Analysis of the Effect of Ordering Policies for a Manufacturing Cell Transitioning to Lean Production

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Abstract

Over the past two decades, Lean Production has begun to replace traditional manufacturing techniques around the world, mainly due to the success of the Toyota Motor Company. One key to Toyota's success that many American companies have not been able to emulate is the transformation of their suppliers to the lean philosophy. This lack of supplier transformation in America is due to a variety of reasons including differences in supplier proximity, supplier relationships, supplier performance levels, and the ordering policies used for supplied parts. The focus of this research is analyzing the impact of ordering policies for supplied parts of a manufacturing cell utilizing Lean Production techniques.

This thesis presents a simulation analysis of a multi-stage, lean manufacturing cell that produces a family of products. The analysis investigates how the ordering policy for supplied parts affects the performance of the cell under conditions of demand variability and imperfect supplier performance. The ordering policies evaluated are a periodic-review inventory control policy (*s*, *S*) and two kanban policies. The performance of the cell is measured by the flowtime of the product through the cell, the on-time-delivery to their customer, the number of products shipped each week, the amount of work-in-process inventory in the cell, the approximate percentage of time the cell was stocked out, and the average supplied part inventory levels for the cell. Using this simulation model, an experimental analysis is conducted using an augmented central composite design. Then, a multivariate analysis is performed on the results of the experiments.

The results obtained from this study suggest that the preferred ordering policy for supplied parts is the (*s, S*) inventory policy for most levels of the other three factors and most of the performance measures. This policy, however, results in increased levels of supplied part inventory, which is the primary reason for the high performance for most response variables. This increased inventory is in direct conflict with the emphasis on inventory and waste reduction, one of the key principles of Lean Production. Furthermore, the inflated kanban policy tends to perform well at high levels of supplier on-time delivery and low levels of customer demand variability. These results are consistent with the proper conditions under which to implement Lean Production: good supplier performance and level customer demand. Thus, while the (*s, S*) inventory policy may be advantageous as a company begins transitioning to Lean Production, the inflated kanban policy may be preferable once the company has established good supplier performance and level customer demand.

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CHAPTER I

INTRODUCTION

Lean Production has become a popular topic in research and in practice over the last two decades in the United States and many other countries. This is evidenced by the growing number of conferences, seminars, and academic programs devoted to Lean Production (Institute of Industrial Engineers, 1999; Institute of Industrial Engineers, 2000; Institute of Industrial Engineers, 2001; McDonald, Hafner, Van Aken and Ellis, 2002; Beasley, n.d.). This popularity has seen companies utilizing or transitioning to Lean Production in many countries including the United States, Sweden, Spain, Australia, and England (Karlsson and Norr, 1994; Sohal and Egglestone, 1994; Miller, 1995; Liker, 1998; Perez and Sanchez, 2001).

Lean Production was developed after World War II in Japan as Toyoda Kiichiro, president of Toyota Motor Company said "Catch up with America in three years. Otherwise, the automobile industry of Japan will not survive" (as cited in Ohno, 1988 p. 3). He and his staff knew an American worker produced approximately nine times as much as a Japanese worker, so they studied mass production methods for automobile assembly in America (Ohno, 1988). What they discovered was long setup times required for machines forced companies to use large lot production to reduce the cost of each part. Taiichi Ohno, one of Toyoda's employees, knew these methods would not work in Japan, where demand was much lower, so he found methods to improve the American's system (Ohno, 1988). What he determined was that the U.S. was wasting large amounts of energy and money on long setup times, poor quality, and other issues. Based on the understanding he gained, he developed the Toyota Production System (later termed Lean Production by Womack, Jones, and Roos (1990)), which would continually focus on reducing these wastes, or *muda*, to increase profit (Ohno, 1988). Through the use of Lean Production, Toyota became one of the most renowned car manufacturers in the world and one of the United State's toughest competitors for the foreign as well as the domestic market during the mid- to late-80's (Ohno, 1988; Monden, 1998).

The traditional Western view has been that the manufacturer can dictate the selling price of a product by adding the manufacturing cost and their desired profit. The Japanese, however, believe customers determine the selling price and profit is the difference between the price and the cost of the product or service. Therefore, the founding principle of Lean Production is to reduce waste because it ultimately decreases the cost of products and services, thereby increasing profits (Ohno, 1988; Monden, 1998). Toyota proposed to generate more profit by eliminating seven wastes, overproduction, waiting, transportation, processing, inventory, movement, and defects (Ohno, 1988).

To eliminate these wastes, lean companies use concepts depicted in the *Lean Production Pyramid*, displayed in Figure 1-1. The ultimate goal of Lean Production is to create the highest quality product for the lowest cost with the shortest leadtime. To accomplish this, companies need a solid foundation, which is created with stable manufacturing processes, standardized work, and utilizing Just-in-Time (JIT). From this base, autonomation (Jidoka), and production leveling (Heijunka) will lead to the ultimate goal. However, the foundation cannot be built unless the majority of machine downtime is scheduled through Total Productive Maintenance

(TPM), the company has a culture emphasizing continuous improvement (Kaizen), the 5S techniques are utilized, and the quality of the incoming products are high. The following sections describe and explain the main aspects of the Lean Production Pyramid, and will describe the focus and contributions of this research.

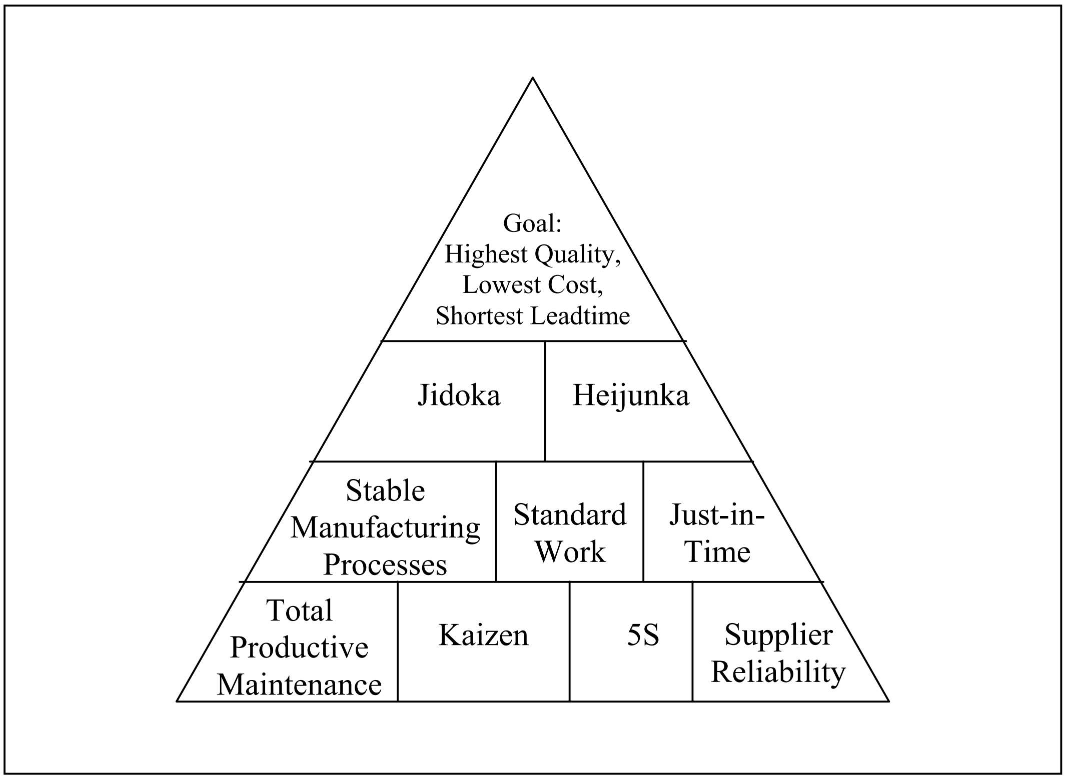


Figure 1-1. Lean Production Pyramid

1.1. TPM, KAIZEN, 5S, AND SUPPLIER RELIABILITY

The goal of Lean Production begins with establishing a strong base. The lowest level of the pyramid utilizes four blocks to build this base: Total Productive Maintenance, Kaizen, 5S, and supplier reliability and are described in this section.

Total Productive Maintenance is the process of eliminating all unscheduled downtime for machines. This includes preventative maintenance and maintenance usually performed by operators. TPM allows for the machine to have a predictable output.

The second block in the base is kaizen, or continuous improvement, and involves the continuous implementation of improvement activities (Monden, 1998). This improvement can be anything from reducing the distance the material travels, to reducing the amount of inspection done to the product, to working with suppliers to improve their performance.

Another block is 5S, which is a system to clean and organize the facility, and consists of the Japanese words seiri, seiton, seiso, seiketsu, and shitsuke (Monden, 1998). The purpose of 5S is to reveal waste hidden in the plant, such as excess WIP, defective inventories, unnecessary jigs, unneeded carts, and even documents and stationary (Monden, 1998). These words have been mapped to the English words **sort, straighten, sweep and clean, standardize, and sustain** (Press Development Team, 1998). A description of the 5S's is as follows (adapted from Monden, 1998; Danaher Business Systems, 2001):

- Seiri – to clearly distinguish between what is necessary and what is unnecessary and disposing of the latter (**sort**);
- Seiton – to organize the necessary items so they can be used and returned easily (**straighten**);
- Seiso – to always clean up, to maintain tidiness and cleanliness in all areas of the workplace (**sweep and clean**);
- Seiketsu – to constantly maintain and improve the standards of the first three S's (**standardize**);
- Shitsuke – to achieve the discipline or habit of properly maintaining the correct 5S procedures (**sustain**).

The final S, shitsuke, is the most important, because 5S needs to be a part of the company's culture, not just something that is done when the cell is unorganized, and operators need to be continually looking for improvement opportunities (Monden, 1998). It is especially important for top-level managers who might not understand how cleaning and straightening can help the organization's bottom line.

Supplier reliability, the final block in the base, is an often overlooked step to reducing waste. Supplier reliability refers to working with the supplier to provide parts with 100% on-time delivery rates, with 100% quality levels. The closer a supplier is to reaching this goal, the less safety stock the manufacturing cell will have to carry to adjust for missed shipments and defects.

1.2. Stable Manufacturing Processes, Standard Work, and JIT Production

After building a solid base, the effort to reach the goal is supported with a manufacturing cell that has stable manufacturing processes and utilizes both standardized work and JIT techniques. These three blocks of the pyramid are described in this section.

The stable manufacturing processes block refers to the manufacturing processes themselves, including operator interaction and material handling. Stable manufacturing processes produce a consistent product with a predictable cycle time. This allows for more effective production and resource scheduling.

Another block of the pyramid is the standardization of employee operations. The purpose of standardized work is to eliminate wasted movement. If the most effective processing steps are followed every time, the process will contain as little non-value added time as possible. According to Hines and Taylor (2000, p. 10), non-value added time is the time spent performing an activity that "in the eyes of the final customer, [does] not make a product or service more valuable." At every Toyota factory, operators are expected to complete the same set of steps in the same order every time. For example, if they are installing car seats, they tighten the bolts in the same order every time, regardless of the employee working at that station (Spear and Bowen, 1999). An employee not following the process in the specified order serves as a physical signal to both themselves and the supervisor that a problem with the process has occurred and requires attention.

The third block in this level of the Lean Production Pyramid is JIT production. The focus of JIT is to provide each process with the correct number of the necessary parts, at exactly the right point in time (Shingo, 1989; Karlsson and Åhlström, 1996). The difference between this and traditional manufacturing is that JIT systems start with a signal from the customer buying a product (or a simulated customer purchase), and then the inventory is drawn through the manufacturing cell to replace the item (Ohno, 1988), thus creating a pull effect. Market forecasts are used to determine a perception of customer demand, but the system is flexible enough to change if the demand fluctuates significantly. Also, the operators can only work until specified buffers are filled between subsequent processes, reducing the amount of inventory in the system, thus reducing the waste of storage.

Traditional manufacturing, on the other hand, uses a push system that takes the market forecast and determines how often parts should be entered into the line. Then, the associates tend to process the product until they are "starved," meaning that they have no work-in-process inventory (WIP) available. Also, in some cases associates work on products regardless of the forecast, taking any available material and working until it is completely consumed. This process may result in large buffers between processes, hiding defects, and reducing communication between workers.

1.3. Jidoka and Heijunka

After establishing the first two levels of the pyramid, the goal is reached through the implementation of jidoka and heijunka. These two blocks of the pyramid are described in this section.

Jidoka is also referred to as autonomation. Monden (1998, p. 12) states that, "autonomation means to build in a mechanism to prevent mass-production of defective work in machines or product lines." One of the tools of jidoka is a pokayoke, the Japanese word meaning error proof. A pokayoke is a device on a machine that stops the machine or even an entire manufacturing cell if a defective product has been produced. It can also be a device that an employee uses to ensure that the product is defect-free. Another type of jidoka is a manual stop that allows employees to stop the entire line if they determine a problem exists with the quality of the parts (Monden, 1998). The improvements that jidoka bring are two-fold. First, it reduces the defects in the product, which reduces the size of the rework department, and second, it allows employees to work on multiple machines, because they aren't required to watch a machine operate, reducing the amount of employee waiting time.

The purpose of heijunka, or production leveling, is to ensure that the manufacturing process runs at a steady rate with little variation in production quantities from month-to-month, day-to-day, and even hour-to-hour. As Monden (1998, p. 8) points out, heijunka is the "most important condition for production by kanban and for minimizing idle time in regard to manpower, equipment, and work-in-process." If the time between parts is not constant, there will be stocks of WIP in certain areas while other areas are starved.

Production smoothing can be achieved using two different methods, the smoothing of the total production quantity and the smoothing of every model's production quantity. The first concerns production over a certain time period, usually one month, ensuring that each day a similar number of products are produced. The second type is creating a system where each product in a family is produced every day, instead of producing one product for a day, a second on the next, a third on the next, and then repeating the cycle. This system keeps the production of all of the internal suppliers to the final assembly running every day, and at a constant pace, as opposed to working for a day and then having two days off. One key to ensure the success of heijunka is to reduce waste by eliminating setup, or change over times.

