Enhanced integration between the design and production phases, minimizing lead time uncertainty. The success of SD-based engines in construction underscores the feasibility of integrating this model with other tools and software to create a comprehensive planning system. By adapting such approaches to ETO environments, this research lays the groundwork for practical applications in production planning, advancing both the theoretical understanding and operational efficiency of ETO systems.

9.2.2 Practical Implications from Addressing Research Objective 2

The response RQ 2 focuses on the dynamic performance of the ETO archetypes. The contributions of this research are significant and can be summarised into the following points:

Mark up the unstable zone for the ETO system

The stability analysis offers practical insights by providing managers with a ‘stability map’. This map indicates potentially hazardous parameter settings across various systems characterised by different delays and rework ratios. Such a tool is invaluable for managers, as it helps in avoiding unstable zones that could lead to operational inefficiencies and increased costs due to fluctuations. This proactive approach to managing system parameters ensures smoother operations and can significantly reduce financial losses attributed to system instability.

Derive the MRL and MRC for the ETO system

Insights from the Bode plot are instrumental in determining the MRC required for a production system. Given that demand patterns are often cyclical, managers can use a Bode plot to accurately estimate this capacity threshold, thereby preventing potential capacity shortages. Additionally, when the frequency of demand changes is known, managers can fine-tune the system's responsiveness by adjusting the τ_{OB} (order book time constant). This adjustment helps in reducing the magnitude of fluctuations, which in turn minimises the costs associated with frequent capacity adjustments.

9.2.3 Practical Implications from Addressing Research Objective 3

The answer to RQ 3 significantly enhances practical applications by focusing on resilience improvement in an ETO system. The contributions can be outlined as below:

Provide a quantitative method for resilience measurement and improvement:

In Chapter 6, the ITAE is adopted to measure the resilience of the ETO system. This index allows managers to assess the system's resilience quantitatively and provides a straightforward method to investigate the influence of system parameters on resilience performance. Additionally, a resilience optimisation method using the PSE simulation is introduced. This approach illustrates how selected parameters affect the system's resilience performance, aiding managers in selecting optimal parameter settings. One of the key advantages of this method is its simplicity—it does not require complex calculations and this makes it suitable for higher-order systems typically encountered in real-world applications.

Highlight the importance of preventing production to design rework from happening:

The research conducted in Chapter 7.3 provides quantitative backing for the strategy termed ‘Think Slow, Act Fast’. This strategy allows decision-makers to evaluate the optimal ‘thinking’ time required to maximise lead time reductions from a holistic system perspective. By quantifying the effects of decision-making speed on system performance, managers can more effectively balance deliberation and action, thereby leading to more efficient and responsive operations.

Overall, the outcome from research objective 2 enriches the existing body of knowledge by illustrating how dynamic performance metrics—such as stability boundaries, Bode plots, and strategic response times—can be practically applied to enhance the management and operation of ETO systems. These insights not only improve theoretical understanding but also offer tangible, actionable strategies that can be implemented in real-world ETO environments to optimise performance and reduce risks.

9.3 Limitations and Future Research Agenda of Model Development

The limitations of the ETO archetype developed in this thesis are summarized in Section 9.3.1, and the future research agenda is provided in Section 9.3.2.

9.3.1 Limitations

The developed archetype has notable limitations. The first limitation stems from the assumption that the system is linear. To maintain this assumption, the model sacrifices some fidelity by standardising the flow into working units and assuming that all demands can be quantified using these units. While this approach enables working units to represent working packages in practice, it overlooks unique working packages that may require specialised technicians.

The second limitation of this archetype is that it describes the process of a traditional linear supply chain. It fails to accurately represent modern ETO companies that base their production planning on frontline foremen, known as the foreman planning system. In such systems, foremen are tasked with planning the work for their teams, which are typically composed of multi-certified workers with diverse skills.

The third limitation is that the archetype focuses solely on working units and neglects the coordination between working units and materials. This oversight occurs because the scope of this research is confined to studying single flow systems. Including material flows would complicate the investigation of working flow behaviours in the ETO supply chain, potentially detracting from the primary focus of this study.

9.3.2 Future Research Agenda

Based on the limitations discussed in Chapter 4, further research could focus on following key areas:

Hybrid modelling

To further improve the applicability and fidelity of the system, future research could integrate multiple techniques to model the system across different layers. A hybrid model can better capture the features of the production system and provide a more holistic platform for decision-making. The SD model developed in this research can serve as the core engine for aggregate-level planning. Other methods, such as discrete-event modelling or agent-based modelling, can be used for lower-level modelling. This hybrid modelling concept has already been adopted in the construction field and was found to significantly enhance the effectiveness of ETO systems (Lee et al. 2006a).

Verify the model through actual case studies

The archetype developed in this research has not been verified by actual case studies, which raises concerns regarding model fidelity. Future research could apply the developed archetype in real-world scenarios to verify its accuracy. Additionally, adopting archetypes provides an opportunity to compare theoretical models with actual production systems, thereby offering a vital opportunity for model enhancement and validation.

MIMO simulation platform

Future research could enhance model fidelity by incorporating material flow into the system, thereby improving realism by integrating the coordination between work and material flows. While this upgrade enhances the model's accuracy, it also increases the difficulty and complexity of system analysis. Adopting a multi-input multi output (MIMO) concept would be essential for effectively studying such systems. The outcomes of this research could significantly benefit inventory and production management in an ETO environment.

Demand smoother

Another future research agenda could incorporate a demand smoother function into the developed archetypes. In this thesis, the archetypes assume that 'demand' directly becomes the 'order book'. However, in reality, when customers place orders, their demand is broken down into a production plan, which corresponds to the demand smoothing process. Future research should integrate the demand smoother into the model archetype to enhance understanding of its influence on the planning process of an ETO system.

9.4 Limitation and Future Research Agendas for Dynamic Analysis

The limitations of the dynamic analysis of ETO archetype in this thesis are summarized in Section 9.4.1, and the future research agenda is provided in Section 9.4.2.

9.4.1 Limitations

The limitations of the dynamic analysis can be summarised into two main aspects: the applicability of the dynamic analysis tools, and the challenge of linking theoretical outcomes from dynamic analysis to real-world practice**.**

First, the methods developed and used in this thesis are specifically designed for SD based models. However, dynamic analysis tools are lacking for other types of models, particularly for hybrid production system models.

Second, the research outcomes of this thesis are theoretically driven, thereby creating a gap between these results and their practical application. Bridging this gap requires further study to adapt and validate the theoretical findings in real-world settings.

9.4.2 Future research agendas

Based on these limitations, two future research agendas are proposed:

Adopting SD analysis for hybrid models

Further research could focus on developing more efficient analytical methods for hybrid models, providing system modellers with vital tools for system analysis. This includes stability analysis tools for hybrid, high-order systems to derive stable conditions for hybrid models. Additionally, frequency domain analysis should be able to assess the dynamic performance of complex hybrid models under various demand frequencies. These analyses are critical for fully utilising the developed model. At the current stage, most hybrid models primarily serve as simulation tools and their dynamic performance has not been fully investigated.

Determine the real-world parameter

The dynamic analysis in this thesis focuses on the rework ratio and τ_{OB} value. The rework ratio corresponds to the proportion of non-conforming working units among the total working units. However, the τ_{OB} value has different meanings in various production systems, thereby leading to the issue that the research outcomes regarding τ_{OB} are difficult to apply in real-world cases. In future research, to utilise the findings from the dynamic analysis effectively, more work needs to be done to link the τ_{OB} concept with the planning decisions made in production systems.

9.5 Limitations and Future Research Agenda for Resilience

The limitations of the resilience study in this thesis are summarized in Section 9.5.1, and the future research agenda is provided in Section 9.5.2.

9.5.1 Limitations

Resilience improvement in practice

To test the production system's resilience, this research assumes when disturbances happen, the management allow the system to recover independently without any external intervention. However, in real practice, when a crisis occurs, the company initiates emergency actions to address the disturbance. However, in this research, it is assumed that no intervention occurs, and recovery depends solely on the system's order book controller. Therefore, adapting theoretical outcomes to practical scenarios is challenging. Although Figure 6.20 attempts to link theoretical results with practical strategies, it is still in its initial stage and lacks practical benchmarks.

To improve the resilience of a real production system, a systematically designed reaction plan is needed, which contains different strategies for specific disturbances. However, such a plan is not investigated in this research. The resilience improvement strategies proposed in this research are based on the τ_{OB} concept, a core parameter in this archetype. In actual practice, improving the resilience of the production system requires a systematic procedure or mechanism. This research does not investigate such a mechanism and, thus, the adoption of τ_{OB} remains underexplored.

Considering disturbances other than those on the supply side

The ETO system operates within a complex and uncertain environment. To explore the resilience of the ETO system, it is crucial to assess how various types of disturbances impact overall performance. However, testing step change input offers limited insight into system resilience. The impact of process disturbances remains unexplored. Additionally, during a crisis, the production system may be simultaneously affected by multiple disturbances. The coupling effect of these disturbances on the production system is also yet to be discovered.

9.5.2 Future Research Agenda

Consider other types of disturbances

Further research could focus on simulating other types of disturbances, such as production time changes, productivity losses, and order book losses. Simulating these disturbances can provide a better understanding of how the system reacts and can be beneficial for resilience improvements. To achieve this, and to conduct the simulation via the SD method, the MIMO concept could be introduced in production system modelling.

In this approach, disturbances to the production system can be simulated as additional inputs while outputs could include metrics such as delivery rate and lead time. The benefit of utilising this concept is that it not only provides a method to simulate process disturbances but also offers a platform for analysing disturbance coupling. This enables the model to investigate system behaviour when multiple disturbances occur simultaneously. This research direction offers a methodology to examine the resilience performance of the production system and will likely significantly improve the fidelity of resilience simulations.

How to improve the resilience of real-world ETO systems?

The outcomes of this research shed light on how to improve resilience based on the developed archetypes. However, in reality, resilience improvement is a complex target that needs to be considered from a systematic perspective. Future research could focus on applying the findings from this research to real-world systems, developing resilience improvement strategies, and creating reaction plans for different types of disturbances at various stages.

The newly designed crisis strategy plans could be tested on the archetypes developed in this thesis. Such tests could provide quantitative and systematic perspectives of how these strategies affect the overall system's resilience performance.

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Appendix

A.1 Bode Plots

ETOAR#D Internal Design Rework

Work Rate

The Figure A.1 demonstrates the system's dynamic performance under various frequency. It can be found that, In the area where the frequency is below 0.02 rad/week (including the red box area), the magnitude value is 0 dB, which means that the output curves' fluctuation (difference between peak and bottom) is 1 time of the fluctuation of the input magnitude (the expression is shown in (5.39)). And the influence of the τ_{OB} value to the magnitude curve is trivial. The magnitude curves keep increasing until 0.06 rad/week, and then start to decrease. In the high frequency area, between 0.1 rad/week to 1 rad/week, the magnitude curves decrease first and then increase. From the $\tau_{OB,}$ perspective, the smaller the τ_{OB} the smaller the magnitude. However, there is one exceptional situation, when $\tau_{OB} = 2$, which is an unstable setting, the magnitude curve is higher than all other curves, especially when frequency is above 0.08 rad/week.

The magnitude curve in Figure A.1 is the phase chart which describes the phase difference between output and input. It also represents the lag between two signal's waveforms. The unit of the phase chart is degree. According to the phase chart, the line on top is when $\tau_{OB} = 2$. It implies that such systems react to the change faster and the lag of the waveform is shorter than the others. Although, the system's output is not convergent, it is very dangerous to use 2 as the value for τ_{OB}.

From practical perspective, the Figure A.1 indicate that, for ETOAR#D system whose demand frequency range from 0.01 to 0.02 rad/week, the value of τ_{OB} has minor influence on the work rate magnitude.

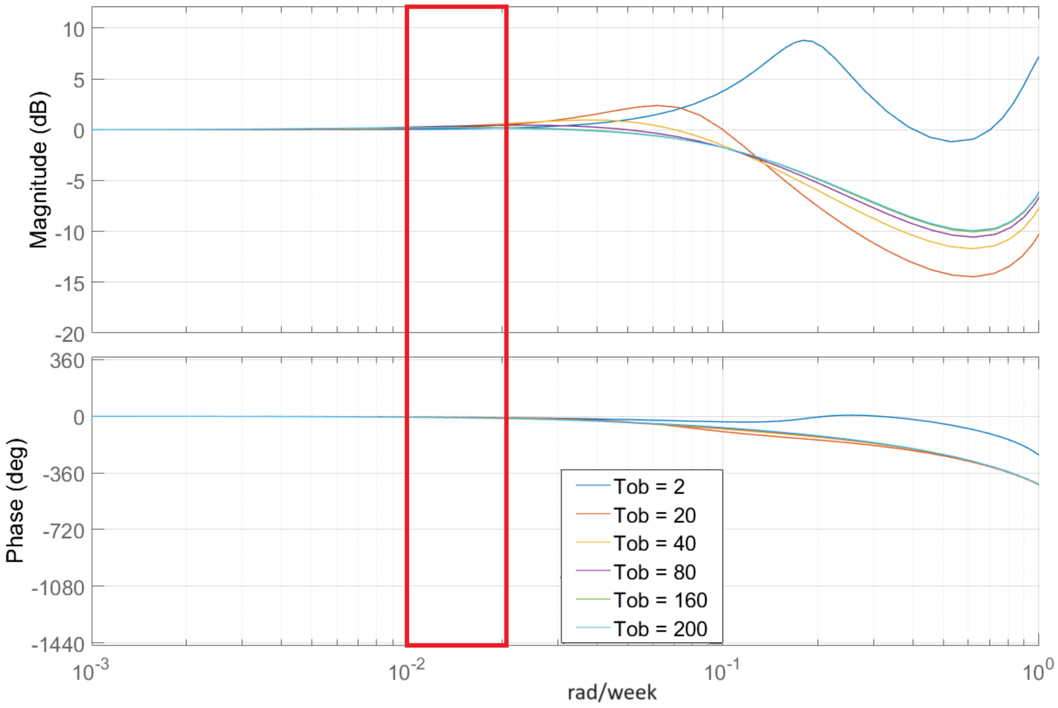

Figure A.1 Bode plot for the ETOAR#2 τ_{OB} orientated RW = 0.5

The Figure A.2 demonstrates how RW ratio affects the frequency response of the system. The τ_{OB} is set to 20. It can see that, in the red box, the rate of the rework has a negative influence on the magnitude of the system. And for the low frequency area (Below 0.01 rad/week), the magnitude is 0 dB and the output's waveform is 1 times of the input. Between 0.01 and 1 rad/week, all curves go down and then go up.

