Integrating Inventory and Transport Optimisation in Multi-Retailer Supply Chains

by

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Abstract

Purpose – This thesis studies the Inventory Routing Problem (IRP) consisting of one supplier and multiple retailers who face a stochastic demand that is assumed to be independently and identically distributed over an infinite planning horizon. The aim of the study is to examine the impact of replenishment flexibility and efficient routing strategies on costs, vehicle energy consumption and effectiveness. The flexibility is generated from the opportunity of the supplier to make an early replenishment in order to consolidate the replenishment between retailers. The study also aims to evaluate the potential of the IRP model as a business process reengineering strategy in the context of private healthcare industry in Malaysia.

Design / methodology / approaches – A leading private healthcare organization that owns a chain of clinics in Malaysia is used to explore typical supply chain process leading to practical contextualization of an IRP model. The new IRP model is proposed based on (s,c,S) policy to evaluate the trade-off between inventory cost and transportation cost. The analysis, based on a spreadsheet simulation model, numerically evaluates the performance of the proposed IRP model using different vehicle effectiveness strategies including the Travelling Salesman Problem (TSP) approach, the Overall Vehicle Effectiveness (OVE) and Modified Overall Vehicle Effectiveness (MOVE) metrics.

Findings – The results show that the proposed periodic "can-deliver" model provides a significant cost saving compared to the common inventory control policy, (s,S) and a slight additional marginal benefit compared to the $(s,S\text{-}1,S)$ policy. The findings also indicate that the MOVE metric consistently outperformed the OVE metric and TSP approach. The MOVE metric determines the delivery sequence that generates high vehicle effectiveness which in return minimizes the cost, vehicle distance travelled, and vehicle energy consumed.

Practical implications – An appropriate inventory policy together with an appropriate routing policy is crucial in the IRP approach. The integration of flexible inventory control policies with the MOVE metric leads to minimized operating costs and low vehicle energy consumption as well as improving total vehicle effectiveness.

Results limitations and further research – Only a single vehicle is considered to perform the replenishment activity without capacity constraint, and the supplier is assumed to have sufficient stock to fulfill retailers' requirements. Future research could consider more complex network designs, capacity constraints and use of heuristic / meta-heuristic methods.

Originality/value – Provides insights into the application of the IRP approach as a potential business process reengineering solution in the healthcare industry, specifically in the context of Malaysia's private healthcare industry. The research widens the application of well-known multi-item single supplier joint replenishment approaches in the periodic scenario of multi-retailers single item context. This is the first study to explore an optimal replenishment decision incorporating inventory control and vehicle effectiveness strategy, that considering both economic and environmental factors.

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Chapter 1 Introduction

This chapter first presents the foundation and structure of the thesis. It begins by discussing Supply Chain Management (SCM) and logistics concepts that are used in Operations Management research. It then continues with an examination of the traditional supply chains, and supply chain coordination strategies with regard to the whole supply chain performance. This is followed by an explanation of the motivation to conduct this research, a statement of the research objectives, and presentation of the research questions. The chapter subsequently briefly describes the methodology for conducting the research to address the research questions. Finally, the organisation of the chapters in this thesis and the contributions of the research to the body of knowledge are presented.

1.1 Research Background

Recently there has been an emerging trend in supply chain management (SCM) to integrate inventory management among the players in the supply chain. According to Ruston et al. (2006), SCM and logistics are terms used interchangeably in the academic literature and in industry. SCM can be viewed as a new name for logistics since the two can overlap or be seen as a function of the other (Larson and Poist (2007). However, a survey conducted by Lummus et al. (2001) among practitioners indicated that, generally, logistics is the process of planning and managing the inventory in an organisation that includes management of the inbound and outbound activities between the organisation and its suppliers and customers. In contrast, SCM includes a broader function that monitors the overall activities between all points in the supply chain. Generally, supply chain stages consist of customers, retailers, wholesalers or distributors, manufacturers and component or raw material suppliers that are known as the supply network (Chopra and Meindl, 2004). Figure 1.1 shows the structure of the supply chain.

However, Chopra and Meindl (2004) have argued that an appropriate supply chain structure depends on customers' requirements and the role of each stage in the supply network. Sometimes, the functions in the middle stages can be eliminated. As can be seen from Figure 1.1, retailers can be directly served by the supplier or manufacturer without going through the distributor.

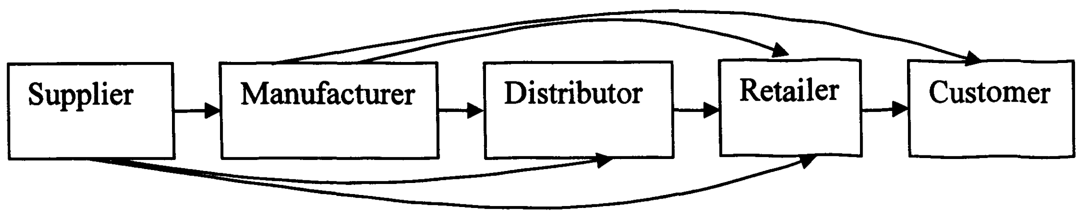


Figure 1.1: Supply chain structure (adapted from Chopra and Meindl, 2004)

1.2 Supply Chain Strategy

Traditionally, a decentralised inventory system is used for managing the supply chain across multiple stages. Each stage is responsible for managing their inventory independently, and the order is placed with the supplier based on their individual requirements without considering the situation of others. For example, the retailer will monitor their own inventory and generate the order to the distributor based on the current inventory level and their local forecast demand for the next period. The distributor is then responsible for making deliveries based on the exact order quantity made by retailers. This kind of inventory management has some disadvantages for the retailer and the other players in the supply chain. It may lead to demand uncertainty for the distributor as the time and the number of orders from retailers can vary. Hence, the distributor may face difficulty in managing their own inventory and scheduling the deliveries in an efficient way. The demand uncertainty from the retailers can lead to an uncertain order quantity between customer and supplier. This phenomenon is called the bullwhip effect (Disney and Towill, 2003). It causes an extra cost for the distributor who has to deal with problems such as inventory shortage and resource utilisation problems. Moreover, Kleywegt et al. (2002) have indicated that the lack of information with regard to retailer inventory level in conventional inventory management can affect the decision at the distributor level. They point out that without the visibility of inventory level information at the retailers, the supplier is unable to determine the priority of shipment between retailers. Thus, suppliers may possibly end up replenishing non-critical customers, causing a stock-out problem in that other retailers that really require items are unable to fulfil their end customer demand.

Thus, a single efficient decision at one particular stage is possibly not efficient for the whole supply chain. Yu et al. (2001) indicated that this problem occurs as a result of a decentralised control approach and 'the whole system may not achieve the optimum performance, even though each member optimises its own performance'. Thus, the decisions between the stages in the supply chain need to be integrated in a manner that is beneficial for the entire supply chain in both operational and economic terms. Information sharing and the Vendor Managed Inventory (VMI) are among supply chain integration strategies that have been studied by several researchers, for instance, Sari (2008), Zhao et al. (2002), Hosoda and Disney (2006), and Waller et al. (1999).

Holweg et al. (2005) have classified supply chain coordination configurations based on inventory collaboration and planning collaboration factors. The information sharing approach is classified as Type 1 where the company considers only planning collaboration in their decision-making processes. On the other hand, the VMI approach is associated with inventory management collaboration and planning collaboration within the supply chain. The characteristics and the behaviour of each configuration is described by Holweg et al. (2005) using a water-tank analogy.

The information sharing strategy structure is similar to the traditional supply chain strategy approach where the planning and optimisation decision for inventory management is still made separately by the supplier and the retailers. However, the demand information at the retailer is made available via the information sharing strategy, and thus assists the supplier in the decision-making process, instead of just relying on the forecast data. The information sharing strategy can therefore help to reduce the demand uncertainty and thus reduce or eliminate the bullwhip effect in the supply chain (Yu et al., 2001). Zhao et al. (2002) stated that this approach is able to improve the total cost for the entire supply chain by up to 60 percent in some circumstances. However, they also stated the information sharing strategy is not beneficial for the retailer even though it improves the total supply chain cost and customer service level under certain demand patterns and low capacity conditions.

Centralised decision-making using the Vendor Managed Inventory (VMI) approach (Holmström et al., 2003) presents a beneficial and good opportunity for both supplier and customers to manage the inventory. In VMI, the supplier is responsible for replenishing the retailer's inventory based on information available from the retailer, such as inventory level, expected demand and cost (Claasen et al., 2008). In the case of setting customers' priority, as highlighted by Kleywegt et al. (2002), VMI allows both supplier and customer to gain benefit from an efficient replenishment decision since the supplier is able to distribute the available stock based on customers' requirements and coordinate the deliveries to improve the service.

This approach is becoming increasingly popular since the existence of low-cost technology facilitates accurate monitoring of required information (Campbell et al., 1997). For example, a telemetry unit is used to measure the level of fluid in tanks in the petrochemical industry. The most widely used technology with regard to VMI is Electronic Data Interchange (EDI) (Altekar, 2005). For many suppliers, producers, distributors and retailers worldwide, EDI has become the backbone for computerised business-to-business communications. Use of the Internet has also enhanced the connections between retailers and suppliers via online systems.

VMI as a collaboration approach has been shown to strongly enhance customer service levels and improve supply chain control. However, collaboration is influenced by the quality of the buyer-supplier relationship, IT systems, and the intensity of information sharing factors (Campbell et al., 1997). Waller et al. (1999) point to the reduction of cost in VMI as a result of improving resource utilisation with reduction in stock and use of full truckload shipments together with more efficient routes for delivery. The supplier is also able to balance the available stock with retailer requirements by determining the priority of deliveries to critical retailers and thus distribute the stock to those retailers in an efficient manner (Kleywegt et al., 2000). Yang et al. (2003) termed this phenomenon "vendor flexibility" and it is one of the factors that influences the performance of the supply chain. As a result of vendor flexibility, the supplier is able to maintain the inventory level of the retailer who can then fulfil end-customer demand.

1.2.1 Inventory Routing Problem

Usually, the optimisation of inventory and transportation decisions are solved separately using different approaches. In an organisation, both types of decision are commonly managed by different departments. Generally, the decision of the global best replenishment time and the quantity of delivery for each retailer is determined via the inventory control policy, whilst the route to make the delivery is determined by using routing algorithms via the travelling salesman problem or vehicle routing methods. However, there is a trade-off between the inventory and the transportation costs. Reducing the inventory holding cost by keeping a low inventory level at retailers will result in frequent deliveries, which may increase the transportation cost. On the other hand, longer replenishment cycles may possibly be costly as organisations have to hold extra stock. Therefore, it is important to coordinate these two decisions in order to achieve a more economic result. Coordination of the inventory and transportation costs in the centralised control system is known as the Inventory Routing Problem (IRP). IRP research is basically concerned with determining three main decisions as described by Campbell et al. (1997):

- which customers should be replenished at what times,
- which inventory items should be replenished and how much of each item,
- the route that each vehicle should use in order to minimise the total cost over the planning horizon.

The central decision-maker has to construct an effective inventory management policy and delivery strategy in response to each question in order to balance the trade-off between inventory and transportation cost. As described by Kleywegt et al. (2000):

> "The central decision maker can be the supplier, and the inventory can be kept at independent customers, or the central decision-maker can be a manager responsible for inventory management at a number of warehouses or retail outlets of the same company."

With IRP, the manager for the organisation has the flexibility to manage the transportation and inventory management to minimise the total operating cost and maximise the system performance for the entire organisation. The central decision-maker is also able to coordinate the retailers during the replenishment in order to utilise the transportation usage.

Most IRP solutions based on routing solutions minimise the total distance travelled by vehicles. Some researchers have also used a static route in the decision where a similar route is used for the replenishment. This is usually applied to deterministic problems.

With regard to IRP solving approaches, previous researchers have solved the different dimensions of the IRP by using various mathematical models such as Lagrangian Relaxation (Bell et al., 1983), Integer Programming (Campbell and Savelsbergh, 2002), and Dynamic Programming (Kleywegt et al., 2004). Recent studies have also solved the IRP using meta-heuristic approaches such as Tabu search (Cousineau-Ouimet, 2002) and Local search (Lau et al., 2002) techniques.

The IRP has proved beneficial in many different industries. The decision support system developed by Bell et al. (1983) has been reported to be able to increase vehicle productivity and reduce the operation cost at Air Product and Chemicals, Inc. an industrial gases producer. The IRP application at PRAXAIR, engaged in the petrochemical industry, is reported to outperform the current industry approximation approach. Further, the IRP implementation for vending machine supply chains (Rusdianshah and Tsao, 2005) and supermarket chains, (Gaur and Fisher, 2004) have achieved substantial cost savings.

1.3 Research Motivation and Research Objectives

The success of IRP implementation in various industries in reducing cost has provided the motivation for the researcher to conduct this study in an healthcare industry. The study is conducted in a developing country since most studies to improve the supply chain of the healthcare industry have been carried out in developed countries and it is therefore considered necessary to ascertain the suitability of the IRP for the healthcare supply chain in developing countries. Moreover, inventory management and routing strategy are among the main research topics investigated in the Industrial Computing Department of the University Technology Malaysia where the author works as a lecturer. Since previous research in the aforementioned university has focused on inventory management and routing strategy, it is this researcher's aim to integrate these areas in the decision-making process. Further, environmental considerations are becoming increasingly important given the need to reduce global warming, therefore ensuring vehicles are fully utilised and vehicle energy consumption is reduced are important according to the FreightBestPractise (2007) report. Accordingly, this research aims to determine how the flexibility that the IRP provides is able to increase utilisation of vehicles and at the same time reduce the energy used by vehicles and, in turn, CO_2 emissions. Importantly, Kara et al. (2007) found that by minimising only the distance travelled, vehicle energy consumption can, in fact, increase.

Thus, in general, the aims of this thesis are to evaluate the suitability of implementing the IRP approach in a Malaysian case study and then to explore the proposed replenishment strategy which integrates an efficient inventory policy and routing strategy in order to replenish multiple retailers facing a stochastic demand. The aim of the proposed replenishment strategy is not only to minimise the total inventory and transportation cost but also to minimise the energy consumed by the vehicles used.

Given the above aims, the thesis' objective is to widen the application of the IRP to another industry not observed by previous research. Thus, this study will observe current supply chain process practice and evaluate whether the IRP is capable of improving the distribution strategy of the healthcare industry. Few studies have evaluated the supply chain process of the healthcare industry in a developing country and none as far as the researcher is aware has focused on the private healthcare context in Malaysia where chains of clinics exist under one organisation.

Since the IRP permits flexibility for the supplier when making a replenishment decision, this research is interested in observing the behaviour of flexible replenishment policies to facilitate an early replenishment decision, and coordinate the delivery between retailers in order to reduce the total operating costs and enhance vehicle effectiveness. Determining the optimal inventory control parameters for minimising the total inventory and transportation costs over the planning horizon based on the conceptual model developed from the first part of the study and the theory from the literature is the focus of the second part of the study.

This research also intends to evaluate different routing strategies with regard to the inventory policy in order to determine the optimal delivery sequence between multiple retailers and thereby reduce the total cost, minimise vehicle energy consumption, and maximise vehicle effectiveness.

1.4 Research Questions and Methodology

Based on the research aims and objectives presented above, four research questions are addressed in this thesis as follows:

i) **How is the supply chain process carried out in the healthcare industry in the context of developing countries' private healthcare, especially in Malaysia? Can the Inventory Routing Problem approach be used to improve supply chain operations?**

This question is formulated in an attempt to examine the appropriateness of the IRP as a business process reengineering strategy to improve the performance of an organisation providing private healthcare involving a central warehouse and chain of clinics. Improvement of the organisation's performance is based on two factors: (1) the existing supply chain policy in the healthcare industry as identified from a case study, and (2) the organisation's capability to adopt the improvement strategy proposed by this research. In the course of addressing the research question, the suitability of other strategies to improve performance, e.g. Just In Time (JIT) policy and stockless policy, will also be considered.

ii) **How should the parameters in the Inventory Routing Problem be set? How should the supplier decide on which retailers should be replenished during each replenishment period?**

The characteristics of the new IRP model for solving periodic stochastic multi-retailer problems that allow an early replenishment are examined under this question. Further, the condition that triggered the replenishment together with the condition of flexibility to coordinate the replenishment are evaluated based on the proposed inventory policy.

iii) **How does the proposed policy perform in the single item multi-retailer case? How do the variables influence the result?**

This question is developed in connection with research question 2 to explore the impact of different variables in the IRP model, i.e. inventory control parameters and costs, on the performance measurement, using explicit numerical analysis. This question is also related to the next research question which seeks to observe the behaviour of the proposed IRP model when implementing different routing strategies.

iv) **How should the routing strategy be incorporated into the IRP model to reduce cost, improve vehicle effectiveness, and reduce energy consumption?**

The appropriate routing strategy that is able to facilitate the efficient sequence of delivery in terms of cost, vehicle effectiveness, and vehicle energy consumption is examined through this research question.

These research questions emerged from the literature review and the study process itself. Initially, research question 1 was derived from the IRP literature in Chapter 2, which identified weaknesses in the traditional supply chain strategy, advantages of the IRP to various industries, and the lack of implementation of the IRP in the healthcare industry. This research question is answered in Chapter 4, the case study chapter which discusses the suitability of implementing this approach with regard to current supply chain processes and problems. The supply chain management policy to improve performance in the healthcare industry is based on the supply chain management policy described in the literature.

The findings derived from research question 1 as well as inventory policy theory presented in the literature review were used to develop research question 2. Answers to this question are found at the beginning of Chapter 5 in this thesis.

As this study is the first to evaluate the "can order" policy known as the (s,c,S) policy in the multi-retailer context, it is necessary to explore the behaviour of the proposed model with different inventory control parameters and costs. Hence, research question 3 was developed to accomplish this aim and the findings are detailed in the Chapter 5.

Since the IRP approach integrates inventory management and transportation management, research question 4 was developed to evaluate different routing strategies for the purpose of reducing the total cost as well as the energy consumption of a vehicle. The behaviour of the IRP model with different routing strategies was examined in this research question and findings were also used to address research question 3. The detailed specification of the routing strategies and the effect of the proposed IRP model's coordination with different routing strategies is discussed in Chapter 6. The linkage between research questions and the discussion of findings is illustrated in Figure 1.2.

With regard to the research methodology, a case study and spreadsheet simulation were employed to address all the research questions. The case study was developed after the author spent two and a half months in one of the leading private healthcare organisations in Malaysia to examine the supply chain processes in the organisation. The ordering and delivery processes were analysed in order to identify the performance of the current supply chain strategy and determine how the IRP approach could overcome existing problems. A IRP model was developed via spreadsheet simulation and the interaction between variables in the model was explored to gain insight into the model's effect on performance measurement. Details of the research methodology are presented in Chapter 3.

1.5 Structure of the Thesis and Research Contributions

This thesis is organised into 7 chapters as shown in Figure 1.2. This chapter introduces the research. Chapter 2 provides a review of the literature focusing on previous IRP research, identifies the research gap, and presents the conceptual model of the research. Chapter 3 discusses the research methodology.

In Chapter 4, the result of the case study is presented, beginning with the description of healthcare supply chain management in general followed by a description of it in the Malaysian context. The chapter then continues by describing the case study's supply chain process and analysing the problems faced by the organisation under study. Finally, the chapter focuses on the improvement strategy that points to the suitability of implementing the IRP strategy in the organisation.

Chapter 5 presents the development of the suggested IRP simulation model using a spreadsheet and analyses the impact of the various variables in the model on total cost. The analysis focuses on the effect of the inventory control parameters on inventory holding, shortage and transportation costs. Here, the routing decision is identified based on the minimum distance travelled by the vehicle during the delivery process. At the end of this chapter, the proposed model is compared with other inventory policies.

Chapter 6 enhances the routing part in the IRP model. The effect of different vehicle effectiveness methods, including the Travelling Salesman Problem (TSP), Overall Vehicle Effectiveness (OVE) metric, and Modified Overall Vehicle Effectiveness (MOVE) metric on total cost, vehicle effectiveness and vehicle energy consumption factors, is examined. The best strategy that is able to minimise the cost and vehicle energy consumption is implemented for further investigation of the model.

Chapter 7 provides a discussion of how the analysis answers the research questions. This chapter also explains the contributions and implications of the research, addresses IRP model generalisation, presents the limitations of the research, and suggests areas for further study.

The contributions expected from this research are the development and analysis of an IRP model that gives flexibility for the central decision-maker to make early replenishments in order to reduce costs and improve vehicle effectiveness. The study evaluates the trade-off between inventory and transportation costs. Implementation of the new routing strategy using the Modified Overall Vehicle Effectiveness strategy facilitates minimisation of the distance as well as the energy consumed in the transportation. The result therefore proves that both distance travelled and vehicle energy consumption could be minimised together using an efficient routing strategy. Nevertheless, the result also shows that only a slightly higher total cost will occur if the model only considers the distance travelled as the factor to identify the best replenishment route compared with the new routing strategy.

1.6 Conclusion

This chapter has provided the route map for this thesis. First, it focussed on supply chain management and logistics concepts and then discussed supply chain integration strategies, comparing them to the traditional supply chain approach. The research aims and objectives were subsequently outlined and the motivation for this research was explained. Finally, the thesis structure was presented to illustrate the linkage between the chapters presented in this thesis. The next chapter will offer a review of the relevant literature to provide an overview of the application and methods used by previous researchers to solve the IRP. The gap in the literature is also identified to determine the scope of research needed for further investigation of the IRP area.

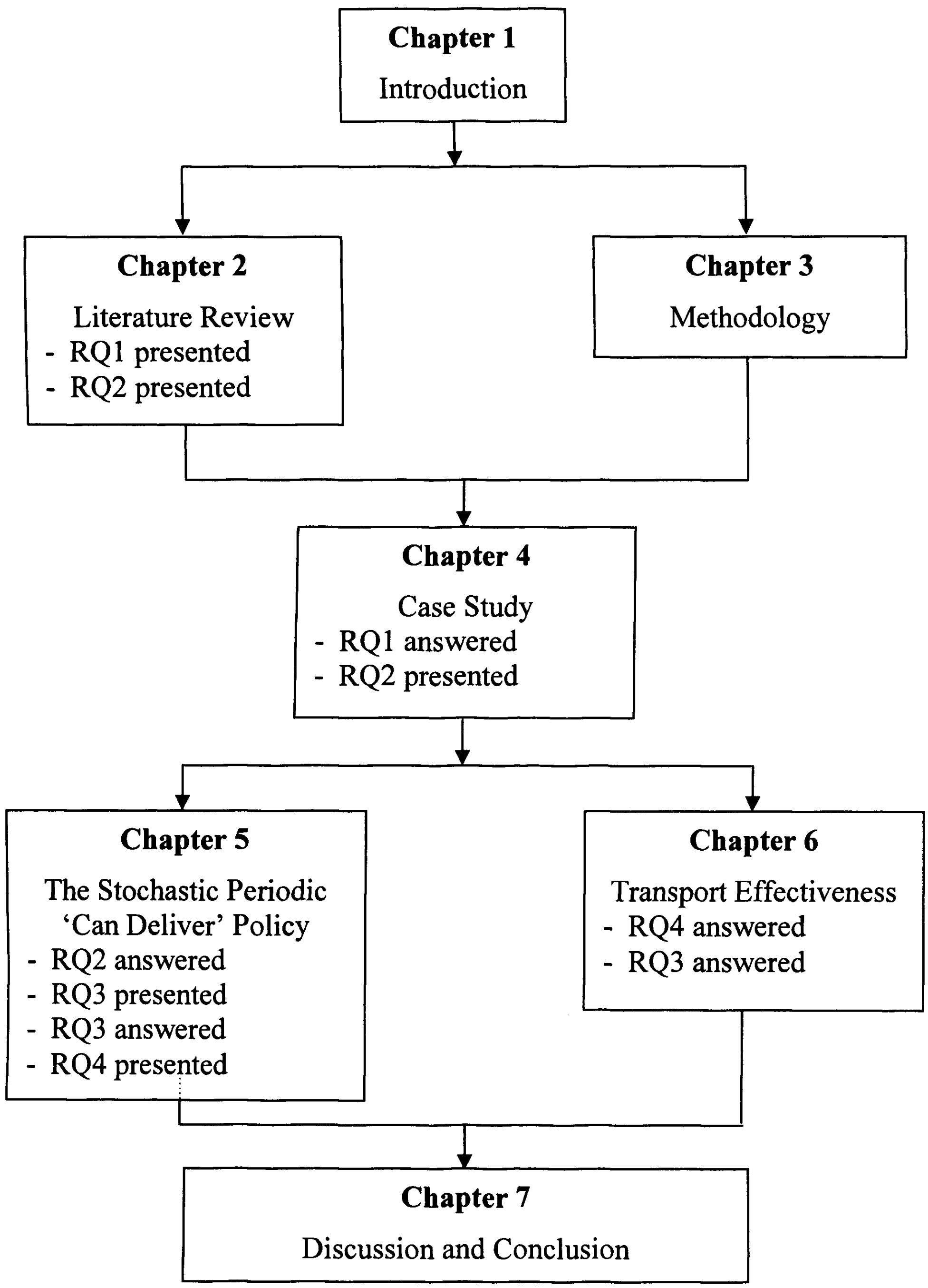


Figure 1.2: The thesis structure

Chapter 2 Literature Review on the Inventory Routing Problem

This chapter provides an overview of previous research on the Inventory Routing Problem (IRP). Section 2.1 describes the general characteristics of the IRP. Then, Section 2.2 and Section 2.3 review the various dimensions of the IRP and methods used to solve the IRP. The performance measurement and the structure of the objective function used in the IRP model are examined in Section 2.4. Finally, Section 2.5 explores the replenishment policy adopted by previous researchers before identifying the research area that requires further investigation in Section 2.6.

2.1 Introduction

As has been discussed earlier in Chapter 1, the IRP is concerned with inventory and transportation integration for determining the optimal decision in a centralised control system. Generally, the IRP is concerned with the repeated delivery of a single product from a central facility or supplier to a set of customers using a fleet of M homogeneous vehicles with known capacity over a planning horizon. The supplier knows the demand rate at each customer. Thus, the inventory level, I for each customer i, can be measured by the supplier at any time, t. Usually, the IRP model assumes an unlimited capacity at the supplier whilst customers have unlimited capacity to store the product. The transportation cost is associated with the route used to make the round-trip delivery from the supplier to all the customers. The inventory cost also includes the holding cost per unit item in the stock and the penalty cost in the case of a shortage or out of stock situation. The supplier is responsible for determining an effective decision that minimises the total cost or maximises the profit. The decision is made regarding the best time and quantity to replenish the customer as well as the efficient routes. This makes the IRP different from the vehicle routing problems approach. While the vehicle routing problems approach attempts to find the best route to make a delivery for a single particular period, the IRP deals with a longer horizon period and the decision made at a current period will impact upon the decision in the next period (Campbell et al., 1997).

2.2 IRP dimensions

A considerable amount of literature has been published on solving the IRP. Researchers have categorised the IRP scenario along a number of different dimensions including:

- The length of planning horizon
- Customer demand pattern
- Number of customers visited during the delivery
- Vehicle characteristics
- Number of delivered products

The length of planning horizon of the IRP solution can be a single-period, multi-period or an infinite time horizon. These categories are known as time demand approaches in Dynamic Routing and Inventory Problem (DRAI) problems (Baita et al., 1998). The single-period problem determines the solution that balances the transportation and inventory costs at the beginning of every single time period based on the inventory level information. Federgruen and Zipkin (1984), Federgruen et al. (1986) and Chien et al. (1989) addressed the IRP in this context. In multi-period problems, the improvement solutions for the delivery schedule and the routes for delivery are determined for a specific period of time. A number of studies have solved the multi-period problem such as those of Dror and Ball (1987), Trudeau and Dror (1992) and Dror and Trudeau (1996). They determined the long-term solution by reducing the multi-period problem into a single period problem. The idea has been extended by Jaillet et al. (2002) and Bard et al. (1998) who considered the use of a satellite facility to reload the item into the vehicle to make another delivery trip. According to Moin and Salhi (2006), multi-periods are more practical to use as they provide a realistic trade-off between the strategic and the operational requirements of a solution. On the other hand, the infinite time horizon solves a long-term problem by evaluating the performance of replenishment policies and the routing approach that minimises the total cost average. Anily and Federgruen (1990, 1993) and Gallego and Simchi-Levi (1990) are among those that have studied the infinite IRP.

The demand pattern is another dimension that differentiates the IRP categories. Most researchers assume the customer demand is deterministic to simplify the problem. However, in reality, the customer demand is stochastic. Lourenco and Ribeiro (2003) examined demand characteristics in the model. Stochastic IRP models have been solved by Trudeau and Dror (1992), Kleywegt et al. (2000), Berman and Larson (2001), and Kleywegt et al. (2004). With respect to the number of customers visited for a single vehicle trip, several researchers have studied the direct delivery case where only one customer is considered on a single vehicle route to simplify the solution (Kleywegt et al., 2000). However, it is not efficient to deliver a small amount of items to one customer for one delivery trip. Thus, in many situations, vehicles are scheduled to visit multiple customers during the delivery trip. Furthermore, the characteristics of vehicles for the delivery can be categorised based on the capacity, type and the number of units used for delivery. The capacity of the vehicle can be either unlimited or capacitated, whilst the number of vehicles can be single or multiple. In terms of vehicle type, it can be either homogeneous or heterogeneous. Supplier characteristics are other IRP characteristics where it can be unlimited or limited supply in a two-echelon supply chain. Recently, Zhao et al. (2008) studied the IRP in a three-echelon supply chain structure that consisted of a supplier, central warehouse and multiple retailers. The IRP also can be categorised by the number of items delivered to the customer. However most of the research assumes a single item in the model. Sindhuchao et al. (2005) stated that the research in inventory routing area that considered multi items is quite limited and suggested that the study by Vismanathan and Mathur (1997) and Qu et al. (1999) are the most significant contribution in this area. Aziz and Moin (2007) is another research that considered a multi product scenario in their study.

2.3 Research Method and Approaches to Solve an IRP

In this subsection, we are interested in the methods used to solve an IRP. Generally, quantitative modelling has been used by previous researchers, employing either exact analytical or heuristic approaches. Integer programming, Mixed Integer programming, Dynamic programming or Markov decision processes are examples of exact analytical methods used to obtain the optimal IRP solutions. On the other hand, the heuristic or Meta-heuristic methods are preferred solutions for the complex problems.

2.3.1 Exact method

Bell et al. (1983) used the Lagrangian Relaxation algorithm to solve a large mixed integer programming problem. It is reliably able to obtain near optimal scheduling decisions in the Air Product and Chemicals Inc. online vehicle scheduling system. This system is also integrated with a shortest route planning algorithm to determine inter-customer distances and travel times. The exponential smoothing forecasting method is used to forecast customers' demand rate at individual locations. The system produces individual customer replenishment schedules for the next two to five days. Solutions are obtained using the Lagrangian Relaxation algorithm to produce a feasible solution that traditional mixed integer linear programming methods cannot handle.

Campbell and Savelsbergh (2002) implemented the Integer Programming method to solve the deterministic IRP problem at a large industrial gases company in North America, PRAXAIR. PRAXAIR uses remote telemetry units to monitor customer inventory levels. The system uses a two-phase approach. Integer Programming is used in the first phase in order to determine which PRAXAIR customers require replenishment as well as the quantity that is needed at each customer location to prevent out-of-stock situations. The customer's capacity, vehicle capacity and any time windows are considered in this phase. Since PRAXAIR has over 10,000 customers and it is difficult for integer programming to handle such a large problem, clustering and aggregation are used to reduce the number of routes used and the length of planning horizon. The delivery routes and replenishment schedules that minimise the inventory and transportation cost are then determined by the second phase.

Differently, Kleywegt et al. (2004) formulated a stochastic IRP problem as a discrete time Markov process, extending the Dynamic Programming investigation in Kleywegt at al. (2002). They used real data from the air products industry to validate their model. The model captures the customers' inventory level over time and creates a set of feasible replenishment schedules determined by vehicle availability and work load constraints as well as customers' inventory holding capacity. Overall, the problem is decomposed into smaller sub-problems of specific subsets of customers to simplify the process.

2.3.2 Heuristic method

A heuristic method based on an Iterated Local Search (ILS) was developed by Lourenço and Ribeiro (2003) to solve a multi-period Inventory Routing Problem for two types of customers, VMI customers and conventional replenishment customers. The VMI customers' demand is considered to be a continuous random variable that follows an exponential distribution. The ILS meta-heuristic is capable of producing good, effective, quality and robust results. It is iteratively applied to obtain effective delivery routes, since the Vehicle Routing Problem (a closely related sub-problem of the IRP) is N-P hard. A balance is made between the delivery costs and inventory cost. Tabu search is another meta-heuristic method that can be used to solve deterministic IRP problems (Cousineau-Ouimet, 2002). This method is efficient and flexible enough to solve an IRP with multi-customers and multi-vehicles.

2.3.3 Hybrid method

Recently, hybrid methods have become popular approaches in order to quickly obtain feasible and quality solutions within a reasonable computation time. Examples of hybrid techniques that have been used to solve the IRP can be found in Lau et al. (2002) who integrated local search and network flow techniques, and Lau et al. (2003) who combined an ant colony optimisation with the Tabu search method.

2.3.4 Simulation

Simulation is another method that has been used to explore the behaviour of the IRP model, see, for instance, Reiman et al. (1999), Jaillet et al. (2002) and Aghezzaf (2008).

2.4 The IRP Objective Function and Performance Measurement

Most IRP solutions aim to determine the optimal replenishment timing and quantity for delivery as well as an efficient route that minimises the total cost. However, there are various combinations of costs included in the objective function used by researchers in the IRP model. Bertazzi et al. (2007), Bertazzi et al. (2002), and Gallego and Simchi-Levi (1990) are among those that have included inventory holding costs in the objective function. On the other hand, Gaur and Fisher (2004), Trudeau and Dror (1992) and Berman and Larson (2001) have preferred to just include the transportation cost. Some researchers such as Anily and Federgruen (1993) have also included the inventory cost at the warehouse in situations when warehouses keep stock. Otherwise, the inventory cost only occurs at the customers. This is relevant for the cross-docking scenario which has always been used as an assumption in the model. The shortage cost is considered by some researchers as the cost to make direct replenishment to the customer that needs an urgent delivery. However, others (Abdelmaguid et al., 2008) have viewed the shortage cost as the charge per unit shortage supply when inventory on hand is insufficient to meet demand at the end of each period in each location. The shortage cost here is included in the cost function.

Also, different variations of transportation cost functions have been considered. Anily and Federgruen (1990,1993) included the fixed transportation cost per trip and variable cost per distance travelled. On the other hand, Campbell (2002) and Trudeau and Dror (1992) only considered variable costs in their cost function.

2.5 The Replenishment Policy

Flexibility will help the supplier to deal with the uncertainty scenario in a stochastic IRP. Accumulating the retailers' requirement to deliver a full vehicle load is an approach that has been applied by researchers to address the vehicle utilisation problem and reduce the transportation cost (Cetinkaya and Lee, 2000). However, there is an issue of delaying the replenishment at retailer level where there is a possibility of the retailers running out of stock, thus increasing the inventory backlog costs. Gurbuz et al. (2007) implemented another approach to replenish all retailers whenever one of the retailers reaches the reorder level, or when the total demand for all retailers reaches a certain point. However, they used fixed transportation cost for the delivery and a penalty transportation cost for excessive vehicle capacity requirements. Thus, the solution is intended to optimise the inventory management by determining the appropriate joint replenishment point that minimises the cost. The partition approach has also been used as a replenishment approach, where all customers in one cluster are replenished at a particular time. However, these replenishment strategies as well as other inventory policies that have been used to solve the inventory problem (such as the Economic Order Quantity (EOQ) policy, zero inventory ordering policy and the order-up to policy, (s,S)) do not allow flexibility in the decision making process.

Route selection for the replenishment is mostly based on the distance travelled by the vehicle, and the same route will be used for each delivery. In some cases, the minimum cost is determined based on a constant cost between two points. However, with different quantities of items being delivered to different points, the cost may change based on the weight and the vehicle distance travelled. To our knowledge, only one paper (Kara et al., 2007) has discussed the relationship between weight and distance when determining the optimal route based on the minimum energy consumed by a vehicle.

A list of studies which have used IRP research in the past is summarised in Table 2.1 according to customer demand types, the number of available vehicles and the condition of vehicles, length of the planning horizon, number of customers visited on a vehicle trip, methods used to solve the IRP, objective function, replenishment policy and inventory policy.

The research contribution of this study is also highlighted at the bottom of the table.

2.6 Potential Research Area

The "can order" policy known as the (s,c,S) policy introduced by Balinfy (1964) seems to be a promising idea to solve the IRP as it gives flexibility to the supplier to make replenishments when it is convenient. With this approach, customers' deliveries can be consolidated with other customers that also require a delivery through the introduction of the flexible inventory control parameter, c, as well as two others inventory control parameters. These specify the reorder level, s and the maximum inventory level, S which are commonly used parameters in a replenishment policy. This approach may allow the supplier to make decisions more economically and increase the effectiveness of vehicles.

Further, vehicle routing is supposedly evaluated based on the weight of goods and travel distance, in order to determine the actual cost incurred by the vehicle. This is consistent with the suggestion by Moin and Salhi (2006) that IRP solutions need to be considered based on their environmental impact. Therefore, this thesis is concerned with determining the best solution that integrates the inventory policy and the routing policy which is beneficial not only from the economic perspective but will also help to reduce the energy consumed during the delivery process through replenishment coordination and a new vehicle efficiency approach.

2.7 Conclusion

This chapter has reviewed the various ways of solving the IRP. Many different dimensions and methods have been explored in previous research for determining the best decision based on certain replenishment policies that minimise various cost functions. The gaps in the literature are identified with respect to the replenishment policy that gives flexibility to the supplier in the decision-making process. Furthermore, the optimal sequence of customer delivery takes into account the weight carried by vehicles in cost determination has not been considered before in the literature. Thus, further research along this direction is required. In the next chapter, we discuss the methodology that is appropriate for conducting this research.

Table 2.1: Previous Inventory Routing Problem research

Researcher	Year	Demand	Vehicle Number	Vehicle Condition	Time Horizon	Delivery Type	Methods	Objective	Replenishment Policy	Inventory Policy
Federgruen and Zipkin	1984	Stochastic	Limited	Capacitated	Finite	Multiple	Stochastic programming	Min cost	Cluster first- route second	
Burns et al.	1985	Deterministic	Unlimited	Capacitated	Finite	Direct, Multiple	EOQ/Theoretical analysis	Min cost	Cluster (distance)	EOQ
Dror et al.	1985	Stochastic	Limited	Capacitated	Finite	Multiple	Integer programming, Decomposition	Min cost	Determine delivery time then schedule scustomer delivery by route	(s,S) policy
Dror and Ball	1987	Stochastic	Limited	Capacitated	Finite	Multiple	Mixed Integer programming Heuristic	Min cost	Cluster first-route second	Minimum level
Chien	1989	Deterministic	Limited	Capacitated	Finite	Multiple	Mixed Integer programming Heuristic and Bound	Max profit	Vehicle assigment	
Anily and Federgruen	1990	Deterministic	Unlimited	Capacitated	Infinite	Multiple	Heuristic, Bound	Min cost	Cluster first(distance)-route second	Zero-Inventory Ordering
Gallengo and Simchi-Levi	1990	Deterministic	Unlimited	Capacitated	Infinite	Direct	Bound	Min cost	Cluster first(distance)-route second	Zero-Inventory Ordering
Trudeau and Dror	1992	Stochastic	Limited	Capacitated	Finite	Multiple	Heuristic, Mixed Integer programming	Min cost	Cluster first(time)-route second	
Anily and Federgruen	1993	Deterministic	Unlimited	Capacitated	Infinite	Multiple	Heuristic, Bound	Min cost	Cluster first(distance)-route second	Zero-Inventory Ordering
Herer and Levy	1997	Stochastic	Unlimited	Capacitated	Finite	Multiple	Heuristic, Simulation	Min cost	Retailer selection	
Chan et al.	1998	Stochastic	Unlimited	Capacitated	Infinite	Multiple	Analysis and Heuristic	Min cost	Clustering	Zero-Inventory Ordering
Qu et al.	1999	Stochastic	Single	Unlimited	Infinite	Multiple	Heuristic, Lower bound	Min cost	Retailer selection	Perriodic Review

Table 2.1 (cont.)

Researcher	Year	Demand	Vehicle		Time Horizon	Delivery Type	Methods	Objective	Replenishment Policy	Inventory Policy
			Number	Condition						
Park et al.	2002	Stochastic	Single	Unlimited	Infinite	Multiple	Heuristic, Simulation	Min cost	Dynamic allocation	Least-inventory first
Jaillet et al.	2002	Stochastic	Limited	Capacitated	Finite	Multiple	Simulation	Min cost	Retailer selection-combine in one or more route and assign a vehicle to each route	(s,S)
Kleyweght et al.	2002	Stochastic	Limited	Capacitated	Infinite	Direct	Markov Decision process, Heuristic	Max profit	Bound	EOQ
Gaur and Fisher	2004	Deterministic	Unlimited	Capacitated	Infinite	Multiple	Heuristic	Min cost	Clustering	
Campbell and Savelsbergh	2004	Deterministic	Limited	Capacitated	Finite	Multiple	Integer Programming, Heuristic	Min cost	Clustering	Bound
Kleyweght et al.	2004	Stochastic	Limited	Capacitated	Infinite	Multiple	Markov Decision process, Heuristic	Max profit	Retailer selection	
Zhao et al.	2006	Deterministic	Limited	Capacitated	Infinite	Multiple	Heuristic	Min cost	Clustering	EOQ
Gurbuz et al.	2007	Stochastic	Limited	Capacitated	Infinite	Multiple	Simulation	Min cost	Retailer selection	Hybrid policy (s,S-1,S) and echelon policy
Abdelmaguid et al.	2008	Deterministic	Limited	Capacitated	Finite	Multiple	Mixed Integer Programming Heuristic	Holding, Stockout	Fixed, Direct	Min cost
Raa	2008	Deterministic	Limited	Capacitated	Infinite	Multiple	Heuristic	Min cost	Cyclic distribution	
Mustaffa	2008	Stochastic	Single	Unlimited	Infinite	Multiple	Simulation	Min cost strategy effectiveness	Retailer selection	(s,c,S)

Chapter 3 Methodology

In this chapter, the research methods and methodology used to conduct the research and the relationship between of the research approach and the research philosophy are described. Section 3.1 deals with the research philosophy, while Section 3.2 evaluates research commonly used in Operation Management, specifically in the Logistics or Supply Chain Management area. Then, the description of the methods used to conduct the study in addressing the research questions is presented in Section 3.3. The framework used in this research is discussed in Section 3.4. The details of each method are described separately in subsection 3.5 and 3.6. Finally, Section 3.7 evaluates the ethical considerations with regard to the study.

3.1 Research Philosophy

Identifying and understanding the relationship between research philosophy and research methodology is important when designing projects. The ontological and epistemological research philosophy paradigm position will underlay the methodology and the methods adopted for the research (Solem, 2003; Reich, 1994; and Frankel et al., 2005).

According to Solem (2003), Ontology and Epistemology are terms both derived from Greek words. Ontology comes from the word "ontos" and "logos" and means "being" and "word", whilst Epistemology comes from the words "epi", "histemi" and "logos" and means "upon or on", "stand" and "word". Therefore, ontology refers to the 'philosophical study of being' and epistemology 'deals with the background of knowledge' that may be viewed as referring to 'how do we know what we know' (Ibid). Generally, ontology is concerned with the nature of reality that determines the existence of the objectivity of the reality, whilst epistemology is concerned with the approach used to understand reality and the relationship between the researcher and their knowledge (Reich, 1994; and Frankel et al., 2005). Reich (1994) and Frankel et al. (2005) describe the methodology as the methods used to understand the world that are concerned with the way the research is executed. This includes the methods used to collect the data, test the theory, as well as interpret the results.

Wass and Wells (1994) establish the relationship between the epistemological perspectives categorized as positivism, realism or naturalism with the ontological position, methodology and techniques for data collection. Naturalism can also be referred to as interpretivism, phenomenology, and constructionism, (Fisher, 2004, p. 17).