In summary, the success of a company's transition to Lean Production relies on a few key factors. First, they need to build a solid foundation with stable manufacturing processes, standardized work processes, and just-in-time (JIT) production. From this base, building autonomation (Jidoka) and level production (Heijunka) can lead to the ultimate goal of high quality parts produced with fewer expenses in a shorter amount of time. However, the foundation cannot be built unless the majority of machine downtime is scheduled, the company strives to improve continuously, the concepts of 5S are utilized, and the quality of the incoming products are high.

1.4. FOCUS OF THIS RESEARCH

Because the supplier is so vital to cell performance in a Lean Production environment, the focus of this research is to study the impact of a manufacturing cell's ordering policy for supplied parts on the performance of that cell under conditions of customer demand variability and various levels of supplier performance. The multi-stage manufacturing cell produces a family of parts and is transitioning to Lean Production. The ordering policies considered are a periodic-review policy and two just-in-time ordering policies using kanbans. The performance of the cell will be evaluated using the following measures: the flowtime of the product through the cell, the on-time-delivery to their customer, the number of motors shipped each week by the cell, the average work-in-process inventory level in the cell, the approximate percentage of time the cell will be down due to stockouts, and the average supplied part inventory levels for the cell. The results of this analysis will provide important guidance in two fundamental areas, improving incoming quality and ensuring level demand, as companies transition to Lean Production.

In this thesis, Chapter 2 provides the relevant background on inventory control. Chapter 3 explores previous research that has been completed on this topic. Chapter 4 describes the research methodology completed in this study. Chapters 5 presents the ordering policies evaluated in this research, and Chapter 6 describes the case application and the manufacturing cell analyzed. Chapter 7 explains the development of the simulation model used to analyze the ordering policies. Chapter 8 displays the results and analyses generated from this research. Finally, Chapter 9 summarizes the analyses and gives conclusions that can be drawn from this research.

CHAPTER II

BACKGROUND ON INVENTORY CONTROL

In order to set the framework and establish the terminology used in this research, this section describes the history of inventory control, the periodic-review inventory control technique, and the just-in-time technique. This section also explains how kanbans support the JIT technique.

2.1. HISTORY OF INVENTORY CONTROL

The advent of Scientific Management by Frederick W. Taylor led to the formation of the Operations Management (OM) discipline. His work formulas were the precursors to a variety of mathematical models that assist management at all levels of plant design and control. From the operations management field, a number of sub-disciplines were created for different OM problem areas. "Of the operations management subdisciplines that spawned mathematical models, none was more central to factory management nor more typical of the American approach to OM than that of inventory control," (Hopp and Spearman, 1996).

One of the earliest and simplest forms of inventory control was the economic order quantity (EOQ) model, in which a mathematical equation was used to determine the most economic number of parts to order each time the inventory levels at the plant reached zero (Hopp and Spearman, 1996). The equation for the EOQ model is $Q^* = \sqrt{\frac{2AD}{h}}$, where Q^* is the optimal ordering quantity, A is the ordering or set-up cost, D is the demand per unit time, and h is the annual inventory holding cost per unit (Sipper and Bulfin, 1997). The reorder point, T, is defined as $\frac{Q*}{D}$. The limitation to the EOQ model is that it assumes a known and constant demand level and that stockouts do not occur (Nahmias, 1997).

Other early models, which are more sophisticated but mostly based on the EOQ formulation, are the economic production lot model, and the probabilistic reorder point approaches (which include the Newsvendor model, the base stock model, and the (Q, r) model) (Hopp and Spearman, 1996). For example, the (Q, r) model is a variation of the EOQ model that allows for a probabilistic demand and the possibility of stockouts. In this model, Q is the order quantity, and r is the reorder point. The heuristic used to calculate the values in the (Q, r) model, as shown in Hopp and Spearman (1996), are as follows:

Step 0. Use the EOQ formula to determine Q_0

$$Q_0 = \sqrt{\frac{2AD}{h}} \tag{2.1}$$

Where: A = Ordering cost
D = Average demand during the leadtime
h = Holding cost

Then, find the smallest r_0 such that

$$G(r) \geq 1 - \frac{hQ_0}{bD} \tag{2.2}$$

Where: h = Holding cost
b = Backorder cost
D = Average demand during the leadtime

Set $t = 1$

Step 1. Compute Q_t as

$$Q_t = \sqrt{\frac{2D(A + bn(r_{t-1}))}{h}} \tag{2.3}$$

Then, recalculate r_t as the smallest value of r such that

$$G(r) \geq 1 - \frac{hQ_t}{bD} \qquad (2.4)$$

Step 2. If $|Q_t - Q_{t-1}| < 1$, and $|r_t - r_{t-1}| < 1$, stop and set $Q^* = Q_t$, $r^* = r_t$, otherwise, set $t = t+1$ and return to Step 1.

Another variation to the EOQ formulation is the periodic-review, or (s, S) inventory model. Often, the periodic-review model is a more realistic and maintainable policy for a manufacturing firm (Nahmias, 1997).

In contrast to the simple EOQ model is the more sophisticated MRP system. In the 1960's, employees at IBM developed the MRP system, as computers were becoming more frequently used in accounting, as well as for other repetitive functions (Hopp and Spearman, 1996). The basic function of the MRP system is to plan the materials that are required to meet the customer's demand. In order to meet this demand, MRP utilizes a formal plan that dictates what will be produced and when, based on the Master Production Schedule (MPS), and the Bill of Materials (BOM), to create a schedule.

Around the same time that the MRP revolution began in the United States, a completely different form of inventory control was being developed on the other side of the globe (Hopp and Spearman, 1996). This Japanese paradigm, called just-in-time, focuses on reducing waste, with one of the wastes being inventory (Hopp and Spearman, 1996). The inventory control function in JIT is accomplished through the use of kanbans.

The three inventory policies of importance for this research are a periodic-review, (s, S) model, and two versions of JIT policies using kanbans. These policies will be described in more detail in the following three sections.

2.2. Periodic-Review Inventory Control Policy

A periodic-review inventory policy is a policy where the inventory is reviewed periodically to see if more inventory is needed. This policy is in contrast to a continuous review policy, where the inventory is monitored continuously, and replenishment inventory is ordered exactly when the inventory level reaches the reorder point. Sipper and Bulfin (1997) describe two different models for periodic-review inventory control policies, the (S, T) model and the (s, S) model, both of which are extensions of the EOQ and (Q, R) models.

The (S, T) model is similar to the EOQ model, except that the (S, T) model is based on the value of the reorder period. In this model, S is the inventory target level and T is the review period, and the difference between S and the current inventory will be ordered every review period. The equation for S is $S = \overline{D}(T + \tau) + s$, where $\overline{D}$ is the average demand, T is the reorder period, τ is the leadtime, and s is the amount of safety stock. The reorder period can be convenience based (once per week, month, etc.) or based on the EOQ model (Sipper and Bulfin, 1997). If the optimal value for the reorder period (T^*) is used, the only difference between the EOQ model and the (S, T) model is that the (S, T) model includes safety stock.

The (s, S) model, also called the optional replenishment system, is based on two inventory levels, defined as (s, S) (Nahmias, 1997; Sipper and Bulfin, 1997). If the inventory at any review point is less than s, then the decision is to order the difference between S and the current inventory level. However, if the inventory at the review point is greater than s, then no inventory is ordered at that time. The advantage of the (s, S) model over the (S, T) model is that inventory is only ordered if the inventory level is at or below a certain point. Therefore, inventory is only ordered if it has dropped below the reorder point, reducing the average inventory level. According to Sipper and Bulfin (1997), this model is particularly useful when both review and ordering costs are significant.

2.3. JUST-IN-TIME

The focus of JIT is to provide each process with the exact number of the exact part, at the exact point in time it is needed (Shingo, 1989; Karlsson and Åhlström, 1996; Kasul and Motwani, 1997). The ultimate goal of JIT is to have one part arrive at a process precisely when the operator has completed the previous part, with reference to the individual products on the line (Karlsson and Åhlström, 1996). For example, if a minivan were following a sports car in the manufacturing cell, the seat that is placed in the minivan follows the seat that is placed in the sports car, and arrives at the workstation the same time as the minivan. To accomplish JIT flow, Lean Production Systems often use kanbans.

2.4. HOW JUST-IN-TIME PRODUCTION IS SUPPORTED BY A KANBAN SYSTEM

The kanban, which is Japanese for card, controls the production quantities in every process from the supplier to the customer. According to Monden (1998), in a kanban system, the type and quantity of units needed are displayed on a card which is sent between processes. This card indicates which parts an upstream process needs to produce for one of its downstream processes. The functions of a kanban, as described by Ohno (1988), are as follows:

1. Provides pick-up or transport information;
2. Provides production information;
3. Prevents overproduction and excessive transport;
4. Serves as a work order attached to goods;

5. Prevents defective products by identifying the process making the defects; and
6. Reveals existing problems and maintains inventory control.

Although many types of kanban systems exist, the most common type is the two-card system. As the name implies, the systems contains two types of cards, the withdrawal kanban, and the production-ordering kanban (Monden, 1998). The withdrawal kanban tells a worker how many parts they should take from the upstream process; while the production-ordering kanban tells the upstream process how many parts they need to produce. An example of this system, shown in Figure 2-1, is explained below.

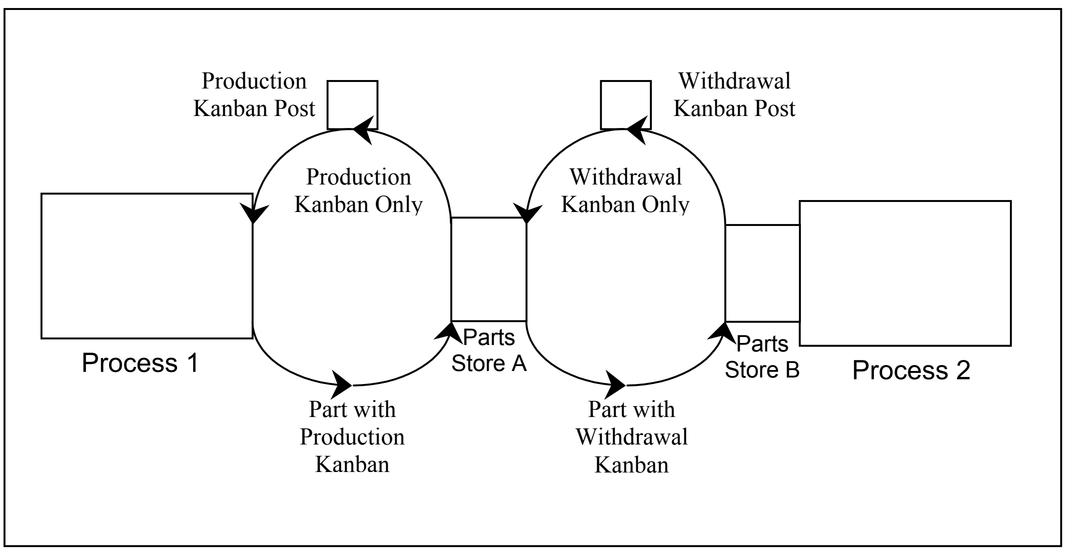


Figure 2-1. Two card kanban system

The two-card kanban system employs two types of kanbans: withdrawal kanbans and production kanbans. The withdrawal kanban serves as a signal to the material handler that a downstream process requests additional parts. The production kanbans serve as a signal that a process is authorized to produce additional parts. The two-card kanban system is often employed if the processes are distributed and not located close together or if additional control is needed on the inventory

The two-card kanban system, shown in Figure 2-1, should be considered as an isolated set of links in a chain of processes connected by kanbans. This chain can extend from the customer to the suppliers of the raw material, where the processes in the chain are both consumers of components and producers of work-in-process inventory. For simplification purposes, assume that Process 1 is a feeder to Process 2 and that Process 2 is only a consumer of parts supplied to it by Process 1. Also assume that the processes are distributed in the facility. The storage location for the output of Process 1 is Parts Store A, and the storage location for the input of Process 2 is Parts Store B.

As Process 2 consumes components, the withdrawal kanbans are removed from the components and placed on the withdrawal kanban post. At regular intervals, the material handler takes the available withdrawal kanbans and retrieves the same number of bins of parts from Parts Store A. As the material handler takes the bins of parts, the production kanban is removed from those bins and placed on the production kanban post as a signal for Process 1 to produce the part indicated on the kanban card. Then, the available withdrawal kanbans are placed in the bins of parts and taken to Parts Store B. Once Process 1 produces a bin of parts signified by the production kanban, the card is attached to the bin, and the bin is placed in Parts Store A.

The kanban system has two main advantages. First, since operators only need to make what is needed, they can help other operators in bottleneck areas (Ohno, 1988). Second, it reduces the amount of inventory in the factory, which results in achieving reduced waste due to overproduction. Finally, the kanban system highlights problem areas in production, allowing associates to focus on areas needing improvement (Hendrickson, n.d.).

The focus of this research is comparing a periodic review policy (s, S) with two versions of a kanban ordering policy. Specifically, this research will evaluate these policies for a Lean Production cell under conditions of demand variability and imperfect supplier performance. The following chapter will review relevant research to position this analysis with respect to that research.

CHAPTER III

LITERATURE REVIEW

This section describes the analyses of ordering policies completed in the literature. This review includes studies that specifically focus on the effect of supplier performance and variations in customer demand on the performance of a manufacturing cell.

3.1. GENERAL ORDERING POLICY

Numerous reviews in the literature compare different ordering policies. Many types of ordering policies are compared in these reviews, using different methods, measures, and under different environmental conditions, which provided for different, and sometimes conflicting results. Axsater and Rosling (1999), Luss (1989), Detty and Yingling (2000), Hoshino (1996), Rees *et al.* (1989), and Savsar and Al-Jawini (1995) compare some form of MRP push systems to kanban or JIT systems. Takahashi and Nakamura (1999), on the other hand, compare two different JIT ordering policies, the kanban and concurrent ordering systems. Steele and Malhotra (1997) analyze a technique called period batch control, which is common in Europe, over a variety of conditions. Chalmet, *et al.* (1985) analyze different MRP ordering policies. Finally, Weng (1997), Gurnami (1996), and Hariga and Goyal (1995) analyze mathematical ordering policies.

