Proactive inventory policy intervention to mitigate supply chain disruptions

by

Takako Kurano

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Management Sciences

Waterloo, Ontario, Canada, 2011

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Risk management is one of the critical issues in supply chain management. Supply chain disruptions negatively impact on the performance and the business continuity of a firm, and the disruptions should be managed proactively if possible. One of the approaches for supply disruption management is to raise the level of inventory: supply disruptions can be reduced by simply increasing the safety stock level. However, inventory costs will be increased at the same time. Therefore it is assumed that having extra safety stock when and where needed is better than keeping a high safety stock all of the time.

In this thesis, the concept of dynamic inventory management by supplier behavior monitoring is suggested and explored. Key to the concept is the assumption that out-of-control situations at a supplier can be causal triggers for stockouts, and that these triggers can be potentially predicted by using statistical monitoring tools. In the suggested approach, the statistical process control approach of using run tests is employed to monitor and evaluate the supplier behavior. The supplier's yield rate is monitored as the performance measure, and the receiver's safety stock level is increased when the supplier's performance is detected to be potentially out-of-control (or about to reach an out-of-control situation). The simulation results under different yield rates indicate that stockouts can be reduced by monitoring the supplier behavior and dynamically adjusting inventory policy when production capacity is relatively loose and enough variability can be seen in the performance measure.

Acknowledgements

My deepest gratitude is to my supervisor, Dr. Kenneth McKay, who fostered my research and educational progression. Thank you for your support, patience and encouragement throughout my graduate studies. It is your inspirational energy and motivational direction that enabled me to complete this thesis.

I am grateful to my undergrad supervisor, Dr. Toshiya Kaihara, who first opened the door of opportunity to my master's at University of Waterloo.

I am grateful to my readers, Dr. Elizabeth Jewkes and Dr. Miguel Anjos for valuable comments.

I would like to thank to my colleagues and friends. I'm grateful to Jen and Lulu for all your care, support and entertainment in and outside of the office. I'd also thank Candy for proof reading this thesis.

Finally, I want to express my sincere gratitude to my family. Even from a different part of the world, your love and support gave me the strength to achieve my goals.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

In the late 2000s, the economic crisis forced many firms to restructure their business model to survive in the industry. Many manufacturing firms implemented production adjustments to cut inventory level, introduced cost reduction, reduced preventative maintenance, and tried to practice bare-bones manufacturing. These types of practices reduced the robustness of many supply chains, and customers found themselves either increasing inventory levels across the board, or reacting just-in-time to disruptions such as stock-outs. My interest in supply chain risk management has arisen from these disruptions and the impact on customers – is it only possible to react to them in hindsight, or to take broad sweeping measures? Or is it possible to dynamically monitor the situation and take a pro-active stance before the upstream situation negatively affects the situation. In lean manufacturing, recovering from such disruptions is urgent, but it is not an easy task once the disruption actually occurs. It is reported that firms suffering from supply chain disruptions experienced 33-40% lower stock returns compared to industry benchmarks and the disruption does not only impact the firm's immediate performance but also impact the long-term performance (Tang 2006). Therefore whenever possible, it is important to prevent the disruption as well as recovering from it.

Supply chain risk management has been brought to the forefront in recent years, and is reported to be the second biggest concern next to supply chain visibility among world-wide supply chain executives (Butner, 2010). However, most of the studies about supply chain risk management focus on conceptual frameworks and concepts and the literature discussing mathematical models is limited (Giunipero, 2008). In addition, supply chain risk management is a broad area of research including such topics as flows of material and information, financial arrangements, production mechanisms, and delivery models for products and services. One of the most important aspects that affect the supply chain performance is inventory management (Caballini and Revetria, 2008).

In this thesis, a proactive approach for supply disruption management is focused upon, and a dynamic inventory policy using supplier monitoring is suggested. In order to preliminary study the suggested strategy, a single echelon, four stages supply chain model with pull inventory system is explored.

In this thesis, the literature review related to this thesis is first provided in Chapter 2. Chapter 3 describes the characteristics of the problem, the model structure and the associated simulation model is developed. The experimental design is detailed in Chapter 4. Chapter 5 presents the results from the experimentation and those results are discussed and analyzed in Chapter 6. Chapter 7 provides the limitations and implications of this study. Chapter 8 summarizes the conclusions that have been obtained from this study and outlines future research.

Chapter 2

Literature Review

This thesis focuses on supplier monitoring and inventory control strategy as a way to proactively manage supply disruption. This chapter provides a summary of related literature and subjects which are associated with the proposed method.

Section 2.1 explores supply chain risk management. Supply chain risks and the mitigation approaches are reviewed. Section 2.2 provides a review of inventory management strategy in supply chain. Supply chain modeling approaches including system dynamics, and the supplier monitoring method of statistical process control are reviewed in Section 2.3 and 2.4. Finally, Section 2.5 concludes with a summary of this thesis' research direction.

2.1 Supply Chain Risk Management

Supply chain networks are inherently vulnerable to disruptions, and failure in any of the elements within a chain could cause the entire supply chain to failure (Rice and Caniato, 2003). Although many firms have not been able to quantify the cost of supply chain disruptions (Blackhurst et al, 2005), a company surveyed by Rice and Caniato (2003) estimated a $50-100 million cost impact for each day of disruption in its supply network. Other literature has also studied the impact of supply chain disruptions (Hendricks and Sinfhal, 2003; Knight and Pretty, 1996), and the results indicate that disruptions will likely negatively affect the performance and business continuity of a firm. In addition, current trends of global sourcing, increased responsiveness, and higher levels of agility and lower inventory levels increase the potential for disruptions to occur (Blackhurst et al, 2005). These research results illustrate the perceived importance of supply chain risk management.

According to Tang (2006), supply chain management is defined as “the management of material, information and financial flows through a network of organizations that aims to produce and deliver products or services for the consumers” and supply chain risk management as “the management of supply chain risks through coordination or collaboration among the supply chain partners so as to ensure profit ability and continuity.” Based on these definitions, issues in supply chain risk management can be addressed in two dimensions:

- Supply chain risk
- Risk mitigation approach

2.1.1 Supply Chain Risk

Supply chain risk is defined as “the variation in the distribution of possible supply chain outcomes, their likelihood and their subjective values” (March and Shapira, 1987). There are two types of risk in supply chain: operational risk and disruption risk. Disruption risk is referred to as inherent uncertainties such as uncertain customer demand, uncertain supply and uncertain costs. Disruption risks are those caused by natural disasters such as earthquake, floods, hurricanes, terrorist attack and economic crises (Tang, 2006). Although the business impact associated with disruption risk is much greater than that of the operational risk, operational risk is more predictable and proactively manageable. Therefore, whether or not operational risk management approach is implemented can make a huge difference on business continuity.

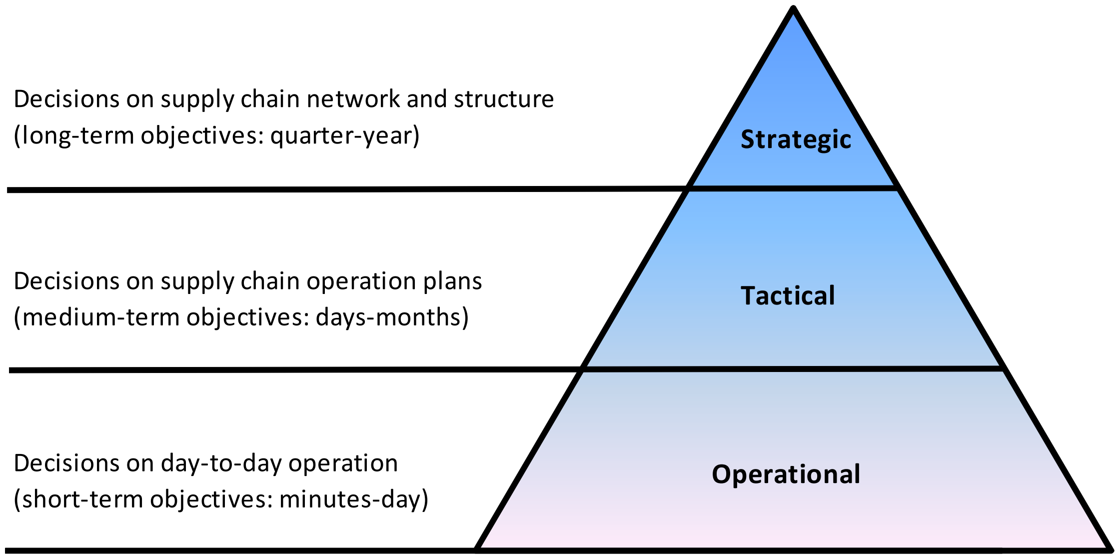


Figure 2.1: Strategic, tactical and operational risks in supply chain

Supply chain risks can also be divided into three categories according to the decision level: operational, tactical and strategic (Paulsson, 2004; Gaonkar and Viswanadham, 2004). In supply chain risk management, this differentiation is helpful as different risk management approaches may be applied to different risks (Ritchie and Brindley, 2007). As shown in Figure 2.1, strategic decisions are associated with long-term objectives such as selection of suppliers, transportation routes, manufacturing facilities and production levels. Tactical decisions are medium term, and focus on policies, capacity turning, capability adjustments, and planning and scheduling; what it will take the plant to meet actual demand. Decisions on day-to-day operations include resource assignments, what will be made each day, and personnel assignments. These operational decisions can affect the quality of produced goods, inventory levels and capacity utilization, which are included in operational risks (Fox et al, 2000; Gunasekaran et al, 2001; Ritchie and Brindley, 2007). Examples of the performance metrics to measure supply chain risks at each decision level are listed in Table 2.1 (Gunasekaran et al, 2001).

Table 2.1: Performance metrics in strategic, tactical and operational level

Decision Level	Performance Metrics
Strategic	Total supply chain cycle time Total cash flow time Customer query time Range of product and services Rate of return on investment Buyer-supplier partnership level Supplier lead time against industry norm
Tactical	Accuracy of forecasting techniques Product development cycle time Purchase order cycle time Delivery reliability Responsiveness to urgent deliveries Effectiveness of master production schedule Effectiveness of distribution planning schedule
Operational	Cost per production hour Total inventory as: - Incoming stock level - Work-in-progress - Scrap level - Finished goods in transit Supplier rejection rate Frequency of delivery Quality of delivered goods

2.1.2 Risk mitigation approach

Before discussing the risk mitigation approaches, it is important to know how to implement supply chain risk management. A typical risk management process that is widely suggested consists of four steps and is described as follows (Blackhurst et al 2008; Halikas et al, 2004; Juttner et al, 2003; Wagner and Bode, 2008):

1. Risk identification
2. Risk assessment
3. Implementation of risk management
4. Risk monitoring

Risk identification is a fundamental phase in the risk management practice. This enables a decision-maker to be aware of events or phenomena that create uncertainty, and be ready to take proactive approaches for these scenarios. Interruptions, quality failures and delivery fluctuations are commonly strong signals of risks in production systems. Once risks are identified, suitable management approaches toward the risks are chosen in the risk assessment phase and those which in turn are implemented in the implementation phase. Note that, it is important to keep monitoring the supply chain system even after risk management action is implemented. The company and its environment are not static, and thus the risk status changes; therefore, potential risk factors should be updated correspondingly.

Juttner et al (2003) provides four approaches for supply chain risk mitigation based on the risk management framework for international businesses as suggested by Miller (1992). These are Avoidance, Control, Cooperation and Flexibility (Figure 2.2). In the avoidance approach, a firm could drop a specific product, supplier or geographical market if the supply is unreliable. Control appears to be the most widespread approach amongst firms. Vertical integration, increased stock keeping, use of buffer inventory, and maintaining excess capacity in production and inventory are categorized in this approach. Many control approaches do not require coordination between firms and therefore it is easier for firms to start with. On the other hand, while cooperation has the potential for better supply chain execution, it does involve joint agreement between firms. Firms can improve supply chain visibility and understanding by joint agreement; however, the application of this approach is mainly restricted to initiatives with key suppliers. The last approach for supply chain risk management is flexibility. While the control approach attempts to increase the predictability, the flexibility approach increases responsiveness toward risk factors. Examples of this approach are postponement in decision making, configuring products and shipping, multiple sourcing, and localised sourcing with short lead-times.

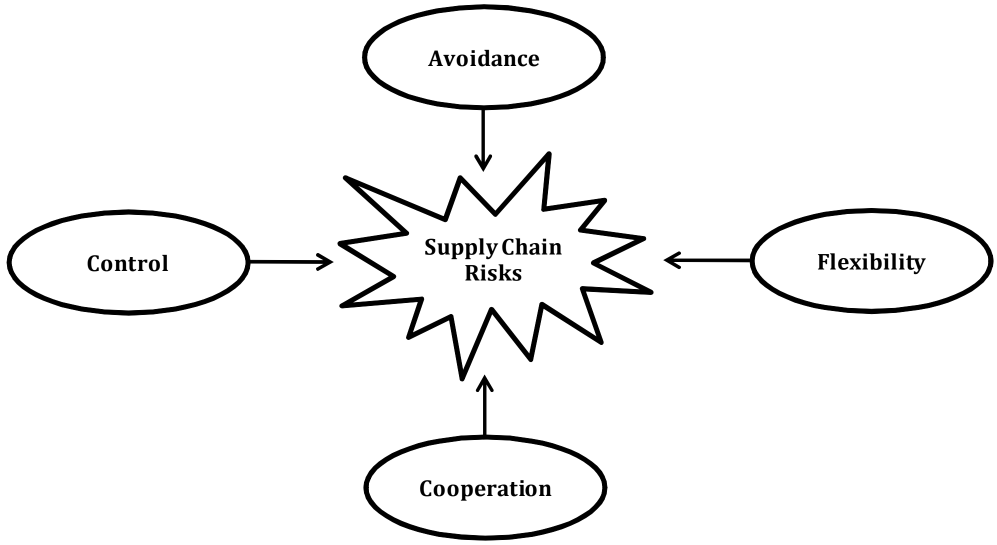


Figure 2.2: Four approaches for supply chain risk management

The effectiveness of each approach depends on the situation a firm is in. Also, it is important to be aware that there are always trade-offs existing behind the decision making. Some examples of trade-offs in supply chain decisions are repeatability versus unpredictability, lowest bidder versus known supplier, collaboration versus secrecy, centralisation versus dispersion, and redundancy versus efficiency. Furthermore, 'managing risk versus delivering value' itself is a trade-off and may be the paramount trade-off in supply chain risk management (Sheffi, 2002).

2.2 Inventory control in Supply Chain Risk Management

Inventory control plays an important role in supply chain management. Fluctuation in demand or supply at a downstream supplier can be amplified as it goes through the supply chain. Such phenomena, the "bullwhip effect", causes excessive inventory, loss of revenue and inaccurate production plans throughout supply chain systems (Lee and Wu, 2006). Therefore inventory management is a critical problem in supply chain risk management.

The bullwhip effect can be reduced by managing inventory. For example, Fransoo and Wouters (2000) study daily demand variability in convenience food and prove that eliminating the demand variability helps to reduce the bullwhip effect. Disney and Towell (2003) also suggest a way to control inventory variance and develop an order policy which minimizes bullwhip effect.

Starting from the basic EOQ model introduced in 1915, many researchers have been creating and extending inventory models in order to make inventory management efficient and effective. However, these works have largely focussed on developing numerically efficient techniques and designing effective control systems for relatively static environments, and not for dynamic situations resembling real supply chain. Since real world inventory systems operate in dynamic environments, it is reasonable to suggest that a control theoretic approach be taken to the inventory management policies and methods themselves: assess the system's effectiveness in an ongoing fashion and make dynamic adjustments to the system; as suggested by Watts et al (1994).

When an inventory system does not perform as planned, there must be reasons for that. It is necessary to identify what causes the performance deviation before taking any corrective actions. Watts et al. (1994) classified the source of supply chain performance deviations into two categories and suggests the approaches as follows:

- Causes related to system fitness

    When the source of performance deviation is attributable to a faulty design or selection of a system, or an obsolete system due to the dynamic nature of operating environment, the system should be changed. A manager must ensure that the inventory system is consistent with the operating environment and the system is monitored to ensure ongoing compatibility.

- Causes related to ongoing operations

> When a system has been selected and installed, but it is not used according to its design specifications, performance deviation can occur. In such cases, the manager must first be alerted to the problem, be able to detect the causes of the malfunction in timely matter, and to make the necessary changes in system usage.

