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Measuring The Effect Of Erratic Demandon Simulated Multi-channel Manuf

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MEASURING THE EFFECT OF ERRATIC DEMAND ON SIMULATED MULTI-CHANNEL MANUFACTURING SYSTEM PERFORMANCE

by

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ABSTRACT

To handle uncertainties and variabilities in production demands, many manufacturing companies have adopted different strategies, such as varying quoted lead time, rejecting orders, increasing stock or inventory levels, and implementing volume flexibility. Make-to-stock (MTS) systems are designed to offer zero lead time by providing an inventory buffer for the organizations, but they are costly and involve risks such as obsolescence and wasted expenditures. The main concern of make-to-order (MTO) systems is eliminating inventories and reducing the non-value-added processes and wastes; however, these systems are based on the assumption that the manufacturing environments and customers' demand are deterministic. Research shows that in MTO systems variability and uncertainty in the demand levels causes instability in the production flow, resulting in congestion in the production flow, long lead times, and low throughput. Neither strategy is wholly satisfactory.

A new alternative approach, multi-channel manufacturing (MCM) systems are designed to manage uncertainties and variabilities in demands by first focusing on customers' response time. The products are divided into different product families, each with its own manufacturing stream or sub-factory. MCM also allocates the production capacity needed in each sub-factory to produce each product family.

In this research, the performance of an MCM system is studied by implementing MCM in a real case scenario from textile industry modeled via discrete event simulation. MTS and MTO systems are implemented for the same case scenario and the results are studied and compared.

The variables of interest for this research are the throughput of products, the level of on-time deliveries, and the inventory level. The results conducted from the simulation experiments favor the simulated MCM system for all mentioned criteria. Further research activities, such as applying MCM to different manufacturing contexts, is highly recommended.

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CHAPTER 1: INTRODUCTION

1.1 Problem statement

Production planning and scheduling based on forecasted demand are important tasks for a manufacturer. Smooth production flow depends on accuracy and stability in demand forecasts and production scheduling. Schedule changes are often initiated in response to uncertainties in demand, leading to negative consequences such as increased cost, reduced productivity, a lower service level, and a general state of confusion on the shop floor (Kadipasaoglu, and Sridharan, 1995).

Two of the types of problems causing errors in demand forecasts are demand variability and uncertainties in demand variability. Variable demand refers to a situation where the demand fluctuations are directly connected to specific times, such as seasonal demand. Though demand varies from time to time, the pattern of its variations is predictable. While variability in demands is foreseeable, the uncertainty in demand variability is characterized by an absence of foreknowledge of the behavior of demand. Brennan and Gupta (1993) mention that a clear distinction between variability in demand and uncertainty in demand variability is not always observed in the literature. According to Kulonda (2002) erratic demand refers to a situation when the number and size of orders both vary in an unpredictable pattern . Variations in demand with deterministic patterns are not of concern for this research since such variations can be predicted.

Uncertainties in demand trigger different complications in pull systems and push systems. These difficulties are listed below.

1.1.1 Errors in demand forecast

Demand forecasts are essential for manufacturers for production planning and for capacity planning decisions in a pull system (Hopp and Spearman, 1996). In a MTS system, demand forecasts are important for inventory decision making. The unpredictable variations in demand complicate the job of forecasting the future demands and increase the chance for significant forecasting errors. The complications caused by errors in demand forecasts can be divided into over-reactions and under-reactions to the latest trend. The risks associated with under-reactions, have a negative effect on the customer satisfaction level. The over-reaction risks involve increases in wastes and costs. Under-reaction risks trigger the same type of negative consequences in both pull systems and push systems while the over-reaction risks increase the costs of unsold inventory in push systems and excess cost of idle production capacity in pull systems. The risks involved with each error type are described as follows (SM Thacker & Associates, 2004):

Under-reaction - When the actual demand is higher than the forecasted demand, the production capacity is not adequate for producing all of the requested orders, resulting in the following problems:

- Long lead time (congestions in production process).
- Missing the market.
- Lost sales.

- Dissatisfied customers.

Over-reaction - The following complications are recognized in inventory keeping systems when the forecasted demand is higher than the actual demand:

- Obsolescence, out-of-shelf-life stock.
- Wasted expenditures or spending too early.
- Low stock-turn, the ratio between annual sales and average annual inventory (Heikki et. al. 2002).

An over-capacity (when customers' demands are lower than production capacity) in MTO systems causes problems such as excessive cost of idle production capacity.

1.1.2 Unpredictable demand variability causes instability in the production flow

Just in time (JIT) manufacturing, a continuous improvement methodology associated with the Toyota Motor Company, has no need for inventory or stock for raw materials, work in progress, or finished goods (Ohno, 1988). Another manufacturing system derived from the Toyota production system or JIT production is lean manufacturing (LM). The essential feature of LM is reducing any non-value-added process and wastes. Over the last two decades, JIT, LM, and other MTO manufacturing methodologies have received much attention as firms strive to attain competitive advantage. Lower production costs, higher and faster throughput, better production quality, and on-time delivery of finished goods are benefits gained from successful implementation of these methodologies (Goyal and Deshmukh, 1992; Norris, 1992; and Orth et al, 1990). These methodologies gained success by promoting a smooth production flow, which is achievable with a stable unvarying demand. When demands vary unpredictably, production capacity cannot be adjusted in time to cope with these variations, causing instability in the production flow that leads to congestion in the production flow, long lead times, and high machine utilization (Hopp and Spearman, 1996). Savsar and Al-Jawini (1995) have also noted that variability in demand has a negative effect on JIT production systems by decreasing the throughput and increasing work in process (WIP).

1.1.3 Scheduling changes and demand uncertainty

Uncertainties in demand variability have a negative effect on a production process by forcing scheduling changes. Materials requirements planning (MRP) systems were initially designed in the manufacturing area to handle inventory control, scheduling, and managing demand patterns (McLeod and Schell, 2001). According to Brennan and Gupta (1993), the success of MRP system implementation is based on the assumption of deterministic demand; therefore, the uncertain nature of the manufacturing environment opposes the successful operation of MRP by forcing schedule changes.

In the literature, shifting of scheduled setups and the instability in planned orders are recognized as system nervousness. Ho, Law, and Rampal (1995) define system nervousness as the negative effects of the rescheduling of planned and open production orders introduced to satisfy changing demand. Savsar and Al-Jawini (1995) mention low throughput and increase in WIP levels as the negative effects of uncertainty in demand under an MRP system.

1.1.4 Manufacturing flexibility

In a push system, the inventory acts as a buffer to level out the demand variations; however, the cost of inventory keeping and the risks associated with errors in demand forecasts have convinced many firms to convert to MTO systems with volume flexibility as an alternative to the traditional use of inventories to deal with uncertainty and variability in demand levels. LM systems are MTO systems and thereby more volume flexible, however, one should consider that these systems are more suitable for the flow shop and repetitive manufacturing environments with few production variations (Huang and Kusiak, 1998).

A pull system, the fundamental concept of JIT/LM, is usually implemented by using Kanban cards. Though a Kanban system has many advantages according to Browne et al. (1998), the Kanban approach is inflexible and cannot respond quickly to unpredicted changes in the market demand. Monden (1993) has concluded that Kanban systems are difficult to use when there are large, unpredictable fluctuations in demand.

The time between completions of each piece in a JIT/LM system is called takt time. Adjustments are made so that every operation step takes the takt time or less. The use of takt time is impractical when daily demand or variability in processing needs is changing.

As global competition among the firms tends to grow, the importance of manufacturing flexibility and responsiveness will become undeniable (D'Souza, and Williams, 2000). Though different studies have different perspectives when defining manufacturing flexibility, they all agree that manufacturing flexibility is the ability of the manufacturing function to react to changes in its environment (Upton, 1994; Watts et al., 1993; Olhager, 1993; Swamidass, 1988). As firms strive to become more competitive, a manufacturing approach that drives toward meeting the market's demands and increases the flexibility to react to changes in the environment is highly desirable.

1.2 Importance of research

The research over the last thirty years displays a major trend in the manufacturing world: from one extreme that promoted stock keeping to the other extreme that promotes a MTO strategy with zero inventory. This shift between two extremes includes a change from stable and predictable demand, standardized products, and a homogeneous market to a wide variety of products with uncertain fluctuations in their demands.

Volume flexibility is one of many mechanisms applied to manufacturing companies to handle uncertainties and variability in customer demand (Newman et al., 1993). Suarez et.al. (1996) defined volume flexibility as the ability to vary production volume to meet variation in demand without excessive inventory costs or a decrease in efficiency. Many manufacturing companies have adopted a MTO system to increase their volume flexibility to cope with changes in demand. By contrast, inventory acts as a buffer to smooth uncertain demand. While many studies investigate the trade-offs between volume flexibility and varying inventory levels to fit orders, very few suggest a method to combine these strategies. According to Oke (2002), a manufacturing company should consider the nature of its product families and process types before implementing a make-to-order policy, especially when the manufacturer has more than one product line. Each product family might require different response time or have different life cycle, shelf time, and level of demand uncertainty.

Kulonda (2002) claims that MCM is an approach suited for a dynamic market environment. MCM requires choosing a mechanism or a combination of mechanisms in the production process by first considering the demand variability. This methodology focuses on the nature of the products to choose a different process for each product family. The purpose of this research is to analyze the performance of the MCM approach in a hypothetical flow shop layout in an erratic demand environment using discrete event simulation. No earlier research of this type has been conducted for the MCM approach.

1.3 Outline of the thesis

This research investigates how MCM, MTO and MTS systems perform under conditions of erratic demand by applying MCM, as well as MTO and MTS, to a realistic case example from the textile industry. Simulation experiments are conducted to compare the performances of the three different manufacturing methodologies. The results for these methodologies are compared with respect to throughputs, lead times, capacity utilizations, average wait time, backorders, and inventory levels.

The next chapter discusses relevant literature and provides more details on the problem identified here. Chapter 2 is divided into two main parts. In the first part, previous studies about advantages and disadvantage of different manufacturing methodologies are reviewed. In the second part, the MCM concept is discussed. Chapter 3 explains the implementation of MCM in the case example and describes the creation of the simulation model. In Chapter 4, the three different simulation models are described and the results from each model are compared and discussed. Chapter 5 lists the results for each model and analyzes the combined results. Chapter

6 concludes the thesis with an overview of the contributions made by the research. It also contains a list of possible future studies.

CHAPTER 2: LITERATURE REVIEW

Because of the similarity in the MTO systems, LM and JIT, the acronym LM is used to represent both of these systems in the remaining parts of this research.

Volume flexibility as a competitive advantage has its importance in its ability to adjust the volume of output to respond to changes in the customers' demand according to D'Souza and Williams (2000). New and Sweeney (1984) define a truly volume flexible operation to be a MTO system in which the production process and the purchasing of raw materials would not be triggered before receiving an order. Manufacturing toward customers eliminates the need for demand forecasts since no product is produced without receiving an actual order. Being independent of demand forecasts, LM systems have gained increasing popularity and are implemented in manufacturing companies to improve volume flexibility and to mange the uncertainties and variable demand. Expected benefits from implementation of LM, such as reduction of in-process inventories and waste have persuaded many firms to invest in these methodologies (Savsar, and Al-Jawini, 1995). As mentioned in Chapter 1, LM's effectiveness depends on the assumption that the manufacturing environment and its parameters, such as product demands, are deterministic. Built upon this assumption, LM methodologies have a well scheduled, uni-directional production flow which allows these methodologies to have a smooth production flow. The smooth production flow, however, is only attained for a certain number of demand epochs for which production capacity is planned. Even with the best forecasts, the problems caused by variable demand, such as long lead time, missed sales opportunities associated with inadequate production capacity, and costs of idle production capacity (when there is excessive production capacity) will remain (Jolayemi, and Olorunniwo, 2003).

In the next section, the problems related to demand uncertainty and comparisons of some of the manufacturing methodologies are discussed. At the end of this chapter, the differences between the MCM approach and LM and quick response methodologies (QRM) with respect to handling erratic demand are presented.

2.1 Manufacturing methodologies and erratic demand

Hopp and Spearman (1996) articulate the importance of forecasts of future demand by claiming that demand forecasts are essential for solid manufacturing planning decisions. The uncertainties in these forecasts have been pointed out in the "laws" of forecasting mentioned by the authors:

- Forecasts are always wrong!
- Forecasts always change!
- The further into the future, the less reliable the forecast will be!
- Since actual demand varies from the forecasted demand, a manufacturing methodology that can handle these variations is needed.

2.1.1 Lean manufacturing

As mentioned earlier, LM methodologies with their flow shop designs are successful only when the changes in demand are predictable and the production variations are few. To determine the production capacity, LM uses both qualitative and quantitative forecasting methods, such as a regression model, or moving average model, autoregressive integrated moving average model (Box et al, 1994; Robinson, 1998) to forecast the future demand. However, none of these methods can guarantee the exact demand values.

2.1.2 Push/Pull system

Huang and Kusiak (1998) recognize that manufacturing control with a push-pull approach suitable for both job shops and flow shops has managed to reduce in-process inventory, shorten lead time, and increase the productivity and machine utilization. It is however still not flexible enough to respond to the unexpected changes in the production demand.

2.1.3 Quick response manufacturing

Another approach that claims to increase production flexibility is Quick response manufacturing (QRM). According to Suri (1998), the purpose of QRM systems is to relentlessly reduce the waste by first reducing the lead time. QRM's application is effective for companies with highly engineered products, as well as for companies with large production variety. QRM systems help these companies to build cells focused on subsets of the production processes for similar parts, and then send the customer orders between these cells based on the order's specifications. A disadvantage of this approach is that it does not consider different marketing channels and variation among customers' orders.