From practical perspective, for ETOAR#D system with demand frequency range from 0.01 to 0.02 rad/week, the rework has a negative influence on the fluctuation.

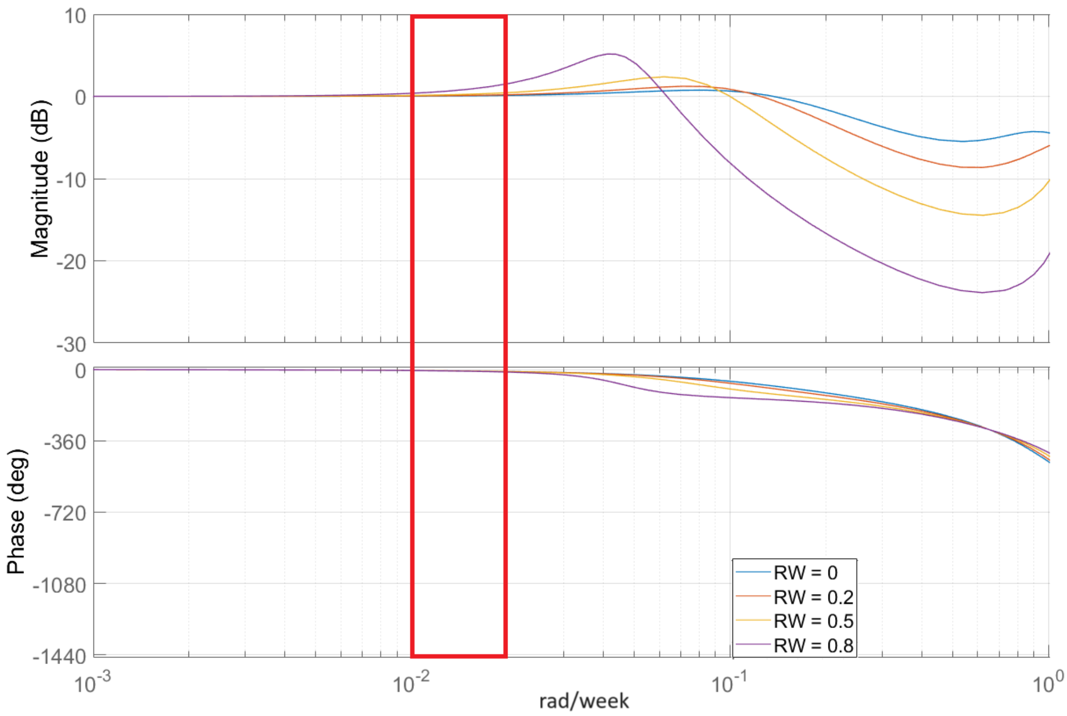

Figure A.2 Bode plot for the ETOAR#2 rework orientated $\tau_{OB} = 20$

Order Book

Figure A.3 and Figure A.4 illustrate the bode plots for the order book. From Figure A.3, the order book magnitude is decreasing along with the increase in the frequency, when frequency is below 0.04 rad/week, including the red box area. In the red box area, the smaller the τ_{OB} the higher the magnitude. According to the phases plot, when τ_{OB} = 2, the order book's phases lag is smaller than the systems with other τ_{OB} value. The system with other τ_{OB} value, the phases shift is around 0, with some trivial fluctuation.

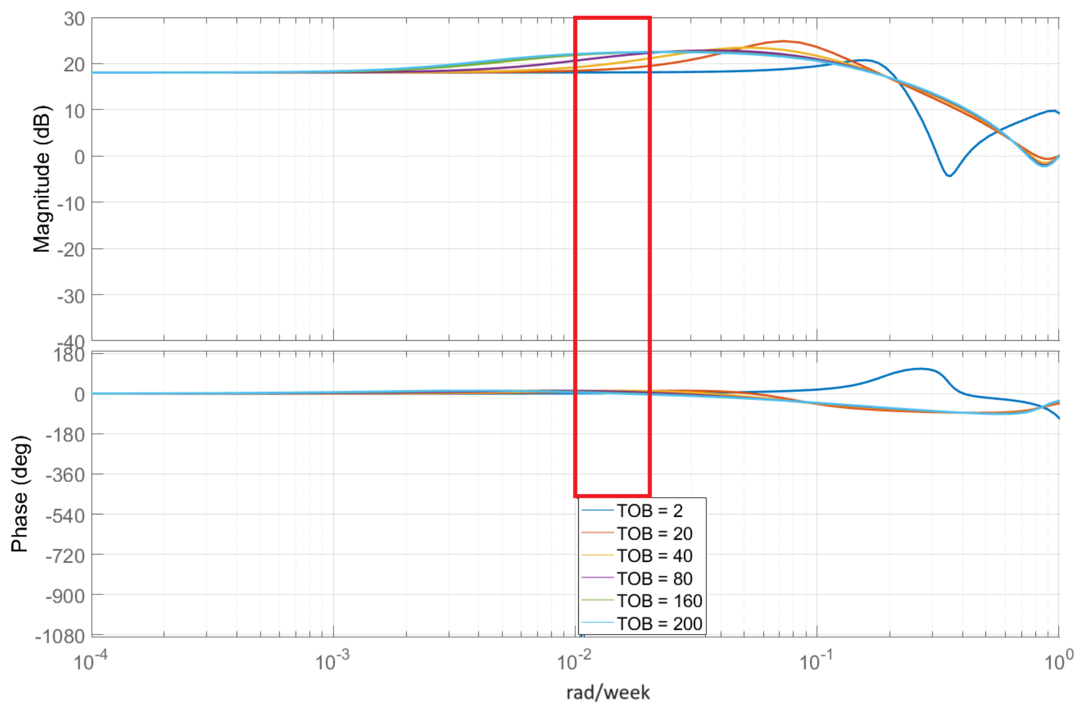

Figure A.3 Order book bode plot of the ETOAR#D, τ_{OB} orientated. RW = 0.5

Figure A.4 investigates the rework ratio's effect on the system's frequency responses. According to the magnitude curve, it can be seen that when frequency is lower than 0.04 rad/week (including the red box area), all curves increase with the increase in frequency. At the same time, it is also observed that the higher the rework ratio is, the higher the fluctuation will be for the order book. When frequency is higher than 0.1 rad/week, the magnitude curve starts to decrease, which means that the order book's fluctuation becomes milder if the frequency of the input increases.

According to the phases plot, it can be seen that all curves experience an increase at the beginning and a decrease when the frequency is below 0.03 rad/week. This means when the frequency is low, the system's phases lag increases with the frequency, but after 0.03 rad/week the system's phases shift decreases when the frequency increases.

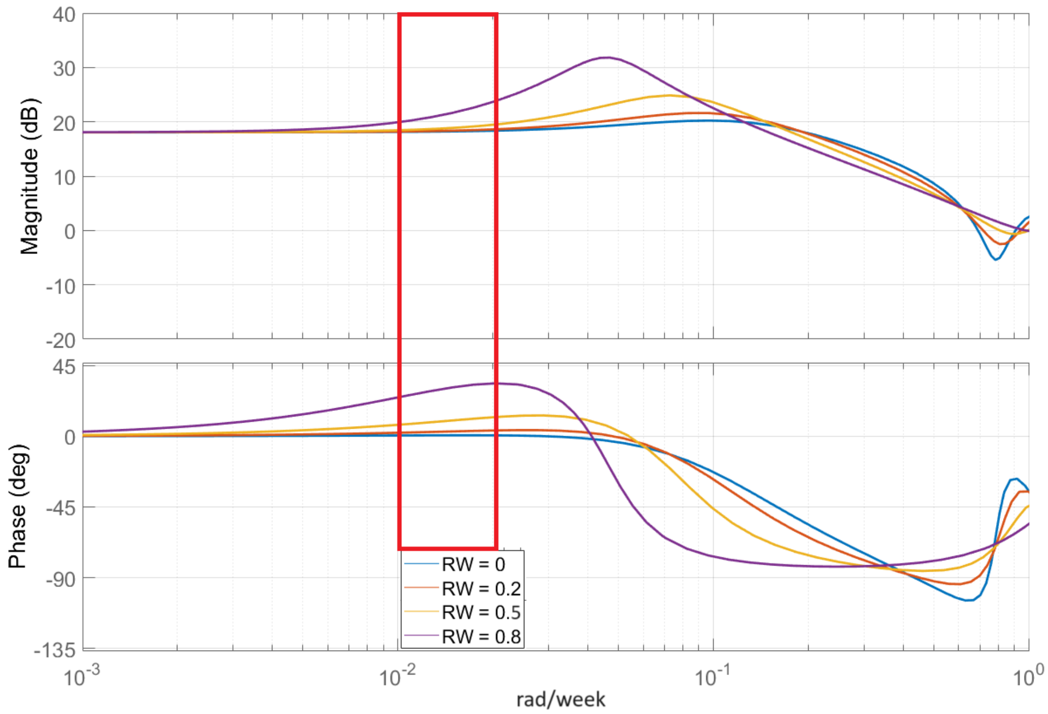

Figure A.4 Order book bode plot of the ETOAR#D, rework ratio orientated $\tau_{OB} = 20$

Lead Time

According to Figure A.5, it can be seen that when frequency is lower than 0.03 rad/week, an increase in τ_{OB} increases the magnitude of the lead time. At the same time, when frequency is lower than 0.03 rad/week (including the red box area), the smaller the τ_{OB}, the smaller the magnitude. When τ_{OB} = 2, the system has the lowest magnitude, but only when the demand frequency is below 0.06 rad/week. The phases plots in Figure A.5 maintain at 90 degrees at the beginning (when frequency is lower than 0.01 rad/week) and when frequency is higher than 0.01 rad/s, the phase lag start to decreases. The value of τ_{OB} does not have a significant influence on the phases shift.

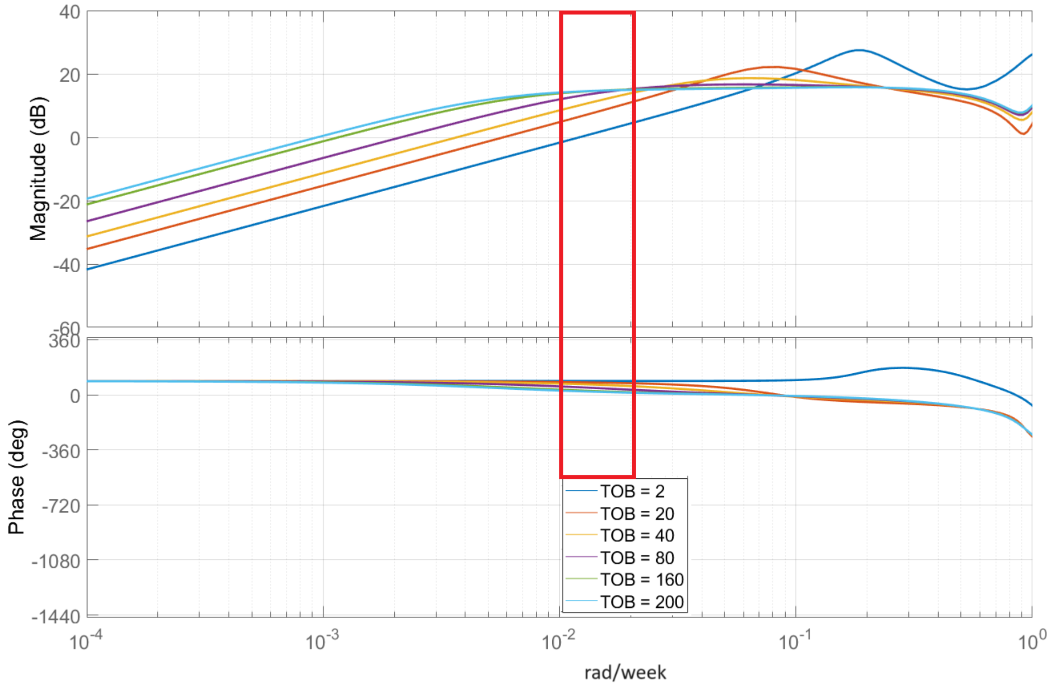

Figure A. 5 Lead time bode plot of the ETOAR#D, τ_{OB} orientated. RW = 0.5

Figure A.6 demonstrates the lead time performance of ETOAR#D. From the magnitude plot, it can be seen that in the low frequency zone (when frequency is lower than 0.02 rad/week), the magnitude curves increase with the frequency, and larger the rework ratio is, higher the magnitude is. When frequency is higher than 0.02 rad/week, the curves start to decrease and rework ratio's effect starts to change. Especially when frequency is above 0.2 rad/week, the higher the rework ratio, the lower the magnitude is for lead time.