The relationship between the research philosophy and the research strategy and the research approach has been illustrated by Saunders et al. (2003) in Figure 3.1 as the research process 'onion'. Positivism and interpretivism paradigms are placed at opposite poles. The positivism position uses the deductive approach and quantitative research strategies such as experimental and survey methods.

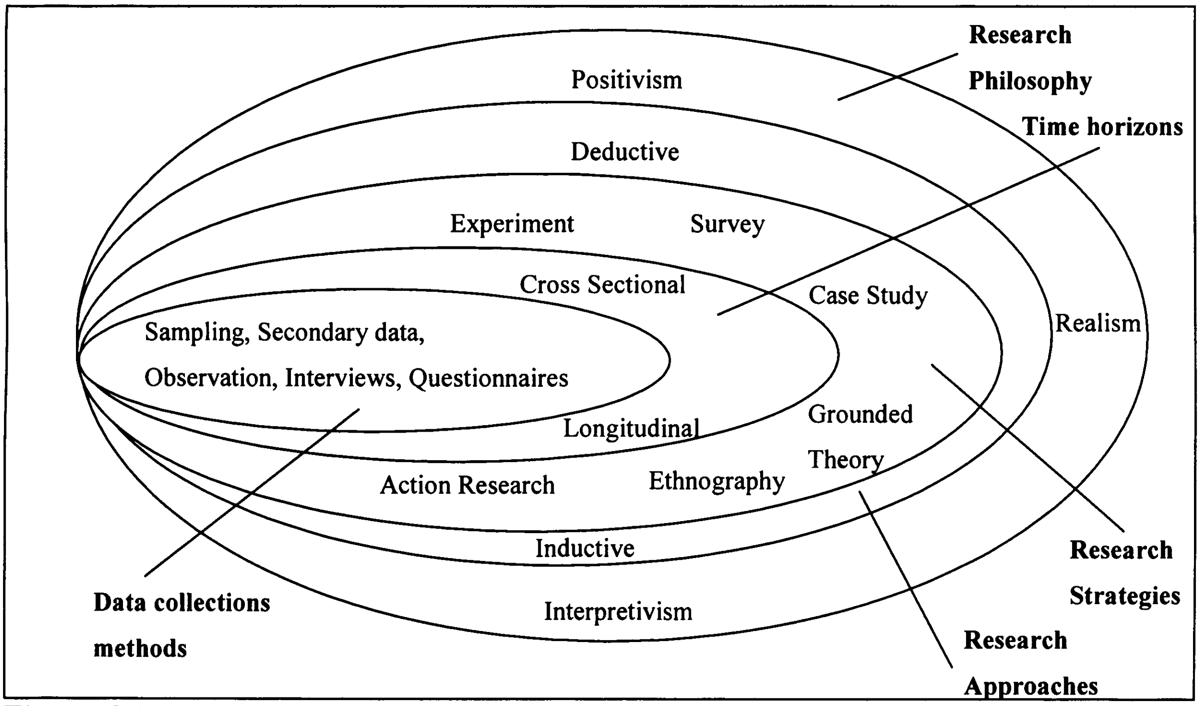


Figure 3.1: The research process onion (Source: Saunders et al., 2003)

3.2 Research Methods in Supply Chain Management or Logistics

The discussion of the philosophy of science and the methodology in this section is specially related to logistic or supply chain research. According to Frankel et al. (2005):

> Many logisticians would say that their research tends to more positivist in nature and utilizes variations of quantitative approaches as the primary research method. Conversely, other logisticians tend to be more interpretive in nature which leads to a greater use of qualitative approaches

Solem (2003) supports the statement by stating that the positivism and realism approaches dominate the logistics area, even though some researchers have moved towards the new perspective that is closer to the interpretive approach. Ticehurst and Veal (2000, p. 15), cited in Knox (2004, p.122) also reveal that the quantitative approach is widely employed in management science or operational research. Even though case study methods are used in logistics to solve real-world logistics problems, Naslund (2002) point out that case study method can be quantitative as well and seems to be primarily based on the positivist paradigm.

Sachan and Datta (2005) analyzed trends in the research design of logistics research based on papers published in three well-known logistics journals from 1999 to 2003. Their results are summarized in Table 3.1. A higher total percentage of quantitative methods compared to the qualitative method in *Journal of Business Logistic* (JBL) and *International Journal of Physical Distribution & Logistics Management* (IJPDLM) indicates that the research design was more towards the positivism position. In general, it can be seen from the table that the total percentage of quantitative research is higher than that of qualitative research. However a trend can be seen towards increasing use of the qualitative technique, since the total percentage of desk qualitative approach is higher than the total percentage of desk quantitative approach. In order to understand this phenomenon, the percentage of several research methods used in logistic research by various researches is summarized in Table 3.2.

Table 3.1: Research design applied in logistics research based on papers published in three top journals between 1999 to 2003

Research design	JBL (percent)	SCMIJ (percent)	IJPDLM(percent)	Total (percent)
Empirical quantitative	52 (57)	38 (26)	72 (35)	162 (37)
Empirical qualitative	5 (5)	41 (28)	32 (16)	78 (18)
Desk quantitative	22 (24)	14 (10)	42 (21)	78 (18)
Desk qualitative	13 (14)	53 (35)	51 (25)	117 (26)
Empirical triangulation	-	1 (1)	6 (3)	7 (2)
Total	92 (100)	147 (100)	203 (100)	442 (100)

Source: Sachan and Datta, 2005

JBL : Journal of Business Logistic

SCMIJ: Supply Chain Management : An International Journal

IJPDLM: International Journal of Physical Distribution & Logistics Management

Table 3.2: Research methods applied in logistics research

Research methods	Mentzer and Kahn (1995)	Larson and Halldorsson (2004)	Sachan and Datta (2005)				Frankel et al. (2005)
			JBL	SCMIJ	IJPDLM	Total	
Surveys	54.30 %	54.30 %	52.20 %	22.40 %	35.50 %	34.60 %	37.0 %
Simulations	14.90 %	19.20 %	9.80 %	2.0 %	4.90 %	5.0 %	14.80 %
Maths model	4.30 %		13.00 %	12.80 %	12.80 %	10.40 %	
Interviews	13.80 %	13.80 %	3.30 %	5.90 %	5.90 %	6.80 %	19.50 %
Case Studies	3.20 %	3.20 %	4.30 %	25.20 %	14.80 %	16.10 %	6.70 %
Archival studies	-	9.60 %	-	-	-	-	-
Conceptual model	-	-	4.30 %	7.50 %	6.40 %	6.30 %	-
Others	9.60 %	-	13.0 %	27.20 %	19.70 %	20.80 %	22.15 %

Source: Mentzer and Kahn, 1995; Larson and Halldorsson, 2004; Sachan and Datta, 2005 and Frankel et al., 2005

As can be seen from Table 3.2, the methods used in logistics research are more quantitative than qualitative with the survey as the preferred method. Simulation and mathematical modelling methods stand in second position in the table (Mentzer and Kahn, 1995 and Larson and Halldósson, 2004).

The ontological and epistemological positions for this thesis are more towards the realism and positivism paradigms. The positivism position is more appropriate to the interpretivism paradigm because research on the Inventory Routing Problem is an economic approach, since the research attempts to find the best solution that minimises cost or maximises profit via quantitative technique. Mentzer and Khan (1995) state that the economic and behavioural approaches are influenced by a positivism position since their goal is 'to explain and predict reality'. According to Mentzer and Flint (1997 p.199), "positivism is inherently a process of induction leading to deduction, leading to induction". The process to conduct the research based on the positivism position is discussed in the next section.

3.3 Research question and methodology selection

Generally, research is based on qualitative, quantitative or a combination of these techniques. As discussed in the previous section, the research philosophy position will influence the methodology chosen for the research. In addition, the research questions and research objectives also contribute as factors to the methodology decision (Frankel et al., 2005; and Ellram, 1996). Thus, this section provides an overview of the selection of the methodology to address the research question described in Section 1.4.

i) How is the supply chain process carried out in the healthcare industry in the context of developing countries' private healthcare, especially in Malaysia? Can the Inventory Routing Problem approach be used to improve supply chain operations?

Ellram (1996) states that the case study methodology is suitable for answering the 'how' and 'why' questions in both exploratory and explanatory research. On the other hand, quantitative methods like the survey or secondary data analysis need to be used in order to answer the 'how much', 'how many', 'who', 'what' and 'where' questions in explorative, descriptive and predictive research.

Therefore, the case study approach is chosen as the method to explore the existing supply chain process in the case organization, since the research endeavours to answer the 'how' question. Moreover, additional information and a better understanding of the performance of the current policies can be obtained via secondary organisation data analyses.

This study is also interested in investigating the potential of implementing the IRP approach in the Malaysian healthcare industry, to manage several clinics in one organisation. Generally, previous research in the IRP area has mostly determined a solution for the gas industry, (Bell et al., 1983; and Campbell and Savelsbergh, 2002). The benefit of the centralised decision making that integrates two important elements in the supply chain has motivated other researchers to expand the application of the IRP to other industries. According to Meredith (1998), the case study strategy can be used as an early exploratory investigation where the variables are still unknown and the phenomenon not yet fully understood. The case study is therefore considered to be the best strategy to investigate existing supply chain processes, evaluate the problems that occur as well as identify the improvement strategies needed to overcome the problems.

Furthermore, the information on the general healthcare supply chains in Malaysia and improvement supply chain strategies that exists in the healthcare supply chain is reviewed from the literature. The sources of the literature and the design of case study that appropriate for this research are discusses in detail in Section 3.5.1. and 3.5.2 respectively.

ii) **How should the parameters in the Inventory Routing Problem be set? How should the supplier decide on which retailers should be replenished during each replenishment period?**

The various replenishment approaches to solve the Inventory Routing Problem that used by previous researchers are examined from the literature. Nevertheless, the review of the appropriate replenishment procedures to be implemented has also considered the joint replenishment approach as this could be used to solve the multi-item problem for a single location. Furthermore, the appropriateness of the inventory control policy to be adopted in this thesis also taking into account the suitability of the case study organisation based on their supply chain environment.

It has been found that the periodic "can-order" policy is the best approach to solve the multi-items problem. This concept seems appropriate as a new replenishment policy for IRP gives flexibility for the supplier to consolidate the replenishment among retailers. Therefore, the characteristic of the new IRP model including the parameters and the condition that triggered the replenishment are evaluated based on the "can-deliver" policy concept in the literature and the analysis in the organisation.

iii) How does the proposed policy perform in the single item multi-retailer case? How do the variables influence the result?

Analysis of the new IRP policy is carried out using quantitative methods. Quantitative modelling in operations management is appropriate for understanding the causal relationship between control variables and the performance variable of the model. Further, these approaches are able to examine the behaviour of the suggested policies under different scenarios and quantify the best solution that optimises the performance measurement in either the physical or economic aspects of the model. Bertrand and Fransoo (2002) categorise model-based quantitative research as axiomatic and empirical research, since both can be classified as descriptive and normative/prescriptive research. Axiomatic normative (AN) research is a typical type of model-based quantitative research in the Operational Research field. The AN research is primarily concerned with finding the best solutions for improving previous research or solving a newly defined problem as a scientific contribution to the existing knowledge (ibid).

Similarly, Ragsdale (2004) categorised mathematical models into prescriptive, predictive and descriptive categories based on the characteristics of the mathematical function and independent variables of the problem. Table 3.3 shows the difference between the three model categories and suitable management science techniques for each category.

Table 3.3: Mathematical models categories' characteristic

Category	Form of functional relationship, f(.)	Values of Independent variables	Management Science Technique
Prescriptive Models	Known, well-defined	Known or under decision-makers' control	Linear Programming, Networks, Integer programming, Critical Path Method (CPM), Goal programming, Economics order quantity (EOQ), Nonlinear Programming
Predictive Models	Unknown, ill-defined	Known or under decision-makers' control	Regression Analysis, Time Series Analysis, Discriminant Analysis
Descriptive Models	Known, well-defined	Unknown or uncertain	Simulation, Queuing, Program Evaluation and Review Technique (PERT), Inventory Models

Source: Ragsdale, 2004

In contrast, Beamon (1998) eliminated the optimisation model and categorised the analytical model into two different categories, namely, deterministic analytical models and stochastic analytical models and introduced economic models as a new category in multi-stage models for supply chain design and analysis. The supply chain's taxonomies discussed in Min and Zhou (2002) also included hybrid models which contain both deterministic and stochastic elements and IT-driven models as a result of growing IT software usage in modelling the supply chain.

With regard to the modelling process, Law and Kelton (2000) indicate that the relationship between variables for a simple problem may be modelled to obtain an exact solution using analytical mathematical methods such as calculus and probability theory. However, a simulation method is more appropriate to model and solve a complex system numerically using a computer. According to Harrell et al. (2003), the complexity of the system is related to the interdependencies and the variability factors. Duncan (1972) refers to the environmental complexity based on the number and interdependencies of the environment variables. Figure 3.2 shows the relationship between the analytical difficulty and the level of complexity as illustrated by Harrell et al. (2003). It can be seen from the figure that an increasing number of interdependencies and uncertainty levels in the system raises the level of analytical difficulty exponentially.

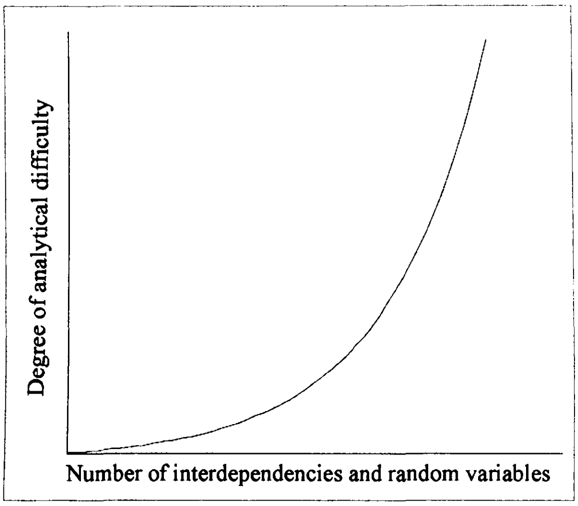


Figure 3.2: The relationship between analytical difficulty and the number of interdependencies and random variables (Source: Harrell et al., 2003)

It has been suggested by Ragsdale (2004) that the simulation approach is more useful for studying stochastic inventory control since the solution to determine an optimal ordering level, time and quantity is not possible to express just using a simple formula. Banks et al. (1999) also state that simulation is an appropriate tool for studying an internal interaction in a complex systems or subsystems. Banks et al. (1999) also contend that simulation is suitable for identifying an improvement in the system under study. It is also able to determine the consequence of implementing a new design or approach to the system as well as provide valuable insight into the systems regarding the effect of each variable and highlight those variables most likely to have a large impact in the systems (Ibid). Chang and Makatsoris (2001) also report that supply chain simulation is beneficial for the organisation to carry out what-if analyses by testing different alternative improvement strategies and identify the impact of the changes without interrupting the current process. Moreover, Terzi and Cavalieri (2004) state that simulation is a powerful method among other quantitative methods for supply chain decision making. Similarly, Law and Kelton (2000) indicate that simulation is among the most common techniques used in operations research and management besides mathematical programming and statistical techniques. The growing trend of simulation usage by various industries to redesign and improve their existing system proves that the simulation is a practical tool for studying the supply chain (Chu, 2003).

Accordingly, the simulation model is adopted in this thesis to address this research question. Simulation is capable of evaluating the behaviour of the proposed IRP model to various input factors. The comparison of a new improvement strategy with other inventory policies can also be simply obtained via simulation by updating the model configuration. The detail on simulation model is discusses in Section 3.6.

iv) How should the routing strategy be incorporated into the IRP model to reduce cost, improve vehicle effectiveness, and reduce energy consumption?

The simulation model is expanded to evaluate the impact of different vehicle effectiveness strategies on the IRP model. The appropriate vehicle effectiveness strategies to include in the analysis are reviewed from the literature. Similarly, the literature is the primary source to develop new transportation cost function in the IRP model that considers minimizing a route based cost to yield a minimum energy consumption and high vehicle effectiveness.

3.4 Research Framework

The research design is a framework to conduct research that links the data to be collected and data analysis to the initial questions and objective of the study. Figure 3.3 illustrates the framework to conduct the research. It starts with the problem formulation and conceptualisation phase, followed by a modelling and the generalisation phase based on the logistic research framework suggested by Mentzer and Kahn (1995) and Mitroff et al. (1974).

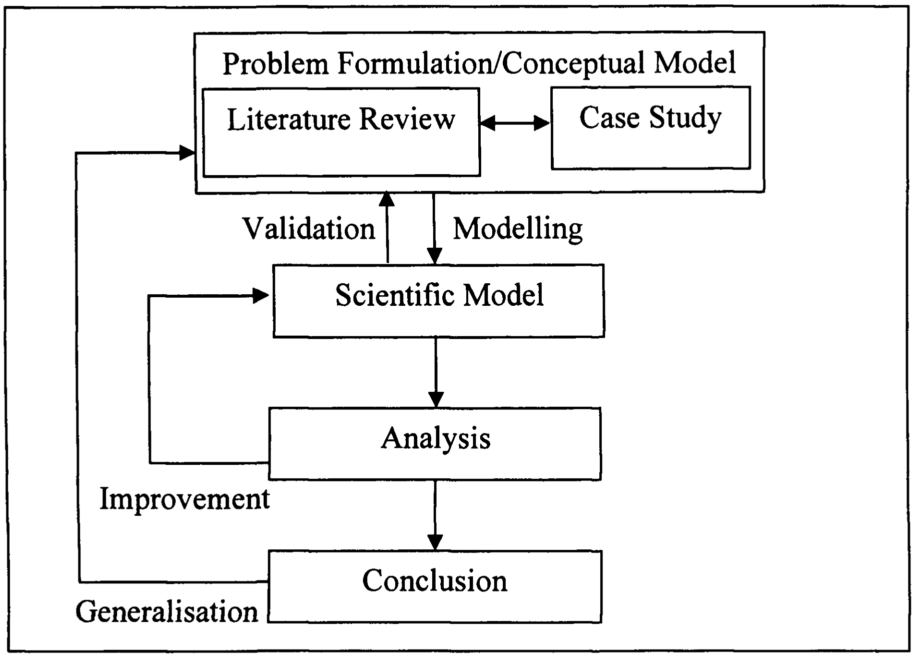


Figure 3.3: Research framework

3.5 Problem Formulation and Conceptual Model

The conceptual model for the study was generated from reviewing the literature to obtain a broad overview of the research area as well as from via case study method in order to observe of a real life phenomenon, i.e. the supply chain process. It was important to identify the problem considered in this research and the scope of the research.

3.5.1 Literature Review

As discussed in Section 3.3, the literature review provides an overview of the improvement supply chain strategies that exists in the healthcare supply chain, different IRP methods used by previous researchers to solve the IRP, the vehicle effectiveness strategies and the information to develop new transportation costs. In addition, the information collected from the literature helped to define the research gap so that this thesis could contribute to the existing body of knowledge.

The literature for this review was captured from various sources, including:

i) University online databases and electronic journal databases

Relevant papers and journals were identified based on key words like 'Inventory Routing Problem', 'Vendor Managed Inventory', 'Joint Replenishment' and 'Supply Chain Methodology' and obtained from the online database provided by Cardiff University. The Scopus, Pro quest, Emerald and Science Direct databases are common databases used to find the published academic journal papers or articles from magazines. The author also accessed and reviewed special issues of top journals in the logistics area such as the *'Journal of Business Logistics'*, *'European Journal of Operation Research'*, *'Transportation Science'*, *'International Journal of production Economics'* and the *'International Journal of Production Research'*.

ii) Conference proceedings

Papers from conference proceedings were useful for obtaining the latest information regarding the research area that had not been published yet in journals.

iii) Cardiff University library

The University library offered a wide range of books and magazines that was used as a foundation and starting point for providing general information about the research area. The library also provided a hardcopy of journal papers and previous student theses for reference. Further, the university provided an inter-library loan service to obtain those resources not provided by the university.

iv) Internet

This is the fastest growing resource for obtaining research information which can be obtained easily from a search engine like Google (www.google.com). The information given from the internet came from various sources, including lecture notes, journal papers, newspapers, information from the organization under study, and academic websites. The Google scholar websites provides more relevant information for research as it locates scholarly information such as journals, peer-reviewed articles, theses and technical reports from universities, (Noruzi, 2005).

3.5.2 Case Study

The design of the case study appropriate for a research study needs to be determined before conducting the research. Yin (2003) categorised four types of case study design, namely: single-case (holistic) design, single-case (embedded) design, multiple-case (holistic) design, and multiple-case (embedded) design. Figure 3.4 shows these four classifications based on Yin (2003). The present study design can be classified as an embedded type since it involves more than one unit of analysis. According to Bryman and Bell (2007), the best-known research in the business and management area is based on the single-case study approach where the study normally focuses on a single organisation, a single location, a person or a single event. Voss, Tsikriktsis and Frohlich (2002) contend that the single case study approach provides an opportunity to gain in-depth knowledge but has the possible disadvantage of misjudging the single event and limited scope for generalisation. On the other hand, multiple case studies can enhance the external validity but may reduce the depth of the study.

Ellram (1996) states that a single case study is suitable for representing a critical case to test a theory and is also appropriate for studying a unique case as well as to study the phenomenon that has previously been difficult to get access too. Yin (2003) also advocates these reasons for using the single case study method. A single case study was viewed as appropriate for the first phase of this research to study in detail the structure of supply chain activities within the private healthcare industry, which can be considered unique when compared to other supply chain processes studied previously in the IRP area. The strong academic collaboration between the case study organisation and the research Faculty of Computer Science and Information System of the University Technology Malaysia provided the author with an opportunity to gain access to the organisation. Furthermore, the in-depth investigation of one of the leading private healthcare companies in Malaysia that owns the largest chain of clinics in the country offering private health care will reveal whether the IRP a possible, feasible re-engineering approach.

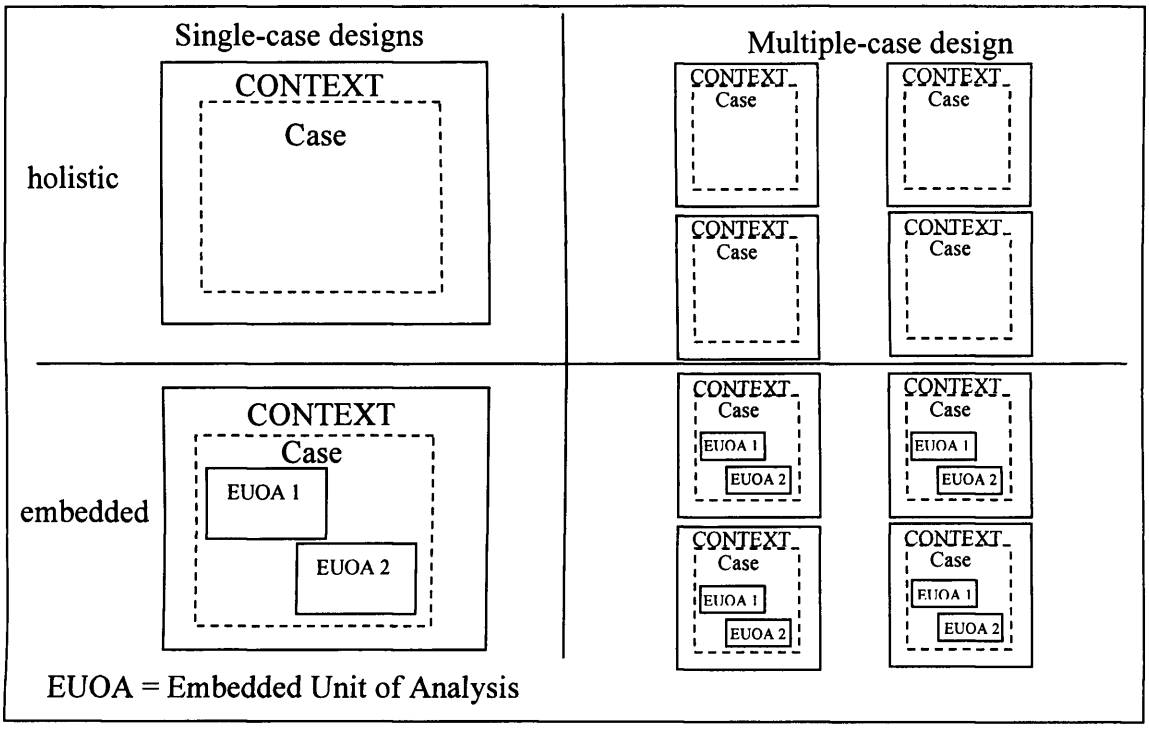


Figure 3.4: Case study design type (Source: Yin, 2003)

The study can be classified as an embedded single case study since the study will explore several aspects, including inventory management, transportation management, and the ordering process within a two echelon supply chain in an organisation. The organisation has a central warehouse that receives deliveries from a large number of suppliers that is represented as a single wholesaler in this study. On the other hand, retailers are represented by the chains of clinics that are owned by the organisation. Relevant data for the analysis process is collected using a triangulation technique that combines process mapping, interviews and company documentation and archival data. The use of multiple sources for the data collection process will address the issues construct validity. The interview sessions with personnel in charge of supply chain activities, an IT manager from the IT Department, and staff members from clinics started with broad and open-ended questions. Questions then become more specific as interviews progressed as suggested by (Voss, Tsikriktsis and Frohlich, 2002), open-ended questions allowed interviewees to freely express their opinion regarding the supply chain process in the organisation. The data collection technique is discussed in chapter four, Section 4.3. The process to develop a simulation model which is a valid model of the system under study is discussed in the next section.

3.6 Simulation model

Banks (1998) and Banks et al. (1999) define simulation as "the imitation of the operation of a real-world process or system over time". The behaviour of this system is evaluated by building a simulation model. The valid simulation model can then be used to investigate what-if questions and predict the effect of changes within the existing system as well evaluate the performance of new systems.

However, the simulation method has several weaknesses. According to Law and Kelton (2000), simulation can be used to model a complex supply chain system that contains stochastic elements but it is time consuming to develop such a model and carry out the analysis. In addition, Banks (1998) and Banks et al. (1999) state that the simulation result is likely to be difficult to interpret due to the randomness of the input variables. On the other hand, Banks (1998) and Banks et al. (1999) indicate that simulation allows a better understanding of the interaction between variables in a complex system. Furthermore, every aspect of the modification for the system can be tested and investigated via the simulation method without interruption of the existing system. However, Law and Kelton (2000) claim that the result from simulation is less valuable if the model does not represent the actual system. Moreover, the model requires several independent runs for each combination of input in order to obtain a close estimate point of the true expected performance of the system.

Generally, simulation models are classified into three different categories (Law and Kelton, 2000; Banks et al., 1999; Brooks et al., 2001 and Harrell et al., 2003):

i) Deterministic or Stochastic

A deterministic model deals with certain and known input variables which will produce a similar outcome each time the model is executed. In contrast, the stochastic model takes into account uncertainty and the inputs to the model where will generate random outputs. According to Harrell et al. (2003), the random value will vary within a certain range according to the specific density which is defined by the probability distribution.

ii) Static or Dynamic

A characteristic of the simulation model in this category is that it depends on whether the system output varies over time. A static simulation model represents a system that that does not change with time. In contrast, the dynamic simulation model represents a system that changes over time.

iii) Continuous or Discrete

The state of changes in the system over time can be discrete or continuous. For example, the level of petrol in tanker that continuously changes can be classified as a continuous system. However, this phenomenon can also be modelled using a discrete system. Therefore, Banks et al. (1999) and Law and Kelton (2000) state that selection of the type of the model, whether to use a continuous or discrete model, depends on the characteristics and the objective of the system under study. Generally, Greasley (2004) differentiates between both models based on the level of application. He believes the discrete model is more appropriate to use in modelling the operational manufacturing and service system, whilst the continuous model is appropriate for investigating the cause and effect of parameter change in an organisation's system.

Kleijnen and Smits (2003) classified simulation types to solve supply chain management problems into different categories, i.e. spreadsheet, system dynamics (SD), discrete-event dynamic system (DEDS) and business games. Law and Keaton (2000) described the discrete-event simulation model as having discrete, dynamic and stochastic characteristics. Greasley (2004) stated that the system dynamic simulation type uses a continuous model approach and the spreadsheet simulation type is significant for analyzing a static model, such as the Monte Carlo method. In fact, spreadsheet simulation can also be used in modelling discrete-event or system dynamics simulation (Pecherska and Merkuryev, 2005; Greasley, 1998 and Stent and McCallum, 1995). We will further discuss spreadsheet simulation in the simulation modelling tool context in the following section.

3.6.1 Simulation modelling tool

Generally, a simulation model can be developed based on three main categories of simulation modelling tools (Robinson, 2004):

i) Spreadsheets
ii) Programming languages
iii) Specialist simulation software

Pidd (2004) reports that writing the simulation using programming languages, such as FORTRAN was the only option available in the late 1950s. However, these general purpose languages are still useful nowadays since they give the developer the flexibility to design a model with minimum restriction on output format, even though it requires a longer developing time (Shannon, 1975 and Robinson, 2004). Furthermore, Brooks et al. (2001) and Seila (1995) point out that low modelling cost is another advantage of using this approach.

The earliest specialist simulation software like SIMULA, GPSS and SIMCRIPT, also known as simulation language (Brooks et al., 2001), or special purpose language (Shannon, 1975) was able to simplify the modelling process and reduce the modelling time by having extra features, such as experimental support, a well-suited syntax, automatic data generation, collection and reporting of statistics as well as animation facilities (Pidd, 2004; Brooks et al., 2001; and Shannon, 1975). Then, a new generation of specialist simulation software started to appear with the existence of powerful computers that have the capability to develop, execute and analyse the models visually and interactively. Such software can be classified as general purpose packages such as Arena, Extend, SIMUL8, and AweSim, or application-oriented simulation packages such as ProModel, ServiceModel, MedModel, MODSIM 111, AutoMod, WITNESS and SIMPROCESS which are suitable for modelling a specific application (Law and Kelton, 2000). A detailed summary of simulation software including the typical applications, cost of software, and the features available for model building is provided in Swain (2007).

The detailed history and development of simulation software can be obtained from Robinson (2005) and Pidd and Carvalho (2006). Among such software, ProModelPC, WITNESS and Simul8 are the softwares most commonly used by academia and industry to develop simulation models according to a survey conducted by Hlupic (2000).

Although these simulation specialist packages offer advantages in terms of being able to develop simulation models easily in a graphical manner through the available menu functions, the user requires extra time to explore all features provided in the software as well as time to obtain the skills needed to develop the simulation models. On the other hand, spreadsheet simulation is convenient for developing simulation models since the user is generally familiar with spreadsheets like Microsoft Excel. Ragsdale (2004) stated that the electronic spreadsheet has been reported to be one of the most effective and useful approaches for developing computer models by millions of business people. Coles and Rowley (1996) also report the increasing use of spreadsheets by managers as decision support systems. In addition, Evans (2000) and Pecherska and Merkuryev (2005) have shown that the spreadsheet is a powerful tool for teaching both static and dynamic simulation models. With spreadsheets, the user is able to integrate graphics to visualise the results that are updated dynamically with the change of model input. A spreadsheet also provides statistical tools and functions that allow the user to perform an analysis of the result directly (Evans, 2000). Seila (2005) indicated that a large number of functions are available in the spreadsheet and an automation programming language such as Visual Basic Application (VBA) is among spreadsheet features which are capable of being a platform to conduct a simulation. Moreover, Seila (2005) reported that spreadsheet simulation is appropriate in developing stochastic models and undertaking sensitivity analysis of the models with variation of the unknown parameters, but has a limitation with regards to modelling the complex algorithm and large amounts of data.

Table 3.4 presents a comparison of the main categories of simulation modelling tools based on several features, such as range of application and the time required to obtain the skills and build the model. Generally, programming languages provide a high range of application, flexibility and small execution time. However, the specialist simulation software is better than programming language in terms of duration of model building, ease of use and ease of model validation. As has been previously discussed, users only require a short time to obtain the software skills necessary to use the spreadsheet simulation that is also affordable in terms of price. The long execution time for spreadsheet simulation might be overcome by using powerful computer specifications or performing the simulation on multiple computers using a parallel and distributed simulation approach (Brooks et al., 2001).

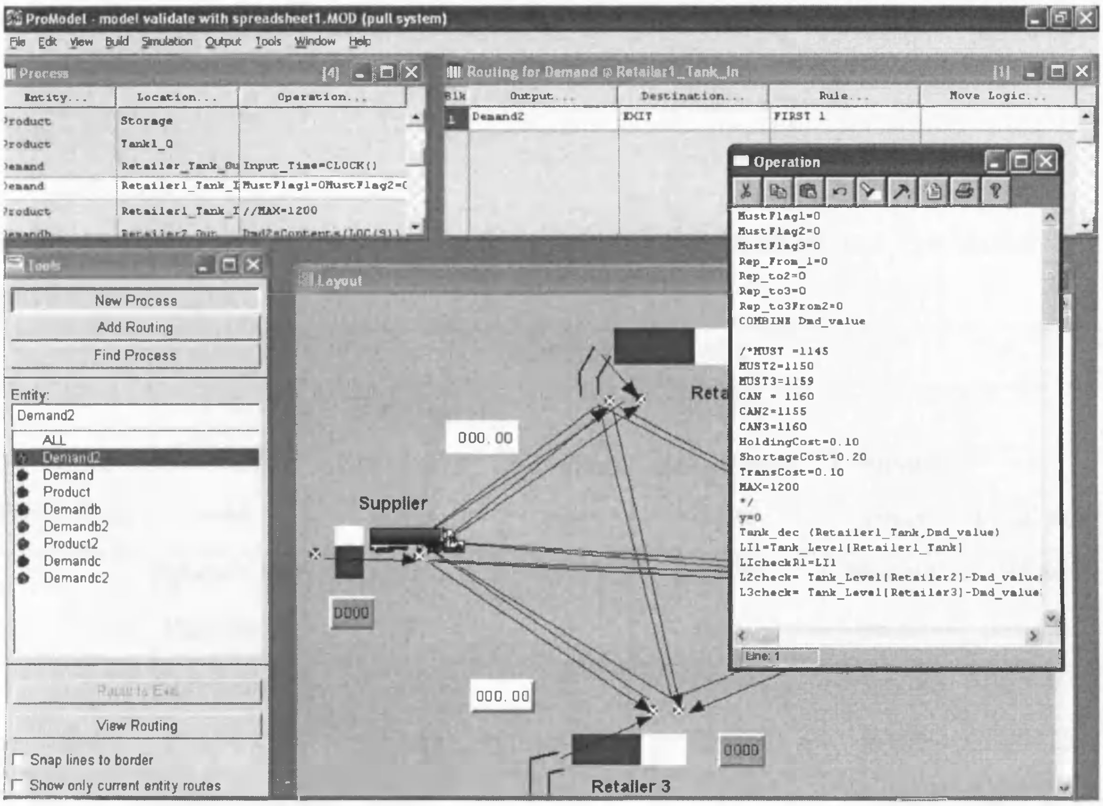
Table 3.4: A comparison of main categories of simulation modelling tools (Source: Robinson, 2004)

Features	Spreadsheet	Programming language	Specialist simulation software
Range of application	Low	High	Medium
Modelling flexibility	Low	High	Medium
Duration of model building	Medium	Long	Short
Ease of use	Medium	Low	High
Ease of model validation	Medium	Low	High
Run-speed	Low	High	Medium
Time to obtain software skills	Short (medium for macro use)	Long	Medium
Price	Low	Low	High

Apart from the cost and learning time factors, Sezen and Kitapci (2007) indicate that spreadsheet simulation and commercial simulation software can also be distinguished 'based on the appropriateness to the specific need'. According to Robinson (2004) and Pidd (2004), the majority of specialist simulation software are Visual Interactive Modelling Systems (VIMS). As the result, the simulation model can be developed interactively by select the model's objects via the available menus in the software. For example the "machine" object can be used to model part of a manufacturing process whereas a "counter and people" object can be used to model the service model or queuing model. In addition, the logic and the flow of entities for the simulation model can be defined through an existing menu. The simulation software also provides a visualisation of the model to display the animation when the model has been executed and user is able to interact with the model at any particular time to obtain the results or modify the model. Thus, the simulation software is more appropriate to develop the event-scheduling approach that is able to define the flow of entities, event logic and visualize the movement of entities to get more understanding of the model. On the other hand, Robinson (2004) stated that the 'spreadsheet is a relatively straightforward approach to develop a simple time-slice model' but it is 'difficult to develop a model animation using spreadsheet'. Nevertheless, several researchers have preferred to use spreadsheet simulation to model a queuing system since the time to develop the queuing model with other applications requires extra time to gain knowledge of programming languages or special purpose simulation languages (Seal, 1995)

An analysis of the outcome generated by the spreadsheet and the commercial simulation software can be used to examine the performance and impact of the simulation model using different simulation modelling tools. Interestingly, the deterministic supply chain analysis performed by Chwif et al. (2002) showed similarity of the total cost margin for a one year simulation period between spreadsheet and supply chain guru software, with less than 1% of deviation. It is probably because the rounding of the input data and truncating of the processes during the simulation model development process. However, Chwif et al. (2002) claimed that the spreadsheet result might be misleading if the model has variation in demand. The analysis of inventory management problems by Zabawa and Mielczarec (2007) using Monte Carlo proved that the spreadsheet is capable of producing a similar outcome with Extend software for variable demand and lead time.

To choose an appropriate simulation software tool for this study, an analysis of a simple deterministic IRP model using Microsoft Excel Spreadsheet and Pro Model software is conducted in order to test the capability of these simulation tools in terms of the accuracy of results, modelling time and execution time. A detailed explanation of the IRP model notations and objective function is presented in Chapter Five. For simplicity, the simulation model is analysed using spreadsheet and Pro Model software for 100 periods of simulation time using similar demand data. Figure 3.5 shows the screen shoots of the simulation model for spreadsheet and Pro Model software.



(a)

(b)

Figure 3.2: Simulation model screen shots (a) Pro Model (b) Spreadsheet

As predicted, the results of six different inputs generated by spreadsheet and Pro Model software as presented in Table 3.5 showed similarity for all measurement costs.

Table 3.5: Results of comparison analysis between Spreadsheet and Pro Model software

		Simulation results				
Experiment	**Simulation tools**	**Holding Inventory costs**	**Shortage cost**	**Total Inventory cost**	**Transport costs**	**Total cost**
1	Spreadsheet	5202	0	5202	96.8700	5298.8699
	Pro Model	5202	0	5202	96.87	5298.87
2	Spreadsheet	5167.6	0	10404	99.6648	5267.2648
	Pro Model	5167.6	0	10404	99.66	5267.26
3	Spreadsheet	5175	0	5175	96.2506	5271.2506
	Pro Model	5175	0	5175	96.25	5271.25
4	Spreadsheet	3046.3	6.8	3053.1	19.3807	3072.4807
	Pro Model	3046.3	6.8	3053.1	19.38	3072.48
5	Spreadsheet	3058	4	3062	17.6903	3079.6903
	Pro Model	3058	4	3062	17.69	3079.69
6	Spreadsheet	3090.8	5.2	3096	16	3112
	Pro Model	3090.8	5.2	3096	16	3112

However, throughout the modelling and execution phase of the simulation model, the spreadsheet model outperformed the Pro Model software. The total modelling time for the simulation model using the Pro Model software was longer than the modelling time for the spreadsheet model. Extra time was required to learn and build an advanced simulation model, even though the author had been used to this software for basic simulation modelling previously. Building this model not only required determining general elements of the model like locations, entities, path networks and resources but also required using advanced elements, including attributes, variables and external file features. Further, the operation logic statement to specify the activity of entities at a defined location based on specific conditions needed advanced programming logic skill. Further information regarding the modelling elements and other features in the Pro Model software can be found in Harrell and Price (2002) and Benson (1997).

Surprisingly, in this analysis we found that the execution time of a 100 simulation period for the Pro Model software at full speed was longer than the execution time for the spreadsheet model at each change of input parameters. Therefore in this thesis we adopt spreadsheet simulation as a simulation tool to develop the model. This decision supported by Sezen and Kitapci (2007) who also contended that 'spreadsheets can be effectively used in modelling and simulation of supply chain inventory problems'.

3.6.2 The spreadsheet simulation modelling process

According to Robinson (2004), the modelling process of the spreadsheet simulation model is generally similar to the common simulation process used in specialist simulation software or a programming language. The development of the simulation process in this thesis is based on general simulation study steps that have been outlined by Law (2003) and Law and Kelton (2000) as follows:

i) Define the problem
ii) Collect the data and construct the conceptual model
iii) Build the spreadsheet model
iv) Validate and verify the spreadsheet model
v) Design the simulation experiment
vi) Analysis of output
vii) Document and present the simulation results

This flow is consistent with Chang and Makatsoris (2001) who suggested understanding the supply chain process is the initial step in supply chain simulation before modelling the particular area that needs to be improved. Problem formulation together with conceptual model construction obtained from the literature review and case study analysis have been discussed earlier in Section 3.4. Therefore, in the next subsection, we focus on the remaining spreadsheet simulation study processes in more detail.

3.6.2.1 Spreadsheet modelling

Winston (2005) described spreadsheet modelling as 'the process of entering the inputs and decisions into a spreadsheet and then relating them appropriately, by means of formulas, to obtain the outputs'. Thus, the layout of the spreadsheet model needs to be constructed clearly to differentiate the functions of cells in the worksheet so that they become understandable and flexible for the analysis. Seila (2005) classified cells in the spreadsheet model into inputs, intermediate computations and outputs of the model. The input cells can be either constant or random values. To model a stochastic model, Simon (1998) provided a guide to generate the simulation model in a spreadsheet without using add-in software such as Crystal Ball.

Generally, the random input data can be generated via the "RAND( )" function or by the random number generator in Analysis Toolpak (ATP) in Excel. The intermediate computations contain the formulas that are assigned to the cells, either using calculation operators such as arithmetic operators (addition, subtraction, multiplication and division) or comparison operators (equal, greater than, less than, greater than, less than or equal to, greater than or equal to and not equal), or using appropriate functions. The calculation for the intermediate computations will be updated automatically with changes of input value when cell references are used in the formulas. The spreadsheet also allows the user to create their own functions via the Visual Basic Application (VBA), and to formulate the long and complex calculations that can be easily used in the spreadsheet. The automatic repetition of decision variables for the sensitivity analysis can also be generated via the VBA. Moreover, the results generated from one combination of decision variables can be copied and written into different worksheets via commands such as those shown in Figure 3.6.

```
Sheets("ModelSheet").Select
Range("Result_cell").Select
Selection.Copy
Sheets("NewSheet").Select
Cells(Row_number, Coloum_number).Select
```

Figure 3.3: Command to copy and write results in new worksheets in Excel

Martin (2000) shows how VBA offers significant capability extension to a spreadsheet. This may also include a dialog box to interact with the user and provide advanced control of the model.

Pecherska and Merkuryev (2005) have indicated that the simulation length of the spreadsheet simulation can be increase by assigning more rows in the worksheet with the relevant formula. The output cells represent the performance measurement of the model. We will discuss in detail the development of our IRP simulation model in Section 5.4 and the custom functions which were designed in Section 6.7.

3.6.2.2 Verification and validation

In this phase, the spreadsheet model is verified and validated to test the accuracy of the model for the analysis. Law and Kelton (2000) describe verification as the process to check the correctness of the translation process from conceptual model to computer model. On the other hand, validation is the process of determining the accuracy of the simulation model compared to the system under study. The model can be verified and validated in a number of different ways. Checking the simulation result is one approach that can be used for verification besides tracing and debugging the computer program (Law and Kelton, 2000). In this study, the result of the simple spreadsheet IRP model for a certain simulation period is verified by hand calculation using different constant input values to check the rationality of the output. The correctness of the logical process and the formula assigned at intermediate computation cells were traced manually by plotting the graph of the inventory level of each location on paper as shown in Figure 5.2. Further, the VBA modules used to enhance the capability of the spreadsheet model can automatically detect syntax errors while coding the programmed parameter and processes in the Visual Basic programming language.

