ARTICLE IN PRESS

Int. J. Production Economics xxx (xxxx) xxx

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

The impact of design rework on engineer-to-order lead-time dynamics

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ARTICLE INFO

Keywords:
System dynamics
Modelling
Bullwhip
Lead-time

ABSTRACT

Design rework is a major challenge in Engineer-to-Order (ETO) systems, often leading to significant cost and time overruns. It arises in two forms: errors or customer design changes identified during the design phase and those discovered later in downstream production. This study aims to investigate the impact of these rework types on ETO lead times and evaluates the effectiveness of the "Think Slow, Act Fast" philosophy in improving system performance. To achieve this, two ETO archetypes are developed to quantify the benefits of this approach and determine the optimal time allocation for the design phase.

While several studies emphasize minimizing design errors before production, often through extended design lead time or additional inspection resources, the justification for such measures and their impact on production dynamics remain unclear. This research provides a quantitative framework to assess the "Think Slow, Act Fast" philosophy by comparing two ETO system archetypes.

Key findings reveal that allocating additional time to the design phase can reduce lead-time variability and mitigate the bullwhip effect. Simulation results demonstrate a reduction in production workload, as represented by formula: RW/(1-RW), if design errors or changes are prevented from transferring to the production system. From a practical perspective, this study offers managers a method to optimize time and resource allocation, ensuring design errors are resolved before reaching production and minimizing their impact on the overall system. These insights support informed decision-making for improving performance in ETO systems.

1. Introduction

Engineer-to-Order (ETO) is a unique production system where the customer is involved in the design stage. Unlike Make-to-Stock (Towill, 1982), Make-to-Order (Wikner et al., 2007) or Assemble-to-Order (Lin et al., 2020) systems, ETO includes design and engineering activities 'to-order'. ETO companies allow their customers to customize their products from the design stage, resulting in unique or even first-of-a-kind products.

The first-of-a-kind and project-oriented features make rework an inevitable issue in the ETO products' manufacture. Rework may be due to poor workmanship, quality issues, defects or design changes as requested by the customer (Ford et al., 2023). Amongst these causes, design errors and design changes contribute to the majority of rework (Han et al., 2013).

Understanding the different impact of design errors that are detected in different stages, and consequently, reducing the negative influence of reworks, a philosophy of 'Think Slow, Act Fast' has been proposed. The philosophy emphasizes the importance of spending more time on design and detailed planning prior to the start of action. By doing so, the chances 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 a system dynamics perspective. Therefore, this paper utilizes a System Dynamics (SD) method to investigate this philosophy from a quantitative perspective.

This paper aims to study how different types of design rework affect the lead-time of the ETO system, and how a strategy based on the "Think Slow, Act Fast" philosophy might improve the system's performance. The aim can be divided into two objectives. The first objective is to develop a model which can represent the scenario where extra time is given to the design process. The second objective is to examine how the "Think Slow, Act Fast" concept can benefit the system's performance though the simulation of various experiments.

This article is part of a special issue entitled: IWSPE 2024 published in International Journal of Production Economics.

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https://doi.org/10.1016/j.ijpe.2025.109763
Received 30 April 2024; Received in revised form 8 May 2025; Accepted 4 August 2025
Available online 6 August 2025
0925-5273/© 2025 Published by Elsevier B.V.

Please cite this article as: Yuxuan Zhou et al., *Int. J. Production Economics,* https://doi.org/10.1016/j.ijpe.2025.109763

2. Literature review

2.1. ETO system and rework

ETO systems are characterized by their project-oriented nature, customer-driven design processes, and inherent rework challenges. The project-oriented feature of ETO systems implies that ETO companies typically treat each ETO product as a project, and the design and production processes are usually completed by a specialized project delivery team (Kjersem and Jünge, 2016; Cannas et al., 2020; Alfnes et al., 2021). In accordance with the Customer Order Penetration Point (CODP) concept, ETO is defined as a system where the CODP is located at the design stage (Olhager, 2003; Gosling et al., 2017). Typical ETO industries include: shipbuilding (Mello et al., 2017), construction (Dallasega et al., 2017) and capital goods (Adrodegari et al., 2015). The challenge of customization begins at the design stage and, because of the novelty in design and production, creates a significant burden of rework for managers.

Rework is typically regarded as waste in the lens of traditional production systems. However, in an ETO environment, it is often unavoidable due to design changes, iterations, and the inherent challenges of producing first-of-a-kind products. These characteristics significantly hinder the attainment of the "right first time" paradigm, thereby, shifting the focus from preventing rework to effectively managing it (Love et al., 2019). Love et al. (2024) developed and analysed the 'error-as-process' archetype, which views errors as dynamic phenomena that evolve over time through a chain of triggers, adaptive activities, and social interactions. The archetype emphasizes that rework is inevitable, hence, highlighting the importance of proactively managing it to minimize adverse impacts.

Rework can be observed using Non-Conformance Reports (NCRs), a commonly used tool in the construction industry to record deviations from design specifications or quality standards. NCRs provide a systematic approach to tracking errors and the associated corrective actions, offering valuable data for understanding rework's frequency and impact (Love et al., 2019; Ford et al., 2023). For typical projects, managers can estimate the rework ratio (RW) using historical NCR records and prior experience, enabling them to plan capacity and develop appropriate solutions.

Design rework is a common issue in the ETO environment (Jiao et al., 2007), often arising from changes or errors in the design. Depending on when the error or change is detected, design rework can be categorized into internal and external rework. Internal design rework occurs when errors or changes are identified during the design stage, whereas external design rework arises when errors or changes are discovered after production has commenced (Flyvbjerg and Gardner, 2023). In practice, it is common for design errors to surface during the production phase, requiring companies not only to amend the design but also to review and rectify completed products or work (Love et al., 2024). Preventing design errors or changes from carrying over into the production phase is critical in ETO systems. A widely recognized approach to address this challenge is the 'Think Slow, Act Fast' method. This concept, which emphasizes the importance of granting extra time to planning and design and swift execution, serves as a key strategy in project management and is explored in greater detail in Section 2.2.

2.2. "Think slow, act fast"

Flyvbjerg and Gardner (2023) proposed that detailed planning and design is the key to successful project execution, and rework reduction. They suggest that those associated with design and planning activities should take more time to plan and identify errors before any production/construction begins. In summary, "Think Slow, Act Fast" (Philbin, 2023). In practice, "Think slow" can be reflected in measures such as a design freeze period or allocating additional time for error detection. However, excessive deliberation may have drawbacks, such as delaying the start of production (Han et al., 2013; Li and Taylor, 2014). This trade-off highlights the significance of quantifying the "Think Slow, Act Fast" philosophy.

Compared to the definition of an ETO production system, "think" and "act" align with the engineering design and production processes respectively (Cannas et al., 2019). By incorporating the concept of the CODP, "think slow" and "act fast" also correspond to the pull and push strategies in production systems.

Although, ETO operates as a pure pull production system, it is still crucial to apply different strategies to different phases (Tiedemann et al., 2020). During the design phase, a "think slow" approach is crucial, allocating sufficient time for thorough planning and error detection to prevent costly late-stage rework. In contrast, the production phase requires a "fast" mindset, with adequate capacity reserved to ensure timely delivery and reduced lead times.

2.3. System dynamics in ETO modelling

SD models have been developed for Make-to-Stock (Wikner et al., 2017), Make-to-Order (Wikner et al., 2007) and Assemble-to-Order systems (Lin et al., 2020). However, its adoption in the ETO field is still in its nascent stages (Zhou et al., 2022). Zhou et al. (2022) developed an ETO prototype which only considered the production rework scenario, and this model was further developed by Zhou et al. (2022) to include the design rework scenario into the archetype. However, the external design rework remains insufficiently explored for the scenarios related to design changes or post-production defects. The core elements of the ETO system are summarized in Table 1 which builds on previous research (Zhou et al., 2022). Therefore, this paper develops archetypes to include the design rework scenario and duly complete the ETO archetype suite.