2.1.4 Multi-channel manufacturing

Finally, this leads to the conclusion that, to be able to compete nationally and internationally, there is a need for a manufacturing methodology that can deal with erratic demand. MCM is a composite approach that does not attempt to replace the other manufacturing methodologies but rather extends them by focusing on the end customers' demands and identifying different market channels. MCM recognizes different product families based on the customers' requirements and designs sub-factories for each product family with their own manufacturing strategy. In the sub-factories, production cells are combined to serve a specific market channel.

2.2 Comparison of QRM and LM when demand is stochastic

QRM finds its roots in a strategy used by Japanese enterprises known as time-based competition (TBC). QRM is the term used when TBC is applied in manufacturing firms. The focus of this strategy is to reduce the lead time, that is both the time to produce an existing product and the time to bring a new product to the market, from the time that an order has been released (Suri, 1998).

According to Suri, QRM is best applied to companies with large numbers of different products with high demand variability for each. This is the exact area where the shortcomings of LM are most discernible. To articulate the reasons behind the LM systems' shortcomings when dealing with erratic demand and to demonstrate the differences between QRM and LM, the key concepts of LM are studied and the two systems are compared in regard to these concepts. LM is based on the following three concepts (Womack and Jones, 1996):

- Elimination of waste (muda),
- Implementing flow, and
- Implementing pull.

2.2.1 Eliminating waste in LM versus QRM

Eliminating non-value-added muda (Japanese for waste) is the most fundamental concept of this methodology. Savsar and Al-Jawini (1995) conclude that the pull system associated with LM is designed to reduce the inventories and work in process. While a LM system starts with reducing waste, QRM starts by reducing the lead time. Many additional wastes such as a long learning process, late delivery, and excessive costs throughout the supply chain due to long lead times are not discovered when applying LM (Suri, 1998).

2.2.2 Production flow and cell building in LM and QRM

LM's second important concept is to create a process flow where each process step adds value to the product. This is accomplished by replacing functional departments and their batches and queues with production cells. These cells are focused on a given product family and are provided with all the necessary resources for manufacturing this product family. Each cell functions as a process flow for a specific product family without any backflows or inventories. LM implementation is suitable when there are product families that can follow the same production flow. However, when there is a large number of products with highly variable demand, or products with highly differing specifications, implementing the LM methodology is impractical due to the inflexibility in LM cells' uni-directional flow. To produce products with different specifications, LM has to design different cells for each product type. Similar to LM systems, a QRM system uses cells to produce each production family; however, the production flow in a cell is not unidirectional as in LM systems. In QRM systems, the products can move more freely in each cell. In this way, the routing of products within each cell can differ based on the order specification to handle the variation in demand. Furthermore, QRM manages the variations in demands by creating several cells with different equipment in each so that the combination of cells can be arranged in many different ways to produce the desired products (Suri, 1998).

Production flow in LM systems distinguishes itself from the production flow in QRM systems by also being restricted by the takt time. Takt time is the time between completion of each piece; it has to be maintained to retain the average shipping rate promised to customers. Having no inventories between the processes in the cells and the fact that the production processes are strictly regulated by takt time make the pull system very sensitive to processing time variation required to cope with erratic demand and a high variety of output. Yavuz and Satir (1995) recognize that a higher coefficient of processing time variation disturbs the production flow balance and prevents the smooth flow of material along the process flow. Both Yavuz and Satir (1995) and Savsar and Al-Jawini (1995) comment that push systems perform better than pull systems with respect to throughput rate and average process-station utilization at the same level of processing time variation.

2.2.3 Pull system versus Paired-cell Overlapping Loops of Cards with Authorization (POLCA)

Another reason why LM systems do not cope well with unstable demand is related to the Kanban card systems that are used to give pull signals to the previous step in the production process, as well as to the previous organization in the supply chain. This means that a Kanban signal will create a chain of signals not only to the next step in the supply chain but across each organization as well. One pull signal received by an organization might pull many signals inside the organization, especially when the production has high variation. The number of Kanban cards used increases as the orders move up in the supply chain. As an order moves from one process to the next in an organization, there is a need for a buffer at each process. If the in-process buffer for a process is empty, the process has to freeze until the items required arrive from the previous process. According to Yavuz and Satir (1995), when the in-process buffer levels are small, the negative relationship between processing time variation and throughput rate is more significant.

QRM uses one production control card system called Paired-cell Overlapping Loops of Cards with Authorization (POLCA). POLCA authorizes the beginning of the work and is used to control the material movement among the cells. There are three major differences between POLCA and Kanban cards. First, POLCA cards are used to control the movement only between the cells and not in the cells. Second, they are assigned to pairs of cells instead of being directly assigned to the products. The third difference is that the POLCA card stays with a job during its production process through both cells in the pair that card is assigned to, before the cards loop back to the first cell in the pair.

2.3 MCM's principles

The MCM approach starts by meeting the end costumers' demand and then it works gradually backwards to the beginning of the supply chain, eliminating the finished goods inventory by replacing the finished goods inventory with intermediate inventories where they are needed for responding to the customers' requirements. The principles of MCM can be summarized as divide to conquer, focus on customer response time first and then upon waste elimination, and systems decisions must be based upon rational tradeoffs. These ideas are discussed in more detailed in the following sections.

2.3.1 Divide to conquer

Many manufacturing companies have grown from having one single product line to having broad product lines to satisfy a wide variety of customers with different needs. To manufacture these varieties of products effectively, the production process for each should be based on the product's nature and the customers' desired lead time. MCM identifies the marketing channels and divides the products in product families to serve the customers through different marketing channels. Further, the MCM system suggests designing sub-factories with a proper manufacturing methodology for each product family. For example, while a MTS system may be more suitable for a product family with required lead times as short as 3 days, another product family with 12 days required lead time can be produced more efficiently with a LM system. (Kulonda, 2002).

2.3.2 Focus on customer response time first and then upon waste elimination

Inventories are used to reduce the effects of variability in demands. Removing all the inventories to reduce the waste without focusing on customers' demand and uncertain variability in customers' demand might result in low service level. By implementing an appropriate manufacturing system in each individual sub-factory to match the available production capacity, MCM focuses on customers' response time first but it also uses the production capacity, more effectively eliminating the need for a large finished goods inventory.

2.3.3 Systems decisions must be based upon rational tradeoffs

Though research indicates there is a negative effect of demand variability on the operation of an industrial plant, the manufacturing methodologies consider only problems in production planning without considering demand variation. The LM methodologies assume a deterministic and stable demand; this is not assumed in the MCM methodology. Instead of concentrating on one single facet like eliminating the waste, MCM considers customer satisfaction, reducing inventories, and uncertainty in the demand variations.

2.4 A comparison of LM, QRM and MCM regarding demand variability

MCM is a new manufacturing methodology introduced by Kulonda (2002).
As mentioned earlier, LM is focused on reducing waste, while QRM starts by reducing the lead time and finding the hidden wastes and removing them. MCM goes one step further and focuses on customers' demand. In MCM, the products will be divided into different product families

matching the manufacturing capability to customers' requirements by market channels. MCM uses separate production flows to produce each product family.

In LM, the production flow has only one direction. The production processes are connected to each other and constrained by takt time. The tight connections among the processes will reduce the production flexibility required to deal with variable demand. MCM has a more flexible manufacturing system, by having different production channels for different product families and allowing them to follow different production flows. The different production channels in MCM can be seen as sub-factories. The advantage of having sub-factories is that the production capacity and inventory level for each sub-factory can be changed separately. This will increase the channels' flexibility to deal with the remaining demand variation. Das, Chappell, and Shughart II (1993) have reported evidence that production flexibility is one of the factors that increases competitiveness advantages. Stigler (1993) mentioned that an increase in production flexibility means that the variation in demand can be accommodated at a lower cost. The advantages gained by dividing the production process into sub-factories in MCM are similar to the ones gained in small firms. Both respond quickly to the demand fluctuations by having more flexible production.

QRM creates production cells by having the production processes for similar parts in the same cells. After receiving a customer order, the order will go through different cells depending on the order's specifications. The way that MCM differs from QRM in respect to production design is that MCM creates the production channels (sub-factories) for different production families by identifying customers' demands first. The second step in MCM is to build cells in each sub-factory similar to QRM. These procedures give the manufacturer a chance to reduce the effects of demand variation in two steps, first by dividing the products in different product families, and then by creating different sub-factories with enough flexibility and designed individually to serve the different marketing channels.

CHAPTER 3: MULTI-CHANNEL MANUFACTURING

This chapter presents the principles of MCM methodology and describes the implantation steps of MCM approach in a real case scenario a hosiery mill.

3.1 MCM's three principals

MCM is a composite approach that focuses on the demand and service level first, before it works progressively backwards to the beginning of the production process and deals with the suppliers. This methodology meets variable delivery requirements without the costs of large finished goods inventory or excessive production capacity (Kulonda, 2002). According to Kulonda, MCM's principles will answer the following questions:

- Why should a manufacturer use one single manufacturing system for its diverse products?

Manufacturer should consider implementing multiple manufacturing strategies for different market channels. Manufacturer are recommended that for each product family choose a manufacturing system that respond to customer's demands rather than implementing one system to all. Many manufacturers produce a variety of products to sell to a wide range of customers. In spite of the different natures of these products, the same production strategy is often applied to all production cells. Though the chosen manufacturing system might be effective in producing one type of product or product family, it might not be suitable for another one. Implementing one single manufacturing system to produce a diverse range of products reduces the possibility of choosing a more efficient system for each product family and consequently limits the manufacturer's flexibility.

- Offering high quality customer service gives an important competitiveness advantage, the question is whether or not having high finished goods inventory to avoid stockouts and lost sales is an efficient solution? What about increasing the production capacity? Can we offer a high service level without excessive costs of idle capacity or inventory keeping?

Final product configuration deferred to reduce the inventory levels without lowering customers' satisfaction level.

- Neglecting all the past decisions to implement a totally different methodology, such as LM, may not be the most beneficial approach for the company, why?

Implementing a manufacturing system requires large investments and the entire enterprise's engagement. Most of the strategies and all other past decisions that a manufacturer has chosen have been made upon logical economic realities and previous experiences. Neglecting all the past decisions to implement a totally different methodology, such as LM, may not be the most beneficial approach for the company. Manufacturer should consider logical economic realities and past decisions before implement a different methodology.

With the purpose of coping with erratic demand, the MCM approach is a composite approach based on the following application steps:

- Identify customer demand – This action is the most fundamental and critical one. The steps that follow are essentially based upon this step. Identifying the customer demands is a two-part investigation, to identify the customers' required response time and to distinguish the level of uncertainties in the forecasted demands.

- Divide the products into product families – The customers' required response time is the guideline used to divide the products into different product families to serve different marketing channels. Each product family will then be produced within a sub-factory with cellular design. Each cell will be provided with all the required resources. These cells are similar to the cells in QRM systems and allow the products to follow different paths in a cell according to customers' specifications.
- Diversify production strategies – The manufacturing methodology implemented in each sub-factory is based on logical and economically efficient decisions, where both the customers' required response time and the level of certainty in demand forecasts are considered.
- Replace the finished goods inventory with intermediate inventories – The advantage of deferring the inventory towards the start point of a production process results in fewer stock keeping units (SKUs) in an intermediate inventory, in comparison to a finished goods inventory. A finished goods inventory contains all the different SKUs that customers demand. Planning for a system with finished goods inventory means that manufacturer has to predict the demands for all different SKUs. An intermediate inventory contains fewer SKUs since this inventory provides products earlier in the production process than finished goods inventory. Having fewer SKUs makes the aggregate intermediate inventory needs easier to forecast. A deferment strategy can be compared with Hopp and Spearman's (1996) assemble-to-order approach. According to

Hopp and Spearman, the assemble-to-order approach combines the effectiveness of MTS and MTO procedures by allowing the component to be produced to stock and then assembled according to customers' specification.

- Reduce waste – The MCM methodology is a continuous improvement approach allowing further removal of any waste and reduction of intermediate inventories when the overall conditions support these changes.

3.2 Case study: implementation of MCM in a hosiery mill

The case scenario of a hosiery mill is specifically chosen to demonstrate a range of implementation difficulties, including erratic demand. The case example features a simplified model of a hosiery mill, where the demand is both nondeterministic and uncertain.

3.2.1 Hosiery mill before implementation of Multi-channel manufacturing

The part of the production process of interest for this research starts with pulling the knitted goods that are inventoried in closed tubs (greige goods inventory) after receiving a customer order. The following production step is the dyeing process. Dyeing is a batch process performed in vats. The time allowed for dyeing could be between two to four days. Boarding is a heat setting process using large ovens with a continuous belt moving metal hosiery forms, called boards, through the oven for a specified drying time. The products are inspected and paired after boarding. The accepted products then will be folded and packaged to a variety of specifications.

Table 1 provides the different stages and their processing times, followed by a simplified process flow chart displayed in Figure 1.

Table 1. Production process stages and their processing times.