Unfortunately, literature suggesting concepts or techniques for controlling inventory management via dynamic and ongoing methods is limited. There are some suggestions for how to monitor and adjust the inventory itself in a dynamic fashion. For example, Watts et al (1994) suggests three inventory parameters that can be monitored and adjusted to improve the performance of a typical supply chain system. These are described as follows:

- Order quantity:
  The number of units ordered when a replenishment order is required
- Reorder point:
  The stock position at which a replenishment order should be placed
- Safety stock level:
  The amount of inventory used to protect against uncertainty during replenishment lead time

2.3 Supply Chain Modeling

As the research by Giunipero (2008) shows only 9% of SCM articles employ simulation or model research methods, and that researchers have mostly been trying to provide general frameworks and concepts. In relative terms, little has been written about mathematical modelling of supply chain with the exception of the body of work that focus on general inventory flows and costs, or transportation logistics (Beamon, 1998; Croom et al, 2000). There have been few research results that model supply risk management and dynamic inventory management (Liu, 2009; Tomlin and Snyder, 2006; Watts et al, 1994).

In general, companies cannot rely on a heuristic decision making process, and a systematic approach is necessary (Perea et al, 2000). Among supply chain modeling approaches used to study supply chains in a systematic fashion, control theory (or system dynamics), multi-agent model, and operations research approaches such as optimization theory, game theory and statistical analysis are widely used (Blackhurst et al, 2005; Tian and Tianfield, 2006). Each approach is described as follows:

- System Dynamics

  System dynamics is a top-down approach, where variables and all key relationships between entities are defined before analyzing the overall behavior. By employing concepts from feedback control theory, system dynamics analyzes the dynamic behavior of complex systems.

- Multi-agent model

  Multi-agent modeling is considered as a bottom-up approach, where individual agents interact with each other, operating a set of rules and then overall behavior is simulated. As well as the system dynamic approaches, the multi-agent approach enables the modelling of complex systems, and fits the dynamic nature of supply chain. One major disadvantage of the multi-agent approach is that agents behave individually seeking their own optimal solution and therefore the behavior of the entire system can not always predicted or optimal solution is not guaranteed.

- Operations research approach

  OR approaches (exact solutions, systems of equations, meta-huristic algorithms) are suitable for tightly constrained problems. Usually, simulations are not used in the OR methods, and the methods usually require a more detailed structure of the problem, or the estimation of many parameters. OR approaches have their place at a tactical level in the design of supply chain, and in logistics modelling; however, they have failed thus far to capture and represent the dynamic characteristics of supply chains at the operational level.

There has been debate about which of these three methods is the best for modelling supply chains at the operational level. For example, Riddals et al (2000) suggests that none of the core OR methods are suitable at the operations level, and that the OR methods provide better insights at the tactical level. Others have suggested that a system dynamics or control theoretic approach is suitable. For example, it has been claimed that system dynamics may be the only way to study phenomena such as how a small fluctuation at one end of supply chain is amplified as it goes through the supply chain (Moraga et al, 2008). The significance of simulating supply chains using system dynamics has been emphasised (Minegishi and Thiel, 2000; Sterman 2000; Towill 1993).

The application of system dynamics for supply chain management goes back to Forrester (1961) and now widely applied to analyze and understand the complex dynamic behavior of supply chain. In the studies of Akkermans et al (1999) and Sterman (1989), system dynamics modeling contributes to theory building and it has helped in understanding a system and validating a proposed theory. Barlas and Aksogan (1997) and Anderson et al. (2000) used system dynamics for problem solving. Barlas and Aksogan (1997) developed inventory policies that increase revenue and reduce costs, and Anderson et al. (1997) explained the demand amplification on lead-time, inventory, production, productivity and workforce. As seen in study by Hafeez et al (1996), Naim and Towill (1994), system dynamics modelling can be used with the combination of operation research approach and management science approach. In a full interpretation of system dynamics modelling, causal diagrams are used as modelling tools, with numeric weights (or influence levels) assigned to each influence or relationship arc. Specific numeric values have been problematic to determine in many cases, and the setting of the edge values has been the subject of debate and discussion (Coyle, 2000; Luna-Reyes and Andersen, 2004). Although the values can be problematic, the causal relationship diagrams have been shown to provide value in explaining dynamic situations (Homer and Oliva, 2001; Wolstenholme, 1999).

2.4 Statistical Process Control in Supply Chain Management

In practice, inventory control management usually operates in dynamic environments and therefore the infrequent or periodic calculation of order quantise, reorder points, setting safety stock levels, or reviewing policies are simply not enough. In such environments, the decision makers should monitor the operation and modify the replenishment policies accordingly (Lee and Wu, 2006). Unfortunately, literature discussing concepts or techniques for monitoring the performance of supply chain management systems and performing dynamic adjustments of policies and settings is limited; however, some suggest the employment of statistical process control methods (e.g., Watts et al, 1994).

Statistical process control (SPC) is a statistical tool used in the area of statistical quality control, and it consists of methods for understanding, monitoring, and improving process performance over time (Woodall et al, 2000). SPC has been widely used since Shewhart first introduced the control chart in the early 1930s (Woodall and Montgomery, 1993). The primary application domain for SPC has been in process control and process improvement in manufacturing; however, it has also spread to areas outside of production systems and has now been applied in various domains such as engineering, healthcare and general service sector (MacCarthy and Wasusri, 2002).

It is common practice to call a process in control when it exhibits random behaviour and is within control limits (Paulk, 2001). Getting close to, or exceeding a control limit is a trigger for alerting the work force to a potential situation. The situation might be a momentary problem, or indicative of a situation requiring intervention. Random behaviour between the limits is also used as a trigger for possibly indicating that the process is out-of-control. Because it is possible to obtain patterns of behaviour that appear to be out-of-control when in fact the process is still in control, these pattern based triggers often require further analysis to determine if in fact there is a problem (Plsek, 1999).

Watts et al (1994) introduce the idea of diagnosing problems in reorder point systems by using control charts. In their approach, an inventory system is diagnosed when stockouts occur or at the end of an order cycle. When an unplanned stockout occurs, demand is consulted whether or not the system is in control. In addition to investigating stockouts, the turnover rate is checked to see if it is in control at the end of order cycle. In either consultation, all the causes of the system malfunctions are identified and then corrective action is taken. Although this approach enables the detection of problems in the inventory system in a timely matter, the correcting mechanism is not included in this concept. This approach is also reactive in its response to the situation – waiting until the system is out-of-control before action is taken.

Hill (1996) discusses the use of SPC in monitoring demand from customers. He suggests the application of cumulative sum control chart (CUSUM) to detect significant inaccuracy in demand forecast by comparing the difference between forecast and actual demand. Although no experimental data is provided, he mentions that the suggested approach can be used to quantify the levels of risk and that inventory policy could be decided based on the risk levels. He also mentions that CUSUM method is a compact and easily operated approach; however it is suitable when the deviations are gradual or relatively small. Therefore the optimum approach may be to use with other methods such as Shewhart control chart, which is particularly suitable for detecting large, sudden deviations. It should be noted that Hill (1996) focuses on the demand and forecast, and not on the supplier's behavior or production.

Pfohl et al (1999) conduct a study on generating a set of replenishment rules by the application of SPC techniques. In their study, control charts of demand and inventory are created according to the historical data. Four inventory rules (lower control limit of inventory, slow drift inventory level, excessive inventory, and demand related inventory policies) and three demand rules (drift demand, peak demand, and lumpy demand) are developed based on the control charts, and those rules are used to determine the replenishment policy. The performance of this approach is compared with the actual operation of different warehouses and the results indicate that the SPC-based inventory system reduces inventory levels in different classes of products (A, B and C products). The Pfohl et al (1999) research does not pick up non-random behavior around the mean or patterns close to the mean. However, it does look for undesirable performance close to the control limits as the predictor.

Lee and Wu (2006) also study SPC-based inventory control techniques by modifying the approach suggested by Pfohl et al (1999). Like the Pfohl et al study, control charts based on historical data of demand and inventory are used, and the replenishment quantities are adjusted dynamically according to decision rules developed with the control charts. In their study, two common replenish policies of the lot size-reorder point order-quantity (s, Q), and periodic review order-up-to (R, S) system are considered, and those systems are simulated with and without the application of the SPC-based approach. The experimental results indicate that their approach performed well in reducing backorders; however, average stock level increases except when both the supplier and the receiver use (s, Q) replenishment policy. The Lee and Wu (2006) work also focuses on inventory behavior above the mean and close to the control limit.

The literature reviewed above applies SPC-based methods to monitor and evaluate the receiver's own inventory system. None of the literature monitors the supplier behavior, nor looks at potentially non-random patterns of behavior. In the existing literature, the key issue has been adjusting the inventory system for demand variability; whether or not the supply is reliable has not been a main concern. The literature reviewed does not address the role that the supplier plays in creating supply chain disruptions. It is possible that dealing with supply variability is as important as managing demand variability, or that it is a complementary topic. It does appear that SPC control charts may be a potential way to monitor and evaluate the performance of inventory systems. However, control charts are usually created based on sufficient historical data, and therefore they are best suited to detect out-of-control situations in terms of relatively long-term operation. In order to deal with small deviations occurred in short-term operations, it may be necessary to investigate the use of other SPC methods.

2.5 Summary

In this chapter, literature related to the subject of this thesis and the proposed method was reviewed. The reviewed literature illustrates that risk management is a critical issue in supply chain management, and that inventory management is a key approach to manage supply disruptions. In the dynamic nature of supply chain environment, it is important to assure that a supply chain system fits the current environment and is operated as planned. Therefore a manager should monitor the performance at an ongoing basis and take corrective actions if necessary.

A supply chain system is usually complex and dynamic. In order to capture these characteristics, simulation approaches are considered to be suitable to model supply chains. Concepts related to system dynamics has been widely used to study phenomena like the bullwhip effect, and to analyze the supply chain behavior. In this thesis, a general system dynamics approach is used to model the supply chain behavior caused by the inventory a proactive inventory policy change intervention.

Although the literature describing the concepts or techniques for monitoring and dynamically controlling supply chain systems is limited, SPC is suggested as a potential way to effectively integrate control theory in the model, and statistically monitor the dynamic performance in the supply chain.

Chapter 3

Model Development

In supply chains, a single disruption can be amplified throughout the entire supply chain as it moves down supply chain towards the customer. Therefore, avoiding a disruption such as a stockout is one of the goals in effective supply chain risk management. While increasing safety stock is useful in reducing the disruptions, it increases the inventory cost. A naïve approach would be to just increase safety stock and leave it at the higher level, in a just-in-case fashion. However, this increases the inventory cost and inventory during the times when you really do not need it. Depending on the situation, this can damage the firm's competitive edge. The challenge is to know when you need to increase your safety stock to reduce your risks, and when not to. In this thesis, we are exploring how to temporarily increase safety stock, just before disruptions might occur, or just before a period of instability to reduce the number of stockouts. Although lowering safety stock during stable operation should also be considered as a proactive technique, the focus of this exploratory study is increasing safety stock levels when higher risk of stockout is observed. The lowering of saftety stock below the nominal level increases the decision risk; the cost of holding a limited amount of extra inventory is possibly less than the cost of a stock out situation.

In this study, an inventory policy change strategy based on supplier behaviour monitoring is suggested. This chapter provides the concept of this strategy and describes the development process for the model using a control theoretic, system dynamics approach. The following subsections present the conceptual framework, system dynamics simulation model, monitoring logic for the run test usage, and research questions.

3.1 Conceptual Framework

In today's supply chains, there is more sharing of information. Imagine that operational information about key parameters is shared with the customer. It is up to the customer to set its own policies in accordance with its level of risk acceptance. If the customer feels that there is little risk, a low level of inventory can be kept. If the customer feels that it is in a risk situation, the customer can increase its inventory level. This behavior was seen in McKay (1992) where the scheduler, Ralph, monitored and regularly talked with his friends at key suppliers. It was not a formal sharing of operational data, and was not officially recognized or acknowledged by management. Ralph would use this information to adjust his policies and strategies at his plant. There are a number of operational characteristics that can be monitored, at different levels of sensitivity by a customer. For example:

- Inventory level
- Quality of goods
- Production rate
- Delivery time
- Order accuracy
- Facility utilization

One could rely on a human like Ralph to do the monitoring and the adjustment, but what methods and concepts could be developed which are suitable for modern information systems and algorithms? In this preliminary exploration of the concept of proactive inventory policy adjustment, methods from statistical process control will be used. The supplier provides operational data to the customer, and the customer analyzes the data via the run test method. The run test methodology looks for potentially non-random sequences in either increasing or decreasing data, or non-random oscillations of data around a mean. When the operation is in control, every single event occurring should be mutually independent and the naturally occurring patterns in operation data are supposed to be statistically random. The key concept is that the non-random patterns in the data may indicate that the process is potentially 'statistically' out-of-control and that this signal can be used to identify when an out-of-control situation may be possibly developing at the supplier. It is possible with the run tests to have a false positive. That is, theoretically random sequences can have sequences that appear to be non-random and in practice this situation needs to be consciously considered. In the conceptual framework, when a non-random pattern is detected, the customer changes the inventory reorder point to increase the safety stock level. The key assumption is that there might be higher chance of supply disruptions when the supplier's operation is potentially out-of-control, and that an early detection mechanism can be used to signal an inventory policy change. By applying this strategy, the receiver side can be ready for the possible disruptions by bumping up its inventory level and therefore it is expected that the effects of disruption can be significantly reduced, or avoided in its entirety. A similar method can be used to identify when the system is back in control and the inventory level can be decreased. In this thesis, we will focus on the basic concepts and methods associated with the initial inventory increase in response to an early detection trigger. We will also use only one trigger for the exploration to better present and understand the dynamics. A future exploration could study the benefits of using multiple operational characteristics in parallel. The initial study is also limited to the increase of inventory levels and not the corresponding decrease. It should be possible to detect a condition when the out-of-control situation has been rectified and lower any previously raised levels. The lowering of inventory is not in the scope of this thesis and is left for future research activities to explore.

In practice, the concept would involve the customer picking the performance indicator, determining the sample size and frequency for data to be sent from the supplier, determining the sensitivity of the run tests (i.e., number of running points to consider), how much to increase the reorder point by, how to consider multiple threat triggers, and under what conditions the inventory level can be lowered. The logic must also account for the situation when the system is indeed running well and within specifications, with little variance – as the run tests can create a false positive in this case. In the real world, we would also expect a scheduler or planner to contact the supplier to verify the situation and not automatically increase or decrease inventory without additional information.

The flowchart in Figure 3.1 illustrates the conceptual framework for this study:

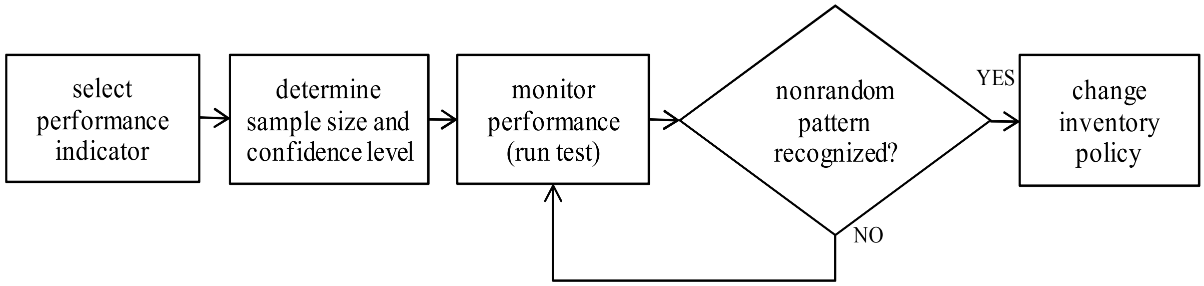


Figure 3.1: Flowchart of the model

3.2 Assumptions and Simplifications

In the real world, supply chains often have a complex structure with more than one echelon and multiple facilities. However, since the main purpose of this study is to explore the dynamics of the suggested strategy and investigate the possibility for further research, a single echelon supply chain consisting of four stages is considered here. The four stages of the supply chain are supplier, factory 1, factory 2, and customer. As the model framework in Figure 3.2 shows, orders are placed from upstream entity while goods flow in the opposite direction. The detailed model of this study is shown in Figure 3.3.