Using the step debugging function helps to verify the semantic error or logical error of VBA modules. The similar results between spreadsheet and ProModel software shown in Table 3.5 verified the accuracy of the spreadsheet simulation model. In this context the black-box validation, (Robinson, 2004) or comparisons with other modelling validation techniques, (Harrell et. al, 2003) is used to compare the two different simulation models of the same system. The decision variables of the model were also tested with scenario variations to check the behaviour of the model. The experimental validity of the model was confirmed through the determination of an appropriate warm-up period, simulation length as well as number of replications for the simulation besides performing the sensitivity analysis (Robinson, 2004). According to Sargent (1994), sensitivity analysis is able to evaluate the effect of a model under different input settings by comparing the behaviour of the system under study. He also stated that the operational validity of the model to examine the model's output behaviour can be evaluated via graphical or statistical test comparison.

3.6.2.3 Simulation Experiment

Brook and Robinson (2001) and Robinson (2004) indicated that obtaining an accurate result and determining the alternative scenario to be simulated are two decisions that need to be made in performing the simulation experiment.

As has been discussed in the previous subsection, the accurate result of the simulation model was obtained by determining the appropriate length of the initialisation period and a number of simulation replications to obtain sufficient output data. However, the technique for dealing with these issues is related to the behaviour of the simulation output. This technique will be discussed in the next subsection.

With regard to the procedure to explore the impact of the solution model with various decision variables or inputs settings, three approaches can be used to achieve this purpose, including (Robinson, 2004):

- Experimental design
- Metamodel
- Optimisation

3.6.2.3.1 Experimental Design

Harrel et al. (2003) and Law and Kelton (2000) indicated that decision variables or inputs are known as factors whilst the output of the model is known as the output response in experimental design terminology. These terminologies are shown in Figure 3.7.

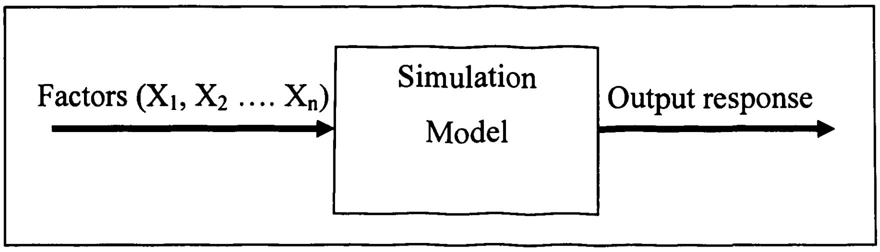


Figure 3.4: Experimental design terminology (source: Harrel et al., 2003)

The factorial design method is an approach that can be used to design the combination of factors and the level of each factor for the simulation experiment. The two level, full factorial (2^k factorial) designs can be used to execute the model for more than two factors, *k,* with two levels. The number of experiments can be reduced to deal with a large number of factors by using fractional factorial designs, and factor-screening strategies eliminate some unimportant factors for the analysis (Law and Kelton, 2000). On the other hand, Taguchi Methods are able to outline the simulation experiment for various numbers of factors and levels via orthogonal arrays (OAs) and examine the factors that influence the model through Analysis Of Variance (ANOVA), (Roy, 1990). Taguchi Methods are therefore employed to design the simulation experiment in the IRP model. The factors that we considered in the analysis included the inventory controls parameters and the cost parameters where five different value is test for each factor in the experimental design analysis. Section 5.6.1 will describe the detailed process using the Taguchi methods applied to the IRP model and result of the most factor that influence the IRP model based on ANOVA.

3.6.2.3.2 Metamodel

Basically, the metamodel is the standard regression model that is used to estimate the behaviour of the model when the input is changed or identify the approximate best solution for the inputs factors (Law and Kelton, 2000). However, the full factor analysis of the IRP model was conducted using the brute force approach with a specific range of factors to evaluate the sensitivity analysis of the model. The effect between the two factors is evaluated with a three-dimension mesh surface known as the response surface. In this way the performance behavior of the model can be comprehensively evaluated

3.6.2.3.3 Optimization

The optimization approach is used to determine the best combination of control factors that optimize the simulation model's objective function. Several approaches can be used in order to obtain the best result such as; stochastic approximation, random searches and metaheuristics techniques, (Olafsson and Kim, 2002). In this study, the best combination of factors that minimizes the total cost for the IRP model was determined by seeking the lowest point of the response surface generated from the sensitivity analysis.

A detailed explanation of design of the simulation experiment and the sensitivity analysis of model factors (as well as the results) is presented in Chapters Five and Six.

3.6.2.4 Output analysis

According to Robinson (2004), the simulation output analysis aims to determine an 'accurate estimation of average (normally the mean) performance' through eliminating the initialisation bias and obtaining a sufficient amount of output from the model. A suitable analysis for such evaluation depends on whether the simulation is classified as a terminating or non-terminating simulation. The terminating simulation starts and ends the simulation within a defined time or at a specified event, whilst for the non-terminating simulation analysis, the steady-state or long-term average behaviour of the model is measured. The non-terminating system will reach a steady-state period after several simulation times. Therefore, it is crucial to determine the transient period or warm-up period in order to eliminate any result bias.

The common practice for dealing with this problem is to truncate some of the observations that do not represent the steady-state at the beginning of the run and use only the remaining observations to estimate the true mean response of the model. Sandikci and Sabuncuoglu (2006) called this method "truncation heuristics" and stated that this approach is often preferred because of its simplicity.

Many techniques have been developed in the literature to determine the warm-up time. Robinson and Ioannou (2003) summarised 42 methods under five categories as follows:

i) Graphical method
ii) Heuristics approaches
iii) Statistical methods
iv) Initialisation bias
v) Hybrid methods

A list of different methods and the relevant reference for each method under these five categories can be found in Robinson(2002). Robinson and Ioannou (2003) also reported that the Welch graphical method is one of the most commonly used techniques for determining a truncation point. Linton and Harmonosky (2002) state that this method may be a good practical choice since it is not based on any assumptions about the type of system being modelled and it is simply applied. Section 5.4.2.1 will discuss the process of determining the warm-up period using Welch's method.

Robinson (2004) also contended that the initialisation problem can be avoided by assigning proper initial conditions to the model. For this reason, the initial inventory level for each retailer in our IRP model is assigned to the maximum inventory level that can be held by the retailers. A sufficient amount of data for the non-terminating simulation can be obtained by running the simulation model for a long simulation period or replicating the simulation using different streams of random data (Robinson, 2004; Harrel et al., 2003; Bank et al.,1999; Law and Kelton, 2000). However, only the multiple replications approach is appropriate for terminating simulations. Section 5.4.3 will explain the technique used to determine the appropriate simulation run length for our simulation model based on 95% of desired half-width of confidence level together with the evaluation of simulation output demand pattern via histogram and goodness-of-fit tests. The outcome of the proposed simulation model is also compared to that obtained from other inventory policy approaches presented in Section 5.7.

3.6.2.5 Documentation of results

Discussion on the development of the simulation model and the reporting of the simulation results are elaborated clearly and concisely in different chapters within this thesis. In general, the literature review chapter and the case study chapter discuss problem identification and the conceptual model in order to identify the objectives, inputs, performance measurement, structure and the assumption used for the IRP simulation model. Chapters five and six are the main analysis chapters that report on the experimental design of the simulation and the outcome of the simulation model. As well as graphical presentation, several figures and tables are provided to improve the interpretation of the result. The external validity of the study is addressed in Section 5.8 and Section 6.10. The model is tested with different input variables in order to observe the behaviour of the model and the predicted effect of the model when it is applied to other scenarios.

3.7 Ethical considerations

Several ethical issues needed to be addressed when employing the case study approach in the chosen case study organisation. First, permission to conduct the research was obtained from the organisation. The research aims were clearly explained to the organisation to provide a broad idea to participants of the information required when conducting the field study. It was important to protect the identity of the organisation under study and confidential data. Therefore the identity of the organisation has not been revealed in this thesis. The research was conducted in accordance with university research ethical requirements in place at the time of the study.

3.8 Conclusion

This chapter has evaluated the methodology used to conduct the research. It began by discussing the general philosophies underlying business and management research and then focused on the methods commonly used by previous logistics or supply chain researchers. From such discussion it was found that the epistemology of this research is more towards the positivism approach. The chapter continued with the description of the research framework. Generally, problem identification and the conceptual model of the research were based on the review of the literature and the case study. The simulation model was considered more appropriate than the analytical model for research purpose as it is able to explore the performance of improvement policy under several input settings. A comparison analysis between spreadsheet and Pro Model software together with supporting references indicated that spreadsheet simulation is the appropriate simulation tool for modelling and simulating the inventory problem. Then, the process of developing and designing an accurate simulation model was explained. The next chapter will report the results of the case study analysis and evaluate the suitability of the IRP approach to overcome the problem faced in the organisation.

Chapter 4 Case Study

This chapter discusses the healthcare industry supply chain and its business's process reengineering approaches. This addresses research question number 1 and a conceptual model is built with regard to the structure of the supply chain between two echelons. This conceptual model provides a foundation for the IRP model presented in Chapter 5. The study specifically investigated the current supply chain process involving a wholesaler and a chain of medical clinics. Secondary and primary data derived from the case study are analysed in order to identify the issues that occur within the process. Relevant improvement processes that can be applied to improve the process are discussed. They are based on the literature that highlights general improvement strategies in the pharmaceutical industry. The improvement strategy suggested in this research is conceptually designed using a Data Flow Diagram (DFD) technique. Generally, the contents of this chapter are based on a paper presented by Mustaffa and Potter at the EUROMA Conference in Glasgow in 2007. This paper has been accepted for publication in the *Supply Chain Management: An International Journal* by Emerald Group Publishing Limited.

4.1 Introduction

The use of an appropriate supply chain management strategy is important in the healthcare industry since it deals with the public's health and it is important to have accurate records and stocks to meet the patients' requirements (Frederick, 1995). Hanna and Sethuraman (2005) pointed out that the healthcare organisation also has to balance operational efficiencies and cost improvement activities to deal with a challenging value chain environment. A number of strategies used to improve the performance of the healthcare supply chain industry is found in the literature. However, there still exist barriers to implementing improvement strategies in developing countries since most of the applications are focused on the developed world. Moreover, much of the research considers a whole sector instead of individual businesses and only a few sources in the literature refer to developing countries.

Kearney (2004) and Corrêa (2004) are examples of healthcare sector research in developing countries. This chapter will therefore evaluate the current healthcare supply chain process of leading private healthcare providers in Malaysia. Specifically, the study aims to identify the problems that exist within the business process and then determine the best strategies to solve the problems.

Section 4.2 explores the general supply chain management in the healthcare industry and the possible improvement strategies to improve the process. The case study is used to gain an in-depth knowledge and understanding of organisational issues in a Malaysian context. The method in conducting the case study is discussed in Section 4.3. The current supply chain process that has been implemented by the organisation is examined in Section 4.4. Discussion on the issues that exist within the supply chain is continued afterwards in Section 4.4.1. Further discussion on why the VMI approach is a more applicable approach to replace the traditional supply chain rather than other approaches such as JIT and how the IRP approach can be implemented to improve the performance in the healthcare supply chain is presented in Section 4.5.

4.2 Supply Chain Management Practices in the Healthcare Industry

4.2.1 General Issues

Within the healthcare industry, the supply chain associated with pharmaceutical products is critical in ensuring a high standard of care for patients and providing adequate supplies of medication for pharmacies. In terms of cost, it is estimated that supply accounts for 25-30% of operational costs for hospitals (Roark, 2005). Therefore, it is essential that this is managed effectively to ensure both service and cost objectives are met.

The typical healthcare supply chain structure is shown Figure 4.1.

Primary manufacture involves the creation of the active ingredients contained within the medication. Because of the need to avoid contamination between products, there are long downtimes in production to allow for cleaning, leading to batch production (Shah, 2004). In effect, this represents mass production.

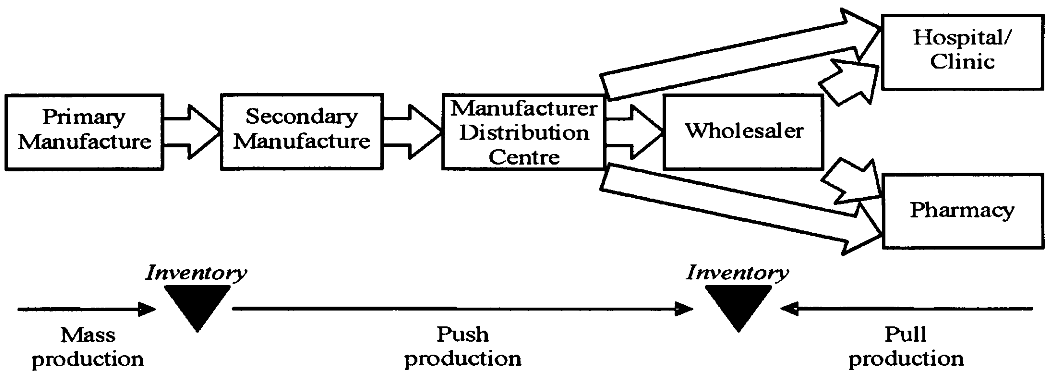


Figure 4.1: Healthcare supply chain structure (based on Shah, 2004, and Morton, 2003)

Secondary production sees the active ingredients converted into useable products (such as tablets, capsules, etc). This can potentially lead to a significant expansion in the number of product lines, especially once packaging is taken into consideration. Altricher and Caillet (2004) suggest a 200:1 growth in products across this stage in the supply chain. With increasing globalisation in the pharmaceutical industry, the location of manufacturing plants is often influenced by factors such as tax benefits (Papageorgiou et al., 2001). Indeed, secondary manufacturing may be geographically separated from primary manufacturing and serve local or regional markets (Shah, 2004).

Turning to the distribution of finished products, there are a number of different channels to the market. The dominant intermediary (in terms of volume at least) is the wholesaler. In the UK, approximately 80% of volume flows through this channel (Shah, 2004). Hospitals and retailers which have large demand requirements receive shipments direct from the manufacturer's distribution centre. Hospitals may also leverage economies of scale by consolidating their purchasing power through, for example, Group Purchasing Organisations (Roark, 2005). As will be discussed shortly, recent trends in healthcare supply chain management have seen a move towards pull based systems for the final part of the distribution channel, effectively inserting a decoupling point at the wholesaler, where a repository of stock is found (Hoekstra and Romme, 1992).

4.2.2 Healthcare Supply Chain in Malaysia

According to Smith (1996):

> "The economies of most developing countries are growing much faster than those of developed countries, primarily because of private investment. In most developing countries, the private health sector is proportionally much bigger than in developed countries, see for example, Malaysia, Indonesia and Bangladesh".

Malaysia is considered one of the most developed of the developing countries. The study comparing Asian and European logistics systems by Bookbinder and Tan (2002) showed that Malaysia is classified in the same group as top ranking logistics oriented countries like Singapore and Denmark, based on the infrastructure, performance, information systems, human resources and business, political and environmental characteristics of the country.

MacDonald (2007) states:

> "Malaysia is set on encouraging further development of the logistics sector, as outlined in the government's 3rd Industrial Master Plan (IMP3) with incentives for companies to develop integrated logistics solutions across the entire supply chain"

Malaysia is now planning to integrate the primary, secondary and tertiary healthcare sectors via an efficient and effective referral system (Ninth Malaysia Plan Report, 2006). In the three and half decades since Malaya's decolonisation, overall heath standards have improved. Health status in Malaysia is almost as good in other industrial countries. In 2000, infant mortality was 0.79% of live births and maternal mortality 0.02% live births. According to Tham and Yahya (2008), 'Malaysia ranks fifth in healthcare spending, despite a relatively small population' compared with other Asian countries. Malaysia's existing healthcare system comprises public and private systems as a two-tier system. The private sector supplements the public sector in meeting the demand for health services. Generally, private primary care providers are more likely to be located in urban areas. Recently, there have been signs of growth in private clinics in rural areas due to a better infrastructure and road system. Private healthcare is run as a profit-oriented business and patients pay for their services and medicines from their own pocket.

Even though the cost of obtaining treatment in the private sector is more expensive than public healthcare, patients are more attracted to private clinics due to factors such as short waiting time, good interpersonal quality of care, and convenient opening hours.

As report by Ismail (1996) in News Straits Times, most patients are not satisfied with the attitude of the doctor and health workers in the public sector. Private doctors are polite, helpful, patient and spend more time with the patient. Further, patients are free to choose a different primary care doctor according to their preference. The study by Universiti Kebangsaan Malaysia has found that there has, however, been little research conducted on the private healthcare sector because of difficulty in gaining cooperation from private doctors. According to Dr. Syed Aljunid they do not want to waste their time participating in research since they fear it will expose weaknesses (ibid).

The Malaysian government is now considering re-structuring the healthcare system by adopting different systems for financing cost related activities and delivering products between warehouse and healthcare providers in order to better achieve the government's health care policy goals. Healthcare service planning should be based on needs assessment and allocation efficiency in order to attain the appropriate level of access and an equitable distribution of the scarce resources. The aim is now to improve the mix and quality of services and to increase efficiency and effectiveness. The main strategy for healthcare sector development is improving accessibility to affordable and quality health care. The Malaysian government also plans to collaborate with the public and private sectors to achieve a better health care system.

4.2.3 Overview of the case study organisation

The chosen organisation is one of the largest private healthcare company's in Malaysia. It has one headquarter and owns a chain of 35 branches of clinics. The location of these clinics are scattered in south of Peninsular Malaysia. The clinics offer all aspect of medical activities including the medical examination, minor surgery, blood tests as well as the paediatric services.

Generally, the medicine items that are stored at the clinics are categorised into eight different groups. These groups are based on the function and other criteria such as; general drugs, obstetrics and gynaecology stock, stationery stocks category, psychotropic stock, pharmacy stock, over-the-counter (OTC) stock and Group A stock category. Group A stock category consists of the expensive medicines and medicines that are controlled by the Ministry of Health in Malaysia. Overall, the organisation stock about 600 items at clinics.

The inventory of each clinic is managed separately and each clinic is responsible to ensure the stock is sufficient to meet the patient demand. The order is made through the headquarters and the total number and the category of orders are varied based on the clinics' requirement. Thus, the headquarters act as a wholesaler responsible for processing orders and scheduling the deliveries using the organisation's transportation. This consists of one lorry and one van which is also used for other activities within the organisation. Basically, the deliveries are scheduled for two consecutive days for each type of vehicle to deliver too four different groups of clinics that been clustered roughly based on their location. The details delivery process will be discuss in Section 4.4. Figure 4.2 shows the supply chain structure of the case study organisation.

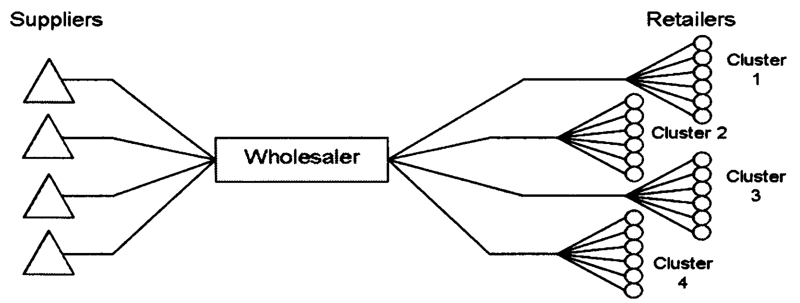


Figure 4.2: Organisation's supply chain structure

4.3 Research Method

A case study approach is adopted to investigate the current level of supply chain management in the healthcare industry in Malaysia. A case study will yield in- depth knowledge and understanding of current operations. Even though the case study is based on a single organisation, the study involves two echelons in the supply chain – the wholesaler and the clinics. Thus, the case study in this research can be classified as an embedded case study design (Yin, 1984). The data is collected using three main techniques:

- Process mapping

Process mapping is a technique used to model the business process flow in graphical form, to visualise the actual process in the organisation, and to look for improvement to make it more effective (Paper et al., 2001). Aguilar-Savén (2004) provides an overview of the many process mapping tools. The basic business process symbols as illustrated in Figure 4.3 are used to illustrated the general activities involved in the organisation's supply chain process and show the flow of the activities between the wholesaler and clinics.

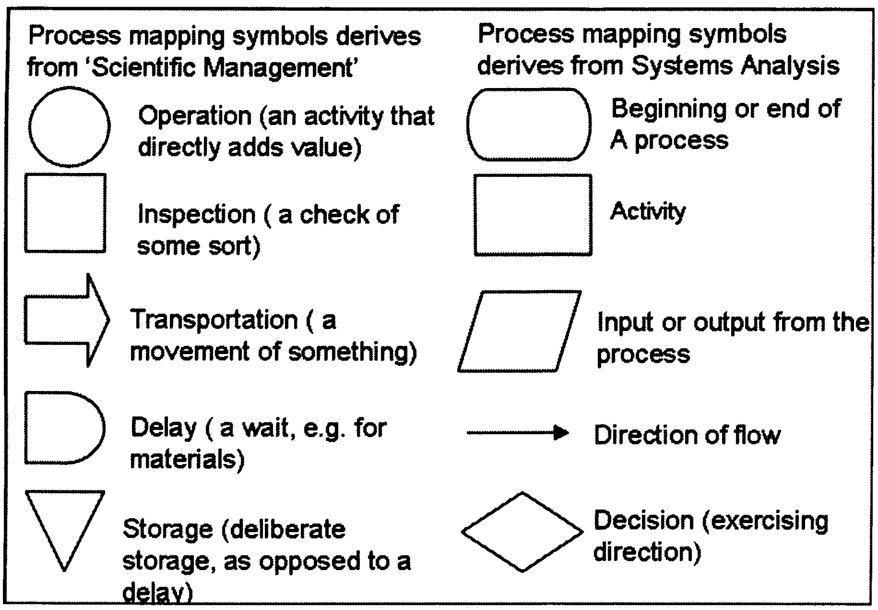


Figure 4.3: Business process symbols (source: Slack et al., 2006)

Details of the current suggested inventory management process within the organisation are provided using the Data Flow Diagram (DFD) technique. Recker et al. (2006) studied the differences in the representational capabilities across leading process modelling techniques and concluded that the DFD is one of the best methods for representing the structure of systems. The process map uses 4 different symbols (see Figure 4.4) to represent the main components – External Entities, Data Stores, Data Flows, and Processes. An External Entity either supplies data to the system or receives data from the system, or both. The Process receives input data and produces outputs. The DFD has data stores which can be either a document, file or a database to archive the output from a process before it is retrieved by another process. Data flows generally are labelled with the name of the data and link sources, process, data store and sinks to represent the data flow in the system.

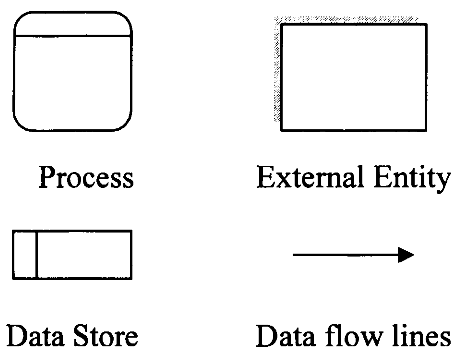


Figure 4.4: Four main DFD components (Gane and Sarson, 1977)

- Interviews

Semi-structured interviews were carried out at the wholesaler and the clinics. Interviewees included personnel in charge of inventory and transportation, an IT manager from the IT department, and staff members from pharmacies in clinics. Information on current inventory approaches, including the ordering process and delivery process to clinics, was obtained during the interview session. The information was visualised using the process mapping approach described above.

- Archival document

Reviews of the organisation's archival records were important and useful to obtain specific and detailed information for analysis purposes. Archival data was collected from the organisation with respect to purchase orders (PO) and delivery orders (DO). These were kept on two different systems. Purchase Order details are extracted from the company's online system used by the clinic to place an order. DOs were extracted from the inventory system and the data was kept in a Microsoft Access database. For this research, three months of PO and DO data were analysed.

From this, the supply chain was analysed to identify main problems that existed, using triangulated findings from primary and secondary sources. Having identified the problems, a potential solution was then proposed, again using the DFD to portray the future state of the supply chain.

4.4 Understanding the "As-is" case study organisation's supply chain

Information on the organisation's supply chain process that was gained through interviews was easily understood by representing the flow of activities and the players involved using the process mapping technique. A broad picture of the key stages of the organisation's inventory management and replenishment processes is presented in Figure 4.5.

The analysis focussed only on the activities involved between the wholesaler and the clinics. The organisation has implemented a pull strategy approach where each clinic is responsible for monitoring and managing their own inventory independently from other clinics. Every first week and third week at each month, they will place an order with the wholesaler to replenish the low volume items. However, the person in charge of making an order is from the general clinic staff. They may not be an expert in managing the inventory. Therefore, the decision on which products are required to be replenished as well as the optimal quantity of order is based on that staff member's personal experience and skill. The headquarters will act as both the wholesaler and the organisation's central management and therefore process the order and schedule delivery of products to each clinic after the packaging process. Finally, the products which are received at each clinic need to be checked for correctness against the delivery list.

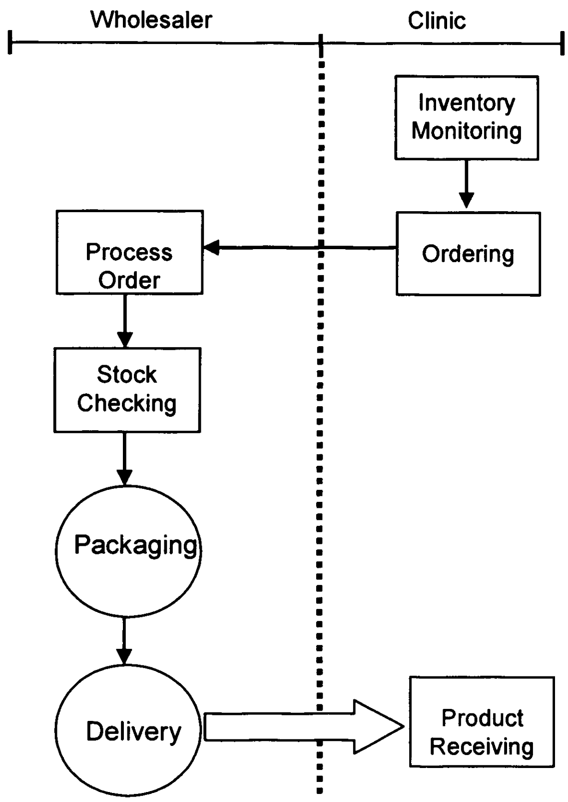


Figure 4.5: Key stages in the organisation's inventory management and replenishment processes

The detailed flow of these processes, including the activities, players and the documents involved in the process is presented in Figure 4.6. The DFD diagram is used to represent the detailed flow of the inventory management and replenishment processes using 4 main DFD components as discussed in Section 4.3. As well as the wholesaler and clinic, the transportation department also plays an important role in the organisation, as it is responsible for the delivery of products. This is categorised as an external entity in the diagram. The flow of activities and documents required to complete the process from monitoring and ordering the product until it has been received at the clinic are shown by the data store and data flow line components.

As can be seen from the figure below, the clinic places an order with the wholesaler based on the decision made during the inventory monitoring process in terms of the type of product and the quantity that is required to satisfy the customer demand.

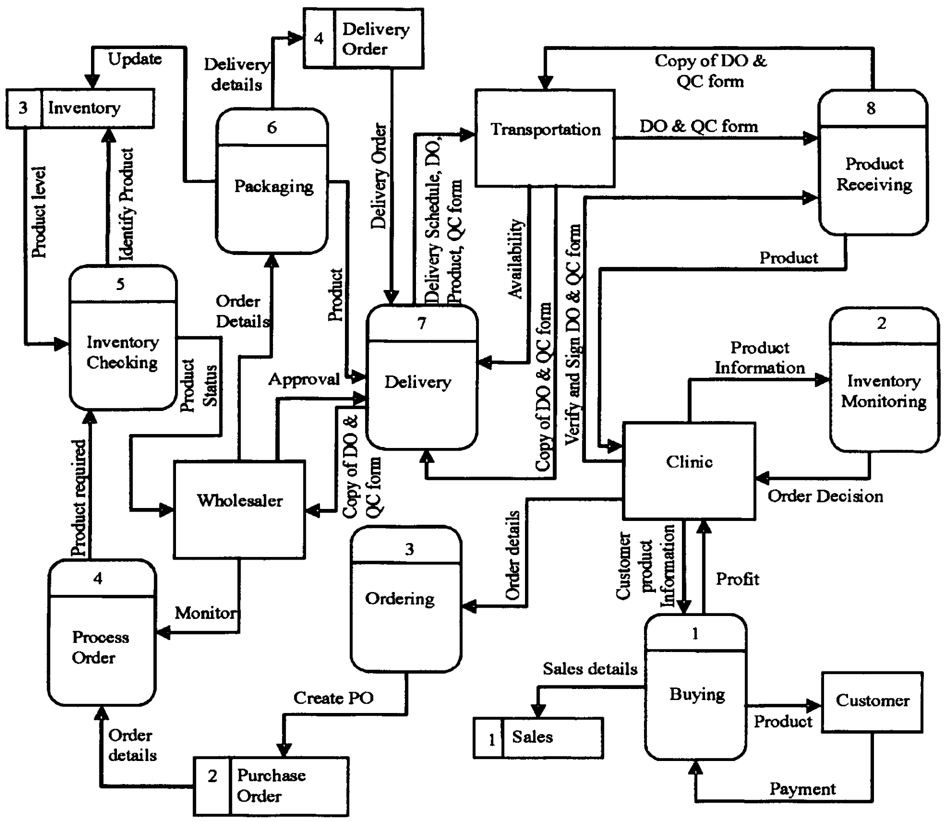


Figure 4.6: "As-is" DFD diagram of the inventory replenishment in the case study organisation

The order is made using the online Purchase Order (PO) system that can be accessed through the organisation's website. The system will generate a unique PO number automatically every time a new order is created. This number is used as an order reference number along the replenishment process. The warehouse will receive the order directly through an online system and generally the replenishment process takes about 5 working days to be completed.

The replenishment process begins with the inventory checking process. At this stage, a hardcopy of POs is sent to the person in charge at the store department to check the availability of products. This process is carried out manually since the inventory on hand for each required product is checked against the inventory stock book. If the product is out of stock, the supply manager is informed for further action to be taken. The supplier will be contacted to check the status of products in the case of outstanding orders. Delivery will be delayed until the product is available in the stock. A new order may be placed with the supplier if no alternative product is available in the stock. Missing stock can also be replaced by available stock that can perform the same purpose. For example, Zecuf Lozenges herbal tablet can replace orange Zecuf Lozenges since the difference is only the flavour.

The next process is the packaging process which needs to be done 3 days before the delivery date. The products are packed based on the order information in the PO. Those products that are ready for delivery are listed on the Delivery Order (DO) form that contains information about the clinic that needs the delivery, together with details of the type of product and the quantity that has been packed for delivery. This form is essential to determine that the correct products have been received by the clinic. This information is also used by the stock keeper to update the current inventory level of the products in the inventory stock book and to ensure the accuracy of the status of the products.

Next, the delivery is scheduled in accordance with the information on the location and the load that is required for the delivery, taking into account the availability of the organisation's transport fleet (one van and one lorry) and drivers. The clinics are clustered roughly on the basis of location, and the area of delivery and each vehicle is scheduled to deliver to a specific cluster at one time. The route to make the delivery depends on the skill of the driver who adopts a milk-run approach to delivery. Basically, the clinic that is situated furthest from wholesaler is visited first followed by other clinics that close to the previously visited clinics and finally delivered to the clinic that is closest to the wholesaler. In average, the total distances occur for the delivery is about 316 km for one delivery trip.

The products that arrive at each clinic are checked to determine whether they are similar to the products listed in the DO forms. The clinic must notify the wholesaler by phone as soon as possible if a difference is found between the number of products received and the DO. Such differences also need to be indicated on the DO. In the case of products that have been left behind or delivered to the wrong branch, a revised delivery will be scheduled to correct this error. Satisfactory products are moved to the store or to the fridge in the case of medication that needs to be kept chilled. Then, the DO and delivery form are signed as a proof of delivery and a copy of each returned to the wholesaler via the driver.

4.4.1 Issues in the supply chain

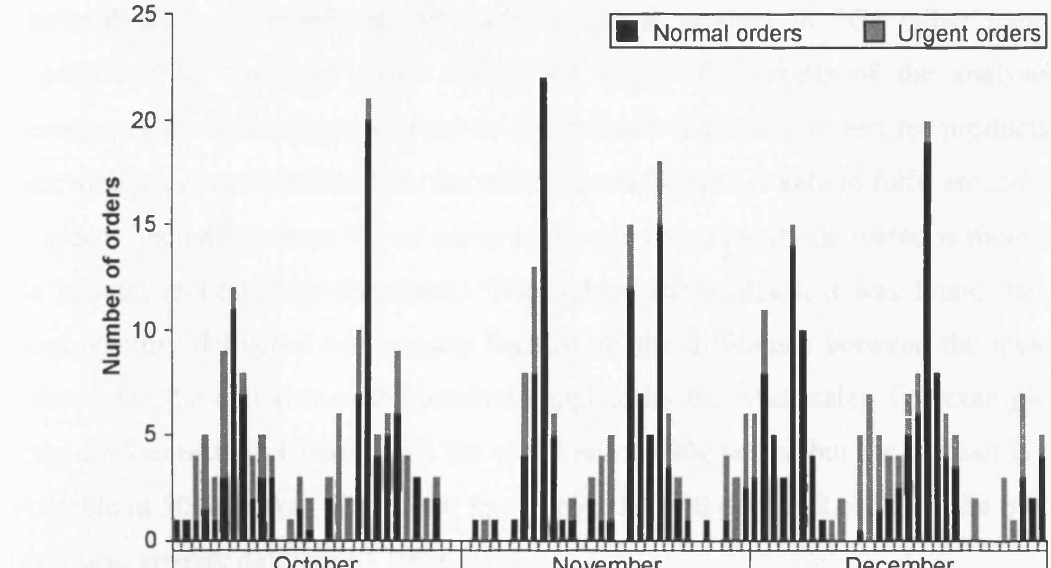
The analysis continued with the investigation of issues that exist within this supply chain. Through the triangulation of primary and secondary organisation data, two main issues were identified as occurring in the organisation that might influence customer service performance, the problem of urgent orders and the lack of inventory at the warehouse.

4.4.1.1 Urgent orders

As mentioned earlier, the decision regarding order details is the responsibility of general staff in clinics who generate orders manually based on individual experience. Therefore, unpredictable demand from customers can cause a problem of low inventory level and stock outs at clinics. As a result, orders for critical products need to be placed with the warehouse immediately since the delivery of a normal order will take at least 5 days. Immediate replenishment is crucial because the medical product is unlike the consumer product in that it is important in providing patient care as there may be no alternative treatment for the patient. Thus, the warehouse needs to process the urgent order immediately and schedule a direct delivery to the required location in order to satisfy the customer demand.

However, urgent orders raise another issue in the organisation. That is, increased operating costs and low vehicle efficiency in dealing with urgent orders. By only delivering to the one particular location that requires an immediate delivery of just a few products can cause lower vehicle utilisation and increase transportation costs. Further, it also causes difficulty for the warehouse which has to manage and schedule a quick replenishment as the process involves different resources and steps to those mentioned in Section 4.4.

An in-depth investigation was carried out to understand the amount of urgent orders compared to normal orders based on POs over a three month period. An urgent order is notified as 'URGENT' at the product status on the PO. The number of normal and urgent orders placed each day from October to December 2005 was counted and the results are shown in graph presented in Figure 4.7. The peak level of normal orders on alternate weeks suggests that clinics are usually placing such orders every first and third week in the month. We can also see a significant number of urgent orders placed between the peaks. Moreover, the percentage of orders categorised as urgent orders is similar for each month and is generally about a third of total orders. This finding points to a problem with the ordering process within clinics since the level of urgent orders remain the same each month. Such a problem may be related to the availability of products at the wholesaler in that the low inventory at clinics may possibly be caused by a delayed delivery of normal orders. Therefore, stock availability at the wholesaler appears as another issue in the organisation and is examined in the next subsection.



	October	November	December
Normal Orders	62.9%	71.0%	69.4%
Urgent Orders	37.1%	29.0%	30.6%

Figure 4.7: Normal and urgent orders placed by clinics with the wholesaler

4.4.1.2 Stock availability at the wholesaler

Within the current supply chain process, the warehouse is responsible for placing replenishments based on separate orders received from clinics. However, the large orders from the clinics in weeks 1 and 3 may cause a difficulty for the warehouse to fulfil the order if the same products are required by many clinics at the same time. As a result, the delivery can only be made based on the availability of the stock and there is some indication that some clinics are not receiving the products that have been requested in the PO.

The scale of this problem is examined by comparing the POs and DOs for a three month period. The analysis is based on four different categories as follows:

i) The product quantity delivered is equal to the amount on the order
ii) The product quantity delivered is lower than the amount ordered
iii) The product is not delivered to clinics
iv) The product quantity delivered is greater than the amount ordered

The analysis was carried out for each individual product in POs rather than the aggregate order for each clinic. Table 4.1 shows the results of the analysis in percentages for each category based on about 2,000 individual orders for products for each month. As can be seen from the table, the wholesaler is able to fulfil around 80% of orders (including about 9% of cases where product quantity delivered is more than the amount requested by the clinic). Throughout the analysis, it was found that the extra quantity delivered was mostly because of the difference between the quantity ordered and the unit size of the product supplied by the wholesaler. For example, an order for Gentacimin Cream from the clinic is for 900g packs, but the product is only available in 500g packs. Therefore, the wholesaler will deliver 2 packs of the product, leading to an over delivery of 100g.

Analysis results indicated that in around 10% to 12% of orders there was an over delivery, while another 7% could not be delivered due to insufficient stock available at the wholesaler. These shortfalls can have a serious impact on the medical treatment available to patients.

Table 4.1: Delivery performance for the wholesaler

Category	October	November	December
Product delivered = Amount ordered	71.5%	72.75%	71.64%
Product delivered > Amount ordered	9.37%	9.12%	8.8%
Product delivered < Amount ordered	12.1%	9.84%	11.69%
Product delivered = 0	6.97%	8.29%	7.87%

4.5 Business process reengineering

4.5.1 Existing strategy

A number of initiatives have been undertaken over recent years with a view to reducing supply chain costs and improving customer service. Initial improvements have been based around implementing just-in-time (JIT) approaches (Kowalski, 1986). These approaches have been developed further with the introduction of stockless inventory systems (Wilson et al., 1992). The JIT and stockless approaches can reduce inventory holding costs in the organisation, while maintaining service levels (Lynch, 1991). More recently, it has been suggested that the stockless inventory system should only be used for high volume products, with a more traditional approach used for low volume medical supplies (Rivard-Royer et al., 2002). However, there is a requirement for improved information and communication technology (ICT) systems to support this stockless inventory strategy, along with automated processing of orders and suppliers (mainly wholesalers) close to the hospital to enable rapid replenishment. Wilson et al. (1992) provides three examples of the implementation of this type of inventory control system within the healthcare industry in the US. Both JIT and stockless approaches represent 'pull' type inventory management systems.

More recently, other inventory control systems have started to be introduced into healthcare supply chains. In particular, there has been interest in the vendor managed inventory (VMI) strategy. Under VMI, the supplier assumes responsibility for the management of inventory at the customer, and takes decisions regarding replenishment (Waller et al., 1999). To some extent, this builds on the information requirements of stockless inventory systems. For the VMI to work successfully, there is a need for accurate information on current stock levels and consumption. However, providing such information within hospitals can be difficult (Haavik, 2000, McKone-Sweet et al., 2005). Nonetheless, examples of VMI implementation do exist in the literature. In Kim (2005), VMI brought a number of benefits, including less administration at the hospital, fewer errors, improved information reliability, and a 30% reduction in inventory. By contrast, Altricher and Caillet (2004) found that, because of a lack of trust in the supply chain, the hospital kept over-ruling the VMI system, holding more stock and eliminating any benefits that accrued.

Since the current management of the organisation under study face a lot of problems, both at the wholesaler and clinics, they should take further steps and consider new approaches to control the inventory more efficiently. This can lower the operating cost and generate more revenue and profit. At the same time, there should be an improvement in service level. In the literature, JIT, stockless inventory, VMI and IRP approaches are among the strategies that have been implemented within the healthcare supply chain. A major issue with implementing JIT and stockless systems is that demand fluctuates and is hard to predict (Kowalski, 1991). The risk associated with a stock out is very high. Therefore, for the JIT approach to be successful, it is important that the wholesaler and clinic are located close to each other with effective transport networks between them. In the case study supply chain, the transport networks are not very effective; a feature of many developing countries that clinics are in rural areas. In addition, there is only limited transport capacity (one truck and one van). Therefore, the capability of the wholesaler to satisfy concurrent demands from a number of clinics is limited. It is therefore believed that a VMI based solution represents the best course of action for the company. According to Brennan (1998), centralised logistics is a key technology for enhancing healthcare supply chain operating efficiencies. As detailed earlier, this kind of approach has gained popularity in the healthcare sector, since it can also reduce the time and effort needed to manage the inventory (Kowalski, 1991). The centralised control system based on VMI gives the opportunity for the wholesaler to integrate the transportation management into the decision-making processes that minimise total inventory and transportation costs via the IRP policy.

4.5.2 IRP implementation "To-be"

A revised DFD diagram for the organisation's improvement strategy based on IRP can be found in Figure 4.8. With this new process, the warehouse monitors daily each product's inventory levels and usage levels at all clinics. By gaining accurate information and integrating the inventory and transportation management, the wholesaler as a central decision maker, is able to made a good decision regarding the time of delivery, the optimal quantity of delivery for each clinic and the efficient replenishment route that minimises the inventory and transportation cost.

The visibility and transparency of the product and demand information helps the wholesaler to identify priority despatches and make a good replenishment. This will help reduce urgent replenishments between the normal replenishment and better utilise the transportation capacity. With customer demand and inventory level information, the warehouse can observe the potential need for a particular product at each clinic and ensure that the inventory at the wholesaler is used to replenish the clinics with the lowest inventory levels. This should overcome customer service issues arising from the wholesaler being out of stock. Thus, the customer service level can be improved by having the right product in stock whenever it is needed.

The wholesaler has more flexibility to plan the replenishment strategy so as to minimise the cost and maximise the vehicle utilisation. It is more practical for the wholesaler to coordinate deliveries to the different clinics that are close to each other during the replenishment time. This approach will overcome the problem of emergency delivery, since an early delivery is made to other clinics that have been integrated to the delivery. However, this approach has the tendency to increase the holding cost at clinics. Thus, an appropriate decision in terms of the optimal delivery time and clinic situation that need to be integrated during the delivery activity has to be made to ensure a low total operating cost.

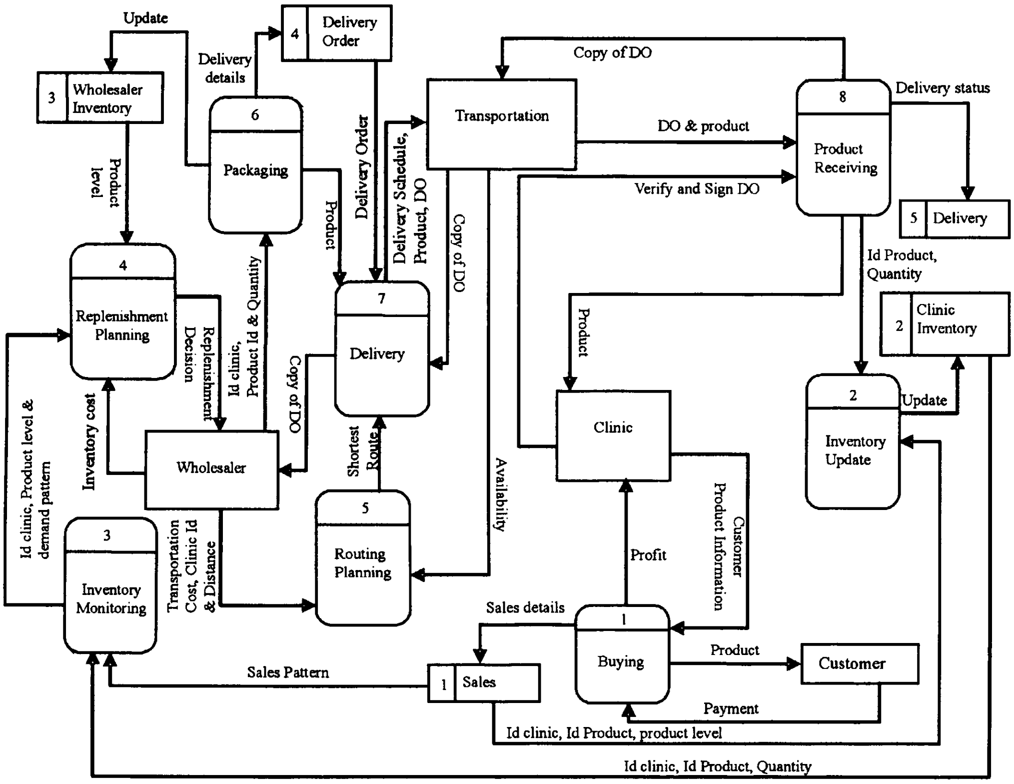


Figure 4.8: "To-be" DFD diagram of the inventory replenishment in the case study organisation

As has been discussed in Chapter 2, the integration approach that coordinates activities amongst other clinics when certain inventory levels are reached based on (s,c,S) policy is a possible improvement strategy. Here, the cost reduction comes from the opportunity that the supplier obtains from delivering certain amounts of products before the clinics reach the actual reorder point.