One article in particular, by Yang (1998), compares reorder point (ROP) and Kanban policies for managing the production of different parts on a single machine. Assuming low demand lumpiness, this paper compares the performance of the two policies under conditions of customer demand variability, differing machine utilizations, and differing setup times for the machine. The demand variability factor has three levels. The low level has a coefficient of variation (CV) of 0.1, the medium level has a CV of 0.5, and the high level has a CV of 1.0 (Yang, 1998). The setup time factor has two levels. The low level is 0.5 days, and the high level is 2.0 days (Yang, 1998). The factor for machine utilization has 3 levels. The low level is 40% utilization, the medium level is 60%, and the high level is 80% (Yang, 1998).

Yang (1998) simulates a single machine that produces four different parts with similar demand characteristics using SLAM II. The kanban system used in the analysis is based on a maximum inventory level for each part, which is equivalent to setting the number of kanban cards allowed in the system. In this simplified kanban system, all kanban cards of a specific part are processed through the machine before a new part is chosen for production. The performance of these environments are analyzed based on the inventory required to achieve a 90% fill rate. The results from this analysis are that the ROP policy requires more inventory than the kanban policy to achieve a 90% fill rate for all of the environments simulated. This article concludes that while the kanban policy outperforms the ROP policy for the environments analyzed, the dominance diminishes as the demand variability, setup time, or machine utilization is reduced.

Of the studies that analyze ordering policies, those that simulate the manufacturing environment include Chalmet *et al.* (1985), Rees *et al.* (1989), Savsar and Al-Jawini (1995), Steele and Malhotra (1997), Yang (1998), Detty and Yingling (2000). Studies conducted using analytical approaches include Luss (1989), Hariga and Goyal (1995), Gurnani (1996), Hoshino (1996), Weng (1997), Axsater and Rosling (1999), Takahashi and Nakamura (1999). The most common performance measures used to analyze the ordering policies are either the total cost of the policies (Chalmet *et al.*, 1985; Rees *et al.*, 1989; Hariga and Goyal, 1995; Gurnani, 1996; Weng, 1997) or the levels of inventory held due to the policies (Luss, 1989; Savsar and Al-

Jawini, 1995; Hoshino, 1996; Steele and Malhotra, 1997; Yang, 1998; Takahashi and Nakamura, 1999; Detty and Yingling, 2000).

Some of the studies use case studies (Detty and Yingling, 2000) or representative manufacturing facilities derived from existing facilities (Steele and Malhotra, 1997) to analyze ordering policies. The majority of studies, however, used hypothetical manufacturing environments (Chalmet *et al.*, 1985; Luss, 1989; Rees *et al.*, 1989; Hariga and Goyal, 1995; Savsar and Al-Jawini, 1995; Gurnani, 1996; Hoshino, 1996; Weng, 1997; Yang, 1998; Axsater and Rosling, 1999; Takahashi and Nakamura, 1999).

The results and conclusions of these analyses are different and sometimes conflicting, attributable to the assumptions made and the factors analyzed by the study. Axsater and Rosling (1999) determine that MRP is a more optimal ordering policy in a multi-stage production-inventory system. Rees *et al.* (1989) determined that if improvements were made to the kanban system from the original MRP system, then the kanban system was preferable. However, when those same improvements were made to the MRP system, it was more preferable than the kanban system. Furthermore, Savsar and Al-Jawini (1995) conclude that while push systems have higher throughput and utilization levels, they also carry more WIP in the system for multiple levels of processing time variance in the system.

These studies are contradicted by a number of articles, including Detty and Yingling (2000), who state that JIT improves the manufacturing system in a company implementing Lean Production. Hoshino (1996) also shows that JIT is more effective than MRP when the variance of the total forecast error is greater than the variance of the total demand itself. Furthermore, Yang (1998) determined that the kanban policy required less average inventory than the reorder point policy in managing the production of a set of single-level parts on a single machine.

Takahashi and Nakamura (1999) determine that both the kanban and concurrent ordering systems work well in reacting to unstable demand. Under conditions of stable demand, the kanban system was preferable when the customers were more strict about on-time delivery (OTD) percentage, while the concurrent ordering policy was preferable with more relaxed policies for OTD percentage to the customer.

3.2. SUPPLIER PERFORMANCE

In terms of studies related to supplier performance and its effect on a manufacturing cell, Gullu *et al.* (1999) develop mathematical proofs to analyze the effect of supplier uncertainty on a periodic review, single-inventory model. Also, Tracey and Tan (2001) empirically examine the relationships among supplier selection criteria (including quality, delivery reliability, product performance, and unit price), supplier involvement in the design stage, customer satisfaction, and firm performance. Davis (1993) discusses the framework that Hewlett-Packard developed to address the uncertainty in supplier performance, as well as other forms of uncertainty that affect the performance of a manufacturing company. Finally, some studies have investigated issues related to supplier performance, such as supplier selection (Choi and Hartley, 1996), ordering policies (Chan *et al.* 2001), supplier on-time delivery (Forker, 1997; Forker and Hershauer, 2000), and supplier quality (Trent and Monczka, 1999).

One article of particular interest, Bassok and Akella (1991), develops a mathematical model to evaluate of supplier performance in terms of their on-time delivery performance and their quality. This paper considers an "aggregate production planning problem in a manufacturing facility with a [single] critical raw material and one or more products whose demand needs to be met" (Bassok and Akella, 1991, p. 1556) using an analytical ordering policy.

Both supplier quality and on-time delivery issues are considered and the customer demand is stochastic and uncorrelated. The performance measures used to evaluate the system are the sum of the inventory holding costs of finished goods and raw material, backlog costs of finished goods, production cost, and ordering costs of raw material. The supplier reliability is set as a probability density function containing both supplier quality and on-time delivery, and is based on the level of release into the production system. The standard deviation of the customer demand is set at two levels, 5% and 25%. The results of this study show that sizable gains can be achieved with policies similar to Just-in-Time.

3.3. VARIABLE DEMAND

The studies that considered variable demand mainly evaluated demand variation around a constant mean (Chalmet *et al.*, 1985; Rees *et al.*, 1989; Tang, 1990; Gurnani, 1996; Hoshino, 1996; Steele and Malhotra, 1997; Yang, 1998; Cachon, 1999; Takahashi and Nakamura, 1999). Two studies, however, analyzed a system using past demand levels as well as increases in the demand levels (Welgama and Mills, 1995; Huq and Pinney, 1996). Finally, Hariga and Goyal (1995), looked at linearly increasing and decreasing demand in determining the optimal replenishment policy.

One article, by Savsar and Al-Jawini (1995), analyzes JIT systems under a variety of conditions. Savsar and Al-Jawini (1995) analyze the effects of random processing times, numbers of kanbans between stations, demand variability, line length and kanban operating policies using a SIMAN® simulation model. The measures used to analyze the performance of the system are throughput rate, average station utilization, and WIP levels. The processing times and the demand intervals are assumed to follow Erlang distributions with a mean of one time unit. The three coefficients of variations for the processing time distributions are 0, 0.1, 0.707, and 1.0, while the coefficients of variation in the demand interval, the amount of time between customer orders, are 0.0, 0.1, 0.316, 0.447, 0.707, and 1.0. The results of the study are that throughput rate and the utilization are significantly affected by the variability in processing times and demand intervals, with the throughput decreasing as the variability in the system increases. However, with highly variable processing times, the performance of the cell is relatively unaffected by changes in the variability of the demand interval.

3.4. Summary of Literature Review

Based on this review, it is evident that periodic-review and JIT inventory control policies have been evaluated based on varying demand and supplier performance using simulation as well as other methods. A lack of research has been completed, however, on comparing the ordering policies under conditions of varying demand along with varying levels of supplier performance. Thus, the focus of this research is to evaluate the impact of the ordering policy for supplied parts on the performance of a manufacturing cell under conditions of varying levels of supplier performance and variability in customer demand.

CHAPTER IV

RESEARCH DESCRIPTION

The purpose of this research is to determine how the ordering policy for a manufacturing cell affects the performance of the cell under conditions of demand variability and various levels of supplier performance. The research involves developing a simulation model of a manufacturing cell and evaluating the effects of different ordering policies for supplied parts on the performance of the cell. This study is conducted on a multi-stage manufacturing cell within a large manufacturing company that produces a family of products. By simulating the manufacturing cell and changing the ordering policy from periodic-review inventory control to kanban with either inflated or uninflated values and collecting performance measures on the cell, the effect of the ordering policy on the performance of that cell can be determined.

4.1. RESEARCH METHOD

The objective of this research is to select the ordering policy and the conditions under which the policy will maximize the performance of the cell with respect to the performance measures and to develop insights for a company in transition from a traditional manufacturing system to a Lean Production system. In this research, a simulation model of an industrial assembly system is developed, using the discrete-event simulation software Arena®. Banks *et al.* (1999) list seven purposes for using simulation as follows:

1) Simulation enables the study of, and experimentation with, the internal interactions of a complex system, or of a subsystem within a complex system.

2) Informational, organizational and environmental changes can be simulated and the effect of these alterations on the model's behavior can be observed.

3) The knowledge gained in designing a simulation model may be of great value toward suggesting improvement in the system under investigation.

4) By changing simulation inputs and observing the resulting outputs, valuable insight may be obtained into which variables are most important and how variables interact.

5) Simulation can be used as a pedagogical device to reinforce analytic solution methodologies.

6) Simulation can be used to experiment with new designs or policies prior to implementation, so as to prepare for what may happen.

7) Simulation can be used to verify analytic solutions.

Simulation is used in this research to accomplish the first four purposes. A manufacturing cell is a complex system. Therefore, changing parts of the system without interrupting the production of the system is an important issue. Also, the knowledge gained from this study would be useful in suggesting improvements to the system. Finally, knowing which variables are most important, and how they interact with each other is useful in this study.

The simulation model incorporates the processes within the cell, the planned delivery of parts from the suppliers, and the supplier performance levels. Using the simulation model, an experiment is conducted that evaluates the effects of the ordering policy for supplied parts on the performance of a production cell under conditions of demand variability and various levels of supplier performance. Supplier performance is evaluated using both supplier quality and supplier on-time delivery. The performance measures that will be used to evaluate the cell's performance are the average flowtime for the product, the on-time delivery to the manufacturing cell's customer, the number of parts shipped each week, the WIP level in the cell, the percent of time the cell is stocked out (stockout factor), and the average number of motors that can be built with the supplied part inventory on hand in the factory (supplied part inventory factor).

4.2. ANALYSIS OF FACTORS

The factors analyzed in this case application are the ordering policy, supplier quality, supplier on-time delivery, and demand variability. The following three ordering policies are considered in this research:

- Periodic-review (s, S) model;
- Uninflated kanban model; and
- Inflated kanban model.

These policies will be described more fully in Chapter 5.

The three ordering policies will be analyzed over three levels of supplier quality, three levels of supplier on-time delivery, and three levels of demand variability. The following levels are evaluated for each of the factors:

- Supplier quality (70%, 85%, 100%);
- Supplier on-time delivery (70%, 85%, 100%); and
- Demand variability (0%, 15%, 30%).

The performance of the system will be evaluated through the use of the following six measures:

- Flowtime of the product through the cell;
- On-time-delivery to the customer;
- Number of motors shipped each week;
- Work-in-process inventory in the cell;
- Stockout factor; and
- Supplied part inventory factor.

The effect of the factors will be analyzed using an experimental design based on an augmented central composite design. The central composite design allows an analysis of the factors without running all possible factor combinations in the analysis. The design considers the combinations of the extreme levels (high and low) for each of the factors and the central level for every factor. The augmentation of the design is used to make the design more complete by looking at some intermediate points in the analysis. The augmented central composite design used for each ordering policy in this research is shown in Table 4-1.

Table 4-1. Augmented Central Composite Design

Supplier Quality	Supplier On-Time Delivery	Demand Variability
70%	70%	0%
70%	70%	30%
70%	85%	15%
70%	100%	0%
70%	100%	30%
85%	70%	15%
85%	85%	0%
85%	85%	15%
85%	85%	15%
85%	85%	15%
85%	85%	30%
85%	100%	15%
100%	70%	0%
100%	70%	30%
100%	85%	15%
100%	100%	0%
100%	100%	30%

The complete experimental design that includes all three ordering policies is shown in Table A-1 in Appendix A. The coded values for the factor levels that are used in the statistical analysis are shown in Table A-2, and the complete experimental design for the coded variables is shown in Table A-3 in Appendix A. The results of the experiments are analyzed using linear regression models based on a 2^{nd}-order Taylor Series. These models are then graphically displayed using contour plots.

Chapter V

Description of Ordering Policies

This section describes the specific ordering policy information used in this analysis. Section 5.1 describes the process used to determine the values for the (s, S) policy. Section 5.2 describes various methods in determining the number of kanbans needed for a manufacturing line. Finally, Section 5.3 explains which kanban model was chosen for this research.

5.1. Determining Periodic-Review Inventory Control Policy Values

Several methods can be used to determine the values for s and S in the periodic-review inventory control policy (Porteus, 1985). One of the most common methods, shown in Hopp and Spearman (1996), utilizes the values derived for the (Q, r) policy, shown in Section 2.1. The value for s is simply the value of r, and the value for S is the summation of Q and r, such that:

$$s = r \tag{5.1}$$

$$S = Q + r \tag{5.2}$$

An important note is that the average demand during the leadtime, D, has been inflated by dividing the average demand by the supplier's quality level and the internal quality level, as this is assumed to be a standard industry practice.