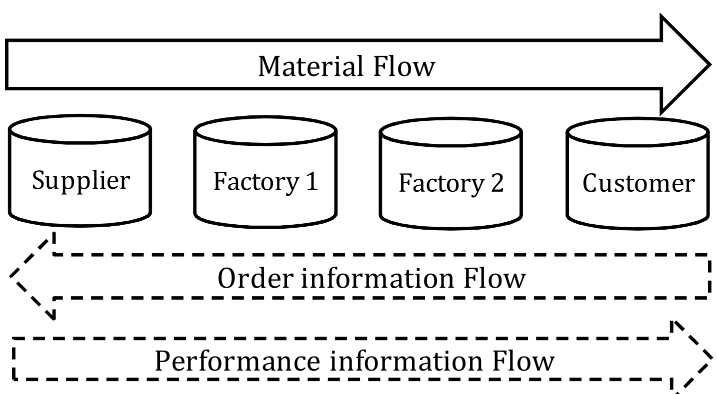


Figure 3.2: Model framework and flow

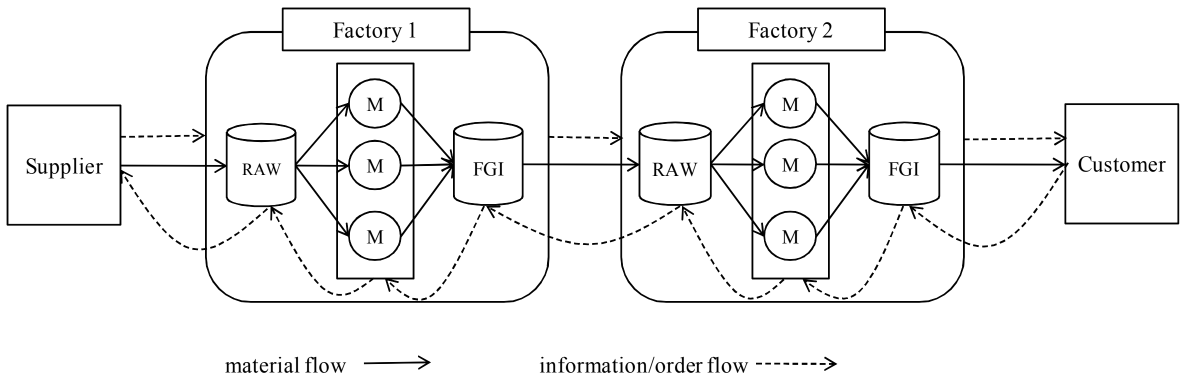


Figure 3.3: Supply chain model in this study

Assumptions and simplifications made on this model are given below.

- The model is a four-stage single echelon supply chain.
- Order quantity and delivery lead time from each stage is fixed.
- There is always enough material supplied from the supplier and there will be no stockout in raw material at Factory 1.
- Each factory is characterized by the maximum capacity constraint of working hour per day and therefore the quantity of goods produced each day is limited.
- There is a certain quantity of order from customers every day.
- Factory 1 and Factory 2 check their raw material inventory level once a day. If their inventory level is lower than their reorder point, place an order.
- Factory 1 and Factory 2 checks their finished goods inventory when the order comes from an upper stage. Then the production schedule at each factory is made based on their finished goods inventory level.
- There are three production lines in each factory. Each line has the same capability and a job is processed at whichever line available at the time.
- Each order is placed only once at the beginning of the day, if necessary.

- Orders are shipped at the beginning of the day if order is placed. However, if the inventory is not enough, the shipment is held until the day the inventory becomes available.
- Machine breakdown and repair does not affect the quantity yield of goods, but scrap rate does affect the quantity yield. As the scrap rate increases, quantity yield decreases.
- Stockout in finished goods inventory is defined when order arrives, but inventory is not enough to meet the demand.
- Stockout in raw material inventory is defined when the day's production still has not met the target quantity set in the schedule, but there is no raw material in inventory.

With the model described above, the operation of Factory 1 and Factory 2 is analyzed in this study. As already stated, the main objective of this study is to explore the possibility and characteristics of the suggested strategy. Therefore, assuming that there is no supply disruption in lower stream than Factory 1 and Factory 1 is the root to cause the supply disruptions, how Factory 2 can proactively manage the disruptions from its supplier of Factory 1 is tested.

3.3 Supply chain modeling using system dynamics approach

Supply chain often has a complex structure and therefore it is difficult to analyze with traditional mathematical methods. Computer simulation model is widely used to analyze such a complex system and one well-known method for analyzing supply chain system is system dynamics (Caballini & Revetria, 2008). System dynamics is a computer-aided approach for analysing and solving complex problems with the viewpoint that feedback and delay cause the behavior of the system (Angerhofer & Angelides, 2000). In order to create a system dynamics model, it is necessary to identify the causal and feedback loops that connect the system components such as demand increases if market share increases, or inventory decreases if deliveries increase (Rabelo et al, 2004).

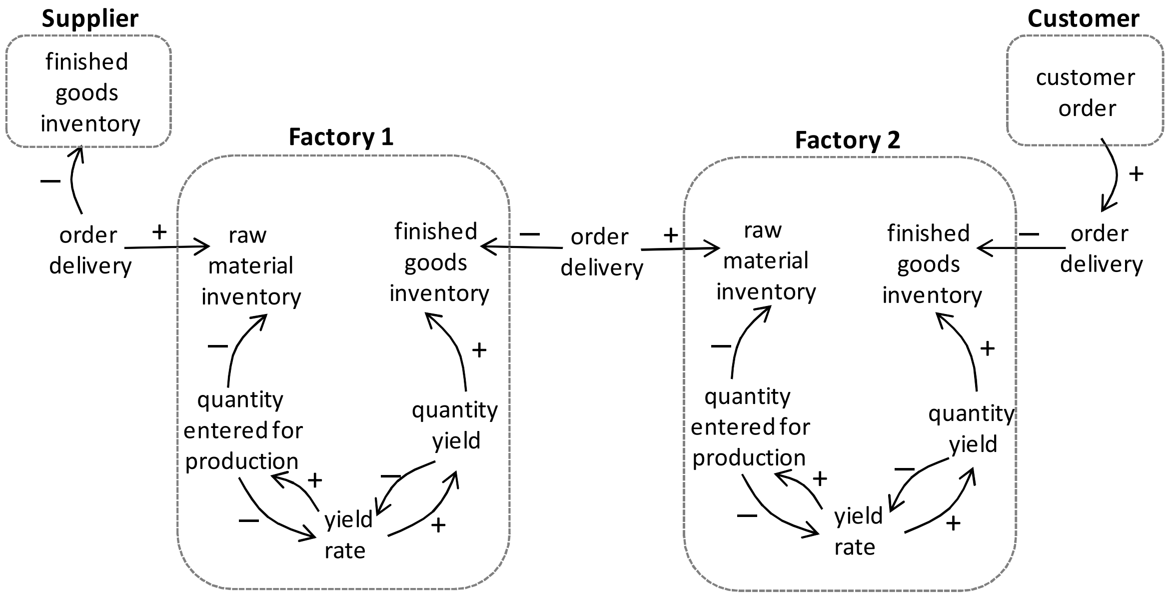


Figure 3.4: Causal loop diagram for the system dynamics model of this study

Figure 3.4 shows the causal loop diagram for system dynamics model of this study. A causal loop diagram consists of variables connected by arrows showing the relations among the variables. A positive feedback, which is shown with '+' arrow, means variables change in the same direction, and a negative feedback shown with '-' arrow means variables change in the opposite direction.

Based on the causal loop relations, the mathematical equations that describe the structure of the inventory system are given as the following:

$$\begin{aligned} &raw\ material\ inventory \\ &\qquad = initial\ raw\ material\ inventory \\ &\qquad + \int (order\ arrived - production)dt \end{aligned}$$

$$\begin{aligned} finished\ goods\ inventory \\ &= initial\ finished\ goods\ inventory \\ &+ \int (production - order\ shipped)dt \end{aligned}$$

The relationship between yield rate, quantity yield, and quantity entered for production can be given as:

$$yield\ rate = \frac{actual\ yield}{quantity\ entered\ for\ production}$$

The quantity entered for production is determined by the production schedule of the day. Production schedule is set when the order arrives, and the daily production schedule until the next order cycle is given by

$$\begin{aligned} daily\ production\ for\ next\ order\ cycle \\ &= \frac{order\ quantity + shortage\ in\ safety\ stock}{order\ cycle\ time} \end{aligned}$$

However, there is a production capacity at each factory, and the daily production cannot exceed the maximum capacity. If the daily production obtained by the equation above is greater then the production capacity, the maximum capacity is set to the production schedule instead. For example, if 220 goods are the target production quantity for the next order cycle of 5 days, but production capacity is 40 goods per day, the production schedule will be 40 goods from day 1 to day 5 and 20 goods to day 6. Therefore, the equation above is modified as:

$$\begin{aligned} &daily\ production\ for\ next\ order\ cycle \\ &= min\ (\frac{order\ quantity + shortage\ in\ safety\ stock}{order\ cycle\ time}, production\ capacity) \end{aligned}$$

In this way, all of the scheduled quantity enters for production every day, and the target production quantity, which is the scheduled quantity, equals the quantity entered for production. Therefore, the yield rate described above indicates how close the produced quantity is to the target quantity.

Shortage in safety stock occurs when safety stock is used to meet the demand, and it is given by:

$$\text{Safety stock shortage} = \max\left(0, \text{current inventory} - \text{order quantity} - \text{safety stock}\right)$$

An example of how production schedule is determined follows:
Assume current raw material inventory is 170 including the safety stock of 30. Order quantity is always fixed to be 150. If the order arrives, 150 out of 170 are shipped from the inventory, and there will be 20 left. There is supposed to be at least 30 left for safety stock; however, 10 safety stock is used to meet the order quantity. Now, we have to order a quantity of 150 and a safety stock replenishment quantity of 10, giving a total order of 160 needing to be produced by the time next order arrives. If the expected order cycle time is 5 days, the daily production schedule for the next 5 days is determined to be 160/5=32 per day.

3.4 Run test

In this study, run tests are applied as a tool to monitor the supplier performance. Run test is a nonparametric statistics method which can be used to determine if there is any trend or patterns in a set of data. Nonparametric statistics are based on fewer assumptions about the population and the parameters and therefore useful when assumption of normality is not appropriate and the sample size is small. From several ways to conduct a run test, two sorts of test called "runs up and down test" and "runs above and below test" are used in this study. In these tests, a series of observation are divided into two types, say +'s and –'s, according to certain rules. In the ordered sequence of the two symbols, a run is determined as a series of +'s or –'s. Then, the hypothesis stated below is tested by using the total number of runs in the sequence. If the null hypothesis is rejected, the sequence is considered to be non-random and there is likely to be special causes of variation in the process the data come from. In this study, the patterns observed in the supplier data are used as a proxy of supplier performance, and when a potentially non-random pattern is observed, the receiver assumes that an undesired situation is developing in the supplier and determines that the supplier's operation is possibly "out-of-control."

Hypothesis:

$$\mathrm{H_0}: \text{The sequence is random}$$
$$\mathrm{H_1}: \text{The sequence is nonrandom}$$

Details about each test are described below.

- Runs up and down test

  In runs up and down test, the magnitude of consecutive observations is compared to each other. If the preceding value is smaller, - is assigned, and if the preceding value is larger, + is assigned. As stated above, a run is a series of +'s or –'s, and the total number of runs in the sequence is counted. Critical value for the number of runs is obtained from the table (appendix) at a desired level of significance (α) and compared to the total number of run in the observation. Let *r* be the total number of run in the observation and r_c be the critical value from the table (Appendix A). If $r_c(lower) \leq r \leq r_c(upper)$, accept $\mathrm{H_0}$; otherwise reject $\mathrm{H_0}$.
- Runs above and below test

  Runs above and below test is very similar to runs up and down test; however, in this test, the magnitude of each observation is not compared to each other but to a single value (mean of the sample). If the value is smaller then the mean, - is assigned, otherwise + is assigned. Then count the +'s and –'s. Let n_+ and n_- be the total number of +'s and –'s in the observation, and *N* be the total number of the observation, $n_+ + n_- = N$. With n_+ and n_-, find the critical value r_c from the table (Appendix B) at the desired level of significance (α). Let *r* be the total number of runs in the observation, if $r \leq r_c(lower)$ or $r_c(upper) \leq r$, reject $\mathrm{H_0}$; otherwise accept $\mathrm{H_0}$.

3.5 Research questions

The objective of this study is to explore the characteristics and possible value of the proposed proactive supplier performance monitoring and inventory policy change strategy. The performance of the strategy is evaluated under different scenarios determined by:

- quantity yield at each factory
- type of run test,

and each scenario is compared using:

- total number of stockouts occurring
- average inventory level
- number of stockouts occurring before and after the inventory policy change

The suggested strategy is explored by the following research questions.

Q1. How worthwhile is it to change the inventory policy based on supplier behavior monitoring?
Q2. How do the operating conditions at each factory affect the performance of the strategy?
Q3. How do the different types of run test affect the performance of the strategy?

Each question is expanded in the following paragraph along with the proposition to explore in the experimentation.

Q1. How worthwhile is it to change the inventory policy based on supplier behavior monitoring?

In the suggested strategy, it is expected that the number of stockout can be reduced by bumping up the inventory level. However, a run test is a statistical tool to test whether or not the operation is in control, and therefore even if the test shows the operation is out-of-control, it doesn't necessarily mean disruptions are occurring. In addition, keeping extra inventory costs more while it is helpful to reduce the risk of disruptions. In order to answer this question, both magnitude of the decrease in number of stockouts and the increase in inventory level should be analyzed.

Q2. How do the operating conditions at each factory affect the performance of the strategy?

When the inventory policy is changed, safety stock level is bumped up and inventory reorder point also goes higher accordingly. It triggers earlier order placement than expected and the supplier needs to deal with the unexpected increase in demand. If the supplier has a capacity to cover the demand or recover from the unexpected increase in demand, the inventory level at the receiver side can be successfully increased when the inventory policy is changed; however, if the supplier’s current operation is close to its maximum capacity, it is unable to deal with the unexpected increase in the demand and therefore, the suggested strategy might not show significant performance. This question can be answered by analyzing the number of stockouts with different operating conditions at each factory.

Q3. How do the different types of run test affect the performance of the strategy?

There are two types of run test used in this study. While the data is compared to each other in the runs up and down test, the data is compared against a single value in the runs above and below test. Since how these differences affect the performance of the strategy is unknown, it has to be explored in the experimentation. Furthermore, the case using both run tests together is also analyzed. In the case using both run tests, a potentially out-of-control condition is determined when at least one of them detects the out-of-control condition, and therefore it is expected that using both tests shows a better performance in reducing the stockouts. For each type of run test, the magnitude of reduction in number of stockouts should be analyzed with different experimental conditions. In addition, how many stockouts occurred before and after the detection of non-random pattern should also be explored.

3.6 Summary

This chapter detailed the development of both the conceptual model and the simulation model followed by research questions. The following chapter describes the experimental design used for the exploration.

Chapter 4

Experimental Design

This chapter describes the experiments used to explore the conceptual model. Simul8 software was used to implement and run the simulation model. In this chapter, a brief overview of experimental structure is explained first, and then the specific experimental parameters are described. The last section discusses the approach used to verify and validate the simulation model.

4.1 Experimentation Structure

The objective of this study is to explore the behavior and the performance of the strategy described in the previous chapter. In order to achieve the goal, the strategy needs to be tested under different experimental cases and scenarios. The following three are the components used in this experiment in order to create such cases and scenarios, and compare the performance of the strategy under them.

- Quantity yield rate at each factory
- Type of run test
- Performance measures

- Quantity yield rate at each factory

  One of the elements to determine different experimental scenarios is quantity yield rate at each factory. In this study, yield rate is the only factor that determines the performance of each factory's operation as it is easy to measure and the variability can be easily applied to the run test. In the simulation, yield rate is sampled randomly by the simulation software of Simul8. Simul8 uses random number streams and generates random numbers based on the percentage yield set to the simulation. Random number streams have naturally occurring patterns of increasing, decreasing, and oscillating data. These naturally occurring patterns will be used as a surrogate for potentially non-random behaviour at the supplier. The simulation length was analysed and set to ensure that potentially non-random behaviour would result. An explicit algorithm for inserting non-random behaviour was not implemented as part of the experimentation as it was felt that the naturally occurring patterns in the random stream would be themselves sufficiently random.

- Type of run test

  The type of run test is the other element to differentiate experimental scenarios. While yield rate creates a different experimental scenario from the supply chain model side, the type of run test used determines different experimental scenarios from the strategy side. As already described above, two sorts of run test, runs up and down test and runs above and below test, are applied in this study.

- Performance measures

  The number of stockouts occurred and inventory level are used to assess the performance of the strategy. Among numbers of performance measures, cost is the most commonly used measure in supply chain performance evaluation. However, firms can no longer compete solely on the basis of the cost and quality focused measures such as customer satisfaction and flexibility have received a lot of attention in recent years (Lockamy, 1998). These qualitative measures cannot directly be described numerically and therefore interpreted in time and quality based measures. In addition, day-to-day control of manufacturing and distribution operations is better handled with non-financial measures (Gibuipero et al, 2008). In this study, run test is employed as a monitoring tool. Therefore it is important that the performance measure is numerically measureable and has variability. Since yield rate meets these requirements and is also related to qualitative measures described above, yield rate is chosen as a performance measure in this study.