The modelling method employed in this paper is rooted in the SD paradigm, which is widely recognized for capturing flows, feedback, stocks and delays in complex systems such as ETO production (Lyneis and Ford, 2007; Love et al., 2019). Unlike discrete-event simulation (DES), which focuses on micro-level sequencing, or agent-based models that require detailed behavioural rules, SD provides a system-level view that is ideal for analysing aggregated level, long-term performance trends, such as lead-time dynamics (Lin et al., 2020) and capacity oscillations under rework scenarios (Spiegler et al., 2012; Zhou et al., 2022).

The use of Causal Loop Diagrams (CLDs) supports conceptual clarity, enabling the identification of core feedback loops and interactions across design, production, and control layers. These loops are especially critical in rework-intensive environments (Lyneis and Ford, 2007), where errors propagate and amplify through dynamic feedback.

Table 1
Explanation of the key elements of ETO archetype (Zhou et al., 2022).

Elements	Reference	Explanation
Rework	Lyneis and Ford (2007); Love et al. (2019)	Rework is a canonical feature in project management; such a problem is often inevitable in practice.
Working units	Pena-Mora and Park (2001); Lee et al. (2006)	Research in the project management field often models working units as opposed to product volume.
Work rate	Lee et al. (2005)	Work rates directly reflect capacity.
Lead time	Wikner et al. (2007); Lin et al. (2020); Spiegler et al. (2012)	Lead time, a vital concept in supply chain management, 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)	One of the distinguishing variables in the Make-to-order system is the order book, which represents the order waiting to be satisfied.

Building on the CLD, we translate the conceptual structure into block diagrams formulated in the z-domain SD model. This choice enables us to reflect the discrete-time nature of ETO systems, where events like inspections, rework cycles, and production releases occur in defined time intervals (e.g., weekly engineering reviews or batch production) (Ecem Yildiz et al., 2020). The z-domain structure also enables mathematical tractability for deriving transfer functions, simulating step changes, and applying performance metrics like ITAE.

Unlike traditional SD tools like Vensim or Stella, which rely on continuous stock-flow modelling, the block diagram formulation in this paper aligns with control theory principles (e.g., Disney and Towill, 2003) and is particularly suited to analysing transient response (Zhou et al., 2022), stability (Disney et al., 2006), and bullwhip effects (Wang and Disney, 2016). This hybrid approach — combining SD feedback logic with control-theoretic precision — offers a novel yet grounded way to understand the dynamics in ETO systems.

2.4. Performance metric: the ITAE

To assess the effectiveness of allocating additional time to the design phase, this study adopts the Integral of Time-weighted Absolute Error (ITAE) as the primary performance metric, as shown in (1). Originating from control theory, ITAE captures both the magnitude and duration of deviation from a target state, with the duration represented by t, target state represented by neutral axis, and deviation represented by $|output - neutral\ axis|$. In the context of ETO systems, where lead-time variability is a critical concern, ITAE provides a rigorous and sensitive measure of system responsiveness to demand change.

$$ITAE = \sum_{t=0}^{t} t \times |output - Neutral\ axis| \cdot \Delta t \tag{1}$$

From an operational and economic perspective, high ITAE values—particularly when applied to lead time—often reflect greater fluctuation in system performance. Volatility can result in substantial production on-costs (Spiegler et al., 2012). For example, in shipbuilding or infrastructure projects, system fluctuations caused by market change, delays and/or reworked designs often leads to contractual penalties, idle specialist trades, or inefficient re-sequencing of work packages (Bertrand and Muntslag, 1993; Wada et al., 2022). In a defence project cited by Lyneis et al. (2001), recurring rework led to a growing workload, which had to be addressed through costly overtime and additional hiring to meet contractual milestones. However, once the project was completed, staffing needs dropped below the current levels, resulting in excess capacity. This decision not only significantly increased costs but also slowed project progress. A similar pattern can be observed in shipbuilding, where market fluctuations often force shipyards to adjust capacity—either by deploying reserve resources or expanding yard facilities. Yet, when demand declines, companies unable to secure sufficient orders may face bankruptcy due to overcapacity and unsustainable operating costs (Wada et al., 2022).

Conversely, a system with lower ITAE shows less volatility in capacity requirements, allowing for better capacity planning and smoother workflows. This increased stability can reduce the need for firefighting measures and improve coordination across interdependent teams. Although this study does not directly monetise ITAE, it positions the metric as a proxy for economic performance (Disney and Towill, 2003; Spiegler et al., 2012) capturing the hidden costs associated with volatility in design-to-production workflows. Future research may develop explicit cost functions that relate ITAE values to rework-related cost factors such as delay penalties, resource inefficiency, and schedule disruption.

3. Method

3.1. Archetype development

The first step of this research is to develop two models that simulate two different types of design reworks based on the elements from Table 1 (Zhou et al., 2023a, 2023b). The archetypes will be developed into a Causal Loop Diagram (CLD) first for logic verification and then will be developed in block-diagram form in the z-domain. The benefit of modelling systems in the z-domain is that it can better capture the discrete time feature of the production system. In ETO production, activities like material procurement, design modifications, or project milestones are updated at specific intervals.

Two archetypes are developed to represent two design rework scenarios. The first model, ETOAR#D + X, is a generalized model of ETOAR#D, ETOAR refers to archetype for ETO system, '#D' refers to the scenario where design defects are detected during the design phase and only require rework on the design. Alternatively, it also applies to the scenario where customers require design changes before production starts. The main difference between ETOAR#D + X and ETOAR#D is that the former model simulates situations where extra time (X) is given to the design process. When X = 0, these two models are identical.

The second model presented in this section is ETOAR#PTD, which refers to the scenario where design defects are detected after the production starts. It also applies to the scenario where customers request design changes after production starts. The developed archetypes establish a basis for comparison between the two rework types.

3.2. Deriving the time X

The second step is to derive the appropriate time for design and planning phase, by conducting a comparison between the developed models. The Integral of Time Absolute Error (ITAE) is employed as the primary performance index. The criterion is, if the X of ETOAR#D + X can make the system's lead time result in a smaller ITAE value, then X is worth allocating as it can improve the overall system's lead time performance, as detailed in the process chart of Figure A.1, Appendix A. Noting here the lead time of archetypes is estimated via Little's Law (Little, 1961).

The reason for adopting ITAE is that it can assess the error between the system's output and the target level with a particular emphasis on penalizing delayed responses as indicated in (1).

By incorporating time as a penalty factor, ITAE effectively captures both the magnitude of the deviation and the system's responsiveness to dynamic conditions (Spiegler et al., 2012; Disney and Towill, 2003).

The input to the ETO archetype is a demand step change, characterized by a sudden and sustained shift at a specific time. This input effectively simulates external shocks, such as the initiation of a new project, which introduces additional workload across subsequent periods (Towill et al., 2007). The adoption of ITAE with this step input enables the analysis of system dynamics under varying rework scenarios, offering valuable insights into workload distribution and fluctuations.

Moreover, this research investigates how the bullwhip effect is affected by this additional time in the design system by calculating the ratio of variance of work rate by demand (Wang and Disney, 2016). The bullwhip measures the capacity variation in the production process. A production sub-system with high fluctuation has a higher operational cost because of frequently changed labour resources and machine utilisation. A smaller bullwhip indicates a system with a lower production on-cost (Spiegler et al., 2012).

4. Modelling

This section outlines the development process of the ETO system, starting with a conceptual Causal Loop Diagram (CLD). Mathematical expressions and two block diagrams are then derived from the CLD. The nomenclature is given in Table 2.

4.1. Causal loop diagram (CLD)

Building on the elements from Table 1, the ETO system's structure is conceptualized and visualized in Fig. 1, comprising three subsystems: design, production, and order book controller. The design subsystem represents the design process. When new demand arrives, the work rate increases, raising the completion rate and reducing the local order book. The production subsystem represents manufacturing activities. Demand positively impacts the work rate, which boosts the completion rate and reduces the order book.