Holmström (1997) notes that VMI implementation can be achieved through robust process design and collaboration. However, effective systems can improve the success of VMI implementation (Kim, 2005). An issue in the context of this particular supply chain is the use of different systems for POs and DOs. Consequently, it is difficult to ensure accuracy between the PO and DO systems, with errors in data entry occurring. In addition, the wholesaler has limited visibility of usage or inventory at the clinics. Therefore, some investment in ICT may be needed before the new supply chain approach can be implemented. The organisation has access and currently utilises the Internet to undertake data transfer between wholesaler and clinics. Therefore, it is believed that no constraints exist in term of infrastructure to implement the centralised IRP approach. With some improvement to the company's existing supply chain systems, it is possible for the wholesaler to get real time data from all branches. However, to automate the process and get an optimal decision on the replenishment schedule and the transportation, they have to make a more significant investment by acquiring inventory control and routing software. The behaviour and effect of the IRP flexibility model on the total cost via simulation will be investigated in the next chapter.

4.6 Conclusion

The case study has shown that the organisation under study is still implementing the traditional supply chain policy where each clinic needs to place an order with the wholesaler twice a month. The analysis of comparison between the ordering and the actual delivered quantity from organisation's Purchase Order and Delivery Order data has shown that the organisation is suffering with poor supply chain performance. About 28 percent of the orders cannot be delivered as required, and about 31 to 38 percent of orders placed from clinics are categorised as urgent orders that require quick replenishment as a result of improper inventory management at clinics' level and low availability of products at the wholesaler needed to fulfil the high volume of orders. Thus, a centralised control system via the VMI approach is the best improvement strategy for the organisation to overcome the stated problems. Furthermore, the wholesaler is able to determine the optimal time and the quantity of replenishment and thereby minimise the total operating cost by implementing the approach-underlying the VMI strategy known as IRP strategy. The impact of implementing the early coordination strategy on the total cost will be observed in the next chapter. The IRP model developed for the simulation is a simplified model of the supply chain process that contains only 1 wholesaler called the supplier and 3 clinics known as retailers. The assumptions, parameters and the objective function of this model are described explicitly in the next chapter.

Chapter 5 The Stochastic Periodic "Can Deliver" Policy

In this chapter, the periodic "can deliver" policy is proposed as a new replenishment policy for the multi-echelon Inventory Routing Problem in order to address research question 2 and 3. The conceptual model developed is based on the literature in Chapter 2 and the findings from the case study in Chapter 4. This policy gives flexibility and opportunity for the centralised supplier to schedule an early replenishment to the retailer. This is done when a certain inventory level is reached and consolidation with deliveries to other retailers is achieved. This replenishment consolidation benefits in terms of reducing total operating costs.

The details about the policy assumptions, notation and the objective function are to be found in Section 5.1 through to Section 5.3. Section 5.4 and Section 5.5, presents the method to develop and design the simulation model. A discussion of numerical results for different parameter settings is presented in Section 5.6 to address research question 3 of this study. The result of the proposed periodic replenishment policy is compared with other inventory policies in Section 5.7. Finally, the effect of different demand distribution patterns and demand variance on the behaviour of the proposed IRP model is examined in Section 5.8.

5.1 The periodic (s,c,S) Policy

The proposed policy is a periodic replenishment policy for a single product in a multiple retailer scenario with stochastic demands. Previously, the "can-order" policy, known as the (s,c,S) policy, had been widely applied in a single-location multi-item scenario, see for instance, Ignall (1969), Federgruen et al. (1984), and Silver and Peterson (1985). The performance of the continuous review version of this policy has been compared to periodic review policies. Recently, Johansen and Melchiors (2003) have shown that the periodic version of the continuous time (s,c,S) policy performed well when compared to other periodic replenishment policies. This motivates us to investigate the capability of this policy in an Inventory Routing Problem (IRP) environment.

The 'can order' concept provides an opportunity for the retailer to order multiple items from a single supplier simultaneously. Application of this concept in a centralised decision-making environment that integrates the inventory and transportation management fields gives flexibility to the supplier to manage and utilise his resources (inventory, transport and capacity) in an efficient manner. The flexibility comes from the opportunity for the supplier to schedule an early replenishment to the retailer whose inventory position has reached a 'can-order' level and at the same time combine the delivery with other retailers who must be replenished at that time.

In order to gain some understanding of the benefits that this policy provides and the mechanism by which these benefits are produced, a basic model of Inventory Routing has been developed using Microsoft Excel. This model considers an outbound centralised distribution system consisting of one supplier, $\{S\}$, and 3 identical retailers, $\{C_1, C_2, C_3\}$.

The model assumes an unlimited supply of inventory is available at the supplier to replenish the retailers' inventory. Each of the retailers' locations is subject to end consumer demand. Customer demand is assumed to be independent and identically distributed. The basic model assumes that the demand, D in time period t, at customer location x, is independent and identically distributed (i.i.d) follows a Binomial distribution with probability of success, p=0.5 in N independent trials, here N=20.

$$D_{t,x} = B(20, 0.5) \tag{1}$$

Unsatisfied demands are assumed to be backordered and charged at a rate of, p_x per unit backorder per period at retailer x. An excess inventory at the end of each period incurs holding cost, h_x per unit item held in stock per period at retailer x. Moreover, the vehicle used for delivery is assumed to make delivery without a capacity constraint.

Also, the model assumes a periodic review system where inventory positions are monitored every time period. As the process of replenishment is classified as the periodic replenishment approach, inventory positions at each location are observed periodically at the end of each period. The decision to make replenishments to individual customers is driven by three time- invariant parameters at each retailer that are called here:

- the "order-up-to" level", I_+
- the "can-deliver" level, I_c
- and the "must-deliver" level, I_m.

The characteristic of the parameters are similar to the (s,c,S) policy introduced by Balinfy (1964). However, different terms are used here to denote the "can-order" level and the "must-order" level. This is reasonable and logical in the IRP context where the supplier takes responsibility to replenish the retailers' inventory.

Replenishment is triggered by one of two conditions. Delivery must be made when the inventory on-hand at customer location, x at the end of period t, falls below a "must- deliver" level. The replenishment is made to bring the inventory up to an "order-up-to" level". The "can-deliver" level gives an opportunity for the retailer to make replenishment early if inventory at a particular location falls below this level and a delivery is required at another location via the "must-deliver" criteria. The amount of delivery sent to the "can-deliver" location is the difference between the current inventory position and the order-up-to level. Thus, the model has a mechanism where the supplier can, opportunistically, gain some economies of scale in the distribution activities.

The evolution of the inventory levels over time and the "order-up-to", "must" and "can" deliver levels at two retailers are shown in Figure 5.1 based on a single simulation run for 26 periods of simulation time. As each customer faces a demand pattern with the same stochastic properties, the basic model also assumes that I_+, I_c and I_m are the same at each customer location.

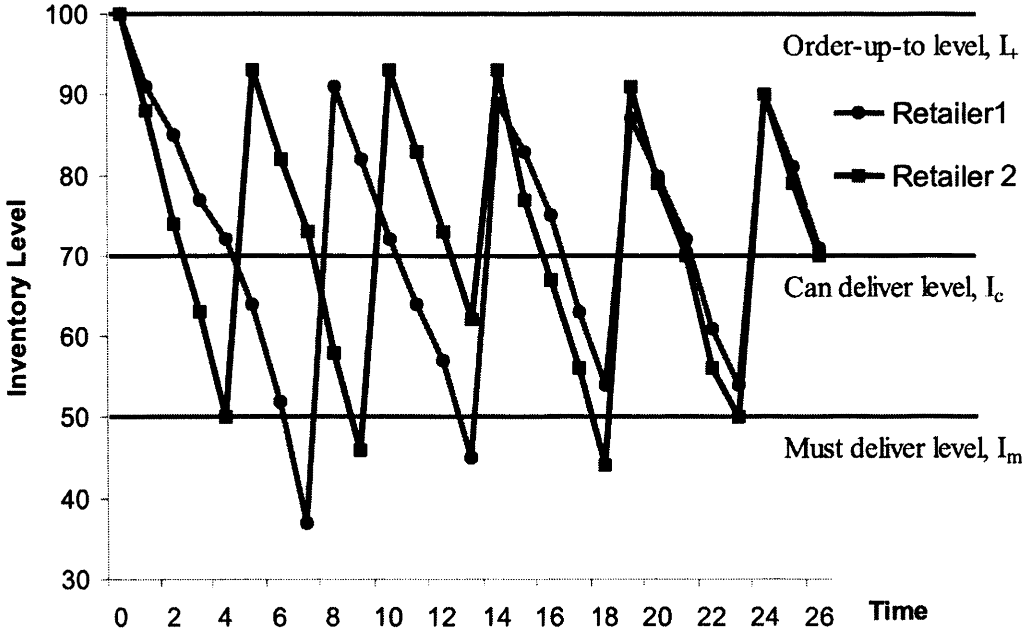


Figure 5.1: The can and must deliver level

The inventory on hand, I at each customer location, x, at the end of period t, $I_{t,x}$, is given by the inventory balance equation:

$$I_{t,x} = I_{t-1,x} - D_{t,x} + R_{t-1,x} \tag{2}$$

where $R_{t-1,x}$ is the inventory replenishments delivered to customer x in the previous period, t-1 and $D_{t,x}$ is the demand in time period t, at customer location x. Thus, although deliveries are made immediately, because of the sequence of events, there is effectively a unit replenishment delay. The replenishments $R_{t,x}$ are driven by the following logic,

$$R_{t,x} = \begin{cases} I_+ - I_{t,x} \text{ if } I_{t,x} \le I_m \\ I_+ - I_{t,x} \text{ if } I_{t,x} \le I_c \text{ and } \{I_{t,y} \le I_m \text{ or } I_{t,z} \le I_m\} \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

where y and z are used to denote customers other than customer x. Equation (3) shows that if the inventory level is below the "must-deliver" level then the difference between the order-up-to level and the current inventory level is ordered. If the inventory level is below the "can-deliver" level, then an order (that will bring the inventory back up to the order-up-to level) is placed if one of the other customers has reached the "must" deliver criteria. Otherwise no delivery is made. Note that if all the customers have reached the "can-deliver" level, but neither has reached the "must-deliver" level, then no replenishment takes place, as it is assumed that this would result in unnecessarily increased inventory levels. Since the vehicle capacity is assumed unlimited, the model is considered to satisfy all the requirements.

In order to clarify the policy behaviour, the conceptual overview of inventory position at 3 customer locations for 14 time periods that are based on a single simulation run is illustrated in Figure 5.2. The initial inventory at each retailer is set equal to the "order-up-to" level. Values for all policy control parameters are I_{+}=30, I_{c}=12 and I_{m} =8. The retailers who need replenishment will receive products in the next time period. As can be seen from Figure 5.2, the inventory levels at all customers at the end of the first period (t=1) are still high and no replenishment is needed at that time. However, at end of next period, inventory level at customer 2 drops to 4, which is below a "must-deliver" level, and 26 items must be delivered to bring its inventory up to I_{+}. At the same time, the inventory level at customer 3 has reached the "can-deliver" level. This triggers an opportunity for the supplier to combine a replenishment at t=3 to both customers in one delivery.

Accordingly, a total of 44 items are placed on the truck as 18 items are required for customer 3. No replenishment is required at this time for Customer 1 since its inventory level is still above I_c. As a result, at the end of period t=3, a demand has decreased the inventory level of customer 1 to below I_m and action is needed to raise the inventory to 30. At the end of period t=4, inventory levels at both customers 2 and 3 has fallen below I_c. However, no replenishment takes place since no customer's inventory level has reached I_m. The delivery despatched in the previous period increases the inventory level at customer 1. Demands arrive in the next period, reducing inventory level of customer 3 to below I_m and causing out of stock problem at customer 2. As a result, some of the demand for customer 2 will be backlogged. Therefore, a total of 32 items needed to be delivered to customer 2 in order to raise the inventory level up to I_+ and fill the two unmet end customers' demand together with 27 items replenishment for customer 3 for the delivery trip at t=6.

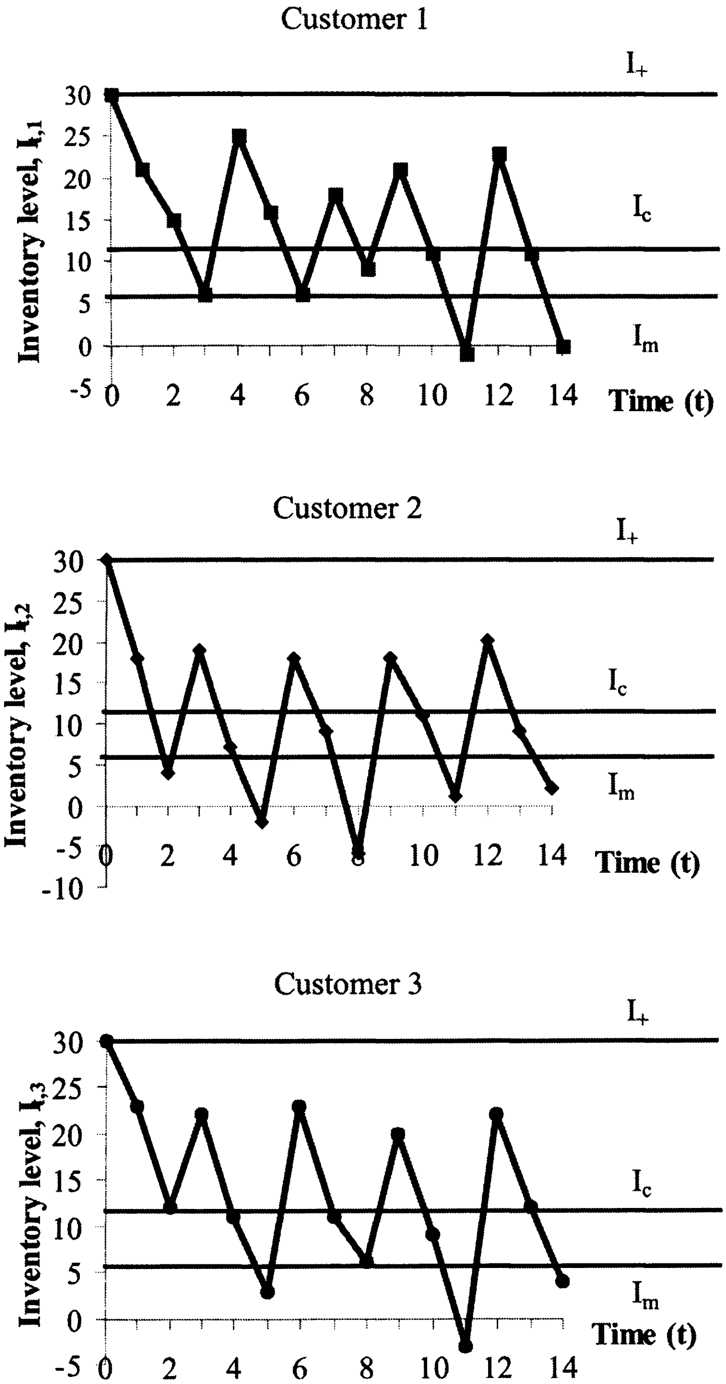


Figure 5.2: Conceptual overview of Inventory level over time for the "can deliver" policy

Similar with the condition at t=2, only two retailers can be consolidated together at this delivery at time t=7 since the inventory level for customer 1 is still above I_c. Thus, the supplier needs to make another delivery at the next time period t=7 in order to replenish customer 1 that has reached the I_m level. No replenishment is required at t=7 because none of the customers have reached the I_m level even though customer 2 and customer 3 have reached the I_c. Consequently, once again customer 2 faces a backlogged problem at t=8. This time, the supplier can schedule the delivery to replenish all three customers at one time as the inventory level for customer 1 is below the I_c and the inventory level for customer 3 has reached $I_{m.}$. It can be seen from Figure 5.2 that at t=9 the inventory levels at all customers are greater than the two policy control parameters so no replenishment is required at that time. Similarly at t=10, even though all retailers have reached the "can-deliver" level, no retailer has yet reached the "must-deliver" level. Hence, no replenishment is required in this time period. As a result, the demand occurring at t=8 has cause a backlogged problem at both customer 1 and customer 2. Replenishment is scheduled to replenishment all three retailers in the next time period to fill the backlog and raised the inventory level up to I_+. From Figure 5.2, it can be seen the same scenario occurs where no replenishment is required at t=12 and t=13 and three customer can be replenished together at t=14 as all customer's inventory level are below the $I_{m.}$.

5.2 Route generation

As has been mentioned previously, the model assumes having one vehicle with unlimited capacity, 1 supplier and 3 retailers. A very simple geographical layout connecting a supplier/depot to all customers and the undirected arcs between all customers are shown in Figure 5.3.

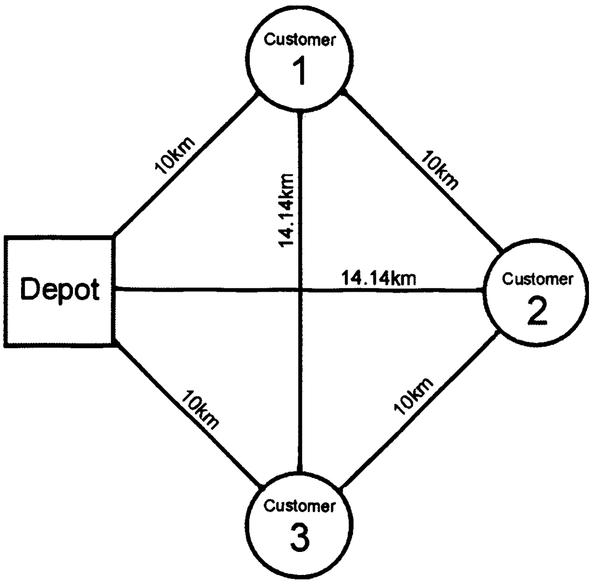


Figure 5.3: Supply chain physical layout

Consider for a moment the transportation distance incurred for different delivery scenarios. The vehicle leaves the depot to make a delivery once to each of the required customers and then returns back to the depot at the end of the period. The optimal routes that minimise the distance travelled along the supply chain network can be solved using the Travelling Salesman Problem (TSP) approach, (Lawler, Lenstra, Rinnooy and Shmoys, 1985). The layout for this basic model is classified as a symmetric TSP as the distance travelled is identical in both directions. For example, the distance travelled from customer 1 to customer 2 is exactly the same as the distance travelled from customer 2 to customer 1. So, the model is not concerned with the direction of travel, providing it is a minimum route. Since the network size in this model is small (it only contains 4 nodes), the route travelled may be calculated using the brute-force search method. The brute-force method may be viewed as the simplest technique for searching all possible combinations of the solution space and selecting the best result based on the problem statement. Based on the physical layout of the distribution system shown in Figure 3, the minimum distance travelled for different numbers of deliveries in a single period is given by Table 5.1.

Table 5.1: Calculating the minimum distance travelled for the number of deliveries

No. of customer requiring deliveries		Customers served	Minimum Distances travelled
	1	1	10*2=20 km
		2	14.14*2=28.28 km
		3	10*2=20 km
	2	1 and 2	10+10+14.14=34.14 km
		1 and 3	10+14.14.+10=34.14 km
		2 and 3	14.14+10+10=34.14 km
	3	1, 2 and 3	10+10+10+10= 40 km

5.3 The objective function

Performance is measured by the total cost (*TC*). This is based upon the inventory cost and transportation cost. An inventory cost is charged only at the customer's location and consists of the holding cost and the shortage cost. The inventory holding costs in each period are assumed to be the total of each customer's inventory position at the end of each period, $I_{t,x}$, multiplied by the cost to hold a single unit, (*h*) per unit inventory in each location, whilst the shortage cost is the charge per unit shortage supply, *p*, when inventory on hand is insufficient to meet demand at the end of each period in each location, $Sh_{t,x}$. The transportation costs are the sums of the distances travelled to make a replenishment in *km* in each period multiplied by the transportation cost, *c* incurred per km. The total cost is the accumulation of costs for the overall simulation period. Equation (4) highlights the assumed structure of the total cost equation for this basic model.

$$\mathrm{TC} = \sum_{t,x}(I_{t,x} * h) + \sum_{t,x}(Sh_{t,x} * p) + \sum_{t,x}(km_t * c) \tag{4}$$

Thus, the total cost per period is estimated based on average total cost over the simulation period. The model evaluates the parameter settings that minimise the total cost produced by the inventory replenishment activity. The "must deliver" level could possibly be determined using traditional safety stock techniques prevalent in the inventory literature. However, the "can deliver" level is somewhat unusual. Therefore, a simulation analysis was performed via simulation in order to investigate the impact of this IRP flexibility on inventory, transportation and total costs.

5.4 Overview of the simulation method

As discussed in Chapter 3, a spreadsheet simulation model is developed in Microsoft Excel to represent the IRP model and evaluate the model sensitivity analyses for this study. The impacts of flexibility on inventory transportation and total costs are observed by varying inventory control parameters as well as the cost parameters. The stochastic nature of simulation that uses random data generation as the model's input may generate different outputs every time the model is executed. This uncertainty will affect the accuracy of estimating the performance measurement result. Therefore, it is important to specify the appropriate length of the warm-up period and the number of replications needed for simulation.

5.4.1 Developing the Simulation Model

The simulation model is built by assigning the inputs, model formulations and outputs to specific cells in the spreadsheet. Figure 5.4 shows the part of the model design for the periodic "can-deliver" policy in the Excel Spreadsheet. The three inventory control parameters, the "order-up-to" level (I_+), the "can-deliver" level (I_c) and the "must-deliver" level (I_m) are given in cells C3, C4 and C5 for customer 1. Since customers are assumed to be identical to each other in the model, these parameters are set to be equal for customer 2 in cells L3, L4 and L5 and customer 3 in cells V3, V4 and V5 in the spreadsheet as shown in Figure 5.4.

Order-up-to 20 | Holding costs 339200
Must Delivery 3 | Shortage 37426
Can Delivery 10

Order-up-to2 20 | Holding costs 338477
Must Delivery2 3 | Shortage 37437
Can Delivery2 10

Order-up-to3 20 | Holding costs 337042
Must Delivery3 3 | Shortage 37815
Can Delivery2 10

Holding costs	202943.8
Transportation costs	240221.856
Shortage cost	22535.6
Total cost	
Total cost per period	7.7616876

Customer 1

Day	Demand	Stock	Must flag	Can Flag	Order Flag	Deliveries	Shortage	Holding
0	8	20	0	0	0	0	0	20
1	10	10	0	10	0	0	0	10
2	10	0	20	20	1	20	0	0
3	6	14	0	0	0	0	0	14
4	12	2	18	18	1	18	0	2
5	7	13	0	0	0	0	0	13
6	8	5	0	15	1	15	0	5
7	9	11	0	0	0	0	0	11
8	7	4	0	16	1	16	0	4
9	9	11	0	0	0	0	0	11
10	8	3	17	17	1	17	0	3
11	10	10	0	10	0	0	0	10
12	12	-2	22	22	1	22	2	0
13	7	13	0	0	0	0	0	13
14	10	3	17	17	1	17	0	3
15	10	10	0	10	0	0	0	10
16	11	-1	21	21	1	21	1	0
17	14	6	0	14	0	0	0	6
18	10	-4	24	24	1	24	4	0
19	11	9	0	11	0	0	0	9
20	10	-1	21	21	1	21	1	0
21	8	12	0	0	0	0	0	12
22	10	2	18	18	1	18	0	2
23	10	10	0	10	0	0	0	10
24	11	-1	21	21	1	21	1	0
25	12	8	0	12	0	0	0	8
26	14	-6	26	26	1	26	6	0
27	12	8	0	12	0	0	0	8
28	12	-4	24	24	1	24	4	0
29	13	7	0	13	0	0	0	7
30	12	-5	25	25	1	25	5	0
31	12	8	0	12	0	0	0	8
32	11	-3	23	23	1	23	3	0
33	12	8	0	12	0	0	0	8
34	9	-1	21	21	1	21	1	0
35	14	6	0	14	0	0	0	6
36	11	-5	25	25	1	25	5	0
37	11	9	0	11	0	0	0	9
38	7	2	18	18	1	18	0	2
39	10	10	0	10	0	0	0	10
40	11	-1	21	21	1	21	1	0
41	12	8	0	12	0	0	0	8

Customer 2

Day	Demand	Stock	Must flag	Can Flag	Order Flag	Deliveries	Holding	Shortage
0	11	20	0	0	0	0	20	0
1	16	4	0	16	0	0	4	0
2	10	-6	26	26	1	26	0	6
3	14	6	0	14	0	0	6	0
4	5	1	19	19	1	19	1	0
5	10	10	0	10	0	0	10	0
6	10	0	20	20	1	20	0	0
7	9	11	0	0	0	0	11	0
8	11	0	20	20	1	20	0	0
9	10	10	0	10	0	0	10	0
10	12	-2	22	22	1	22	0	2
11	10	10	0	10	0	0	10	0
12	10	0	20	20	1	20	0	0
13	8	12	0	0	0	0	12	0
14	9	3	17	17	1	17	3	0
15	11	9	0	11	0	0	9	0
16	5	4	0	16	1	16	4	0
17	10	10	0	10	0	0	10	0
18	6	4	0	16	1	16	4	0
19	7	13	0	0	0	0	13	0
20	13	0	20	20	1	20	0	0
21	11	9	0	11	0	0	9	0
22	8	1	19	19	1	19	1	0
23	7	13	0	0	0	0	13	0
24	9	4	0	16	1	16	4	0
25	10	10	0	10	0	0	10	0
26	14	-4	24	24	1	24	0	4
27	11	9	0	11	0	0	9	0
28	10	-1	21	21	1	21	0	1
29	10	10	0	10	0	0	10	0
30	11	-1	21	21	1	21	0	1
31	11	9	0	11	0	0	9	0
32	10	-1	21	21	1	21	0	1
33	7	13	0	0	0	0	13	0
34	10	3	17	17	1	17	3	0
35	8	12	0	0	0	0	12	0
36	14	-2	22	22	1	22	0	2
37	11	9	0	11	0	0	9	0
38	8	1	19	19	1	19	1	0
39	9	11	0	0	0	0	11	0
40	11	0	20	20	1	20	0	0
41	11	9	0	11	0	0	9	0

Day	Demand	Stock	Must flag	Can Flag	Order Flag	Deliveries	Holding	Shortage	Deliveries	Miles
0	10	20	0	0	0	0	20	0	0	0
1	10	10	0	10	0	0	10	0	0	0
2	11	-1	21	21	1	21	0	1	3	40
3	10	10	0	10	0	0	10	0	0	0
4	12	-2	22	22	1	22	0	2	3	40
5	9	11	0	0	0	0	11	0	0	0
6	9	2	18	18	1	18	2	0	3	40
7	8	12	0	0	0	0	12	0	0	0
8	9	3	17	17	1	17	3	0	3	40
9	8	12	0	0	0	0	12	0	0	0
10	9	3	17	17	1	17	3	0	3	40
11	11	9	0	11	0	0	9	0	0	0
12	9	0	20	20	1	20	0	0	3	40
13	13	7	0	13	0	0	7	0	0	0
14	10	-3	23	23	1	23	0	3	3	40
15	10	10	0	10	0	0	10	0	0	0
16	10	0	20	20	1	20	0	0	3	40
17	7	13	0	0	0	0	13	0	0	0
18	9	4	0	16	1	16	4	0	3	40
19	9	11	0	0	0	0	11	0	0	0
20	10	1	19	19	1	19	1	0	3	40
21	12	8	0	12	0	0	8	0	0	0
22	8	0	20	20	1	20	0	0	3	40
23	13	7	0	13	0	0	7	0	0	0
24	10	-3	23	23	1	23	0	3	3	40
25	8	12	0	0	0	0	12	0	0	0
26	12	0	20	20	1	20	0	0	3	40
27	12	8	0	12	0	0	8	0	0	0
28	15	-7	27	27	1	27	0	7	3	40
29	11	9	0	11	0	0	9	0	0	0
30	11	-2	22	22	1	22	0	2	3	40
31	15	5	0	15	0	0	5	0	0	0
32	11	-6	26	26	1	26	0	6	3	40
33	12	8	0	12	0	0	8	0	0	0
34	11	-3	23	23	1	23	0	3	3	40
35	9	11	0	0	0	0	11	0	0	0
36	13	-2	22	22	1	22	0	2	3	40
37	7	13	0	0	0	0	13	0	0	0
38	12	1	19	19	1	19	1	0	3	40
39	14	6	0	14	0	0	6	0	0	0
40	14	-8	28	28	1	28	0	8	3	40
41	7	13	0	0	0	0	13	0	0	0

Figure 5.4: The periodic "can-delivery" model

However, the best combination of the inventory control parameters that emerge from the analysis that minimises the total cost might be not the "true" optimal value for customer 2. This is because the location of customer 2 as illustrated in Figure 5.3 is further from the depot point when it compared to the location for customer 1 and customer 3.

The model will generate the results based on these inputs as well as the demand distribution for each customer. Although demand data can be generated from the random number generator function in Excel through the Analysis Toolpak (ATP) and RAND( ) function, there is an accuracy issue with the results. McCullough and Wilson (2005) report that the random number generator function in Excel 2003 can produce negative numbers with the ATP. Although this problem has been fixed in the RAND( ) function in Excel 2003, there is still a problem with the accuracy of statistical distributions. Knusel (2005) states that this is due to the fact that the lower tail probabilities for the Binomial distribution that are generated with the BINOMDIST Excel function have been rounded to zero.

Therefore, some different 3rd party software was used to generate the demand data for the model. We used instead the Stat:Fit software provided in ProModel simulation software as it can generate large random data (more than 8000) with reliable random number generators, i.e. the Prime Modulus Multiplicative Linear Congruential Generator and Mixed Prime Modulus Multiplicative Linear Congruential Generators, for simulation (Harrell et. al., 2003).

Input data and variables for the simulation like the demand, inventory control parameters, holding and shortage quantity, are assigned to different blocks of cells in Excel. Three flag variables are used to monitor an inventory condition at each customer. If the customer's inventory on hand reaches the "must-deliver" level, the replenishment quantity value will be calculated automatically in the must flag column. The same conditions also apply to the can flag column that calculates the quantity that can be replenished in order to combine with other customers. The order flag is related to the must flag level. It acts as an important variable for the supplier to make the decision whether a replenishment needs to be made in a particular time period. The decision is based on all the customer conditions. A Boolean number is used to represent the decision. If the order flag value is 1, the delivery quantity is generated based on the value that has been calculated in the must flag or can flag variable.

The order flag value is assigned for customer 1 at simulation period 14 for cell F14 in Figure 5.4 is based on this formula:

= IF (D14 > 0, 1, IF (M14 > 0, 1, IF (V14 > 0, 1, 0)))

Where cells D14, M14 and V14 represent must flag for customer 1, customer 2 and customer 3, respectively.

The distance (*km*) travelled to make that delivery is also calculated based on customers who need delivery using the IF…THEN…ELSE function in EXCEL. The minimum distance travelled value is referred to in Table 5.1 above. The model performance measure is calculated as a total of the inventory cost and the transportation cost over the whole simulation period. This value is represented in cell AD6 in Figure 5.4 as the total value of cells AD3, AD4 and AD5. The holding and shortage cost per unit item is an input in the model and is used to calculate the total holding cost and shortage cost value that accumulates for all customers. The transportation cost is based on the total distance travelled at the end of the simulation period and the cost to travel per km that is an input in the model. The model total cost per period calculated in cell AD7 as shown in the spreadsheet model illustrated in Figure 5.4, is based on these costs and the number of simulation periods. This value will change each time the model is modified with different input parameters.

5.4.2 Warm-Up period

This inventory model is categorised as a non-terminating simulation since we are interested in analysing the long term average behaviour of the model. In modelling steady-steady state behaviour, there is a problem determining the time the model takes to reach steady-state. This start-up period is called a warm-up or transient period. If observations are collected in the transient period, this may cause inaccurate results due to the stochastic nature of the model that deals with random data.

5.4.2.1 Welch's method

Welch's method is a graphical method for estimating a truncation point, *l,* based on a number of independent replications, averaging the output value at each simulation time period across replications and observing the time that the model reaches the steady state. This point is identified when the averaged output response that is plotted in a line graph begins to flatten out. However, it is sometimes difficult to identify the point when the output is inconsistent. The variability of the plot can be reduced and the graph can be smoothed by using a moving average. This is calculated by taking the average of the most recent data points in the data set based on moving average window, *w* value, (Harrell et al., 2003). The smoothness of the graph plot will increase by increasing the value of *w*.

The truncation point, *l*, for the IRP model using Welch's method is determined by the four steps of Law and Kelton (2000). The simulation model is replicated 5 times, each replication has a length of 65000 time periods. The total cost, TC_{jt} at each simulation time period, (t = 1, 2, 3,......,65000) from the *j*th replication is observed, (j=1 to 5) and the average total cost, $\overline{TC}_t$ for t =1 to 65000 time periods over 5 replications is calculated based on equation (4) below:

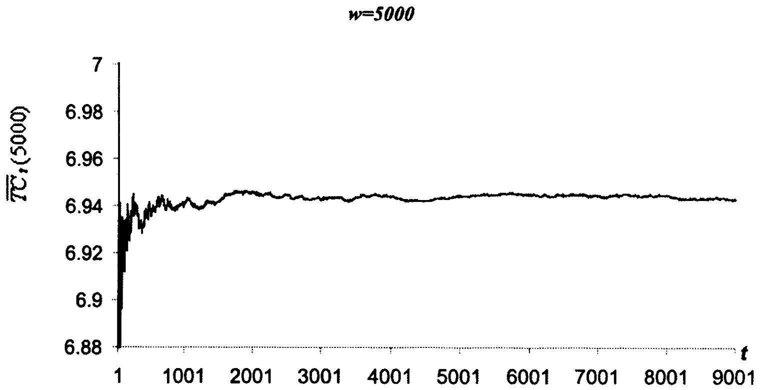
$$\overline{TC}_t = \sum_{j=1}^{5} \frac{TC_{jt}}{5} \tag{4}$$

The next step is to define a moving average, $\overline{TC}_i(w)$ to smooth out the high frequency oscillations in the average total cost observations, $\overline{TC}_1, \overline{TC}_2, \overline{TC}_3, \ldots\ldots, \overline{TC}_{65000}$ using equation (5). That value is plotted and the truncation point is chosen when the moving average plot begins to flatten out. A small window size, *w*, is chosen at the beginning of the analysis and the value is increased until the plot of moving average becomes smooth.

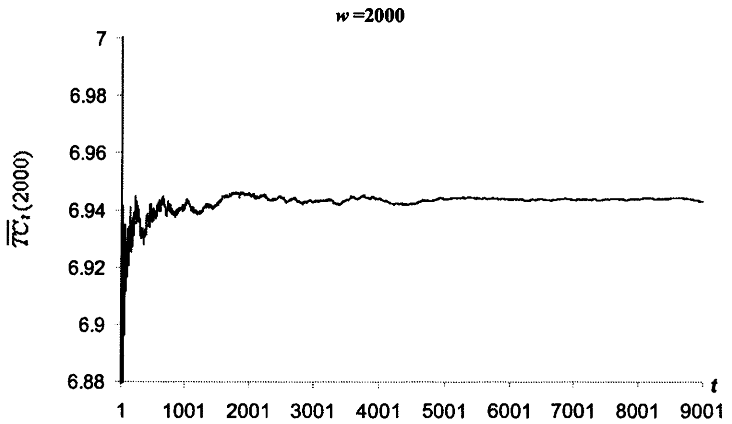
Law and Kelton (2000) recommend the size be less or equal (m/4), where m is the total number of observations in simulation. The analysis is therefore done by using the two moving average windows (w= 2000, 5000). The moving average window is less than 16250 (65000/4).

$$\overline{TC}_t(w) = \begin{cases} \dfrac{\sum_{s=-w}^{w} \overline{TC}_{t+s}}{2w+1} & \text{if } t = w+1,\ldots.,m-w \\ \dfrac{\sum_{s=-(i-1)}^{i-1} \overline{TC}_{t+s}}{2t-1} & \text{if } t = 1,\ldots\ldots,w \end{cases} \tag{5}$$

Figures 5.5 (a) and 5.5 (b) show the moving average, $\overline{TC}_i(w)$ for w=5000 and w=2000.



(a)



(b)

Figure 5.5: Moving averages for total cost per period : (a)w=5000 (b)w=2000

The graph for w=5000 is smoother than the graph for w=2000. Therefore, Figure 5(a) is used to determine the appropriate warm up period for this model. It shows that the steady state is reached at t=5000 time periods. As a result, observations up to 5000 time periods are ignored and the model is analysed only with observations beyond this point.

5.4.3 Simulation size

In analysing the model's output, it also important to determine an appropriate sample size, *n,* in order to establish a confidence interval between the estimated point and the model's true expected performance. Basically, by increasing the number of simulation time periods, the closer the results can be expected to be to the true value. However, conducting the simulation for a very long period is computationally expensive. Therefore, a minimum sufficient sample size needs to be determined in order to obtain an accurate result in a reasonable time.

Bienstock (1996) states that the sample size can be adjusted by using multiple replications or by raising the quantity of subintervals. He also reported that the replication approach is recommended because it can avoid the independence issue between observations. However, there is a question about how many replications are necessary.

Law and Kelton (2000) state that the replication/deletion approach is the easiest method to construct the point estimate and confidence interval for steady state based on the desired confidence level. Point estimates for mean, μ and standard deviation, σ of a population are estimated by calculating the mean, $\bar{x}$, and standard deviation, *s,* of sample data, (Harell et.al, 2003). The confidence interval measures the gap between the estimated and true point. The gap becomes smaller as the number of replications increases.

The appropriateness of the confidence interval depends on the assumption that the observations are independent and identically distributed. Running multiple replications with different streams of random numbers ensures that sample observations are statistically independent. Harell et al. (2003) state that most statistical methods assume that the observations are normally distributed as well; thus, the confidence interval half-width value can be computed from the Student's t distribution. However, Law and Kelton (2000) claim this assumption is not essential for the sequential procedure which has a similar process to the replication/deletion approach. Therefore, the normality test is conducted in order to verify the distribution of the observations.

5.4.3.1 Normality test

The test is carried out by plotting the frequency histogram and performing the goodness-of-fit test on the simulation output. The histogram is plotted to recognise the shape of the observation based on the distribution's probability density function (pdf) or probability mass function (pmf). It can be seen from Figure 5.6, that the total cost per period may follow the normal distribution, since the histogram has a bell-shaped pattern similar to the probability density function of the normal distribution.

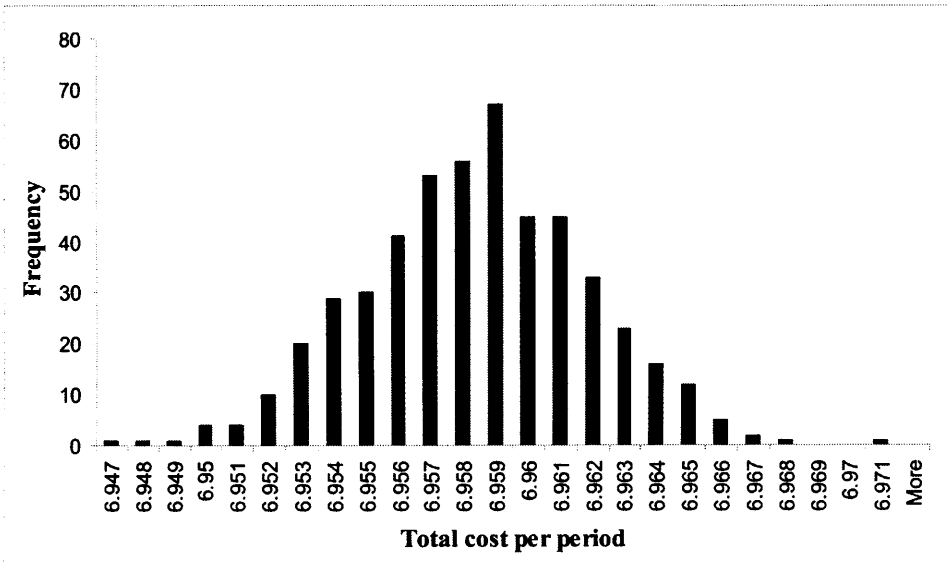


Figure 5.6: Histogram of the total cost per period.

The histogram pattern may be slightly affected by the number of data points and the size of class intervals that construct the histogram. Therefore, statistical tests can be used to determine the distribution of empirical data more objectively. The common goodness-of-fit tests are the Chi-square test, the Kalmogorov-Smirnov Test (K-S), the Anderson-Darling (A-D) test, and the Shapiro-Wilk (S-W) test. Among the tests, the K-S test performs better than the Chi-square test, but is less powerful than the A-D test (Law and Kelton, 2000). The S-W test is as powerful as the A-D test (D'argosto and Stephens, 1986). The K-S and A-D tests are empirical cumulative distribution function tests (ECDF) whilst the S-W test is based upon regression and correlation tests. These tests are provided in the MINITAB software package.

The K-S and A-D tests were implemented in Microsoft Excel and compared to the MINITAB software output. Both tests were calculated based on the 500 observations of total cost per period sorted in ascending order. The null hypothesis for the goodness-of-fit test is

H_0= The data are independent and identically distributed (i.i.d) random variables with normal distribution.

The statistic D can be determined based on equation (6).

$$D = \max(D^+, D^-) \tag{6}$$

Where $D^+ = \max_{1 \le i \le N} \left\{ \frac{i}{N} - Z_i(x) \right\}$ and $D^- = \max_{1 \le i \le N} \left\{ Z_i(x) - \frac{i-1}{N} \right\}$

The A-D test is computed using equation (7)

$$A_n^2 = \left(\frac{-\left\{ \sum_{i=1}^{n} (2i-1)[\ln Z_i(x) + \ln(1 - Z_{n+1-i}(x))] \right\}}{n} \right) - n \tag{7}$$

The A-D test result is used in computing the adjusted A-D test as shown in equation (8).

$$\text{Adjusted A-D} = \left(1 + \frac{4}{n} - \frac{25}{n^2} \right) A_n^2 \tag{8}$$

Table 5.2 shows part of the K-S and A-D test calculation and Table 5.3 summarises the results for both tests. Results for K-S, A-D and S-W tests from the MINITAB software are shown in Figure 5.7.