In the initial experimentation of the simulation using the values determined through these calculations, all of the parts stocked out for at least three days. This is due to the design of the (s, S) policy since the reorder point (s) contains only enough inventory to last during the leadtime. Suppose the inventory level is checked at the end of each week and the supplier leadtime is τ_s weeks (where $\tau_s = 2$). If $s < S$, an order is placed to arrive τ_s weeks later. If the inventory level falls below the reorder point at the beginning of the week, however, the next shipment of supplied parts will not arrive until nearly three weeks later. This means that the cell will be stocked out for almost a full week. Therefore, for this analysis, a planning leadtime (τ_p) of τ_s+1 weeks (three weeks) is used to calculate the value of *r*, in order to reflect this issue and to reduce the possibility of a stockout. In general terms, the leadtime used to calculate the value of the reorder point is the summation of the supplier's leadtime (τ_s) and the review period (*p*) for the cell, such that:

$$\tau_p = \tau_s + p \tag{5.3}$$

The (*s*, *S*) calculations are determined using the planning leadtime, τ_p, to account for both the supplier leadtime, τ_s, and the review period, *p*. However, the actual supplier leadtime is assumed to be τ_s. Thus, τ_s is used as the supplier leadtime in the simulation model.

5.2. VARIOUS MODELS FOR DETERMINING THE NUMBER OF KANBAN CARDS IN A SYSTEM

In addition to the periodic review inventory control policy, two kanban ordering policies are investigated. Both kanban ordering policies are adapted from existing approaches for kanban systems. One of the kanban ordering policies is inflated by the supplier's quality level and one is not inflated by the supplier's quality level. The uninflated kanban model is analyzed because most research uses the kanban system without inflating the number of kanbans due to supplier quality. Both kanban policies analyzed, however, inflate the demand for the internal quality levels.

Two common approaches for determining the required number of kanban cards for a manufacturing cell are shown in Equations 5.4 and 5.5. These approaches are developed specifically for processes within the manufacturing cell. Very few approaches have been adapted, however, to use between suppliers and customers to account for transit time.

Equations (5.4) and (5.5) are used to determine the number of kanbans within a manufacturing plant, to be delivered between cells. Equation (5.4) determines the number of kanbans by multiplying the demand by the result of the lead time and then multiplying this by a safety factor, and then dividing the result by the container size (Olhager, 1995; Nahmias, 1997; Sipper and Bulfin, 1997). This approach allows flexibility in the amount of safety stock in the manufacturing cell. Equation (5.5), by Monden (1998), is quite similar to the first, except it does not use a safety factor. Instead, it uses an order cycle and safety period, along with the lead-time. The order cycle is the time interval between signaling consecutive production orders to the cell. The safety period is the amount of inventory held in response to instability in the manufacturing process. It is important to note that all of these equations must be rounded up to the nearest whole number to ensure that a sufficient number of kanban cards are used.

$$K = \left\lceil \frac{D * L * (1 + \alpha)}{C} \right\rceil \tag{5.4}$$

$$K = \left\lceil \frac{D * (O + L + S)}{C} \right\rceil \tag{5.5}$$

<u>Notation:</u>

K	Number of kanbans required
D	Daily demand
L	Lead time
α	% safety stock desired
C	Container size
O	Order cycle
S	Safety period

5.3. KANBAN MODELS CHOSEN FOR THIS ANALYSIS

The model used to determine the number of kanbans used for each supplier is based on Equation (5.4). This equation is commonly used in textbooks and the literature to determine the number of kanbans. In this equation, D is the average daily demand, L is the leadtime in days, α is the safety factor, and C is the container quantity. As in the periodic-review inventory model, the daily demand used to calculate the number of kanbans has been inflated by dividing by the internal quality level of the manufacturing cell. According to Nahmias (1997) and Sipper and Bulfin (1997), the value for α is usually no more than 10%, which is the value used in this study. Finally, in accordance with the periodic-review inventory control policy, the leadtime is adjusted to account for the delays in the review period (as described in Section 5.1). Thus, the planning leadtime, L_p, is the supplier leadtime, L_s, adjusted by the review period, p, such that:

$$L_p = L_s + p \tag{5.6}$$

The number of kanbans required is determined by:

$$K = \left\lceil \frac{D * L_p * (1+\alpha)}{C} \right\rceil \tag{5.7}$$

The kanban calculations are determined using the planning leadtime, L_p, to account for both the supplier leadtime, L_s, and the review period, p. However, the actual supplier leadtime is assumed to be L_s. Thus, Ls is used as the supplier leadtime in the simulation model.

No information on distinguishing between the planning leadtime and the actual supplier leadtime is found in the research literature. However, a recent approach for determining the number of kanbans for supplied parts, by Binning (1999), was published on a website. In this case, the number of kanbans required for the cell is:

$$K = \left\lceil \frac{D * (2+T) * (1+\alpha)}{DD * C} \right\rceil \tag{5.8}$$

Equation (5.8) is similar to Equation (5.7), although it is used for determining the number of kanbans in a supplier-customer system. This equation introduces two new variables, transit delay (T) and the number of deliveries per day (DD). These two variables allow the equation to account for suppliers with short or long turnarounds, and frequent or infrequent deliveries. In this case, $\frac{2+T}{DD}$ represents the planning lead-time, which is equivalent to L_p in Equation (5.7). Unfortunately, the approach used to develop this expression was not provided on the website, and the site is no longer available. It is interesting to note, however, that the kanban calculations in this research use adjusted leadtimes in an equivalent manner as the recent results of Binning (1999).

Thus, the two kanban models evaluated in this research include:

- Uninflated kanban model; and
- Inflated kanban model.

The uninflated kanban model is calculated using Equation (5.4). The inflated model uses the same calculation as the uninflated model, except the average daily demand is inflated by the supplier quality level (by dividing the average daily demand by the supplier quality level for a given experiment). Therefore, the number of kanban cards is dependent on the supplier quality.

CHAPTER VI

CASE APPLICATION COMPANY AND THE MANUFACTURING CELL

This case application is adapted from a high-performance motion control products manufacturing plant in the southeastern United States. This plant is one of several within a larger global corporation in the motion control industry. Motors manufactured in the case application company are used in the machine tool, medical products, and aerospace and defense industries.

Recently, the plant has faced increased pressures, both externally and internally, to improve the performance of a specific manufacturing cell dedicated to a single, high-demand customer. Each day seemed to bring another crisis relating to schedule, production, supplied parts, or engineering changes, creating a chronic reactive mode. On-time delivery to the end customer was declining, forcing additional hours in overtime and airfreight shipment costs to the customer.

According to Spencer and Crosby (1997), on-time delivery to customers is one of the key attributes in determining purchasing decisions. Therefore it is vital that the manufacturing cell improve their on-time delivery performance to maintain the high-demand customer. Faced with these challenges, the plant engaged in a number of integrated improvements to transform its product design, engineering, and production processes. One of these initiatives was to determine the effect of the ordering policy for supplied parts on the performance of the manufacturing cell. The next three sections will describe the products manufactured in the cell, the process used to manufacture the products, and the current supplier information for the manufacturing cell.

6.1. PRODUCTS CREATED IN THE MANUFACTURING CELL

The product family consists of three sizes of motors, 630 kg, 800 kg, and 1,000 kg, which are sold to a dedicated customer. Each of these motors has one of two brake settings (herein referred to as A and B), resulting in six different motor types assembled by this line. The customer purchases an average of 120 total motors each week, and the percent demand for each motor type is shown in Table 6-1. The product family is manufactured in a dedicated cell with 12 associates performing all tasks within the cell, with some associates responsible for more than one task.

Table 6-1. Approximate Percentage of Each Motor Type

Motor Type	Percent of Total Demand
630 A	2%
630 B	58%
800 A	2%
800 B	5%
1000 A	6%
1000 B	27%

6.2. DESCRIPTION OF THE PROCESSES

The manufacturing process involves producing two subassemblies, the stator and rotor. Then these subassemblies are combined into the final assembly. The following paragraphs describe the assembly of the stator and rotor subassemblies and the final assembly.

The stator subassembly begins with the stacking of the stator laminations. The laminations are then processed through the winding operation, H-paper is inserted, the non-lead end gets shaped and laced, and the leads are soldered. The thermostat is installed, the lead end is laced, and a pretest is completed. The stator is then skewed, and the housing is placed around the stator. After a 10 minute cool down, the pins are connected, and a direction/rotation test is completed, as well as another pretest. A mold is placed around the stator, and both the stator and mold are preheated. The stator is then filled with epoxy, and baked in an oven. After removal from the oven, the stator is allowed to cool and the mold is removed before a third pretest is performed. A machining operation is completed, and then the stator is inspected and placed in a queue to be match to a rotor subassembly.

The rotor subassembly begins in two places, with the shaft subassembly and the rotor laminations. In the shaft subassembly, two bearings are heated and then installed onto the shaft. In the rotor lamination assembly, the rotor laminations are stacked. Then the shaft is installed to the frame and the stacked rotor laminations are attached to the shaft. The rotor assembly is then balanced, magnetized, and placed in a queue to be matched to the stator subassembly.

The final assembly begins with the mating of the rotor and stator subassemblies. Then, the brake, rescue encoder, and primary encoder are installed, a vibration test is completed, and the final test is completed. After the final test, the motor is packed, ready to be shipped to the customer. A visual representation of this flow is shown in Figure 6-1.

The case application company conducted time studies to determine the processing and setup times for each of the operations. The results of the time studies show that all operations have a processing time less than the *takt* time, which is the unit production pace that is necessary to meet customer requirements. Since the processing times are less than the *takt* time, the cell is capable of meeting the customer's demand if the processes perform as expected and the necessary supplied parts arrive as expected. The workers assigned to each task, and the processing and setup times for each operation are shown in Table 6-2.

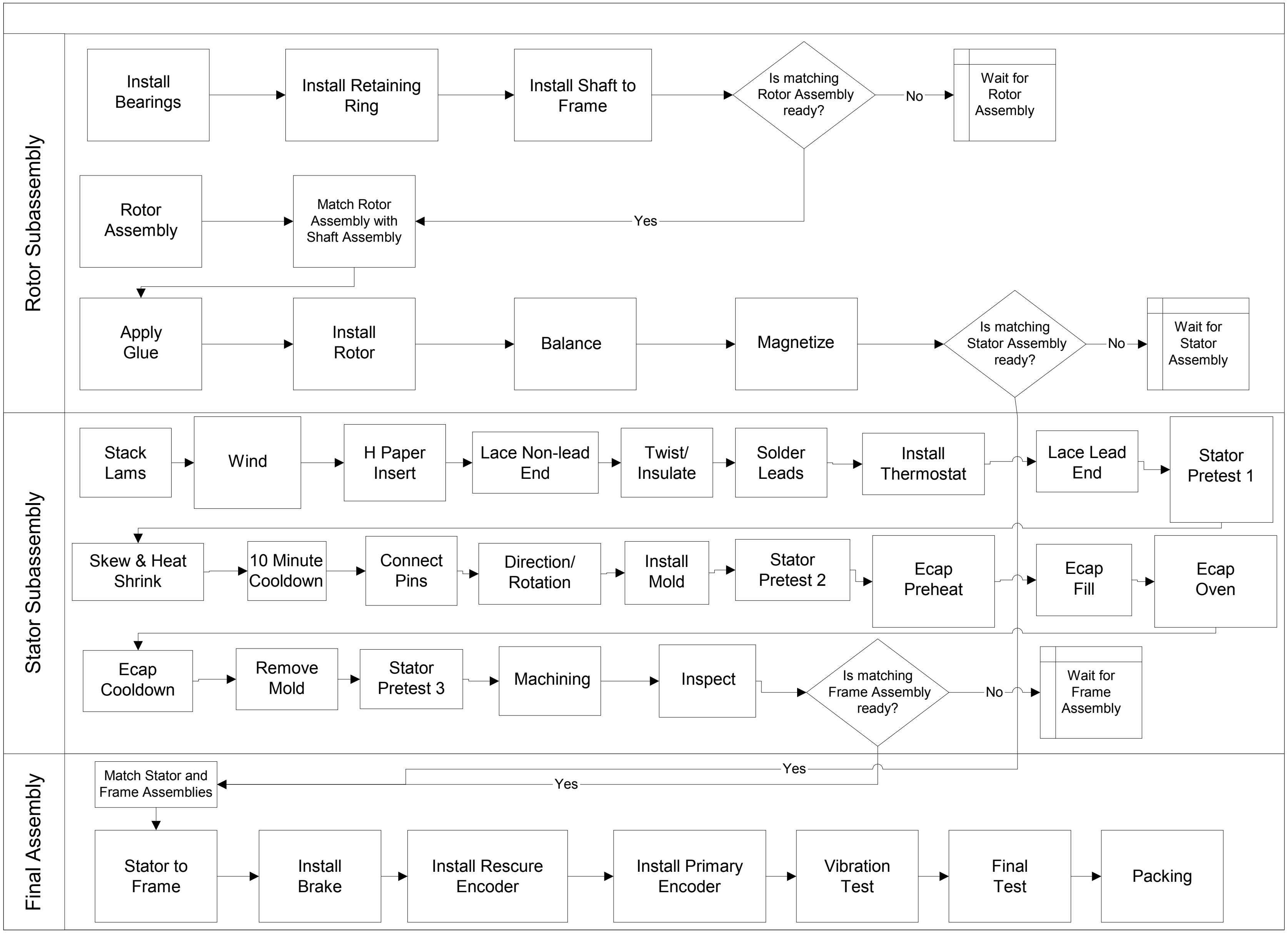


Figure 6-1. Case Application Manufacturing Cell Process Diagram

Table 6-2. List of Processes

	Name	Resource	Resource Capacity	Process Time (minutes)	Setup Time (minutes)
Rotor Subassembly	Shaft-Bearing Assmbly	Worker 9	1	TRIA(2,2.5,3.25)	
	Frame Shaft Rotor Assmbly	Worker 8	1	TRIA(4.5,5,5.5)	
	Rotor Assembly	Worker 8	1	TRIA(4.5,5,5.5,6)	
	Balance	Worker 9	1	TRIA(5.5,6.5,7)	
	Magnetize	Worker 9	1	TRIA(2,2.5,3)	
Stator Subassembly	Order Processor	Order Processor	1	2137/ Weekly Demand	
	Stack Lams	Worker 1	1	TRIA(2,2.5,3)	
	Winding	Worker 2	1	TRIA(9,10,11)	TRIA(2,2.5,4)
		Winder	1		
	Shape and Lace 1	Worker 1	1	TRIA(6,7.5,8.5)	
	Shape Lace LE 1	Worker 3	1	TRIA(10,11,12)	
	Shape Lace LE 2	Worker 4	1	TRIA(10,11,12)	
	Skew_Test_Crimp_Solder	Worker 5	1	TRIA(10,10.5,12)	
	House_Connector Assembly	Worker 12	1	TRIA(9,11,11.5)	
	Housing Cooldown		1	10	
	Install Mold	Worker 6	1	TRIA(1,1.2,1.5)	
	Ecap Preheat		12	120	
	Ecap Fill	Worker 6	1	TRIA(4,5,6.5)	
	Ecap Ovens	Ovens	24	135	
	Remove Mold Cooldown		6	60	
	Remove Mold	Worker 6	1	TRIA(2.75,3,3.25)	
	Cooldown		18	180	
	Stator Pretest 3	Worker 7	1	TRIA(1,1.1,1.2)	
	Machining *	Worker 7	1	8	3
		CNC Lathe	1		
	Load Unload Deburr	Worker 7	1	TRIA(4.5,5,6)	
	Inspection	Worker 7	1	TRIA(1.5,2,5)	
Final Assembly	Stator to Frame	Worker 10	1	TRIA(4,5,6)	
	Install Brake	Worker 10	1	TRIA(4.5,5,5.5)	
	Install Rescue Encoder	Worker 11	1	TRIA(0.9,1,1.2)	
	Install Primary Encoder	Worker 10	1	TRIA(0.9,1,1.2)	
	Vibration Test	Worker 11	1	TRIA(2.2,2.5,3)	
	Final Test	Worker 11	1	TRIA(1.3,1.5,2)	
	Pack and Ship	Worker 11	1	TRIA(4,4.5,5)	
	Transfer to Truck	Worker 11	1	TRIA(1.9,2,2.1)	