Process stages	**Number of Machines**		**Process Time**
			(uniformly distributed)
Dyeing	25	tubs	2-4 Days
Boarding	8	lines	8-24 hours
Pairing	8	stations	8-24 hours
Folding	16	stations	4-12 hours
Packing	12	stations	4-12 hours
Assumptions: 2 shifts per day, 8 hrs/shift			

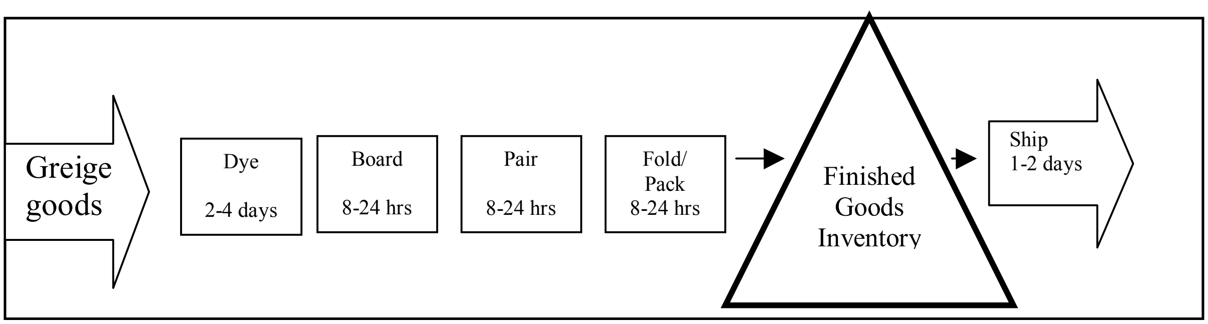


Figure 1. Functional process flow in hosiery mill before implementing MCM (Kulonda, 2002).

3.2.2 Implementation of Multi-channel manufacturing

The implementation process is described in the following three steps:

Step 1. Identify the market channels by separating the different demand streams. Sort the products based on the demand streams and create product families for each to match the manufacturing capacity for each market channel.

This step is the fundamental one for the MCM approach. While many LM methodologies focus on reducing waste, the MCM approach emphasizes the importance identifying customer demands. When the market channels are identified, the products can be divided into different product families. Each product family will then follow a different production channel. The production channels have their own response times. Table 2 shows the two product families catalog items and standard items and their response times in the hosiery company:

Table 2. Two product families and their response times.

Family Category	Response Time (Days)	Channel	Production Strategy
Catalog Items Orders (Small orders)	3	Company Brand	Flexpath
Standard Items Orders (Large orders)	11	Large Retail Chains	Fastpath

The hosiery mill has two different product families with different response times: standard items and catalog items. Customers demand a response time of 11 days for standard items and 3 days for catalog items. Standard-item orders are large orders of 100 to 300 items. These orders will follow a production channel called Fastpath. Catalog-item orders are small orders of 5 to 35 items. The production channel for these orders is called Flexpath.

Step 2. For each channel, create a different sub-factory with a matching production strategy.

Flexpath Channel – This market channel is focused on customers that order catalog items. The numbers of items requested in each order is between 5 and 35. These orders have a required response time of 3 days. The production process from greige goods inventory to shipping takes about 7 days on average; this indicates that for offering a 3 days response there is a need for an intermediate inventory in the Flexpath channel. Therefore, the Flexpath items are stored in an intermediate inventory: longfold inventory, just before folding and packaging. Storing the products in longfold, rather than in finished goods inventory, will eliminate the need for prepackaged goods in each variety of packaging and style, while still providing next day service. With this new production flow, the catalog items are expected to be delivered to the customer within the three day limit. Figure 2 shows the Flexpath process steps in the hosiery mill.

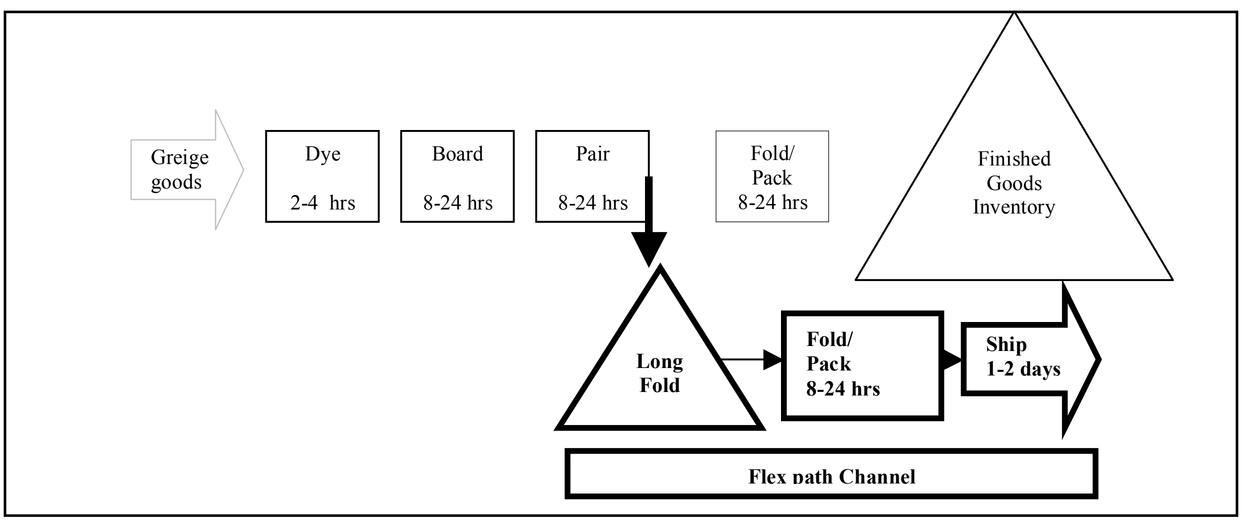


Figure 2. Process revision for Flexpath.

The modules in bold face in Figure 2 are the production process steps in the Flexpath channel. The arrow after the pairing module displays where the Flexpath starts. After the pairing process, the catalog items will be stored in longfold inventory and will eventually be pulled from longfold inventory when an order for catalog items arrives.

Fastpath Channel – Customers require eleven days response time for standard items. The average processing time is 7 days if there are no delays. Therefore, there is no need for inventory to deliver these orders within the required response time, assuming that there is enough production capacity. The path that standard items follow after implementing MCM is the same path as the original production flow but without the finished goods inventory. Consequently, the production strategy chosen for this channel uses a MTO strategy. The production process starts after receiving an order, and will work backwards to pull out necessary items from greige goods inventory. Figure 3 demonstrates the Fastpath process steps implemented in the case example:

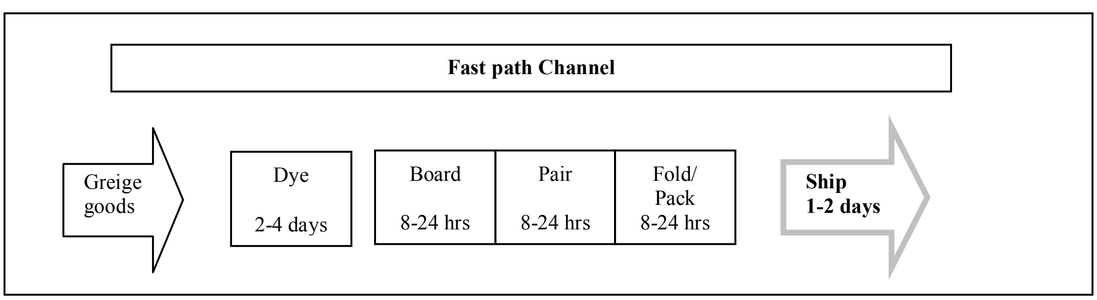


Figure 3. Fastpath process steps.

Step 3. Reduce the in-process inventory by connecting the workcells. In Fastpath the workcells (expect for dyeing) are directly connected to each other without any intermediate inventory to reduce the cycle times. Under MCM, the folding and packaging stations are allocated to the manufacturing channels, as follow: for Flexpath, there are 10 folding stations and 8 packaging stations; for Fastpath, there are 6 folding stations and 4 packaging stations.

3.3 The next phase in MCM's implementation

The goal is to gradually replace the intermediate inventories with quick response systems to replenish inventories in small lots or eliminate them if the customer service requirements are still to be achieved. The next phase in implementing MCM in the hosiery mill would be to remove the greige goods inventory by starting the Flexpath in a process that comes before greige goods inventory. This is, however, beyond the range of this research.

3.4 The new production process flow

When an order is received, instead of checking the finished goods inventories to see if there are enough items in inventory, the order will follow one of the two channels: Flexpath and Fastpath. If the order size is between 5 to 35 items, the order will follow the Flexpath channel; otherwise, it will follow the Fastpath channel. If Flexpath is chosen, then the order will be pulled from longfold inventory.

The figure below demonstrates the hosiery mill's process flow after implementing MCM, here with only two channels, Flexpath and Fastpath.

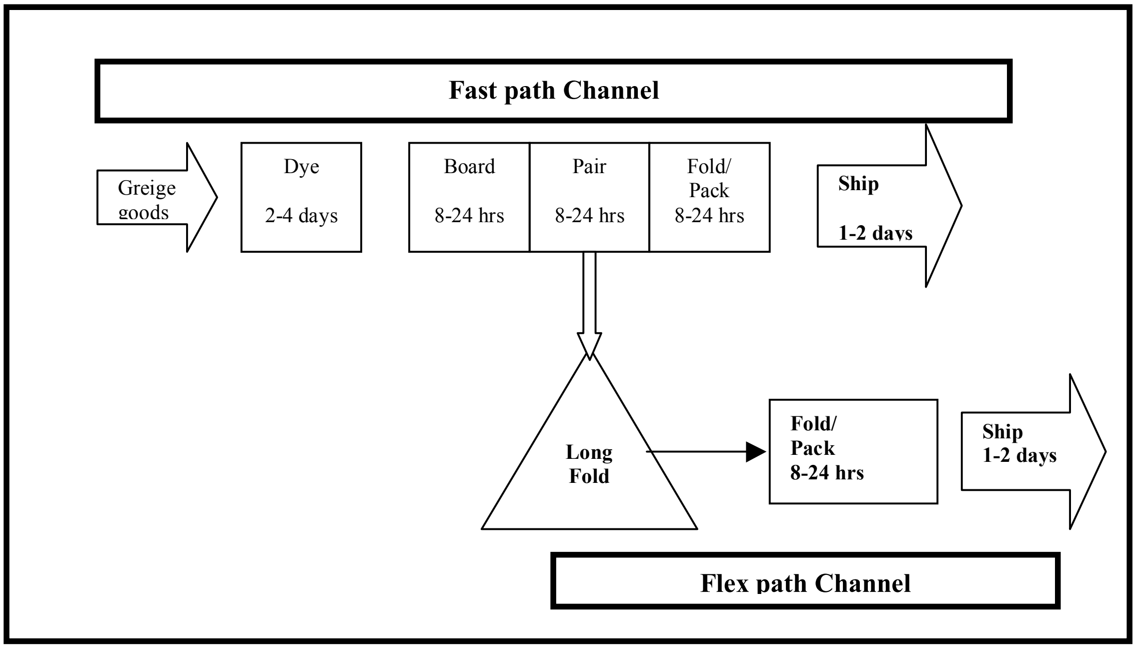


Figure 4. Flexpath and Fastpath's process steps.

As can be seen in this figure, there are no finished goods inventories in the MCM system. All manufacturing follows one of the two paths. Flexpath's longfold inventory is replenished via Fastpath and has to compete with the Fastpath orders for production capacity.

3.5 How will these steps improve a manufacturing situation?

MCM implementation helps to replace expensive and high volume finished goods inventories with smaller intermediate inventories. The finished goods inventory was kept to respond to variability in demand. These variabilities are managed in a MCM system by choosing a production system that responds to customers' requirements for each product family. MCM will develop the flexibility required to respond to the remaining demand variation and reduce the resource wastage.

3.6 Implementation consideration

MCM is an approach that combines different LM concepts to suit different market channels. However, there are many barriers that have to be overcome to achieve a desirable outcome. The channels must be identified and their order patterns must be studied. To enable ways to develop quick response systems, the effect of demand variability must be managed and reduced. The trade off between the cost of idle capacity, customer satisfaction level, and inventory keeping cost must be analyzed. Most importantly, management should be convinced and committed to invest in surplus capacity and provide resources. This is sometimes difficult because a management fixated on measuring production capacity utilization may be reluctant to add excess capacity. Further, lean manufacturing concepts must be applied to find reasonable ways to balance the flow between cells and among channels. To accommodate real-time allocation of orders to supply channels, a resource planning software is needed. Though all these changes seem to be a bit overwhelming, these issues of implementations are not any more complicated than any other implementation of a traditional lean manufacturing system. The results received from the simulation model built upon the case example show that the MCM approach enables the hosiery company to meet the variable delivery requirement without a large finished goods inventory.

CHAPTER 4: RESEARCH METHODOLOGY

To conduct numerical experiments and to gain a better understanding of the behavior of the MCM system for a given set of conditions, we have created a computerized model of the hosiery mill described in Chapter 3. A simulation model is often used for analyzing production problems, especially in stochastic environments. The complexity of the production environment makes the use of analytical techniques inappropriate. Using other methods than simulation requires strong simplifying assumptions about the system, which might reduce the model's validity. Statistical experiments conducted by simulation reflect reality better than mathematical models when dealing with random phenomena, such as variable order entry and production delays. The high cost and difficulty of physical studies can make simulation experiments more desirable (Kelton, Sadowski, and Sadowski, 2002).

This chapter is organized into three sections. The first section will describe the simulation model's parameters. In the second section, three different application scenarios are described. The first scenario demonstrates the application of MCM principles. To visualize the effects of the MCM application, two other scenarios are used for comparison purposes. Scenario 2 is designed to demonstrate a MTS alternative, where all the orders are pulled from a finished goods inventory. A MTO solution has been applied in the third scenario. The third section discusses the variables of interest in the simulation experiments. To verify the robustness of the MCM approach, some of the parameters are changed and additional simulation runs are made.

4.1 Systems assumptions and parameters

The data used to design the simulation models are based on the actual case scenario studied by Kulonda (2002). In the absence of information, reasonable parameter values were assumed so that the study could be conducted. The variables in the simulation models refer to the set of changeable values characterizing the components of the case example. For example, we assume that the hosiery mill manufactures socks in 10 different colors, and each color is available in 5 different packaging styles.