4.2 Experimental Design

Experiment in this study is conducted in two phases. The first phase of experiment is set to explore the performance of strategy with different types of run tests. Based on the result obtained by the first experiment, the second experiment is conducted in order to analyze the sensitivity of the strategy under a different yield rate.

Experimentation with different types of run tests

In the first phase of experimentation, the following four experimental cases are created based on the run test applied in the simulation.

Case 1: Strategy is not applied
Case 2: Strategy is applied with runs up and down test
Case 3: Strategy is applied with runs above and below test
Case 4: Strategy is applied with both of the run tests

The cases can be grouped into two: the strategy is not applied (Case 1) and the strategy is applied (Case 2-4). The performance of the strategy is compared against the case where strategy is not applied. Case 2-4 are created in order to see if the performance of the strategy would be different depending on the run test used for monitoring, and if yes, how it would be different. As shown in Table 4.1, the performance of run tests was tested under different yield rates of 95%, 90%, and 85%.

Table 4.1: Experimental cases in first phase experiment

	Quantity yield rate		
Case 1: No strategy applied	95%	90%	85%
Case 2: Runs up and down test	95%	90%	85%
Case 3: Runs above and below test	95%	90%	85%
Case 4: Both of the run tests	95%	90%	85%

Experimentation under different yield rate

In the second phase of the experiment, the run test which showed the best performance in the first experiment is selected out of three (Case 2-4). Performance of the case selected is compared with the case without strategy application (Case 1) by changing the yield rate between 80% and 100%, in order to better understand the behavior of the strategy and analyze the sensitivity.

4.3 Simulation Design

The simulation had 50 runs with different random number set under the following condition. The mean and the standard deviation of the number of stockouts are compared between 50 runs and 100 runs of simulation, and 50 runs of experiment is considered to be large enough and reasonable (Appendix C). Table 4.2 shows the constant settings at Factory 1 and Factory 2. Parameters used for run tests are determined based on preliminary experiment and the one showed the best performance is selected (Appendix D, Appendix E), and set as confidence level of α=0.1 and number of sample data point of 10. Therefore, supplier monitoring using run test starts from day 10, and when a non-random pattern is detected, safety stock level is increased by 30 goods, which is worth one day demand.

Table 4.2: Constant setting at Factory 1 and Factory 2

	Factory 1	Factory 2
Max production capacity	39 goods / day	42 goods / day
Initial finished goods inventory level	170	60
Safety stock of finished goods inventory	20	30
Initial raw material inventory level	180	170
Safety stock of raw material inventory	60	20
Reorder point of raw material inventory	90	110
Raw material order quantity	150	150
Delivery lead time of raw material supply	1 days	3 days

- Simulation period: 100 days
- Order rate from customer: 30 goods / day
- Expected daily demand: 30 goods / day
- Amount increase in safety stock when inventory policy changed: 30 goods
- Confidence level for run test: α=0.1

4.4 Verification and Validation

In order to understand the behavior of inventory policy change strategy, it is important to make sure other experimental conditions are fixed. Also, the same random number sets are used across the different experiments. In this way, the variations obtained can be verified due to the changes in the scenarios, not due to the inaccurate transformation of conceptual model to simulation model, or the variations in random numbers.

Since there is no test data available from other related research, the simulation model was validated by evaluating input-output transformation and using graphical methods. Every input and output were recorded in test runs, and compared whether or not the data matches the expected values. In addition, inventory levels are graphed in order to graphically validate the model. Figure 4.1 and 4.2 show the inventory levels when the model is tested with 95% yield rate with and without strategy application. In this test run, a non-random pattern in quantity yield at Factory 1 was detected at the day of 51 and Factory 2 increased its raw material safety stock level by 30. Therefore raw material inventory level at Factory 2 slightly went up after the day of 51, compared to the case where strategy was not applied. On the other hand, finished goods inventory level at Factory 1 shifted forward after the day since the order from Factory 2 was placed earlier than the normal cycle. From this result, it can be ensured that the model behaves as expected.

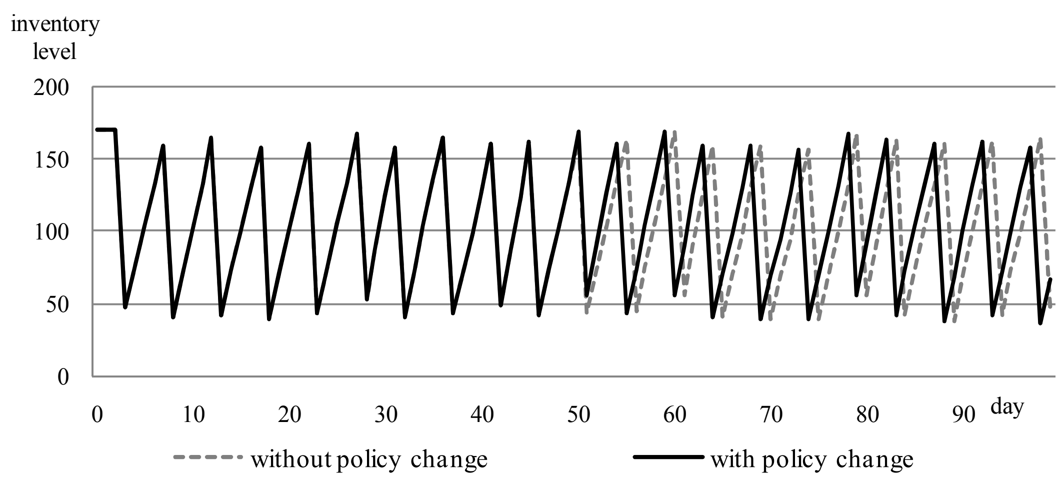


Figure 4.1: Inventory levels of finished goods at Factory 1 with and without the inventory policy change

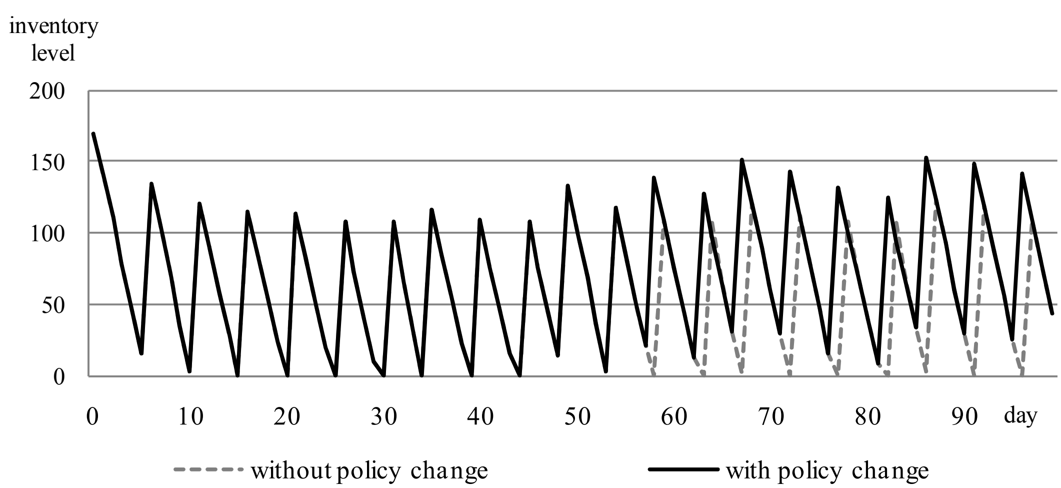


Figure 4.2: Inventory levels of raw material at Factory 2 with and without the inventory policy change

4.5 Summary

This chapter described the design of the experimental framework used to explore the supplier monitoring and inventory policy change strategy, along with the approach for verification and validation of the simulation model. The following chapter presents the results obtained during the experimentation.

Chapter 5

Experimentation Results

This chapter presents the results from the simulation experiments and analyzes them to understand the characteristics of the strategy and to determine if the results are rational. In all experimental cases, the number of stockouts and average inventory level are examined in order to analyze the performance of the strategy.

5.1 Results with different type of run test

The first experiment was set to explore the general characteristics of the strategy. The experiment was conducted with the quantity yield of 95%, 90%, and 85%, and the following cases were examined:

Case 1: Strategy was not applied
Case 2: Strategy was applied with runs up and down test
Case 3: Strategy was applied with runs above and below test
Case 4: Strategy was applied with both of the run tests

Total number of stockouts

Table 5.1 shows the mean and the standard deviation of the number of stockouts at each inventory (Factory 1 raw material, Factory 1 finished goods, Factory 2 raw material and Factory 2 finished goods) under four experimental cases described above. Since the simulation was set to provide enough raw materials for Factory 1, no stockouts occurred in raw material inventory at Factory 1. How many stockouts were reduced when the strategy is applied is shown in Table 5.2. The number of stockouts reduced was calculated for each run and the average of the number is listed in the table. A positive value indicates the decrease in the number of stockouts and a negative value indicates the increase in the number of stockouts when compared to the case where strategy was not applied. The % decrease in the number of stockouts compared to the case without strategy employment is also listed in the table.

The result also shows that the number of stockouts in finished goods inventory at Factory 1 slightly increases when the strategy is applied. This is because order from Factory 2 was placed earlier than the usual order cycle when the inventory policy was changed. If the order is placed earlier than expected, Factory 1 may not have enough inventories or need to use safety stock to cover the order at the moment. Therefore, stockouts are more likely to occur for one to two order cycles after the inventory policy change.

Table 5.1: Mean and standard deviation of total number of stockouts

		95% yield				90% yield				85% yield			
		Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	4.44	5.00	5.34	5.34	9.52	10.76	11.60	11.80	16.70	16.78	16.74	16.72
	StDev	0.50	0.67	0.56	0.52	1.50	1.70	1.44	1.26	1.49	1.34	1.45	1.44
F2 RAW	Mean	13.34	9.30	5.48	4.88	19.70	17.92	17.50	17.04	28.56	28.50	28.38	28.38
	StDev	1.44	4.78	3.90	3.72	1.82	3.43	2.66	3.24	2.15	1.53	1.66	1.66
F2 FGI	Mean	0.10	0.08	0.06	0.04	5.08	4.28	3.66	3.46	13.34	13.20	13.02	12.98
	StDev	0.30	0.27	0.24	0.20	1.08	1.33	1.24	1.18	0.87	0.83	0.87	0.84

Table 5.2: Number and percentage reduction in stockouts

	95% yield			90% yield			85% yield		
	Case2	Case3	Case4	Case2	Case3	Case4	Case2	Case3	Case4
F1 RAW	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)
F1 FGI	-0.56 (-12.9%)	-0.90 (-20.7%)	-0.90 (-20.8%)	-1.24 (-13.72%)	-2.08 (-23.75%)	-2.28 (-26.06%)	-0.08 (-0.61%)	-0.04 (-0.39%)	-0.02 (-0.28%)
F2 RAW	4.04 (31.49%)	7.86 (59.01%)	8.46 (63.90%)	1.78 (9.49%)	2.20 (11.23%)	2.66 (13.89%)	0.06 (0.21%)	0.18 (0.64%)	0.18 (0.64%)
F2 FGI	0.02 (2.00%)	0.04 (4.00%)	0.06 (6.00%)	0.80 (16.07%)	1.42 (28.37%)	1.62 (32.62%)	0.14 (1.00%)	0.32 (2.34%)	0.36 (2.62%)

Average inventory level

Table 5.3 shows the mean and the standard deviation of the average inventory level for each experimental case. Table 5.4 shows the difference in the average inventory level compared to the case where the strategy was not applied. Similar to Table 5.2, the positive value means the decrease and negative value means the increase in the average inventory level compared to the case without strategy employment.

Table 5.3: Mean and standard deviation of average inventory level

		95% yield				90% yield				85% yield			
		Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4	Case1	Case2	Case3	Case4
F1	Mean	113.40	113.16	112.79	112.78	111.18	110.76	110.53	110.42	109.92	109.68	109.69	109.66
RAW	StDev	1.31	1.16	1.21	1.16	1.59	1.70	1.72	1.62	1.88	1.88	1.74	1.76
F1	Mean	92.18	92.22	92.23	92.22	89.65	90.14	90.17	90.20	97.85	97.75	97.58	97.52
FGI	StDev	0.82	0.80	0.85	0.85	2.02	1.80	1.67	1.66	2.18	2.16	2.43	2.36
F2	Mean	65.98	73.06	79.24	80.43	62.29	64.08	64.43	64.92	55.86	55.94	56.16	56.16
RAW	StDev	1.32	7.83	6.79	6.36	1.48	3.18	2.69	3.13	0.98	1.02	1.24	1.24
F2	Mean	45.48	46.34	47.08	47.22	41.15	41.74	41.89	42.06	35.96	35.98	36.03	36.03
FGI	StDev	0.65	1.12	0.90	0.84	0.97	1.35	1.15	1.29	1.28	1.26	1.27	1.26

Table 5.4: Change in average inventory level

	95% yield			90% yield			85% yield		
	Case2	Case3	Case4	Case2	Case3	Case4	Case2	Case3	Case4
F1 RAW	-0.24 (-0.20%)	-0.61 (-0.53%)	-0.61 (-0.54%)	-0.42 (-0.37%)	-0.66 (-0.58%)	-0.76 (-0.67%)	-0.23 (-0.21%)	-0.23 (-0.20%)	-0.26 (-0.23%)
F1 FGI	0.04 (0.04%)	0.05 (0.05%)	0.04 (0.04%)	0.48 (0.55%)	0.52 (0.60%)	0.55 (0.64%)	-0.10 (-0.10%)	-0.27 (-0.27%)	-0.33 (-0.33%)
F2 RAW	7.08 (10.70%)	13.26 (20.10%)	14.45 (21.89%)	1.79 (2.87%)	2.14 (3.43%)	2.62 (4.21%)	0.08 (0.15%)	0.30 (0.53%)	0.30 (0.53%)
F2 FGI	0.86 (1.89%)	1.61 (3.54%)	1.74 (3.83%)	0.59 (1.44%)	0.75 (1.82%)	0.91 (2.21%)	0.02 (0.07%)	0.07 (0.21%)	0.07 (0.20%)

Stockouts before and after the policy change point

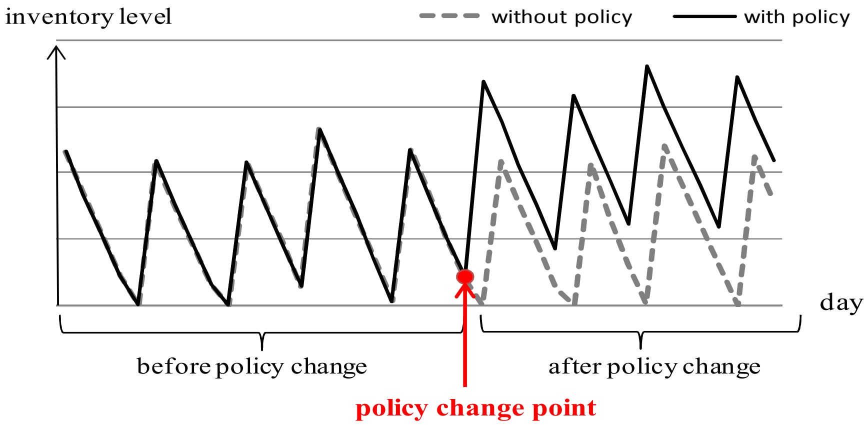


Figure 5.1: Description of inventory policy change point

In addition to the total number of stockouts, the number of stockouts before and after the policy change point is analyzed. As Figure 5.1 describes, policy change point is the point where a non-random pattern was detected for the first time during the run and the inventory policy was changed to have additional safety stock.

Table 5.5: Number of stockouts before and after the policy change point

		Case2		Case3		Case4	
		Before	After	Before	After	Before	After
95%	Mean	8.22	1.08	4.10	1.38	3.38	1.50
	StDev	5.41	1.16	4.10	1.05	3.92	0.99
90%	Mean	11.96	5.96	6.32	11.18	4.78	12.26
	StDev	7.23	5.87	5.56	5.51	4.57	4.81
85%	Mean	19.64	8.86	11.32	17.06	10.38	18.00
	StDev	9.22	9.75	8.61	9.00	8.16	8.51

Table 5.6: Number of times inventory policy change occurred in 50 runs

	Case2	Case3	Case4
95% yield	31 (62%)	46 (92%)	48 (96%)
90% yield	34 (68%)	46 (92%)	48 (96%)
85% yield	27 (54%)	45 (90%)	46 (92%)

The number of stockouts occurred before and after the policy change point is showed in Table 5.5. Table 5.6 shows the number of times inventory policy change occurred in 50 runs of the experiment. In some runs, a non-random pattern was not detected and therefore inventory policy change did not occur at all in 100 days of simulation period. The number that the inventory policy change occurred was counted and listed in the table along with the ratio in a total of 50 runs. The larger the value is, the better the run test detects non-random patterns.