*Associate need not be present for machining operation, only setup

6.3. SUPPLIER INFORMATION

The final assembly includes eight supplied parts identified as critically important by the case application company. These parts are: frames, shafts, housings, bearings, brakes, primary encoders, and laminations (both for the stator and the rotor subassemblies). Each of these parts has their own supplier, meaning different supplier performances and container quantities. Furthermore, for some of these supplied parts, more than one part is required in each motor. In terms of costs, each has its own cost per part, but all are assumed to have the same interest on holding (20%), ordering costs ($50), and shortage costs ($250). Although exact cost is considered company sensitive information, a relative estimate of the cost per part is assumed in this research. Table 6-3 shows the necessary information for each of the critically supplied parts. It is also assumed for this analysis that the leadtime is two weeks for all suppliers.

Table 6-3. Critically Supplied Part Information

	# Used per 630 Motor	# Used per 800 Motor	# Used per 1000 Motor	Container Quantity	Approximate Cost/Part (630 Motors)	Approximate Cost/Part (800 Motors)	Approximate Cost/Part (1000 Motors)
Frame	1	1	1	20	$25.00	$35.00	$35.00
Shaft	1	1	1	16	$100.00	$150.00	$150.00
Housing	1	1	1	24	$50.00	$75.00	$75.00
Bearing	2	2	2	30	$25.00	$35.00	$35.00
Brake	1	1	1	12	$200.00	$200.00	$200.00
Primary Encoder	1	1	1	24	$2.00	$2.00	$2.00
Stator Laminations	279	434	434	10000	$0.01	$0.01	$0.01
Rotor Laminations	271	421	421	10000	$0.01	$0.01	$0.01

CHAPTER VII

DESCRIPTION OF SIMULATION MODEL

This section describes the development of the simulation model used in this analysis. Section 7.1 describes the logic of the simulation model. Section 7.2 explains how this model was then verified and validated. Finally, Section 7.3 explains how statistical validity was obtained for this analysis by showing the process of determining the warm-up period, run length, number of replications, and initial starting points for the random numbers.

7.1. SIMULATION LOGIC DESCRIPTION

To represent the system under study, a simulation model was created, capturing the important aspects of the system in order to make decisions about the system. The main sections of this model were the arrival of the parts, the processing of each of the individual subassemblies, the operating of lean manufacturing practices, the collection of the performance measures, and the functioning of the ordering policies. This section describes, in detail, the logic of the simulation used for this study.

It is important to note that the model used in this analysis was adapted from a previous simulation model. The original model was used to analyze throughput and staffing issues in the cell. Therefore, in order to make this model useful in this analysis, several changes were made. First, the supplier logic was adapted to use a kanban and a periodic-review system instead of an MRP system. Second, the delay for the suppliers was changed to use a truncated normal distribution instead of a constant. A pull system was implemented through the manufacturing cell, and the entry of the motors into the line was spaced due to *takt* time. Another change made was to add the logic for the performance measure work-in-process inventory.

7.1.1. Arrival Logic

Four types of arrivals exist in this simulation model. Arrivals are used for generating customer orders and releasing motors into the system, for determining customer demand, for operating the ordering policies, and for calculating performance measures. This section will focus on the customer orders arrivals and the arrivals of motors into the system, and the arrivals for the system variables. The arrivals for ordering policy operation and calculating the performance measures will be explained in their respective sections.

Customer demand arrives each week through seven create nodes. The first node signifies the first order for each week, while the other six nodes signify the orders for each of the six different motor types for the rest of the week. The first create node sends the first part through the system. This entity is sent to an assign block, where it is given attributes to signify its motor type and brake type. After the assign node, the entity is sent to another assign node, where it is assigned an attribute used to calculate the amount of time it spends in the system, a variable is incremented to determine the number of motors in the system, and then is counted according to its motor type. Once this entity is counted, it is replicated into three identical entities, to begin the processes at the stator subassembly, and the two stations (stack rotor laminations and shaft assembly) in the rotor subassembly.

After the first motor enters the system, the other six arrive nodes then create the rest of the demand for the week. Each of these entities are assigned attributes to signify the motor and brake type, and then are sent to a process node where the orders are spaced apart based on the demand for that week. Once an entity is released from the process node, it is assigned an attribute to calculate the time it spends in the system and follows the same process as the first entity. The data for these arrivals into the system is shown in Table 7-1.

Table 7-1. Arrival Information for Demand Creation and Motor Entry into the System

Arrival Node	First Arrival (Days)	Time Between Arrivals (Days)	Entities per Arrival
Create Demand	2	5	1
First Arrival	.00001	5	1
630A Arrivals	.00010	5	ROUND(Customer Demand*P6A) - 1
630B Arrivals	.00011	5	Customer Demand – (ROUND(Customer Demand*P6A)+ ROUND (Customer Demand*P8A)+ ROUND (Customer Demand*P8B)+ ROUND (Customer Demand*P10A)+ ROUND (Customer Demand*P10B))
800A Arrivals	.00012	5	ROUND (Customer Demand*P8A)
800B Arrivals	.00013	5	ROUND (Customer Demand*P8B)
1000A Arrivals	.00014	5	ROUND (Customer Demand*P10A)
1000B Arrivals	.00015	5	ROUND (Customer Demand*P10B)

The number of entities sent into the system are calculated by taking the customer demand for the week and multiplying that number by the percentage of motors of that type. To account for rounding errors, the calculation for the motor type with the largest percentage of the total demand was modified. For this motor type, 630B, the number of motors sent into the system is calculated by subtracting the number of motors for all of the other types of motors from the customer's demand for that week.

The customer demand begins at 120 motors per week in the simulation model. For subsequent weeks, the demand is updated three days prior to the start of the next week. Since it takes approximately two days for a motor to complete production, the rate that the motors are sent into the system must be adjusted at least two days prior to the beginning of the week when the demand changes. In this simulation, three days were used to add flexibility. Essentially, this assumes that the demand for a week is known three days in advance and appropriate planning can begin. The calculation to determine the customer demand is:

*ROUND(TRIA(((1-Demand_Var)*Average Demand), Average Demand, ((1+Demand_Var) * WD1))).*

The Average Demand in motors per week is 120, and Demand_Var is the amount of variation in customer demand set for the system.

7.1.2. Stator Subassembly Logic

After the entity signifying the motor is duplicated, one of the three entities is sent into the stator subassembly with no delay. Upon entering the subassembly, the simulation determines if stator laminations are available for that specific motor. If not enough stator laminations are in inventory, the motor waits at this station until enough parts enter the system. If enough stator laminations are in inventory or if enough parts arrive, the stator laminations are taken out of inventory and stacked. Then, the winder is setup, if necessary, and the winding is put into the stator lams. Then, the motor is sent through the shape and lace stations where it is processed and tested. The probability of passing the first pretest is 99%. If the motor fails the test, it is scrapped and a motor is sent back to the beginning of the process to replace it. If it passes, however, the system checks to ensure a housing is available, and holds the motor if one is not available. If, or when, a housing is available, the housing is taken out of inventory and placed on the motor. Then, after the housing cools down for 10 minutes, the connector is assembled and another test is performed. The second pretest, that includes a test for direction and rotation, has a 97.5% probability of passing. If the motor fails the test, it is scrapped and another motor is begun. If the motor passes the test, it is sent to the molding station. In the molding station, the mold is installed on the motor, filled with epoxy and the motors are put in batches of 12 to go into the ovens. After the oven, the motors are separated, the mold is removed and the motors are allowed to cool. After cooling, a third test is performed. The third and final pretest has a 99.9% chance of passing. If the motor fails, again it is scrapped and another motor begins the process at the stator lamination station. If it passes, the machine is setup, if a setup is required, the motor is machined, deburred, and sent to complete a visual inspection. Approximately 99% of the motors pass this visual inspection. As in the other inspections, if the motor fails, it is scrapped and another is started at the beginning of the subassembly. If it passes, it is sent on to final assembly, where the stator and rotor are merged.

7.1.3. ROTOR SUBASSEMBLY LOGIC

As previously mentioned, the rotor subassembly begins in two places, the stacking of the rotor laminations and the shaft subassembly, accounting for the two duplications of the entity after the motor's arrival into the system. Both of the entities sent to the rotor subassembly are delayed for one day to account for the extra assembly time needed by the stator subassembly. The shaft subassembly begins by checking the system to see if both the shaft and bearing are available to assemble. If not, the entity waits until sufficient inventory of both parts are available. When enough inventory is available, or if the cell had enough inventory to begin with, the system removes a shaft and two bearings from their respective inventories, and the parts are assembled.

After the rotor laminations are stacked, they are matched to the shaft subassembly to ensure that they are for the same motor, and are sent to the next station. When they arrive at the next station, the system checks to see if frames are available in inventory. If not, the motor will wait at the station until they become available. If a frame is in stock, the frame is assembled to the rotor, and the rotor is balanced and magnetized. After this station, the rotor is sent to final assembly to be matched to a stator.

7.1.4. Final Assembly Logic

When a stator and rotor of the same type of motor are available in the Final Assembly station, the two subassemblies are matched, assembled together, and placed on a conveyor. Then, a brake is assembled to the motor, if one is available, according to which type of brake is needed for the specific motor. Next, the rescue encoder is attached, and a primary encoder is added, if one is available. If one is not available, the motor waits for one. Finally, the motor goes through a vibration and a final test. The probabilities for passing these tests are 99.999% and 99%, respectively. If the motor fails either of these tests, it is started back at the stator, rotor, and the shaft subassemblies. If it passes, it is packed and shipped to the customer.

7.1.5. Lean Logic

The logic defining this cell as a lean manufacturing cell is implemented by seizing and releasing resources representing kanban cards. When a part enters a current process, the associated kanban cards (if available) are seized along with the resources used in that process. Then, the kanban card from the previous process is released (if a previous process exists). After the release, the entity is delayed for the current process, and then the resource used in this process is released. In the next process, the current kanban card is released after the next kanban card and resource for that process are seized.

For example, suppose processes *A* and *B* are in sequence and utilize kanban cards *a* and *b* respectively. Kanban card *a* is seized along with the resources used for process *A*, and the product is processed through process *A*. Then, the resource used in Process *A* is released, while the card proceeds with the motor to process *B*. Next, the resource used in process *B* is seized along with kanban card *b*, if both are available. If they are not both available, the motor waits in the queue for process *B* until both the process and card are available. Once both the process and kanban card are seized, kanban card *a* is released and process *B* commences.

Some of the motors are scrapped in the cell, which can cause different motor types to enter the match node at the same time. If two processes are matched, such as the stator and frame, only one of these processes will utilize a kanban card. Removing the kanban from one of the processes allows the same motor type to be matched.

Finally, because this manufacturing cell utilizes one-piece flow, only one kanban is typically allocated to each process. For example, in assembly only processes, and processes with an associate and a single machine, such as the winder and the CNC lathe, one kanban is allocated. For other processes with multiple resources, however, more kanbans must be added, such as the oven and some of the cooldown processes. In these processes, the number of kanbans allocated to the process is equivalent to the number of resources allocated to the process. The other exception to the single kanban rule is the kanban for the Ecap Fill process, because these kanbans are not released until the stators are batched and placed in the ovens. This requires 24 kanbans for the Ecap Fill process to account for the 24 resources in the Oven process. The number of resources assigned to each process is shown in Table 6-2.

7.1.6. PERFORMANCE MEASURE CALCULATIONS

The variables that calculate the metrics used in this study are the average on-time delivery to the customer, the average number of motors shipped each week, the amount of time a motor spends in the system, the amount of WIP in the system, the number of stock-outs for each of the critically supplied parts, the average amount of time each part is stocked out for, and the average amount of inventory in the system for each of the critically supplied parts.

The amount of time the motor spends in the system is calculated through two nodes in the simulation. The first node used to calculate the amount of time in the system is an assign block as the motor enters the system, and assigns the value "TNOW" to an attribute called "Time In." The second node used is a Record block that determines how long the motor spent being built. This value is averaged over every motor that exits the system.