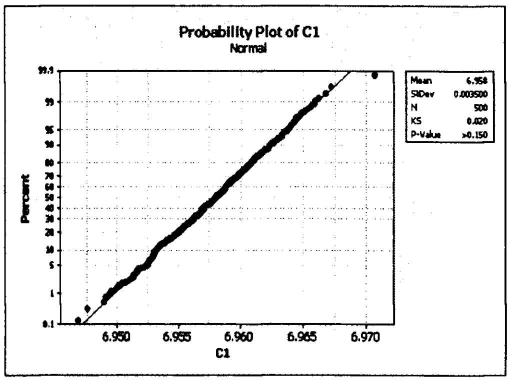
Table 5.2: Summary of K-S and A-D test results

K-S test		A-D test	
D^{+}	0.017998	$\sum_{i=1}^{n}(2i-1[\ln Z_i(x)+\ln(1-Z_{n+1-i}(x))])$	-250106.91
D^{-}	0.020232	A_n^2	0.213801
D	0.020232	Adjusted A-D	0.215491

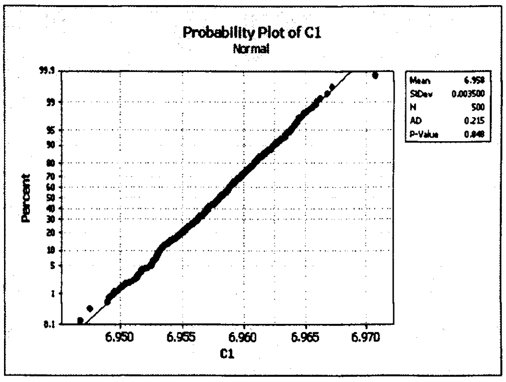
The results show that the D value and the adjusted A-D value are similar to the normality test conducted in MINITAB. The critical value, D_{α}, for the significance level, α =0.05 and sample size, N = 500, based on the Kalmogorov-Smirnov Critical Values table is 0.060821, while the modified critical value for the A-D test for the same significance level is 0.870. Since 0.020 < 0.061 and 0.215 < 0.870; it can be assumed therefore that the data is normally distributed. p values for all tests in MINITAB also support this assumption since all the values are greater than the stated alpha level, 0.05.

Table 5.3: K-S and A-D test calculation

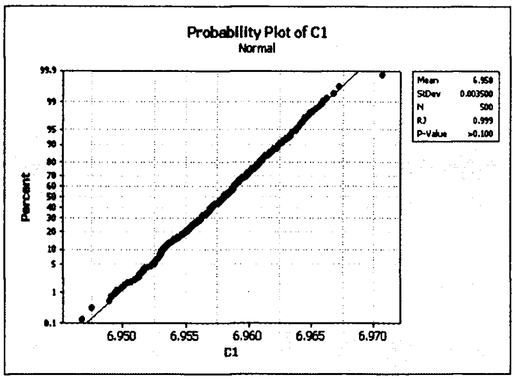
i	x	$Z_i(x)$	K-S test			A-D test				
			$\frac{i}{n}$	D^+	D^-	n+1-i	$A = \ln(1 - Z_{n+1-i}(x))$	$B = \ln(Z_i(x))$	C=A+B	(2i-1)* C
1	6.946718	0.000659	0.002	0.001341	0.000659	500	0.000126	-8.979387	-16.30458	-16.3045776
2	6.94755	0.001469	0.004	0.002531	-0.00053	499	0.004196	-5.473656	-11.99674	-35.9902086
3	6.948961	0.005074	0.006	0.000926	0.001074	498	0.005639	-5.177987	-10.46162	-52.308102
4	6.949092	0.005652	0.008	0.002348	-0.00035	497	0.008825	-4.730124	-9.905826	-69.3407844
5	6.949347	0.006944	0.01	0.003056	-0.00106	496	0.011232	-4.488958	-9.458829	-85.129463
6	6.949483	0.007729	0.012	0.004271	-0.00227	495	0.011734	-4.445274	-9.308011	-102.388125
7	6.949911	0.010754	0.014	0.003246	-0.00125	494	0.014733	-4.21766	-8.7501	-113.751303
8	6.950095	0.012347	0.016	0.003653	-0.00165	493	0.016875	-4.081944	-8.476265	-127.143975
9	6.950424	0.015692	0.018	0.002308	-0.00031	492	0.021022	-3.862188	-8.016804	-136.28566
10	6.950698	0.019044	0.02	0.000956	0.001044	491	0.023507	-3.750459	-7.711478	-146.518079
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
496	6.965927	0.988768	0.992	0.003232	-0.00123	5	0.993056	-0.006968	-0.018264	-18.0997867
497	6.966244	0.991175	0.994	0.002825	-0.00083	4	0.994348	-0.005668	-0.014533	-14.4311015
498	6.966807	0.994361	0.996	0.001639	0.000361	3	0.994926	-0.005087	-0.010742	-10.6884755
499	6.967163	0.995804	0.998	0.002196	-0.0002	2	0.998531	-0.00147	-0.005675	-5.65788358
500	6.970744	0.999874	1	0.000126	0.001874	1	0.999341	-0.000659	-0.000785	-0.78415434



(a)



(b)



(c)

Figure 5.7: Normality test results in MINITAB (a) K-S test (b) A-D test (c) S-W test remove the colour from this figure.

The process of point estimation and the analysis of the appropriate number of replications will be discussed in next section.

5.4.3.2 Number of Replications

The point estimate is calculated using observations after the warm-up period that was determined previously with Welch's method. In the last section, the warm-up period, l, for the inventory model was reached when t= 5000 time periods for 5 replications of length m=65000. Therefore, observations for total cost, TC_{jt} are for 60000 time periods from t=5001 until t=65000 for each replication.

The average of the total cost, X_j from the jth replication can be computed using equation (7).

$$X_j = \frac{\sum_{i=5001}^{65000} TC_{ji}}{60000} \quad \text{for } j \in \mathrm{N}^+ \leq 5 \tag{7}$$

The X_j values for each simulation replication are presented in Table 5.4.

These results are used to estimate the mean, ν and standard deviations, σ of the population by calculating the average of the results across all replications, $\overline{X}(n)$ via equation (8) and the standard deviation of the results, *S(n)* via equation (9).

Table 5.4: The simulation result from 5 independent replications

Replication (j)	$\sum_{i=5001}^{65000} TC_{ji}$	Average total cost , X_j
1	4168.13.4	6.94689
2	416288.4	6.93814
3	416467.2	6.94112
4	416298.4	6.93831
5	416556.1	6.94260

$$\overline{X}(n) = \frac{\sum_{1}^{n} X_j}{n} \tag{8}$$

$$S(n) = \frac{\sum_{1}^{n} [X_j - \overline{X}]^2}{n-1} \tag{9}$$

The confidence interval estimation is used to estimate the confidence interval half-width, *hw* value, and the relative precision, γ between point estimates, $\overline{X}$, from the true mean, ν, with probability of confidence, *P*. The probability that ν will fall outside the confidence interval is referred to as the significance level, $\alpha = 1 - P$. Thus, the probability ν will fall inside is $1 - \alpha$.

The confidence interval half-width, *hw*, for significance level, α is calculated by equations (10)

$$hw = (t_{n-1,1-\alpha/2})\sqrt{\frac{S^2(n)}{n}} \qquad (10)$$

An approximate confidence level of $100(1\text{-}\alpha)$ percent for ν, and relative precision, γ ($0<\gamma<1$), can be computed using equation (11) and equation (12)

$$\overline{X}(n) \pm hw \qquad (11)$$

$$\gamma = \frac{hw}{\overline{X}(n)} \qquad (12)$$

The confidence interval result means that the expected average is $100(1\text{-}\alpha)$ per cent sure between the lower confidence level $(\overline{X}(n) + hw)$ and upper confidence level $(\overline{X}(n) - hw)$. The target value for the relative precision in this study is assumed at 0.5% or 0.005. A confidence interval analysis can be easily carried out using Microsoft Excel. In Microsoft Excel, the TINV(α, n-1) function can calculate the student t-distribution value automatically with significance level, α, and degrees of freedom (n-1). The standard deviation and mean values can be calculated using the STDEV( ) and MEAN( ) function.

The confidence interval results and the relative precision for different numbers of replications and significance level are shown in Table 5.5 for the simulated IRP model with 60,000 simulation periods for each replication. The results show that we are 95 per cent confident that the average total cost value is between a lower confidence interval of 6.88693 and a upper confidence interval of 6.99810 and 99 per cent confident that the value is between 6.66402 and 7.22101 for n=2. The confidence interval and relative precision will increase as the significance level increases, whereas, the interval between estimated values and the true value decreases as the number of replications is increased.

The relative precision for n=3 for both significance levels is close enough to the mean estimated value, as the relative precision value is within 0.005% of the real value. Therefore, the analysis will be conducted with 3 replications, each with a warm up of 5000 periods and 60, 000 periods of actual simulation time for each problem instance.

Table 5.5: Simulation results for significance level, 0.05 and 0.01 and 4 different numbers of replications

Significance level	Replication	Point estimates	Confidence interval half-width	Relative precision	Lower confidence interval	Upper confidence interval
0.05	2	6.94252	0.05590	0.00801	6.88693	6.99810
	3	6.94205	0.01105	0.00159	6.93100	6.95310
	4	6.94111	0.00650	0.00094	6.93462	6.94162
	5	6.94141	0.00447	0.00064	6.93694	6.94589
0.01	2	6.94252	0.27850	0.04012	6.66402	7.22101
	3	6.94205	0.02550	0.00367	6.91656	6.96754
	4	6.94111	0.01193	0.00172	6.92918	6.95305
	5	6.94141	0.00741	0.00107	6.93400	6.94883

5.5 Running and designing the simulation

The multi-replications simulation model was executed by replicating the identical simulation spreadsheet models using different streams of random numbers for demand data in each replication. As discussed in Section 5.4.1, the periodic "can-deliver" model contains inventory control and costs parameters that influence the model's output. Therefore, a sample experiment will be executed first to evaluate how the outputs might be affected by changes in these input parameters. The range for the order-up to level parameter is considered to be within the range of 0 to 60 units. The lower range for "must-deliver" is set equal to zero to represent the scenario where the replenishment only can be made when customers have no inventory available in the stock. The value of the "must-deliver" level is limited by the "order-up to" level value, whilst the range for "can deliver level" must be in between the "must" deliver level and the "order-up-to" level. Thus,

$$I_m \leq I_c \leq I_+ . \tag{13}$$

The shortage cost and transportation cost are examined in the range from 0.1 to 1.0 per unit, whereas the holding costs are only tested from 0.1 to 0.5 cost per unit.

The analysis to test all possible combinations of these inputs to determine the true optimal performance measure output value is performed by applying the brute force approach, (Wan et. al., 2007). The optimal value for this model is found using a search grid with an increment of step size 1 for the inventory control parameter for each combination of costs. The optimal combination of these inputs is determined based upon the minimum total cost per period of the solution space. The process of analysing the relationship between a factor and its response is visualised by a 2D or 3D graph. The surface that visualises the response of the full combination of two factors is called a response surface (Law and Kelton, 2000). The optimal combination of factors that minimises the total cost per period is the lowest point in the grid and the behaviour of the model can be evaluated from the shape of the graph. Analysis with the brute-force approach over enough time periods will generate a good response surface and guarantee the optimal result.

Running the model with a series of model inputs requires a sequence of recalculations and saving processes in the spreadsheet model. These processes become much easier when Visual Basic (VBA) macros are developed as these can be used to alter input parameters as well as automatically read and write results from specific cells. There are various looping function available in VBA such as For...Next, Do...Until and Do...While function. Writing that value in the cell of the spreadsheet model requires a specific location that can be identified by cell name using the "range" command, or by the cell row and column numbering scheme using the "cell" command. The copy and paste function can also be used to read and write the value in the selected location. The logic of simulation model analysis using the brute-force approach is defined by the pseudo code algorithm in Figure 5.8. As can be seen in the figure, the brute force approach is used in the analysis in order to test the IRP model with all possible combination of inventory control parameters and the costs parameters within the specified range as discuss above. All inventory control parameters includes the "order-up-to" level (I_+), "must-deliver" level (I_m) and "can-deliver" levels (I_c) which are have an increment of 1 unit size. The cost parameters includes the; holding cost (h), shortage cost (c) and transportation cost (p) and these are incremented by 0.1 unit size in each loop. The result of the analysis including the holding cost per period, shortage cost per period, transportation cost per period and total cost per period values are written into a different worksheet of the IRP model spreadsheet. The same procedure of the analysis is applied to all 3 replications. Each replication has different demand values due to the different streams of random numbers used as the input into the demand data. The optimal combination of inventory control parameters for specific value of costs parameters is determined based on the average value of the total cost per period from the 3 replications.

```
For h from 0.1 to 0.5 Step 0.1; Range("AJ1")=h
  For c from 0.1 to 1.0 Step 0.1; Range("AJ2")=c
    For p from 0.1 to 1.0 Step 0.1; Range("AJ3")=p
      For I+ from 0 to 60 Step 1; Range("c1")= I+
        For Im from 0 to I+ Step 1; Range("c2")= Im
          For Ic from Im to I+ Step 1; Range("c3")= Ic
            Write the I+ , Im , Ic ,holding cost per period, shortage cost per period,
            transportation cost per period and total cost per period value for 60, 000
            periods of actual simulation time.
          Next Ic ;
        Next Im ;
      Next I+ ;
    Next p;
  Next c;
Next h
Repeat the above procedure for all 3 replications
Average of all costs value from these 3 replications.
min = ∞
For average total cost per period for all combinations of h,p,c, I+ , Im , Ic
    If average total cost per period < min Then
    min = average total cost per periodd;
    optimal inventory control combination = I+ , Im , Ic
    EndIf
```

Figure 5.8: The pseudo code algorithm for the logic of simulation model

5.6 Numerical Analysis

The analysis begins by evaluating the impact of the IRP flexibility on inventory and transportation costs by varying the "can-deliver" level and "must-deliver level" while fixing the "order-up-to" level and the cost parameters. The traditional supply chain is the benchmark for quantifying the benefit of this model which happens when the "can-deliver" level is equal to the "must-deliver" level. It can be seen from Figure 5.9(a), the total cost per period for the benchmark scenario is lower than that of the total cost per period for the proposed model at high "must-deliver" level settings. However, that cost is not the minimum total cost per period in the solution space. The total cost per period first decreases when the "must-deliver" level is increased but then it rises sharply when the level is increased further. Interestingly, the benchmark scenario is an expensive option compared to the lowest total cost per period. In order to clarify the relationship between variations of "can-delivery" level for a specific "must-deliver" level at higher level with the inventory and transportation cost, a 2 dimensional graph is plotted for the optimal "must-deliver" level, which in this case is equal to 3 in Figure 5.9(b).

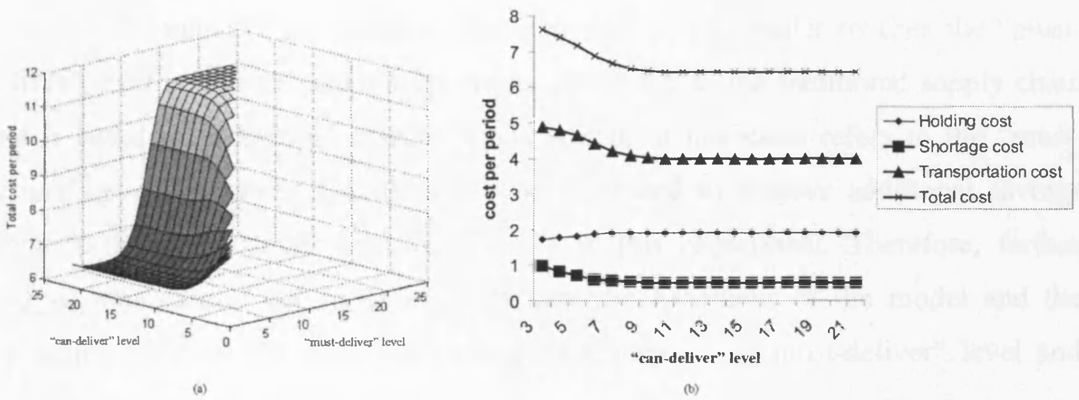


Figure 5.9: (a) Total cost with various "can-deliver" level and "must-deliver" levels

(b) With inventory holding cost, shortage cost and transportation cost when the "must-deliver" level is equal to 3.

As can be seen from the figures, the inventory cost rises very slightly when the "can-deliver" level increases at I_c=10, which is about 5 units higher than the benchmark condition. However, this is more than compensated for by the reduction in transport costs and shortage cost, as they fall dramatically at the same time. The finding suggests that the IRP flexibility allows a significant reduction in transportation costs and also prevents out-of-stock problems. As a result, the total cost reduces by approximately 16%. Nevertheless, the initial benefits realised by providing a "can-deliver" level, seem to saturate out, and further flexibility provides zero marginal benefit. The costs remain constant when the "can-deliver" level reaches the maximum inventory level. Therefore, further flexibility will not affect the quantity of items and number of retailers to which they should be delivered. For example, situations when the replenishment is required at retailer 1 and inventory on hand at 2 other retailers are 9 and 16 units at time t. With the "can-deliver" level value equal to 15, only 2 retailers can be integrated with the delivery at that time, whereas all retailers can be replenished together with a higher "can-deliver" level, even with a value equal to "order-up-to" level.

Essentially, the result shows that the costs are minimised when I_c=13 before the graph flattens out. However, this is hard to see in the figure since the increasing percentage is quite small at approximately <0.01%. It can be concluded that the procedure to replenish all retailers whenever one of the retailer reaches the "must-deliver" level is a more economical choice compared to the traditional supply chain that is based on individual reorder levels which, in this case, refers to the "must-deliver" level. However, that flexibility level tended to achieve additional savings when "order-up-to" level was equal to 21 in this experiment. Therefore, further analysis was carried out in order to explore the behaviour of the model and the interaction between the other two control parameters i.e. "must-deliver" level and order-up-to" level was investigated.

The results are plotted in 3 dimensional graphs to obtain a broad picture of the effects. Figure 5.10 shows that a similar pattern occurs with most of the "order-up-to" level parameters as the "can-delivery" level is increased whilst the "must-deliver" level is equal to 5. The total cost per period decreases rapidly and reaches a low point when I^+=20. The cost increases steadily as the "order-up-to" level, is increased before falling again at I^+=30 to a point slightly higher than the lowest point. This is followed by a sharp increase as the "order-up-to" level is increased further. This suggests that the minimum cost may possibly be located at the second minima with different parameter settings. Thus, the pattern is examined by varying the "must-deliver" level with a fixed value of the "can-deliver" level. For simplicity, the "can-deliver" value is set equal to the "order-up-to" level, since the previous results suggest, that it is possible that this condition will lead to a fall in the total cost. As seen in Figure 5.11, there are similarities with most of the patterns plotted for different "must-deliver" levels, but the cost is dramatically increased as the "order-up-to" level increases.

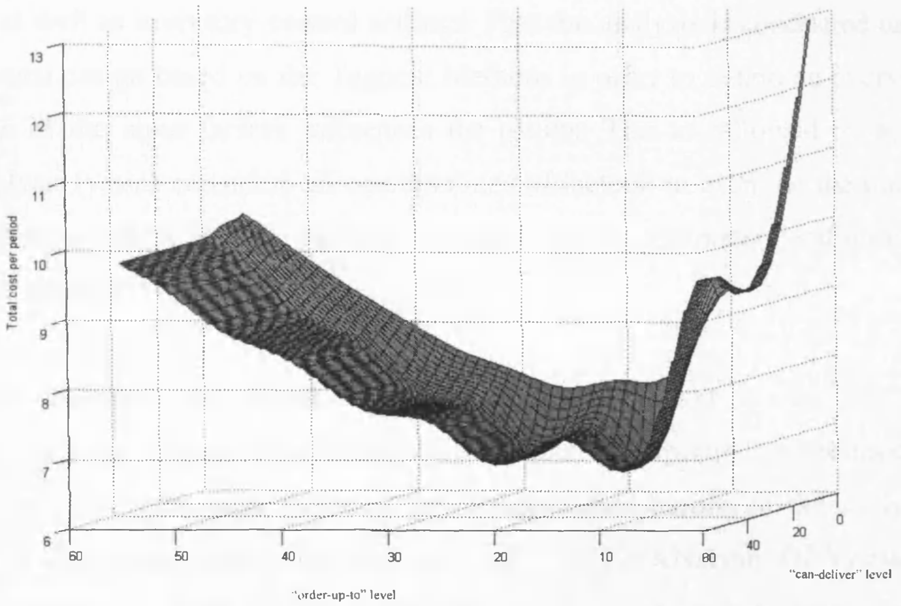


Figure 5.10: Varied "can-deliver" level and "order-up-to" level

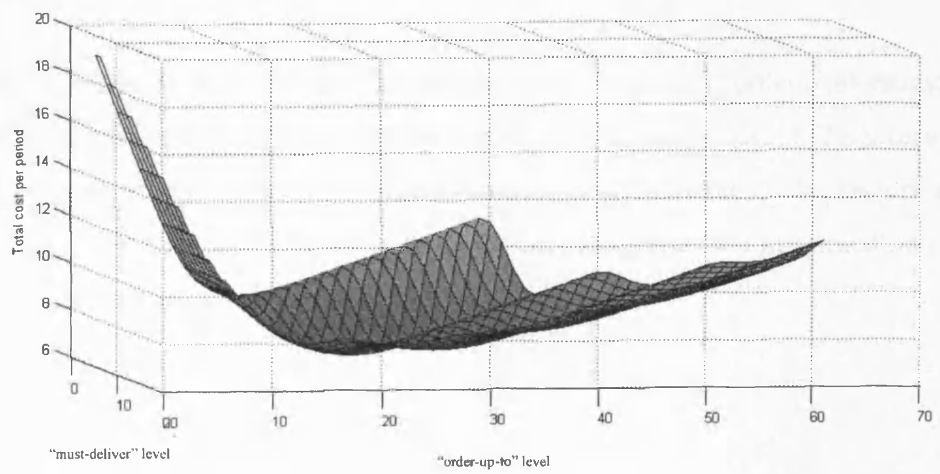


Figure 5.11: Varied "must-deliver" level and "order-up-to" level

The analysis so far has evaluated the effect of the IRP model with different "order-up-to", "must-deliver" and "can-deliver" level settings. The analysis is continued to see how the model reacts with different cost parameters in the next section.

5.6.1 Analysis with cost parameters

As discussed in Section 4.3, the IRP model performance measurement is based upon a particular inventory holding cost, shortage cost and transportation cost. Therefore, further analysis of the Inventory Routing Policy is carried out with different cost parameters as well as inventory control settings. First the analysis is conducted using an experimental design based on the Taguchi Methods in order to obtain an overview of how each of the input factors influences the results. This is followed by a full factorial analysis (which considers all combinations of factors) to examine the impact of the cost parameters on both the optimal inventory control parameters and minimal total cost in Section 5.6.2.

The Taguchi methods use standard orthogonal arrays (OAs) to lay out the experiments. In theory, these OAs reduce the number of experiments required to explore the solution space, thus reducing the computational burden of the analysis. The results of these experiments are then analysed with the ANalysis Of VAriance (ANOVA) technique to determine the factors that will be most likely to have a large impact on model performance based upon their "percentage contribution".

Taguchi's methods help to simplify an Inventory Routing Problem investigation by considering a selected number of factors in a specific combination. This results in a small number of simulation experiments that is easily managed. The factors and the level of each factor need to be determined before designing the experiment in order to select an appropriate OA to structure the experiments.

Six factors identified for evaluation in the analysis are included

- the "must-deliver" level at each of the three retailers (I_{m1}, I_{m2} and I_{m3}), (the model assumes $I_{m1} = I_{m2} = I_{m3}$)
- "order-up-to" level at each retailer (I_{+1} ,I_{+2} and I_{+3}), (the model assumes $I_{+1} = I_{+2} = I_{+3}$)
- the "can" deliver level at each retailer (I_{c1}, I_{c2} and I_{c3}), (the model assumes $I_{c1} = I_{c2} = I_{c3}$)
- holding cost (h),
- shortage cost (p),
- transportation cost (c).

Five levels of each of the above six factors are shown in Table 5.6. The "order-up-to" level is tested for values that are greater than the mean of demand. Therefore level 1 for the "order-up-to level" is assigned a value of 12 as the starting point of the analysis. The value is increased further in the following level to test the IRP model with a slightly higher "order-up-to" level than the previous value. As discuss in Section 5.5, the range of "must-deliver" level value is analysed from the condition when the replenishment only can be made when customers have no inventory in the stock and limited by the value of "order-up-to" level whilst the range of "can-deliver" level must be in between the value of "must-deliver" level and the "order-up-to" level. The range of the holding cost is set to be lower than the value of shortage cost and transportation cost. A high shortage cost is set compared to the holding cost and transportation cost in order to discourage and avoid out-of-stock situations.

Accordingly, the number of simulations needed to fully explore the solution space is 5^6=15625. This can be reduced using Taguchi's Orthogonal Arrays. However, the most suitable OA needed to be selected to specify the factors and levels at which to conduct the experiment. The selected OA must satisfy the following inequality:

Total Degrees of Freedom of OA $\geq$ Total Degrees of Freedom required for the experiment. (14)

Table 5.6: IRP model factor and Level

Factor	Level				
	Level 1	Level 2	Level 3	Level 4	Level 5
$I_{+(1,2,3)}$	12	16	20	24	28
$I_{m(1,2,3)}$	0	$\frac{I^+}{4}$	$\frac{I^+}{2}$	$\frac{3I^+}{4}$	I^+
$I_{c(1,2,3)}$	I_m	$\frac{3I_m + I^+}{4}$	$\frac{I_m + I^+}{2}$	$\frac{I_m + 3I^+}{4}$	I^+
h	0.1	0.2	0.3	0.4	0.5
p	0.6	0.7	0.8	0.9	1.0
c	0.3	0.4	0.5	0.6	0.7

Given 6 factors, each with five levels, the total Degree of Freedom (DOF) required for the experiment are 24, since each factor has 4 DOF (No. of levels – 1). Therefore the L_{25} Taguchi's Orthogonal Arrays matrix is appropriate to use for the analysis. Table 5.7 shows 25 different experiments that combines all factors at various levels (0 to 5).

The analysis of the result using Taguchi's methods can be performed by standard analysis of a single observation. However, Roy (1990) strongly recommends the use of the signal to noise ratio (S/N) analysis for the multiple runs scenario. Since the analysis will be conducted with 3 replications of 5000 warm up periods and 60, 000 simulation time periods, the S/N ratio is used to plot the main effects and carry out the ANOVA analysis based on the procedure explained in Roy (1990).

The S/N ratio for 3 replications is calculated by equation 15

$$\text{S/N} = -10\,\text{Log}_{10}\left(\frac{1}{3}\sum_{i=1}^{3} y_i^2\right) \tag{15}$$

where y_i represents the total cost per period for the replication i.

The signal-to-noise ratios for each experiment as well as the simulation results for 3 replications are shown in Table 5.8.

Table 5.7: L_{25} **orthogonal array matrix**

Experiments	$I_{+(1,2,3)}$	$I_{m(1,2,3)}$	$I_{c(1,2,3)}$	h	p	c
1	1	1	1	1	1	1
2	1	2	2	2	2	2
3	1	3	3	3	3	3
4	1	4	4	4	4	4
5	1	5	5	5	5	5
6	2	1	2	3	4	5
7	2	2	3	4	5	1
8	2	3	4	5	1	2
9	2	4	5	1	2	3
10	2	5	1	2	3	4
11	3	1	3	5	2	4
12	3	2	4	1	3	5
13	3	3	5	2	4	1
14	3	4	1	3	5	2
15	3	5	2	4	1	3
16	4	1	4	2	5	3
17	4	2	5	3	1	4
18	4	3	1	4	2	5
19	4	4	2	5	3	1
20	4	5	3	1	4	2
21	5	1	5	4	3	2
22	5	2	1	5	4	3
23	5	3	2	1	5	4
24	5	4	3	2	1	5
25	5	5	4	3	2	1

The effect of each control factor is evaluated from the average of the S/N ratio for each level. For example, the average S/N ratio for factor h at level 1 and level 2 is as follows:

$$h1 = (-23.3656 - 26.7706 - 24.8732 - 25.575 - 25.0422) / 5$$
$$= -25.12534$$

$$h2 = (-24.9167 - 28.8196 - 24.5947 - 23.9484 - 31.7749) / 5$$
$$= -26.81088$$

The minimum variation is determined based on the highest average S/N value. Therefore, in this example, factor h at level 1 has less variation than at level 2. The effect of all factors is shown graphically in Figure 5.12 to obtain an overview of the impact of each factor at different levels. It is apparent from the figure that the "must-deliver" level, holding cost and transportation cost factors have a large effect on the S/N ratio, whereas the other factors especially the "can-deliver" level, have a small effect. It can be seen from the figure, that the S/N ratios are highest for level 1 for holding and transportation cost, so there will be minimum variation in lowest cost at both factor settings. In contrast, the shortage cost has less variation for the highest cost setting. The "can-deliver" level gives a better result in the middle level, thus shows that the flexibility helps to reduce the total cost. The standard ANalysis Of VAriance (ANOVA) technique can emphasise the effects that have been estimated previously from the graph based on the percentage contribution of each factor.

The steps to carry out the ANOVA analysis of total cost based on Roy (1990) are as follows:-

Step 1 : Calculate the Total of all S/N ratios for each experiment, T

$$T = \sum_{E=1}^{25} S/N_{\mathrm{E}} \tag{16}$$

E = experiment

Step 2: Compute the Correction Factor, *C.F.*

$$CF = T^2/25 \tag{17}$$

Step 3: Square each of the S/N ratios for each experiment, E, and calculate the Total Sum of Squares, S_T using equation (18)

$$S_T = \sum_{E=1}^{25} \mathrm{S/N}_{\mathrm{E}}^2 - \mathrm{C.F.} \tag{18}$$

Step 4: Calculate the total contribution of each factor, F, at correspondence level, L, F_L

$$F_{L=1,2,3} = \text{Sum of all total costs for factor F at level, L.} \tag{19}$$

$F = I_{+(1,2,3)}, I_{m(1,2,3)}, I_{c(1,2,3)}, h, p, c$

and determine the Factor Sum of Squares, S, for each factor as equation (20)

$$S_F = \sum_{L=1}^{5} (F_L{}^2 / N_{FL}) - C.F. \qquad (20)$$

N_{FL} = Number of experiments included at level, L, for each factor, F

$$\text{Error Sum of Square, } S_e = S_T - \sum_{\substack{F=I_{+(1,2,3)},\\ I_{m(1,2,3)}, I_{c(1,2,3)}, h.p,c}} S_F \qquad (21)$$

Step 5: Determine the Total and Factor Degrees of Freedom, f

Total Degrees of Freedom, f_T = number of experiments – 1 (22)

Factor Degrees of Freedom, f_F = Number of level factor, $F-1$ (23)

$$\text{Error Degrees of Freedom , } f_e = f_T - \sum_{\substack{F=I_{+(1,2,3)},\\ I_{m(1,2,3)}, I_{c(1,2,3)}, h,p,c}} f_F \qquad (24)$$

Step 6: Calculate the Mean Square (Variance) for each factor and variance of error value (V_e)

$$V_F = S_F / f_F \qquad (25)$$

$$V_e = S_e / f_e \qquad (26)$$

Note that the variance of error value is not valid with zero f_e.

Step 7: Evaluate the Percentage Contribution for each factor

$$P_F = (S_F / S_T) * 100 \qquad (27)$$

Table 5.8: Total cost per period for 3 replications and S/N ratio

Experiment	Replication 1 y1	Replication 2 y2	Replication 3 y3	S/N
1	14.72779	14.74803	14.72203	-23.3656
2	17.61675	17.61922	17.60352	-24.9167
3	22.52354	22.5196	22.51784	-27.0515
4	27.25725	27.25061	27.25138	-28.7083
5	31.98954	31.9803	31.98303	-30.0987
6	22.74328	22.79962	22.74501	-27.1445
7	16.44176	16.47975	16.46212	-24.3292
8	24.95821	24.94117	24.95657	-27.9421
9	21.80476	21.80098	21.8054	-26.7706
10	27.60673	27.59893	27.60804	-28.8196
11	21.49711	21.49064	21.50069	-26.6472
12	17.52422	17.53605	17.51507	-24.8732
13	16.9492	16.98748	16.97924	-24.5947
14	24.94467	24.92622	24.9401	-27.9369
15	32.00419	31.9878	32.00688	-30.1029
16	15.74733	15.76576	15.75234	-23.9484
17	28.381	28.35342	28.35016	-29.0546
18	37.55114	37.5635	37.53874	-31.4925
19	27.00524	26.98475	27.0086	-28.6271
20	19.00105	18.99695	19.00172	-25.575
21	18.26243	18.25853	18.26491	-25.2309
22	27.1341	27.12418	27.12732	-28.6685
23	17.88558	17.87837	17.8445	-25.0422
24	38.79611	38.78575	38.79523	-31.7749
25	28.20315	28.19085	28.20516	-29.0049

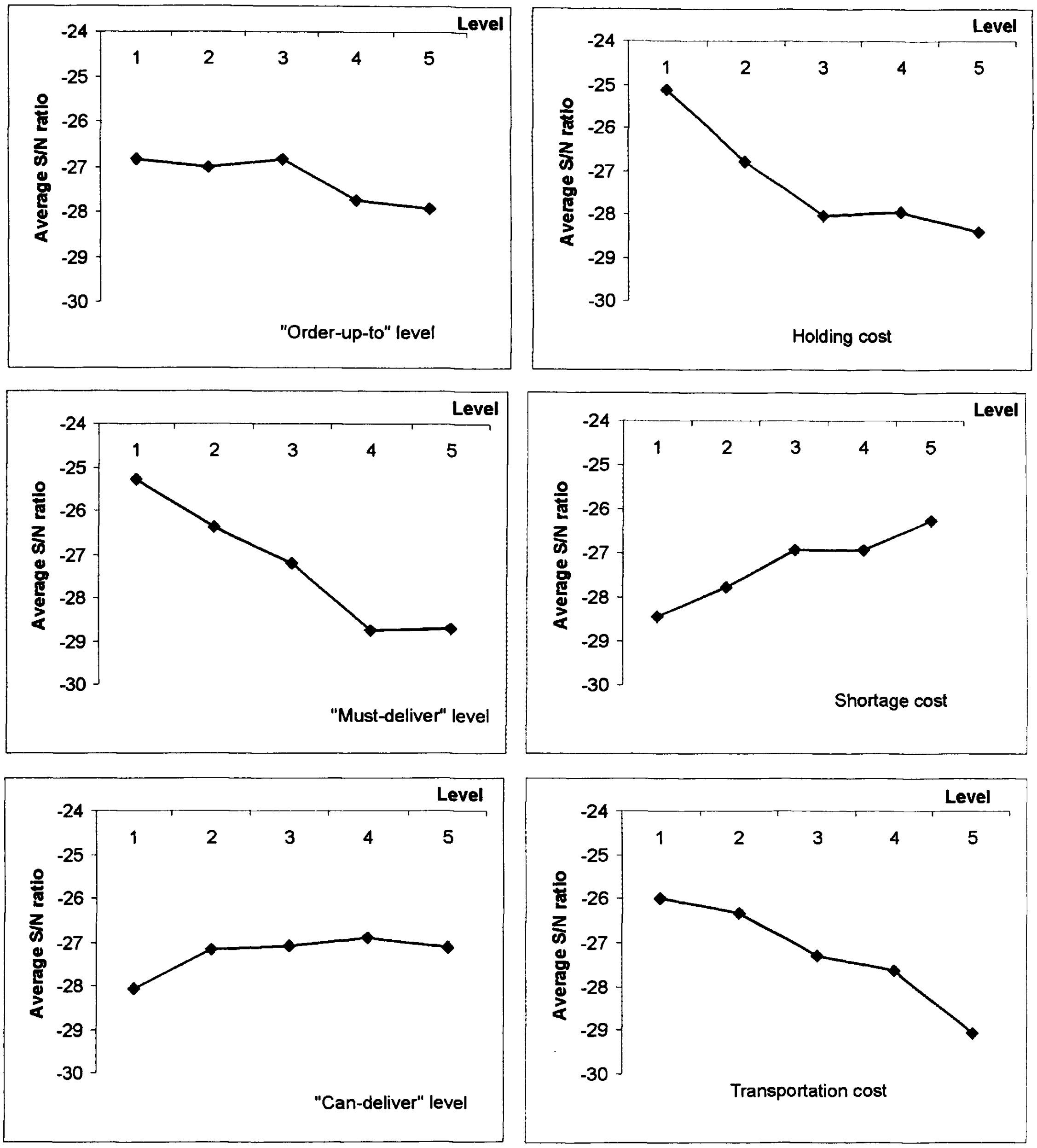


Figure 5.12: Effects of each 6 control factors at 5 levels.

Based on all the total costs in the Table 5.8 above, the Correction factor, *C.F.* and the Total Sum of Squares, S_T are calculated using equations (17) and (18). The *C.F.* value for the experiment is 18589.7393, and the Total Sum of Squares, S_T is 135.56861. The ANOVA results of the degree of freedom (*f*), Factor Sum of Squares (*S*), Mean Square (variance) and Percentage Contribution (*P*) value of each factor are shown in Table 5.9.

Table 5.9: ANOVA of S/N ratio total cost

Column	Factors	f	S	V	$P\%$
1	$I_{+(1,2,3)}$	4	5.67673	1.41918	4.18735
2	$I_{m(1,2,3)}$	4	45.79715	11.44929	33.78153
3	$I_{c(1,2,3)}$	4	4.10992	1.02748	3.03161
4	h	4	35.82159	8.95540	26.42322
5	p	4	14.32085	3.58021	10.56354
6	c	4	29.84237	7.46059	22.01275
All other/error		0	0.00000		0.00000
Total		24	135.56861		100.00000

As can be seen from the table, the percentage contribution of "can-deliver" level and "order-up-to" level are small. Therefore, these factors should be pooled in order to get a higher and nonzero value of f_e and S_e that will raise the confidence level of the significant factor, (Roy, 1990). As a result, the new Sum of Square error (S_e) and Degree of freedom error (f_e) value can be calculated by equation 28 and equation 29.

$$S_e = S_T - (S_{I_{m(1,2,3)}} + S_h + S_c + S_p) \qquad (28)$$

$$f_e = f_T - (f_{I_{m(1,2,3)}} + f_h + f_c + f_p) \qquad (29)$$

With a V_e value greater than zero, the variance ratios (F) can be determined by equation 30 . The percentage contribution is recalculated using the pure sum of square ($S^{'}$) that can be determined by equation 31.

$$F_F = V_F / V_e \qquad (30)$$

$$S'_F = S_F - (V_e x f_F) \qquad (31)$$

$F = I_{+(1,2,3)}, I_{m(1,2,3)}, I_{c(1,2,3)}, h, p, c$

The percentage error is calculated by subtracting the percentage contribution of remaining factors from 100%. Table 5.10 shows the ANOVA table after pooling insignificant factors.

Table 5.10: Pooled ANOVA of S/N ratio total cost

Column	Factors	*f*	*S*	*V*	*F*	*S'*	*P*
1	$I_{+(1,2,3)}$	(4)	(5.67673)	Pooled			
2	$I_{m(1,2,3)}$	4	45.79715	11.44929	9.35911**	40.90383	30.17205
3	$I_{c(1,2,3)}$	(4)	(4.10992)	Pooled			
4	*h*	4	35.82159	8.95540	7.32050*	30.92826	22.81373
5	*p*	4	14.32085	3.58021	2.92661	9.42753	6.95406
6	*c*	4	29.84237	7.46059	6.09859*	24.94905	18.40326
error		8	9.78665	1.22333			21.65689
Total		24	135.56861			135.5686 1	100

* Significant at 95% confidence level $F_{.95}(4,8) = 3.8378$

** Significant at 99% confidence level $F_{.95}(4,8) = 7.006$

In this analysis, the "must-deliver" level was shown to have a significant effect at the 1% level on the S/N ratio for the total cost whereas holding cost and transportation costs were shown to have a significant effect at the 5% level. Shortage cost only contributed 6.95% and as the *F* ratio was greater than the *F* table value, F(4,8) at a 90% confidence level (2.8064), the shortage cost factor could be retained. Nevertheless, the variations of these total costs are based on the values assigned to each level in Table 5.6. The percentage contribution of each significant factor was visualised using a Pie Chart as shown in Figure 5.13.

The chart shows that "must-delivery" level is the factor most influencing total cost since it contributed almost 30 per cent of the variation. The holding cost and transportation cost ratio represented a further 23% and 18% respectively. This suggests that the appropriate order-up-to level needs to be decided for the optimal result. Furthermore, changes in the cost settings will alter the combination of inventory control parameters that optimises the total cost. These impacts will be studied in detail in the next subsection.

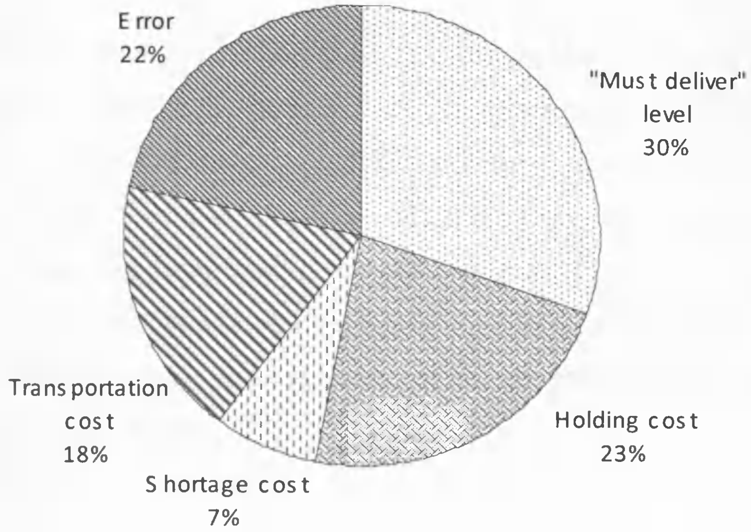


Figure 5.13: Pie Chart for Percentage Contribution of four significant factors in experiment.

5.6.2 Sensitivity Analysis

As explained in Section 4.1, a replenishment is primarily triggered when the inventory reaches the "must-deliver" level and this replenishment will bring the inventory up to an "order-up-to" level. The "can-deliver" level gives an opportunity for the supplier to consolidate other retailers' deliveries into the one load, thus saving transport costs. The last analysis shows that the "must-deliver" level, holding cost and transportation costs factor have large impact on the IRP solution. In this section, the behaviour of the optimal combination of the inventory control parameters that minimise the total cost per period is examined by considering all possible combination of inventory control parameters with respect to different cost parameter settings. The range of cost parameters considered in this experiment is similar to the experimental design in Table 5.6 above. This parameter combination will assure that the shortage cost will be higher than the holding cost whilst it is also able to test the condition when transportation cost is equal to or higher than the holding cost. Table 5.11 shows optimal inventory control parameters (I_{+}, I_c and I_m) and total cost per period, TC, result for different combinations of holding cost, h, shortage cost, p, and transportation cost, c.

It can be seen from Table 5.11 that the results for the total cost per period are as intuitively expected. The total cost value increased as the costs and inventory control parameters were increased. The result also showed that the effect of changes in shortage cost is small with a constant transportation cost and holding cost value. However, the total cost per period is greatly affected by the holding cost as it increases dramatically when the holding cost increases further. The effects of varying shortage cost and holding cost when the transportation cost is equal to 0.5 is illustrated in Figure 5.14.

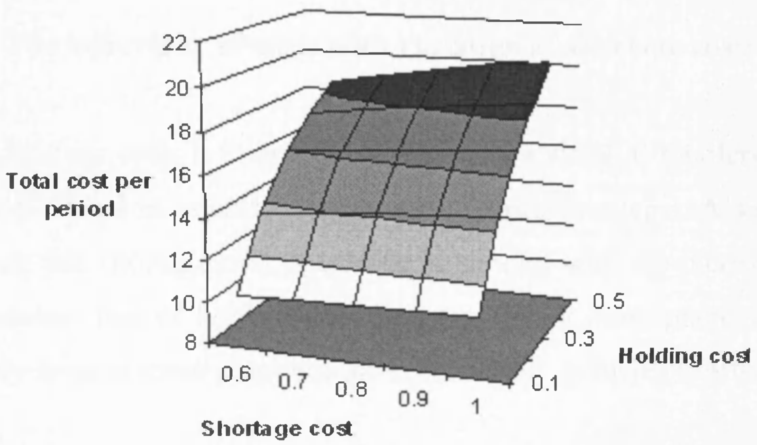


Figure 5.14: Total cost per period for varying shortage cost and holding cost when the transportation cost = 0.5.

The behaviour of the three inventory control parameters throughout the experiment is seen to be quite sensitive to changes in the cost parameters. The analysis first looked at scenarios when the transportation costs are equal to the holding costs to observe the effect of the shortage cost on the optimal inventory policy parameters. The result shows that, generally, the quantity of inventory that is delivered to the retailer remains the same for both low and high shortage costs. The pattern of costs for the optimal combinations of inventory policy in Figure 5.15 indicated that shortage cost increase influences the holding cost value.