The order book controller regulates workflow via feedback. By comparing the target and actual order books, the system adjusts the design and production work rates to ensure orders are completed within the expected lead time. Design rework occurs in two scenarios: before design completion (ETOAR#D) or after production begins (ETOAR#PTD). A dotted line indicates the first scenario, while the second scenario uses a dash line. For cases where additional time is allocated after design completion, these were labelled as ETOAR#D + X. Using this conceptual CLD, the elements are quantified and subsequently transformed into block diagrams. The nomenclature is given in Table 2.

4.2. ETOAR#D + X [ETO archetype design rework with extra X time] development

Figs. 2 and 3 demonstrate the block diagram of the ETOAR#D + X and ETOAR#PTD respectively, which are composed of three subsystems and one rework loop. These two models are developed from Fig. 2. Note here that $\frac{z}{z-1}$ is the integral, representing a stock level and $\frac{1}{Z^n}$ represents an n period pure delay.

Fig. 2 demonstrates the block diagram of the ETOAR#D + X archetype.

DEM_{DES} for the design system is composed of three parts, external demand, compensation value from order book controller, and rework.

$$WRATE_{DES}(t) = DEM(t) + \frac{OB(t) - DEM(t)\cdot(\tau_P + \tau_D)}{\tau_{OB}} + RWRATE_{DES}(t-1) \tag{2}$$

Pure delay τ_D represents the design time, while X refers to the extra time window given to the design error inspection, detection and changes.

$$COMRATE_{DES}(t) = WRATE_{DES}(t - \tau_D - \tau_X) \tag{3}$$

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. This research defines it as the total amount of working units that are required to complete all orders in the queue. In the project management field, this variable is also known as 'work to do' (Lee et al., 2005).

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t) \tag{4}$$

Rework $RWRATE_{DES}(t)$ is assumed to be a proportion of $COMRATE_{DES}(t)$, as represented by (5). In practice, the rework ratio, RW, can be calculated through statistical analysis. This model assumes that rectifying detected errors requires the same amount of work units as completing the original task. Additionally, any work with non-conformities is invalidated and must be redone. Equation (5) is built on prior research in rework simulation, aligning with established assumptions (Lyneis and Ford, 2007; Barbosa and Azevedo, 2019).

$$RWRATE_{DES}(t) = COMRATE_{DES}(t)\cdot RW \tag{5}$$

A design will be sent to the production department after the inspection and design change waiting window. $WRATE_{PROD}(t)$ refers to the work needed to be done by the production sub-system, which is a proportion of the $COMRATE_{DES}(t)$.

$$WRATE_{PROD}(t) = COMRATE_{DES}(t)\cdot(1 - RW) \tag{6}$$

τ_P is a pure delay, which represents the production time.

$$COMRATE_{PROD}(t) = WRATE_{PROD}(t - \tau_P) \tag{7}$$

$$OB_{PROD}(t) = OB_{PROD}(t-1) + WRATE_{PROD}(t) - COMRATE_{PROD}(t) \tag{8}$$

For the ETOAR#D system, it is assumed that production defects are non-existent, as outlined in (9).

$$DRATE(t) = COMRATE_{PROD}(t) \tag{9}$$

Equation (10) shows the order book of the whole system over time.

$$OB(t) = OB(t-1) + DEM(t) - DRATE(t) \tag{10}$$

Little's Law (Potter et al., 2020) is adopted to calculate the lead-time of whole system.

$$LT = \frac{OB\ (t)}{DELRATE(t)} \tag{11}$$

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 realized by (2) and (10). This structure enables the establishment of the productivity decision rule for the model.

Table 2
Nomenclature.

Abbreviation	Full name	Explanation
Order book controller		
DEM	Demand	Demand for the ETO system
OB	Order Book	Order Book for ETO system
LT	Lead-time	The estimated lead-time of the ETO system
$DRATE$	Delivery Rate	Rate of qualified products, which meet the customers' requirement
Design Sub-system		
DES	Design	Abbreviation for design
$WRATE_{DES}$	Work rate of the design system	Demand for the design system.
$COMRATE_{DES}$	Design Completion Rate	Completion rate of the design system
$RWRATE$	Rework rate	The number of units needing rework
OB_{DES}	Design Order Book	Order Book for design sub-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	Order Book for production sub-system
Physical Parameter		
τ_D	Expected Design Delay	Delay caused by designing or design adaptation
τ_P	Expected production Delay	Delay caused by production
X	Extra time for design	Extra time that given to design system
RW	Rework ratio	The percentage of rework produced
Decision Parameter		
τ_{OB}	Time for order book adjustment	Time used for adjusting the production system's order book

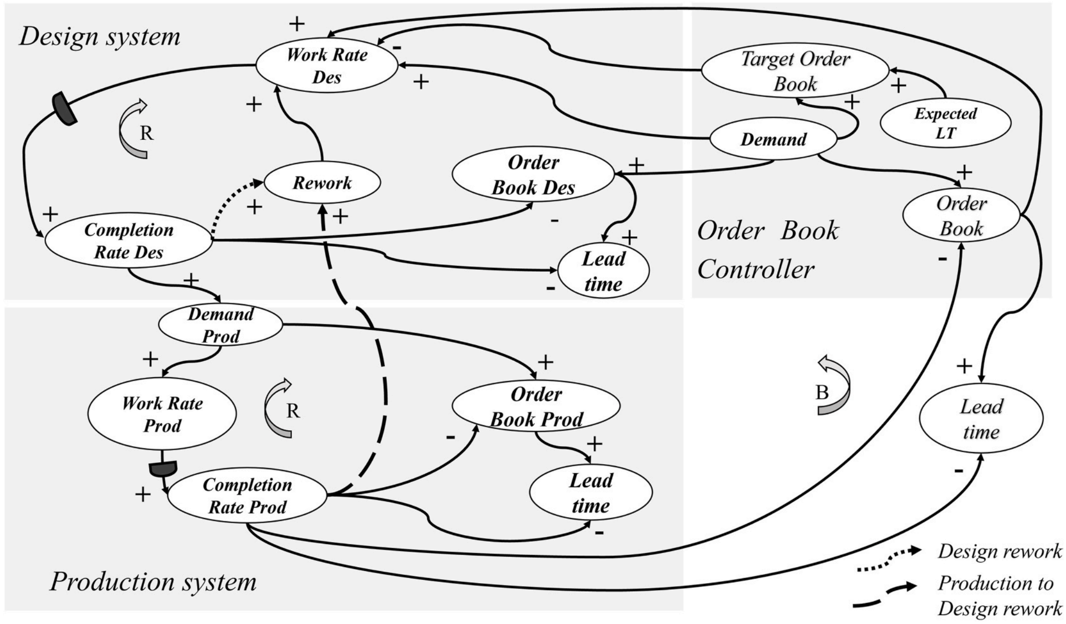

Fig. 1. A causal loop diagram for ETO archetype.