5.2 Results under different yield rate

From the first experiment, Case 4, which uses two run tests together in the strategy, showed the best performance in reducing the total number of stockouts in Factory 2 and also in detecting the non-random patterns. Therefore, Case 4 was selected to analyze the strategy performance and sensitivity under different yield rates. In the second experiment, the performance was compared between:

Case 1: Strategy was not applied

Case 4: Strategy was applied with both run tests

Total number of stockouts

Table 5.7 shows the total number of stockouts at Factory 2 under Case 1 and Case 4. Same as the first experiment, each case was simulated for 50 runs and the value in the table shows the average number of total stockouts in 50 runs. The number and the percentage reduction in stockouts at Factory 2 are listed in Table 5.8. Same as the first experiment, the number of stockouts reduced was calculated in each run and the average is listed in the table. Since no stockouts occurred in finished goods inventory when yield rates are 96% or higher, the corresponding data are not available in Table 5.8.

Table 5.7: Total number of stockout at Factory 2 in Case 1 and Case 4

	Factory 2 raw material		Factory 2 finished goods	
yield rate	Case 1	Case 4	Case 1	Case 4
99%	4.70	0.00	0.00	0.00
98%	8.06	3.28	0.00	0.00
97%	11.84	3.46	0.00	0.00
96%	13.34	4.88	0.00	0.00
95%	14.82	6.02	0.30	0.12
94%	16.02	7.56	0.84	0.80
93%	16.64	11.32	2.18	0.90
92%	17.16	13.62	3.60	1.86
91%	19.70	17.04	3.60	1.86
90%	19.70	17.04	5.80	3.46
89%	21.28	19.92	8.54	7.62
88%	23.74	22.62	8.54	7.62
87%	25.70	25.02	10.42	9.72
86%	27.44	27.02	12.00	11.42
85%	28.56	28.38	13.34	12.98
84%	30.22	30.20	14.54	14.46
83%	30.20	30.14	15.60	15.56
82%	31.86	31.86	16.64	16.62
81%	32.46	32.46	17.68	17.68
80%	33.74	33.74	18.84	18.84

Table 5.8: Number and percentage reduction in number of stockouts at Factory 2

	Factory 2 raw material		Factory 2 finished goods	
yield rate	# reduction	% reduction	# reduction	% reduction
99%	4.66	94.00%	N/A	N/A
98%	4.78	58.46%	N/A	N/A
97%	6.08	67.02%	N/A	N/A
96%	8.38	70.61%	N/A	N/A
95%	8.46	63.90%	0.06	6.00%
94%	8.8	59.67%	0.18	60.00%
93%	8.46	53.38%	0.54	61.76%
92%	5.32	32.24%	1.28	58.50%
91%	3.54	21.13%	1.74	50.27%
90%	2.66	13.89%	1.62	32.62%
89%	1.36	6.36%	1.42	20.17%
88%	1.12	4.69%	0.92	10.62%
87%	0.68	2.73%	0.7	6.70%
86%	0.42	1.54%	0.58	4.79%
85%	0.18	0.64%	0.36	2.62%
84%	0.02	0.07%	0.08	0.53%
83%	0.06	0.20%	0.04	0.25%
82%	0.00	0.00%	0.02	0.12%
81%	0.00	0.00%	0.00	0.00%
80%	0.00	0.00%	0.00	0.00%

Average inventory level

Table 5.9 lists the average inventory levels of raw material and finished goods at Factory 1 and Factory 2. In the table, the average inventory levels are compared between the case that the strategy was not applied (Case 1) and the case that the strategy was applied with two run tests (Case 4). In this table, the results under 100% yield rate are also listed.

Table 5.9: Average inventory level

	Factory 1 RAW		Factory 1 FGI		Factory 2 RAW		Factory 2 FGI	
yield rate	Case1	Case4	Case1	Case4	Case1	Case4	Case1	Case4
100%	129.80	129.80	99.79	99.79	88.10	88.10	50.10	50.10
99%	117.46	116.38	98.74	99.19	75.02	95.34	49.41	49.70
98%	116.39	116.00	97.64	97.87	72.56	85.36	48.57	49.02
97%	115.42	114.59	96.24	95.80	70.81	85.75	47.74	48.50
96%	114.15	114.14	94.11	93.95	68.22	84.42	46.66	48.02
95%	113.40	112.78	92.18	92.22	65.98	80.43	45.48	47.22
94%	112.23	112.24	90.47	90.77	64.70	78.49	44.42	46.60
93%	111.57	111.08	88.98	89.26	64.35	76.27	43.40	45.74
92%	111.24	109.76	87.92	88.75	64.53	71.00	42.99	44.55
91%	112.00	110.62	88.08	90.20	64.07	68.12	42.36	43.47
90%	111.18	110.42	89.65	91.20	62.29	64.92	41.15	42.06
89%	111.03	110.69	91.38	91.36	61.10	61.93	40.26	40.62
88%	110.68	110.40	93.03	93.14	59.55	60.31	38.91	39.28
87%	110.75	110.26	95.62	95.46	58.15	58.74	37.76	37.96
86%	110.02	110.02	97.20	96.68	56.76	57.37	36.80	36.97
85%	109.92	109.66	97.85	97.52	55.86	56.16	35.96	36.03
84%	109.23	109.44	97.83	97.67	54.78	54.85	34.58	34.60
83%	109.69	109.58	96.54	96.44	54.78	54.90	34.44	34.47
82%	109.11	109.08	94.65	94.66	54.32	54.32	33.83	33.83
81%	107.72	107.67	92.80	92.82	54.12	54.12	33.15	33.15
80%	107.03	107.03	91.20	91.20	53.69	53.69	31.79	31.79

Stockouts before and after the policy change point

Table 5.10 shows the number of stockouts before and after the policy change point. The number of stockouts before the change point occurred before a non-random pattern was detected. Two sorts of data are listed as the number of stockouts after the policy change point. One is when the strategy was not applied (Case 1) and the other is when the strategy is applied (Case 4). In 50 runs of experimentation, there were a few cases when a non-random pattern was not detected at all during a run. In such case, the number of stockouts occurred in the run was counted as stockouts before policy change point.

Table 5.10: Average number of stockouts before and after the policy change point in Case 4

	Factory 2 raw material			Factory 2 finished goods		
yield rate	Before	After (Case1)	After (Case4)	Before	After (Case1)	After (Case4)
99%	0.04	4.66	0.00	0.00	0.00	0.00
98%	2.66	5.40	0.62	0.00	0.00	0.00
97%	2.54	9.30	0.72	0.00	0.00	0.00
96%	2.32	11.02	1.14	0.00	0.00	0.00
95%	3.38	11.44	1.50	0.02	0.28	0.02
94%	3.80	12.22	2.22	0.08	0.76	0.04
93%	4.10	12.54	3.46	0.18	2.00	0.12
92%	5.54	11.62	5.78	0.64	2.96	0.26
91%	4.68	15.02	8.94	0.80	2.80	1.06
90%	4.78	14.92	12.26	1.04	4.76	2.42
89%	5.72	15.56	14.20	1.52	7.02	3.82
88%	7.64	16.10	15.98	2.70	5.84	4.92
87%	8.04	17.66	16.98	3.10	7.32	6.62
86%	7.74	19.70	19.28	3.28	8.72	8.14
85%	10.38	18.18	18.00	4.88	8.46	8.10
84%	8.66	21.56	21.54	4.20	10.34	10.26
83%	9.18	21.02	20.96	4.67	10.93	10.90
82%	9.72	22.14	22.14	5.00	11.64	11.62
81%	11.18	21.28	21.28	6.00	11.68	11.68
80%	9.92	23.82	23.82	5.40	13.44	13.44

5.3 Summary

This chapter presented the results obtained from the experimentation. There were two sets of experimentation designed: 1) experimentation under different types of run tests, and 2) experimentation under different yield rates. Under each set of experimentation, three sorts of data: total number of stockouts, average inventory level, and number of stockouts before and after the inventory policy change point are collected in order to analyze the performance of the strategy. A discussion and the analysis of the results are provided in Chapter 6.

Chapter 6

Analysis and Discussion

This chapter presents the discussion on the results obtained from the experimentation. The objective of this chapter is to provide insights into the application of supplier monitoring and inventory policy change strategy. Section 6.1 analyses the performance of the strategy with three different types of run tests. Section 6.2 discusses the performance of the strategy under different yield rates along with the sensitivity analysis.

6.1 Run test and performance

In the first set of experimentation, three types of run test was employed as a supplier monitoring method and the model was simulated under the yield rates of 95%, 90%, and 85%. Figure 6.1 and 6.2 shows the percentage decrease in stockouts and the percentage increase in average inventory level in raw material inventory level at Factory 2. The results indicate that the number of stockouts can be reduced with all three types of run tests. It is expected that the average inventory level increases as safety stock level increases by applying the strategy, and it is shown in the result. The results also indicate that the percentage decrease in stockouts is largest when two run tests were applied together. Since the percentage increase in the average inventory level is corresponding to the percentage decrease in stockouts, it can be concluded that the performance of the strategy in detecting non-random patterns and reducing stockouts is the best when both run tests are applied together.

When both run tests are used in monitoring, a non-random pattern is detected at the earliest time period between two run tests. In addition, as already presented in Table 5.6, run up and down test did not detect any non-random pattern in around 40% to 50% of times in 50 runs of experiment, while run above and below test and both tests together detected over 90%. Therefore, it is assumed that the performance of the strategy in avoiding stockouts depends on how sensitive the run test is in detecting non-random patterns.

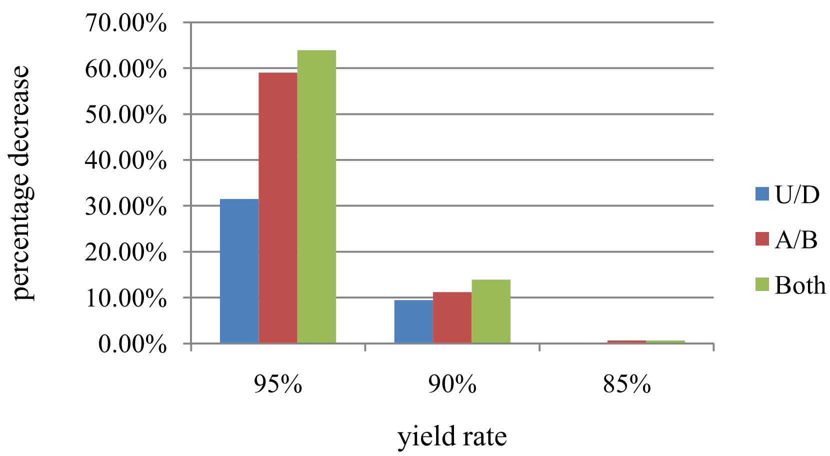


Figure 6.1: Percentage decrease in stockouts at Factory 2 raw material

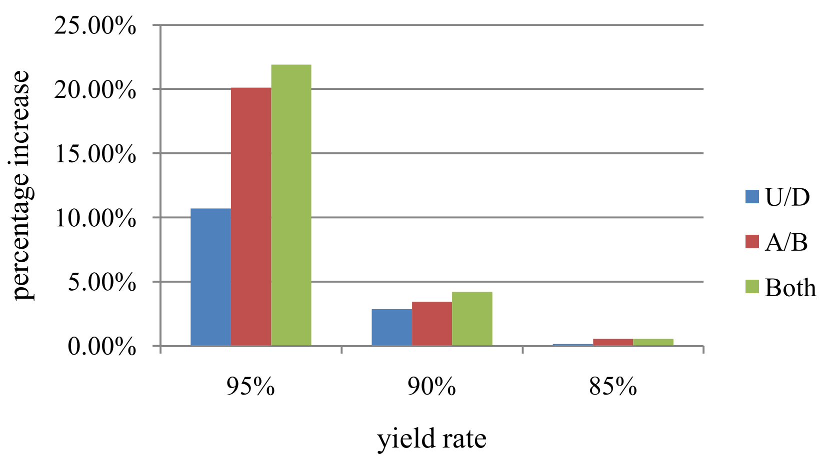


Figure 6.2: Percentage increase in average inventory level at Factory 2 raw material

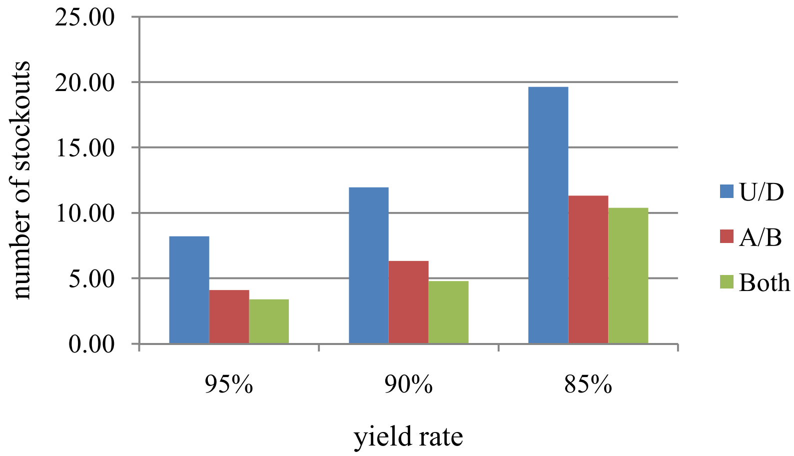


Figure 6.3: Number of stockouts before the policy change point

The number of stockouts before the policy change point is one of the performance indicators of run tests. It is expected that the smaller the number, the better a non-random pattern is detected and stockouts can be avoided before occurring. As shown in Figure 6.3, the number of stockouts before the policy change point is smallest with the employment of both run tests. This indicates that applying both run tests is more sensitive in detecting non-random patterns than the other two cases. Note that the number of stockouts before the policy change point and the total number of stockouts both increase as the yield rate decreases. Therefore, despite the fact that the percentage reduction in stockouts is more significant under larger yield rates, it cannot simply be concluded that the strategy performance is better when higher yield rates are higher.

Based on the results described above and in Section 5.1, the following insights about the strategy are drawn:

- The number of stockouts can be reduced by applying the strategy
- The case where two run tests are applied together showed the best performance in detecting non-random pattern and reducing number of stockouts.

- The performance of the strategy depends on how sensitively the run test detects non-random patterns. The more run test detects non-random pattern, the more stockouts can be avoided beforehand.
- The reduction in stockouts becomes less significant as yield rate decreases. However the total number of stockouts increases as yield rate decreases and therefore the relation between strategy performance and yield rate cannot be concluded from these results.

6.2 Yield rate and performance

In the second set of experiment, the performance of the strategy is analyzed under the yield rates between 80% and 100%. The performance was compared between the case where strategy was not applied (Case 1) and the case where two run tests were applied together (Case 4).

Figure 6.4 shows the number and the percentage reduction in the number of stockouts in raw material at Factory 2. The results show that the number of reduction is most significant at 94% yield rate and then declines as yield rate decreases. Significant reduction can be seen when yield rate is relatively large and once yield rate reaches a certain point, the reduction starts to decline and become insignificant. This trend can also be seen in the average inventory level described in Figure 6.5, where the increase in the average inventory reduces as yield rate decreases and reduction in stockouts becomes insignificant.