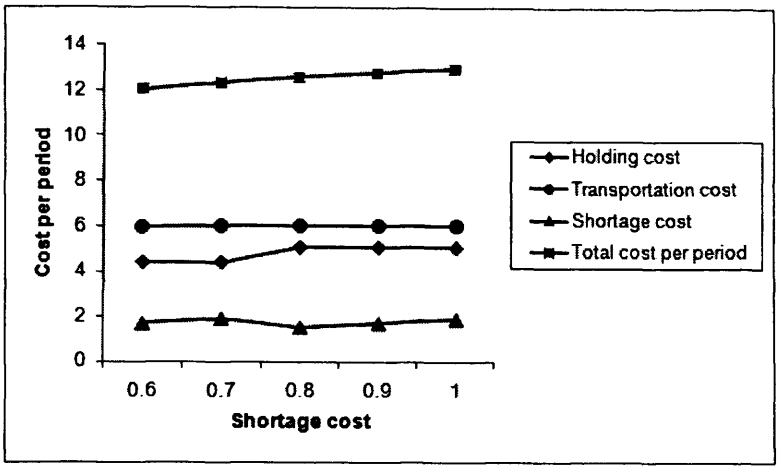


Figure 5.15: The behaviour of costs with variation of shortage costs

With higher shortage cost, it is optimal to keep extra stock at retailers by increasing the "order-up-to" level in order to prevent out of stock problems. Also it can be seen from the figure that shortage cost decreases in parallel with the increase in the stock level. The constant line of holding cost suggests that it more practical to retain the same inventory level at some point but the cost is likely to increase afterwards.

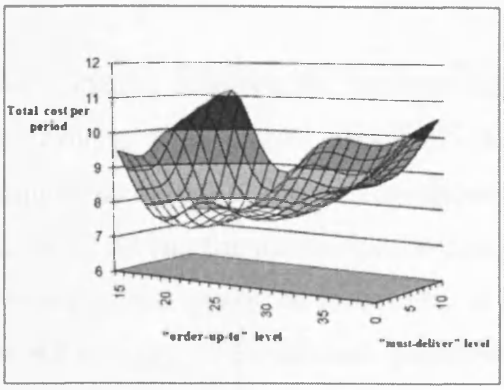
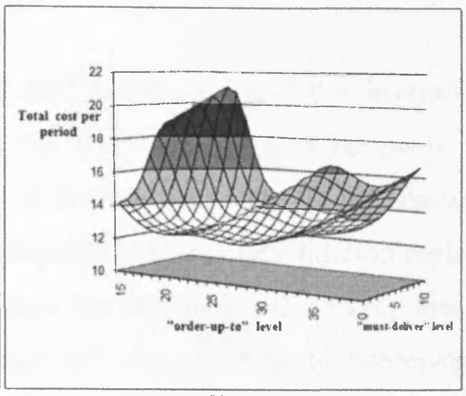
Next, the effect of the optimal inventory control parameter is observed when the holding cost is less than the transportation cost. Since the cost to hold the inventory is low compared to the delivery cost, it is more cost-effective to replenish those retailers with larger inventories at the time of delivery. The results in Table 5.11 show that the "order-up-to" level decreases as the holding cost increases. For transportation cost equal to 0.5, the optimal "order-up-to" level for holding cost equal to 0.1 is more than double compared to the "order-up-to" level at holding cost equal 0.5. Also, the extra stock at the retailers will increase the replenishment cycle period. Therefore less delivery trips are required and a lower transportation cost is incurred. On the other hand, when the holding cost is higher than the transportation cost, the periodic "can-deliver" policy will tend to reduce the quantity in each delivery to the retailers by decreasing the "order-up-to" level. As the result, regular replenishment is required in order to maintain retailers' service level. This pattern can be seen in Table 5.11 starting at holding cost equal to 0.5 and transportation cost equal to 0.3, and the "order-up-to" level is suspected to drop further with increasing holding cost.

Table 5.11: The sensitivity analysis for different combination of holding cost, shortage cost and transportation cost

h	p	C																			
		0.3				0.4				0.5				0.6				0.7			
		I_+	I_m	I_c	TC	I_+	I_m	I_c	TC	I_+	I_m	I_c	TC	I_+	I_m	I_c	TC	I_+	I_m	I_c	TC
0.1	0.6	31	3	22-31	8.07577	31	2	20-31	9.39695	39	0	22-39	10.45403	40	0	21-23	11.4424	48	0	23	12.39587
	0.7	31	3	22-31	8.18491	32	3	21-32	9.51931	40	1	23-40	10.59547	41	1	22-24	11.59352	49	0	24	12.55179
	0.8	32	4	23-32	8.2756	32	3	21-32	9.60619	41	2	24-41	10.71264	41	2	24-41	11.71081	49	0	24	12.70061
	0.9	32	4	23-32	8.34936	32	4	23-32	9.68551	41	3	24-41	10.81335	41	2	24-41	11.81523	42	2	23-25	12.80396
	1	32	4	23-32	8.42312	32	4	23-32	9.75927	42	3	25-42	10.89948	42	3	25-42	11.89765	42	3	25-42	12.89583
0.2	0.6	20	2	12	10.50977	28	0	19-28	12.35396	28	0	19-28	13.69012	28	0	19-28	15.02627	28	0	19-28	16.36243
	0.7	20	3	13	10.70092	28	0	19-28	12.6293	29	0	18-29	13.96468	29	0	18-29	15.28402	29	0	18-28	16.60335
	0.8	21	4	14	10.83281	21	3	13	12.82447	29	1	20-29	14.18583	29	0	18-29	15.51447	29	0	18-29	16.83381
	0.9	21	4	14	10.95565	21	3	13	12.95369	30	2	21-30	14.38553	30	1	19-20	15.70613	30	1	19-30	17.02546
	1	21	4	14	11.07849	21	4	14	13.07987	30	2	21-30	14.5399	30	2	21-30	15.87606	30	1	19-30	17.19784
0.3	0.6	19	1	11	12.05958	19	0	13	14.04662	19	0	13	16.01573	26	0	17	17.52913	26	0	17	18.91519
	0.7	19	2	12	12.33317	19	1	11	14.33163	19	0	13	16.3188	27	0	17-27	17.89748	27	0	17-27	19.254
	0.8	20	3	13	12.57806	20	2	12	14.57334	20	1	14	16.55685	27	0	17-27	18.22415	27	0	17-27	19.58066
	0.9	20	3	13	12.76656	20	3	13	14.76794	20	2	12	16.75996	28	0	19-28	18.53094	28	0	19-28	19.8671
	1	20	3	13	12.95506	20	3	13	14.95644	20	2	12	16.95597	28	0	19-28	18.80628	28	0	19-28	20.14244
0.4	0.6	17	0	10	13.33599	17	0	10	15.33737	17	0	10	17.33876	18	0	10	19.33037	25	0	16	21.19103
	0.7	18	1	11	13.73247	18	0	10	15.73385	18	0	10	17.72447	18	0	10	19.71508	25	0	16	21.59644
	0.8	19	2	12	14.07903	19	1	11	16.07944	19	1	11	18.07005	19	0	13	20.04157	26	0	17	21.98612
	0.9	19	2	12	14.35189	19	2	12	16.35327	19	1	11	18.35149	19	1	11	20.34211	19	0	13	22.31375
	1	19	2	12	14.62475	19	2	12	16.62613	19	2	12	18.62751	20	1	14	20.6195	20	1	14	22.58861
0.5	0.6	16	0	10	14.38232	16	0	10	16.40022	16	0	10	18.41812	17	0	10	20.4334	17	0	10	22.43479
	0.7	17	0	10	14.92239	17	0	10	16.92377	17	0	10	18.92515	17	0	10	20.92654	17	0	10	22.92792
	0.8	11	2	6	15.31464	18	1	11	17.3845	18	0	10	19.37879	18	0	10	21.3694	18	0	10	23.36001
	0.9	11	3	6	15.46591	18	1	11	17.75975	18	1	11	19.76113	18	0	10	21.75411	18	0	10	23.74472
	1	11	4	7	15.61158	19	2	12	18.09913	19	1	11	20.0993	19	1	11	22.08991	19	0	13	24.0674

The results also revealed that flexibility from the "can-deliver" level giving the supplier the opportunity to coordinate the replenishment among retailers, in turn, minimises the total cost. Different "can-deliver" level values indicate that the level of flexibility is influenced by the cost settings. Interestingly, there are several cases where it more economical to consolidate the replenishment with all retailers in each delivery. This situation occurs when the ratio of holding cost is less than half of transportation cost. Thus, it would appear to be more efficient to carry the inventory at the maximum range when there is an opportunity to coordinate the inventory with other retailers. It will also be costly to replenish other retailers separately due to the high transportation cost.

In addition, the results reveal an unexpected pattern in the combination of optimal inventory control parameters for different transportation costs at a constant holding cost. This pattern can be seen from the table at holding cost equal to 0.2. At a transportation cost equal to 0.4, a higher "order-up-to" level is required at low shortage cost to decrease the transportation cost; however, at the higher shortage cost it remains constant. The model suggests that at some point, it is more efficient to increase the quantity of delivery when the shortage cost is low in order to decrease the transportation cost. However, increasing the delivery when higher shortage cost exists tends to slightly increase the holding cost and shortage cost more than the transportation cost. Therefore, it is more efficient to keep the "order-up-to" level at the same level. The different optimal "order-up-to" values causing minimum total cost occur at two different areas shown in Figure 5.16. One minimum total cost occurs at the first slope of the graph in Figure 5.16 (a) whilst another minimum total cost occurs at a higher "order-up-to" level that is shown in Figure 5.16 (b).

(a) (b)

Figure 5.16: Total cost per period for holding cost = 0.2 and shortage cost = 0.6 (a) transportation cost = 0.3 (b) transportation cost = 0.4

From the analysis, it appears that different combinations of cost parameters require at different optimal combinations of inventory policy parameters to minimise the objective function. Therefore, as a decision maker the supplier has to think carefully about the decision parameters to minimise the operation cost for replenishment.

These findings is based on the basic IRP model that considered only 3 retailers and one wholesaler in the analysis under the physical supply chain layout that illustrated in Figure 5.3. The actual scenario that exists in the case study organisation that describe in Chapter 4 is more complex in terms of the number of retailers, number of items and transportation conditions. Nevertheless, the findings from this study still show that IRP could be beneficial for the organisation as it gives flexibility to the decision making. It will be especially useful when the organisation have conditions where 3 retailers need to be replenished at one particular time. It is also believed that the organisation will benefit from a reduction in cost in the case when more retailers required for delivery. However, further analyses needs to be carried out in order to determine the actual behaviour of the IRP model with different numbers of retailers.

5.6.2.1 Causal-loop diagram

The dynamic relationship between the cost parameters and the inventory control parameters, as explained previously in the above section can be easily visualised using a causal-loop diagram as shown in Figure 5.17. The figure shows that the holding cost and the transportation cost impact upon the consolidation replenishment. When the holding cost at the retailer is high, the supplier tends to keep low inventory by reducing the replenishment quantity that is associated with the "order-up-to" level and decreasing the consolidation replenishment. These phenomena generate the negative causal loops, B-1 and B-5, in Figure 5.17. On the other hand, the "order-up-to" level is increased in the scenario when the shortage cost at the retailer is also increased. Increasing the level of stock will help to reduce the shortage cost by decreasing the backlog number in the negative loop, B-2. Also, the same impact occurs by increasing the delivery frequency as indicated in the negative loop, B-3. However, increasing the delivery frequency will increase the transportation cost. The transportation cost can be reduced through consolidating replenishments and increasing the "order-up-to" level as increasing the amount of stock will reduce the number of delivery frequencies in the next period. This scenario is represented by the negative loops, B-4, B-6 and B-7.

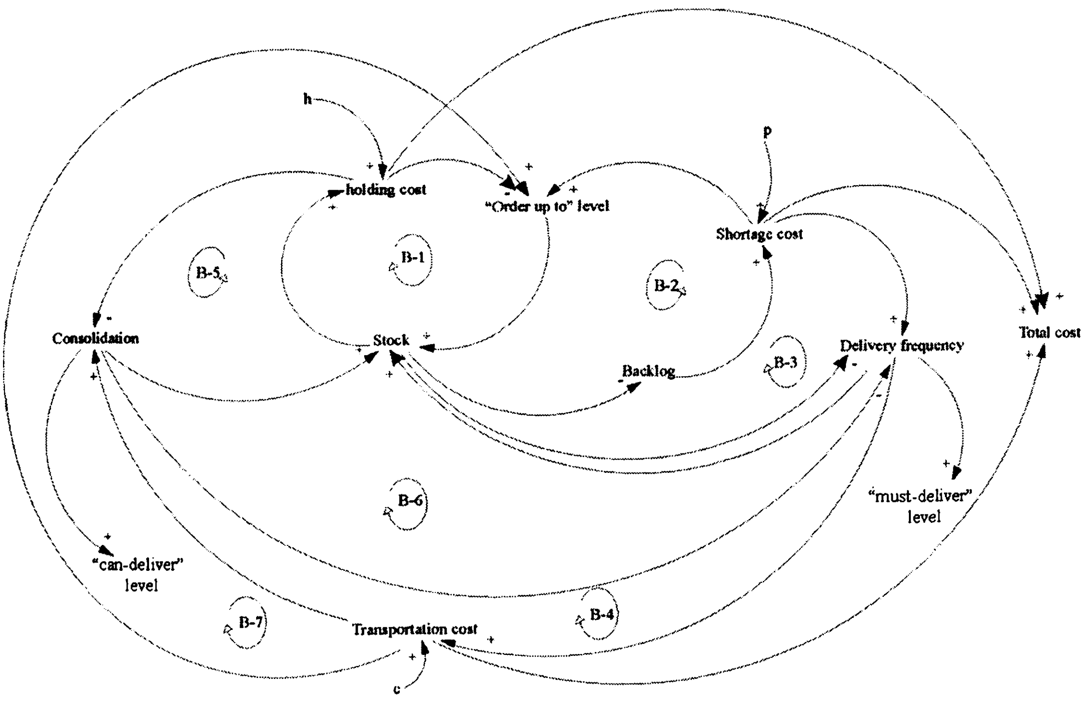


Figure 5.17: Causal loop diagram for sensitivity analysis

5.7 Comparison with other inventory policies

In this section, the performance of the periodic "can-deliver" policy against the (*s*,*S*) policy and (*s*,*S*-*1*,*S*) inventory policy that exist in the literature for joint replenishment is examined. The value of the comparison policies is obtained based on the results of different instances of the "can-deliver" parameter. The periodic (*s*, *S*) policy is generated when the "can-deliver" level, I_c , is equal to the "must-deliver" level, I_m. Section 4.6 discussed the benefit of IRP flexibility with regards to inventory and transportation costs and compared to the (*s*,*S*) policy with the proposed periodic "can-deliver" policy which is used as a benchmark. However, this is just a starting point since the comparison is based only on the same "order-up-to" level. In this section, the optimal (*s*,*S*) policy is examined based on the overall experiments. A comparison is then made of the periodic "can-deliver" policy and the (*s*,*S*-1,*S*) inventory policy which triggered the replenishment to all retailers at each replenishment time. The latter policy was advocated by Gurbuz et. al. (2007) who characterised it as an installation based policy. For the (*s*,*S*-1,*S*) policy, the "can-deliver" level is set equal to the "order-up-to" level -1.

The performance of the periodic "can-deliver" policy is measured based on the percentage of cost saving over the (*s*,*S*) policy and the (*s*,*S*-1,*S*) policy which represent as *P* policy in equation 32 . This the same approach used by Pantumsinchai (1992).

$$\text{Percent saving (\%)} = \frac{\text{(Optimal TC P policy) - (Optimal TC "can - delivery" policy)}}{\text{(Optimal TC policy, } P\text{)}} \text{ x } 100 \quad (32)$$

A positive and higher percent saving value indicated that the periodic "can-deliver" policy is able to yield a cost saving and outperform the two benchmark policies. On the other hand, a low value shows that all policies have similar behaviour. Only 18 experiments from the sensitivity analysis in Section 4.6.2 are considered in this analysis, and only 3 levels are included for all cost parameters. The cost parameter settings and the result of the percent savings for the periodic "can-deliver" policy over (*s*,*S*) policy and (*s*,*S*-*1*,*S*) policy are shown in Table 5.12.

Table 5.12 shows that the periodic "can-deliver" policy outperforms the (*s*,*S*) policy. Results presented in Table 5.12 also reveal that smaller savings will be generated from the IRP flexibility if the holding cost, *h* is higher than the transportation cost, *c*. Without this condition, the average saving is about 13.7% and the highest percentage occurs when transportation cost is equal to 0.7, holding cost is equal to 0.1 and shortage cost is equal to 0.6. The findings show that early replenishment triggered by the "can-deliver" level value provides advantages for the organisation to reduce total cost. However, the marginal benefit of the flexibility decreases as it become higher. It can be seen from Table 5.12 that the highest saving percentage for the "can-deliver" policy over the (s,S-1,S) policy is only 0.018%. Also, there are cases where the periodic "can-deliver" policy has a similar performance with the (*s*,*S*-*1*,*S*) policy when the ratio of transportation cost and holding cost is high.

Table 5.12: Performance of "can-deliver" policy over other two policies.

Cost parameter				Saving Percentage over policy	
c	*h*	*p*	*TC("can-delivery" policy)*	*(s,S)*	*(s,S-1,S)*
0.3	0.1	0.6	8.07577	12.93441	0
		1	8.42311	11.35819	0
	0.3	0.6	12.05958	13.03971	0.00273
		1	12.95506	11.52526	0.00419
	0.5	0.6	14.38232	3.48886	0.00225
		1	15.61158	0.00035	0.01827
0.5	0.1	0.6	10.45403	17.22692	0
		1	10.89948	16.50104	0
	0.3	0.6	16.01573	13.93869	0.00005
		1	16.95597	13.11571	0.00134
	0.5	0.6	18.41812	13.68076	0.00234
		1	20.09930	13.03971	0.00273
0.7	0.1	0.6	12.39587	17.62720	0.00080
		1	12.89583	17.00209	0
	0.3	0.6	18.91519	9.77392	0.00041
		1	20.1424	15.70162	0.00018
	0.5	0.6	22.43479	13.71929	0.00418
		1	24.06740	14.26916	0.00004

5.8 The Effect of demand distribution pattern and demand variance on retailers

The effect of the proposed IRP model on the demand distribution factor is examined by considering Normal and Poisson distributions for identical retailers. The mean values for Normal and Poisson distributions are set equal to the mean of the current demand distribution used in the study. However, the value of the variance parameter for the Poisson distribution is slightly different as a result of the characteristic of Poisson distribution since the variance value is equal to the mean value. Further, five different variance values of the Normal distribution are considered in this analysis, namely, the condition when the variance is approximately similar to the current setting, Normal(10,2.24), the condition when the model have a lower variance value, Normal (10,2.0) and Normal (10,1.0) as well as the condition when the model have a higher variance value, Normal (10,2.5) and Normal (10,3.0) in order to examine the effect of the IRP model with regard to the variation of demand.

The effect of different demand distributions that may have similar mean and variance with current demand distribution used in the IRP model on the optimal inventory control parameters that minimises the total cost is shown in Table 5.13.

Table 5.13: Optimal inventory control parameters and total cost for different demand distributions

Demand Distribution	"Order-up-to" level	"Must-deliver" level	"Can-deliver" level	Optimal total cost
Normal (10,2.24)	19	0	11	22.9644
Poisson(10)	19	0	10	23.7606
Binomial(20,0.5)	19	0	13	22.9528

With a similar warm-up period and length of simulation execution, it is found that the behaviour of the model is consistent, even with different demand distributions, since the optimal inventory control parameter is similar for Normal (10, 2.24), Poisson (10) and Binomial (20, 0.5). Thus, it is anticipated that the model will behave similarly for demand distributions that have similar characteristics. However, different total cost values occur as a result of different values of demand data generated with regards to the demand pattern behaviours. Consistent with ANOVA analysis findings reported in

Mustaffa and Disney (2006), the IRP model performance measurement is highly influenced by the demand distribution factor. With regard to the impact of demand variations, it can be seen in Table 5.14 that shortage cost is increased as the demand variance is increased, which is as expected.

Table 5.14: Effect of demand variance on inventory control parameters and costs

	Demand distribution				
Parameters	Normal (10,1.0)	Normal (10,2.0)	Normal (10,2.24)	Normal (10,2.50)	Normal (10,3.0)
"Order-up-to" level	19	19	19	19	19
"Must-deliver" level	5	1	0	0	0
"Can-deliver" level	9	13	11	11	10
Holding cost	5.5180	5.7767	5.7403	5.8057	5.9384
Shortage cost	1.4398	2.1469	2.6229	2.8117	3.1534
Transportation cost	14.9613	14.8383	14.6012	14.5608	14.5027
Total cost	21.9190	22.7619	22.9644	23.1782	23.5945

Is also been discovered that the optimal combination of inventory control parameters have shown an interesting pattern in the results. Basically, in theory a higher "must-deliver" level is needed in order to deal with high demand variance. However, the findings from Table 5.14 suggest that a lower "must-deliver" level is more economical when there is opportunity to coordinate the replenishment between retailers via the "can-deliver" level by considering of the transportation cost in the performance measurement. A higher "must-deliver" level may increase the number of delivery trips where probably only one or two retailers that reach the "must-deliver" level and "can-deliver" level are required to be delivered in one delivery trip. Therefore, another delivery trip needs to be scheduled in the next period in order to fulfil the requirement for others retailer. Hence, more frequent delivery is required and this phenomenon will cause a higher transportation cost and holding cost. However less total cost will occur with a low "must-deliver" level since the probability to deliver to all retailers in one delivery trip is higher. This is because, there is a gap between the replenishment periods as none of the retailers have reached the "must-deliver" level and no replenishment is required at some period. As a result, the inventory level for all retailers may decrease unvaryingly and all retailers can be consolidated together for each replenishment time. As a result, fewer delivery trips are required. Therefore, less total cost is incurred with a reduction of transportation cost and holding cost even though it may cause a slightly higher shortage cost.

5.9 Conclusion

This chapter has examined the opportunity for a supplier to consolidate retailers' replenishment through an inventory control policy called the "can-deliver" policy. The analysis was carried out using a spreadsheet simulation. The steady state period was determined using the well-known Welch's method. The simulation was executed with multiple replications to ensure accuracy. At the 95 percent and 99 percent confidence level, three replications were found appropriate for this simulation model.

The performance of the "can-deliver" policy was evaluated in 3 phases. First, we examined the model by varying the inventory control parameter with the constant costs parameter. Results showed that the total costs decreased as the "can-delivery" level is increased. However, the benefit seemed to saturate out with high flexibility. The experiment is expanded by varying the cost parameters using the experimental design approach based on the Taguchi methods to get the rough idea of model behaviour. The experiment showed that the "must-deliver" level, holding cost and transportation cost factors had a large impact on the model performance measurement as expected. Then, the sensitivity analysis of the model is analysed by determining the optimal combination of inventory control parameters that minimised the total cost. Total cost of the model is a function of holding cost, shortage cost and transportation cost. 125 combinations of these costs were analysed using the brute-force approach to determine the optimal total cost. Results showed that the "can-delivery" level minimised the total cost for the combination of costs. The result suggested that it is economical to replenish all retailers when there is the opportunity to make replenishment and the ratio of transportation cost is high compared to holding cost. In other situations, the results showed that the minimum total cost existed at a certain flexibility level. The dynamic relationship between costs parameter and the inventory control parameters was visualized using the causal-loop diagram.

Finally, in order to evaluate this model's performance, comparison analysis was performed between the "can-delivery" policy and the (s,S) policy as well as the $(s,S-1,S)$ policy by changing the setting of the "can-delivery" level. The results showed that with the periodic "can-deliver" policy it was possible to get the maximum 17.6% saving compared to the (s,S) policy. On the other hand, only a small additional cost would be incurred if replenishment was made to all retailers at each delivery time.

So far, the optimal routing strategy for the proposed IRP model has been determined based on the route that minimises the total distance travelled during the replenishment activities. However, as the quantity of delivery at each retailer is different based on the condition of retailers and the cost function, further analysis of the optimal sequence of delivery between retailers based on distance, weight of vehicle and the weight of replenishment that minimises the costs and vehicle energy and maximises the overall vehicle effectiveness needs to be carried out. Such analysis is presented in the following chapter.

Chapter 6 Transport Effectiveness

The optimal route for the replenishment analysis conducted in chapter 5 was based on minimising the distance travelled by a vehicle in order to make a round trip delivery from the central supplier to multiple retailers. The sequence by which retailers were serviced was determined employing a Travelling Salesman Problem approach in the hope that minimising the total distance travelled would lower the transportation cost. This assumed the transportation cost for the periodic "can deliver" policy was solely based upon the cost per unit distance (km) travelled. However, only minimising the distance does not guarantee minimisation of vehicles' energy consumption or maximisation of vehicle's effectiveness and this therefore led to the development of research question 4. This chapter attempts to address this research question by examining other routing strategies which can be integrated with the periodic "can-deliver" policy to not only improve the economic performance of IRP model but to reduce the environmental impact of the distribution activities.

This study differs from previous approaches implemented by other researchers in that the decision in determining the optimal route and the sequence of the replenishment considers not only the distance travelled but also the vehicle weight and the load it carries to replenish each retailer. Further, the strategy considered for integration in the IRP model not only evaluates the overall performance of the routing chosen but also other factors, such as the quantity of delivery as well as the time used to carry out the replenishment activities for one delivery trip.

Specifically, this analysis examines the impact of two vehicle effectiveness measures that integrate different vehicle key performance indicator measurements known as Overall Vehicle Effectiveness (OVE) and Modified Overall Vehicle Effectiveness (MOVE) metric. The performance of these metrics is evaluated based on the energy consumed by the vehicle as well as the total distance travelled that is usually examined in the Travelling Salesman Problem (TSP) approach. The study also determines the best policy to use for the routing strategy of the IRP model.

6.1 Introduction

Logistics is playing an increasingly important role in business strategies and can influence the business supply chain process, (Rafele, 2004). It is therefore important for an organisation to so manage its vehicle performance as to successfully deliver customer requirements in an effective way. By correctly evaluating the vehicle performance, an organisation can identify problems that need to be addressed. This may result in increases in the vehicle effectiveness as well as reductions in the energy consumed and cost incurred.

Studies in the literature have used different approaches to monitor the efficiency and effectiveness of vehicles. Most studies have used a set of Key Performance Indicators (KPIs) as a measurement to evaluate the logistics performance. McKinnon (2000) in association with the Energy Efficiency Best Practice Programme conducted a pilot study to measure transport efficiency using a survey approach in the food industry. The performance of transportation operation was measured based on five sets of KPIs, namely:

i) Vehicle fill
ii) Empty running
iii) Time utilisation
iv) Deviation from schedule
v) Fuel consumption

The survey was continued in 2002 with the objectives of benchmarking vehicle efficiency, estimating the average levels of efficiency as well as identifying areas for improvement. In the second survey, more participants and different vehicle types were involved to measure vehicle performance with similar KPI categories, (McKinnon et al., 2003). McKinnon and Ge (2006) then analysed the results from the survey focusing on the routing efficiency and back-loading opportunities.

The same KPI were used also by the FreightBestPractice programme to measure performance across different sectors such as non-food retail distribution and next-day parcel delivery (FreightBestPractice, 2006a, 2006b). The FreightBestPractice programme together with the Freight Transport Association developed a "Fleet Performance Management Tool" to assist organisations in monitoring their vehicle performance based on 24 KPI's that are grouped into costs, operational, service, compliance, maintenance and environmental categories (FreightBestPractice, 2007). For instance, the average cost per unit delivery, the total vehicle cost, total miles run and the percentage average vehicle fill.

Other notable studies that have used KPI's include Donselaar et al. (1998) and Krauth et al. (2005) who both conducted surveys on logistic service providers. Donselaar et.al. (1998) identified critical success factors in the transportation and distribution sectors related to financial and operations performance based on turnover/variable, turnover/direct costs, and turnover/wages elements. Krauth et al. (2005) clustered qualitative KPIs into internal perspectives of management and employees and the external perspective of the customer and the society.

A common performance measurement in the IRP area for measuring the effectiveness in the distribution is the volume delivered per mile travelled. However, Song and Savelsbergh (2007) have contested the correctness of using this measurement for determining the absolute performance and introduced the concept of a 'lower bound on the minimum total mileage required to satisfy customer demand'.

The TSP approach can also be categorised as a KPI measurement where the distance travelled per tour is used as a measure of the performance of the vehicle that will minimise the cost. Kara et al. (2007) recently proposed a cost function that also considers the vehicle load factor to identify the best route for the Capacitated Vehicle Routing Problem that minimises the energy consumption using a weight-distance measurement.

KPI measurement is focused towards the evaluation of effectiveness of specific or individual criteria that need to be analysed separately. Mason. Simons and Gardner (2001) and Simons, Mason and Gardner (2004) have proposed a new metric that can measure the effectiveness of a vehicle in a single metric, called the Overall Vehicle Effectiveness (OVE) measurement. This measurement, founded in the lean thinking approach, aims to reduce wasteful activities and is useful when determining areas for potential improvement. However, this measurement incorrectly assesses round trip schedules as it tends to increase the energy consumed by the vehicle. As a result, Guan et al. (2003) have attempted to modify this metric by adding the time utilisation function to the performance criteria known as the Modified Overall Vehicle Effectiveness (MOVE). The performance behaviour of OVE and MOVE measurements and KPI's was debated at the Freight Logistics Research Group, November 2004 meeting.

In light of the above, this thesis is interested in examining the impact of the OVE and MOVE on the transportation cost function used to determine the total cost in the periodic 'can-deliver" model. Accordingly, the comparison was made between OVE and MOVE metric and the Travelling Salesman Problem approach in terms of cost, distance and energy consumption of the vehicle.

The relevant KPIs, OVE and MOVE metrics are discussed in detail in sections 6.2, 6.3 and 6.4 respectively. This is followed by a numerical illustration of these three measurements for 2 and 3 retailers in section 6.5. Next, a new transportation cost function is presented in section 6.6, followed by the description of a modified spreadsheet simulation in section 6.7. Section 6.8 evaluates the performance of all three metrics in terms of distance, vehicle energy, vehicle effectiveness with a new cost function. The effect of the IRP model is analysed using the recommended vehicle effectiveness measurement with different transportation cost variables in section 6.9. The discussion continues in Section 6.10 with the examination of the effect of different demand distribution patterns and weight converter values on the behaviour of the proposed IRP model, to examine the external validity of the study. These analyses attempt to answer research question 3 by observing the effect of different routing used in the periodic "can-deliver" policy.

6.2 Key Performance Indicators (KPIs)

This study was specifically interested in analysing two KPIs related to the distance and energy consumed by the vehicle. The minimum distance travelled by the vehicle can be determined by solving the Travelling Salesman problem using the brute-force approach based on the route generated in section 5.2 for small instance such as we use in present study. Similarly, the brute-force approach is adopted in determining the minimum energy consumption criterion in this chapter. The best route can be determined using the TSP concept, however the decision now takes into account the vehicle weight load carried as well as distances travelled in order to minimise vehicle energy consumption throughout the trip. According to Kara et al. (2007) the vehicle weight has an impact on the energy used by the vehicle, often referred to as the fuel usage. Vehicles with high weight tend to use more fuel thus reducing the miles per gallon achieved by the vehicle. Coyle (2007) reported that the miles per gallon (MPG) when 26 and 32 tonne vehicles were fully loaded was almost half that of the MPG when running empty vehicles. However, the energy consumed in terms of litres per tonne per kilometre is increased as the vehicle

As the weight of the vehicle changes throughput the trip according to the deliveries to the retailers, it is crucial for the decision-maker to determine the best order of deliveries throughout the trip to minimise the energy consumed based on the un-laden vehicle weight, distance between the delivery points as well as the weight delivered to each of the retailers. The total weight-distance measurement for the multi-retailer replenishment scenario is as follows:

$$wd_t = \sum_{i=1}^{n} \left(d_{i-1,i} \left(v + \sum_{j=i}^{n} w_j \right) \right) + v * d_{n,0} \tag{33}$$

Where

wd_t = total weight-distance of delivery trip at time t

v = un-laden vehicle weight

w_j = weight of replenishment for retailer j

$d_{i,j}$ = distance between location i and j where index 0 represents the base point,

index 1 is the first retailer visited during the delivery trip and so on.

$d_{n,0}$ = distance between last retailer and the base

n = number of retailers

6.3 Overall Vehicle Effectiveness (OVE)

Simons, Mason and Gardner (2004) adopted the OVE measurement from the Overall Equipment Effectiveness (OEE) metric. The OEE metric was historically used in the manufacturing industry to measure the effectiveness of machines. It was developed by Seiichi Nakajima based on the Total Productive Maintenance (TPM) concept, (William, 2007). It focuses on eliminating six main classes of equipment waste that can be categorised into downtime, speed and quality losses. Figure 6.1 is a diagram of the OEE tool illustrating the relationship between losses and the equipment performance as illustrated in Muchiri and Pintelon (2008).

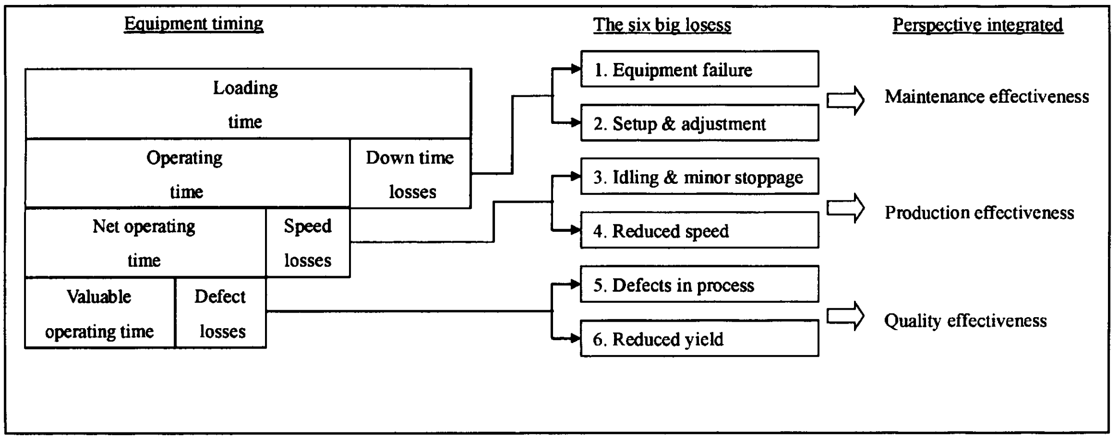


Figure 6.1: The OEE metric with 6 major losses in the equipment process

Muchiri and Pintelon (2008) differentiated between the effectiveness and efficiency measurement and concluded that the OEE metric is classified as a measure of effectiveness since it measures the actual performance against the expected performance of the equipment, (ibid). It can be calculated based on the availability, performance and quality factors as equation (34)

$$\text{OEE} = \text{Availability} * \text{Performance} * \text{Quality} \tag{34}$$

These factors are related to the six main equipment losses where the availability rate is a measure of the percentage of the available time the machine produces good work by considering the total downtime caused by the equipment failure and the setup or adjustment time. The performance rate of the equipment in the period available to produce the product can be affected by idle time or speed reduction. The quality rate is determined by taking the defect and yield losses into account. This basic effectiveness measurement which is limited to measuring individual pieces of equipment, has led to the development of improvement measurements which look at wider aspects, such as the total equipment effectiveness performance (TEEP), production equipment effectiveness (PEE), overall factory effectiveness (OFE), and overall asset effectiveness (OAE) (Muchiri and Pintelon, 2008).

Simons, Mason and Gardner (2004) expanded this performance measurement approach into the field of logistics by using it to measure the total effectiveness of a vehicle with a single measure. A similar concept to OEE is used where the availability, performance and quality are three main factors to calculate the new metric called Overall Vehicle Effectiveness (OVE). This performance measure, inspired by the lean thinking approach, is used to optimise the value adding activities and eliminate the non-value adding activities in road freight transport. With OVE, wasteful activities in the delivery process that can reduce the effectiveness of a vehicle can be identified and eliminated. Simons, Mason and Gardner (2004) found that the value-adding activities in transport are affected by five main losses. These include the extra time used to load and unload a vehicle above the standard load time as well as the vehicle's fill loss, speed loss and quality loss. The total performance is measured in terms of an overall percentage and the identification of the most important activity to reduce is given by the factor that has the lower percentage. The OVE metric uses weight-distance, as it is a common road-freight transport KPI, to evaluate the vehicle's energy efficiency (Aylward and O'Toole, 2007).

6.3.1 The availability rate

The availability of the vehicle is the percentage of the actual vehicle's weight distance (after considering the loss time caused by the waste activities, such as excess loading time) compared to the planned weight distance as shown in equation (35) below:

$$\text{Availability} = \frac{\text{actual weight distance}}{\text{planned weight distance}} \tag{35}$$

where the

(Actual weight distance) = (planned weight distance) – (loss weight distance) (36)

The planned weight distance and loss weight distance are calculated as follows:

$$\text{Planned weight distance} = \begin{pmatrix} \text{Planned time (min)} * \text{ optimal vehicle speed (km/min)} \\ * \text{ vehicle capacity (weight)} \end{pmatrix} \quad (37)$$

$$\text{Loss weight distance} = \begin{pmatrix} \text{Loss time (min)} * \text{ optimal vehicle speed (km/min)} \\ * \text{ vehicle capacity (weight)} \end{pmatrix} \quad (38)$$

Hence, equation (35) can be simplified as $\left(1 - \dfrac{\text{loss time}}{\text{planned time}}\right)$ where the value of loss time is supposed to be less than the value of planned time. The planned time, of course has to account for the statutory breaks during the journey.

Figure 6.2 is a diagram of the OVE availability factor.

Planned weight distance	
Actual weight distance	Loss weight distance

← Availability →

Figure 6.2: OVE availability

6.3.2 Performance

The performance factor is evaluated by the capacity and the speed rate of the vehicle. The capacity rate is measured based on the total weight-distance carried by the vehicle to visit all delivery points against the actual weight distance as equation (39):

$$\text{Capacity rate} = \frac{\text{total weight distance carried}}{\text{actual weight distance}} \quad (39)$$

The total weight distance carried is calculated based on the total distance travelled and the weight carried by the vehicle along the trip, similar to the energy consumption calculation in equation (33), but the total weight-distance in this situation is determined without the vehicle un-laden weight as in equation (40) for the case of direct delivery and equation (41) for multi-retailer scenario:

$$wd_t = w_j * d_{0,1} \tag{40}$$

$$wd_t = \sum_{i=1}^{n}\left(d_{i-1,i}\left(\sum_{j=i}^{n} w_j\right)\right) \tag{41}$$

The speed rate measures the average speed used by the vehicle compared to the optimal speed that is allowed for the vehicle as in equation (42).

$$\text{Speed rate} = \frac{\text{Actual average speed (km/min)}}{\text{Optimal average speed (km/min)}} \tag{42}$$

where

$$\text{Actual average speed} = \frac{\text{Total distance travelled (km)}}{\text{Travelling time (min)}} \tag{43}$$

The travelling time is the actual time the vehicle spends on the route after taking into account the transport losses time such as the loading and unloading time from the whole replenishment planned time. As a result a lower actual average speed will occur if the lost time is low which will increase the travelling time value. Hence, the performance rate of the vehicle can be computed by:

$$\text{Performance rate} = \text{speed rate x capacity rate} \tag{44}$$

A diagram of OVE performance rate presented in Figure 6.3 below

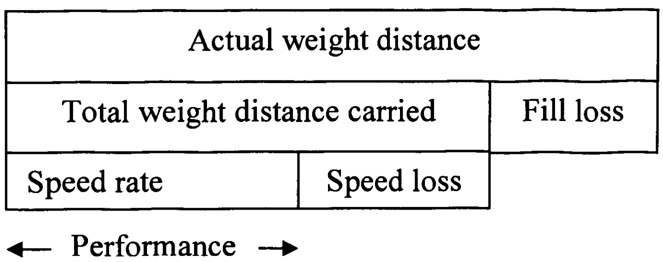


Figure 6.3: OVE performance

6.3.3 Quality

The third factor that is important when evaluating the vehicle performance is the quality of the output, which can cause additional losses, such as time delays and reductions in the total weight distance carried by the vehicle if any problem occurs along the process. For simplicity, the quality rate in the model is assumed at 95%, as this effect is outside of the model boundary in this study.

6.3.4 OVE

The overall vehicle effectiveness can be computed by multiplying the percentages of availability rate, performance rate and quality rate as shown in equation (45):

$$\text{OVE (\%)} = \text{availability (\%)} * \text{performance (\%)} * \text{quality (\%)} \tag{45}$$

A diagram of these three factors with their wasteful activities is shown in Figure 6.4. Some issues occur when using the OVE metric as some wasteful activities are incorrectly classified as value adding activities. The determination of the optimal vehicle speed and quality level is a subjective measurement based on several factors. However, it is not a major problem as it can be overcome by making a clarification based on common logistics procedures and standard measurements, such as the national speed limit.

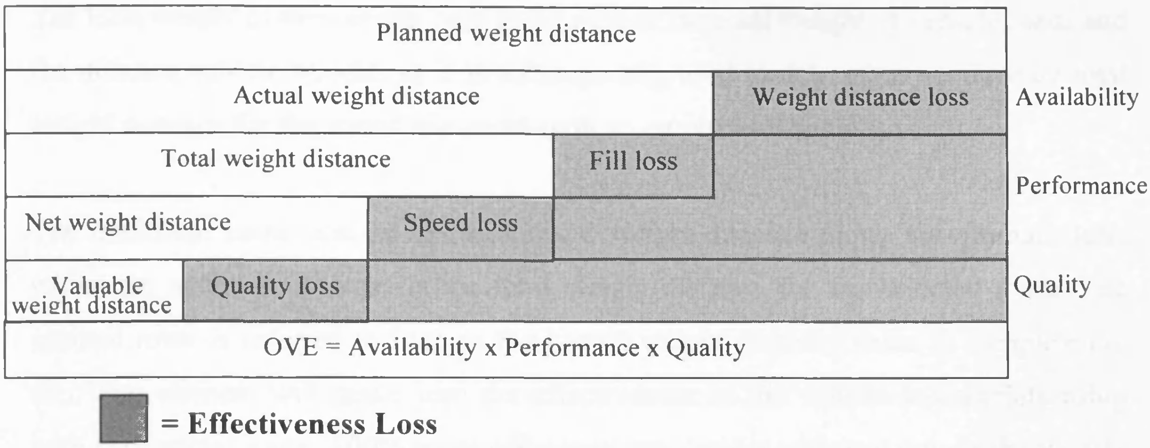


Figure 6.4: OVE diagram

A study by Simon, Mason and Gardner (2004) has revealed that the OVE metric raised a problem with regard to the round trip since the highest effectiveness occurred on trips with the highest weight-distance value. Therefore, Guan et al. (2003) suggested that the OVE metric should first determine the optimal route of the vehicle before the OVE metric is used in order to achieve the correct optimal route decision.

6.4 Modified Overall Vehicle Effectiveness (MOVE)

Guan et al. (2003) made an effort to improve the OVE metric by introducing a new metric called the Modified Overall Vehicle Effectiveness (MOVE) metric. They found that the problem in OVE metric is due to lack of focus on measurement of vehicle effectiveness in that wasteful activities occur when a non- efficient route is selected. They therefore included a route efficiency component as one important additional aspect of the vehicle performance rate.

The efficiency of the selected route in terms of weight distance measurement can be calculated as:

$$\text{Route efficiency} = \frac{\text{minimum route cost (weight - distance)}}{\text{actual route cost (weight - distance)}} \qquad (46)$$

The total weight of the vehicle here is the sum of the total weight of vehicle loads and the unladen vehicle weight, as it is subsequently used to determine an accurate total weight distance for the round trip, even with an empty backhaul.

The minimum route cost is the minimised weight-distance along an optimal route, whilst the actual route cost is the total weight-distance for the selected route. The optimal route is referred to here as the lowest weight-distance value to complete the trip. This element will make sure the effectiveness of the vehicle has a relationship with the optimal route; 100% route efficiency rate can be achieved only if the vehicle follows the optimal route for the trip.