The average on-time delivery (OTD) to the customer is calculated at the end of each week. However, since the demand changes in the middle of the week, an entity must be created at the beginning of each week, and an assign node assigns that week's demand to a variable called *WD_Calc*. The entity is then delayed until the end of the week, and the number of motors shipped that week is added to the number of motors currently in inventory, signified by *MotorsOnHand*. Then, the entity is sent to a decision node to determine if the number of motors in inventory is greater than that week's demand (*WD_Calc*). If the number on-hand is greater, the *OTD* for that week is set to 100%. If the number on-hand that week is less than WD Calc, the entity is sent to another decision node to determine if the number of motors in inventory is less than 0. If *MotorsOnHand* is less than or equal to 0, the *OTD* for that week is set to 0%. If, however, the *MotorsOnHand* is greater than zero, and less than that week's demand, the *OTD* is determined by dividing *MotorsOnHand* by *WD_Calc*. After the *OTD* is set for that week, regardless of the path the entity followed to assign the *OTD*, the value of *WD_Calc* is subtracted from the value of *MotorsOnHand*.

The average number of motors shipped each week is determined with a count block and an assign node. Throughout the simulation, once a motor is shipped, it is counted, using a variable called *NShip*. Then, at the end of each week, the number of motors shipped that week is assigned to a variable called *NumShipped*. Then, *NShip* is set to 0 to count the motors shipped during the next week.

The average amount of WIP in the system is calculated with two nodes in the simulation. An assign block before the entity enters the cell increments the number of motors in the system by one. An assign block at the end of the cell decrements the number of motors in the system by one. The average of this value over time is the average amount of WIP in the manufacturing cell.

The number of stock outs for each of the critically supplied parts is calculated with a sub-model. At the beginning of the simulation, an entity enters this sub-model, and enters a hold node. This hold node stops the entity's progress if not enough parts are in inventory to make the motor. In most cases, that is only one part, as in the shafts, but for some parts, this number is greater than one, as in the stator laminations, where it is 279 and 434, in the 630 kg and 1000 kg motors respectively. After the entity is released from the node, a tally node counts that a stock out occurs. The entity passes through other nodes, and loops back to the hold block.

The average amount of time a critically supplied part is stocked out for is calculated in the same sub-model as the number of stock-outs. After the entity is counted in the sub-model, signifying that a stock-out has occurred, an attribute is given to the entity and assigned a value of "TNOW" to signify that the stock out has begun. The entity then proceeds to another hold node until the parts needed to make the motor have entered the system. After the entity is released from this hold block, a record block calculates how long the part was stocked out for, and the entity proceeds back to the original hold node. At the end of the simulation, the stock-out times for all of the critically supplied parts were averaged by part. The number of stockouts and the length of each are multipled together. Then, they are combined with a weighted average and divided by the run length to determine the average amount of time the cell is stocked out. The weights for each part are determined by the percentage of motors made from that part.

The average amount of inventory in the system for each of the critically supplied parts is calculated internally by Arena®. The average amount of inventory for each part is then divided by the number of parts needed to make one motor (i.e. the average number of bearings on hand would be divided by 2, and the average number of stator laminations for the 630 motors would be divided by 279). The results for each part are summed and divided by eight. The resulting value represents the average number of motors that could be made from the parts on hand. For example, if enough inventory is available to make 50 motors from the rotor lams, 50 from the stator lams, and 10 from each of the other 6 parts, then the supplied part inventory factor is determined as follows:

$$\text{Supplied Part Inventory Factor} = \frac{(50 * 2) + (10 * 6)}{8} = \frac{160}{8} = 20\,\text{motors} \tag{7.1}$$

7.1.7. Ordering Policy Logic

The ordering policy logic is described for both the periodic-review ordering policy and the kanban ordering policy in the following two sections. Since the two policies behave differently, separate models are developed for the periodic-review and the kanban models. The two kanban policies, however use the same logic.

7.1.7.1. PERIODIC-REVIEW ORDERING POLICY LOGIC

The logic for the periodic-review ordering policy begins with a create node for each of the eight critically supplied parts. This node creates an entity at the end of each week. Each of these entities assigns a value for that week's delay for that specific part. The value for the delay was determined through historical data obtained from the case application company. The delay is determined by a truncated normal distribution with a mean of three days, standard deviation of 0.75 days, a minimum of zero days, and a maximum of five days. Since Arena® does not have a truncated normal distribution as one of the common functions, this logic must be developed manually. This logic is created with two decision blocks, which check to ensure that the delay is within the assigned range. If the value set for the delay is not within the range, the value is regenerated, until the value is between zero and five days. If the delay value is in the proper range, the entity moves on to the next assign block.

At the next block, the values for each of the parts in the supply chain are updated. For each part used in each motor, the number of containers due in this week is assigned the value of the number of containers due next week. Also, the number of containers due next week is assigned the value of the number of containers due in two weeks. Then, a branch node sends the entity to one of two blocks based on the amount of inventory on hand and on order (the sum of the number of containers due this week and containers due next week multiplied by the container quantity). If the combined amount of inventory on hand and on order is greater than *s*, the number of containers due in two weeks is set to 0. If the combined value is less than the reorder point, then the number of containers due in two weeks is set to the following:

$$\left\lceil \frac{S - Inventory}{CQ} \right\rceil - ContainersDueThisWeek - ContainersDueNextWeek \qquad (7.2)$$

After determining the number of containers due in two weeks, the amount of inventory due this week is added to the on-hand inventory, after accounting for supplier quality issues.

Finally, the entity enters a decide block that determines whether or not the shipment for that week arrives on time. If the shipment is late, it is delayed the number of days determined by the logic previously described. Then, the number of containers is multiplied by the container quantity and added to the inventory for that part. If the shipment is not delayed, the inventory is updated immediately.

7.1.7.2. KANBAN ORDERING POLICY LOGIC

The Kanban ordering policy logic is very similar to the logic for the (*s*, *S*) policy. At the beginning of each week, the simulation determines the delay time if the supplier's delivery is not on time. If it is late, the delay is determined using the same logic as the periodic-review policy. Then, each week, the numbers of cards at the plant, the supplier, and in route are updated. This update occurs as follows:

$$K_{Order} = K_{Cell} - \left\lceil \frac{Inv}{CQ} \right\rceil \tag{7.3}$$

$$K_{Cell} = K_{Cell} - K_{Order} \tag{7.4}$$

$$Inv = Inv + \left[K_{Route} * CQ * SQ \right] \tag{7.5}$$

$$K_{Cell} = K_{Cell} + K_{Route} \tag{7.6}$$

$$K_{Route} = K_{Supplier} \tag{7.7}$$

$$K_{Supplier} = K_{Order} \tag{7.8}$$

Notation:

K_{Order}	Number of cards to order
K_{Cell}	Number of cards at the case application company
K_{Route}	Number of cards in route
$K_{Supplier}$	Number of cards at the supplier
Inv	Inventory on hand
CQ	Container quantity
SQ	Supplier quality level

As shown in Equation (7.3), the number of cards ordered that week is determined by subtracting the number of cards still in use at the cell ($\left\lceil \frac{Inv}{CQ} \right\rceil$) by the total number of cards at the cell. Then, the number of cards at the cell is updated by subtracting the number of cards at the cell by the number of cards ordered that week. Next, the inventory at the cell is updated by adding the inventory due from the supplier for that week to the current inventory on hand, after adjusting for supplier quality. Then, the number of kanbans in route is added to the number of kanbans at the cell. Finally, the number of cards in route is set equal to the number of cards at the supplier, and the number of cards at the supplier is set equal to the number of cards ordered.

If no delay occurs due to supplier on-time delivery issues, the number of cards at each of the three places is updated and the entity is disposed. To initialize the simulation model, the number of kanbans at the plant, the supplier, and in route are determined using equations described in Appendix B.

7.2. VERIFICATION AND VALIDATION OF THE SIMULATION MODEL

For model verification, a detailed review of the model is conducted and extremes tests are performed. The model is carefully reviewed by multiple developers to determine if the simulation was working properly and that the correct parameters were set in the model. To perform the extremes test, key input values for specific variables are set at very high or low values, and the output was reviewed to determine if the simulation output reflected the change in those variables. The results of the detailed review and the extremes test indicate that the simulation model is an adequate representation of the manufacturing cell for the desired analysis.

The model is validated using a three-step approach suggested by Naylor and Finger, (as cited in Banks *et al.*, 1999) that is widely followed for developing simulation models which are both valid and credible. The three steps in this approach are to develop a model with high face validity, to validate model assumptions, and to determine how representative the data are (Banks *et al.*, 1999). All three steps were used to validate the simulation model created for this research.

To achieve face validity, an animation of the simulation and the simulation outputs have been presented to experts on the system, all of whom regard the simulation as accurate. To validate the model assumptions, system experts reviewed those assumptions and determined they too were accurate. Sensitivity analysis was also performed on the model to determine the validity of these assumptions. Finally, to determine how representative the data were, the output from the simulation was reviewed by the experts and judged to be representative of the system.

7.3. SIMULATION SPECIFICS

To achieve statistical validity, three values must be determined: warm-up period, run length, and number of replications. Allowing the simulation to "warm-up" before collecting statistics allows the simulation to reach steady-state (Law and Kelton, 1991). The simulation must reach steady state because a manufacturing line that is assumed to be in place when the simulation is performed would not start with empty queues at every workstation. The warm-up period is then typically used to determine the run length for the simulation. Multiple replications are used to eliminate the bias made through dependent observations. An interdependence of observations causes the values to not be random, which means that valid conclusions cannot be drawn from the analysis. Running multiple replications of the simulation eliminates this interdependence, and allows conclusions about the performance of the system to be made. Finally, to ensure that the experiments themselves were interdependent, different initial starting points were generated for the random number generators in each of the experiments.

7.3.1. Warm-up Period and Run Length Determination

The warm-up period for this simulation was determined using Welch's Test (Law and Kelton, 1991). With this test, a number of replications of the simulation are run, and the values for each of the observations over the replications are averaged. Then, the averaged values are smoothed out using a moving average. Since this research looks at many different experiments, it would be difficult to find the warm-up period for each of them. Furthermore, since the warm-up period would have to be the same for all models with the same ordering policy, it was determined that it would be best to choose the experiment for each of the three ordering policies that had the most variability. Thus, the warm-up period would be determined by checking the periodic-review policy at every supplier quality level with 70% supplier on-time delivery and 0% demand variability, and the kanban policies at every supplier quality level with 70% supplier on-time delivery, but with 30% demand variability. Each of these experiments was simulated for 25 replications of 500 days, and the window used in the moving average was 521 observations. The values determined through the moving average are graphed to show when the simulation reaches steady state. An example of one of these graphs is shown in Figure 7-1, which illustrates the moving average of the flowtime variable, in days, over the length of the simulation. The warm-up period is the time between the start of the simulation and the time when the moving average of the flowtime reaches steady-state.

Based on this analysis, two of the models, the periodic-review inventory control model and the inflated kanban model, are shown to reach steady state. The uninflated version of the kanban model, however, does not reach steady-state for either the 70% or 85% supplier quality levels. This will be discussed further in Section 7.3.2. From these graphs, it was also determined that both the periodic-review and inflated kanban models reach steady-state after 300 days of simulation. The remaining graphs used to determine the warm-up periods for the periodic-review and inflated kanban models are shown in Appendix C. From the warm-up period, a run length could be determined by adding ten times the length of the warm-up period to the end of the warm-up period, requiring a run length of 3300 days for both ordering policies (Banks *et al.*, 1999).

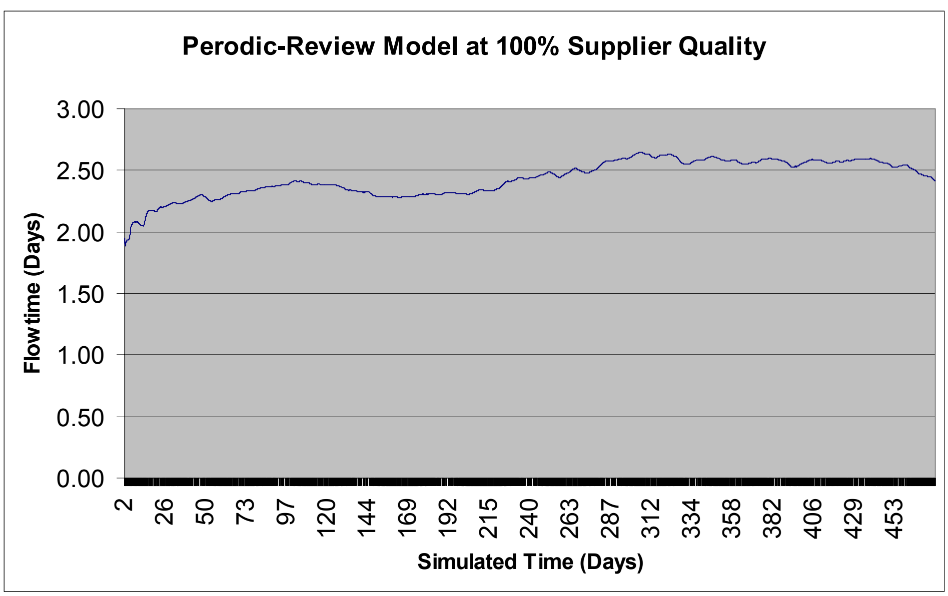


Figure 7-1. Moving Average of Flowtime for Periodic-Review Policy at 100% Supplier Quality

7.3.2. STEADY-STATE ANALYSIS FOR THE UNINFLATED KANBAN MODEL

As previously mentioned, the non-inflated version of the kanban model does not reach steady-state for supplier quality levels of 70% and 85%. This conclusion is determined by running the simulation for an extended period of time and evaluating a graph of the moving average for the flowtime variable. If the graph continues to increase without leveling off, this indicates the simulation does not reach steady-state.

Figure 7-2 and Figure 7-3 show the output from Arena's Output Analyzer of a graph of the moving average for the flowtime variable of the uninflated kanban model with a supplier quality level of 70%, supplier OTD level of 100%, and demand variability level of 0% over 10,000 days. Both graphs use the same values for the factors, but have different initial values for the two random number streams in the simulation. This moving average is for a window of 1,111 observations. The x-axis in these graphs signifies the simulated time in days, while the y-axis represents the moving average for the flowtime of the motors in the system. As shown, the moving average for flowtime continues to increase in value over the entire time period indicating that this system does not reach steady state. The remainder of the outputs from Arena's® Output Analyzer for the uninflated kanban models are shown in Appendix D.