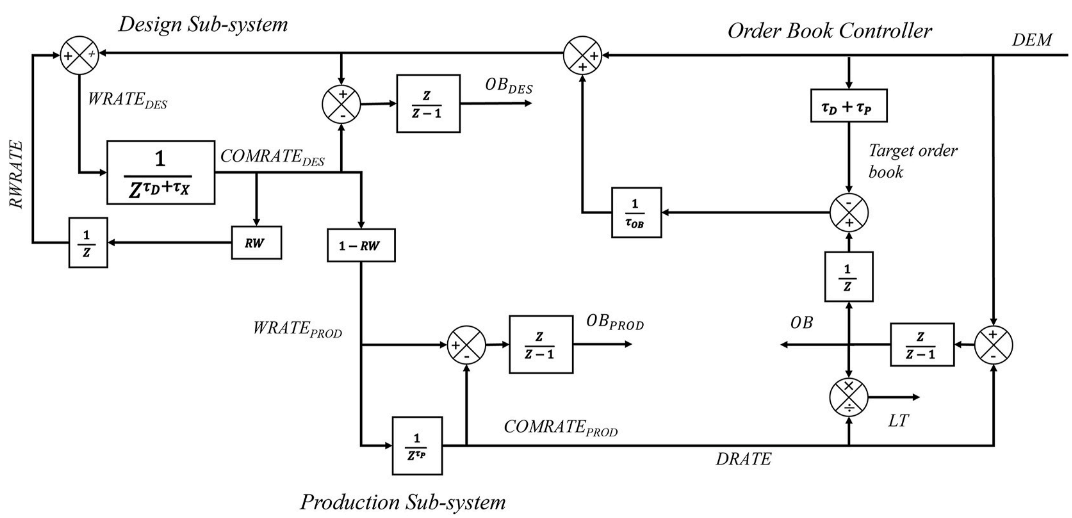

Fig. 2. The block diagram of ETOAR#D + X [ETO archetype design rework with extra X time].

4.3. ETOAR#PTD[ETO archetype production to design rework] archetype development

ETOAR#PTD represents a scenario where design errors are identified or design changes are made after production has already started. In this section, the equations that differ from those in the ETOAR#D + X system are presented. The associated block diagram is shown in Fig. 4, with the full set of equations detailed in the appendix. In (12) it can be seen the $RWRATE(t)$ is added to the $WRATE_{DES}(t)$.

The $RWRATE(t)$ is created in (14) which represent the design defects/changes detected/happens after production starts.

$$WRATE_{DES}(t) = DEM(t) + \frac{OB(t) - DEM(t) \cdot (\tau_{P+}\tau_D)}{\tau_{OB}} + RWRATE(t) \quad (12)$$

$$COMRATE_{DES}(t) = WRATE_{DES}(t - \tau_D) \quad (13)$$

$RWRATE(t)$ refers to the rework created by the design errors or changes, these errors and changes requires rework in both design and production sub-system. RW refers to the rework ratio, the $RWRATE(t)$ is assumed to be a percentage of $COMRATE_{PROD}(t)$

$$RWRATE(t) = COMRATE_{PROD}(t) \cdot RW \quad (14)$$

$DRATE(t)$ refers to the conformant works that can be delivered to the clients. In this scenario, (1-RW) denotes the proportion of completed works ($COMRATE_{PROD}(t)$) that are free from design errors or changes.

$$DRATE(t) = COMRATE_{PROD}(t) \cdot (1 - RW) \quad (15)$$

Equation (11) introduces non-linearity into the system; to keep the linearity of the system, the LT is linearized as shown in (16). The detailed linearization process is demonstrated in Appendix B.

$$LT = \frac{OB - (\tau_D + \tau_P) \cdot DRATE}{DEM} + (\tau_D + \tau_P) \quad (16)$$

5. Findings

This section presents the experimental results and findings, focusing on three key aspects: the transfer function of the archetypes, including

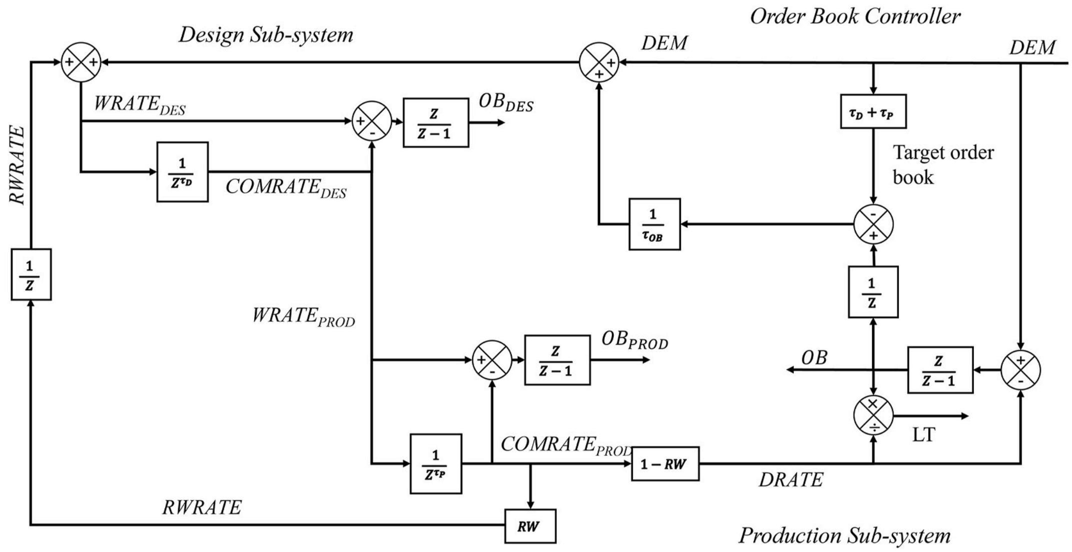

Fig. 3. The block diagram of ETOAR#PTD [ETO archetype with production to design rework].

the application of the initial and final value theorems, and the analysis of transient responses (Section 5.1). Additionally, it explores the maximum allowable time for 'Thinking Slow' during the design stage to incorporate inspection and change processes effectively (Section 5.2).

5.1. Model simulation

To conduct the simulations, transfer functions for both archetypes were derived, as shown in(17) and (18). The derivation follows the standard Z-transform procedure based on the state-space representation (Truxal, 1958), as detailed in Appendix D. In this step, we assume that the delays for both the design and production stages are equal to 4 (i.e., $\tau_D = 4$, and $\tau_P = 4$). This setting is chosen to evaluate the model's performance under high-delay conditions, which are commonly encountered in ETO environments.

$$G_{DES}(z) = \frac{LT(z)_{DES}}{DEM(z)} = \frac{\tau_{OB} z^{9+X} - RW\tau_{OB} z^4 + (72 - 72RW - 9\tau_{OB} + 9RW\tau_{OB})z + (RW - 1)(72 - 8\tau_{OB})}{\tau_{OB} z^{9+X} - \tau_{OB} z^{8+X} - RW\tau_{OB} z^4 + RW\tau_{OB} z^3 + (1 - RW)} \tag{17}$$

$$G_{PTD}(z) = \frac{LT(z)_{PTD}}{DEM(z)} = \frac{\tau_{OB} z^{10} + (72 - 72RW - 9\tau_{OB} + 9RW\tau_{OB})z^2 + (-72 + 72RW + 8\tau_{OB} - 9RW\tau_{OB})z}{\tau_{OB} z^{10} - \tau_{OB} z^9 + (1 - RW - RW\tau_{OB})z + RW\tau_{OB}} \tag{18}$$

Using the derived transfer function, the initial and final value theorems can be applied. The results are demonstrated in (24)–(27). The derivation method follows the approach outlined by Truxal (1958). Equation (19)–(23) demonstrate how to derive the FVT and IVT in discrete time domain.

$$FVT : \lim_{t\to\infty} LT[t] = \left(\lim 1 - z^{-1}\right) \cdot LT(z) \tag{19}$$

$$IVT : \lim_{t\to 0} LT[t] = \lim_{z\to\infty} LT(z) \tag{20}$$

For a unit step input, where $DEM(z) = \frac{z}{z-1}$, we have:
Since:

$$DEM(z) = \frac{z}{z-1} \text{ and } G(z) = \frac{LT(z)}{DEM(z)} \Rightarrow LT(z) = G(z)\cdot\frac{z}{z-1} \tag{21}$$

Then:

$$FVT : \lim_{t\to\infty} LT[t] = \lim_{z\to 1}\left(1 - z^{-1}\right)\cdot G(z)\cdot\frac{z}{z-1} = \lim_{z\to 1} G(z) \tag{22}$$

$$IVT : \lim_{t\to 0} LT[t] = \lim_{z\to\infty} G(z)\cdot\frac{z}{z-1} \tag{23}$$