The MOVE metric also determines the effectiveness of the vehicle by evaluating time efficiency that is, the minimum theoretical time to complete a tour compared to the actual time for the trip including the value-adding and non-value adding activities (see equation 47 below):

$$\text{Time efficiency} = \frac{\text{Shortest possible time (min)}}{\text{Actual time taken (min)}} \qquad (47)$$

The shortest possible vehicle travel time is based on the time taken to complete the tour following the optimal route according to the optimal vehicle speed, with time allocated for other value-added activities and legal requirements. The speed rate measurement used in the OVE metric is modified in the MOVE metric to evaluate the time aspect of vehicle effectiveness.

This MOVE metric also modifies the vehicle capacity rate measurement in the OVE metric with another measurement factor that will give an appropriate measurement to evaluate the vehicle capacity aspect. This new factor measures the capacity carried by the vehicle against the available capacity for that vehicle, and takes into account the distance travelled as well as the weight carried along the optimal route. Thus,

$$\text{Vehicle utilisation} = \frac{\text{optimal route weight - distance (weight - distance)}}{\text{planned available weight - distance (weight - distance)}} \qquad (48)$$

The quality factor remains the same in the new metric to evaluate the quality of the vehicle performance and takes into account factors that can reduce vehicle effectiveness due to failure or error occurring during the delivery process.

Therefore, the MOVE metric can be calculated by multiplying together all the defined factors as follows:

MOVE = Vehicle utilisation x Time efficiency * Route efficiency * Quality (49)

Computation of the MOVE metric has been explained in detail by Guan (2002). His study also evaluated the performance of OVE and MOVE metrics in terms of various factors such as validity, robustness, usefulness, integration, economy and compatibility. In general, the finding from the study by Guan (2002) shows that the MOVE metric outperforms the OVE metric in determining the most efficient route. Further, the MOVE metric can be modified according to organisational requirements and it is possible to extend it for use in measuring performance in other logistical scenarios. This is because with the structure of the MOVE metric, it is possible to add other elements to the existing factors (see Figure 6.5).

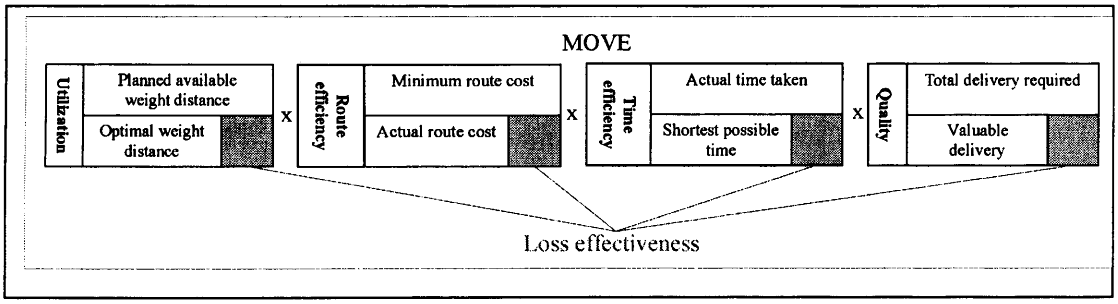


Figure 6.5: The components of MOVE

6.5 Numerical example

The analysis begins with a numerical example for the MOVE and OVE metrics based on the theory previously discussed in Section 6.3 and 6.4.

First, the evaluation of the OVE and MOVE metric's effectiveness percentage is demonstrated based on a simple example involving 2 retailers. The distance between each retailer and the base point and retailers' weight requirement is based on the layout shown in Figure 6.6. Here, the distance between each point is assumed to be symmetric, that is, the total distance is similar for both directions and the unit used for weight of the product is in kilograms (kg). The calculation is determined based on sample input data shown in Table 6.1.

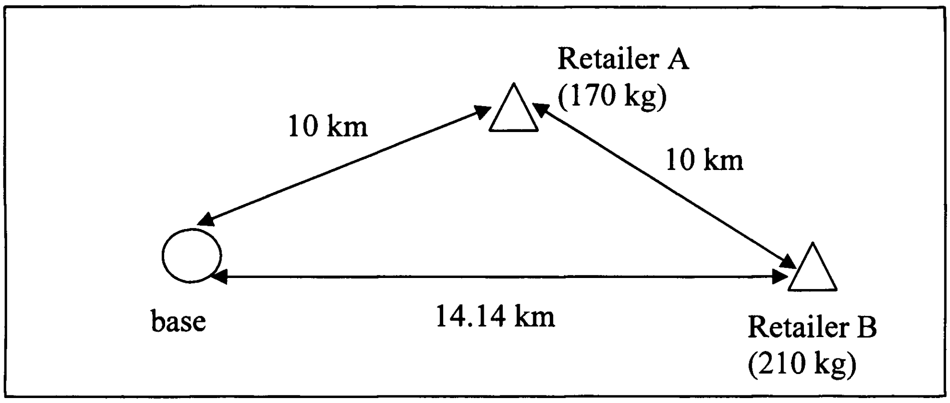


Figure 6.6: Retailers' layout and weight requirement

Table 6.1 Input data for the performance measurement calculation

Input	Data
1 Maximum transportation capacity	400 kg
2 Actual journey time	70 min
3 Maximum Speed	1 km/min
4 Quality	95 %
5 Break time	15 min
6 Excess Loading time	10 min
7 Unladen Vehicle weight	500 kg
8 Available travelling time	55 min

In this case, two possible routes exist to make the replenishment and will be examined using both metrics. The vehicle has an option to choose either to replenish retailer A first followed by retailer B, or the other way around. By only considering the distance factor to determine the optimal route for symmetric cases, it seems that either routes can be chosen when minimising the distance travelled. However, the vehicle energy consumed for each route is different. This is because the load carried by the vehicle varies according to the retailers' requirements. Therefore, it is more accurate to determine an efficient route by considering both distance travelled and vehicle load which influence vehicle effectiveness and energy consumption.

To begin, the total distance travelled and the total weight-distance (both without and with un-laden vehicles) are calculated for both route options. This is done with the brute-force strategy. For simplicity, the route that leaves the base to retailer A followed by retailer B before it returns to the base is named route 1, and the opposite direction is designated route 2. The result in Table 6.2 shows that route 1 is the optimal route, with the least distance (km) and energy consumption (kg-km).

Table 6.2: The distance and weight-distance calculation for route 1 and route 2

Route 1	Distance	34.14 km	
	Weight-distance	With un-laden vehicle	=(500+170+210)kg*10km+(500+210)kg*10km +500kg*14.14km =22970 kg-km
		Without un-laden vehicle	=(170+210)kg*10km+210kg*10km =5900 kg-km
Route 2	Distance	34.14 km	
	Weight-distance	With un-laden vehicle	=(500+210+170)kg*14.14km+(500+170)kg*10km +500kg*10km =24143.2 kg-km
		Without un-laden vehicle	=(210+170)kg*14.14km+170kg*10km =7073.2 kg-km

Using the information in Table 6.1 and 6.2, the OVE and MOVE metric percentages for route 1 and route 2 can be computed using equations (33) to (44) with consideration that all activities are similar even though different routes are used for delivery. The difference in performance between route 1 and route 2 is quantified by the capacity rate in the case of the OVE metric and the route efficiency in the case of the MOVE metric. The other factors remain the same for both metrics. Table 6.3 shows the value of the availability and speed rate factors for the OVE metric whilst the utilisation and time efficiency values for the MOVE metric are shown in Table 6.4.

Table 6.3 : OVE availability and speed rate calculation

Factor	Calculation	
Availability	Planned weight distance	400 kg *1 km/min * 55 min = 22000 kg-km
	Lost weight distance	400 kg *1 km/min *10 min = 4000 kg-km
	Actual weight distance	(22000 – 4000) kg-km = 18000 kg-km
	$\therefore$ Availability	$\dfrac{18000\ \text{kg - km}}{22000\ \text{kg - km}} = 82\%$
Speed rate	Actual travelling time	55 min-10 min = 45 min
	Average speed rate	$\dfrac{34.14\ \text{km}}{45\ \text{min}} = 0.76\ \text{km/min}$
	$\therefore$ Speed rate	$\dfrac{0.76\ \text{km/min}}{1\ \text{km/min}} = 76\%$

Table 6.4 : MOVE vehicle utilisation and time efficiency calculation

Factor	Calculation	
Vehicle utilisation	Optimal route weight-distance	5900 kg-km
	Planned available weight-distance	22000 kg-km
	$\therefore$ Vehicle utilisation	$\dfrac{5900\ \text{kg - km}}{22000\ \text{kg - km}} = 26.82\%$
Time efficiency	Shortest travel time	$\dfrac{34.14\ \text{km}}{1\ \text{km/min}} = 34.14\ \text{min}$
	Shortest possible time	(34.14 + 15) min = 49.14 min
	$\therefore$ Time efficiency	$\dfrac{49.14\ \text{min}}{70\ \text{min}} = 70.2\%$

Then, the capacity rate used in the OVE calculation for both routes can be calculated as follows:

i) Capacity rate for route 1

$$= \frac{5900\ \text{kg - km}}{18000\ \text{kg - km}} = 32.8\%$$

ii) Capacity rate for route 2

$$= \frac{7073.2\ \text{kg - km}}{18000\ \text{kg - km}} = 39.3\%$$

Hence, the performance rate for the OVE metric for both routes is:

i) Route 1's performance rate = 32.8% * 76% = 24.93%

ii) Route 2's performance rate = 39.3% * 76% = 29.87%

The route efficiency for the MOVE metric for both routes is:

i) Route efficiency for route 1

$$= \frac{22970 \text{ kg - km}}{22970 \text{ kg - km}} = 100\%$$

ii) Route efficiency for route 2

$$= \frac{22970 \text{ kg - km}}{24143.2 \text{ kg - km}} = 95.14\%$$

Finally, the total OVE percentage is determined by multiplying the availability rate percentage with the performance rate and quality rate percentages as shown in Table 6.5. The MOVE values for both routes are also shown in Table 6.5.

Table 6.5 : OVE and MOVE values for route 1 and route 2

	Route 1	Route 2
MOVE	26.82%*100%*70.2%*95% = 17.89%	26.82%*95.14%*70.2%*95% = 17.02%
OVE	82%*24.93%*95% = 19.42%	82%*29.87%*95% = 23.27%

A contrast can be seen between the OVE and MOVE results in Table 6.5. Route 2 has a higher performance than route 1 using the OVE metric, but with the MOVE metric, route 1 is superior to route 2. From Table 6.5, it can be seen that the OVE metric is driven by the performance rate, 24.93% for route 1 and 29.87% for route 2. The capacity rate that contributes to the total OVE performance rate percentage is higher in the case where the vehicle has a higher weight-distance value for the trip. This suggests that the OVE metric gives more priority to heavy loads carried along longer distances since the capacity rate value is the total weight-distance divided by the actual weight-distance value. However, as has been discussed before, increasing the vehicle's weight will cause an increase in the fuel consumption. As a result, such increase may influence the vehicle operating cost and also the maintenance cost.

Further, the MOVE metric produces a higher vehicle effectiveness for route 1. Table 6.5 shows that route 2 contributes to a lower route efficiency percentage since the total weight-distance for an actual route taken is longer than the optimal, minimised weight-distance. Therefore, the MOVE metric is capable of identifying the best route that minimises the energy consumed by the vehicle. Moreover, the vehicle utilisation rate in the MOVE calculation points to the most suitable size of the vehicle to be used in order to better utilise resources and reduce wasteful activities. The vehicle utilisation rate will decrease as the vehicle size increases or as the size of the vehicle loads decrease. Figure 6.7 illustrates the effect of different maximum transportation capacities on vehicle utilisation rate and overall MOVE percentage. The effect of vehicle utilisation on the vehicle load factor will be discussed later in Section 6.7.

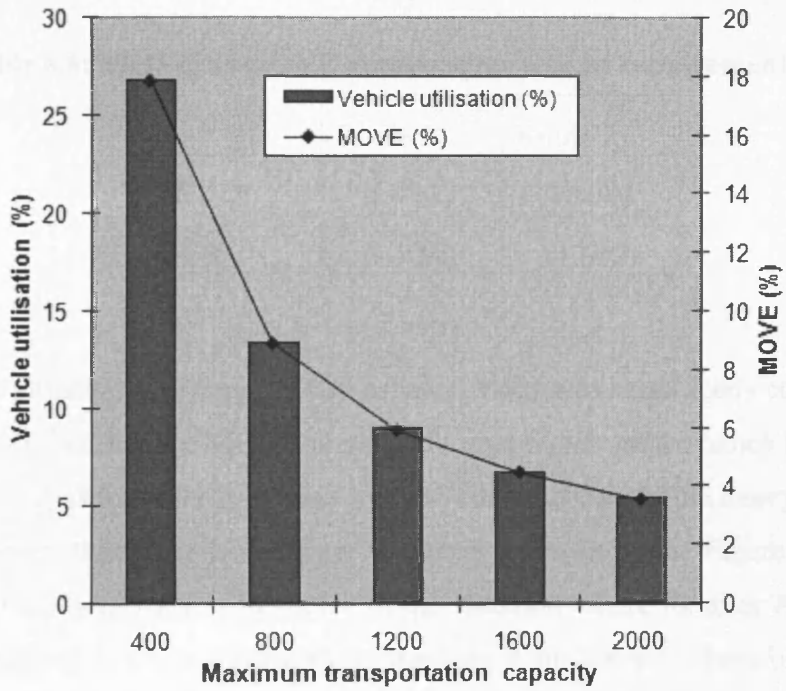


Figure 6.7: The effect of different maximum transportation capacity on vehicle utilisation rate and MOVE percentage

As can be seen in Figure 6.7, the vehicle utilisation rate and total vehicle performance decreases to almost half of the current rate by doubling the vehicle size capacity to 800 kg. The percentage is decreased further as we increase the vehicle capacity. Thus, the decrement of vehicle utilisation rate and MOVE percentage decrement is inversely proportional to the increment of maximum transportation capacity. It is suspected that the same condition also holds for the vehicle capacity rate in the OVE calculation when different vehicle sizes are used for replenishment. A large vehicle capacity will decrease the capacity rate and this influences the performance rate and total OVE score.

Next, the OVE and MOVE metrics are evaluated when the requirement of each retailer is changed by assigning the heaviest load to retailer A instead of retailer B. Interestingly, the new result shown in Table 6.6 is similar to that derived from the previous analysis. It is obvious here that route 2 produces higher weight-distance since the vehicle is carrying the total load from the base along the longer route between the base and retailer B. Furthermore, the vehicle is carrying the heavier load after making the replenishment to retailer B.

Table 6.6: MOVE and OVE results after weight requirement changes

	Route 1	Route 2
MOVE	8.9431	8.5085
OVE	9.7063	11.6071

The situation is different when retailer A requires small loads compared to retailer B. This is because the MOVE metric will give higher performance for route 2 rather than route 1, as less energy is used by the vehicle to deliver the heavy loads first at retailer B, even though it is a longer distance from the base. Figure 6.8 illustrates the 4 MOVE factors for both routes in the situation where Retailer A only requires 70 kg compared to the requirement of Retailer B of 210 kg. Therefore, the decision as to which route to use for the trip is not dependent on either distance or weight factor only but on both factors.

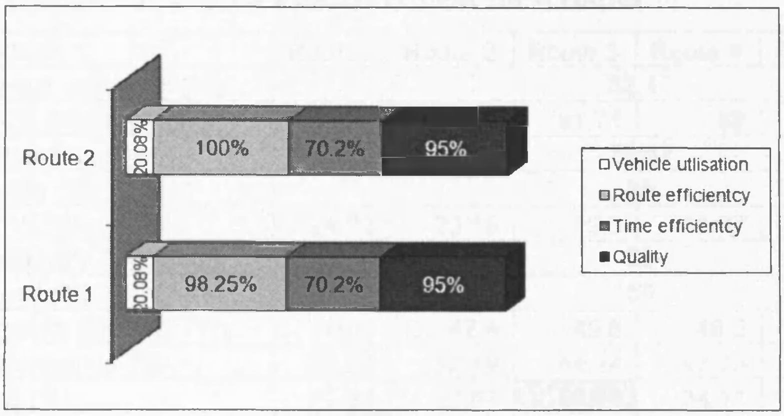


Figure 6.8: MOVE factors

So far, the OVE and MOVE metrics have been computed for equal distances between alternative routes. The analysis continues with the evaluation for 3 retailers where different total distances occur when a vehicle chooses a different sequence of retailers during the trip. With a similar physical layout as in section 5.2, there are two possible total distances for 6 different route combinations.

The results for 6 alternative routes, including the distance travelled and the total weight-distance are summarised in Table 6.7 for conditions when the loads required for retailers A, B and C are 190 kg, 240 kg and 200 kg, respectively. The same data is as used in Table 6.1, except the maximum vehicle capacity is now set to 700 kg to make sure the vehicle capacity is related to the total loads required at all three locations. The route combinations are represented as routes 1 to 6, and the replenishment sequences for each route are as follows:

Route 1 : base – retailer A – retailer B – retailer C – base

Route 2 : base – retailer A – retailer C – retailer B – base

Route 3 : base – retailer B – retailer A – retailer C – base

Route 4 : base – retailer B – retailer C – retailer A – base

Route 5 : base – retailer C – retailer A – retailer B – base

Route 5 : base – retailer C – retailer B – retailer A – base

Table 6.7 MOVE, OVE and KPI measurement for 6 routes

Metrics	Factors	Route1	Route 2	Route 3	Route 4	Route 5	Route 6
MOVE	Vehicle utilisation (%)	32.47					
	Route efficiency (%)	99.39	83.2	81.71	82	82	100
	Time efficiency (%)	78.57					
	Quality (%)	95					
	MOVE (%)	24.09	20.16	19.8	19.87	19.87	24.24
OVE	Availability (%)	82					
	Speed (%)	89					
	Capacity rate (%)	40.3	47.4	49.6	49.2	46.9	39.7
	Performance (%)	35.87	42.19	44.14	43.79	41.74	35.33
	OVE (%)	27.94	32.87	34.39	34.11	32.52	27.52
KPI'S	Distance (km)	40	48.28	48.28	48.28	48.28	40
	Weight-distance (kg-km) with unladen vehicle	32700	39061.6	39776.2	39634.8	38920.2	32500

The routes that give highest performance for all metrics are highlighted in the Table 6.7. It can be seen that route 6 is the best route using the MOVE metric, whilst the OVE metric allocates the highest performance to route 3. The optimal route determined by the MOVE metric is based on the minimum distance travelled and weight-distance carried by the vehicle. Using the OVE metric, routes having higher distances tend to contribute to a high weight-distance value to maximise vehicle performance.

Hence, the examples show that the MOVE metric outperforms the OVE metric as it minimises the vehicle distance travelled and energy consumed. The impact of the MOVE and OVE metrics and TSP approach in terms of cost will be discussed in the Section 6.8.

6.6 New transportation cost function

As the OVE and MOVE metrics measure the vehicle performance in terms of weight-distance, a new transportation cost function is needed to replace the previous transportation cost function, which only takes into account the distance travelled as a factor in the calculation of transportation cost. In the development of a new cost function, other factors related to transportation activities and the delivery process, which may influence the cost. These will now be considered.

In general, transportation costs can be categorised into fixed and variable costs, (Rushton et al., 2006; and Coyle et al., 1999) classified these costs as the direct costs. Various cost functions have been used to determine the cost of transportation in multi-retailer situations, probably because of the different problems and objectives which need to be solved. For example, Burns et al. (1985) considered three different cost components for the transportation cost function, including fixed cost incurred at the beginning of the delivery time, variable cost related to the distance travelled, and fixed cost charged for each stop at their customers. Qu et al. (1999) employed a similar cost function to Burns et al. (1985), which also considered the travelling costs corresponding to the distance travelled and stopover costs excluded from the fixed cost. In contrast, Yu et al. (2008) considered the delivery trip as a fixed cost for each tour made instead of a measure based on the distance travelled. Yu et al. (2008) also included the cost of the empty vehicle travelling from the last customer to the depot, and the shipping cost per unit product in their model cost function. Bolduc et al. (2008) and Chu (2005) included the cost of the carrier in the cost function in the case when an external carrier is used for delivery instead of using the organisation's own private truck. The cost per time unit used for travelling is another type of variable cost that has been used by Chan et. al (1998). The cost function proposed by Kara et al. (2007) considered both distance and vehicle weight to determine the best delivery route to minimise a vehicle's energy consumption.

Accordingly, the new transportation cost function will include the fixed costs per delivery time, a cost related to the distance travelled, the total weight of vehicle and goods delivered, and cost for each stop-over at the customers. Costs per unit travelling time is not added to the cost function since the routing model does not have a travelling time constraint in it. Rushton et al. (2006) indicates that basic driver wage costs are usually considered a fixed cost since the payment is made to the driver based on a fixed monthly basis and not associated with the delivery activities, unless for overtime working. Also, the external carrier cost is not relevant since only one private vehicle is used in the IRP model.

The basic notations for the transportation cost are defined as follows:

C = Transportation cost

Cf = Fixed transportation cost per delivery

Cwd = Delivery cost per weight-distance

wd_t = Actual weight - distance of delivery trip at time t

Cs = Fixed stop-over cost at retailer

$$y_{t,x} = \begin{cases} 1 & \text{if customer } x \text{ is replenished at time } t \\ 0 & \text{otherwise} \end{cases}$$

$$v_t = \begin{cases} 1 & \text{if delivery is made at time } t \\ 0 & \text{otherwise} \end{cases}$$

Hence, the new transportation cost function can be expressed as

$$C = \sum_t Cf * v_t + \sum_t (Cwd * wd_t) + \sum_{t,x} (Cs * y_{t,x}) \qquad (50)$$

The fixed cost, Cf, that is incurred in each delivery time will increase when the number of replenishment frequencies is increased, which is based on the Boolean decision variable, v_t. The delivery cost per weight-distance, C_{wd}, is a variable cost that is related to the vehicle running cost. This may include fuel, lubricants, tyres and maintenance costs. This cost can be minimised by travelling along the minimum distance-weight route that consumes less energy. Figure 6.9 illustrates the general behaviour of the three elements of the transportation cost. However, there is a relationship between the weight-distance and the number of retailers since the weight-distance may be higher when the number of retailers is included in the trip is increased.

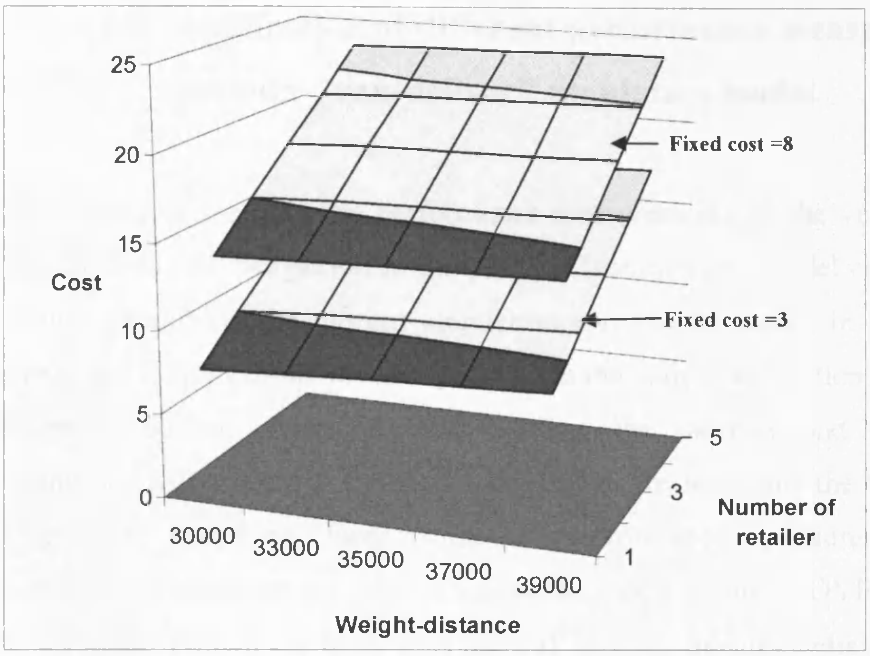


Figure 6.9: Trade off between fixed cost and variables' cost in the transportation cost function

With the new transportation cost function, the total cost function can be formulated as

$$TC = \sum_{t,x}(I_{t,x} * h) + \sum_{t,x}(Sh_{t,x} * p) + \sum_{t} Cfv_t + \sum_{t}(Cwd * wd_t) + \sum_{t,x}(Cs * y_{t,x}) \qquad (51)$$

where

TC =Total cost

$I_{t,x}$ = inventory on hand at each retailer location, *x*, at the end of period, *t*

h= cost to hold a single unit per unit inventory

p= charge per unit shortage supply

$Sh_{t,x}$ = quantity of backlog inventory at the end of period, t , in each location, x

The total cost per period over total number of periods in a simulation, *T*, is given as:

$$TC = \frac{\sum_{t,x}(I_{t,x} * h) + \sum_{t,x}(Sh_{t,x} * p) + \sum_{t} Cf * v_t + \sum_{t}(Cwd * wd_t) + \sum_{t,x}(Cs * y_{t,x})}{T} \qquad (52)$$

6.7 Application of different performance measurements to the periodic "can-deliver" simulation model.

The impact of the different performance measurements on the vehicle effectiveness and the total cost per period in the periodic 'can-deliver" model can be evaluated by slightly modifying the current simulation spreadsheet model in section 5.4.1. The inputs and outputs of the inventory model in the current simulation model, such as the inventory control parameters and holding, the shortage and the replenishment quantities, will remain the same. Adjustments are made for the transportation cost calculation involving three different performance measurement approaches. Additional worksheets are used to assign the inputs for the MOVE and OVE metrics in the model (which currently uses the TSP metric). Specific cells are used to display the outputs of each performance measurement in terms of transportation costs, total costs, vehicle effectiveness, total distance travelled, and energy consumed by the vehicle in order to make comparisons and determine the best approach that can minimise the cost as well as the vehicle's energy consumption.

The first step to evaluate the transportation cost using weight-distance measurement is to convert the retailers' replenishment quantity that had been computed earlier into a weight measurement unit. Generally, the weight of the product (mass) can be computed according to the density and the volume of the product as in equation (53):

$$\text{mass}(kg) = \text{density}\left(\frac{\text{kg}}{\text{m}^3}\right) * \text{volume}(m^3) \tag{53}$$

However, different types of product have different densities. The average density of the product needs first to be determined by comparing its actual total weight with the total volume of products. For example, the Florida Department of Environmental Protection measured the amount of waste in tons at a construction and demolition (C&D) debris facility based on the average density, by dividing the actual weight of 171 different loads with the volume of loads in cubic yards. Similarly, Dicke and Parker (2007) determined the weight of three types of pine timber products in tons by multiplying the volume with the standard weight for one unit of each type of product. Accordingly, the periodic "can-deliver" model was simplified by assuming that one item quantity was equivalent to 10kg of weight unit as the starting point of the analysis.

The new calculation process was more complex than that used in Chapter 5 since the decision regarding the best route for the replenishment trip required many different steps and formulas as discussed earlier in Section 6.3 and Section 6.4. Basic functions in Excel like IF..THEN..ELSE that had been used previously in Chapter 5 were not appropriate for computing the results. It was more practical to define specific functions that could automatically determine the vehicle effectiveness percentage and the energy consumption of best route for MOVE and OVE metrics. This function could be created as a Custom Function or User Defined Function (UDF) in Visual Basic Application (VBA). It could be accessed in Excel just like using a standard Excel's functions or add-in functions, e.g. SUM ( ) and AVERAGE ( ). The UDF was created in the VBA module window using the syntax shown in Figure 6.10.

```
Function Functionname (varName1 As vartype,..........., varNamen As vartype)
        ' body of the unction
         [ statements ]
        ' return statement
        [Functionname = expression]
End Function
```

Figure 6.10: Syntax of User Defined Function

The complex procedure to determine the result involving a group of statements that contained different types of mathematical and comparison operators was defined in the body of the function. The result that is computed in the body of the function is returned to the Excel via the Functionname by assigning the required input variable using this structure: function will return the value that is assigned by expression to the function name when it called in Excel using this structure:

= Functionname(value_1,....,value_n)

where value1,..valuen can be either a constant value or the cell reference in Excel as a passing arguments to the function.

Seven different User Defined functions were created to determine the minimum distance, minimum weight-distance, vehicle effectiveness and the total weight-distance for the best route based on MOVE and OVE metrics and the TSP approach. These functions were used in each simulation period to determine the vehicle effectiveness, transportation costs and total costs for MOVE, OVE and TSP measurements. A similar approach had been used in Chapter 5 for the numerical analysis where 3 replications were carried out using 5000 warm up periods and 60, 000 simulation periods. The end results of the analysis were average costs per period and the average vehicle effectiveness from 3 replications.

6.8 Numerical analysis

This section describes further investigation of the impact of the optimal route that was generated from the OVE and MOVE metrics and TSP approach on vehicle energy, vehicle effectiveness and a new cost function. Three retailers are considered to be included in this analysis based on the supply chain physical layout presented in Figure 5.3. The first numerical analysis to compare the performance of these three measurements was based on the following assumptions:

i) Constant inventory control parameters and cost parameters.

ii) Only one vehicle was used for replenishment with a 2000kg maximum vehicle capacity. The vehicle unladen weight, average speed and other input data, including break time as well as the quality rate, were similar to the data used in Section 6.5.

iii) The route used to replenish retailers in the TSP approach was based on the lexicographical order of retailers (Retailer 1, Retailer 2 and Retailer 3) since the distance between each point was symmetric.

Table 6.8 shows results generated from OVE and MOVE metrics and the TSP approach for 20 simulation periods. It covers the scenario of replenishment involving different numbers of retailers. It can be seen that there is a relationship between the number of retailers in a single delivery trip and the total weight-distance. The optimal weight-distance value in all cases for one retailer is less than the total value for two retailers. The weight-distance to replenish three retailers is the highest. The proportion of the three elements of transportation cost, shows that the fixed transportation cost is charged every time the delivery is made, even to replenish just one retailer.

Accordingly, it is more economical to consolidate other retailers during the replenishment trip and thereby reduce the frequency of replenishment activity and eliminate the fixed delivery cost.

Further, increasing the number of retailers up to 3 retailers will influence other elements of the transportation cost. Therefore, it is crucial for the decision-maker to determine the route and sequence of replenishments that use the lowest energy in order to minimise the total delivery cost. Different delivery costs are incurred with different strategies used to determine the best route for the delivery.

In general, as expected the transportation cost generated by the OVE metric was higher than the results calculated using MOVE metric and TSP approach for all cases. This phenomenon is related to the results reported in Section 6.5, where the OVE metric tends to choose the route that had a high weight-distance value in order to increase vehicle effectiveness. On the other hand, by applying the TSP approach slightly higher transportation cost was incurred than when using the MOVE metric because it is tends to produce two different routes that generated minimum distance travelled in the case of symmetric layout. However, the total weight-distance value for each route differs with a different sequence of delivery due to different loads required at each retailer. Therefore, by using the same route for each replenishment activity with a similar number of retailers might produce an additional weight-distance value.

Table 6.8: The comparison of transportation cost obtained from the OVE and MOVE metrics and TSP approach when *Cf* =5, *Cs* =3 and *Cwd* =0.0005

Period	Replenishment weight				Fixed delivery cost	Stopover cost	OVE			MOVE			TSP		
	Retailer 1	Retailer 2	Retailer 3	Total			weight-distance	Delivery cost	Trans cost	weight-distance	Delivery cost	Trans cost	weight-distance	Delivery cost	Trans cost
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	220	200	230	1150	5	9	41083.2	20.5	34.5	32900	16.5	30.5	33100	16.6	30.6
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	190	150	210	1050	5	9	38886.4	19.4	33.4	30800	15.4	29.4	31200	15.6	29.6
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	200	0	260	960	5	6	25346.4	12.7	23.7	24498	12.2	23.2	25346.4	12.7	23.7
7	0	210	0	710	5	3	17109.4	8.6	16.6	17109.4	8.6	16.6	17109.4	8.6	16.6
8	220	0	180	900	5	6	24180.8	12.1	23.1	23615.2	11.8	22.8	23615.2	11.8	22.8
9	0	220	0	720	5	3	17250.8	8.6	16.6	17250.8	8.6	16.6	17250.8	8.6	16.6
10	220	0	200	920	5	6	24380.8	12.2	23.2	24098	12.0	23.0	24098	12.0	23.1
11	0	0	0	500	0	0	0	0	0	0	0	0	0	0	0
12	190	280	210	1180	5	9	40724.6	20.4	34.4	33400	16.7	30.7	33800	16.9	30.9
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	190	200	230	1120	5	9	40359	20.2	34.2	32000	16	30	32800	16.4	30.4
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	210	190	210	1110	5	9	39934.8	20.0	34.0	32200	16.1	30.1	32200	16.1	30.1
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	240	250	190	1180	5	9	41448.8	20.7	34.7	33100	16.6	30.6	33100	16.6	30.6
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	170	250	160	1080	5	9	38378.8	19.1894	33.2	31500	15.75	29.75	31500	15.75	29.75
									Σ=341.5			Σ=313.2			Σ=314.6

Table 6.8 shows that 25% of the delivery trips followed a higher weight-distance route based on the assumption that the replenishment route to deliver all three retailers was based on the lexicographical order of retailers. It caused an extra 1.32 units of total cost in 20 simulation periods when compared with the total cost generated by the MOVE metric.

Further analysis was required to examine the percentage difference between transportation cost per period, total cost per period, and the average weight-distance using the OVE and MOVE metrics and the TSP approach.

This analysis aims to evaluate the impact of two different routes that minimise the distance travelled and the optimal routes generated from the MOVE and OVE metrics on the weight-distance, transportation cost per period, and total cost per period. To begin, the periodic 'can-deliver' simulation model was tested with 5 sets of input data using different combinations of inventory control parameters to measure the performance of each policy. The results are shown in Table 6.9. Then the percentage cost saving for MOVE metric over OVE metric and two TSP options was computed and results are shown in Table 6.10

According to the results in Table 6.9, the MOVE metric outperforms the OVE metric and TSP approach in all cases. The energy consumed during the delivery trip and the costs per period were high using the OVE metric. As shown in Table 6.10, the transportation cost per period that was generated by the OVE metric was approximately 10-11% higher than the cost generated by the MOVE metric. As a result, the OVE metric tended to generate high total costs per period. Also, the minimum distance route determined by the TSP approach appeared to consume slightly higher energy costs than the optimal value route. This was applicable to both minimum routes represented here as TSP 1 and TSP 2, since the results generated from both routes were seen to be equal to each other. However, the TSP approach showed a better performance than the OVE metric with respect to the cost saving percentage for the transportation cost per period, since for this approach it was less than 1 per cent.

Table 6.9: Simulation results for weight-distance, transportation cost per period and total cost per period for different vehicle measurement approaches when h=0.6, p=0.8, Cf=5, Cs=3 and Cwd=0.0005

Data set	Inventory control parameters			Vehicle performance measurement		Results		
	I^+	I_m	I_c			Weight-distance	Transportation cost per period	Total cost per period
1	5	1	3	OVE		31993.65	30.00	42.02
				MOVE		25748.90	26.87	38.90
				TSP	1	26000.43	27.00	39.03
					2	25999.70	27.00	39.03
2	10	2	4	OVE		31423.99	29.50	32.86
				MOVE		25488.52	26.53	29.90
				TSP	1	25741.32	26.66	30.02
					2	25741.71	26.66	30.02
3	15	4	10	OVE		27837.93	25.54	32.03
				MOVE		22375.27	22.81	29.30
				TSP	1	22608.18	22.92	29.42
					2	22607.47	22.92	29.42
4	20	2	8	OVE		19771.03	16.89	25.18
				MOVE		15812.91	14.91	23.20
				TSP	1	15994.08	15.00	23.29
					2	15993.61	15.00	23.29
5	25	12	16	OVE		22320.24	19.89	33.59
				MOVE		18289.94	17.88	31.57
				TSP	1	18520.45	17.99	31.69
					2	18519.23	17.99	31.69

Table 6.10: Performance measurement of the MOVE metric over the OVE metric and the TSP approach for 5 sets of inventory control parameters

Data set	Percentage saving					
	Transportation cost per period			Total cost per period		
	OVE	TSP		OVE	TSP	
		1	2		1	2
1	10.41	0.47	0.46	7.43	0.32	0.32
2	10.06	0.47	0.47	9.03	0.42	0.42
3	10.69	0.51	0.51	8.53	0.40	0.39
4	11.72	0.60	0.60	7.86	0.39	0.39
5	10.13	0.64	0.64	6.00	0.36	0.36

It would therefore appear that choosing the minimum distance travelled route using TSP approach might also contribute towards lower vehicle energy consumption and costs, even though it did not reach the optimal value. Interestingly, the aforementioned result contrasts with that result found by Kara et al. (2007) where minimising only distance travelled seems to increase the energy consumed by the vehicle in a symmetric scenario.

The analysis continued with an examination of the impact of flexibility by means of the periodic "can-deliver" policy on the new cost function and vehicle effectiveness based on the OVE and MOVE metrics and TSP approach. The "order-up-to" level and "must-delivery" value were fixed in order to determine the behaviour of the total cost per period for all three vehicle performance measurements with varied "can-deliver" level.

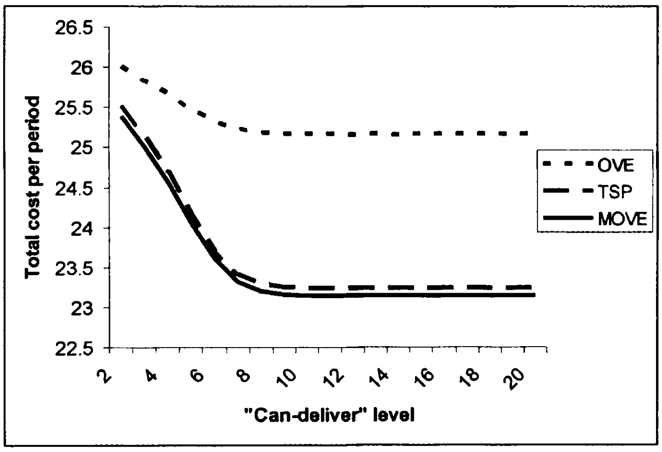


Figure 6.11: Total cost per period with varied I_c and fixed I^+ and I_m (I^+=20, I_m =2) for OVE and MOVE metrics and TSP approach

Figure 6.11 shows that IRP flexibility helps to reduce the total cost for all routing strategies. The behaviour of the new cost function was similar to the results reported in Chapter 5 where the flexibility that came from the 'can-deliver' level tended to reduce the cost. The similar graph pattern for MOVE, OVE and TSP graph patterns indicated that cost saving could be achieved; even though the delivery trip was followed was a less effective route. However, as can be seen from the figure, the OVE metric only contributed a small amount of cost reduction with replenishment coordination, whilst the MOVE metric and TSP approach gained a profit three times more than the cost reduction than the OVE metric could achieve. Further, the large gap between the OVE value and other values in the graph indicated that the optimal sequence of delivery generated by the OVE metric is an expensive way to manage replenishments. As predicted, the TSP approach produced better performance than the OVE metric. In fact the performance it produced was almost as good that produced by the MOVE metric.

This suggests that an appropriate routing strategy was needed as well as a good inventory management strategy in order to minimise the total cost.

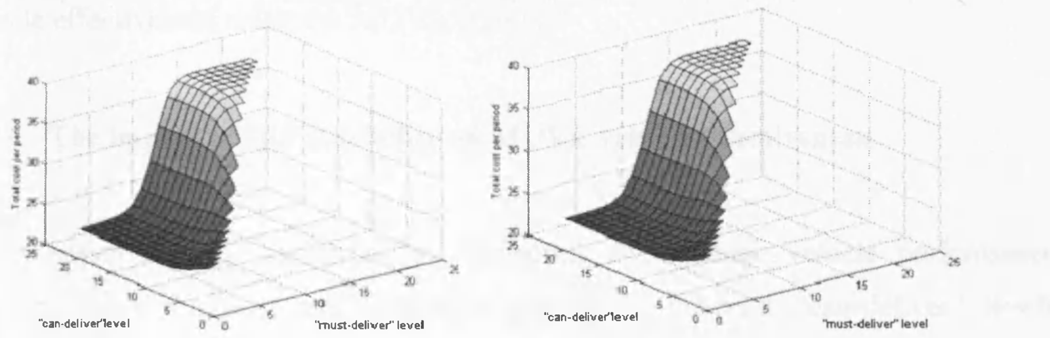
Further analysis was carried out to examine the total cost per period obtained from using the TSP approach and MOVE metric. From such analysis, the optimal inventory control parameters to minimise the total cost per period could be determined. First, the pattern for both measurements was examined when the "can-deliver" level and "must-deliver" level were varied and the "order-up-to" level was equal to 20. As can be seen in Figure 6.12 (a) and 6.12 (b), the patterns generated by the TSP approach and MOVE metric were similar to each other. Neither had a minimum total cost per period at low "must-deliver" levels. The total cost per period value was high when the "can-deliver" level was equal to "must-deliver" level. However the costs dramatically decreased when the "can deliver" level was further increased and the cost reduction levels off when the "can-deliver" level approaches 7.

Next, various "order-up-to" levels and "must-deliver" levels were analysed to observe the behaviour of the model when the "can-deliver" level was set equal to the "order-up-to" level. As in the first analysis, the results were similar for both the TSP approach and MOVE metric. It can be seen in Figures 6.13 (a) and 6.13 (b) that the minimum cost per period for both policies were in the range of 18 to 20 for the "order-up-to" level. Therefore, a further analysis was carried out to determine the accurate optimal combination of the inventory control parameters that minimised the total cost per period using the brute-force strategy. Based on the above preliminary results, the simulation was executed with the range for the "order-up-to" level parameters from between 10 to 30 units. Interestingly, the results presented in Table 6.11 indicate that the minimum total cost per period for the MOVE metric and TSP approach was generated from the same combination of inventory control parameters.

However, as had been the case earlier, the result for the MOVE metric was superior to that for the TSP approach. The results in Table 6.11 show that the cost per period for the MOVE metric was smaller than the cost per period for TSP approach. The percentage saving for one period was as follows:

$$\text{Percentage saving MOVE over TSP} = \frac{(23.0418 - 22.9528)}{23.0418} * 100 = 0.3862\%$$

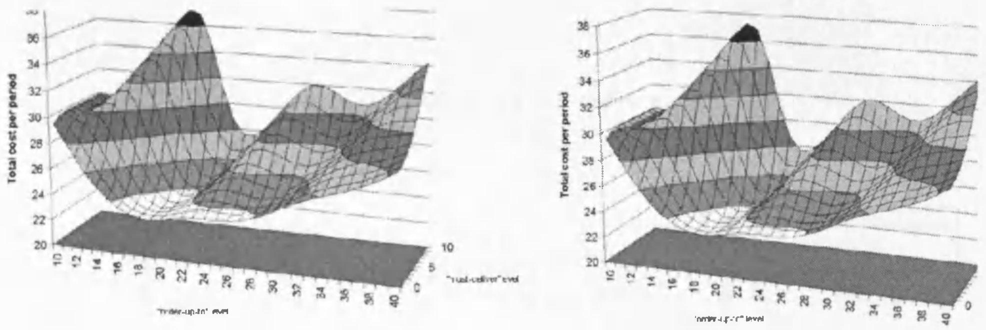
Although this would at first seem to be a small amount if margins are small, it may nevertheless result in increased profits.



(a) (b)

Figure 6.12: Varied "can-deliver" level and "must-deliver" level

(a) MOVE (b) TSP



(a) (b)

Figure 6.13: Varied "must-deliver" level and "order-up-to" level

(a) MOVE (b)TSP

Table 6.11 : Impact of optimal inventory control parameters to minimise total cost per period using the TSP approach and MOVE metric

Vehicle performance measurement	Optimal inventory control parameter			Optimal total cost per period
	I^+	I_m	I_c	
MOVE	19	0	13	22.95281
TSP	19	0	13	23.04181

The analysis also showed that the minimum total cost per period was achieved when the "can-deliver" level is 13 units higher than the "must-delivery" level. This finding suggests that IRP flexibility led to a significant reduction in total cost per period. Accordingly, analysis was expanded to examine how IRP flexibility influenced vehicle effectiveness using the MOVE metric.