The numbers of orders received per day is between 40 to 80 orders, with an average of 60 orders per day. Of the actual orders received per day, it is assumed that 67% are small orders and 33% are large orders. Further, large orders are assumed to contain between 100 and 300 standard items and have a response time of 11 days. Small orders have an order size of 5 to 35 catalog items and have a 3 day response time. The production capacity is balanced to handle the average daily demand rate of 60 orders per day.

4.2 Simulation model description

Customer orders enter the system as entities once per day and in bulk. The number of orders in a day is chosen randomly from a range of 40 to 80 orders using a discrete uniform distribution. The entities are assigned the following attributes: production family, arrival time, order size, and order specification (color and packaging). The table below displays the simulation model's experimental distributions.

Table 3. Simulation model's experimental distributions.

Name	Description	Form and Parameters
Orders per day	Numbers of orders received per day	UNIF(40, 80)
Small or large	Production family; small orders =1, large orders = 2	DISC(0.67, 1,1.0, 2, 2)
Color	Specification; Colors	DISC(0.1,1, 0.2,2, 0.3,3, 0.4,4, 0.5,5, 0.6,6, 0.7,7, 0.8,8, 0.9,9, 1.0,10)
Package	Specification, Packaging	DISC(0.2,1,0.4,2,0.6,3,0.8,4,1.0,5)
Size-small orders	Numbers of items per order for small orders	UNIF(5, 35)
Size-large orders	Numbers of items per order for large orders	UNIF(100, 300)
Arrival time	time of entering the system	TNOW

4.2.1 Clarifications of the forms and parameters in Table 3

Forms and parameters in Table 3 are described below:

UNIF(40, 80) – There are two product families in this case example: catalog items and standard items. In the simulation model, a uniform probability distribution simulates the number of incoming orders per day from a range of 40 to 80.

DISC(0.67, 1,1.0, 2, 2) – Each order will then be assigned one of the two numbers: 1 and 2 with probabilities 67 % and 33 %, respectively. The model interprets the number 1 as a small order (i.e., an order with 5 to 35 items) and the number 2 as a large order (i.e., an order with 100 to 300 items).

DISC(0.1,1, 0.2,2, 0.3,3, 0.4,4, 0.5,5, 0.6,6, 0.7,7, 0.8,8, 0.9,9, 1.0,10) – There are 10 different colors that can be assigned to an order. To simulate the color chosen by the customer for an order, one number between 1 and 10 is randomly chosen. Each number is equally likely and associated with a specific color.

DISC(0.2,1,0.4,2,0.6,3,0.8,4,1.0,5) – There are five different packaging styles that an order can have. To assign each order a packaging style, a random number generator selects a number between 1 and 5. Each number is equally likely and is associated with a different packaging style. Ten different colors and five different packaging styles contribute to a total number of 50 SKUs. Each order is assigned to one of the fifty possible SKUs. It is assumed that all the items in one order have the same SKU.

UNIF(5, 35) – The size of the small orders is randomly chosen from a range of 5 to 35 items by using a uniform probability distribution.

UNIF(100, 300) – A random number generator decides the size of each large order by selecting a number between 100 and 300 with a uniform probability distribution.

TNOW– Each received order will be marked with an Arena simulation clock variable, TNOW, to mark the order's entry time to the simulated model. This mark is later useful when calculating the lead time.

4.2.2 Simulation models variables

The model's variables are of two types, one type keeps track of the orders and order related information and the other type traces the inventory and inventory related information.

The names and descriptions of the model variables related to inventory are presented in Table 4. Table 5 contains the variables related to orders and order sizes

(numbers of items per order).

Table 4. Simulation model variables for tracking inventory parameters.

Name	**Description**
Inventory related variables	
inv	Initial inventory (numbers of items in inventory per SKU)
ROP	Predetermined reorder point
q	Minimum reorder quantity (q = inv-ROP)
ER	Items ordered but not yet received
RR	Items ordered and received
OH	On-hand inventory
d	Number of items per customer order
Q	Reorder quantity (Q = q + (ROP – (OH + ER))

Table 5. Simulation model variables for tracking order related parameters.

Name	**Description**
Entity related variables	
Total Order received	Numbers of orders received
Small order received	Numbers of orders with order size between 100 and 300
Large order received per day	Numbers of orders with order size between 5 and 35
Order out Flex	Numbers of small size order shipped
Order out Fast	Numbers of large size order shipped
Large order size	Numbers of items per large order
Small order size	Numbers of items per small order
Back orders	Stockouts (not in inventory)

4.3 Reordering process

In the reordering process, the goal is to find a balance between the on-hand inventory level, the forecasted future demand, reordering quantity, and the lead time (Stevenson, 2002). The continuous reordering process is chosen for the hosiery mill. The reordering condition is checked every time an order is received. The reordering process is the same for both Scenario 1 and Scenario 2. In Scenario 1, however, only the orders that follow Flexpath will be pulled from inventory, and consequently, the reordering process will consider these orders only.

A continuous review system controls the remaining inventory of an item each time a withdrawal is made by deciding if there is a need for reordering. The simulation model will control the current inventory level (OH) and calculate the difference between the current inventory level and the initial inventory level (inv) to determine the reorder quantity (Q). The reorders that have not yet been received are added to the current inventory level to measure the item's ability to satisfy future demand. When the inventory level reaches the predetermined reordering point, the reorder quantity (Q) will be ordered from the production process. A 9-day reordering process for the hosiery mill might look like the example in Table 6. In this example, the initial inventory level is set as 1800 items per SKU. The reordering condition is checked every time an order arrives. Table 6 shows that three reorders have been placed at each of the following days: Day 3, Day 6, and Day 9. Items reordered on Day 3 are received on Day 7; these are highlighted in red in the table. On-hand inventory has been increased by the same amount. As demonstrated in the table, the reorder quantity (Q) is changing based on the on-hand inventory level at the reordering time. The minimum reorder quantity (q) in this example is set as 800 items. Any difference between the on-hand inventory level (including earlier reordering) and the reorder point is added to the minimum reorder quantity.

Table 6. Example: Nine days inventory process in hosiery mill.

	Day 1	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**	**Day 8**	**Day 9**
inv	1800	1560	1260	960	730	420	130	670	370
RR	0	0	0	0	0	0	840	0	0
d	240	300	300	230	310	290	300	300	250
Ending inventory = inv + RR -d	1560	1260	960	730	420	130	670	370	120
ER	0	0	0	840	840	840	830	830	830
Ending inventory + ER	1560	1260	960	1570	1260	970	1500	1200	950
ROP	1000	1000	1000	1000	1000	1000	1000	1000	1000
Q	0	0	840	0	0	830	0	0	850

4.4 Initial inventory level

The initial inventory level (inv) is the maximum number of items per SKU that an inventory should have. We have assumed that the inventories in each scenario start at the maximum inventory level set for that scenario. Since we did not have access to the cost information for this case example, we only consider forecasted demand and lead time for reordering to decide the initial inventory level. The initial inventory level for Scenario 2 is set as 90 000 items total or 1800 items per SKU. With the average daily rate of demand being 60 orders this inventory level is calculated to satisfy the expected demand for almost 20 days. The longfold inventory level in Scenario 1 starts with 20 000 units, or 400 units per SKU to satisfy demand for small orders during 25 days. The reorder point is set to satisfy the expected demand during the lead time. Recall that the response time for standard items is 11 days. The reorder point for Scenario 1 is reached at 150 units per SKU and 1000 units per SKU for Scenario 2.

4.5 Three different scenarios

The simulation models are designed to demonstrate the hosiery mill's production flow behavior for three different applied scenarios. The three different scenarios applied to the case example are designed as follows:

Scenario 1 – The MCM steps have been applied to this scenario to demonstrate the production flow's behavior after applying the MCM system. As mentioned in the previous chapter, after greige goods inventory, the production will be divided into two different processing channels, Fastpath and Flexpath. Each processing channel serves a different market channel. The process flow diagram in the figure below is used to design the simulation model for Scenario 1.

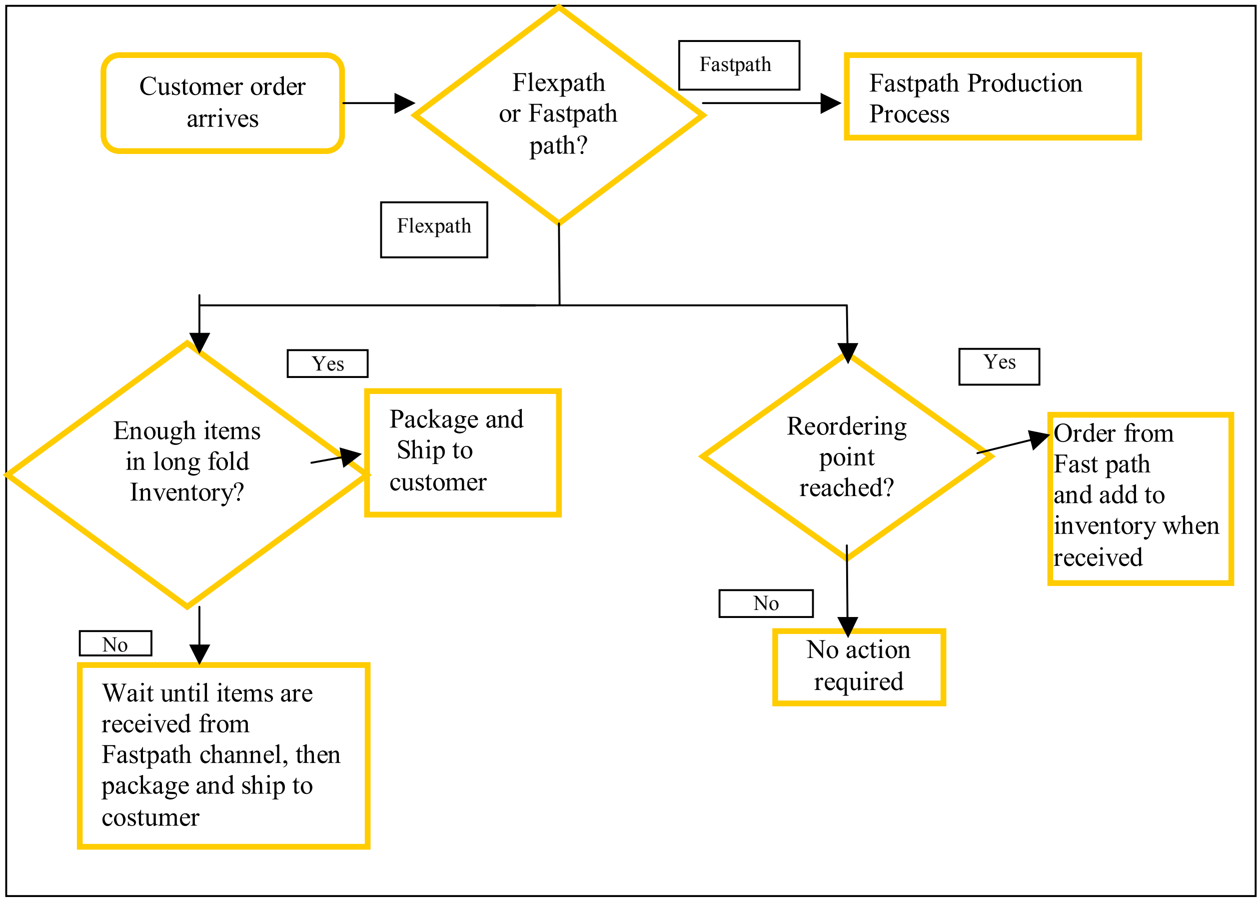


Figure 5. Flow diagram for Fastpath and Flexpath.

The process starts by receiving an order from a customer. The decision about whether the order should follow Fastpath or Flexpath is based on the number of items in the order. Orders with between 100 to 300 units each will follow the Fastpath process from greige inventory to shipping. If the order size is between 5 and 35 items, the order will be pulled from longfold inventory, provided that the items ordered are available in inventory. At the same time, the condition for replenishment for this inventory will be checked. After checking the replenishment condition in longfold, if the reorder point is reached, an order will be placed to replenish the inventory up to the initial inventory level. These orders have to compete with Fastpath orders for production capacity according to first come first serve (FCFS) discipline. After receiving an order, if there are not enough items in longfold inventory to complete the order, the order will be kept in a queue for that specific SKU and will be processed first after receiving the items from the production process and will be shipped according to the first in first out (FIFO) discipline.

Scenario 2 – When an order arrives, it will be pulled from a finished goods inventory if enough items are available. At the same time, the reorder point will be checked. If there are not enough items in inventory, the orders have to wait in queue and will be pulled after receiving the items from the production process according to the FIFO discipline. The reordered items have to compete with each other for the same capacity all the way from finished goods inventory back to greige goods inventory.

Scenario 3 – This scenario is designed as a MTO system without finished goods inventory or any material buffer in the production process. The production process starts after receiving an order by pulling the greige goods from the greige goods inventory. It is assumed that there are always enough items in greige goods inventory. All orders compete for the same production capacity.

4.6 Variables of interest

The objective of these simulations is to illustrate how the various manufacturing approaches compare in terms of several critical variables. To compare the results from each scenario, we need to consider what manufacturing capabilities are critical for winning customer orders.

Some of the variables of interest that may be used to measure these manufacturing capabilities are throughput, lead time, customer satisfaction level, stock outs, and inventory level (Miller and Roth, 1994). The following variables are used in this study to compare the three different scenarios.

4.6.1 Throughput ratio

Throughput ratio for the hosiery mill is calculated as the percentage of the numbers of orders shipped per day relative to the orders received eleven days earlier; this is to compensate for the 11 days requires response time.