Therefore:
For ETOAR#D + X [ETO archetype design rework with extra X time]:

$$Final\ value : \lim_{t\to\infty} LT_{DES}(t) = 0 + \tau_D + \tau_P \tag{24}$$

$$Initial value : \lim_{t\to 0} LT_{DES}(t) = 1 + \tau_D + \tau_P \tag{25}$$

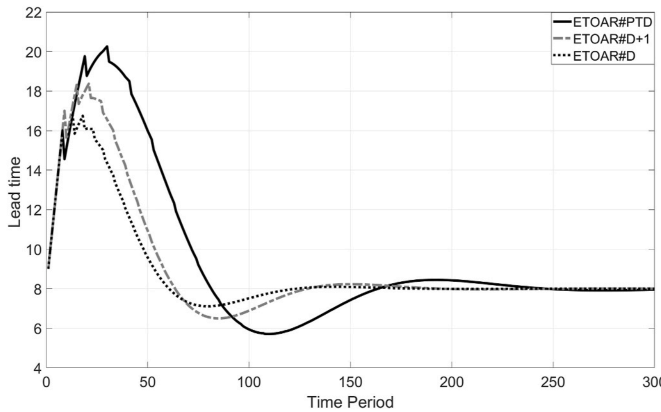

Fig. 4. Transient response for both models.

For ETOAR#PTD [ETO archetype with production to design rework]:

$$\text{Final value} : \lim_{t\to\infty} LT_{PTD}(t) = 0 + \tau_D + \tau_P \tag{26}$$

$$\text{Initial value} : \lim_{t\to 0} LT_{PTD}(t) = 1 + \tau_D + \tau_P \tag{27}$$

Equations (24) and (26) represent the final value, showing that the system eventually stabilizes at the designed lead time level $(0 + \tau_D + \tau_P)$. This result highlights the archetype's ability to maintain the intended lead time and automatically adjust system capacity to meet new demand.

Equations (25) and (27) show the initial value of the system. Since the step input occurs at stage 0, the initial value is $(1 + \tau_D + \tau_P)$, indicating an immediate change in lead time as soon as a new task is added to the order book.

To verify and understand the newly developed models, a lead-time simulation is conducted for both models. The simulations in this section allow us to visualize the systems' dynamic behaviours. The parameter settings for this research, shown in Table 3, were determined based on simulations, which revealed that this configuration reduces system fluctuations. The initial values for simulations for the two models differ to ensure steady-state initial conditions.

Fig. 4 illustrates the lead-time transient response of the three models to a step change input. These systems' lead-times eventually stabilise at 8-time units, which is the desired lead-time for the archetypes. This indicates that all models can maintain the lead-time at the desired level in the long term although only after an increase during the transient.

After comparing the transient responses of systems, it is observed that ETOAR#D, representing the ideal scenario, exhibits the lowest fluctuation and settles down first. ETOAR#D+1, which represents an additional time unit given to the design subsystem, shows moderate fluctuation, with its peak lower than that of ETOAR#PTD, and settles down more quickly. ETOAR#PTD exhibits the greatest fluctuation with the highest peak value and takes the longest time to settle down. These findings suggest that, compared to ETOAR#PTD, ETOAR#D+1 performs better in terms of lead time, exhibiting lower fluctuations and returning to a normal state more quickly. In addition, all models' first period output is 9, which is $1 + t_D + t_P$, and settle down at 8, which is the sum of $t_D + t_P$, corresponding to the result of initial and final value theorem in (19).

Table 3
Initial Value and co-efficient value for ETOAR#D + X and ETOAR#PTD simulation.

ETOAR #D + X	*Initial values*				
	$COMRATE_{DES}$	OB_{DES}	$RWRATE_{DES}$	OB_{PROD}	OB
	250	1000	150	400	800
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	X
	1/26	4	4	0.6	1

5.2. *Findings from the experiment*

Although the model in this study is formulated analytically using z-domain transfer functions (e.g., (17)), the bullwhip effect is assessed through simulation rather than closed-form derivation. This is primarily due to the high-order nature of the transfer functions, which include complex delay structures such as z^{9+X} and multiple feedback terms. These result in rational functions that are analytically intractable without extensive symbolic computation. While it is theoretically possible to expand the transfer function into a power series and calculate bullwhip as the variance amplification factor (i.e., the sum of squared impulse response coefficients), this would require case-specific derivations and offer limited interpretability. Moreover, for the lead time ITAE calculation, we use a step input to reflect the dynamic behaviour of an ETO system during project initiation. Under this type of input, simulation provides a practical and intuitive way to observe how the system responds to dramatic demand change (Towill et al., 2007). While to evaluate the bullwhip effect in the production subsystem, we apply a stochastic demand input to better represent real-world variability. Specifically, the input follows a normal distribution with a mean of 100 and a standard deviation of 10.

5.2.1. *Maximal allowed time for the design sub-system*

The findings indicate that no additional time is needed for the design subsystem when RW = 0.1. For RW values between 0.2 and 0.5, one extra time unit is recommended, while RW values from 0.6 to 0.9 may require one or two extra units, depending on inspection effectiveness and bullwhip ratio requirements. Allocating unnecessary extra time can increase the lead-time ITAE beyond that of ETOAR#PTD.

5.2.2. *How extra time X affects the workload of sub-systems*

Table 4 offers a comparison of workload between ETOAR#D + X and ETOAR#PTD. Percentage values in Table 4 denote the ratio between the total working units throughout the simulation period and the benchmark scenario, expressed by (28). In this context, the benchmark scenario is ETOAR#D with RW = 0. The results indicate that ETOAR#D + X maintains the workload of the total production sub-system at 100 %, despite an escalating rework ratio. Conversely, ETOAR#PTD experiences a dramatic increase in the workload of its production sub-system as the rework ratio rises. This observation implies that ETOAR#PTD necessitates the company to sustain a higher production capacity to accommodate the additional work generated by rework.

Nevertheless, the additional time allocated to the design sub-system in ETOAR#D + X comes with its own set of challenges. Notably, the workload of the design sub-system in ETOAR#D + X not only escalates alongside the rework ratio but also slightly exceeds that of ETOAR#PTD.

$$\text{Work load ratio} = \frac{\text{Total working units of the sub} - \text{systems}}{\text{Total working units of benchmark sub} - \text{system}} \tag{28}$$

5.2.3. *How extra time X affects the bullwhip ratio effect of the production system*

According to Table 4, the bullwhip value decreases with an increase in RW ratio for the ETOAR#D + X scenarios, while for the ETOAR#PTD, the increase in RW ratio leads to an increase in bullwhip. 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 effect appears irregular. For example, when RW = 0.7, the increasing X values creates following bullwhip ratio: 0.092, 0.097,

Table 4
Experiment results.