According to the phases plot, it can be seen that with increase in the frequency, the phases maintain at 90 degrees (when frequency is lower than 0.1 rad/week) while after that, the phases start to decrease.

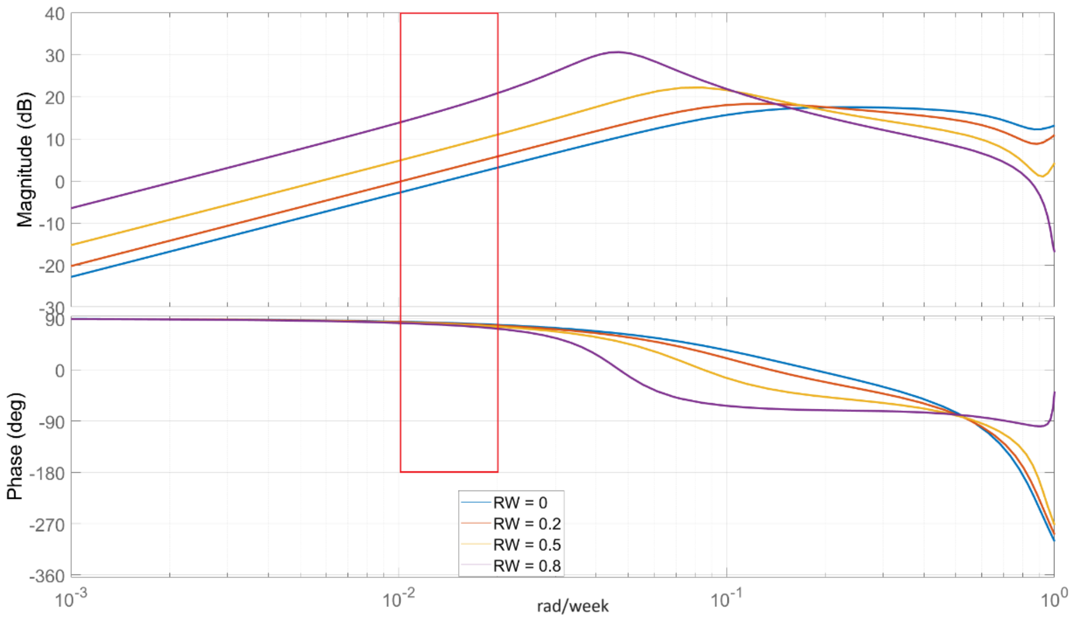

Figure A. 6 Lead time bode plot of the ETOAR#D, rework orientated τ_{OB} = 20

ETOAR#PTD External Design Rework

Work Rate

The bode plot below demonstrates the frequency response of the ETOAR#PTD, wherein, the rework happens in the design stage but it was found in the production stage that the rectification requires extra working units from both design and production system.

From the magnitude chart, it can be seen that when frequency is lower than 0.02 rad/week (Including the red box area), the magnitude of τ_{OB} is around 6 dB, which means that the magnitude of the output is 2 times that of the input. Between 0.02 with 0.1 rad/s, the curve of τ_{OB} = 2,20,40,80,160 and 200, reaches a peak and then goes down.

The phase chart in Figure A.7 shows the phases for all τ_{OB} (except at τ_{OB} = 2) wherein all the configurations go down. This means with the increase in the frequency, the waveform delay between output with input is prolonged.

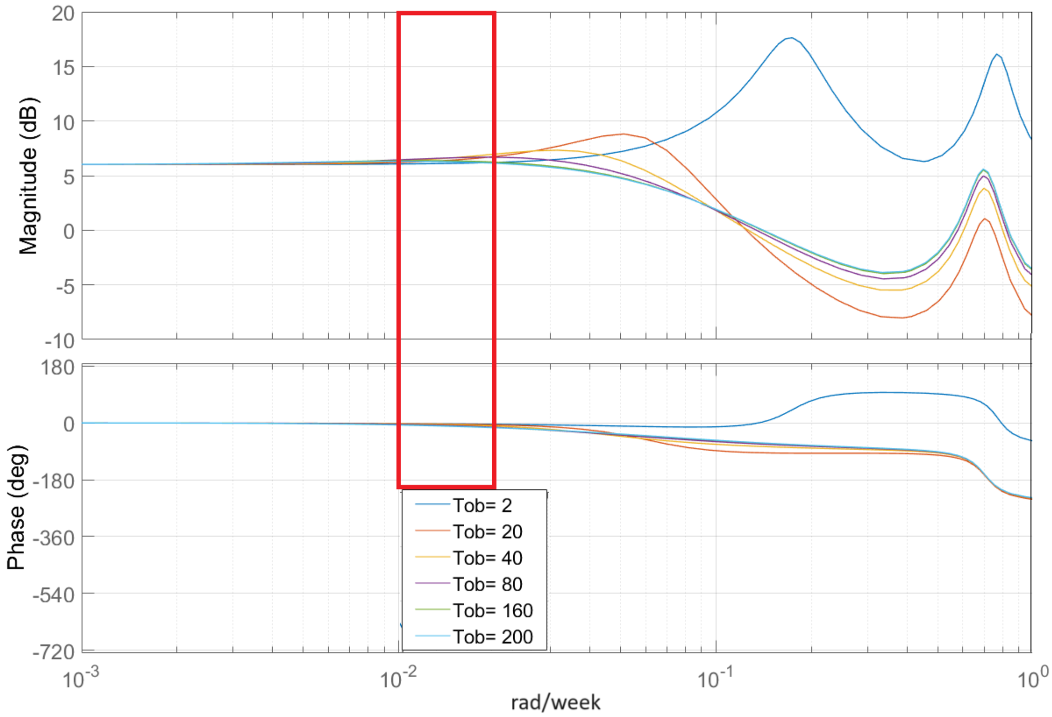

Figure A. 7 Bode plot for the ETOAR#PTD τ_{OB} orientated RW = 0.5

The bode plot that focuses on the rework ratio, is visualized in Figure A.8. It can be seen that when frequency is below 0.07 rad/week, including the red box area, the magnitude curve increases with the increase of the frequency, and the higher the rework, the higher the magnitude. when frequency is between 0.2 to 0.5 rad/week, the increase of the frequency leads the decrease of the magnitude curve, and the bigger the rework ratio, the smaller the magnitude.

The phase chart below illustrates the fact that the rework ratio's change has limited influence on the performance from the phase's perspective.

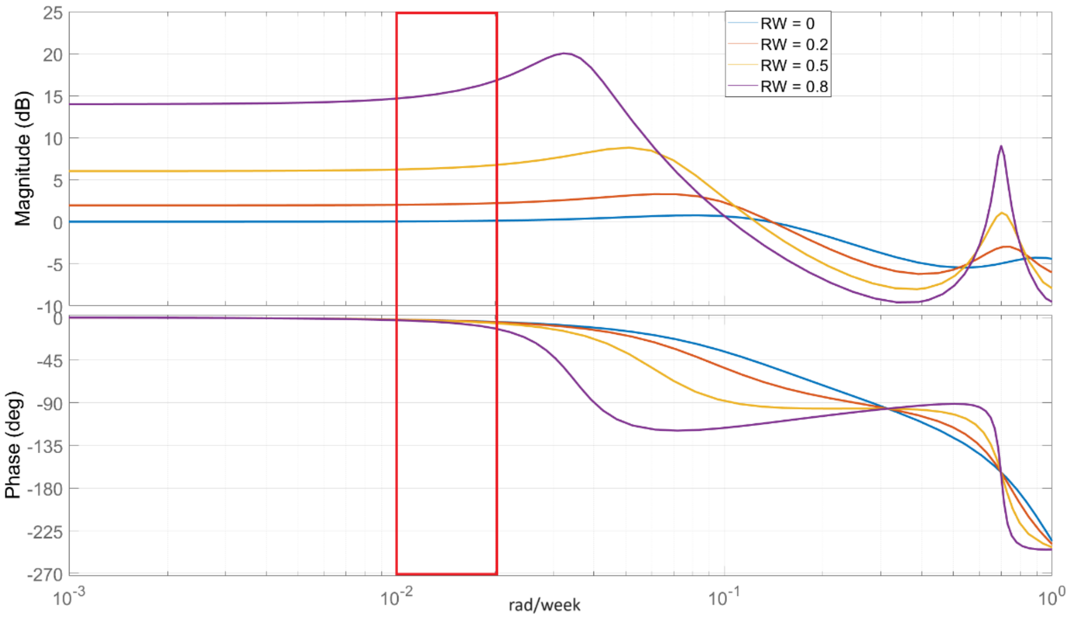

Figure A. 8 Bode plot for the ETOAR#PTD rework orientated $\tau_{OB} = 20$

Order Book

Figure A.9 illustrates the bode plot of the order book of ETOAR#PTD, with various τ_{OB} values. From the magnitude plot, it can be seen that all curves increase when frequency is lower than 0.02 rad/week In the red box area, the higher the τ_{OB} the higher the magnitude. When frequency is above 0.07 rad/week, all curves start to decrease with the increase of the frequency. When τ_{OB} = 2, which is an unstable system setting, the curve manifests dramatic fluctuations in the high frequency zone. According to the phases plot, all curves start to mildly fluctuate when frequency is above 0.1 rad/week while, when τ_{OB} = 2, the curve significantly decreases when frequency is higher than 0.1 rad/week.

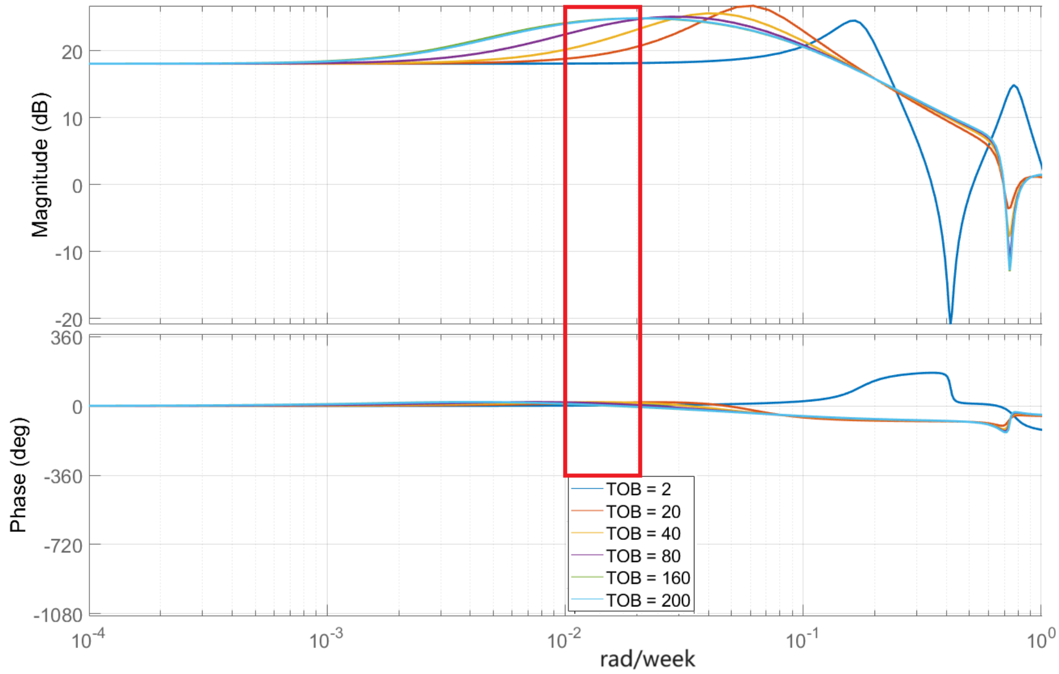

Figure A. 9 Order book bode plot of the ETOAR#PTD, τ_{OB} orientated. RW = 0.5

Figure A.10 demonstrates the bode plot of the order book of ETOAR#PTD, with various rework ratios. It can be seen that for the magnitude plot. When frequency is lower than 0.01 rad/week the rework ratio has little influence of lead time's magnitude. In the red box area, where the frequency ranges from 0.01 to 0.02 rad/week. The magnitude curve starts to increase, and the higher the rework ratio is the higher the magnitude. While with the frequency increasing from 0.02 to 0.1 rad/week, all the magnitude curves experienced an increase and then a decrease. And in this stage, the rework ratio has an impact on the magnitude of the curve; the higher the rework ratio is, the higher the magnitude is. When frequency is higher than 0.1 rad/week, the magnitude curves start to decrease, and higher the rework ratios are, the higher the magnitude is.

Form the phase plot, it can be seen that with the increase in the frequency, the phases lag increases until the frequency increases to 0.02 rad/week, and afterwards, the phases curves start to decrease. When frequency is below 0.02 rad/week, the rework ratio increases the phases shift, while after that, the rework ratio decreases the phase shift.