4.6.2 Utilization

A high utilization means that the production capacity is used very effectively, but also indicates that the manufacturer would not be able to handle a higher demand with this production capacity level.

4.6.3 Customer satisfaction level

Customer satisfaction is one of the factors that increases a firm's competitive advantage. Among many aspects of customer satisfaction, such as service level, expected and actual lead time, availability, product variation, and quality, we are mostly interested in lead time and lead time related aspects in this research. Lead time is defined as the time from receiving an order until the time when the order is shipped to the customer. A comparison between the predicted lead time and the actual lead time gives us an estimate of customer satisfaction level, namely, the lower the difference, the higher the customer satisfaction level is. Further the proportion of the orders that have met the promised lead time is considered. The variables related to customer satisfaction that are considered in this study are:

- The average and maximum lead times observed for each scenario.
- The percentage of orders that have been delivered on time.
- Average and maximum number of backorders (stock outs)

  (It is assumed that there are no lost sales, as in the case of a retailer).
- Average and maximum waiting time for backorders.

4.6.4 Inventory

The maximum and average inventory level in the longfold inventory in Scenario 1's Flexpath is compared with the maximum and average finished goods inventory level in Scenario 3. Scenario 2 is a MTO system and does not have a finished goods inventory. It is assumed that greige goods inventory in all three scenarios can provide all the material required to produce the orders received without delay.

4.7 Variability in the demand processes

Comparing the numerical results received from each scenario is the preferred method used in this research to compare the alternatives. To test MCM's ability to manage and reduce the effects of erratic demand, we have changed the demand related variables in all three scenarios to verify their abilities of dealing with uncertainties in demand variability. Keeping the production capacity constant, the other variables have been changed as presented in the following sections.

4.7.1 Varying the numbers of orders

The number of incoming orders is changed in two different ways to determine the effects of the demand variations on each scenario. The changes are made considering that the daily demand is between 40 and 80 orders.

- This change is made to verify the robustness of each approach when demand has high day-to-day variability. Instead of using a uniform distribution to choose a number in the range of 40 to 80, the model chooses a daily rate of demand of either 40 or 80 orders with equal probability. The daily rate of demand has been changed by changing the value in the entities per arrival section in the create module in the Arena simulation.
- To make the effects of high and low variation in demand more visible, the demand is changed to be a constant 60 orders per day.

4.7.2 Varying the numbers of items per order

It is assumed that the number of items in an order that will go through Flexpath is randomly chosen from 5 to 35 items and from 100 to 300 for Fastpath. To verify the robustness of the simulated models, the numbers of items have been changed in the following ways:

First, the range of the number of items per Flexpath order is changed from between 5 and 35 to a constant 20 items. The numbers of Fastpath items are changed from a range of between 100 and 300 to a constant 200 items.

The second change implies that Flexpath orders can only have one of two numbers of items; namely, 5 and 35, each with an equal chance of being selected. Similarly the Fastpath orders will be assigned either 100 or 300 items each.

Finally, the order size random variable is represented as a summation of two independent uniform random variables. The two new ranges for Flexpath orders are 0 to 20 and 5 to 15. The new ranges for Fastpath orders are 0 to 100 and 100 to 200. By introducing these changes, the range and the mean will remain the same as in the basic model, but the variability in the numbers of items ordered is reduced. Table 7 demonstrates these changes sequentially for each production family.

Table 7. Three ways of changing the numbers of items per order.

Market channel	**Distributions, numbers of items**	**Variance**
Flexpath	20	0
Fastpath	200	0
Flexpath	DISC(0.5, 5, 1.0, 35)	225
Fastpath	DISC(0.5, 100, 1.0, 300)	10000
Flexpath	AINT (UNIF(0,20)) + AINT(UNIF(5,15))	46.66
Fastpath	AINT (UNIF(0, 100)) + AINT(UNIF(100, 200))	1700

4.8 Alternative inventory levels

The initial inventory level and reorder point have a direct impact on the number of stockouts and customer satisfaction. The initial inventory levels and reorder points that are used in Scenarios 1 and 2 are intended to satisfy the future demand. To observe the impact of the inventory level on the numbers of backorders and customer satisfaction, the inventory values are changed as follows:

In Scenario 1 the initial inventory level is reduced from 400 items per SKU to only 200 items per SKU. The initial inventory level in Scenario 2 in changed, first by reducing the inventory level from 1800 items per SKU to 1200 items, and then by increasing the inventory level to 3600 items per SKU. These changes are introduced in Tables 8 and 9, as well as the reorder point and the minimum reorder quantity for each inventory level.

Table 8. Inventory level, reordering point, and reordering quantity for Scenario 1.

Inventory level per SKU	**Reorder point**	**Reorder quantity**
400	150	250
200	75	125

Table 9. Inventory level, reordering point, and reordering quantity for Scenario 2.

Inventory per SKU	**Reorder point**	**Reordering quantity**
1800	1000	800
3600	1400	2200
1200	700	500

4.9 Production process

Production capacity is balanced to handle an average daily rate of demand of 60 orders per day. Each process module in the Arena model represents one production cell in the case example. The machines in each cell are represented by resources in process modules. If a process has more than one resource, we use Arena sets to show the numbers of all resources in one process. To make sure that an order would seize any available resource, the cyclical method is used to seize a resource. This means that orders will seize any resource that is available in a set and release it when they are through being processed. Orders have to compete with each other for service from resources. To make sure there is enough capacity to produce 60 orders per day, each resource has been delegated with enough capacity based on the processing time and the numbers of machines per process.

4.10 Strategy for data collection

The simulation model can be built either as a terminating simulation with start and stopping conditions or as a steady-state simulation. Scenario 1 is designed to observe how MCM would help the hosiery mill to handle the uncertain and variable demand without having a large finished goods inventory. Allowing one year (240 days) as the terminating condition creates an opportunity to observe MCM's ability to mange the erratic demand. For approaching a valid statistical analysis from nonterminating system first, a steady-state must be determined. Although an approximate warm-up period can be detected by using a graphical model, there are no statistical procedures for determining when steady-state has been reached (Huq, and Huq, 1994). According to Kelton, Sadowski, and Sadowski (2002) because of the inconvenience of the steady-state simulation approach, a terminating simulation approach is more desirable if there are natural start and stopping conditions.

4.11 Simulation runs

Since the variation in the simulation outputs was unknown upfront, 10 replications of each scenario were executed. At the 5% level of significance, the correlation coefficients are not statistically significantly different from zero. Table 10 (next page) displays the results of 10 replications for Scenario 1. The value observed in each replication represents the average time between running out of stock for a specific item and the time of shipping the requested order to the customer (in days). The hosiery mill is expected to have two shifts per day, each lasting 8 hours.

Table 10. Average lead time for backorders from ten replications of scenario 1.

Scenario 1	**Average lead time for Backorders**
Replications	**Days**
1	3.60
2	3.68
3	3.68
4	3.60
5	3.64
6	3.68
7	3.68
8	3.63
9	3.57
10	3.70
Standard deviation = 0.0442	
Average lead time for 10 replications = 3.65	
Half with h=0.3	
0.87 percent error in the point estimate of 3.6 days	

4.12 Verification

Verification is the process of debugging the simulation model to ensure that the model behaves as it is planned. Models are tested as a whole and as subsections. For example, the number of SKUs has been reduced to one from fifty, to test the inventory and queue system. All the model times have been changed to constant values. A limited number of demands are released into the system to see if the predicted output matches the output from the model. The production process capacity has been tested, by increasing and decreasing the numbers of orders. Checkpoints are positioned at every section of the process to monitor and calculate the statistics. The queues and utilizations are checked for exceptions. To find and fix model errors, simulation traces have been examined. A time-persistent statistic is used to track the average and maximum inventory level. The performance measure values are collected independently over each run to be statistically reliable. These tests and improvements are made to determine that the three simulation models function as intended.

4.13 Validation

The validation process is an attempt to prove that there exist accuracy and correspondence between the simulation model and the real system being modeled. However, the three simulation models were designed to compare the three different manufacturing systems with each other. Though the models are designed based on a real-case scenario they are not meant to replicate a real-world example. Therefore, they cannot be validated through a comparison of their input and output with a real-world scenario. Consequently, the method used for validation is to test the assumptions of the model empirically as follows:

- To test the validity of the results, the stochastic input values are replaced by deterministic ones. The results from running the model with deterministic values are then compared with results calculated manually.
- Sensitivity tests are done for input data by changing some of the input values, namely inventory level, numbers of incoming orders per day, numbers of items per order as explained in the section variability in the demand processes. Small changes to the values do not influence the performance of the system significantly.

CHAPTER 5: THE RESULTS AND ANALYSES

5.1 Motivation for the hypotheses

To determine whether, for a given flow shop floor, the MCM approach would shorten the lead-time while decreasing the level of inventory, three simulation experiments were designed to compare the performances of three different manufacturing methodologies, namely, MCM in Scenario 1, MTS in Scenario 2, and MTO in Scenario 3 of the same case example. The performance measures are the average of the observations of three scenarios that are generated in ten runs of each simulation models. All three scenarios have a flow shop production process with the same capacity. Scenarios 2 and 3 are compared with Scenario 1 one at a time, since a comparison of a MTO system with a MTS system is not the subject for this study. The impact of employing MCM methodology can be detected in two hypotheses:

- H1: MCM approach offers the same or higher throughput of products.
- H2: MCM approach shortens the lead time without excessive idle capacity cost.

5.2 Outline of this chapter

This chapter is presented in two parts. The main performance measures in this research are throughput and lead time. The performance measures are the observed results conducted from ten runs of each scenario. In the first part, the scenarios are compared regarding the main performance measures and some other closely related results.

Sensitivity analysis is applied to measure the importance of the effects of the inputs on the outputs. The results from the sensitivity analysis are presented in the second part of this chapter.

All three scenarios are synchronized by using the same seed in the random number generator in order to get the same numbers of incoming orders with the same proportion of large/small-sized orders.

5.3 Comparing scenarios

The three scenarios have been compared with respect to throughputs, lead times, wait time in queues and inventory levels.

5.3.1 Throughput

Throughput is the ratio between the daily rates of products delivered and the total orders received. The numbers of products delivered are compared with orders received 11 days earlier to compensate for the 11 days in the production process. In Scenario 1, Flexpath orders have a shorter lead time than Fastpath orders since these orders are pulled from the longfold inventory. Allowing 11 days as the process time in this scenario may result in a throughput ratio higher than 100 percent occasionally. Scenario 2 can also have a throughput ratio higher than 100 percent since the orders are pulled out of the finished goods inventory.

The average throughput values are 1.023 in Scenario 1, 1.001 in Scenario 2, and 0.876 in Scenario 3. The differences in throughput values for the three scenarios are quite moderate, because the production capacity and the numbers of incoming orders are the same for all three scenarios. However, Scenario 3 has a slightly lower throughput ratio than the other models. The table below shows the sum of all throughput values, the average daily throughput ratio, and the standard deviation for throughput for each scenario. The table also presents the total throughput as a percentage of the total product output divided by total order input. The throughputs calculated for each day during 240 days are displayed in Tables 17, 18, and 19 in Appendix A.

Table 11. Throughput values for three scenarios.

Comparison of three scenarios regarding throughputs			
	Scenario 1	**Scenario 2**	**Scenario 3**
Sum of throughputs	234.8	229.2	201.2
Average throughput ratio	1.023	1.001	0.876
Standard deviation	0.237	0.269	0.184
Total orders in	14490	14490	14490
Total orders out	13787	13787	11965
% total out	0.952	0.951	0.826
Assumptions: 1. The scenarios have same capacity. 2. The throughput values are calculated as percentage of numbers of outputs per day divided by numbers of input per day received 11 days earlier.			

To test H1, a comparison of the sample mean throughput values for Scenarios 1 and 2 is undertaken. Normality for the daily average throughout ratio for each scenario is checked with Kolmogorov-Smirnov normality test displayed in Figures 6, 7 and 8 in Appendix B. The results displayed in the table above indicate that Scenarios 1 and 2 offer almost the same average throughput (p-value = 0.1788). This leads to the conclusion that H1 can not be rejected at the 95 percent level of significance. The assertion of the hypothesis is that Scenario 1 offers the same level of throughput with an inventory level that is 4.5 times lower than in Scenario 2.

5.3.2 Lead time

The results from the last section exhibit that Scenario 3 contributes to an almost 88 percent average throughput. However, the utilization of production capacity is almost 100 percent, which indicates that idle production capacity is low.

High utilization is desirable since it will reduce the production capacity idle time; however, when having variable demand, a more flexible system that can handle the variations in demand is more desirable. When demand is variable, a high utilization level implies congestion in the production process in the form of long queues and non-value added wait times. Since Scenario 3 is designed as an idealistic MTO system, there are no intermediate buffers. This means, after an order is received, the customer has to wait for the products to be processed from the initial point of the production process (greige goods inventory). Having no buffer plus the limited production capacity implies that in Scenario 3 the lead time promised to the customer should be at least 23 days on average. The maximum observed lead time was as high as 42 days for this scenario. In Scenario 3 both standard and catalog items follow the same production process, and there are no considerations of differences in response times for customers for each different product family. The required 3 day response time for standard items is never accomplished. In Scenario 3, all the items are made to order, there are no inventories, and all items have to compete for the same production capacity. Increasing the production capacity would reduce the lead time; however, this would increase the cost of idle capacity as well, especially when the variation in demand is high.

The lead time for products that are pulled directly from the inventory is 1.5 days, on average, in both Scenarios 1 and 2. The Fastpath orders in Scenario 1 have an average 5.5 days lead time with a 0.006 standard error. The distinct difference between Scenarios 1 and 3 with respect to their lead times indicates the veracity of H2. The null hypothesis proposing that both scenarios have equal lead time is rejected at the 95 percent significance level with a p-value that is almost zero. The conclusion of this test is that Scenario 1 offers shorter lead time while having the same production capacity as Scenario 3.