RW ratio	X: Extra time	Lead-time ITAE (Step input)		Workload (using ETOAR#D, RW = 0, as benchmark)				Production Bullwhip (Stochastic)	
		ETOAR#D + X	ETOAR#PTD	ETOAR#D + X		ETOAR#PTD		ETOAR#D + X	ETOAR#PTD
				Design workload	Production workload	Design workload	Production workload		
0.1	0	1164	1406	111.36 %	100 %	111.36 %	111.11 %	0.373	0.463
	1	1692		111.42 %	100 %	111.36 %	111.11 %	0.371	
0.2	0	1496	2380	125.28 %	100 %	125.28 %	111.11 %	0.312	0.497
	1	2348		125.35 %	100 %	125.28 %	125.00 %	0.311	
	2	3547		125.42 %	100 %	125.28 %	125.00 %	0.294	
0.3	0	2175	4076	143.17 %	100 %	143.17 %	142.86 %	0.267	0.532
	1	3442		143.25 %	100 %	143.17 %	142.86 %	0.266	
	2	5206		143.33 %	100 %	143.17 %	142.86 %	0.244	
0.4	0	3339	7200	167.04 %	100 %	167.04 %	166.67 %	0.224	0.590
	1	5324		167.13 %	100 %	167.04 %	166.67 %	0.224	
	2	8066		167.22 %	100 %	167.04 %	166.67 %	0.199	
0.5	0	5473	13380	200.44 %	100 %	200.44 %	200.00 %	0.181	0.680
	1	8899		200.56 %	100 %	200.44 %	200.00 %	0.184	
	2	13642		200.67 %	100 %	200.44 %	200.00 %	0.157	
0.6	0	10034	27307	250.56 %	100 %	250.56 %	250.00 %	0.132	0.782
	1	16431		250.70 %	100 %	250.56 %	250.00 %	0.136	
	2	25027		250.83 %	100 %	250.56 %	250.00 %	0.112	
	3	36652		250.80 %	100 %	250.56 %	250.00 %	0.113	
0.7	0	21573	67765	334.07 %	100 %	334.07 %	333.33 %	0.092	0.838
	1	35616		334.26 %	100 %	334.07 %	333.33 %	0.097	
	2	54405		334.45 %	100 %	334.07 %	333.33 %	0.077	
	3	79837		334.63 %	100 %	334.07 %	333.33 %	0.081	
0.8	0	62395	206231	501.11 %	100 %	501.11 %	500.00 %	0.054	1.195
	1	103515		501.39 %	100 %	501.11 %	500.00 %	0.060	
	2	160094		501.67 %	100 %	501.11 %	500.00 %	0.047	
	3	232589		501.95 %	100 %	501.11 %	500.00 %	0.053	
0.9	0	365768	1161779	1002.23 %	100 %	1001.97 %	999.78 %	0.026	2.972
	1	611410		1002.29 %	100 %	1001.97 %	999.78 %	0.033	
	2	927740		1003.43 %	100 %	1001.97 %	999.78 %	0.027	
	3	1269755		1003.58 %	100 %	1001.97 %	999.78 %	0.028	

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).

6. Discussion

6.1. Completed IOBPCS family

Compared with other types of production systems, such as Make-to-Stock (Towill, 1982), Make-to-Order (Wikner et al., 2007), and Assemble-to-Order (Lin et al., 2020), the ETO community has yet to develop a widely recognized SD archetype for modelling and benchmarking. In contrast, Inventory and Order-Based Production Control System (IOBPCS) concepts have been extensively adopted in other production systems, providing valuable insights into bullwhip effect mitigation and capacity estimation (Lin et al., 2020).

This research addresses a gap in the IOBPCS (Inventory Order Based Production Control System) family of models (Wikner et al., 2007) by developing ETO system archetypes that incorporate rework dynamics and feedback-driven control. Previous work introduced an initial ETO archetype focusing on production rework and single-unit delay (Zhou et al., 2022). This was later extended to include design rework, with particular attention to system stability and resilience under dynamic conditions (Zhou et al., 2023a, 2023b). The archetypes have been discussed in peer-reviewed academic forums, contributing to a growing body of literature on ETO-specific control logic. The present study further advances this work by proposing an order-based control system tailored to the ETO environment, offering two new archetypes that explicitly model design rework scenarios. In doing so, it completes the foundational ETO archetype suite, covering critical operational challenges specific to ETO production systems. Particular emphasis is placed on the role of the design phase—a distinguishing feature of ETO systems—and how different forms of design rework impact overall system performance.

Moreover, the completed ETO archetype suite extends the applicability of SD modelling to the ETO field, providing a toolbox for system analysis and benchmarking (Willner et al., 2016). This suite enables practitioners to evaluate system performance, simulate scenarios, and make informed decisions. By integrating this archetype suite into practice, organizations can better understand and optimize their ETO production systems, ultimately expanding the utility of SD in complex production environments.

6.2. Re-visiting 'think slow, act fast' from a SD perspective

This research delves into the "Think Slow, Act Fast" philosophy (Flyvbjerg and Gardner, 2023), 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′) on the ETO system's lead time is examined. The findings reveal a direct correlation between the rework ratio and the feasibility of allocating extra design time. Additionally, the archetypes provide a quantitative platform for determining the maximum allowable extra time for 'thinking,' ensuring that excessive time spent on planning does not lead to project time overruns.

The benefits of allocating extra time to the design subsystem to prevent design defects/changes from going to production sub-system can be summarized as follows: 1) Although it prolongs the time spent in the design subsystem, it improves the lead time dynamic performance. A reduced ITAE value refers to a more stable system. 2) It reduces the bullwhip effect of the production system. The negative effect of such a strategy is that it can lead to an increase in the workload of the design subsystem. However, the increase of design workload is trivial. This makes the benefits of assigning extra time to the design subsystem outweigh its disadvantages.

Aligning with the principles outlined in ’How Big Things Get Done’ (Flyvbjerg and Gardner, 2023), this study echoes the segmentation of project management into ’Planning’ and ’Delivery’ phases. This segmentation resonates with the ’Engineer design’ and ’Production’ phases in an ETO context (Gosling et al., 2017), reinforcing the concept that thorough planning (or design) is crucial for efficient delivery (or production). This research supports the book *How big things get done* by Flyvbjerg and Gardner (2023) advocacy for comprehensive planning, emphasizing the importance of cross-departmental collaboration and early-stage prototyping and modelling.

6.3. Managerial implications

The findings advocate for the implementation of design inspection protocols and the introduction of a ’design freeze’ window in an ETO system (Ford and Sobek, 2005). This approach minimizes the transfer of design changes or errors to the production phase while reducing fluctuations in the production system’s work rate and capacity requirements. Comparison of the ETOAR#D + X and ETOAR#PTD models across various rework ratios (RW) and extra time allocations (X), consistently shows that ETOAR#D + X achieves more favourable outcomes in terms of lead time and workload management. These findings provide a practical framework for determining the optimal timing and duration for design freezing (X period of time), particularly in projects with significant overlap between engineering and production phases (Mello et al. 2015a).

The insights from this research offer actionable strategies for ETO managers: ***1. Design Strategies:*** The models support the determination of optimal inspection durations. ***2. Risk Management:*** By proactively managing rework, organizations can adjust the system’s capacity according to the developed archetype, and reserve extra resources for rework. 3. ***Empowering:*** this research recommends empowering inspection and design leaders with greater decision-making authority, further preventing the design changes’ or defects’ transfer to production.

Furthermore, in the field of project management, SD-based decision engines have been effectively utilized in construction management (Park, 2005; Lee et al., 2006; Shin et al., 2014). These engines, integrated with various software tools, have demonstrated practical effectiveness in managing real-world projects. The archetypes presented in this paper address a critical gap in the production field by providing a tailored framework for the ETO environment. This development not only enhances the existing suite of SD models but also establishes a foundational tool for decision-making and system benchmarking in ETO production systems.

7. Conclusion

This paper determines the impact of ETOAR#D + X and ETOAR#PTD on a system’s lead-time performance from a system dynamics perspective. The first objective, to determine an ETO model by including the scenario where extra time is given to inspection and design changes, is addressed by the models presented in Section 4. The second objective, to investigate how many time periods could be given to the design process for inspection and re-specification, is addressed through a comparison between ETOAR#D + X and ETOAR#PTD, where Table 4 demonstrates how many extra time units given to the design process is beneficial for the total lead-time. And Section 5.2 summarizes the pro and cons of assigning extra time to the design sub-system. This paper provides quantitative evidence for the ’Think Slow, Act Fast’ philosophy based on SD models, and offers a methodology to determine the maximum extra time for the design freezing or inspection (Mello et al. 2015b).

Like any other research, there are some limitations. Although, the research addresses how rework types affect lead-time performance but their impact on production capacity is not fully explored. While extra lead-time reduces defects in production, it increases pressure to improve efficiency, a trade-off not fully analysed. Additionally, the assumption that inspection eliminates all design reworks excludes hybrid scenarios where multiple rework types coexist. Potentially, future research can examine workload impacts and develop models for mixed rework scenarios, thereby addressing the gaps and enhancing production accuracy.