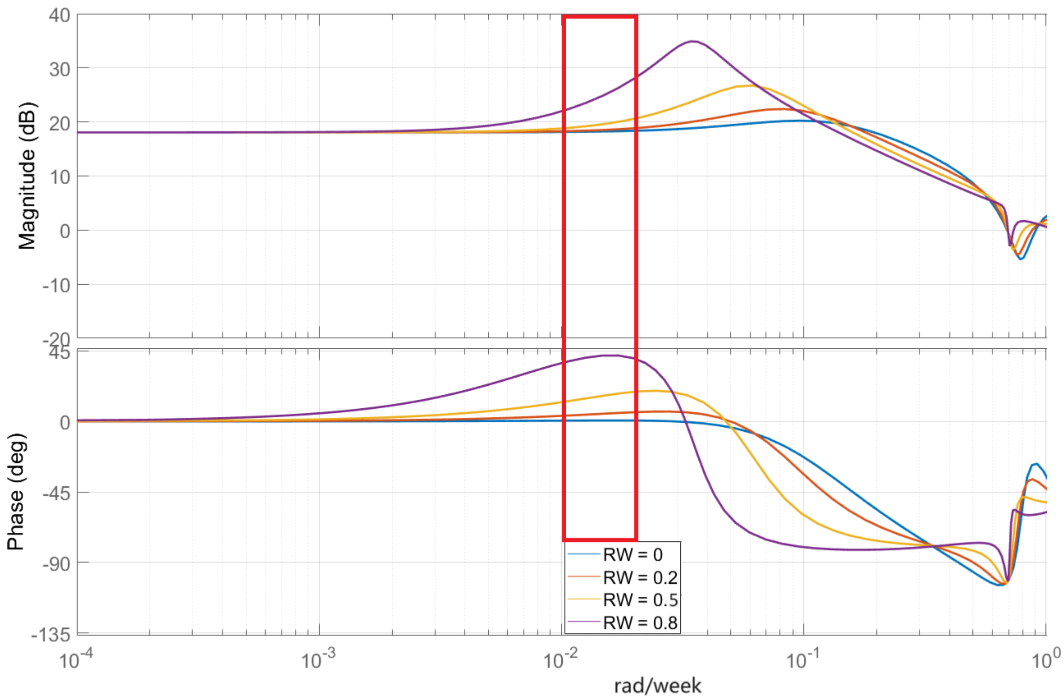

Figure A. 10 Order book bode plot of the ETOAR#PTD, rework orientated $\tau_{OB} = 20$

Lead Time

Figures A.11 and A.12 demonstrate the bode plot of the lead time of the ETOAR#PTD system. The Figure 5.18 places the focus on the effect of the τ_{OB} value, and 5.19 focuses on the rework ratio's effect.

According to Figure A.11, it can be seen that when τ_{OB} = 2 (which is an unstable parameter setting), the magnitude curve starts from 13 dB and increases with the increase in the frequency and ends up with some fluctuation. The other τ_{OB} values can keep the system in stable, while the increases of the τ_{OB} leads to an increase in the magnitude in the low frequency zone (0.0004 to 0.002 rad/week, in including the red box area). When frequency increases to 0.1 rad/week, the curve starts to decrease and ends up with fluctuations in the high frequency zone. The phases plot indicates that with the increase in the input frequency, the phase lad of the system will keep decreasing.

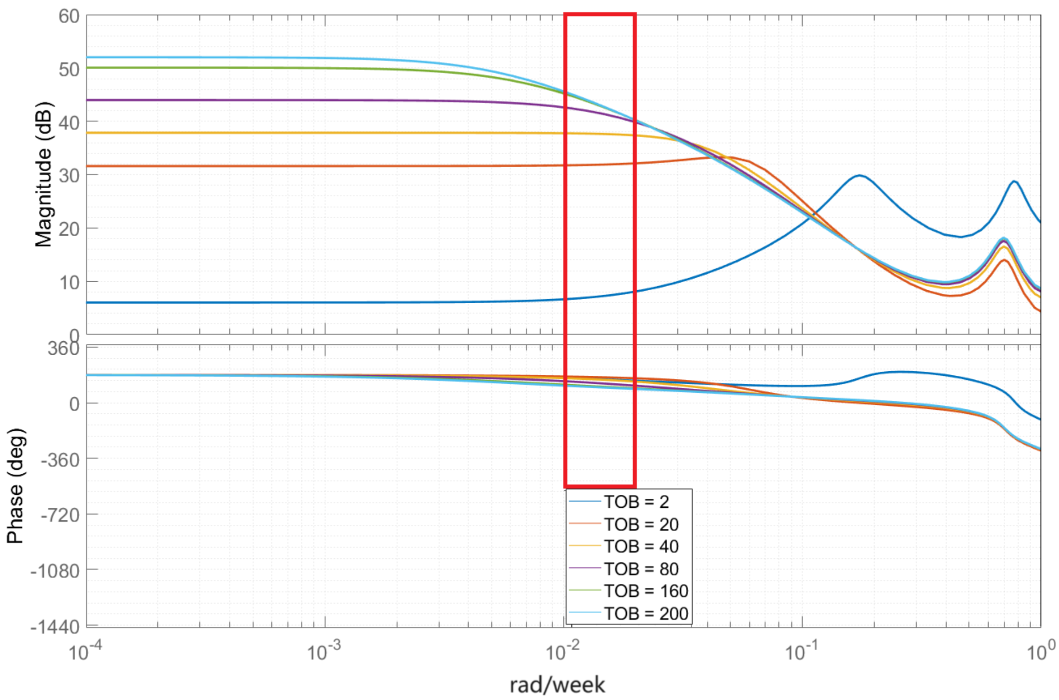

Figure A. 11 Lead time bode plot of the ETOAR#PTD, τ_{OB} orientated. RW = 0.5

Figure A.12 demonstrates the effect of the rework ratio. From the magnitude curve, it can be seen that with the increase in the rework ratio, the lead time magnitude increases in the low frequency zone (when frequency is lower than 0.02 rad/week, including the red box area). When frequency is higher than 0.03 rad/week, all curves start to decrease and end up with some fluctuation in the high frequency zone. The phase chart illustrates that with the increase of the input frequency, the phases shift keeps decreasing and the rework ratio has little impact on lead time's performance.

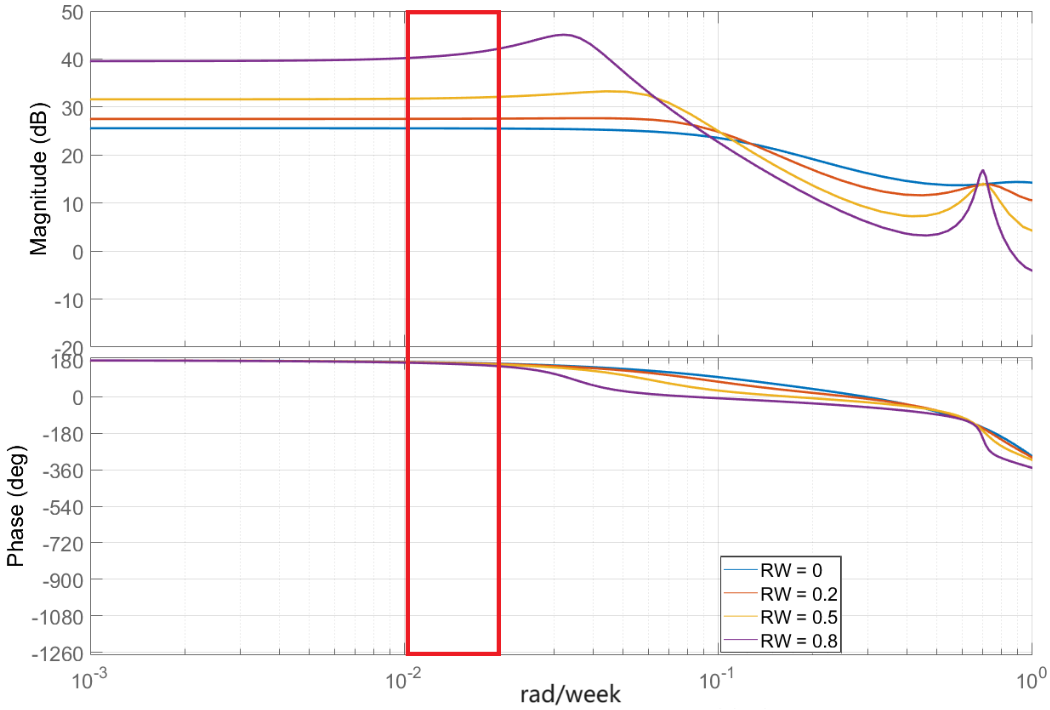

Figure A. 12 Lead time bode plot of the ETOAR#PTD, rework orientated $\tau_{OB} = 20$

A.2 Verification

This sub-section aims to verify the model, by cross checking the simulation results of the models. The following figures are created in the spreadsheet, by using the differential equations modelling technique. These figures act as a comparison with the transient responses presented in the section 4.4, thereby guaranteeing the correctness of the model that was developed.

The figure A.13 demonstrates the spreadsheet simulation result of order books, and the simulation result from the Simulink. It can be seen that the transient responses from both software are the same. Besides, the numerical results of both outputs were also directly compared leading to the same conclusion.

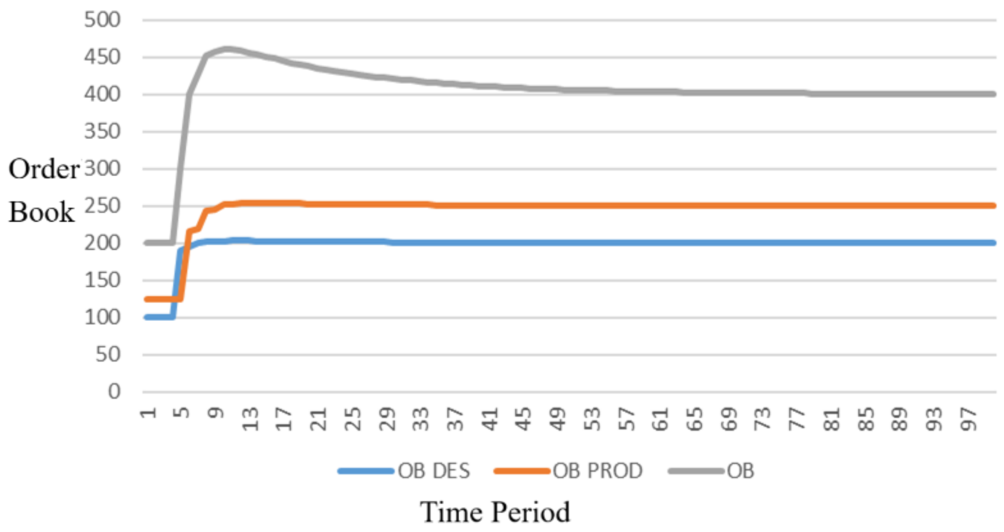

Figure A. 13 Order book transient responses produced by spreadsheet.

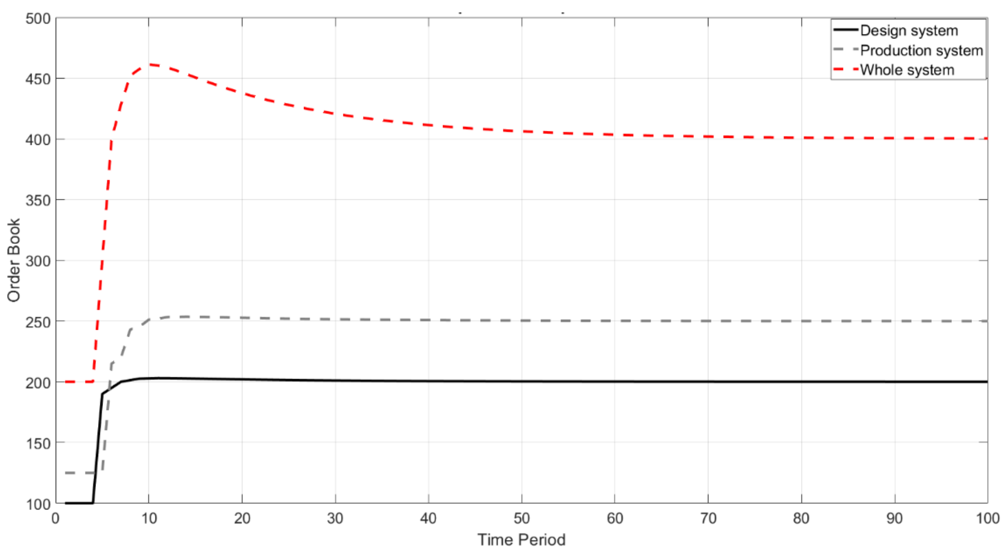

Figure A. 14 Order book transient responses produced by Simulink.

The Figures A.15 and A.16 demonstrate the lead time simulation from both software.

The transient responses are the same.

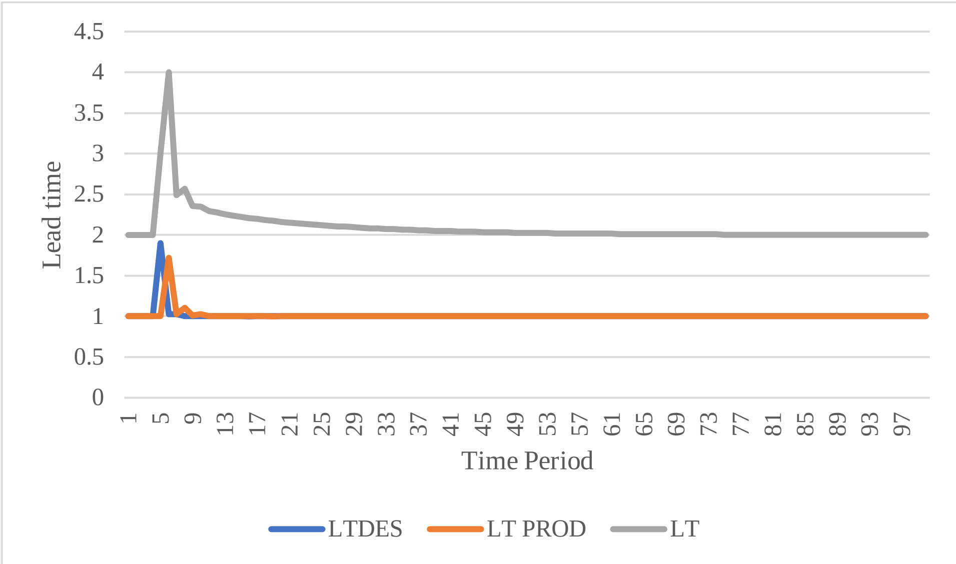

Figure A. 15 Lead time transient responses produced by spreadsheet.