5.3.3 Wait time in queues

A high service level for customers is desirable as it increases the competitiveness advantage. Therefore, short queues are to be preferred. In Table 12, there is a clear difference in non-value added waiting times in Scenario 3 compared to the other two scenarios. This was expected since this scenario does not have any buffer in the form of inventory to level out the demand variations.

Table 12 . Waiting time for each process in three scenarios.

Average waiting time for each process in the production (days)			
	Scenario 1	Scenario 2	Scenario 3
Boarding	0	0	6.23
Dyeing	0	0	0.84
Folding	0	0	0.01
Pairing	0	0	8.17
Shipping from process	0		2.64
WIP Average	185	126	1309
WIP maximum	275	206	2458

5.3.4 Comparing inventory levels and customer satisfaction

The longfold inventory in Flexpath in Scenario1 serves to satisfy the customer's demand for Flexpath orders. The initial inventory level for this path is set to be 400 items per SKU or 20 000 total. With inventory being at this level, the orders can be pulled out from inventory without delay 98 percent of the time. This means that stockouts are as low as 2 percent. The results displayed in Table 13 indicate that the hosiery mill needs to invest in a large finished goods inventory if it adapts the methodology implemented in Scenario 2. In fact they need 90 000 items in the inventory initially to cover the demand 97 percent of the time. This inventory is 4.5 times larger than the inventory in Scenario 1.

Table 13. Initial inventory level and demand satisfaction in Scenarios 1 and 2.

Simulating models	Initial inventory level (total numbers of items)	Numbers of items ordered from inventory	Numbers of items that were pulled directly from inventory	Meeting the demands %
Scenario 1	20 000	9771	9572	98
Scenario 2	90 000	13984	13974	97

5.4 Changing the number of incoming orders

To intensify the effects of demand variability, the three scenarios have been designed with both a deterministic demand of 60 orders per day and a demand that is either 40 or 80 orders per day. In all three scenarios the production capacity is balanced to produce 60 orders per day. The results of this comparison ascertained in Table 14 on the next page are in accordance with our predictions about the behaviors of these methodologies.

Table 14. Comparing the results regarding the changes in the numbers of incoming orders.

Scenarios	**Incoming orders and changes**	
Scenario 1 (Flexpath and Fastpath)	*uniform(40,80)*	
	Fastpath orders	5.5
Backorders	Flexpath orders	3.7
	Constant 60 orders	
	Fastpath orders	5.5
Backorders	Flexpath orders	3.6
	40 or 80 orders equally distributed	
	Fastpath orders	5.5
Backorders	Flexpath orders	3.74
Scenarios	**Incoming orders and changes**	
Scenario 2 (MTS)	*uniform(40,80)*	
Backorders	Large orders	4.6
Backorders	Small orders	4.55
	Constant 60 orders	
Backorders	Large orders	4.6
Backorders	Small orders	4.6
	40 or 80 orders equally distributed	
Backorders	Large orders	4.75
Backorders	Small orders	4.66

Scenario 3 (MTO)	*uniform(40,80)*	
	Large orders	23.5
	Small orders	22.8
	Standard deviation	1.8
	Constant 60 orders	
	Large orders	23.6
	Small orders	23
	40 or 80 orders equally distributed	
	Large orders	24.2
	Small orders	23.5
	Standard deviation	3.3

While these changes did not have a significant effect on Scenarios 1and 2, the lead time in Scenario 3 for large orders was increased from the average 23 days with a standard deviation of 1.83 to 24 days with a standard deviation of 3.32. The increase in the standard deviation in this scenario is caused by the variation in incoming orders, with lower lead time when the numbers of incoming orders are fewer and vice versa.

The lead times displayed in Table 14 refer to the time it takes to deliver the backorders in Scenarios 1 and 2 from the time these orders are received. In Scenario 3, where there is no inventory, the lead time is the average time to deliver an order. As mentioned previously in this chapter, the lead time for products that are pulled directly from inventory is only 1.5 days on average.

5.5 Changing order sizes

The numbers of items per order has been changed as explained in Chapter 4.

The difference in the results caused by these changes in the three scenarios are not statistically significant. This indicates that the models are not considered sensitive to the numbers of items per order as a variable input. The performance measures observed from running each model are presented in Tables 20, 21 and 22 in Appendix C.

5.6 Changing inventory level

The inventory level has an inverse effect on the numbers of backorders. As the inventory level decreases, the number of stockouts tends to increase. In a uniform MTS system, when all the products have to be pulled from a finished goods inventory, the level of inventory is the only parameter that the manufacturer can regulate to make the system cost efficient. The manufacturer decides the inventory level based on a trade off between the level of customer satisfaction and the cost of inventory keeping. Table 15 displays the different inventory levels applied to Scenario 2 and the percent stockouts related to each inventory level.

Table 15. The effects of changing the inventory levels in Scenario 2.

Inventory level (Numbers of items per color and size)	**Items were found in inventory (% o f time)**	**Backorders (% of time)**
900	55.1	44.9
1200	73.6	26.4
1800	97.1	2.90
3600	99.9	0.10

In Scenario 1, only Flexpath orders are made to inventory, and eventually the inventory level changes will primarily effect these orders. The overall effect of an inventory level reduction in this scenario is therefore subdued by having two different manufacturing systems for each production family. Table 16 ascertains the effect of reducing the inventory level by 50 % in Scenario 1. The overall effects are less than the effects on Flexpath orders.

Table 16. Reduced inventory level and its effect on Flexpath orders and the whole system in Scenario 1.

Inventory level (Numbers of items per color and size)	**Items found in inventory (% of time)**	**Backorders (% of time)**	**Fastpath items delivered on time (% of time)**	**Total items delivered without delays (% of time)**
400	98	2	100	99
200	70.5	30	100	85

CHAPTER 6: CONCLUSIONS

The case scenario demonstrates the application of the MCM approach to a real case example. Problems associated with erratic demand are abated by first dividing the system into two sub-factories, Flexpath and Fastpath channels, and second, by choosing a system for each sub-factory that respond to the customers' demand specifications. In this research, three simulation models have been designed based on the same actual scenario observed in the apparel industry. Each scenario corresponds to a specific manufacturing methodology. The interpretation of the results obtained from executing the models give the incipient state of knowledge on the subject.

6.1 Research contributions

The results from the simulation models favor the MCM production planning methodology with respect to throughput, lead time and inventory level.

There are two possible explanations for this:

- The MCM methodology is superior to the other two analyzed manufacturing methodologies with respect to the mentioned dimensions.
- The results could be directly related to the assumed conditions and values such as production capacity, numbers of incoming orders and the mix of small and large orders.

From this research it can be concluded that, although the results may vary when the models are executed under different assumptions, the MCM approach will improve the flexibility at the manufacturing floor by implementing sufficient manufacturing systems tailored to its specific channels rather than implementing a single system to all. The increased flexibility can be recognized in the lower production capacity utilization used to neutralize the demand variability. With the unleashed production capacity, MCM has managed to keep the required delivery time.

6.2 Research limitations regarding simulation model results

An examination of the relationships between the MCM approach and financial performance is highly recommended as the next step. The results obtained from simulation models in this research demonstrate an improvement in operations and the production process. Higher throughput, on-time delivery, and lower inventory levels are some of the advantages of implementation of the MCM approach. However, affiliation between improved operations and financial performance is only assumed. This research only implies a linkage between financial performance and MCM approach.

6.3 Research limitations regarding simulation model utilization

The results and conclusions attained from simulation models are conditional on the assumed operational and structural conditions described in the research. For instance, the results might be different if material buffers were allowed in the scenarios.

6.4 Correction for simulation assumptions

The conclusion deduced from the results favor Scenario 1 with respect to lead time, utilization and inventory level reduction in all tests undertaken in this research. These tests were conducted to demonstrate each manufacturing methodology's ability to handle erratic demand. However, Scenario1 demonstrated performance superior to those of Scenarios 2 and 3 even when a constant number of incoming orders was applied to the models. Therefore, for future research it is recommended to test the MCM ability to handle erratic demand compared to other scenarios when these scenarios demonstrate similar results as MCM systems when demand is constant. This can be done for example by increasing the production capacity in Scenario 3.

6.5 Future research

Possible modifications of simulation models are outlined as follows:

- Implementing the MCM approach in various manufacturing contexts facing erratic demand. For example, a manufacturing with high inventory carrying cost such as furniture manufacturing.
- Including order modifications and cancellations.
- Permitting each order to incorporate more than one SKU.
- Allowing channel switching, determined by a rule-based decision model.
- Operation of the flow shops with different material buffer capacities and placement in the models.
- Including supplier and supplier-side uncertainties in the model.

- Introducing setup times at workstations.
- Allowance for defective production and machine breakdowns.

6.6 Further steps in implementation of MCM

As mentioned before the next step in implementation of MCM would be to gradually remove all of the in-process inventories. Greige goods inventory in the hosiery mill can be reduced by abbreviating the time for greige replenishment by increasing the connection and communication between the two production processes prior to greige goods inventory: closing (process before greige good inventory) and knitting (process before closing) in order to reduce in-process levels. Further, the knitting capacity can be increased to leverage the reduced greige goods inventory level.

APPENDIX A: THROUGHPUT RATIOS FOR SCENARIO 1, SCENARIO 2 AND SCENARIO 3

Table 17. Daily throughput ratios for Scenario 1.

Days	**Orders in**	**Orders out**	**Throughput**
1	45	0	
2	52	0	
3	52	13	
4	73	32	
5	48	35	
6	61	49	
7	59	71	
8	54	61	
9	45	60	
10	70	57	
11	63	53	1.18
12	56	48	0.92
13	53	57	1.10
14	49	49	0.67
15	64	75	1.56
16	76	47	0.77
17	51	72	1.22
18	41	53	0.98
19	78	56	1.24
20	45	54	0.77
21	70	56	0.89
22	47	65	1.16
23	43	56	1.06
24	48	45	0.92
25	67	44	0.69
26	47	52	0.68
27	60	60	1.18
28	48	50	1.22
29	64	62	0.79
30	70	59	1.31
31	75	52	0.74
32	75	65	1.38
33	73	67	1.56
34	69	61	1.27
35	60	71	1.06
36	43	65	1.38
37	41	62	1.03
38	77	68	1.42
39	79	48	0.75

Days	**Orders in**	**Orders out**	**throughputs**
41	63	71	0.95
42	66	57	0.76
43	40	62	0.85
44	77	63	0.91
45	55	56	0.93
46	62	52	1.21
47	68	62	1.51
48	66	62	0.81
49	45	68	0.86
50	61	62	1.05
51	43	54	0.86
52	71	56	0.85
53	50	58	1.45
54	46	53	0.69
55	58	60	1.09
56	43	50	0.81
57	46	63	0.93
58	66	41	0.62
59	70	57	1.27
60	65	50	0.82
61	57	67	1.56
62	75	54	0.76
63	43	63	1.26
64	78	58	1.26
65	54	63	1.09
66	71	56	1.30
67	70	72	1.57
68	50	60	0.91
69	73	62	0.89
70	68	57	0.88
71	64	66	1.16
72	67	65	0.87
73	76	49	1.14
74	71	70	0.90
75	69	83	1.54
76	65	72	1.01
77	64	73	1.04
78	58	62	1.24
79	60	59	0.81

Days	Orders in	Orders out	Throughput
80	75	65	0.96
81	73	55	0.86
82	60	63	0.94
83	60	77	1.01
84	52	60	0.85
85	66	63	0.91
86	47	59	0.91
87	63	72	1.13
88	67	57	0.98
89	74	48	0.80
90	45	64	0.85
91	45	64	0.88
92	76	54	0.90
93	46	52	0.87
94	49	62	1.19
95	73	58	0.88
96	71	44	0.94
97	77	62	0.98
98	41	64	0.96
99	52	69	0.93
100	70	63	1.40
101	43	49	1.09
102	61	73	0.96
103	79	49	1.07
104	65	49	1.00
105	51	69	0.95
106	54	59	0.83
107	61	63	0.82
108	77	66	1.61
109	63	61	1.17
110	71	57	0.81
111	78	53	1.23
112	58	68	1.11
113	67	74	0.94
114	58	74	1.14
115	70	49	0.96
116	47	55	1.02
117	49	54	0.89
118	67	62	0.81
119	53	71	1.13
120	41	60	0.85
121	50	55	0.71

Days	Orders in	Orders out	Throughput
122	64	40	0.69
123	60	67	1.00
124	40	47	0.81
125	62	60	0.86
126	75	45	0.96
127	73	63	1.29
128	68	61	0.91
129	44	56	1.06
130	44	53	1.29
131	68	63	1.26
132	64	49	0.77
133	63	58	0.97
134	43	59	1.48
135	47	57	0.92
136	52	55	0.73
137	65	61	0.84
138	71	47	0.69
139	54	53	1.20
140	67	72	1.64
141	55	50	0.74
142	68	61	0.95
143	60	74	1.17
144	49	54	1.26
145	54	63	1.34
146	47	44	0.85
147	41	57	0.88
148	76	57	0.80
149	75	43	0.80
150	50	61	0.91
151	44	66	1.20
152	75	62	0.91
153	67	50	0.83
154	48	55	1.12
155	41	70	1.30
156	65	47	1.00
157	46	54	1.32
158	79	58	0.76
159	63	49	0.65
160	76	64	1.28
161	64	65	1.48
162	61	63	0.84
163	72	64	0.96
164	43	57	1.19

Days	Orders in	Orders out	Throughput
165	51	74	1.80
166	49	52	0.80
167	69	58	1.26
168	56	63	0.80
169	59	50	0.79
170	75	60	0.79
171	70	58	0.91
172	53	55	0.90
173	47	76	1.06
174	58	56	1.30
175	47	60	1.18
176	63	70	1.43
177	59	44	0.64
178	77	60	1.07
179	48	43	0.73
180	49	64	0.85
181	45	66	0.94
182	63	57	1.08
183	72	44	0.94
184	74	53	0.91
185	52	55	1.17
186	44	66	1.05
187	73	63	1.07
188	77	52	0.68
189	48	65	1.35
190	71	57	1.16
191	69	55	1.22
192	49	75	1.19
193	60	80	1.11
194	52	51	0.69
195	41	62	1.19
196	64	58	1.32
197	68	49	0.67
198	63	49	0.64
199	61	53	1.10
200	43	62	0.87
201	42	62	0.90
202	75	58	1.18
203	60	43	0.72
204	57	62	1.19
205	62	58	1.41

Days	Orders in	Orders out	Throughput
206	76	56	0.88
207	75	56	0.82
208	43	64	1.02
209	60	65	1.07
210	72	46	1.07
211	68	66	1.57
212	58	65	0.87
213	60	67	1.12
214	67	72	1.26
215	70	63	1.02
216	59	54	0.71
217	70	70	0.93
218	77	59	1.37
219	49	68	1.13
220	72	66	0.92
221	70	66	0.97
222	65	61	1.05
223	62	60	1.00
224	79	63	0.94
225	53	73	1.04
226	61	70	1.19
227	72	74	1.06
228	54	62	0.81
229	72	76	1.55
230	79	47	0.65
231	77	55	0.79
232	48	76	1.17
233	78	77	1.24
234	51	52	0.66
235	51	78	1.47
236	59	66	1.08
237	70	49	0.68
238	45	55	1.02
239	57	62	0.86
240	64	64	0.81

Table 18. Daily throughput ratios for Scenario 2.