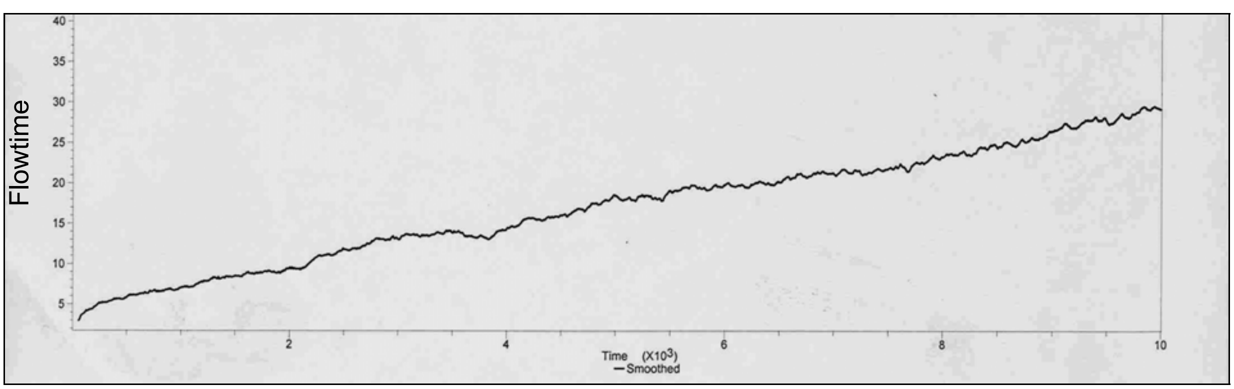


Figure 7-2. First Graph from Arena's® Output Analyzer for the Uninflated Kanban model

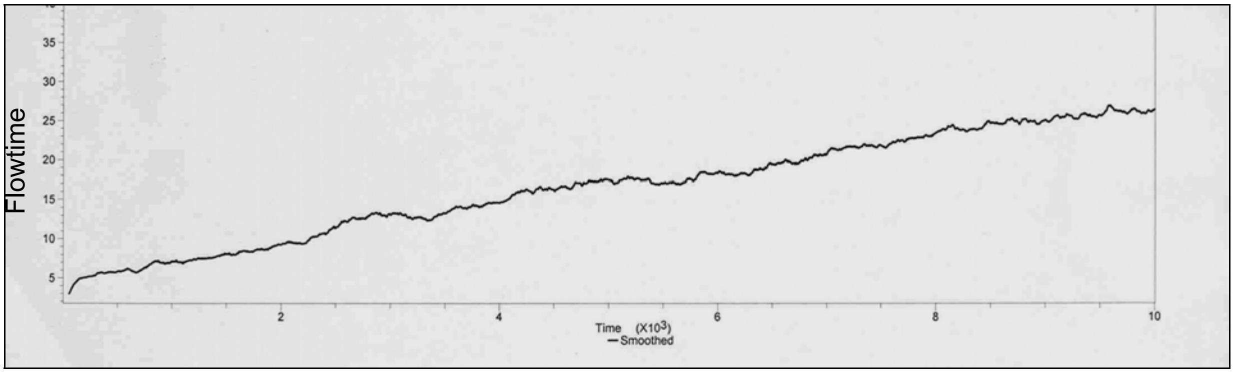


Figure 7-3. Second Graph from Arena's® Output Analyzer for the Uninflated Kanban model

7.3.3. DETERMINATION OF THE NUMBER OF REPLICATIONS

Multiple replications are used when analyzing simulation models to reduce the variance associated with individual replications. Therefore, multiple scenarios are run using the most variable experiment for each ordering policy; the experiment with 100% supplier quality, 70% supplier on-time delivery, and 30% demand variability for the inflated kanban policy, and 100% supplier quality, 70% supplier on-time delivery and 0% demand variability for the periodic-review policy. First, the experiments are run using five replications. If the half-width for a 95% confidence interval is less than or equal to 5% of the mean for each measure of interest, the variance has been reduced enough to analyze the output. However, if this half-width is not reached within five replications, more replications are completed until the half-width reaches 5% of the mean or less.

The same number of replications are run for each experiment in a particular ordering policy, so the maximum number achieved through the previous process for a given ordering policy is used for every experiment in that policy. To ensure a high level of confidence in the results, the inflated kanban models are run for 25 replications, and the periodic-review inventory control models are run for 15 replications.

7.3.4. *INITIAL STARTING POINT GENERATION*

To ensure that each of the experiments used a different set of random numbers, the initial starting points of two different random number streams were randomly generated for each experiment. One of these random number streams (Stream #1) is used in the generation of the random demand. The other stream (Stream #2) is used in the generation of each of the individual processing times for the manufacturing line. These values are five-digit numbers generated in Excel® using the "Rand()" function. Furthermore, the order in which the experiments are run is randomized using the same function. The order the experiments are run and the initial values used for the random number streams are shown in Table 7-2. With the important aspects of the simulation model determined, the experiments can be completed and analyzed.

Table 7-2. Experiment Order and Initial Random Numbers

Experiment	SEED - 1	SEED - 5	Experiment Order	Ordering Policy	Supplier Quality	Supplier OTD	Demand Variability
1	99912	67190	23	Inflated Kanban	70	70	0
2	44532	40701	12	Inflated Kanban	70	70	30
3	50060	19410	10	Inflated Kanban	70	85	15
4	52723	93026	13	Inflated Kanban	70	100	0
5	61696	49628	7	Inflated Kanban	70	100	30
6	9537	32741	24	Inflated Kanban	85	70	15
7	91811	44491	16	Inflated Kanban	85	85	0
8	35386	19969	29	Inflated Kanban	85	85	15
9	15566	42839	31	Inflated Kanban	85	85	15
10	86287	74666	33	Inflated Kanban	85	85	15
11	86701	74659	19	Inflated Kanban	85	85	30
12	34030	66215	27	Inflated Kanban	85	100	15
13	27138	20995	4	Inflated Kanban	100	70	0
14	47305	11159	18	Inflated Kanban	100	70	30
15	3985	11600	5	Inflated Kanban	100	85	15
16	59751	46952	14	Inflated Kanban	100	100	0
17	36745	38863	15	Inflated Kanban	100	100	30
18	94670	94912	20	Periodic Review	70	70	0
19	76240	48580	26	Periodic Review	70	70	30
20	76673	23178	22	Periodic Review	70	85	15
21	29942	50117	8	Periodic Review	70	100	0
22	78136	19849	2	Periodic Review	70	100	30
23	99096	55461	25	Periodic Review	85	70	15
24	46254	3992	34	Periodic Review	85	85	0
25	11197	20332	1	Periodic Review	85	85	15
26	89555	97939	6	Periodic Review	85	85	15
27	77130	31046	30	Periodic Review	85	85	15
28	36794	75326	21	Periodic Review	85	85	30
29	77277	1866	32	Periodic Review	85	100	15
30	53656	50190	28	Periodic Review	100	70	0
31	79105	33380	9	Periodic Review	100	70	30
32	12341	50185	11	Periodic Review	100	85	15
33	18920	90008	3	Periodic Review	100	100	0
34	34087	92226	17	Periodic Review	100	100	30

CHAPTER VIII

CASE APPLICATION RESULTS AND ANALYSIS

The purpose of this study is to determine how the performance of a Lean Production Cell responds to changes in the ordering policy for supplied parts under conditions of imperfect supplier performance and variability in customer demand. Thus, an experimental investigation is conducted to determine how a combination of factors affects the manufacturing cell for each ordering policy. This investigation is then analyzed using a linear regression model based on a 2^{nd} order Taylor Series.

The results obtained from the experiments for this case application are shown in Table 8-1. The experiment number indicates the order the experiments were run. For the levels of each of the four factors (ordering policy, supplier quality, supplier on-time delivery, and demand variability), the values for the performance measures (flowtime, on-time delivery, number of motors shipped, work-in-process inventory, stockout factor, and supplied part inventory factor) are summarized.

An important note is that for each policy at 85% supplier quality (SQ), 85% supplier on-time delivery (SOTD), and 15% customer demand variability (DV), the differences in the performance measures between the three experiments are very small. This low variability between the experiments provides an extremely low pure error term. A low pure error term will cause a regression model to exhibit Lack-of-Fit (LOF) with only slight differences between the expected values from the model and the actual values achieved by the simulation.

In the process of analyzing the results, one of the experiments was significantly different from the other experiments. The periodic-review policy at 100% SQ, 70% SOTD, and 0% DV resulted in unusually high values for flowtime, WIP, and stockout factor, and an unusually low value for on-time delivery to the customer. Therefore, to determine if this point was a trend, or an anomaly, two more experiments are completed. The first extra experiment is conducted at the midpoint between the central experiment for the design for the periodic-review policy, and the possible anomaly point, resulting in an experiment at 92.5% SQ, 77.5% SOTD, and 7.5% DV. The performance of this experiment is evaluated to determine if it performed more like the central point of the design, or the possible anomaly point. After determining that the performance of the cell at the first extra point is more similar to the performance of the cell at the central point of the design, a second extra experiment is conducted to see how the cell reacts as the factors approached the possible anomaly point. This second experiment was conducted at the midpoint between the first extra experiment and the possible anomaly point, or 96.25% SQ, 73.75% SOTD, and 3.75% DV. The performance of the cell at this point is more comparable to the central point of the design, providing more support that for the periodic-review policy, the experiment at 100% SQ, 70% SOTD, and 0%DV is an anomaly, and should not be included in the regression analysis.

Analytical and statistical analyses of the results from this research are described in the following sections of this chapter. The analysis is divided into seven sections, one for each of the six performance measures, followed by a summary of the results. In the following sections, the three central experiments conducted at 85% SQ, 85% SOTD, and 15% DV are averaged for each policy and shown in the tables as the average value. This averaged value is often shown multiple times in the same table to more easily compare trends in the data.

Table 8-1. Case Application Results

Exper	Ordering Policy *	Supplier Quality (%)	Supplier OTD (%)	Demand Variability (%)	Flowtime (Days)	OTD (%)	Motors Shipped (# of Motors)	WIP (# of Motors)	Stockout Factor (%)	Inventory Factor (# of Motors)
1	IK	70	70	0	2.03	97.1	119.8	48.8	4.90%	152
2	IK	70	70	30	2.22	89.7	119.8	53.2	10.00%	151
3	IK	70	85	15	2.04	96	119.7	48.9	4.60%	152
4	IK	70	100	0	1.96	99.2	119.8	47.1	0.00%	153
5	IK	70	100	30	1.97	97.5	119.9	47.4	0.00%	153
6	IK	85	70	15	2.21	93.6	119.9	53.2	12.90%	139
7	IK	85	85	0	2.06	97.1	119.8	49.4	6.50%	141
8	IK	85	85	15	2.1	94.3	119.8	50.3	7.60%	140
9	IK	85	85	15	2.1	95.2	119.8	50.5	7.90%	140
10	IK	85	85	15	2.08	95.3	119.7	50	7.40%	141
11	IK	85	85	30	2.19	90.8	119.8	52.5	9.60%	140
12	IK	85	100	15	1.97	98.2	119.7	47.2	0.00%	142
13	IK	100	70	0	2.22	93.1	119.8	53.2	12.80%	141
14	IK	100	70	30	2.49	84.2	119.8	59.7	18.40%	140
15	IK	100	85	15	2.13	94	119.8	51.1	8.30%	142
16	IK	100	100	0	1.96	99.1	119.8	47.2	0.00%	144
17	IK	100	100	30	1.97	97	119.8	47.4	0.10%	144
18	PR	70	70	0	1.96	99.4	119.8	47.1	0.00%	673
19	PR	70	70	30	1.97	96.1	119.8	47.3	0.00%	1398
20	PR	70	85	15	1.97	98.4	119.9	47.2	0.00%	1086
21	PR	70	100	0	1.96	99.1	119.8	47.1	0.00%	673
22	PR	70	100	30	1.97	96.5	119.8	47.3	0.00%	1398
23	PR	85	70	15	1.97	96.8	119.9	47.2	0.00%	845
24	PR	85	85	0	1.97	99.1	119.8	47.3	0.60%	530
25	PR	85	85	15	1.97	96.8	119.8	47.2	0.00%	855
26	PR	85	85	15	1.97	98.2	119.9	47.2	0.00%	855
27	PR	85	85	15	1.97	98.1	119.7	47.2	0.00%	856
28	PR	85	85	30	1.97	96.9	119.6	47.3	0.00%	1095
29	PR	85	100	15	1.97	98.3	119.9	47.2	0.00%	867
30	PR	100	70	0	2.53	83.6	119.7	60.7	14.10%	433
31	PR	100	70	30	1.99	95.1	119.9	47.9	1.00%	881
32	PR	100	85	15	2.01	96.4	119.9	48.2	1.60%	711
33	PR	100	100	0	1.97	98.9	119.8	47.2	0.20%	453
34	PR	100	100	30	1.97	95.9	119.9	47.4	0.00%	904
35	PR	92.5	77.5	7.5	1.98	98.6	119.8	47.5	1.60%	656
36	PR	96.25	73.75	3.75	1.99	98.2	119.8	47.7	2.80%	584

* IK – Inflated Kanban Policy, PR – Periodic Review Policy

8.1. FLOWTIME

The results for the flowtime performance measure are summarized in Table 8-2. This table includes the levels for the factors supplier quality, supplier on-time delivery, and demand variability, and the flowtime for each ordering policy for each of the experiments associated with that set of factor levels.

As shown, the lowest flowtime (1.96 days) was achieved at four different experiments. These four experiments are: the periodic-review policy with 70% SQ, 70% SOTD, and 0% DV, and with 70% SQ, 100% SOTD, and 0% DV; and the inflated kanban policy with 70% SQ, 100% SOTD, and 0% DV, and with 100% SQ, 100% SOTD, and 0% DV. The highest flowtime (2.53 days), on the other hand, was achieved at the experiment signifying the periodic-review policy with 100% SQ, 70% SOTD, and 0% DV. In fact, this was the experiment that led to the two extra experiments. As shown, the two additional experiments generate flowtimes closer to the expected value for the policy.