CRediT authorship contribution statement

Yuxuan Zhou: Writing – original draft, Methodology, Validation, Visualization. **Mohamed Naim:** Supervision, Writing – review & editing, Methodology, Validation. **Jonathan Gosling:** Methodology, Writing – review & editing, Supervision, Validation. **Xun Wang:** Writing – review & editing, Supervision, Validation, Methodology.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ‘Grammarly’ in order to correct the grammar. After using this tool/service, the author (s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Appendix A

To determine the value of X, a comparative procedure is conducted between the ETOAR#D + X and ETOAR#PTD systems under varying rework ratios (RW). For each increment of RW (from 0.1 to 0.9), the ITAE (Integral of Time-weighted Absolute Error) value of the lead time in ETOAR#PTD is calculated and used as a benchmark. Starting from $X = 0$, the ETOAR#D + X model is iteratively simulated, increasing X until its lead time ITAE equals or exceeds that of the ETOAR#PTD model for the same RW. The corresponding $X-1$ value is recorded as the minimal extension required for ETOAR#D + X to match ETOAR#PTD’s performance. This process is repeated for all RW values, with bullwhip effects also computed at each step for both models.

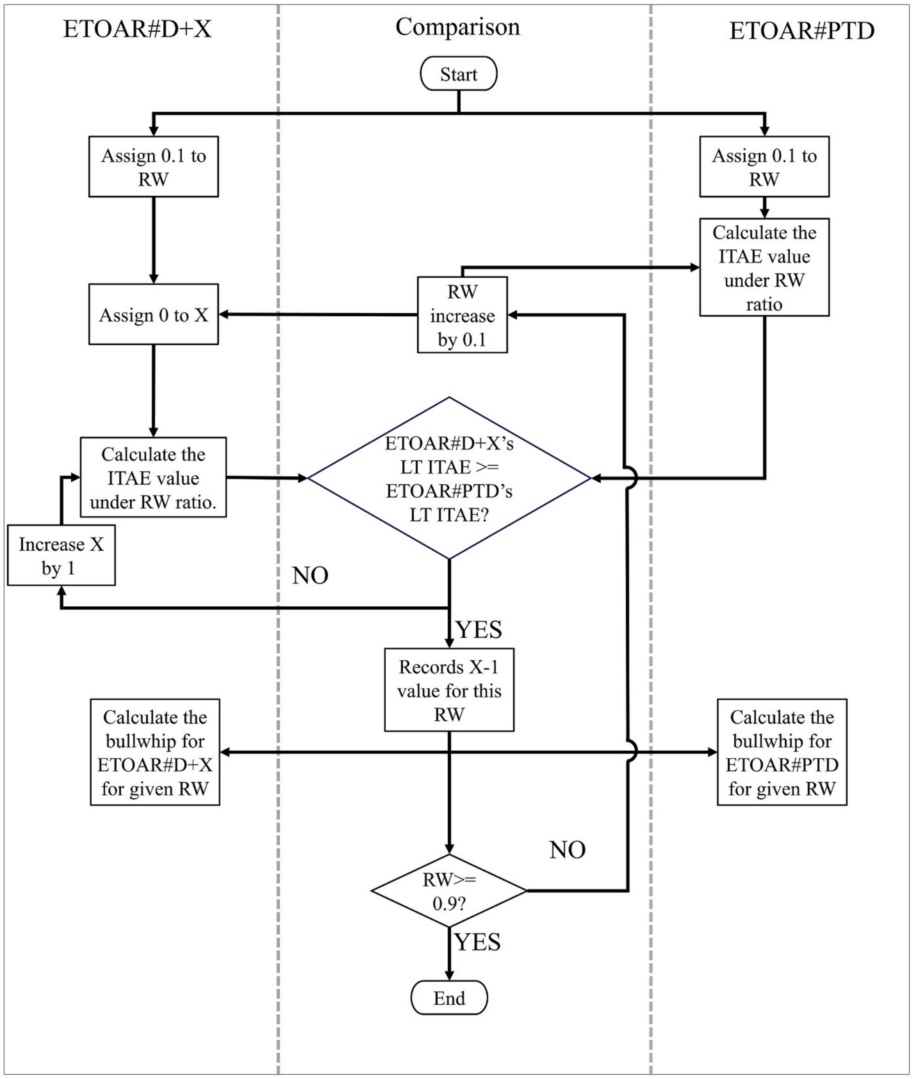

Fig. A.1. Derivation Process for the Maximal Allowable Time X in Design

Appendix B

The mathematical formulation for the ETOAR#PTD system is presented below. The model is composed of two interlinked subsystems: design and production. Rework is incorporated into the system, triggered by design defects or late-stage adjustments, which are detected during the production phase.

ETOAR#PTD.

Design sub-system.

The work rate of the design subsystem, denoted as $WRATE_{DES}(t),$ is determined by the incoming demand ($DEM(t)$) the order book adjustment term ($\frac{OB(t)-DEM(t)\cdot\ (\tau_{P+}\tau_D)}{\tau_{OB}}$) and the rework rate ($RWRATE(t)$).

$$WRATE_{DES}(t) = DEM(t) + \frac{OB(t) - DEM(t)\cdot\ (\tau_{P+}\tau_D)}{\tau_{OB}} + RWRATE(t) \tag{A.1}$$

τ_D represent the pure delay of the design sub-system.

$$COMRATE_{DES}(t) = WRATE_{DES}(t - \tau_D) \tag{A.2}$$

$$OB_{DES}(t) = OB_{DES}(t-1) + DEM_{DES}(t) - COMRATE_{DES}(t) \tag{A.3}$$

Production sub-system

$$WRATE_{PROD}(t) = COMRATE_{DES}(t) \tag{A.4}$$

τ_P represent the pure delay of the production sub-system.

$$COMRATE_{PROD}(t) = WRATE_{PROD}(t - \tau_P) \tag{A.5}$$

$$OB_{PROD}(t) = OB_{PROD}(t-1) + DEM_{PROD}\ (t) - COMRATE_{PROD}(t) \tag{A.6}$$

$RWRATE(t)$ represents the rework detected in the production subsystem. These reworks require additional effort from the design subsystem, as illustrated in (A.1).

$$RWRATE(t) = COMRATE_{PROD}(t) \cdot RW \tag{A.7}$$

$$DRATE(t) = COMRATE_{PROD}(t) \cdot (1 - RW) \tag{A.8}$$

$$OB(t) = OB(t-1) + DEM(t) - DRATE(t) \tag{A.9}$$

Lead time is estimated via little's law (Little, 1961)

$$LT = \frac{OB\ (t)}{DELRATE(t)} \tag{A.10}$$

Appendix C

Linearization.

The main structure of the archetype is developed in Section 4 and provides a foundation for the mathematical analysis. However, a key non-linearity arises from the formulation of lead time, which is modeled as a state-dependent function of demand and delivery rates. This feedback-driven lead time obstructs the direct adoption of standard transfer function techniques.

In this research, lead time is calculated using Little's law (Little, 1961), as given in (11). 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

$$Lead\ time, LT = \frac{OB(t)}{DRATE(t)} \tag{A.11}$$

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

$$LT^{*} - (\tau_D + \tau_P) = \frac{\partial LT}{\partial OB}(OB^{*} - OB) + \frac{\partial LT}{\partial DRATE}(DRATE^{*} - DRATE) \tag{A.12}$$

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.

$$\frac{\partial LT}{\partial OB} = \frac{1}{DRATE} = \frac{1}{DEM} \tag{A.13}$$

$$\frac{\partial LT}{\partial DRATE} = -\frac{OB}{DRATE^2} = -\frac{(\tau_D + \tau_P) \cdot DEM}{DEM^2} \tag{A.14}$$

If (13) and (14) are taken into (12), after reorganisation, (15) can be obtained:

$$LT = \frac{OB - (\tau_D + \tau_P) \cdot DRATE}{DEM} + (\tau_D + \tau_P) \tag{A.15}$$

It is evident from (15) that DEM at the resting point will be a constant, thereby making LT a linear expression. As presented in Section 4, the ETO archetypes with design rework includes two 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 (15) is the expression for lead time for all ETO archetypes.