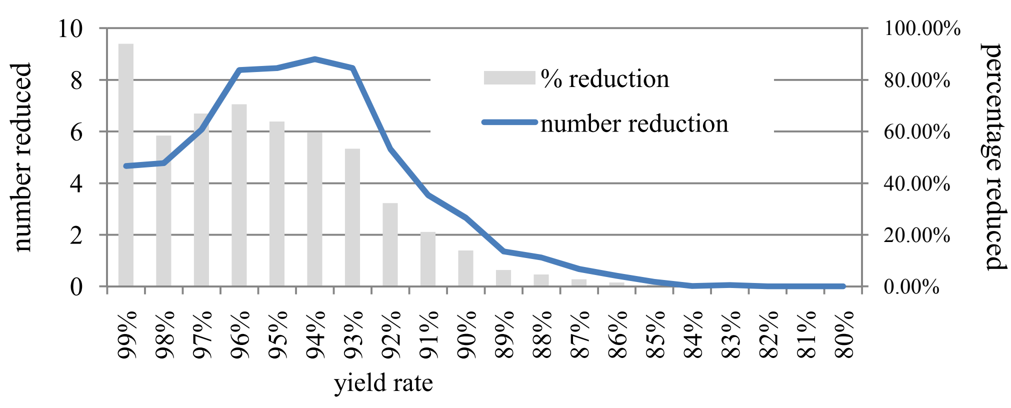


Figure 6.4: Number and percentage reduction in stockouts at Factory 2 raw material inventory

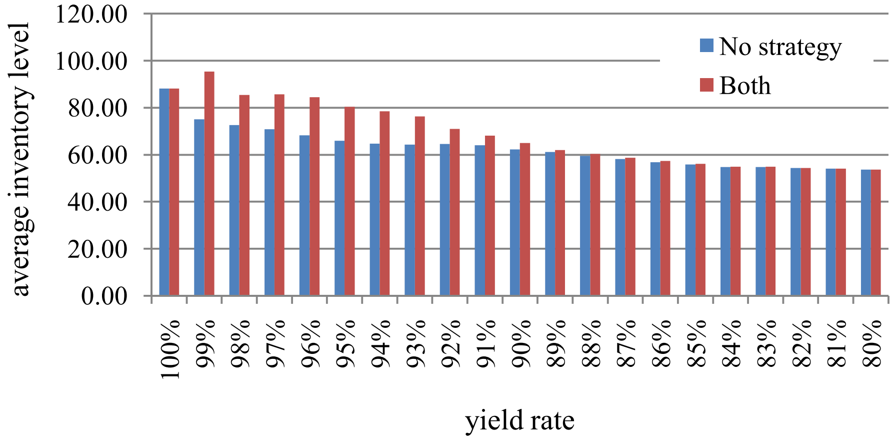


Figure 6.5: Average inventory levels at Factory 2 raw material inventory

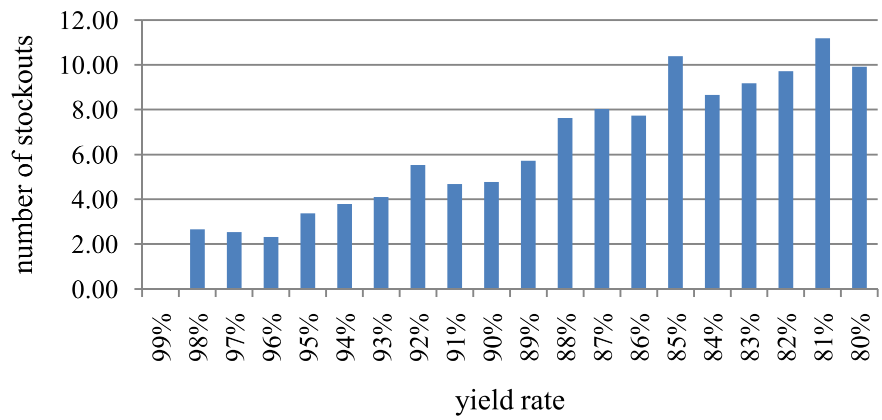


Figure 6.6: Number of stockouts before the inventory policy change point

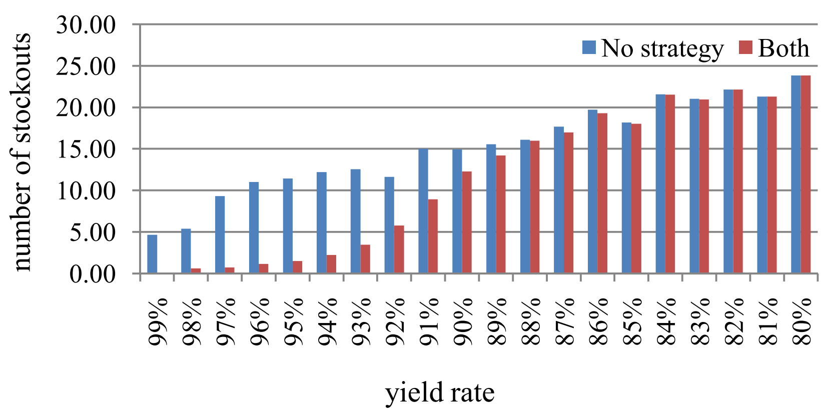


Figure 6.7: Number of stockouts after the inventory policy change point

In addition to the total number of stockouts and average inventory level, it is also important to examine the number of stockouts before and after the policy change point. Regarding these numbers, there are two points that should be noted. First, the number depends on how often stockouts occurs, and the number tends to be larger with smaller yield rate. Second, the number also depends on the time period the inventory policy is changed. For example, if the policy change occurred at day 20, the number of stockouts occurred after the time period (from day 21 to day 100) is likely to be larger compared to the case the policy change occurred at day 50.

Figure 6.6 and Figure 6.7 shows the number of stockouts before and after the policy change point. The results indicate that the number of stockouts after the policy change point reduced dramatically and only a few stockouts occurred when yield rate was 95% or larger. However, the number reduced becomes less significant as yield rate decreases and no change can be seen when yield rate is 84% or smaller. There are two possible reasons for this. As already stated, one is that a non-random pattern was detected at the very end of the simulation time period and the simulation ended before the effect of the strategy was reflected. The other is that the production capacity was too tight to cover the yield loss.

Based on the results described above and in Section 5.2, the following insights about the strategy are drawn:

- The trend that the reduction in stockouts declines as yield rate decreases is not true when yield rate is relatively large.
- The performance of the strategy is insignificant with lower yield rate.
- The two possible reasons of insignificant performance of the strategy are 1) non-random pattern was detected at the very end of the simulation, and 2) production capacity was not large enough to cover the yield loss.

In order to explain and understand these insights, analysis is conducted in terms of production capacity, variability in yield rate and stockouts under different yield rates.

Production capacity

Table 6.1 shows how many goods can be produced with maximum production under different yield rates. When the yield rate is 80%, an average of 31.2 goods and 33.6 goods can be produced in Factory 1 and Factory 2 respectively with maximum production. These numbers are very close to the daily demand and therefore it is nearly impossible to recover from additional yield loss or to meet unexpected demand. In such case, Factory 1 cannot increase its production when an order arrives earlier. If the order didn't arrive on time, Factory 2 cannot successfully bump up the inventory level even if a non-random pattern was detected. This explains the reason why the performance of the strategy is less significant at small yield rates. Therefore, it is important that Factory 1 has enough capacity to increase its production in order to effectively employ this strategy. If the yield rate is extremely low at Factory 1, even the daily demand cannot be guaranteed to be met in all cases. Furthermore, Factory 1 cannot replenish its finished goods inventory, and the system will lock up. If Factory 1 is potentially out-of-control the majority of the time or generally has a low yield, the only real solution is to carry greater levels of inventory at the finished goods level, and the customer's raw material location.

Table 6.1: Maximum yield at different yield rate

	Factory 1 (max production capacity = 39/day)	Factory 2 (max production capacity = 42/day)
95% yield rate	39×0.95=37.05	42×0.95=39.90
90% yield rate	39×0.90=35.10	42×0.90=37.80
85% yield rate	39×0.85=33.15	42×0.85=35.70
80% yield rate	39×0.80=31.20	42×0.80=33.60

Variability in yield rate

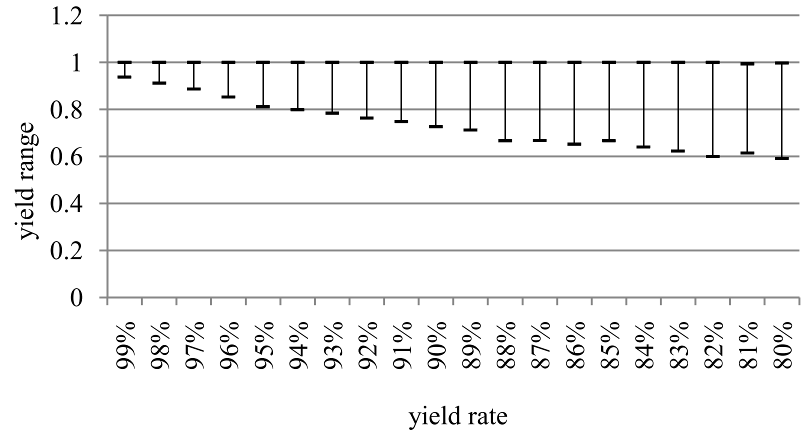


Figure 6.8: Variability in yield rate

Figure 6.9 shows the average time period when a non-random pattern was detected and the inventory policy was changed. Significant differences can be seen when the yield rates are 97% or larger, and the average time periods when non-random patterns were detected are 25.5, 45.2, and 36.6 accordingly. Compared to the results with yield rate of 96% or lower, a non-random pattern was detected in earlier time periods when the yield rate is 99%, and in later time period when the yield rates are 98% and 97%. From these results, it is expected that a non-random pattern would be detected more under 99% yield rate and less detected under 98% and 97% yield rates. How many potentially out-of-control situations were observed in one simulation run are shown in Figure 6.10. According to the data, potentially out-of-control situations were observed more than 10 times in average under 99% yield rate while the number is less than 6 times when the yield rates are 98% and 97%.

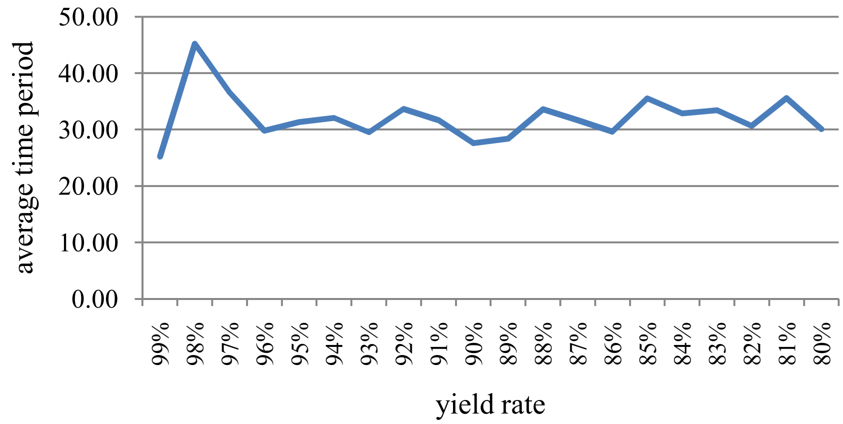


Figure 6.9: Average time period where non-random pattern was detected

Figure 6.10: Number of out-of-control cases in average

Some of the non-random patterns observed under 99% and 98% yield rates are shown in Figure 6.11 and 6.12. In a run test, non-random patterns are detected when too few runs or too many runs were observed. When the yield rate was 99%, more non-random patterns were detected because of too little runs. This is because variability in yield rate is too small under a 99% yield rate, and therefore the number of runs in observation tends to be smaller. On the other hand, there were more situations of too many runs that were observed under a 98% yield rate. However, variability in yield rate is relatively small and therefore less non-random patterns were observed compared to other yield rates. This explains why the performance of the strategy in detecting non-random patterns and reducing stockouts has its peak at around 95% yield rate except for the extreme case of 99% yield rate. Based on the results 6.8 through 6.11, it can be concluded that the performance in detecting non-random pattern depends on variability in yield rate, and non-random patterns tend to be detected more under too little variability but also less detected under relatively small variability.

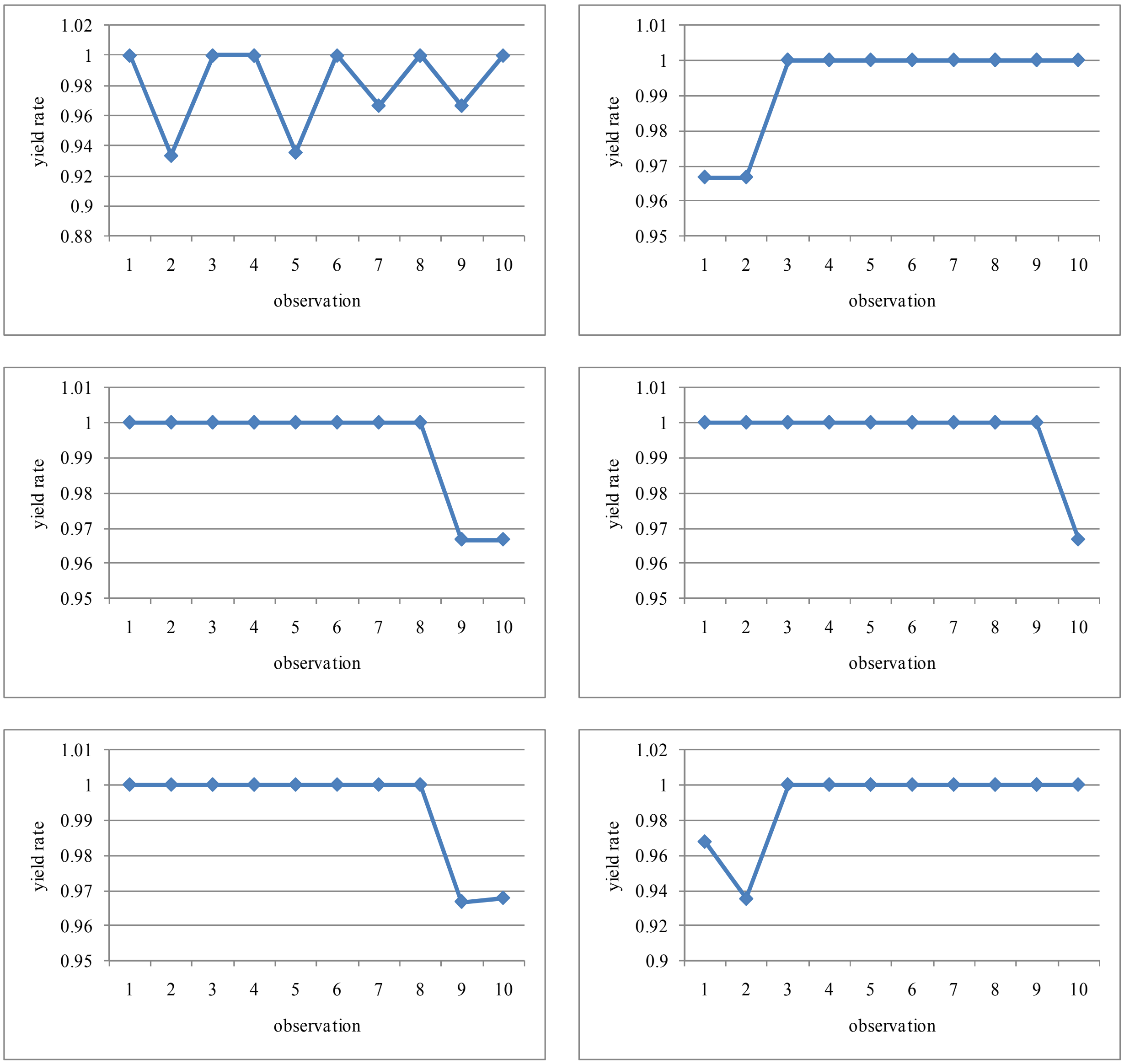


Figure 6.11: Out-of-control patterns under 99% yield rate

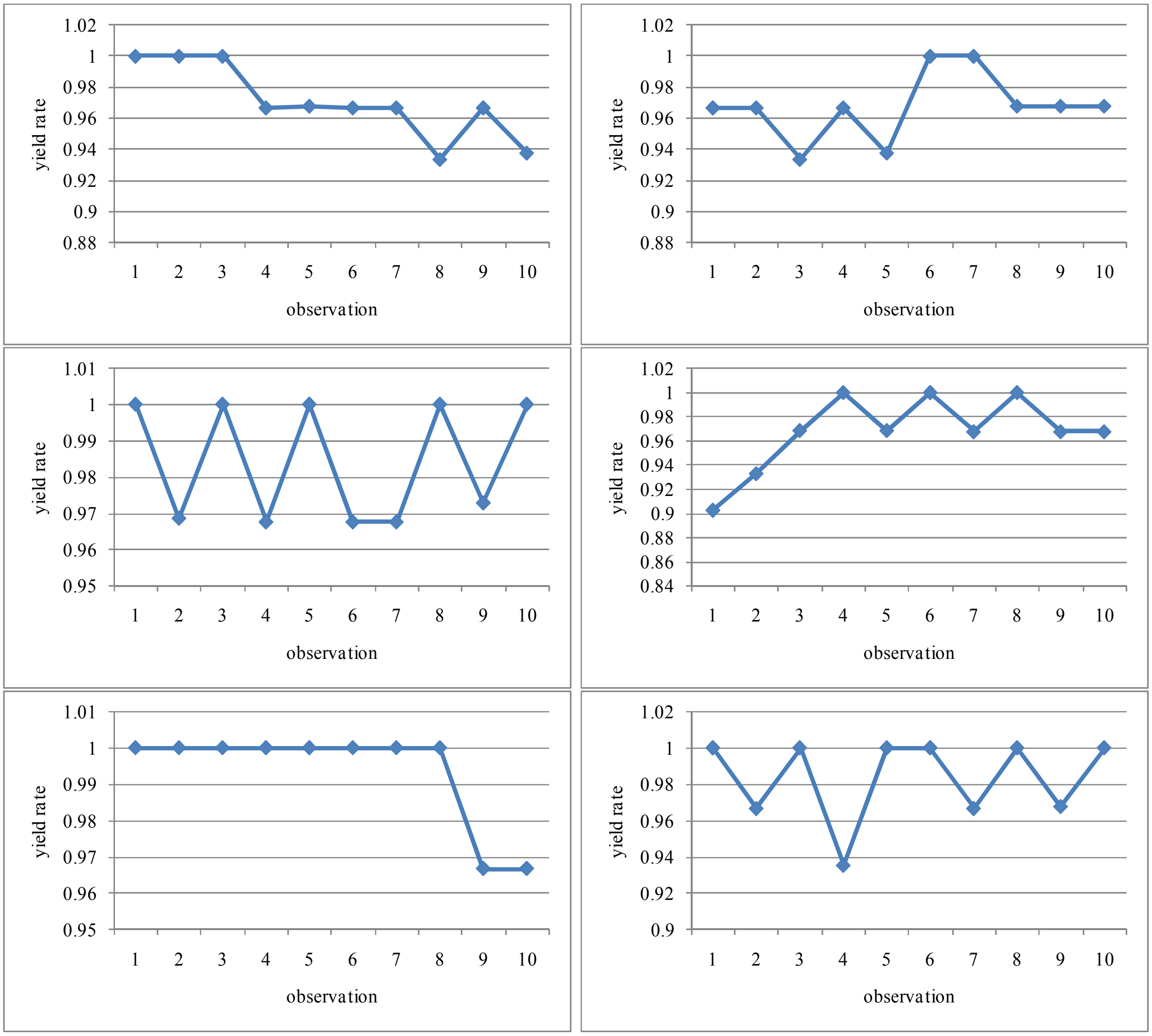
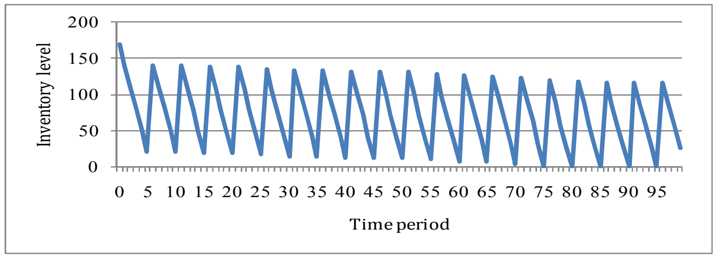