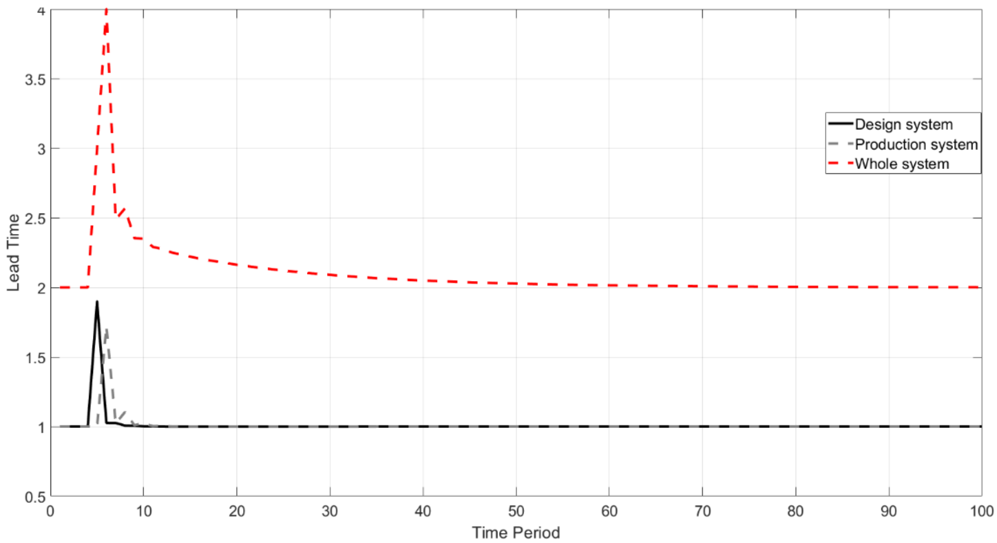

Figure A. 16 Lead time transient responses produced by spreadsheet.

The Figure A.17 illustrates the order book transient responses of the ETOAR#D archetype from Spreadsheet simulation. By comparing it with the Simulink simulation result, the correctness of the model is guaranteed.

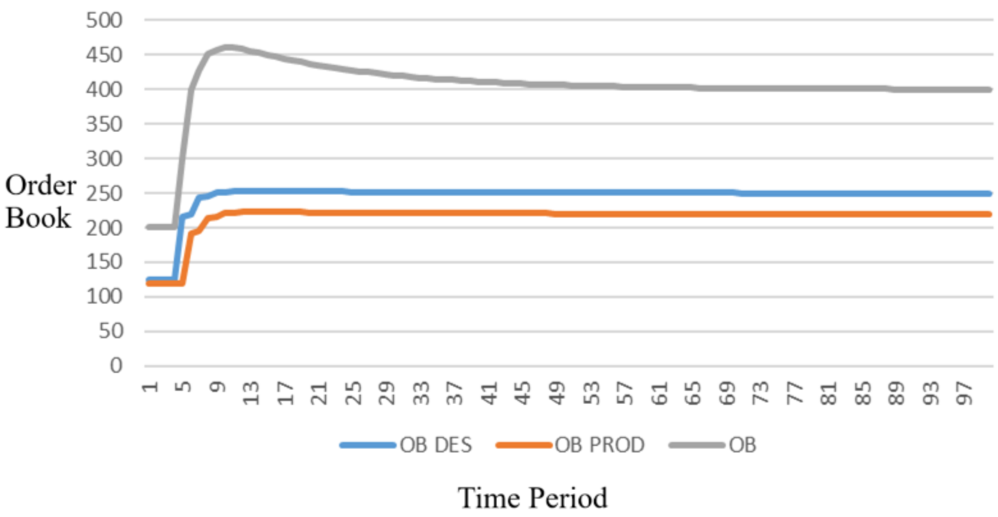

Figure A. 17 Order book transient responses produced by spreadsheet.

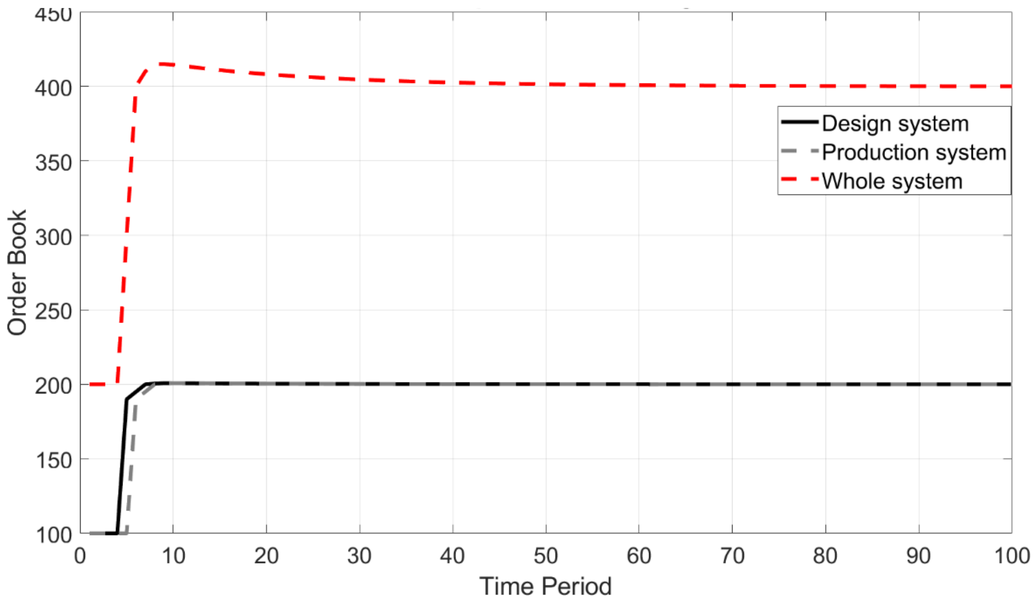

Figure A. 18 Order book transient responses produced by spreadsheet.

Figure A.19 demonstrates the lead time transient responses of the ETOAR#D archetype, and the result from the spreadsheet simulation are the same with the Simulink simulation in Figure A.20.

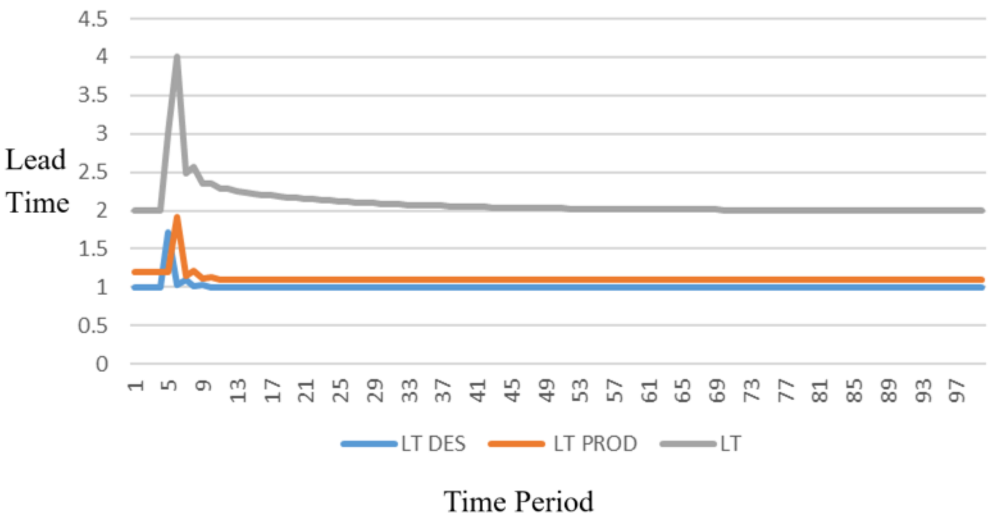

Figure A. 19 Lead time transient responses produced by spreadsheet.

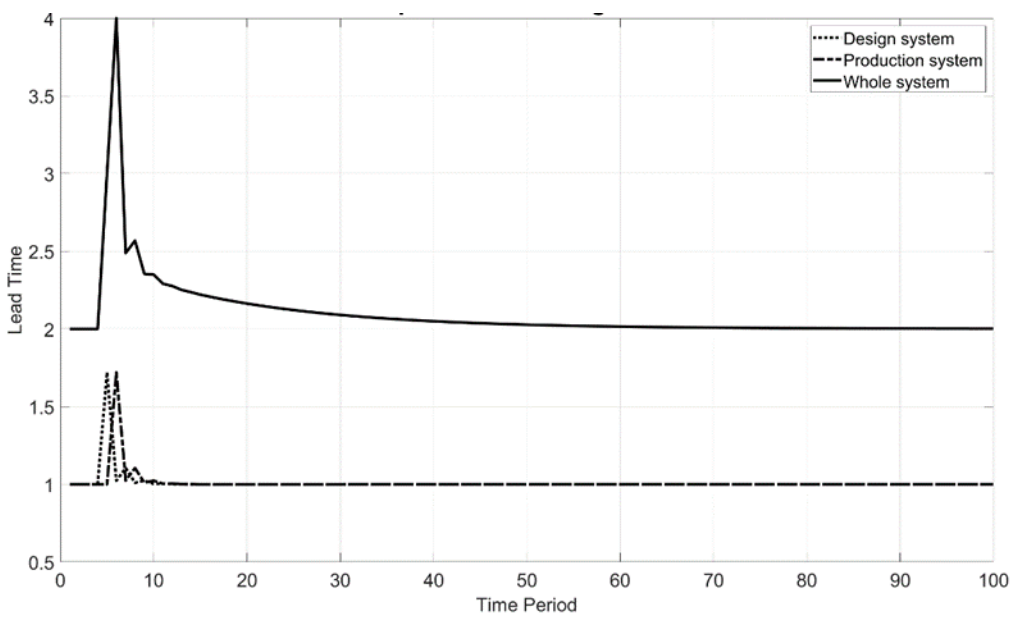

Figure A. 20 Lead time transient responses produced by Simulink.

The Figure A.21 demonstrates the spreadsheet simulation result of the order book transient responses of ETOAR#PTD. The responses are the same with the simulation from Simulink as shown in A.22.

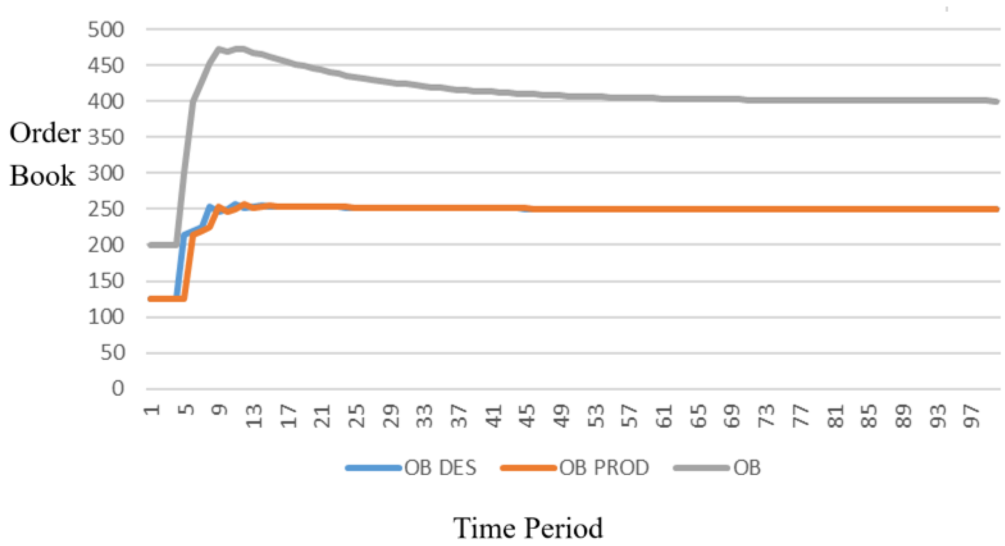

Figure A. 21 Order book transient responses produced by spreadsheet.

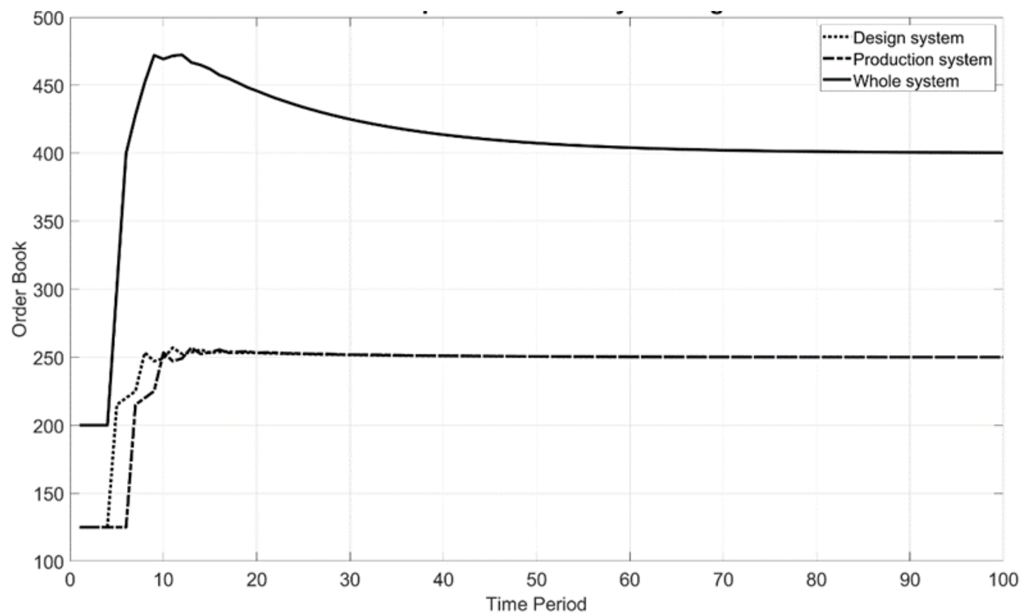

Figure A. 22 Order book transient responses produced by Simulink.