6.8.1 The impact of IRP flexibility on MOVE vehicle effectiveness

The observation was conducted by measuring the average vehicle performance measurement throughout the simulation period for different "can-deliver" levels between the optimal "must-deliver" level and optimal "order-up-to" level values. The averages of vehicle effectiveness percentage and the total cost per period with varied "can-deliver" levels are shown in Figure 6.14.

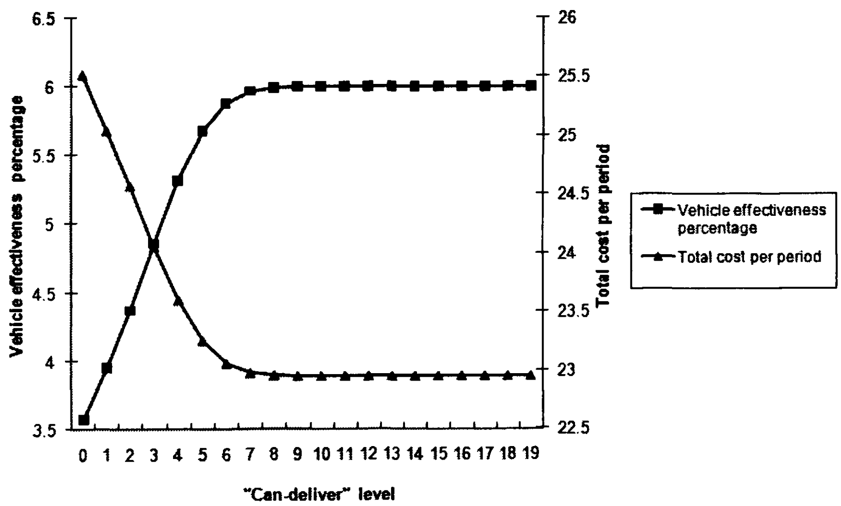
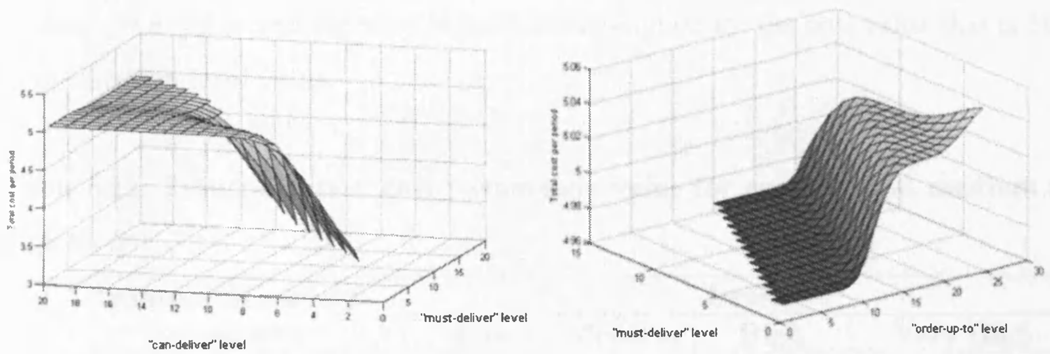


Figure 6.14: MOVE average percentage and total cost per period with various "can-deliver" levels

It can be seen from figure 6.14 that replenishment coordination improved the performance of the vehicle by approximately 40%. The vehicle effectiveness percentage dramatically increased at first until the “can-deliver” level was equal to 8 units. Then, further flexibility only contributed a small increase in vehicle performance. Interestingly, results showed that this vehicle effectiveness average behaviour pattern was connected to the total cost per period pattern. This indicated that, in general, the total cost per period had an inverse relationship with the vehicle effectiveness as would be expected.

It was anticipated that the MOVE percentage would decrease for higher “must-deliver” levels because the replenishment quantity would decrease as the “must-deliver” level increased. Similarly, the MOVE percentage would increase with higher “order-up-to” levels as the vehicle load also increased. Such phenomena are illustrated in Figure 6.15 (a) for various “must-deliver” levels and Figure 6.15 (b) for various “order-up-to” levels when the “can-deliver” level was set equal to the “order-up-to” level.



(a) (b)

Figure 6.15: Behaviour of MOVE percentage average with a) varied “must-deliver” level and varied “can-deliver” level and b) varied “order-up-to” level and varied “must-deliver” level

The behaviour of the inventory control parameters with different transportation cost parameters is explored in the next section.

6.9 Transportation cost sensitivity analysis

As indicated in Section 6.6, a new cost function was constructed with three different elements of transportation cost. These elements were a fixed delivery cost, a variable cost per weight-distance, and a cost for each customer stop-over. So far, the numerical analysis had been conducted with assumed costs. Therefore, additional analysis was carried out to determine the effect of periodic "can-delivery" model by varying these elements of transportation cost with fixed holding and shortage costs. The experiment was conducted by comparing the current cost setting used in the numerical analysis section (Section 6.8) with the different cost values for each transportation cost element as indicated in Table 6.12.

The range of the cost values that were evaluated in the analysis is divided into four different cost levels in order to evaluate the IRP model with various input values. The transportation costs setting used in the previous analysis is assigned as the medium level. The low level is assigned a cost which only a fifth of medium cost settings. Similarly, the high level is assigned with the value which is 60% higher than the medium level value and the very high level is assigned for the cost value that is 300% of the medium level value.

Table 6.12: Transportation cost parameters value for current, low, medium and high level

Transportation cost parameters	Level			
	Low	Medium	High	Very High
Fixed delivery cost, *Cf*	1	5	8	15
Delivery cost per weight-distance, *Cwd*	0.0001	0.0005	0.0008	0.0015
Fixed stopover cost, *Cs*	0.6	3	5	9

Accordingly, the number of experiments needed for the full analysis was $64(4^3)$. The evaluation criteria for this analysis were similar to the criteria used in the sensitivity analysis conducted in the previous chapter. Table 6.13 shows the optimal inventory control parameters (I^+, I_c, I_m) and total cost per period, TC, for all combinations of the transportation cost parameters.

As can be seen from the results, in general, the total cost per period increased as the level of each transportation cost parameter increased. However, the increase rate is different for the changes of different cost parameters. The impact of the changes in the cost per weight-distance parameter was higher than the impact of other transportation cost elements. As can be seen in Table 6.13, the total cost per period when the cost per weight distance parameter was at a very high level was about 46% higher than the total cost per period when the cost per weight-distance was at a low level with other transportation parameter costs at a high level. On the other hand, the cost per period increased only about 26% and 15% with regard to the changes in cost per stop-over cost parameter and fixed delivery cost parameter, respectively. The effect of changes in the cost per weight-distance and stop-over cost at low and very high delivery cost is illustrated in Figure 6.16.

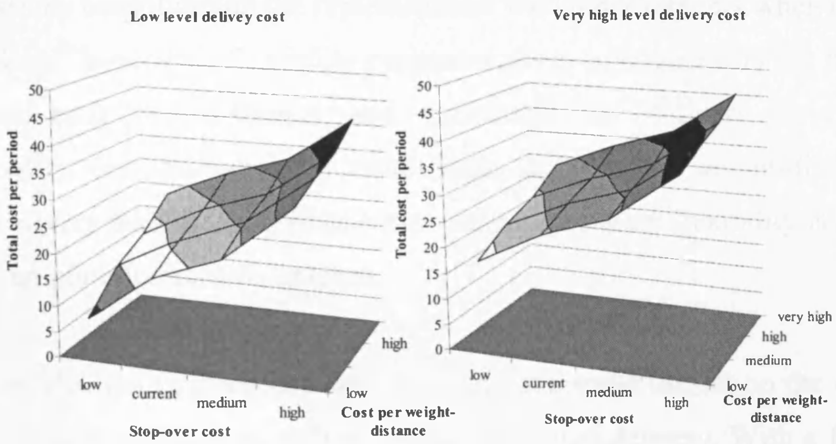


Figure 6.16: Cost per weight-distance and stopover cost effect at low and very high level delivery costs

Interestingly, the results showed that the effects to both cost per weight-distance and stop-over on the optimal inventory control parameters to minimise the total cost per period were similar. For example, in the current cost setting, the optimal inventory control was (I^+=19, I_m=0 and I_c=13). By increasing the cost per weight-distance to a very high level, the optimal inventory control was (I^+=27, I_m=0 and I_c=16). This was also the optimal combination for very high stopover cost, indicating that in general, the same plan of action might be used when changing either the cost per weight-distance or the stop-over cost.

With a low fixed delivery cost level, it is more economical to keep a minimum stock at retailers and make a frequent delivery for low weight-distance and stop-over costs level. However, a higher amount of stock is needed with an increase in weight-distance and stop-over costs to reduce the number of delivery times. Similarly, the amount of deliveries also increases the number of retailers who can be consolidated into a single delivery trip. Accordingly, it is more cost effective for retailers to hold higher stock in order to reduce the delivery frequency by increasing the "order-up-to" level and lowering the "must-deliver" level when these transportation cost parameters are increased.

Thus, it can be seen that, in general, the optimal reorder time for replenishment at very high and high cost per weight-distance (as well as stop-over cost) is when the inventory level at one of the retailers is empty. However, the cost can only be minimised by consolidating the replenishment with other retailers when they reach the "can-deliver" level. This flexibility parameter gives an opportunity for the supplier to make an early replenishment and coordinate the delivery to minimise the transportation cost. However, in some cases, the cost per weight-distance requires more flexibility than the stop-over costs. Generally, higher flexibility is required with higher transportation cost parameters.

Moreover, changes in fixed delivery cost can have some impact on the optimal stock level decision at retailers as well as on the scheduled delivery. With a fixed delivery cost that is five times higher, in general, the periodic "can-deliver" policy will tend to reduce the delivery frequency by decreasing the "must-deliver" level. There are cases where the level of coordination is increased when this reorder level is maintained. Also, dramatic changes in the order-up-to level required for retailers to minimise the total cost per period were found with a high cost per weight-distance and the stop-over cost was at medium level or vice versa. A similar pattern was discovered as the value of the fixed delivery cost parameter increased to a very high level. It is therefore practical to keep an additional stock at a retailer when the fixed delivery cost is high. It can be seen from Table 6.13 that at high fixed delivery cost, a high "order-up-to" level occurred with changes in the weight-distance and stop-over cost parameters.

Table 6.13: Transportation costs sensitivity analysis results

		Cwd															
		low				medium				high				very high			
Cf	*Cs*	Γ^+	I_m	I_c	*TC*	Γ^+	I_m	I_c	*TC*	Γ^+	I_m	I_c	*TC*	Γ^+	I_m	I_c	*TC*
	low	11	5	7	8.26603	19	2	12	17.38993	19	1	11	22.13046	26	0	14	32.42414
	medium	19	2	12	14.660789	19	1	11	20.980901	19	0	13	25.684108	26	0	14	34.919088
	high	19	1	11	17.656673	19	0	10	23.937324	26	0	14	28.051513	27	0	16	36.954353
low	very high	24	0	2	23.03524	26	0	7	28.35645	27	0	16	32.17917	27	0	16	41.02382
	low	11	5	7	12.26603	19	1	11	19.38863	19	0	13	24.10883	26	0	17	33.81032
	medium	19	1	11	16.661562	19	0	13	22.952809	26	0	14	27.35888	27	0	16	36.276175
	high	19	0	13	19.639251	26	0	14	25.603703	26	0	14	29.438002	27	0	16	38.310908
medium	very high	26	0	14	24.64955	27	0	16	29.74516	27	0	16	33.53573	27	0	16	42.38038
	low	19	2	12	14.56131	19	1	11	20.88165	19	0	13	25.58567	26	0	17	34.84987
	medium	19	1	11	18.154578	19	0	13	24.429642	26	0	17	28.398616	27	0	16	37.293592
	high	19	0	13	21.116084	26	0	14	26.64357	26	0	17	30.477694	27	0	16	39.328325
high	very high	26	0	14	25.68942	27	0	16	30.76258	27	0	16	34.55314	36	0	20	43.33221
	low	19	1	11	18.05532	19	0	13	24.3312	26	0	17	28.32934	27	0	17	37.22582
	medium	19	0	13	21.608373	26	0	17	26.99017	27	0	17	30.822898	27	0	17	39.667538
	high	26	0	17	23.957163	27	0	16	29.067087	27	0	16	32.85765	27	0	16	41.702297
very high	very high	27	0	16	28.08247	27	0	16	33.13655	27	0	16	36.92712	36	0	20	45.1797

Overall, the results showed that the appropriate inventory stock level at retailers has a strong relationship with the transportation cost elements. It is more economical to make small frequent deliveries when the transportation cost is low. However, as the cost of transportation parameters increases, optimal strategies to minimise the total cost per period are to reduce the delivery trip and keep extra stock at the retailers by increasing the "order-up-to" level.

6.10 Generalisation of results

The analysis of the proposed IRP model was based on several model parameter assumptions. This section will therefore address the issue of the model's external validity by looking at the effect of the optimal inventory control parameter that minimize the total cost, and the effect on vehicle effectiveness of different assumption parameters' values, including the demand pattern and weight converter value.

6.10.1 The Effect of demand pattern on vehicle effectiveness

The evaluation of demand distribution in terms of different vehicle effectiveness strategies in Table 6.14 shows that the MOVE metric consistently outperforms the OVE metric and TSP approaches and results in cost savings of 0.4% to 8.0%. This supports previous findings reported in Section 6.8.

Table 6.14: Performance of MOVE metric over OVE metric and TSP approach

Demand distribution	Vehicle measurements	Transportation cost	Total cost	Saving percentage of MOVE policy over OVE, TSP and TSP2
Normal (10,2.24)	MOVE	14.6012	22.9644	
	OVE	16.5890	24.9531	7.9697
	TSP	14.6905	23.0537	0.3873
	TSP2	14.6895	23.0527	0.3830
Normal (10,2.0)	MOVE	14.8383	22.7619	
	OVE	16.6177	24.7439	8.0103
	TSP	14.9182	22.8418	0.34996
	TSP2	14.9173	22.8409	0.3460
Poisson (10)	MOVE	14.6522	23.7606	
	OVE	15.1305	25.6413	7.3343
	TSP	14.7772	23.8857	0.5234
	TSP2	14.7765	23.8849	0.5202

6.10.2 The Effect of Weight Converter value

The weight converter used to measure the weight of one unit product is another parameter assumption that was included in the periodic "can-deliver" model. In the model, it is assumed that 1 unit item is equal to 10 kg. Further analysis with a lower and higher weight converter was carried out in order to generalise the result. As expected, the result in Table 6.15 shows that increasing the weight converter will increase the vehicle effectiveness without affecting the optimal inventory control parameter that minimises the total cost. However there are changes in total cost per period since the cost is the function of the weight of the product. Higher cost is incurred as a result of the higher weight-distance generated from a high weight converter value.

Table 6.15: Different weight converter factors

Weight converter	"Order-up-to" level	"Must-deliver" level	"Can-deliver" level	Total cost	MOVE (%)
15	19	0	13	24.4084	7.5428
5	19	0	13	21.4972	2.5157

6.11 Conclusion

In this chapter, the best vehicle performance evaluation metric used to identify effective replenishment routes was determined. Routes that had highest MOVE and OVE metric percentage were evaluated based on the vehicle distance travelled and the vehicle energy consumption. Results in Section 6.5 showed that the routes generated by the MOVE metric were more efficient than the routes generated by the OVE metric because the OVE metric tended towards a longer distance and higher vehicle energy route in order to increase vehicle effectiveness. Thus, the MOVE metric was capable of determining the optimal route to minimise vehicle distance travelled and energy consumed. Further, different aspects of vehicle performance that had been previously determined separately (i.e. vehicle utilisation rate) via KPI's measurement were examined using a single MOVE metric.

The study also developed a cost function that included the cost per weight-distance as a variable cost to compare the performance of MOVE and OVE metrics and TSP approach in terms of cost. The new cost function also considered the fixed delivery cost and stop-over cost as other elements of the transportation cost function. A numerical analysis was conducted using simulation and, as expected, the OVE metric generated a 10% higher cost than the MOVE metric. Interestingly, the results showed that the cost saving achieved by minimising the distance travelled using the TSP approach was less than 1 per cent higher than using the MOVE metric. As a result, both generated similar optimal inventory control parameters that minimised the total cost per period. When comparing higher optimal "can-deliver" levels with the optimal "must-delivery" level, the comparison showed that the consolidation replenishment from the IRP flexibility allowed a reduction in costs. Nevertheless, different values of the transportation cost elements influenced the decision with regard to the appropriate inventory stock level at retailers, the essential replenishment time as well as the optimal consolidation time.

A sensitivity analysis showed that, in general, it is more cost effective to keep extra stock at the retailers and increase the IRP flexibility level to reduce the delivery frequency when the transportation cost increases. It is shown that similar findings were found when different weight conversion units were used in the analysis, even though a higher weight converter value may result in higher vehicle effectiveness percentage and a cost per period value.

Next chapter will present an overview of the research, its contributions to the literature, implications of the findings for practical situations in the field, limitations of the research and the suggestions for future research.

Chapter 7 Discussion and Conclusion

This chapter presents an overview of the research findings in relation to the research objectives and research questions presented earlier in Chapter 1. The chapter begins by restating the study objectives and methodology used to conduct the research in Section 7.1. It follows with a discussion of the research findings by evaluating how the results of analysis contributed towards addressing the research questions in Section 7.2. Then, the research contributions and implications of the research for theory and practice are highlighted in Section 7.3 and 7.4, respectively. Section 7.5 discusses the limitations of the research. Finally, areas for future studies are recommended in Section 7.6. Final comments on the study are presented in Section 7.7.

7.1 Research Overview

This thesis has studied the Inventory Routing Problem (IRP) consisting of one supplier and multi-retailers which faces a stochastic demand that is assumed to be identical and independently distributed over a long planning horizon. The study indicates that the IRP inspired integrated supply chain is more beneficial in terms of cost and performance for the entire supply chain than the independent inventory management and transport planning activities in the traditional supply chain strategy.

The visibility of retailers' information such as demand and inventory levels enables the supplier to make a decision that balances inventory cost and transportation cost. Also, a centralised system of control gives the supplier the flexibility to manage the replenishment in an efficient manner. However, a review of the literature reveals a scarcity of studies on inventory control policies in IRP that permit flexibility in the decision making process. This thesis is therefore aimed to explore the effect of early replenishment on total cost and vehicle effectiveness that allow the supplier to coordinate the replenishment between the retailers.

Further, the successful application of the IRP model to reduce cost and improve customer service level in practice (Bell et al., 1983; Rusdiansyah and Tsao, 2005;

Gaur and Fisher, 2004) inspired the author to investigate the suitability of implementing the IRP approach in the healthcare industry. Specifically, this study was focused on investigating the improvement of the supply chain strategy in a developing country. This is because most academic journals and papers have studied the business process reengineering in developed countries (Wilson et al., 1992; Kowlaski, 1986). The study was also interested in examining the implications of route selection and delivery arrangement when weight was considered as a decision factor as well as the distance between two successive points.

The research analyses supported the appropriateness of the case study and simulation methods for achieving the research objectives and addressing the research questions. The case study is a relevant method to explore supply chain phenomena in the real world and examine the problem in order to evaluate the feasibility of IRP policy as a potential way of improving the supply chain strategy for the organisation. The findings from the case study also contribute towards the development of the problem formulation and the conceptual model of the research. The simulation model was considered more appropriate for this study compared to the analytical model. As indicated earlier in Chapter 3, simulation approaches make it possible to evaluate the interaction between variables for a complex system and provided valuable insight of the behaviour of the system under several inputs factor.

A discussion of how these methods addressed the research questions is presented in the next section.

7.2 Discussion on the research question

Different analysis procedures were conducted in this research in order to address the research questions. The analysis of findings with regards to the research questions stated in the introduction chapter, Chapter 1, will be discussed in the following subsections:

7.2.1 Research Question 1

Research Question 1 was

"How is the supply process carried out in the healthcare industry in the context of developing countries' private healthcare, especially in Malaysia? Can Inventory Routing Problem approaches be used to improve supply chain operations?"

This question was addressed in Chapter 4 by exploring the literature on general supply chain practices in the healthcare industry and using a single case study of a leading private healthcare organisation that owns a large chain of clinic branches in Malaysia. Very little was found in the literature on the healthcare industry's supply chain business process re-engineering in a developing county. Thus, the supply chain process and the problems faced by the case study organisation needed to be understood in order to determine an appropriate supply chain improvement strategy.

The organisation's supply chain process also needed to be investigated in order to understand the activities involved and the flow of activities between the headquarters that acted as a wholesaler and clinics. The information was gathered from interview sessions with personnel in charge of supply chain process activities in both the wholesaler and clinics and the manager of the IT department in the wholesaler. The supply chain process was visualized using process mapping tools as illustrated in Figure 4.5. The information obtained revealed that the organization still implemented a traditional supply chain policy in that each clinic placed an order with the wholesaler independently twice a month and the wholesaler was responsible for delivery based on the orders. The analysis of three months' archival data showed that the organisation faced issues with urgent orders from retailers and low stock availability at the wholesaler to fulfil clinics' orders as a result of demand uncertainty.

From a review of literature, Vendor Managed Inventory (VMI), Inventory Routing Problem (IRP), Just in time (JIT) and stockless policy were found to be possible improvement strategies to implement in the healthcare supply chain. However, JIT and stockless policy were not practical to use as the geographical locations of the wholesaler and clinics were remote from each other. The wholesaler was located in an urban area while retailers were scattered which is common in rural areas. Further, the form of transportation used for delivery was limited in terms of capacity and availability. Road congestion problems were also another factor that made these improvement strategy approaches inappropriate for implementation in a developing country such as Malaysia.

A centralised decision-making approach under a Vendor Managed Inventory would be more effective since in the traditional supply chain approaches, order quantity decisions are determined by general staff in who are not experts in managing the inventory. Transparency of information promotes efficient management of the entire supply chain. However, a VMI approach is specifically concerned with inventory management. The transportation management is managed separately and the decision on the optimal replenishment time and quantity of replenishment is not taking into account the transportation aspect. Therefore, since the decision is now made centrally, it is practical to integrate these two main activities of supply chain process to generate the optimal decision that balances inventory and transportation costs.

The case study has shown that the conventional supply chain process caused problems to both warehouse and clinics. Thus, it is suggested that IRP approach could be an appropriate as an improvement strategy for the organisation since the IRP approach allows the wholesaler to manage the entire supply chain with the aim of making it more efficient, which in turn, will minimise the cost and maximise the vehicle utilisation. The wholesaler is able to identify delivery priorities based on clinics' requirements and thereby ensure a sufficient amount of inventory is available at clinics in order to fulfill end customer demand. Further, the organisation's own transportation is used for servicing the clinics, thus the IRP approach may allow the inventory to be replenished early which can increase the utilization of vehicle use. Consequently, the wholesaler finds it beneficial to control their own inventory to ensure a sufficient amount of stock is available for retailers' replenishment.

However, the success of implementing this approach relies on IT facilities at the organisation to access the information as well as to make good replenishment decisions. These activities can be achieved by improving the existing online supply chain system and obtaining a control system to assist the decision making process. A study by Le and Koh (2002) revealed that Malaysia is capable of providing a good ICT infrastructure through the existence of Multimedia Super Corridor.

The study of research question 1 had provided evidence that the traditional approach produces problems in managing the supply chain for both supplier and retailers and the need of new practices to improve the performance of the organisation and overcome the problems. It is apparent that the IRP policy could be a suitable strategy in order to improve the healthcare industry in Malaysia, particularly by private companies who own a chains of clinics under one organisation and manage their own transportation. However, it is crucial that the central decision-maker determines the appropriate inventory policy and routing strategy to effectively implement the IRP strategy in multi-retailers supply chain scenarios that faced a stochastic demand pattern. This lead to the development of research question 2.

7.2.2 Research Question 2

Research Question 2 was

"How should the parameters in Inventory Routing be set? How should the supplier decide on which retailers should be replenished during each replenishment period?"

The first part of Chapter 5 answered this question through an evaluation of replenishment policies in the literature and the analysis from Chapter 4. From a review, several replenishment approaches were found to have been used by previous researchers, like delaying the delivery until a full vehicle load is reached, replenishing all retailers when one retailer reaches the reorder level or making replenishments to only those retailers who reach the reorder level.

As the IRP approach allows flexibility for the retailer to schedule the replenishment to the retailer, the proposed model required another parameter to facilitate flexibility. The "can-order" concept is commonly used for joint replenishment in the multi-item single supplier scenario and is appropriate to adopt for examining the effect of flexibility in multi-retailer single item scenario. The same measurement parameter for the (s,c,S) policy used in the joint multi-item scenario was employed in the proposed IRP model. However, two different terminologies were used for the parameters in the IRP situation ("can-deliver" rather than "can-order" and "must-deliver" rather than "must-order") since in the IRP context the replenishment decision is made by the supplier not the retailer. The following three parameters were used in the proposed IRP solution;

- the "order-up-to" level", I_+
- the "can-deliver" level, I_c
- and the "must-deliver" level, I_m

where $I_m <= I_c <= I_m$.

The delivery decision is made based on the inventory position at retailers, x, at the end of period, t, that has been evaluated using the inventory balance equation. At each time period, the supplier will monitor the inventory position of each retailer and note the replenishment which needs to be carried out to the retailer who has reached the must-deliver level. However, by making delivery to only one retailer the delivery trip will generate low vehicle efficiency. Thus, it is practical to replenish other retailers in that delivery trip. The "can-deliver" level can act as indicator for the supplier to make needed early replenishments and combine them with delivery to other retailers before they reach the "must-deliver" level. Thus, replenishments can be consolidated into one trip. The delivery quantity for all retailers is based on the difference between the current inventory level and the "order-up-to" level. However, no replenishment is required if none of the retailers reach the "must-deliver" level, even though all retailers may have reached the "can-deliver" level.

The replenishment policy that delivers to all retailers when one of the retailer reaches the reorder level policy is generated when the "can-delivery" level is equal to the "order-up-to" level"-1 is known as $(s,S\text{-}1,S)$ inventory control policy. The traditional inventory policy, (s,S) replenishes the individual retailer based on the reorder level which occurs when the "can-deliver" level is set as equal to the "must-deliver" level.

The traditional inventory policy scenario is used as a benchmark to quantify the benefits of early replenishment offered by the proposed periodic "can-deliver" policy. The replenishment triggered by the periodic "can-deliver" policy led to the development of research question 3 to evaluate the performance of the proposed IRP model in regard to cost and vehicle effectiveness, and to examine the effect of the policy on changes in input variables.

7.2.3 Research Question 3

Research question 3 was

"How does the proposed policy perform in the single item multi-retailer case? How do the variables influence the result?"

The behaviour of the proposed IRP model was evaluated by examining the performance input variables with respect to the total cost via simulation methods. Question 3 was addressed in Chapter 5 by performing an analysis based on three retailers and one supplier setting. The model also assumed one vehicle was used for delivery. Different combinations of inputs were evaluated throughout the analysis in order to examine the impact of input variables on the model's performance measurement. The results of varied "can-delivery" levels with fixed "must-delivery" and "order-up-to" levels in Figure 5.9 (b) show that the use of a "can-delivery" level reduced the total cost by almost 16 percent compared with the scenario when no flexibility was adopted in the replenishment decision. However, as the benefits saturates with higher "can-deliver" levels, this suggests that the proposed IRP model did not generate further benefits with very high flexibility. In fact, there was an optimal "can-deliver" level that minimised the total cost, although this was difficult to see from the graph as the percentage of different between points was rather small. The analysis of the model behavior with changes in the "order-up-to" level showed that with a consistent reorder level, increasing the maximum level of capacity at retailers decreased the total cost. However the model behavior changed when the "order-up-to" level reached a certain level. As regards the variation in "must-delivery" level, the results showed that it was more economical to trigger the delivery at a certain reorder point before the inventory reached the zero position at retailers. Further, delaying the delivery or having a large gap between deliveries dramatically increased the total inventory and transportation cost.

Further evaluation on how the three inventory control parameters ("can-deliver", "must-deliver" and "order-up-to") together with different cost parameters influenced the periodic "can-deliver" model was examined in Section 5.6.1 via Taguchi Methods. The analysis evaluated the main effects of six different factors. These were the three inventory control parameters and holding, shortage, and transportation cost, on the "can-deliver" model performance. Analysis results showed only three factors i.e. "must-delivery" level, holding cost and transportation cost influenced the model's performance. Analysis of the results from ANOVA suggested that the "must-deliver" level highly influenced the model since it generated almost 30 per cent of the variation in total cost and 23 and 18 per cent of variation in holding cost and transportation cost, respectively.

The result thus suggests that different cost settings impact on the optimal combination of parameter settings that generate minimum cost. This effect was evaluated in Section 5.6.2. The results of the sensitivity analysis of the impact on total cost per period of increasing cost parameters and inventory cost parameters was as expected, since the total cost per period increased with the increment of cost parameters and inventory control parameters. In general, it was optimal to keep extra stock at retailers by increasing the "order-up-to" level in order to prevent out of stock problems, as it is more cost-effective to replenish the retailers with larger inventories when the inventory holding cost is lower than the transportation cost. Higher stock will reduce the frequency of delivery and thus reduce the transportation cost. On the other hand, frequent delivery should be scheduled when transportation cost is lower than holding cost. This will ensure a low amount of inventory is kept at retailers. The optimal inventory control parameters that combined with a certain "can-deliver" level showed the flexibility of the periodic "can-deliver" model to be beneficial for minimising the total cost per period. The effect of each parameter was summarised using a causal-loop diagram in Figure 5.17. The comparative analysis in section 5.7 indicated that the periodic "can-deliver" model's flexibility outperformed the (s,S) inventory control policy. The findings also suggested that the cost benefit derived from the proposed

IRP model was similar to that obtained from the $(s,S-1,S)$ policy when the ratio between transportation cost and holding cost was high.

So far, the proposed model had only quantified the optimal route based on the minimum distanced travelled. However, following this route, that only considered the distance factor in the decision-making process, could possibly affect the environment. This led to the development of research question 4 in order to evaluate an appropriate routing strategy that is economically, environmentally friendly and efficient.

7.2.4 Research Question 4

Research Question 4 was

"How should the routing strategy be incorporated into the IRP to reduce cost, improve vehicle effectiveness, and reduce energy consumption?"

This question was addressed by examining the model effect with different routing strategies in Chapter 6. The Travelling Salesman Problem (TSP) approach was used in the basic routing strategy for model analysis in Chapter 5, where the optimal route was determined based on the minimum distanced travelled by the vehicle for the delivery trip. The same route was used to replenish the same combination of retailers. However, in reality different loads are carried by a vehicle at different periods of replenishment which not only influences the sequence of delivery but also vehicle energy consumption and transport efficiency. Thus, the IRP model was examined in Chapter 6 using two vehicle effectiveness measurements known as Overall Vehicle Effectiveness (OVE) and Modified Overall Vehicle Effectiveness (MOVE) metrics. Both metrics integrate different KPI's measurements that have been previously evaluated separately in a single metric measurement (McKinnon, 2000). The analysis of the optimal route in the "can-deliver" model obtained from OVE and MOVE metrics and the TSP approach in terms of the new transportation cost function was based on the spreadsheet simulation model. This new transportation cost function included fixed transportation costs per delivery, delivery cost per weight-distance and fixed stop-over cost at retailer replaced the cost per distanced traveled used in the IRP model in Chapter 5. With this new transportation cost function, the minimum transportation cost can be generated for a route that gives minimum energy consumption. In general, the OVE metric produced the highest cost compared to that produced by the MOVE metric and TSP approach since the highest vehicle effectiveness in the OVE metric was determined by the highest weight-distance value. On the other hand, the TSP approach produced better performance than the OVE metric, whilst the MOVE metric produced the best vehicle effectiveness strategy to minimize vehicle energy consumption and total cost. However, analysis of the optimal combination of inventory control parameters indicated that the same optimal combination was generated from both the MOVE metric and TSP approach. Thus, it may be concluded that the TSP approach performs as well as the MOVE metric, producing only a marginally slightly higher total cost. Nevertheless, the MOVE metric has advantages in measuring overall vehicle effectiveness in term of vehicle utilisation, route efficiency, time utilisation and quality factors in one metric.

7.3 Research Contributions

Research on the integration of inventory and transportation management through the Inventory Routing Problem approach has been undertaken previously to solve various dimensions of the problem using several mathematical modelling methods. However, existing replenishment policies in previous studies mostly view the IRP as an extension of the vehicle routing problem. Therefore, the solution method is more towards solving solely based on routing that satisfies the constraints and performance measurement. Only a small number of studies have considered including inventory policy solution methods such as (s, S), EOQ and zero ordering policy. However, few studies have explored the flexibility offered by the IRP approach to assist the central decision-maker in balancing the inventory cost and the transportation cost. Further, the optimal route decision is commonly based on distance travelled or just used a static route for each replenishment period. Also, few studies have taken into account the vehicle efficiency factor in making the decision. Thus, this thesis offers a number of contributions to the literature since it fills identified gaps through a number of analyses in Chapter 4 through to Chapter 6.

In general, this thesis has presented an extensive numerical study which has quantified the gains from the flexibility that comes from early replenishment opportunities in terms of operating costs and the vehicle effectiveness along with a dynamic routing strategy with regard to vehicles' energy consumption in making the replenishment. Moreover, this study provides insights into the application of the IRP approach as a potential business process reengineering solution in the healthcare industry, specifically in the context of Malaysia's private healthcare industry. The problem of replenishing multiple-retailers who face a stochastic demand based on the case study organization has been simplified and studied via simulation in order to evaluate the effect of flexibility to make early replenishments on transportation and inventory costs.

Such flexibility is implemented in the model based on the periodic (s,c,S) inventory policy. Accordingly, this study contributes to the literature by widening the application of well-known joint replenishment approaches to periodic scenarios with multi-retailers and a single item. However, the parameters that trigger the replenishment have been slightly modified to fit implementation in the IRP scenario where the responsibility for making decisions on the time and the delivery quantity is that of the supplier, not the retailer. The flexibility of scheduling an early replenishment to consolidate replenishments with other retailers is quantified by the "can-deliver" level value.

The first part of the analysis in Chapter 5 presents an extensive numerical study of the effect of inventory control parameter settings on the trade-off between inventory holding cost, inventory shortage cost, and transportation cost. This is a further contribution of the study since investigation of replenishment flexibility obtained from (s,c,S) policy with a wide range of the flexible parameter ("can-deliver" level, c) has not been carried out before in solving the multiple-retailer scenario. Another contribution of the study is that the model also considered shortage cost per unit shortage supply in the objective function where the researchers mostly use the delivery cost as the shortage cost in the model. The findings show that by having another indicator that triggers an early replenishment before the inventory level reaches the reorder level is beneficial for reducing the transportation cost and overcoming the out of stock problem. The result also shows that the early replenishment strategy does not significantly influence the inventory holding cost at the retailers. Hence, the study indicates that the periodic "can-deliver" policy provides a significant cost saving and outperforms the (s,S) policy.

The study continued with an examination of the effect of flexibility with regard to vehicle effectiveness and total cost by modifying the routing strategy and taking into account distance and load factors to decide the dynamic replenishment sequence of retailers during the delivery trip in Chapter 6. The analysis was performed by investigating vehicle performance and route selection based on the Travelling Salesman Problem (TSP), and Overall Vehicle Effectiveness (OVE) and Modified Overall Vehicle Effectiveness (MOVE) metrics. Another contribution of the study was its identification of the relationship between Key Performance Indicator (KPIs) used to evaluate vehicle performance and single OVE and MOVE performance metrics. This relationship had previously been questioned by the Freight Logistic Research Group in 2004.

Incorporation of the OVE and MOVE performance measurements in the IRP model to examine total vehicle effectiveness and the impact of vehicle energy consumption with regards to the route selection during the replenishment period is a further contribution of the study to the existing body of literature. In addition, as far as the researcher is aware, this is the first study to explore the effective replenishment decision incorporating inventory control and vehicle effectiveness strategy that consider both economic and environmental factors in the decision. Thus, a new transportation cost function is developed, which includes fixed delivery cost and variable transportation costs related to the weight-distance and number of retailers visited during the replenishment. The analysis of the comparison between the MOVE and OVE metric and the TSP approach in terms of the optimal inventory control parameters and total cost provides further insight into the effect of different routing strategies incorporated in the IRP model.

In addition, this study also contributed to research methodology since comprehensive analyses were performed to determine an appropriate simulation tool to conduct the study as well as identify a warm-up period and the number of replications required to obtain an accurate result for the simulation analysis. Further, the normality test was conducted using both graphical and statistical tests in order to verify the assumption that the observations were normally distributed. This is important when computing the half-width confidence interval to determine the appropriate number of replications using Student's t distribution.

7.4 Research Implications

The findings of this study have a number of important implications for the field of study, researchers and practice at industry or government level. The current findings add to a growing body of literature on the applicability of implementing the (s,c,S) in a multi-retailer scenario to reduce the total operating cost. By implementing this policy, the decision-maker is able to gain cost saving by allowing an early replenishment for others when there is an opportunity to collaborate with retailers that require replenishment.

Furthermore, the findings have shown that basing routes solely on distance may produce slightly higher transportation costs and increase vehicle energy consumption, even though the optimal inventory decision is employed in the decision making process. Therefore, the integration of flexible inventory control policies with the MOVE metric is able to minimise operating costs and ensure low vehicle energy consumption; as well as improve total vehicle effectiveness.

The findings showed that total cost is higher when using the traditional inventory control approach since the replenishment decision is triggered based on reorder level which is represented in this study as the "must-deliver" level, usually known as the (s,S) inventory control policy. However, this is the inventory control policy commonly used by researchers and organizations. For instance, see Hollier et al. (2005) that used (s,S) inventory control policy to solve the problem. Accordingly, the periodic "can-deliver" policy proposed in this study provides another option for industry to manage their inventory. This presents an opportunity to move from the traditional inventory management approach to a centralised strategy that is proven to be efficient for managing the entire supply chain.

By extending the (s,S) policy by incorporating flexibility from the "can-deliver" parameter, the organisation can save cost and manage the vehicle more efficiently.

The total cost can be reduced by allowing some flexibility if there is a constraint on the stock availability at the supplier. More cost saving can be achieved if the replenishment for the other retailers is generated earlier, since as shown in Table 5.11, the optimal total cost occurs when the "can-delivery" level is about half that of the "order-up-to" level. Also, the coordination between retailers during the delivery trip will increase the vehicle utilisation. The study has also shown that a slightly lower or zero cost margins benefit occurs if flexibility is too high. Thus, the policy to replenish all retailers in one cluster when one of the retailers needs a replenishment, generates slightly higher costs in the long term as it requires the supplier to hold more inventory in stock to replenish all retailers.

In the Malaysian context, the IRP application can also support Malaysia's 3rd Industrial Master Plan (IMP3) by integrating "logistics solutions across the entire supply chain" (MacDonald, 2007).

In the broad context, the implementation of the IRP policy to the healthcare industry, can be realized by the application of future healthcare supply chain 'to centralise contracting, procurement, distribution and logistics operations' between multiple hospitals and healthcare systems (Parker and DeLay, 2008).

The findings also reveal that an appropriate inventory policy together with an appropriate routing policy is crucial in the IRP approach. This offers another variation on inventory policy in solving the multi-retailer scenario and opens up an opportunity for researchers to explore the benefit and effect of early replenishment in other scenarios.

7.5 Limitations of the research

A number of important limitations of the findings need to be considered. The current study only examined the influence of early replenishment strategies using a single vehicle during the delivery trip. However, the use of a single vehicle in the analysis to examine the effect of the proposed IRP model is reasonable because only small number of retailers is considered in the proposed IRP model and the retailers are reasonably close together. Therefore, replenishment can be delivered to retailers by one vehicle at each delivery time.

Further, the study only considered three retailers and one wholesaler as a central decision-maker in the model with a specified physical layout. This network structure facilitated an explicit numerical study which evaluated the impact of the proposed periodic "can-deliver" policy based on the basic model that could be used to implement this approach. The results have shown that the flexibility that comes from an consolidate replenishments leads to a reduction in total cost. However, this finding is limited to the specific instance of three retailers. It is believed that the cost reduction may also occur when there are a more retailers present. However, further analysis is needed to examine the actual behaviour and performance of IRP model for these more complex scenarios. The analysis may consider multiple-item scenarios as well as the situations that involve more customers. In addition, further analysis may consider procedures for handling out-of-stock situations.

Also, the assumptions on unlimited vehicle capacity and supply from supplier permitted quantification of the effect of the proposed model with regard to the optimal replenishment quantity and consolidation without any constraint. However, the study did include the analysis of the effect of vehicle utilisation rates with different maximum transportation capacities in Chapter 6.

The research based on a single case study was another limitation of the research to generalise the findings. Nonetheless, it is believed the study has produced significant findings, as the organization chosen for the study is a leading private healthcare organisation in Malaysia which owns a large chain of clinics. Furthermore, as discussed in methodology chapter, a single case study is applicable in research where the case is unique and has been found difficult to access previously (Ellram, 1996; Yin, 2003). Accordingly, the proposed periodic "can-deliver" model could be implemented in other organisations in various sectors as the replenishment strategy deals with multiple customers.

The suggested business reengineering strategy to improve the performance of the organisation is based on an evaluation of the current business strategy and the capability of the organisation to adopt the new strategy. The analysis of the benefit of the proposed IRP model is also simulated based on several assumptions. The willingness of the organisation to implement the new strategy and the evaluation of actual total cost benefit derived from the current supply chain process and the proposed supply chain strategy are beyond the scope of this study. However, in general, the study found that the flexibility from the periodic "can-deliver" model is able to generate cost savings and increase vehicle effectiveness in a multi-retailer scenario.

7.6 Recommendations for further research

This section provides recommendations for further research extensions to the study to contribute to the existing body of knowledge. A number of directions can usefully expand the study of the flexibility of an early replenishment strategy using the proposed IRP model.

First, it would be interesting to examine the behaviour of the model under different scenarios. The investigation of the trade-off between the inventory cost and transportation cost for the optimal decision solution based on the proposed IRP model would be more interesting if the holding cost at wholesaler is included in the model. Analysis could also be conducted on the behaviour of optimal control parameters in the situation of non-identical retailers. A further study could consider more complex network designs by including more retailers in the model with different physical layouts between retailers and wholesaler.

In addition, the study could take the capacity constraints for both wholesaler and vehicle into consideration. A further study could consider different IRP dimensions in a periodic "can-deliver" model.

Further investigation could be carried out on a scenario where multiple vehicles are used to make a delivery trip. The analysis could be expanded to examine the effect of homogenous and heterogeneous vehicle types on solving a multiple vehicle scenario. The overall vehicle effectiveness could be measured by accumulating MOVE percentage for each vehicle. It would also be interesting to examine the total effectiveness of the IRP model with regard to the inventory and vehicle performance. Also the effectiveness measurement can be expanded to evaluate the overall effectiveness for the entire supply chain.

Finally, another study could focus on the methods used to determine the optimal solution of the proposed model with regard to the routing decision and the inventory control parameters that minimise the total cost. An intelligent approach using heuristic or metahueristic methods enable quick determination of near optimal solutions. The simulation model can be optimised directly via simulation software packages and Microsoft Excel add-in software that uses various search strategies. For example, the OptQuest package in ARENA software and the Crystal Ball add-in use scatter search, tabu search and neural network, whilst the Optimizer package in Witness software uses simulated annealing and tabu search strategy (Fu et al., 2005 and Law and Kelton, 2000). Studies by Kleijnen and Wan (2007) and Wan et al. (2007) have shown that the Optquest software is capable of giving an accurate result similar to the result generated from the brute-force technique. With regard to the optimal routing decision, further studies could consider applying approaches such as the Genetic Algorithm, Simulated Annealing and Local Search to determine the optimal sequence. Such approaches are already widely applied in the area of vehicle routing, for instances, Baker and Ayechew (2003), Pankratz (2002) and Backer et al. (2000).

7.7 Final comments

The integration of inventory and transportation management via the Inventory Routing Problem approach is beneficial to enhance the efficiency of the entire supply chain. This study has provided insight on how implementation of the IRP model can improve the supply chain in the healthcare industry. The simulation result has shown that the flexibility of making the replenishment decision at a central point through the (s,c,S) policy, which is commonly used in joint replenishment for a multi-item problem, not only generates a low total operation cost but also gives opportunity for the supplier to manage a vehicle effectively. It is hoped that the findings of the research will be useful to the decision-maker in managing the entire supply chain more economically and in an environmentally friendly manner.

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