Days	Orders in	Orders out	Throughput
1	45	0	
2	52	45	
3	52	52	
4	73	52	
5	48	73	
6	61	48	
7	59	61	
8	54	59	
9	45	54	
10	70	45	
11	63	70	1.56
12	56	62	1.19
13	53	56	1.08
14	49	52	0.71
15	64	47	0.98
16	76	64	1.05
17	51	74	1.25
18	41	53	0.98
19	78	40	0.89
20	45	74	1.06
21	70	43	0.68
22	47	67	1.20
23	43	44	0.83
24	48	43	0.88
25	67	46	0.72
26	47	64	0.84
27	60	46	0.90
28	48	59	1.44
29	64	45	0.58
30	70	64	1.42
31	75	68	0.97
32	75	71	1.51
33	73	70	1.63
34	69	66	1.38
35	60	73	1.09
36	43	54	1.15
37	41	40	0.67
38	77	36	0.75
39	79	70	1.09
40	59	73	1.04
41	63	63	0.84
42	66	64	0.85
43	40	63	0.86
44	77	39	0.57
45	55	76	1.27
46	62	51	1.19
47	68	57	1.39
48	66	65	0.84
49	45	61	0.77
50	61	43	0.73
51	43	54	0.86
52	71	37	0.56
53	50	71	1.78
54	46	45	0.58
55	58	44	0.80
56	43	58	0.94
57	46	43	0.63
58	66	46	0.70
59	70	65	1.44
60	65	69	1.13
61	57	59	1.37
62	75	62	0.87
63	43	70	1.40
64	78	46	1.00
65	54	75	1.29
66	71	52	1.21
67	70	70	1.52
68	50	68	1.03
69	73	51	0.73
70	68	71	1.09
71	64	65	1.14
72	67	61	0.81
73	76	65	1.51
74	71	68	0.87
75	69	67	1.24
76	65	66	0.93
77	64	57	0.81
78	58	63	1.26

Days	Orders in	Orders out	Throughput
79	60	57	0.78
80	75	60	0.88
81	73	75	1.17
82	60	64	0.96
83	60	62	0.82
84	52	56	0.79
85	66	46	0.67
86	47	64	0.98
87	63	47	0.73
88	67	62	1.07
89	74	65	1.08
90	45	70	0.93
91	45	48	0.66
92	76	43	0.72
93	46	75	1.25
94	49	45	0.87
95	73	46	0.70
96	71	73	1.55
97	77	68	1.08
98	41	71	1.06
99	52	49	0.66
100	70	51	1.13
101	43	69	1.53
102	61	43	0.57
103	79	61	1.33
104	65	74	1.51
105	51	64	0.88
106	54	54	0.76
107	61	54	0.70
108	77	54	1.32
109	63	72	1.38
110	71	60	0.86
111	78	68	1.58
112	58	69	1.13
113	67	53	0.67
114	58	59	0.91
115	70	56	1.10
116	47	68	1.26
117	49	41	0.67
118	67	48	0.62
119	53	67	1.06
120	41	53	0.75
121	50	41	0.53

Days	Orders in	Orders out	Throughput
122	64	50	0.86
123	60	62	0.93
124	40	58	1.00
125	62	39	0.56
126	75	59	1.26
127	73	71	1.45
128	68	66	0.99
129	44	66	1.25
130	44	43	1.05
131	68	40	0.80
132	64	62	0.97
133	63	62	1.03
134	43	60	1.50
135	47	41	0.66
136	52	46	0.61
137	65	52	0.71
138	71	65	0.96
139	54	68	1.55
140	67	53	1.20
141	55	67	0.99
142	68	54	0.84
143	60	67	1.06
144	49	55	1.28
145	54	44	0.94
146	47	52	1.00
147	41	46	0.71
148	76	39	0.55
149	75	76	1.41
150	50	61	0.91
151	44	64	1.16
152	75	44	0.65
153	67	73	1.22
154	48	61	1.24
155	41	47	0.87
156	65	39	0.83
157	46	65	1.59
158	79	46	0.61
159	63	76	1.01
160	76	59	1.18
161	64	73	1.66
162	61	68	0.91
163	72	57	0.85
164	43	67	1.40

Days	**Orders in**	**Orders out**	**Throughput**
165	51	40	0.98
166	49	48	0.74
167	69	45	0.98
168	56	69	0.87
169	59	56	0.89
170	75	58	0.76
171	70	73	1.14
172	53	62	1.02
173	47	50	0.69
174	58	46	1.07
175	47	56	1.10
176	63	45	0.92
177	59	63	0.91
178	77	59	1.05
179	48	73	1.24
180	49	45	0.60
181	45	49	0.70
182	63	45	0.85
183	72	63	1.34
184	74	70	1.21
185	52	65	1.38
186	44	59	0.94
187	73	44	0.75
188	77	71	0.92
189	48	67	1.40
190	71	56	1.14
191	69	65	1.44
192	49	65	1.03
193	60	47	0.65
194	52	59	0.80
195	41	51	0.98
196	64	41	0.93
197	68	64	0.88
198	63	64	0.83
199	61	58	1.21
200	43	59	0.83
201	42	40	0.58
202	75	37	0.76
203	60	74	1.23

Days	**Orders in**	**Orders out**	**Throughput**
204	57	56	1.08
205	62	55	1.34
206	76	62	0.97
208	43	65	1.03
209	60	43	0.70
210	72	56	1.30
211	68	61	1.45
212	58	65	0.87
213	60	55	0.92
214	67	53	0.93
215	70	65	1.05
216	59	68	0.89
217	70	60	0.80
218	77	68	1.58
219	49	69	1.15
220	72	46	0.64
221	70	69	1.01
222	65	67	1.16
223	62	63	1.05
224	79	60	0.90
225	53	70	1.00
226	61	55	0.93
227	72	61	0.87
228	54	68	0.88
229	72	56	1.14
230	79	66	0.92
231	77	74	1.06
232	48	67	1.03
233	78	53	0.85
234	51	69	0.87
235	51	48	0.91
236	59	47	0.77
237	70	55	0.76
238	45	67	1.24
239	57	40	0.56
240	64	52	0.66

Table 19. Daily throughput ratios for Scenario 3.

Days	**Orders in**	**Orders out**	**Throughput**
1	45	0	
2	52	0	
3	52	0	
4	73	0	
5	48	6	
6	61	37	
7	59	52	
8	54	51	
9	45	49	
10	70	47	
11	63	51	1.133
12	56	55	1.058
13	53	45	0.865
14	49	55	0.753
15	64	48	1.000
16	76	55	0.902
17	51	51	0.864
18	41	42	0.778
19	78	50	1.111
20	45	52	0.743
21	70	52	0.825
22	47	49	0.875
23	43	53	1.000
24	48	53	1.082
25	67	46	0.719
26	47	55	0.724
27	60	50	0.980
28	48	48	1.171
29	64	46	0.590
30	70	58	1.289
31	75	50	0.714
32	75	48	1.021
33	73	49	1.140
34	69	47	0.979
35	60	49	0.731
36	43	50	1.064
37	41	52	0.867
38	77	47	0.979
39	79	52	0.813

Days	**Orders in**	**Orders out**	**Throughput**
40	59	54	0.771
41	63	42	0.560
42	66	49	0.653
43	40	54	0.740
44	77	48	0.696
45	55	48	0.800
46	62	50	1.163
47	68	57	1.390
48	66	51	0.662
49	45	48	0.608
50	61	51	0.864
51	43	53	0.841
52	71	56	0.848
53	50	53	1.325
54	46	52	0.675
55	58	48	0.873
56	43	46	0.742
57	46	49	0.721
58	66	44	0.667
59	70	57	1.267
60	65	52	0.852
61	57	50	1.163
62	75	57	0.803
63	43	56	1.120
64	78	45	0.978
65	54	53	0.914
66	71	55	1.279
67	70	52	1.130
68	50	51	0.773
69	73	52	0.743
70	68	53	0.815
71	64	48	0.842
72	67	48	0.640
73	76	53	1.233
74	71	50	0.641
75	69	52	0.963
76	65	55	0.775
77	64	47	0.671
78	58	55	1.100

Days	Orders in	Orders out	Throughput
79	60	55	0.753
80	75	49	0.721
81	73	50	0.781
82	60	54	0.806
83	60	50	0.658
84	52	50	0.704
85	66	49	0.710
86	47	54	0.831
87	63	53	0.828
88	67	53	0.914
89	74	47	0.783
90	45	49	0.653
91	45	44	0.603
92	76	48	0.800
93	46	51	0.850
94	49	62	1.192
95	73	48	0.727
96	71	48	1.021
97	77	49	0.778
98	41	53	0.791
99	52	52	0.703
100	70	51	1.133
101	43	48	1.067
102	61	52	0.684
103	79	48	1.043
104	65	55	1.122
105	51	46	0.630
106	54	56	0.789
107	61	50	0.649
108	77	49	1.195
109	63	53	1.019
110	71	52	0.743
111	78	49	1.140
112	58	46	0.754
113	67	56	0.709
114	58	54	0.831
115	70	49	0.961
116	47	56	1.037
117	49	48	0.787
118	67	52	0.675
119	53	50	0.794
120	41	54	0.761
121	50	52	0.667

Days	Orders in	Orders out	Throughput
122	64	48	0.828
123	60	54	0.806
124	40	55	0.948
125	62	55	0.786
126	75	51	1.085
127	73	49	1.000
128	68	48	0.716
129	44	53	1.000
130	44	50	1.220
131	68	51	1.020
132	64	51	0.797
133	63	54	0.900
134	43	51	1.275
135	47	50	0.806
136	52	48	0.640
137	65	52	0.712
138	71	55	0.809
139	54	52	1.182
140	67	51	1.159
141	55	50	0.735
142	68	55	0.859
143	60	56	0.889
144	49	44	1.023
145	54	55	1.170
146	47	50	0.962
147	41	58	0.892
148	76	45	0.634
149	75	55	1.019
150	50	53	0.791
151	44	44	0.800
152	75	48	0.706
153	67	62	1.033
154	48	48	0.980
155	41	48	0.889
156	65	51	1.085
157	46	45	1.098
158	79	61	0.803
159	63	46	0.613
160	76	57	1.140
161	64	45	1.023
162	61	59	0.787
163	72	49	0.731
164	43	50	1.042

Days	Orders in	Orders out	Throughput
165	51	54	1.317
166	49	51	0.785
167	69	51	1.109
168	56	51	0.646
169	59	43	0.683
170	75	52	0.684
171	70	50	0.781
172	53	51	0.836
173	47	50	0.694
174	58	50	1.163
175	47	55	1.078
176	63	46	0.939
177	59	59	0.855
178	77	51	0.911
179	48	50	0.847
180	49	47	0.627
181	45	49	0.700
182	63	49	0.925
183	72	47	1.000
184	74	53	0.914
185	52	46	0.979
186	44	57	0.905
187	73	47	0.797
188	77	50	0.649
189	48	51	1.063
190	71	53	1.082
191	69	47	1.044
192	49	50	0.794
193	60	54	0.750
194	52	50	0.676
195	41	54	1.038
196	64	51	1.159
197	68	50	0.685
198	63	45	0.584
199	61	49	1.021
200	43	53	0.746
201	42	54	0.783
202	75	49	1.000
203	60	54	0.900
204	57	47	0.904
205	62	55	1.341
206	76	54	0.844

Days	Orders in	Orders out	Throughput
207	75	45	0.662
208	43	51	0.810
209	60	50	0.820
210	72	49	1.140
211	68	54	1.286
212	58	51	0.680
213	60	55	0.917
214	67	48	0.842
215	70	52	0.839
216	59	51	0.671
217	70	53	0.707
218	77	53	1.233
219	49	50	0.833
220	72	46	0.639
221	70	55	0.809
222	65	47	0.810
223	62	55	0.917
224	79	51	0.761
225	53	51	0.729
226	61	49	0.831
227	72	49	0.700
228	54	54	0.701
229	72	54	1.102
230	79	45	0.625
231	77	53	0.757
232	48	52	0.800
233	78	51	0.823
234	51	56	0.709
235	51	50	0.943
236	59	49	0.803
237	70	51	0.708
238	45	53	0.981
239	57	56	0.778
240	64	47	0.595