The lead time transient responses from spreadsheet are also the same with the Simulink simulation result, as shown in A.23 and A.24.

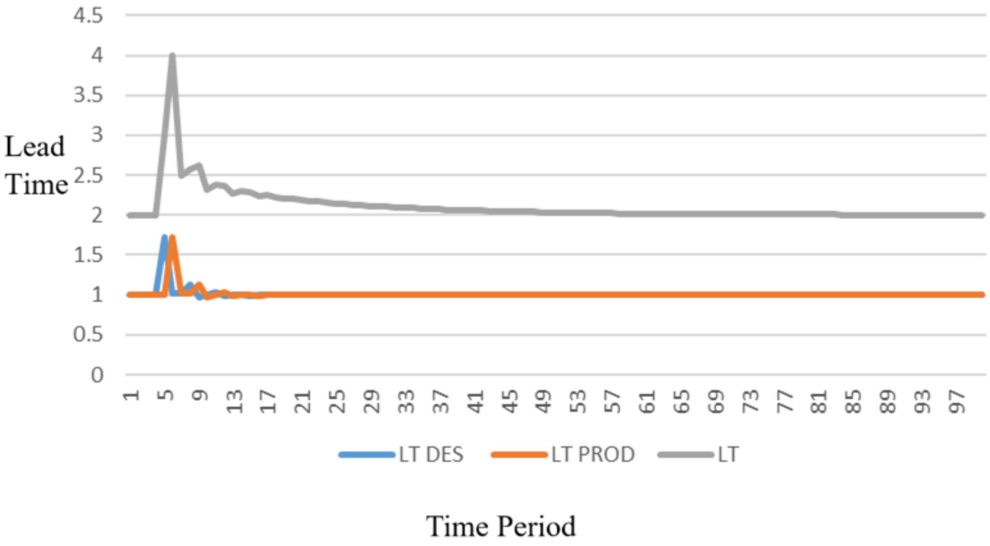

Figure A. 23 Lead time transient responses produced by Spreadsheet.

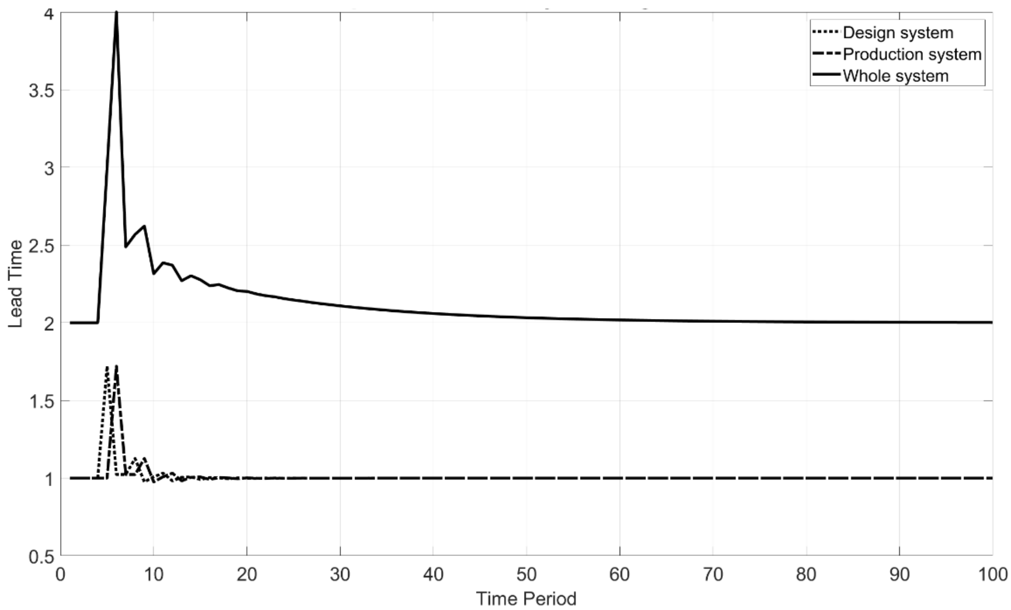

Figure A. 24 Lead time transient responses produced by Simulink.

A.3 Sensitive Analysis

Sensitivity Analysis on the Lead Time Change.

ETOAR#D Design Rework

Table A.1 The initial value and parameter setting for the ETOAR#D lead time sensitivity analysis.

Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
125	500	25	100	400	800
Co-efficient values					
τ_{OB}	τ_D	τ_P	RW	RW scheduling time	
20	1(25%) 4(Baseline) 8(200%)	1(25%) 4(Baseline) 8(200%)	0.2	1	

The parameter setting is as follows is shown in Table A.1. To control the variable the τ_P (Lead Time for production) is fixed, and the system's transient responses when τ_D = 1, 4, 8 are visualized.

Determined demand analysis.

Figure A.25 demonstrates how the deliver rate of the system changes when design Lead Time changes. At the beginning of the transient response, the input response is first indicated by the blue curve, the red curve responses the second, and the yellow curve the third. Such phenomenon is caused by the design lead time's change. According to the Table A.1, the lead time for design is 1,4,8, which means the total lead time of the ETO process are 5, 8 and 12. The difference of the total lead time leads to the different response times. Another observation is that longer the design lead time is, the higher the peak is, which can be interpreted as, longer lead time triggers higher overshoot. This finding has been discussed in following sections. In general, no matter how design lead time changes, the system can always stabilize at 1. This demonstrates the advantages of order book controller, although different lead time may affect the system dynamic behaviour, while order book controller maintains the system steady output in the long-term run. The other graph demonstrates how sensitive the system is to the production lead time change; the yellow and red line in the Figure 7.2 are similar to the line in Figure A.25, which can be explained as for the design rework scenario that design and production lead time change has a similar effect on the system.

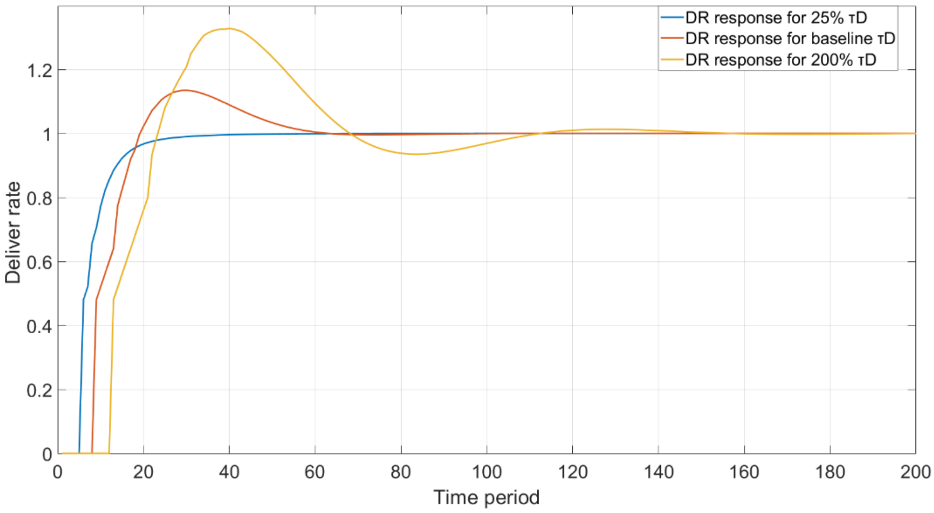

Figure A.25 Sensitivity analysis of ETOAR#D's deliver rate to the design Lead time, with determined demand.

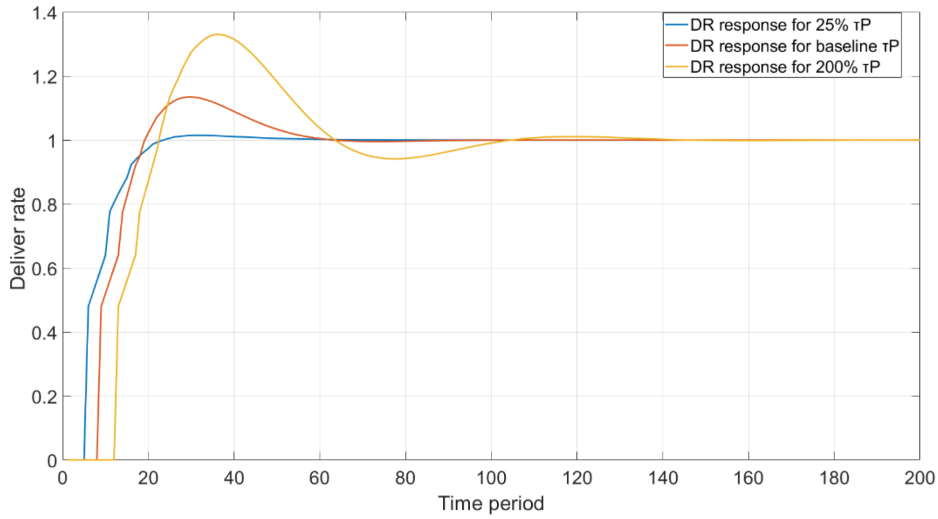

Figure A. 26 Sensitivity analysis of ETOAR#D's deliver rate to the production Lead time, with determined demand.

Stochastic demand analysis.

To further analyse the sensitivity of the system to the design and production lead time change, another experiment is conducted with stochastic demand input; the demand is assumed under normal distribution, mean value is 1 and standard deviation is 0.1. It can be seen that yellow line's behaviour has a clear lag to the red line, and the red line has a lag to the blue line. The longer the design lead time, the slower the system reacts to the demand change.

To control the variables, the same set of the demand pattern is used to test the sensitivity of the system to the production lead time change. The form of the curve is like the design lead time figure and same finding is observed from the figure.

The bullwhip ratios are demonstrated in Table A.2:

Table A.2 Bullwhip ratio for each experiment

Experiment	Bullwhip
Design lead time sensitivity analysis	
25% design delay: (total lead time: 5)	0.259387
Baseline design delay:(total lead time: 8)	0.259387146
200% design delay:(total lead time: 13)	0.261222172
Production lead time sensitivity analysis	
25% production delay:(total lead time: 5)	0.256144
Baseline production delay:(total lead time: 8)	0.267258
200% production delay:(total lead time: 13)	0.267258

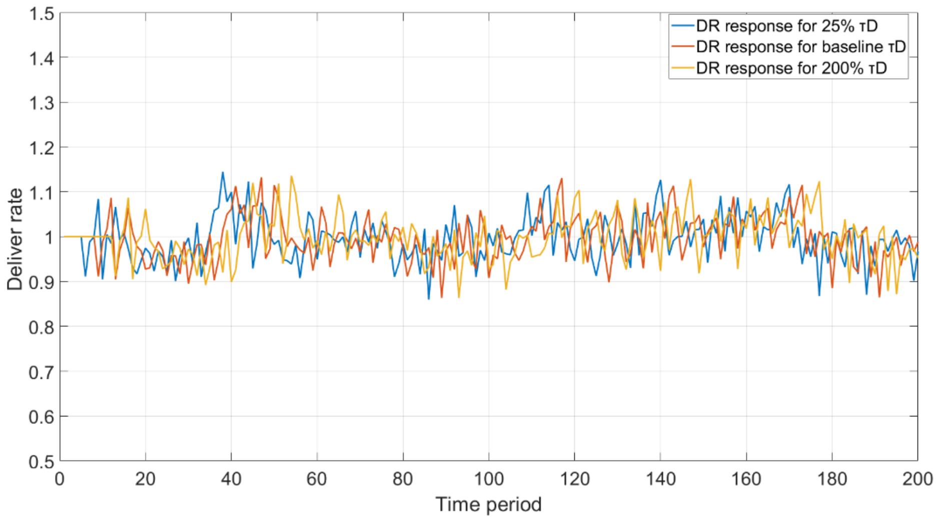

Figure A. 27 Sensitivity analysis of ETOAR#D's deliver rate to the design Lead time, with stochastic demand.

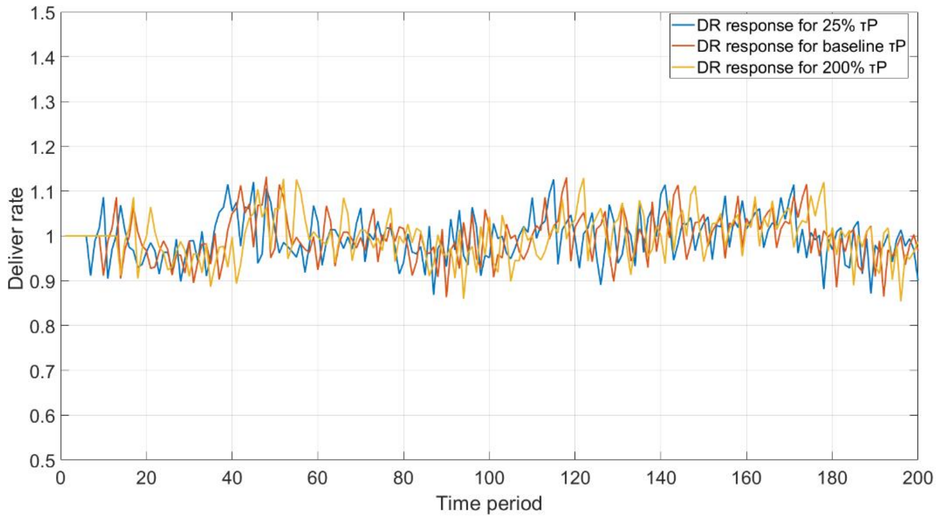

Figure A. 28 Sensitivity analysis of ETOAR#D’s deliver rate to the production Lead time, with stochastic demand.