Appendix D

State-space representation and transfer function:

The state-space representation is used as a basis to derive the system's transfer function, enabling analysis of lead time responses in the Z-domain.

The discrete-time state-space representation of the ETOAR#PTD system is given by:

$$x[t+1] = Ax[t] + B \cdot DEM[t] \tag{A.16}$$

$$LT[t] = Cx[t] + D \cdot DEM[t] \tag{A.17}$$

where $x[t]$ is the state vector representing system states across the design and production subsystems, $DEM[t]$ is the external demand input, and $LT[t]$ is the resulting lead time output. The matrix A incorporates the internal feedback dynamics, delay propagation $(\tau_P + \tau_D)$, and rework pathways, while B reflects how demand feeds into the system. The output matrix C extracts the lead time from the relevant state. Matrix D is zero in this model, as there is no direct feedthrough from the input to the output.

ETOAR#D + X [ETO archetype design rework with extra X time]:

Matrix A_{DES} represents the internal system dynamics of the ETOAR#D + X model. It captures the structural dependencies between states in both the **design** and **production** subsystems. Each element in matrix A encodes either a delay, modeled using the operator $\lambda = z^{-1}$; a rework fraction RW, reflecting the proportion of work requiring redesign; or a direct transfer, representing immediate influence from one state to the next.

The matrix includes pure delays represented by λ^{τ_D} and λ^{τ_P}, modeling the time required to complete design and production processes. Rework routing, where fractions of production output flow back to the design subsystem, governed by RW and 1−RW. Accumulation and buffer stages, which simulate how order book records all unfinished works.

$$A_{DES} = \left[\begin{array}{c|cccccccccc}
 & WRATE_{DES} & COMRATE_{DES} & OB_{DES} & RWRATE & WRATE_{PROD} & COMRATE_{PROD} & OB_{PROD} & DRATE & OB & LT_{DES} \\
\hline
WRATE_{DES} & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & \frac{1}{\tau_{OB}} \\
COMRATE_{DES} & \lambda^{\tau_D+X} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
OB_{DES} & \lambda^{-1} & -\lambda^{-1} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
RWRATE & 0 & \frac{RW}{\lambda} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
WRATE_{PROD} & 0 & \frac{1-RW}{\lambda} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
COMRATE_{PROD} & 0 & 0 & 0 & 0 & \lambda^{\tau_P} & 0 & 0 & 0 & 0 & 0 \\
OB_{PROD} & 0 & 0 & 0 & \lambda^{-1} & -\lambda^{-1} & 1 & 0 & 0 & 0 & 0 \\
DRATE & 0 & 0 & 0 & 0 & 0 & \lambda^{-1} & 0 & 0 & 0 & 0 \\
OB & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\lambda^{-1} & 1 \\
LT_{DES} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-(\tau_P+\tau_D)}{\lambda} & \lambda^{-1}
\end{array}\right] \tag{A.18}$$

Matrix B represents the influence of external demand. DEM(t) on the state dynamics of the ETOAR#D + X system. Specifically, it defines how incoming demand affects the internal flow of work in the system. The first row of B includes a controller term: $\frac{1-\frac{1}{\tau_{OB}}(\tau_P+\tau_D)}{\lambda}$. which adjusts the input based on the expected delay between order and fulfilment, acting as a time-scaled feedback compensator for the order book. This ensures that demand is fed into the system with consideration for design and production delays.

Further down, the non-zero entry in row 9: $\frac{1}{\lambda}$ allows demand to propagate into the later stages of the system — influencing the states directly associated with order book. This represents how new demand drives work downstream, supporting the simulation of delay accumulation and eventual output generation.

$$B_{DES} = \left[\begin{array}{c|c}
WRATE_{DES} & \frac{1-\frac{1}{\tau_{OB}}(\tau_P+\tau_D)}{\lambda} \\
COMRATE_{DES} & 0 \\
OB_{DES} & 0 \\
WRATE_{PROD} & 0 \\
OB_{PROD} & 0 \\
COMRATE_{PROD} & 0 \\
RWRATE & 0 \\
DRATE & 0 \\
OB & \frac{1}{\lambda} \\
LT_{DES} & 0
\end{array}\right] \tag{A.19}$$

Vector C represents the output vector. The 10th column corresponds to the lead time (LT) and is set to 1 to indicate that we are extracting the transfer function specifically for lead time.

$$C_{DES} = \left[\begin{array}{cccccccccc}
WRATE_{DES} & COMRATE_{DES} & OB_{DES} & WRATE_{PROD} & OB_{PROD} & COMRATE_{PROD} & RWRATE & DRATE & OB & LT_{DES} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right] \tag{A.20}$$

ETOAR#PTD [ETO archetype production to design rework]

ETOAR#PTD's transfer function is also derived based on state space representation:

$$A_{PTD} = \left[\begin{array}{c|cccccccccc} & WRATE_{DES} & COMRATE_{DES} & OB_{DES} & WRATE_{PROD} & OB_{PROD} & COMRATE_{PROD} & RWRATE & DRATE & OB & LT_{DES} \\ WRATE_{DES} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & \frac{1}{\tau_{OB}} & 0 \\ COMRATE_{DES} & \lambda^{\tau_D} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ OB_{DES} & \lambda^{-1} & -\lambda^{-1} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ WRATE_{PROD} & 0 & \lambda^{-1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ OB_{PROD} & 0 & 0 & 0 & \lambda^{-1} & 1 & -\lambda^{-1} & 0 & 0 & 0 & 0 \\ COMRATE_{PROD} & 0 & 0 & 0 & \lambda^{\tau_P} & 0 & 0 & 0 & 0 & 0 & 0 \\ RWRATE & 0 & 0 & 0 & 0 & 0 & \frac{RW}{\lambda} & 0 & 0 & 0 & 0 \\ DRATE & 0 & 0 & 0 & 0 & 0 & \frac{1-RW}{\lambda} & 0 & 0 & 0 & 0 \\ OB & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\lambda^{-1} & 1 & 0 \\ LT_{DES} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-(\tau_P+\tau_D)}{\lambda} & \lambda^{-1} & 0 \end{array}\right] \quad (A.21)$$

#(.)

$$B_{PTD} = \left[\begin{array}{cc} WRATE_{DES} & \frac{1-\frac{1}{\tau_{OB}}(\tau_P+\tau_D)}{\lambda} \\ COMRATE_{DES} & 0 \\ OB_{DES} & 0 \\ WRATE_{PROD} & 0 \\ OB_{PROD} & 0 \\ COMRATE_{PROD} & 0 \\ RWRATE & 0 \\ DRATE & 0 \\ OB & \frac{1}{\lambda} \\ LT_{DES} & 0 \end{array}\right] \quad (A.22)$$

$$C_{PTD} = \left[\begin{array}{cccccccccc} WRATE_{DES} & COMRATE_{DES} & OB_{DES} & WRATE_{PROD} & OB_{PROD} & COMRATE_{PROD} & RWRATE & DRATE & OB & LT_{DES} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}\right] \quad (A.23)$$

Following the standard Z-domain procedure, the transfer function was obtained from the discrete-time state-space representation. This approach involved computing (A.24). Afterwards the transfer function can be obtained. Note: In the expression I represents a 10×10 identity matrix, matching the dimensions of the state matrix.

$$G(z) = C(ZI - A)^{-1}B + D \quad (A.24)$$

Data availability

No data was used for the research described in the article.

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