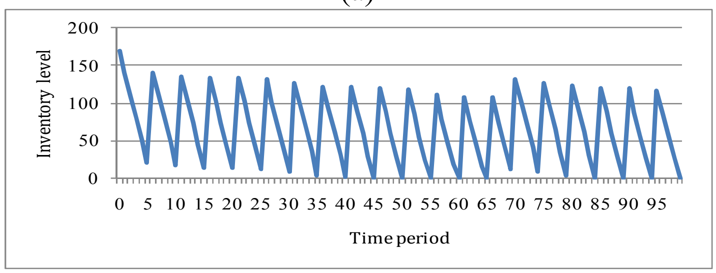
Figure 6.12: Out-of-control patterns under 98% yield rate

Stockouts under different yield rate

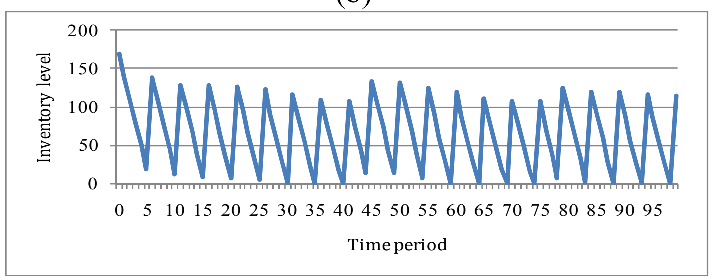
How many stockouts occur depends on the yield rate; however, when stockouts occur also depend on it. Figure 6.10 shows the example of inventory level when production yield was set as 99%, 98%, 97%, 96%, and 95%. The smaller the yield rate is, the earlier the time period stockouts occur. Stockouts appear to be occurring constantly when yield rate is 97% or smaller. As already discussed, potentially out-of-control situations were detected more under 99% yield rate while stockouts occur only in a later time period; this explains the significantly better performance of the strategy under 99% yield rate.



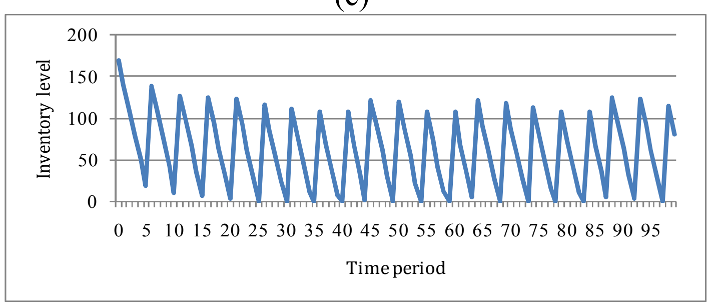
(a)



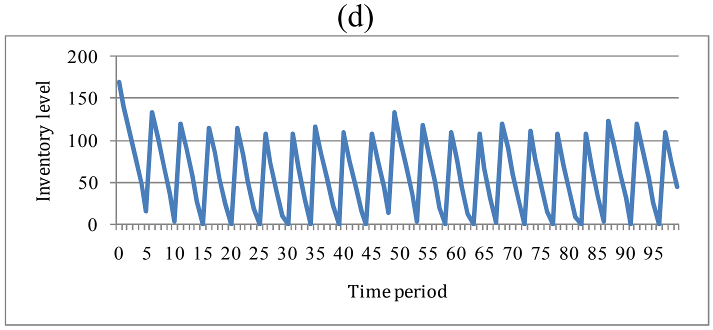
(b)



(c)



(d)



(e)

Figure 6.13: Inventory level at Factory 2 raw material under different yield rate: (a) 99%, (b) 98%, (c) 97%, (d) 96%, (e) 95%

Summary of the analysis above are:

- The performance of the strategy depends on production capacity and yield rate.
- It is important that the factory has enough production capacity in order for the strategy to perform as expected and to reduce stockouts.
- If variability in yield rate is too small, non-random patterns tend to be detected more as the number of runs in observation is likely to be small. However, even if the variability is not too small but still relatively small, non-random patterns tend to be detected less as the observations tend to be stable.
- When the yield rate is high, stockouts are likely to occur less and therefore it is easier to reduce the stockouts by applying the strategy.
- Except for the case where variability is extremely small, the performance in detecting non-random patterns is better under smaller yield rates as the variability increases. However, it becomes harder to catch up to the higher yield loss and therefore the reduction in stockouts is less significant at small yield rates.

6.3 Summary

This chapter discussed the results of the experimentation and analyzed the performance of supplier monitoring and inventory policy change strategy. The results indicate that the strategy has positive impact in reducing stockouts. The analysis of different types of run tests suggests that the performance of the strategy is best when two run tests are applied at the same time. The analysis under different yield rates indicate that the performance of the strategy depends on production capacity and yield rate, and the findings related to these factors are 1) it is necessary for the supplier to have enough production capacity in order to reduce stockouts by the strategy; and 2) performance measure should have a certain level of variability so that a non-random pattern is detected by the strategy.

Chapter 7

Implications and Limitations

7.1 Implications

The purpose of this thesis is to explore and carry out a preliminary analysis of the supplier monitoring and inventory policy change strategy. Key to the concept is the assumption that potentially out-of-control situations at a supplier can be causal triggers for stockouts and that these triggers can be predicted by using statistical monitoring tools. It is also assumed that a dynamic policy is better than simply setting an artificially high safety stock trying to have extra safety stock only when and where needed. One of the objectives of the thesis was to also understand the conditions under which it makes sense to implement such a policy.

The results from the simulation experiments suggest that a potentially out-of-control situation can be detected by run tests and that stockouts can be reduced by applying the strategy. As shown in the results, it is possible to reduce 70.61% of stockouts by adding 23.75% more inventory once the out-of-control situation is detected. Although the average inventory level increases and the cost associated with the inventory may also increase accordingly, considering the negative impact of supply disruption to entire supply chain, it appears reasonable to recommend supplier monitoring and inventory policy change strategy for supply chain environments that have high risk of disruption due to yield uncertainties.

The benefit of supplier monitoring and inventory policy change strategy is most significant when the supplier has enough production capacity, and there is a certain amount of variability in yield rate. Even though the strategy has a positive benefit in reducing stockouts, the magnitude of the improvement is not significant or sometimes even zero when production capacity is tight. In addition, it is hard to detect out-of-control situations if variability in performance measure is relatively small. Therefore, it is necessary to assess first whether or not the supplier has enough capacity to increase production and the performance measure has variability.

One of the challenges in the application of this strategy in a real world situation is the obtaining of actual data from its supplier. In certain hostile supply chains, it is likely unreasonable to think that suppliers provide information about their actual operation especially when they are not operating well. There are supply chains where the relationships are not hostile and are long term (e.g., Japanese model for key suppliers) and where information sharing is more forthcoming. In these friendly situations, the concept is feasible to implement, and as long as reliable information can be obtained, and the two criteria described above are met, it is worth applying the strategy. In the environment where reliable data cannot be obtained from the supplier, communication with the supplier such as notice for delay or negotiation to change quantity in ordered materials might be used as a proxy of supplier performance.

7.2 Limitations

Certain assumptions and limitations regarding the simulation model and experimental setting may have yielded different results from those described in this thesis. These include:

1. Only quantity yield was considered as the factor to determine factory operation and other factors such as machine breakdown and production cycle time were either not

considered or set as constant. In reality, there are a number of factors that determine the performance of factory operation and those need to be recognized and analyzed.

2. In the experiment under different yield rate, both Factory 1 and Factory 2 were set to have the same yield rate. The combination of different yield rate need to be tested in order to establish stronger relationship between yield rate and strategy performance.
3. It was assumed that Factory 1 always has enough supply of raw material and no stockouts occur at the raw material inventory. The case that stockouts occur at raw material inventory of Factory 1 was not considered.
4. The model in this study only counted for a single echelon, four stages supply chain, and therefore only the relationship between two factories was analyzed. In order for the model to be more realistic, it is necessary to expand to multi echelon with multiple stages.
5. Two sorts of run tests applied in this study, run up and down test and run above and below test, only consider the number of runs in the sequence to determine non-random patterns.
6. The dynamic lowering of the inventory policy was not simulated. If this was included, the overall average inventory levels would be lower. Without its inclusion, the results are considered more cautious and conservative.
7. The most conservative posture was taken when interpreting the run test results, and false positives were not considered, nor dealt with in the algorithm.
8. The naturally occurring patterns in a random sequence were used as a proxy for a synthetic out-of-control situation. An alternative would have been for a specific model for out-of-control insertions. The simulations were run sufficiently long enough for multiple synthetic out-of-control to arise.

Chapter 8

Future Research and Conclusions

8.1 Future Research

In this study, the concept of dynamic inventory management by supplier monitoring was explored. Since the study conducted in this study is exploratory and preliminary, there are a number of factors that could be expanded in future research. These are discussed in the following section.

Performance measures

Besides the yield rate, there are a number of other potential performance measures. These include, but are not limited to ,mean time between breakdown, mean time to repair, production cycle time, inventory level, and delivery time. These performance measures can be considered individually or in combinations for future research.

Performance monitoring tool

The up/down, above/below run tests are two sorts of run tests used to statistically monitor the behavior of supplier and both are used to determine if the data sequence is random or non-random. There are other potential methods for monitoring, such as testing the length of a run and using a control chart, and these tests could be considered in future work. In addition, the application of two run tests together showed better performance in detecting non-random pattern, and various combinations of the different tests could also be considered. The potential false positive triggers detected by the run tests should be considered in future research.

Case without stockouts

In this study, only situations where stockouts occurred were studied and therefore whether or not the number of stockouts could be reduced was the main concern. However, if the inventory policy was changed but no stockouts occur, it only ends up increasing the cost of carrying inventory. In order to fully explore the performance of the strategy, it is necessary to study the case where stockouts do not occur.

Supply chain simulation

Expanding the supply chain simulation to be multi-echelon with multiple facilities would produce a more extensive test situation and would result in a deeper analysis.

Inventory policy changes

The key concept of the supplier monitoring and inventory policy change strategy explored in this thesis was to increase the inventory level when stockouts are likely to occur. Therefore, safety stock level was increased only once when a potentially non-random pattern was first detected in the supplier's behaviour. However, if the supplier's operation is back in control, there is no need for the receiver to keep the extra safety stock. Future research can include the lowering of inventory levels during periods of stability and control. It is also possible that when the supplier's operation has been out-of-control for a long time period, it might be necessary to increase the safety stock even more or maybe find other supplier. Or, when multiple trigger points are picked up in different performance measures, a non-linear increase might be warranted. In future research, a more sophisticated inventory policy could be considered.

8.2 Conclusions

The objective of this thesis was to explore an innovative strategy to proactively manage supply chain disruptions. The concept of dynamic inventory management by supplier behavior monitoring was suggested and explored. As the study is exploratory, a single echelon supply chain considering four stages was used to explore the characteristics and the performance of the strategy. In order to capture the complexity of the problem, a general system dynamics approach was used to model the supply chain, and simul8 was used for experimentation. The SPC concept of applying run tests to detect potentially out-of-control situations was employed as a means of supplier monitoring, and the supplier's yield rate was used as the performance measure.

The results from the experimentation showed that stockouts can be reduced by employing the strategy and it is possible to reduce 70.61% of stockouts by increasing 23.75% of inventory level. However, performance of the strategy is not significant when production capacity is tight. In addition, the run test methodology requires the performance measure to have a certain range of variability in order to successfully detect a potentially non-random pattern. Therefore, it is reasonable to suggest the proactive inventory policy control using supplier monitoring when production capacity is relatively loose and enough variability can be seen in the performance measure.

Although limited in scope, this research has demonstrated that if operational information can be shared between the supplier and receiver, the receiver can deploy relatively simple logic to dynamically respond, before a potentially out-of-control situation is encountered. In these cases, it is possible to reduce the number of receiver disruptions, in turn calming the downstream supply chain. In a real world situation, it is assumed that a scheduler would check with a supplier before altering the inventory policy.The sharing and use of such information is nor currently found in supply chain practice, nor is it found in the research literature no supply chain management. Hopefully, this exploratory research will provide insights and inspiration for further research into proactive supply chain risk management.

References

Akkermans, H. A., Bogerd, P. and Vos, B. (1999). Virtuous and vicious cycles on the road toward international supply chain management, *International Journal of Operations & Production Management*, 19 (5/6), 565-581.

Anderson, E. G., Fine, C. H. and Parker, G. G. (2000). Upstream Volatility in the Supply Chain: The machine tool industry as a case study. *Production and operations management*, 9, 239-261

Angerhofer, B. J. and Angelides, M. C. (2000). System dynamics modelling in supply chain management: Research review. *In: Proceedings of the 2000 Winter Simulation Conference*, 342–351.

Barlas, Y. and Aksogan, A. (1997). Product Diversification and Quick Response Order Strategies in Supply Chain Management. Retrieved April 16, 2011, from http://www.systemdynamics.org/conferences/1996/proceed/papers/barla051.pdf

Beamon, B. M. (1998). Supply Chain Design and Analysis: Models and Methods, *International Journal of Production Economics*, 55 (3), 281-294.

Blackhurst, J., Craighead, C. W., Elkins, D. and Handfield, R. B. (2005). An empirically derived agenda of critical research issues for managing supply-chain disruptions. *Int. J. Product. Res.*, 43(19), 4067–4081.

Blackhurst, J. V., Scheibe, K. P. and Johnson, D.J. (2008). Supplier risk assessment and monitoring for the automotive industry, *International Journal of Physical Distribution & Logistics Management*, 38 (2), 143-165

Bosman, R. (2006). The New Supply Chain Challenge: Risk Management in a Global Economy. Retrieved Aug 19, 2009, from http://www.fmglobal.com/pdfs/chainsupply.pdf

Butner, K. (2010). The smarter supply chain of the future, *Strategy & Leadership*, 38 (1), 22-31.

Caballini, C. and Revetria, R. (2008). A system dynamics Model for The Simulation Of a Non Multi Echelon Supply Chain: Analysis of Optimization Utilizing The Berkeley Madonna Software, *International Journal of Mathemarical Models and Methods in Applied Sciences*, 4 (2), 503-512.

Coyle, G. (2000). Qualitative and quantitative modelling in system dynamics: some research questions, System Dynamics Review, 16 (3), 225-244.

Croom, S., Romano, P. and Giannakis, M. (2000). Supply chain management: an analytical framework for critical literature review, *European Journal of Purchasing & Supply Management*, 6, 67-83.

Disney, S. M. and Towill, D. R. (2003). On the bullwhip and inventory variance produced by an ordering policy. *Omega*, 31 (3). 157-167.