Days	Orders in	Orders out	Throughput
79	60	57	0.78
80	75	60	0.88
81	73	75	1.17
82	60	64	0.96
83	60	62	0.82
84	52	56	0.79
85	66	46	0.67
86	47	64	0.98
87	63	47	0.73
88	67	62	1.07
89	74	65	1.08
90	45	70	0.93
91	45	48	0.66
92	76	43	0.72
93	46	75	1.25
94	49	45	0.87
95	73	46	0.70
96	71	73	1.55
97	77	68	1.08
98	41	71	1.06
99	52	49	0.66
100	70	51	1.13
101	43	69	1.53
102	61	43	0.57
103	79	61	1.33
104	65	74	1.51
105	51	64	0.88
106	54	54	0.76
107	61	54	0.70
108	77	54	1.32
109	63	72	1.38
110	71	60	0.86
111	78	68	1.58
112	58	69	1.13
113	67	53	0.67
114	58	59	0.91
115	70	56	1.10
116	47	68	1.26
117	49	41	0.67
118	67	48	0.62
119	53	67	1.06
120	41	53	0.75
121	50	41	0.53

Days	Orders in	Orders out	Throughput
122	64	50	0.86
123	60	62	0.93
124	40	58	1.00
125	62	39	0.56
126	75	59	1.26
127	73	71	1.45
128	68	66	0.99
129	44	66	1.25
130	44	43	1.05
131	68	40	0.80
132	64	62	0.97
133	63	62	1.03
134	43	60	1.50
135	47	41	0.66
136	52	46	0.61
137	65	52	0.71
138	71	65	0.96
139	54	68	1.55
140	67	53	1.20
141	55	67	0.99
142	68	54	0.84
143	60	67	1.06
144	49	55	1.28
145	54	44	0.94
146	47	52	1.00
147	41	46	0.71
148	76	39	0.55
149	75	76	1.41
150	50	61	0.91
151	44	64	1.16
152	75	44	0.65
153	67	73	1.22
154	48	61	1.24
155	41	47	0.87
156	65	39	0.83
157	46	65	1.59
158	79	46	0.61
159	63	76	1.01
160	76	59	1.18
161	64	73	1.66
162	61	68	0.91
163	72	57	0.85
164	43	67	1.40

Days	Orders in	Orders out	Throughput
165	51	40	0.98
166	49	48	0.74
167	69	45	0.98
168	56	69	0.87
169	59	56	0.89
170	75	58	0.76
171	70	73	1.14
172	53	62	1.02
173	47	50	0.69
174	58	46	1.07
175	47	56	1.10
176	63	45	0.92
177	59	63	0.91
178	77	59	1.05
179	48	73	1.24
180	49	45	0.60
181	45	49	0.70
182	63	45	0.85
183	72	63	1.34
184	74	70	1.21
185	52	65	1.38
186	44	59	0.94
187	73	44	0.75
188	77	71	0.92
189	48	67	1.40
190	71	56	1.14
191	69	65	1.44
192	49	65	1.03
193	60	47	0.65
194	52	59	0.80
195	41	51	0.98
196	64	41	0.93
197	68	64	0.88
198	63	64	0.83
199	61	58	1.21
200	43	59	0.83
201	42	40	0.58
202	75	37	0.76

Days	Orders in	Orders out	Throughput
203	60	74	1.23
204	57	56	1.08
205	62	55	1.34
206	76	62	0.97
208	43	65	1.03
209	60	43	0.70
210	72	56	1.30
211	68	61	1.45
212	58	65	0.87
213	60	55	0.92
214	67	53	0.93
215	70	65	1.05
216	59	68	0.89
217	70	60	0.80
218	77	68	1.58
219	49	69	1.15
220	72	46	0.64
221	70	69	1.01
222	65	67	1.16
223	62	63	1.05
224	79	60	0.90
225	53	70	1.00
226	61	55	0.93
227	72	61	0.87
228	54	68	0.88
229	72	56	1.14
230	79	66	0.92
231	77	74	1.06
232	48	67	1.03
233	78	53	0.85
234	51	69	0.87
235	51	48	0.91
236	59	47	0.77
237	70	55	0.76
238	45	67	1.24
239	57	40	0.56
240	64	52	0.66

APPENDIX B: NORMALITY TESTS

Figure 6. Kolmogorov-Smirnov normality test for throughput ratios, Scenario 1.

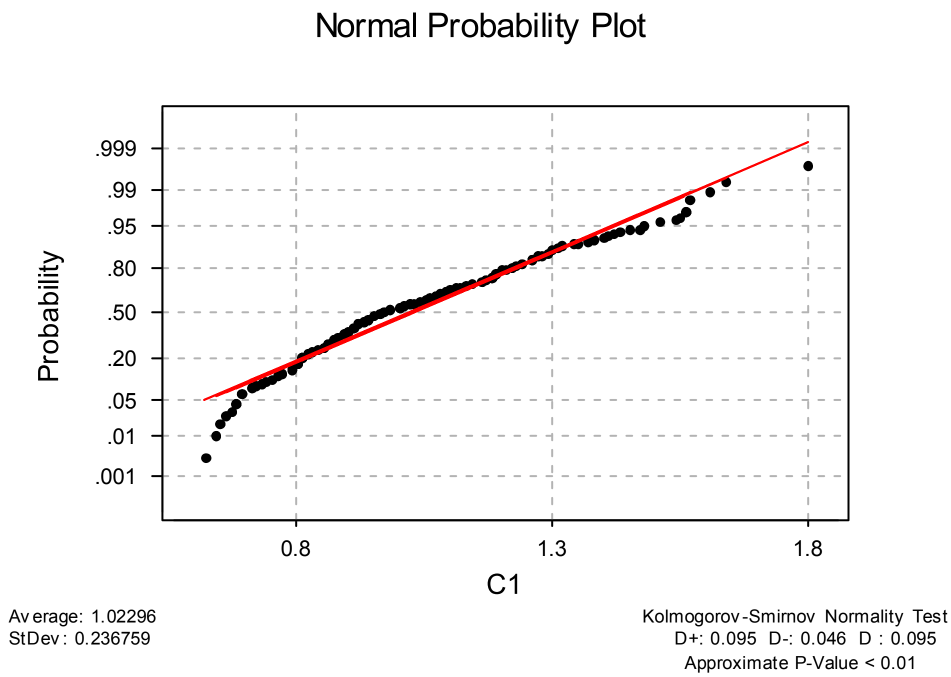


Figure 7. Kolmogorov-Smirnov normality test for throughput ratios, Scenario 2.

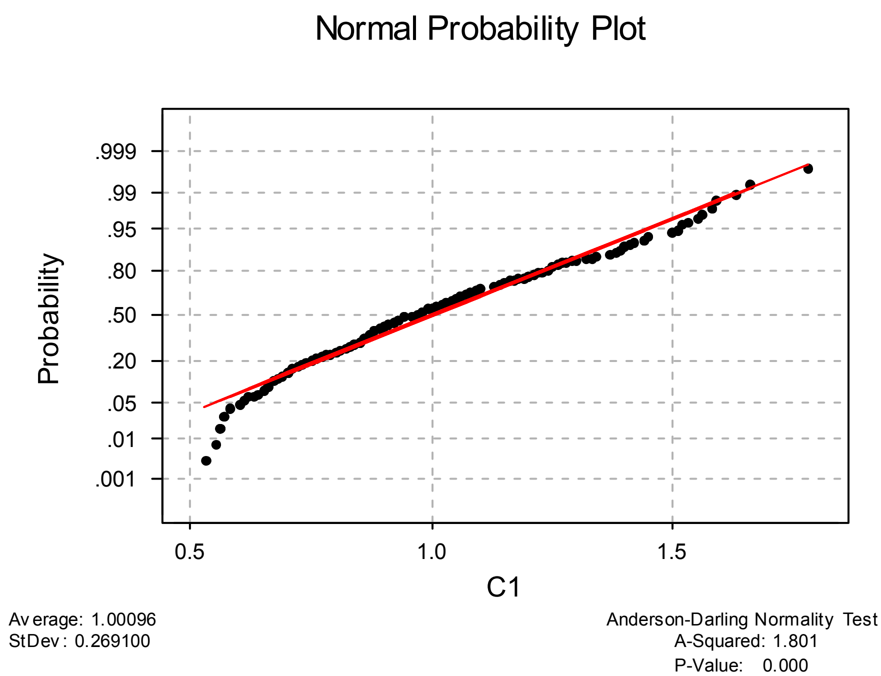
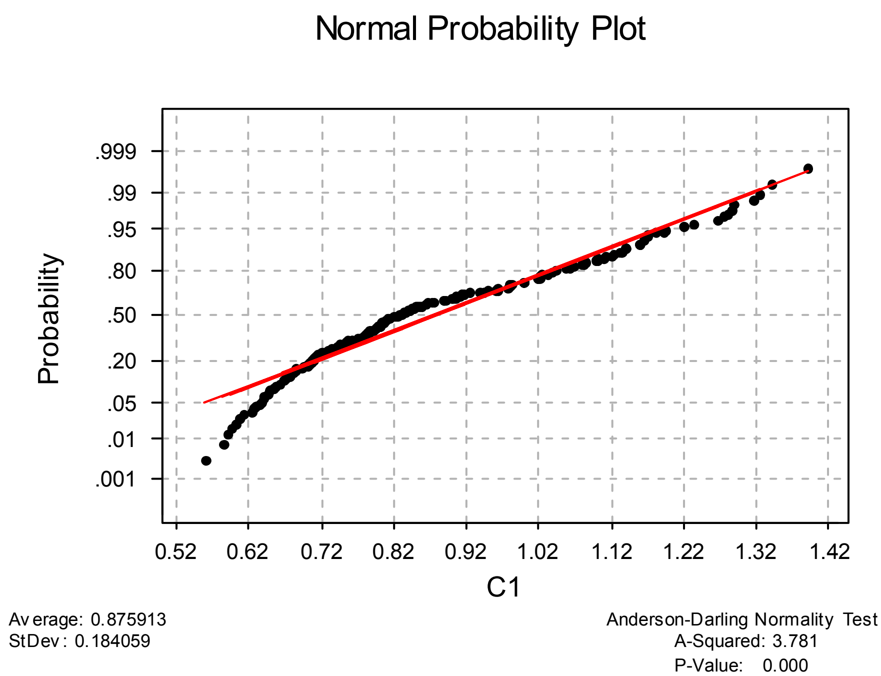


Figure 8. Kolmogorov-Smirnov normality test for throughput ratios, Scenario 3.



APPENDIX C: CHANGING THE SIZE OF THE ORDERS

Table 20. Changing numbers of items. Scenario 1 Multi-channel manufacturing.

Changes	**Change 1**	**Change 2**	**Change 3**
	Order size is fixed	**Order size could be either of the two numbers**	**Order size is the sum of two numbers each chosen from a different range**
Fastpath items	**200 Items per order**	**Either 100 or 300 items per order**	**One number between (0 and 100) plus one number between (100 and 200)**
Flexpath items	**20 items per order**	**Either 5 or 35 items per order**	**One number between (5 and 15) plus One number between (0 and 20)**
Average lead time, Fastpath orders	**5.52**	**5.51**	**5.51**
Average lead time for backorders (Flexpath orders)	**4.08**	**4.21**	**4.08**
Standard deviation for Backorders (Flexpath)	**0.042**	**0.017**	**0.018**
Average lead time Flexpath from inventory	**1.99**	**1.99**	**1.99**
Average numbers of backorders (% of total orders)	**0.01**	**0.01**	**0.01**

Table 21. Changing numbers of items. Scenario 2 MTS system.

Changes	**Change 1**	**Change 2**	**Change 3**
	Order size is fixed	**Order size could be either of the two numbers**	**Order size is the sum of two numbers each chosen from a different range**
Numbers of items per Large order	**200 Items per order**	**Either 100 or 300 items per order**	**One number between (0 and 100) plus one number between (100 and 200)**
Numbers of items per small order	**20 items per order**	**Either 5 or 35 items per order**	**One number between (5 and 15) plus One number between (0 and 20)**
Average lead time for backorders (large size orders)	**4.63**	**4.89**	**4.69**
Average lead time for backorders (small size orders)	**4.59**	**4.73**	**4.61**
Standard deviation for backorders (large size orders)	**0.06**	**0.08**	**0.05**
Standard deviation for backorders (small size orders)	**0.08**	**0.06**	**0.07**
Average numbers of large size backorders (% of total orders)	**0.02**	**0.03**	**0.02**
Average numbers of small size backorders (% of total orders)	**0.02**	**0.02**	**0.01**

Table 22. Changing numbers of items. Scenario 3 MTO system.

Changes	Change 1	Change 2	Change 3
	Order size is fixed	Order size could be either of the two numbers	Order size is the sum of two numbers each chosen from a different range
Numbers of items per Large order	200 Items per order	Either 100 or 300 items per order	One number between (0 and 100) plus one number between (100 and 200)
Numbers of items per small order	20 items per order	Either 5 or 35 items per order	One number between (5 and 15) plus One number between (0 and 20)
Average lead time (large size orders)	**21.5**	**23.5**	**23.6**
Average lead time (small size orders)	**22.1**	**22.8**	**22.9**
Standard deviation for large size orders	**2.1**	**2.8**	**2.1**
Standard deviation for small size orders	**2.2**	**2.9**	**2.3**

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