To further investigate the system’s sensitivity to the sub-system’s lead time change, the sub-systems’ lead times are set to 1,2,4,6,8,10,12,14 and 16. The bullwhip ratios changing trend are demonstrated in Figure A.29 and A.30. And it is found that the bullwhip ratios fluctuating with the increase of the sub-system’s lead time.

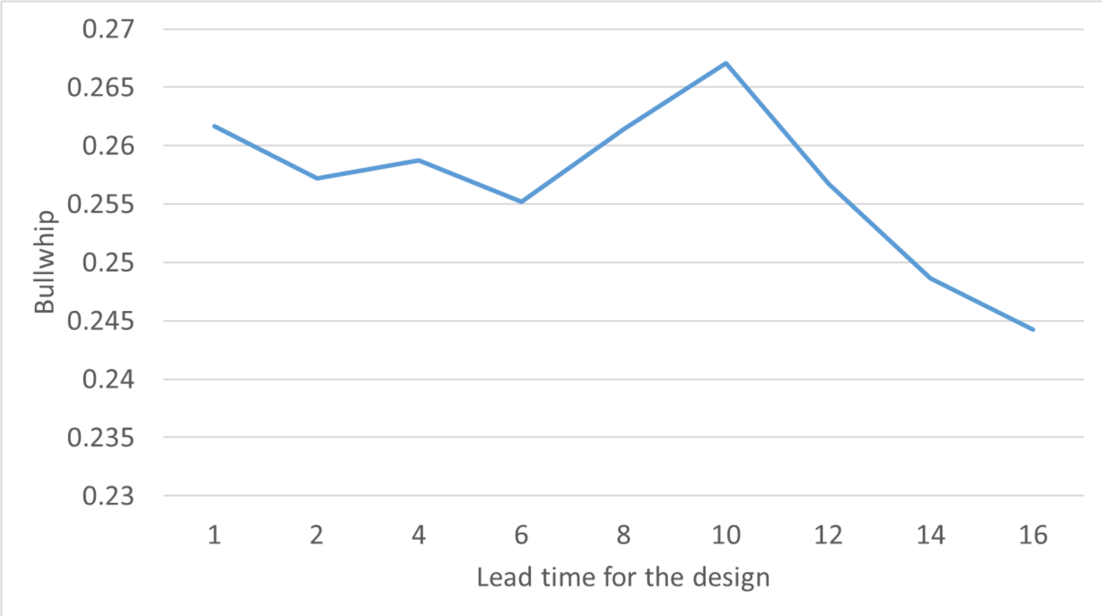

Figure A. 29 Sensitivity analysis of the ETOAR#D on the bullwhip effect.

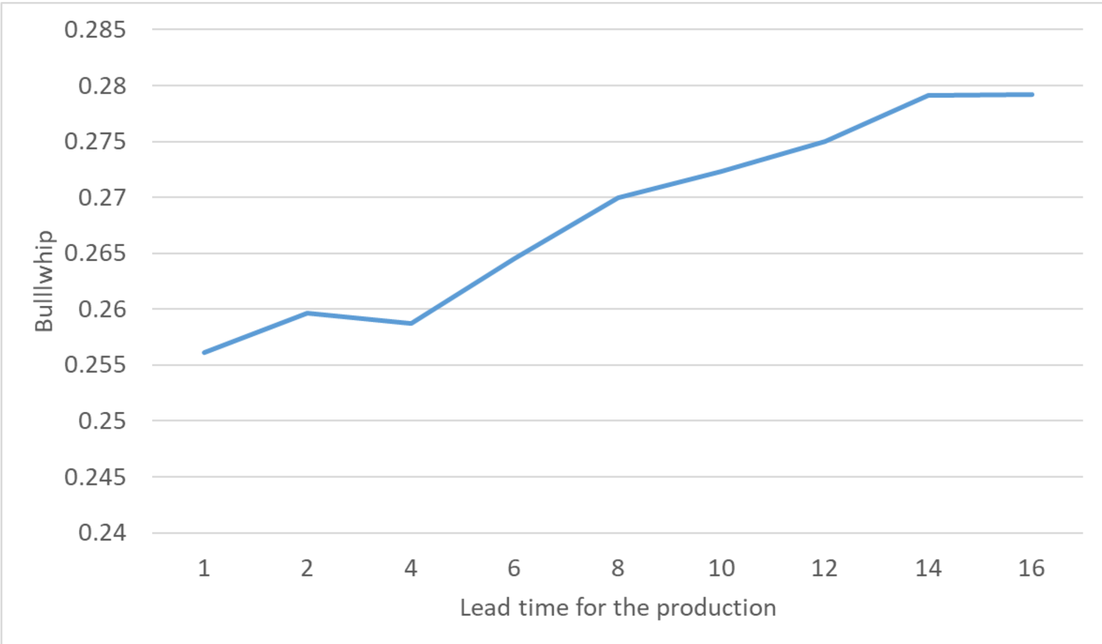

Figure A. 30 Sensitivity analysis of the ETOAR#D on the bullwhip effect.

ETOAR#PTD Delayed design rework

The initial value and parameter settings for simulation are demonstrated in Table A.3.

Table A.3 The initial value and parameter setting for the ETOAR#PTD lead time sensitivity analysis.

Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
125	500	25	100	400	800

Co-efficient values				
τ_{OB}	τ_D	τ_P	RW	RW scheduling time
20	1(25%) 4(Baseline) 8(200%)	1(25%) 4(Baseline) 8(200%)	0.2	1

Determined demand analysis.

For the delayed design rework scenario, the Figures A.31 and A.32 demonstrate the experiment results. When the delay happens to the design system, the transient responses demonstrate a delay between three curves. And such delay is caused by the prolonged total lead time of ETO system. At the same time, higher delay has a higher peak; the existence of the peak represents the system might exaggerate the fluctuation of the input.

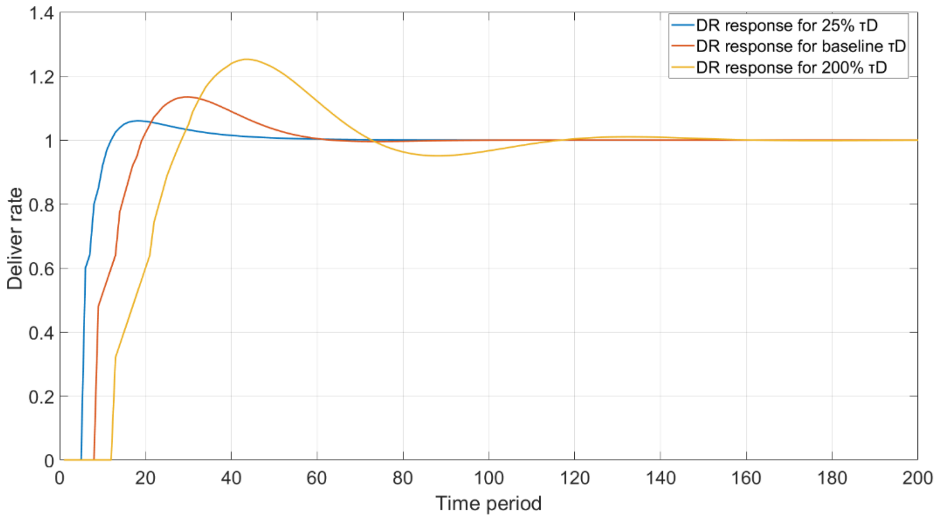

Figure A. 31 Sensitivity analysis of ETOAR#PTD’s deliver rate to the design Lead time, with determined demand.

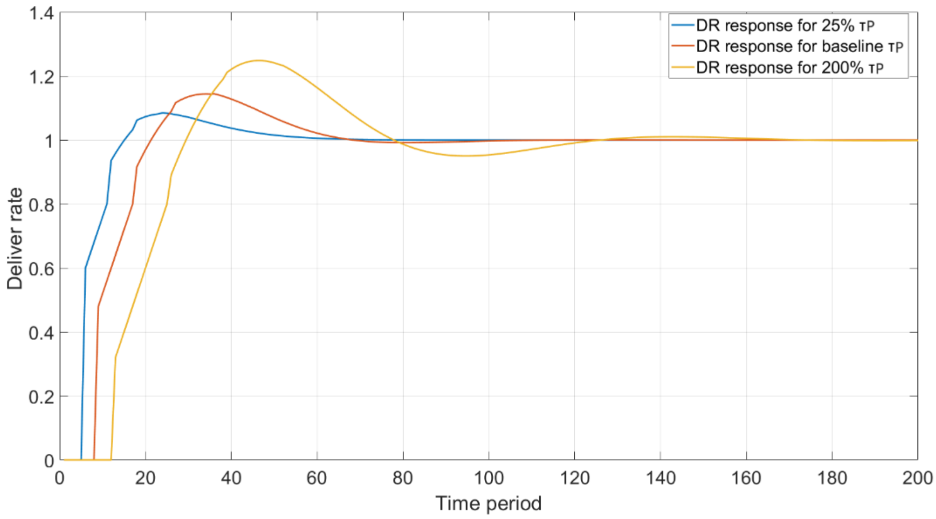

Figure A. 32 Sensitivity analysis of ETOAR#PTD’s deliver rate to the production Lead time, with determined demand.

Stochastic demand analysis.

Other than the experiment under determined demand, the experiment under the stochastic demand is also conducted. According to the figure below, a lag between peaks is observed; such delay is caused by the prolonged total lead time. In the meantime, it is also noticed that the peaks value for all these three curves are decreasing with the increase with the design and production lead time. To verify this observation, the bullwhip ratio for each curve is calculated, and summarized in Table A.4.

Table A.4 Bullwhip ratio for each experiment

Experiment	Bullwhip
Design lead time sensitivity analysis	
25% design delay: (total lead time: 5)	0.384984161
Baseline design delay:(total lead time: 8)	0.249019706
200% design delay:(total lead time: 12)	0.124778521
Production lead time sensitivity analysis	
25% production delay:(total lead time: 5)	0.384984161
Baseline production delay:(total lead time: 8)	0.249019707
200% production delay:(total lead time: 12)	0.124778521

The numerical result support the observation that with the increase of either design or production lead time, the system's bullwhip effect would be decreased. In the meantime, the place where the delay happens (design or production) has no significant impact on the bullwhip effect for the system.

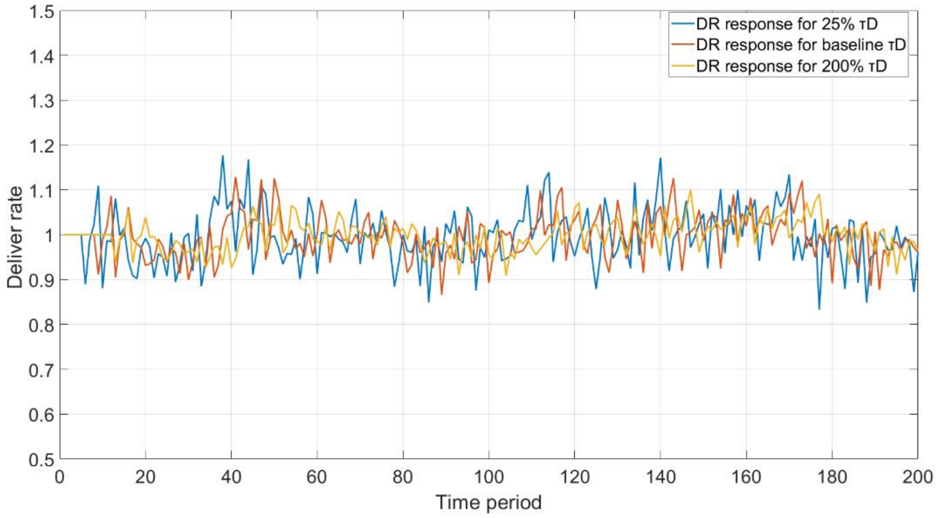

Figure A. 33 Sensitivity analysis of ETOAR#PTD's deliver rate to the design Lead time, with stochastic demand

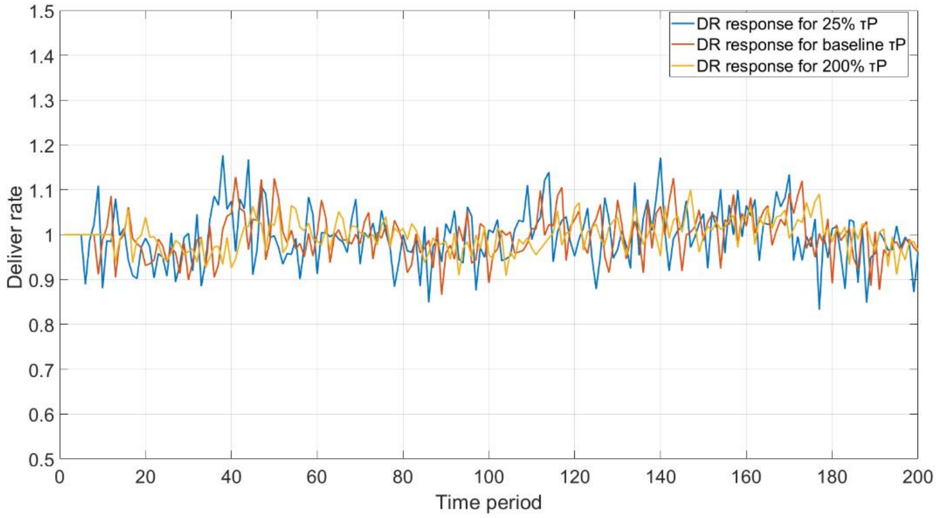

Figure A. 34 Sensitivity analysis of ETOAR#PTD's deliver rate to the production Lead time, with stochastic demand

To further investigate the system's sensitivity to the sub-system's lead time change, the sub-systems' lead times are set to 1,2,4,6,8,10,12,14 and 16. The bullwhip ratios changing trend are demonstrated in Figure A.35 and A.36. And it is found that the bullwhip ratios fluctuating with the increase of the sub-system's lead time.