Forrester, J. W. (1961). *Industrial Dynamics*. Productivity Press, Cmbridge, MA, USA

Fox, M. S., Barbuceanu, M. and Teigen, R. (2000). Agent-Oriented Supply-Chain Management, *The international Journal of Flexible Manufacturing Systems*, 12, 165-188.

Fransoo, J. C. and Wouters, M. J. F. (2000). Measuring the bullwhip effect in the supply chain, *Supply Chain Management*, 5 (2), 78-89.

Gaonkar, R. and Viswanadham, N. (2004). A Conceptial and Analytical Framework for the Management of Risk in Supply Chains, *Proceedings of the 2004 IEEE International Conference of Robotics & Automation*, 2699-2704

Giunipero, L. C., Hooker, R. E., Joseph-Matthews, S., Brudvig, S., and Yoon, T. (2008), A decade of SCM literature: past, present, and future implications, *Journal of Supply Chain Management*, 44 (4), 66-86.

Gunasekaran, A., Patel, C., and Tirtiroglu, E. (2001). Performance measure and metrics in a supply chain environment. *InternationalJournal of Operations & Production Management* 21 (1/2), 71–87.

Hafeez, K. M., Griffiths, J. and Naim, M. M. (1996). Systems design of a two-echelon steel industry supply chain. *International Journal of Production Economics*, 45, 121-130.

Hallikas, J., Karvonen, I., Pulkkinen, U., Virolainen, V. M. and Tuominen, M. (2004). Risk management processes in supplier networks, *International Journal of Production Economics*, 90 (1), 47-58.

Hendricks, K. and Singhal, V. (2003). The effect of supply chain glitches on shareholder wealth, *J. Oper. Manage*., 21, 501–522.

Hill, J. F. (1996). Monitoring information and materials to enhance logistics performance, *Logistics Information Management*, 9 (2), 10-15

Homer, J. and Oliva, R. (2001). Maps and models in system dynamics: a response to Coyle, *System Dynamics Review*, 17 (4), 347-355.

Juttner, U., Peck, H. and Christopher, M. (2003). Supply Chain Risk Management: Outlining an Agenda for Future Research, *International Journal of Logistics: Research and Applications*, 6 (4), 197-210

Knight, R. and Pretty, D. (1996). The impact of catastrophes on shareholder value. *In The Oxford Executive Research Briefings*, University of Oxford: Oxford.

Lee, H. T., and Wu, J. C. (2006). A study on inventory replenishment policies in a two-echelon supply chain system, *Computer & Industrial Engineering*, 51, 257-263

Liu, Z. (2009). Risk Mitigation of Supply Chain Disruptions, PhD thesis, Northwestern University: USA.

Lockamy III, A. (1998). Quality-focused performance measurement systems: a normative model, *International Journal of Operations and Production Management*, 18 (8), 740–766.

Luna-Reyes, L. F. and Andersen, D. L. (2004). Collecting and analyzing qualitative data for system dynamics: methods and models, *System Dynamics Review*, 19 (4), 271-296.

MacCarthy, B. L. and Wasusri, T. (2002). Non-standard applications of SPC charts A review of non-standard applications of statistical process control (SPC) charts, *International Journal of Quality & Reliability Management*, 19 (3), 295-320.

Mahamani, A., Prahlada Rao, K. and Pandurangadu, V. (2008). The development of a simulation-based approach to optimise the inventory policy in a single-echelon supply chain: a case study. *International Journal of Data Analysis Techniques and Strategies*, 1 (2), 173-192.

March, J. and Shapira, Z. (1987). Managerial perspectives on risk and risk taking, *Management Science*, 33 (11), 1404-1418.

Miller, K. (1992). A framework for integrated risk management in international business, *Journal of International Business Studies*, Second Quarter, 311-331.

March, J. and Shapira, Z. (1987). Managerial perspectives on risk and risk taking, *Management Science*, 33 (11), 1404-1418

McKay, K. N. (1992), *Production Planning and Scheduling: A Model For Manufacturing Decisions Requiring Judgment*, PhD Thesis. University of Waterloo: Waterloo Canada

Minegishi, S. and Theil, D. (2000). System dynamics modelling and simulation of a particular food supply chain, *Simulation Practice and Theory*, 8 (5), 321-339

Moraga, R., Rabelo, L. and Sarmiento, A. (2007). Towards a methodology for Monitoring and Analyzing the supply chain behavior, to appear in *Handbook on Compurational Intelligence in Manufacturing and Production Management*.

Naim, M. M. and Towill, D. R. (1994). Establishing a Framework for Effective Materials Logistics Management. *International Joutnal of Logistics Management*, 5 (1), 81-88.

Perea, E., Grossmann, I. E., Ydstie, B. E. and Tahmassebi, T. (2000). Dynamic modeling and classical control theory for supply chain management. *Computers and Chemical Engineering*, 24, 1143– 1149.

Paulk, M. C. (2001). Applying SPC to the Personal Software Process, *Proceedings of the 10th international Conference on Software Quality*, October.

Paulsson, U. (2004), Supply chain risk management, 79-96 in Brindley, C. (Ed.), *Supply Chain Risk Management*, Ashgate, Aldershot.

Pfohl, H.C., Cullmann, O. and Stolzle, W. (1999). Inventory management with statistical process control: Simulation and evaluation. *Journal of Business Logistics*, 20 (1). 101-121

Plsek, P. E. (1999). Quality improvement methods in clinical medicine. *Pediatrics*, 103, 203-214.

Rabelo, L., Helal, M. and Dawson, J. W. (2004). Detecting and analysing patterns in supply chain behavior, *Food and Chemical Toxicology*, 42, 1157-1180

Rice, J. and Caniato, F. (2003). Building a Secure and Resilient Supply Chain. Supply Chain Management Review, 7 (5), 22–30.

Riddalls, C.E., Bennett, S. and Tipi, N.S. (2000). Modelling the dynamics of supply chains. *International Journal of Systems Science*, 31, 969–976.

Ritchie, B. and Brindley, C. (2007). Supply chain risk management and performance. A guiding framework for future development, *International Journal of Operations & Production Management*, 27 (3), 303-322.

Sheffi, Y. (2002). Supply chain management under the threat of international terrorism, *International Journal of Logistics Management*, 12 (2), 1-12.

Spearman, M. L. and Zazanis, M. A. (1992). Push and Pull Production Systems: Issues and Comparisons, Operations Research, 40 (3), 521-532.

Sterman, J. D. (1987). Modeling Managerial Behavior: Misperceptions of Feedback in a Dynamic Decision Making Experiment, *Management Science*, 35 (3), 321-339

Sterman, J. D. (2000). *Business Dynamics – System Thinking and Modelling for a Complex World*, McGraw Hill, NY, USA.

Swaminathan, J. M., Smith, S. F. and Sadeh, N. M. (1998). Modeling supply chain dynamics: a multiagent approach, *Decision Sciences*, 29 (30), 607–632.

Tang, C. S. (2006). Perspectives in supply chain risk management, *International Journal of Production Economics*, 103, 451-488.

Tian, J. and Tianfield, H. (2006). Literature Review Upon Multi-agent Supply Chain Management. *Proceedings of the Fifth International Conference on Machine Learning and Cybernetics (ICMLC)*, 89-94.

Tomlin, B. T. and Snyder, L. V. (2006). On the value of the threat advisory system for managing supply chain distruptions, *Working Paper*.

Towill, D. (1993). System Dynamics – background, methodology and applications, *Computing and Control Engineering Journal*, 4 (6), 261-268

Wagner, S. M. and Bode, C. (2008). *Dominant Risks and Risk Management Practices in Supply Chains, In Supply Chain Risk: A Handbook of Assessment, Management, and Performance*, Springer, NY, USA

Watts, C. A., Hahn, C. K. and Sohn, B. K. H. (1994). Monitoring the performance of a reorder point system: A control chart approach. *International Journal of Operations and Production Management*, 14 (2), 51-62

Wolstenholme, E.F. (1999). Qualitative vs quantitative modelling: the evolving balance, Journal of the Operational Research Society, 50, 422-428.

Woodall, W. H. (2000). Controversies and contradictions in statistical process control, *Journal of Quality Technology*, 32 (4), 341-350

Woodall, W.H. and Montgomery, D.C. (1993). Research issues and ideas in statistical process control, *Journal of Quality Technology*, 31 (4), 376-386

Zsidisin, G. and Ellram, L. (2003). An agency theory investigation of supply risk management, *Journal of Supply Chain Management*, 39 (3), 15-27.

Appendices

Appendix A: Critical values for run up and down test

Table A.1: Critical values for run up and down test for α=0.05

sample size	Lower	Upper
8	2	N/A
10	3	N/A
12	4	11

Table A.2: Critical values for run up and down test for α=0.1

sample size	Lower	Upper
8	2	N/A
10	3	9
12	4	11

Source: Adapted from Edgington, E. S. (1961). Probability table for number of runs of signs of first differences, *Journal of the American Statistical Association*, 56, 156-159.

Appendix B: Critical values for run above and below test

Table B.1: Critical values for run above and below test for α=0.05

sample size = 8				sample size = 10				sample size = 12			
n-	n+	Lower	Upper	n-	n+	Lower	Upper	n-	n+	Lower	Upper
0	8	0	9	0	10	0	11	0	12	0	13
1	7	0	9	1	9	0	11	1	11	0	13
2	6	1	6	2	8	1	6	2	10	1	6
3	5	1	8	3	7	2	8	3	9	2	8
4	4	1	9	4	6	2	9	4	8	3	10
5	3	1	8	5	5	2	10	5	7	3	11
6	2	1	6	6	4	2	9	6	6	3	11
7	1	0	9	7	3	2	8	7	5	3	11
8	0	0	9	8	2	1	6	8	4	3	10
				9	1	0	11	9	3	2	8
				10	0	0	11	10	2	1	6
								11	1	0	13
								12	0	0	13

Table B.2: Critical values for run above and below test for α=0.1

sample size = 8				sample size = 10				sample size =12			
n-	n+	Lower	Upper	n-	n+	Lower	Upper	n-	n+	Lower	Upper
0	8	0	9	0	10	0	11	0	12	0	13
1	7	0	9	1	9	0	11	1	11	0	13
2	6	1	6	2	8	2	6	2	10	2	6
3	5	2	8	3	7	2	8	3	9	2	8
4	4	2	8	4	6	3	9	4	8	3	10
5	3	2	8	5	5	3	9	5	7	3	10
6	2	1	6	6	4	3	9	6	6	3	11
7	1	0	9	7	3	2	8	7	5	3	10
8	0	0	9	8	2	2	6	8	4	3	10
				9	1	0	11	9	3	2	8
				10	0	0	11	10	2	2	6
								11	1	0	13
								12	0	0	13

Source: Adapted from Swed, F. S. and Eisenhart, C. (1943). Tables for testing Randomness of Grouping in a Sequence of Alternatives, *Annals of Mathematical Statistics*, 14, 66-87.

Appendix C : Experimental results under 50 runs and 100 runs of simulation

Table C.1: Mean and standard deviation of the number of stockouts under 50 runs and 100 runs of simulation (95% yield rate)

		No policy		U/D		A/B		Both	
		50 runs	100 runs	50 runs	100 runs	50 runs	100 runs	50 runs	100 runs
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	4.44	4.22	5.00	4.95	5.34	5.29	5.34	5.30
	StDev	0.50	0.42	0.67	0.66	0.56	0.57	0.52	0.54
F2 RAW	Mean	13.34	13.17	9.30	9.61	5.48	5.66	4.88	5.09
	StDev	1.44	1.03	4.78	4.58	3.90	3.93	3.72	3.86
F2 FGI	Mean	0.10	0.05	0.08	0.05	0.06	0.03	0.04	0.02
	StDev	0.30	0.22	0.27	0.22	0.24	0.17	0.20	0.14

Appendix D: Experimental results under different sample size (N=8, 10, 12)

Table D.1: Mean and standard deviation of the number of stockouts with sample size of 8, 10 and 12 (95% yield rate)

		NP	U/D			A/B			Both		
			8	10	12	8	10	12	8	10	12
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	4.44	4.44	5.00	4.70	5.22	5.34	5.22	5.22	5.34	5.28
	StDev	0.50	0.50	0.67	0.61	0.65	0.56	0.58	0.65	0.52	0.54
F2 RAW	Mean	13.34	13.34	9.30	11.84	6.66	5.48	7.34	6.66	4.88	6.92
	StDev	1.44	1.44	4.78	3.62	4.56	3.90	4.27	4.56	3.72	4.23
F2 FGI	Mean	0.10	0.10	0.08	0.10	0.08	0.06	0.06	0.08	0.04	0.06
	StDev	0.30	0.30	0.27	0.30	0.27	0.24	0.24	0.27	0.20	0.24

Table D.2: Mean and standard deviation of the number of stockouts with sample size of 8, 10 and 12 (90% yield rate)

		NP	U/D			A/B			Both		
			8	10	12	8	10	12	8	10	12
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	9.52	9.52	10.76	10.16	11.34	11.60	11.24	11.34	11.80	11.34
	StDev	1.50	1.50	1.70	1.74	1.64	1.44	1.60	1.64	1.26	1.59
F2 RAW	Mean	19.70	19.70	17.92	18.76	17.66	17.50	18.00	17.66	17.04	17.88
	StDev	1.82	1.82	3.43	2.61	2.50	2.66	2.53	2.50	3.24	2.56
F2 FGI	Mean	5.08	8.08	4.28	4.64	3.74	3.66	3.96	3.74	3.46	3.88
	StDev	1.08	1.08	1.33	1.35	1.24	1.24	1.25	1.24	1.18	1.29

Table D.3: Mean and standard deviation of the number of stockouts with sample size of 8, 10 and 12 (85% yield rate)

		NP	U/D			A/B			Both		
			8	10	12	8	10	12	8	10	12
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	16.70	16.70	16.78	16.66	16.74	16.74	16.76	16.74	16.72	16.72
	StDev	1.49	1.49	1.34	1.47	1.45	1.45	1.46	1.45	1.44	1.44
F2 RAW	Mean	28.56	28.56	28.50	28.52	28.40	28.38	28.38	28.40	28.38	28.38
	StDev	2.15	1.54	1.53	1.58	1.64	1.66	1.57	1.64	1.66	1.63
F2 FGI	Mean	13.34	13.34	13.20	13.26	13.02	13.02	13.08	13.02	12.98	13.04
	StDev	0.87	0.87	0.83	0.90	0.87	0.87	0.97	0.87	0.84	0.95

Appendix E : Experimental results under different confidence level (α=0.05, α=0.1)

Table E.1: Mean and standard deviation of the number of stockouts with α=0.05 and α=0.1 (95% yield rate)

		No policy	U/D		A/B		Both	
			α=0.05	α=0.1	α=0.05	α=0.1	α=0.05	α=0.1
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	4.44	4.50	5.00	5.14	5.34	5.14	5.34
	StDev	0.50	0.58	0.67	0.67	0.56	0.67	0.52
F2 RAW	Mean	13.34	12.82	9.30	8.30	5.48	8.12	4.88
	StDev	1.44	2.75	4.78	4.55	3.90	4.49	3.72
F2 FGI	Mean	0.10	0.10	0.08	0.08	0.06	0.08	0.04
	StDev	0.30	0.30	0.27	0.27	0.24	0.27	0.20

Table E.2: Mean and standard deviation of the number of stockouts with α=0.05 and α=0.1 (90% yield rate)

		No policy	U/D		A/B		Both	
			α=0.05	α=0.1	α=0.05	α=0.1	α=0.05	α=0.1
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	9.52	9.58	10.76	11.14	11.60	11.14	11.80
	StDev	1.50	1.51	1.70	1.67	1.44	1.67	1.26
F2 RAW	Mean	19.70	19.62	17.92	18.14	17.50	18.14	17.04
	StDev	1.82	1.93	3.43	2.60	2.66	2.60	3.24
F2 FGI	Mean	5.08	5.06	4.28	4.00	3.66	4.00	3.46
	StDev	1.08	1.08	1.33	1.34	1.24	1.34	1.18

Table E.3: Mean and standard deviation of the number of stockouts with α=0.05 and α=0.1 (85% yield rate)

		No policy	U/D		A/B		Both	
			α=0.05	α=0.1	α=0.05	α=0.1	α=0.05	α=0.1
F1 RAW	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	StDev	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F1 FGI	Mean	16.70	16.70	16.78	16.74	16.74	16.74	16.72
	StDev	1.49	1.49	1.34	1.45	1.45	1.45	1.44
F2 RAW	Mean	28.56	28.56	28.50	28.42	28.38	28.42	28.38
	StDev	2.15	2.15	1.53	1.58	1.66	1.58	1.66
F2 FGI	Mean	13.34	13.34	13.20	13.12	13.02	13.12	12.98
	StDev	0.87	0.87	0.83	0.92	0.87	0.92	0.84