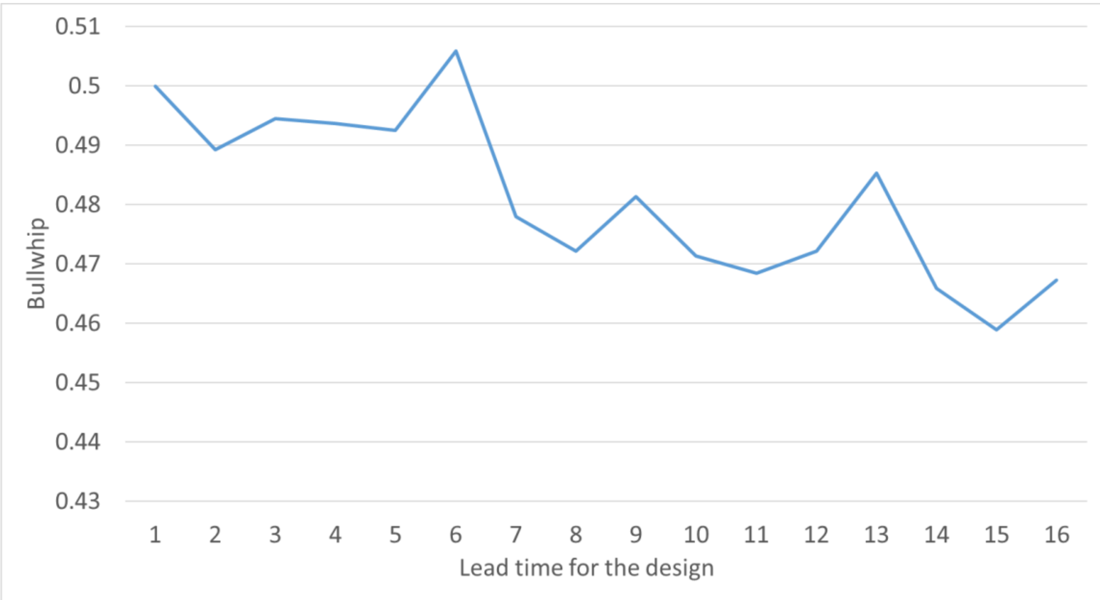

Figure A. 35 Sensitivity analysis of the ETOAR#PTD on the bullwhip effect.

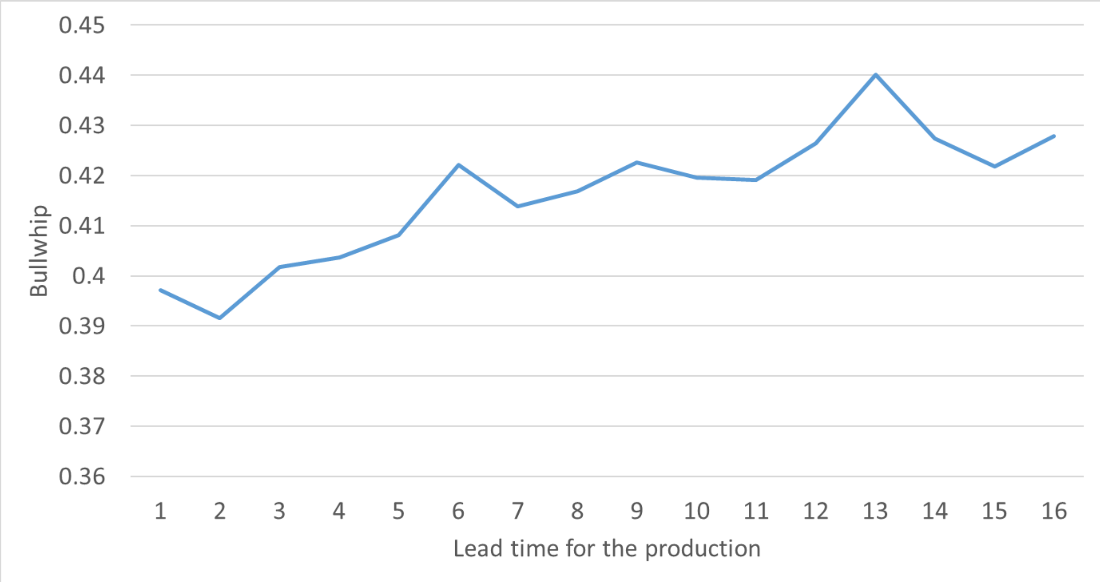

Figure A. 36 Sensitivity analysis of the ETOAR#PTD on the bullwhip effect.

Sensitivity Analysis on the Rework Scheduling Time.

The simulation parameters and initial value settings are demonstrated in Table A.5

Table A.5 The initial value and parameter setting for the ETOAR#D rework scheduling time sensitivity analysis

Initial values					
$COMRATE_{DES}$	OB_{DES}	$RWRATE_{PROD}$	$COMRATE_{PROD}$	OB_{PROD}	OB
100	400	25	125	500	800

Co-efficient values				
τ_{OB}	τ_D	τ_P	*RW*	*RW* scheduling time
20	4	4	0.2	1(Baseline) 2 (200%) 4 (400%) 8 (800%)

ETOAR#D Design rework

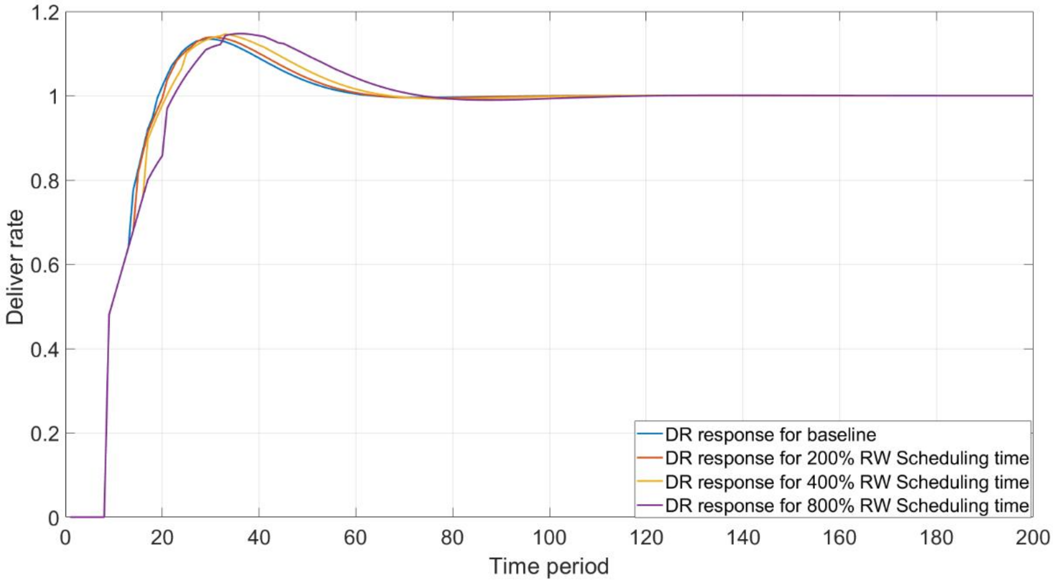

Figure A. 37 ETOAR#D delivery rate transient response with determined demand

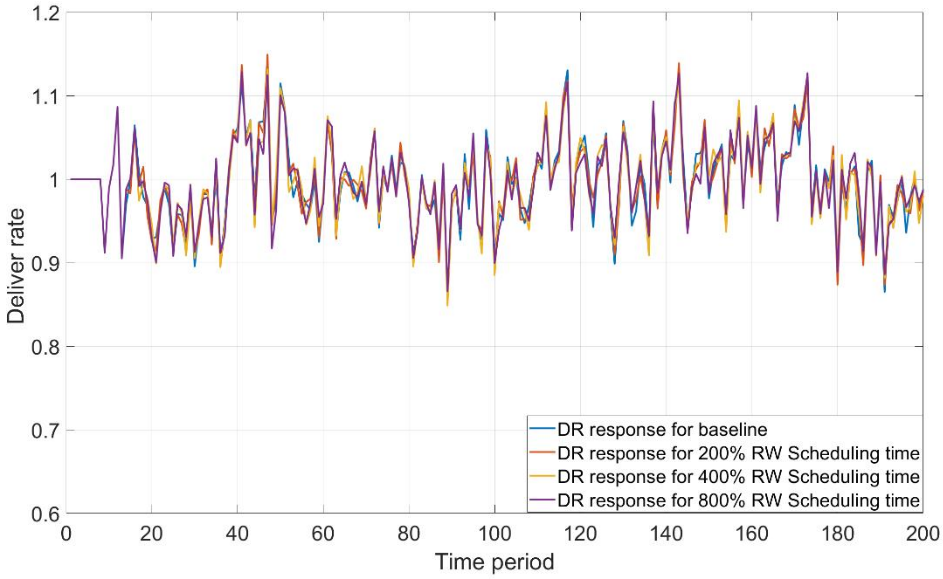

Figure A. 38 ETOAR#D delivery rate response with stochastic demand

ETOAR#PTD Delayed design rework

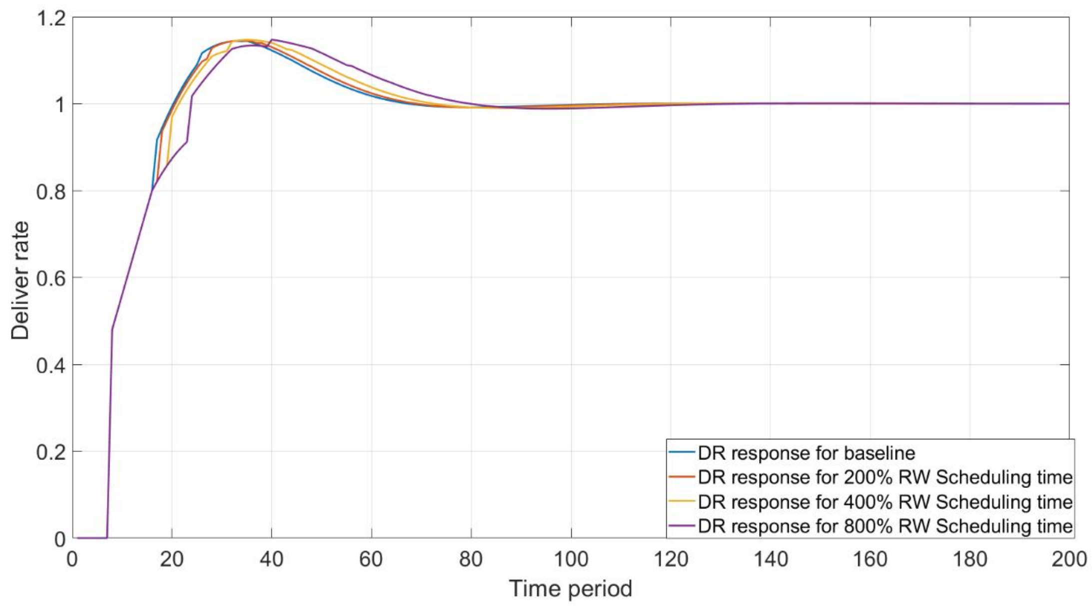

Figure A. 39 ETOAR#PTD delivery rate transient response with determined demand

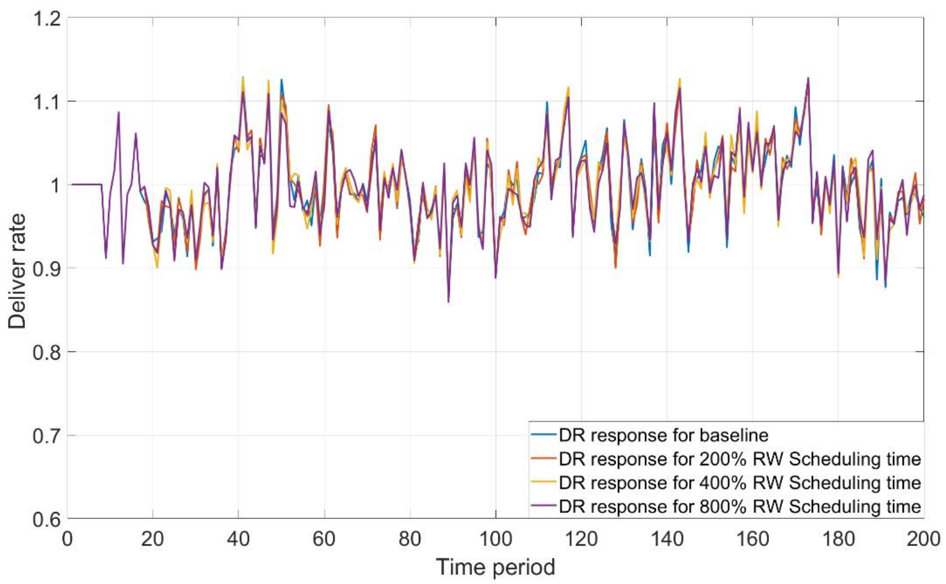

Figure A. 40 ETOAR#PTD delivery rate response with stochastic demand