In general, the periodic-review model tends to outperform the inflated kanban model with respect to flowtime, where a lower value is more desirable. Within the periodic-review policy, the flowtime tends to be relatively constant except when the supplier quality is at 100% (flowtime increases). Finally, it appears that for the inflated kanban policy, the flowtime tends to improve as supplier quality decreases, supplier on-time delivery levels improve, and demand variability decreases.

Table 8-2. Flowtime for Varying Levels of Factors for Each Policy

Experiment Number		Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)	Periodic-Review (Days)	Inflated Kanban (Days)
Periodic-Review	Inflated Kanban					
20	3	70	85	15	**1.97**	2.04
25, 26, 27	8, 9, 10	85	85	15	**1.97**	2.10
32	15	100	85	15	**2.01**	2.13
23	6	85	70	15	**1.97**	2.21
25, 26, 27	8, 9, 10	85	85	15	**1.97**	2.10
29	12	85	100	15	**1.97**	**1.97**
24	7	85	85	0	**1.97**	2.06
25, 26, 27	8, 9, 10	85	85	15	**1.97**	2.10
28	11	85	85	30	**1.97**	2.19
18	1	70	70	0	**1.96**	2.03
19	2	70	70	30	**1.97**	2.22
21	4	70	100	0	**1.96**	**1.96**
22	5	70	100	30	**1.97**	**1.97**
30	13	100	70	0	2.53	**2.22**
31	14	100	70	30	**1.99**	2.49
33	16	100	100	0	1.97	**1.96**
34	17	100	100	30	**1.97**	**1.97**
35	----	92.5	77.5	7.5	1.98	----
36	----	96.25	73.75	3.75	1.99	----

From a statistical perspective, each policy can be represented with a linear regression model as shown in Table 8-3. These models represent the coded experiments, which means that the lowest value for each factor is represented by –1, the moderate value is represented by 0, and the highest value is represented by 1. The table summarizes the intercept value, the coefficient values for all terms in the regression model, and the t-values for the intercept and coefficient terms.

Table 8-4 shows the R^2 values and p-values for the Lack-of-Fit test. As shown in this table, both models have high R^2 values, signifying that each model tends to fit the data well. The low p-value for the periodic-review policy, however, signifies that the model exhibits Lack-of-

Fit, meaning the model does not contain enough terms to completely represent the policy. To decrease this Lack-of-Fit, higher order terms must be added to the regression model. However, it was determined that a 2^{nd}-order Taylor Series is an appropriate approximation for this analysis, so higher terms were not added to this model. The inflated kanban model, on the other hand, has a p-value greater than 0.05, indicating that no statistically significant Lack-of-Fit is present in the model.

The t-values for each of the coefficients of the factors and factor interactions are evaluated to determine the factors that have the largest absolute values, indicating a significant effect on flowtime. As evidenced by Table 8-3, supplier quality appears to have the most significant effect on the flowtime for the periodic-review model, since supplier quality has the highest t-value for the coefficients of the individual factors, supplier quality^2 has the highest coefficient of the quadratic terms, and the coefficients for the two interactions including supplier quality are higher than the coefficient for the other interaction term. Similarly, supplier on-time delivery has the most significant effect for the inflated kanban model.

Table 8-3. Linear Regression Model for Flowtime

Factors	Periodic-Review		Inflated Kanban	
	Coefficient	**t-value**	**Coefficient**	**t-value**
Intercept	1.97	673	2.1	431
Quality	0.01	4.75	0.055	8.65
Time	-0.005	-2.09	-0.133	-20.9
Demand	0.001	0.58	0.06	9.48
Quality^2	0.014	3.2	----	----
Time^2	-0.006	-1.49	----	----
Demand^2	-0.006	-1.49	----	----
Quality * Time	-0.006	-2.28	-0.0569	-8.01
Quality * Demand	-0.003	-1.33	----	----
Time * Demand	0.001	0.37	-0.0549	-7.73

Table 8-4. Summary of Linear Regression Model for Flowtime

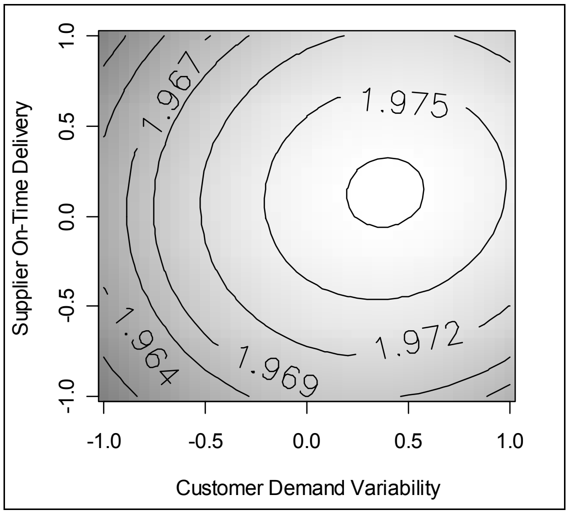
	Periodic-Review	Inflated Kanban
R-Squared Value	0.8419	0.9851
Lack-of-Fit p-Value	<0.0001	0.1735

Contour plots have been generated from these regression models and are shown in Figure 8-1. Individual plots are shown for each ordering policy for each of the three supplier quality levels. Three different plots are shown for the different levels of supplier quality since contour plots only show two factors, meaning one factor must be held constant. Since the models are based on the coded experiments, the values on each axis represent the coded values. The contour lines represent the expected flowtime for the given factors at a certain point on the graph. For example, for the Periodic-Review policy at 70% SQ, 85% SOTD, and 15% DV, or at 0.0 DV, 0.0 SOTD in Figure 8-1a, the flowtime value is expected to be slightly greater than 1.975 days based on the regression model.

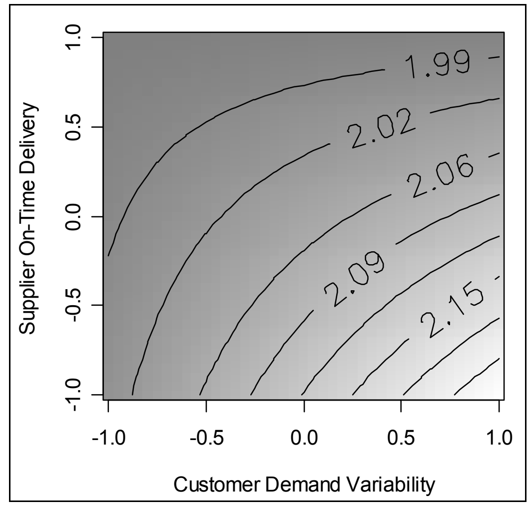
The contour plots illustrate the impact of supplier on-time delivery and customer demand variability on flowtime. From these plots, it appears that in terms of the flowtime variable, the periodic-review policy tends to outperform the inflated kanban policy for most levels of each factor. The two policies are however, comparable at high levels of supplier on-time delivery. Also, for the periodic-review policy, shown in Figure 8-1a, c, and e, flowtime tends to be more preferable if supplier quality is less than 100%. For the inflated kanban model shown in Figure 8-1b, d, and f, the flowtime measure tends to improve as supplier quality decreases, supplier on-time delivery increases, and demand variability decreases.

In summary, the periodic-review policy tends to outperform the inflated kanban policy in terms of the flowtime of the motors through the manufacturing cell for most levels of the factors.

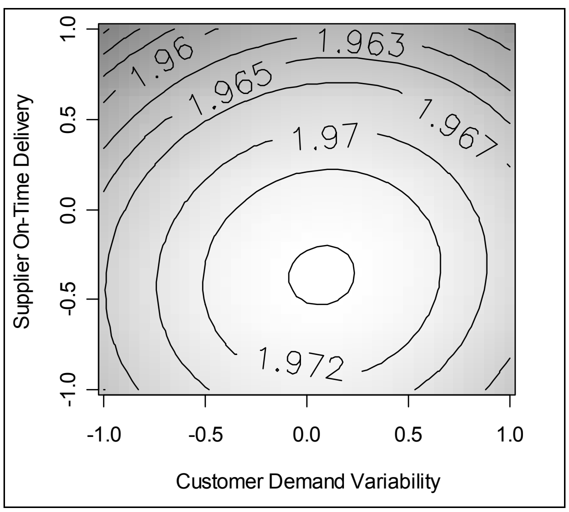
However, at high levels of supplier on-time delivery, the inflated kanban model achieves a comparable flowtime. For the periodic-review model, supplier quality has the largest impact on the flowtime variable, and the flowtime appears to be preferable at supplier quality levels below 100%. For the inflated kanban policy, supplier on-time delivery has the largest impact on the value of flowtime, and the flowtime improves as supplier quality decreases, supplier on-time delivery increases, and demand variability decreases. Again, both the periodic-review policy and the inflated kanban policy are adjusted for supplier quality, which provides evidence for why the policies perform well for lower quality levels.



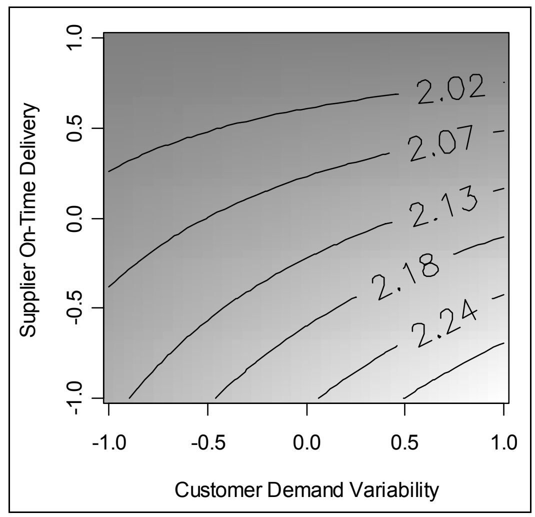
a) Periodic-Review Policy at 70% Supplier Quality



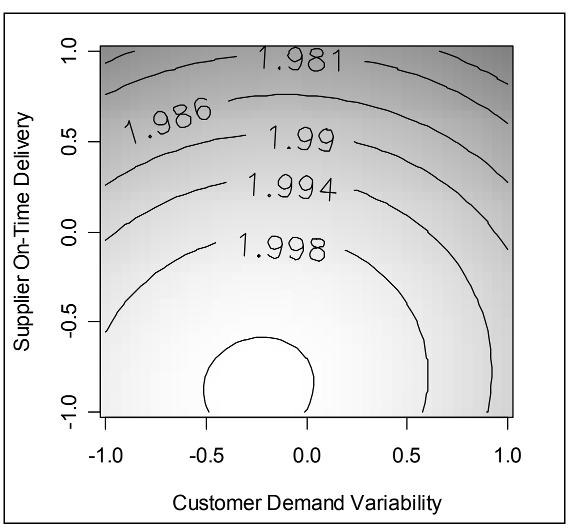
b) Inflated Kanban Policy at 70% Supplier Quality



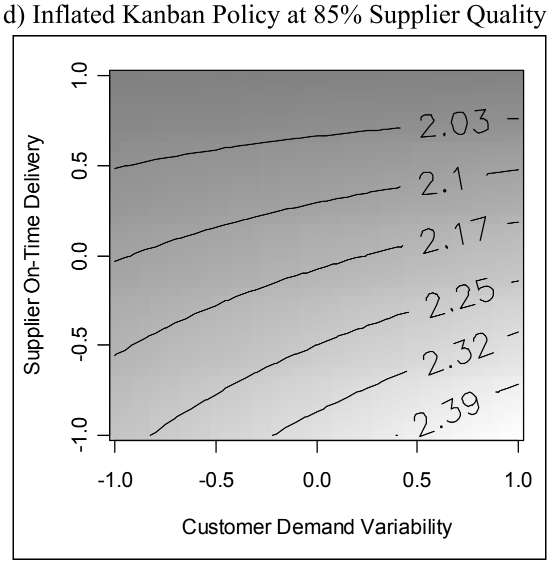
c) Periodic-Review Policy at 85% Supplier Quality



d) Inflated Kanban Policy at 85% Supplier Quality



e) Periodic-Review Policy at 100% Supplier Quality



f) Inflated Kanban Policy at 100% Supplier Quality

Figure 8-1. Contour Plots for the Flowtime Variable

8.2. On-Time Delivery

The results for the on-time delivery performance measure are summarized in Table 8-5. This table includes the levels for the factors supplier quality, supplier on-time delivery, and demand variability, and the on-time delivery percentage for each ordering policy for each of the experiments associated with that set of factor levels.

As shown, the highest on-time delivery percentage (99.4%) was achieved at the experiment signifying the periodic-review policy with 70% SQ, 70% SOTD, and 0% DV. The lowest on-time delivery percentage (83.6%) was achieved at the experiment signifying the periodic-review policy with 100% SQ, 70% SOTD, and 0% DV. However, as shown, the poor on-time delivery with this experiment is an abnormality as the two extra experiments generated on-time delivery percentages closer to the expected value for the policy.

In general, the periodic-review model tends to outperform the inflated kanban model with respect to the on-time delivery rate, where a higher value is more desirable. Within the periodic-review policy, the OTD tends to improve as the supplier quality reduced, supplier on-time delivery improves, and demand variability is reduced. Finally, the data suggest that for the Inflated Kanban policy, the OTD tends to improve as supplier quality decreases, supplier on-time delivery improves, and demand variability is reduced.

Table 8-5. On-Time Delivery for Varying Levels of Factors for Each Policy

Experiment Number		Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)	Periodic-Review (%)	Inflated Kanban (%)
Periodic-Review	Inflated Kanban					
20	3	70	85	15	**98.4**	96.0
25, 26, 27	8, 9, 10	85	85	15	**97.7**	94.9
32	15	100	85	15	**96.4**	94.0
23	6	85	70	15	**96.8**	93.6
25, 26, 27	8, 9, 10	85	85	15	**97.7**	94.9
29	12	85	100	15	**98.3**	98.2
24	7	85	85	0	**99.1**	97.1
25, 26, 27	8, 9, 10	85	85	15	**97.7**	94.9
28	11	85	85	30	**96.9**	90.8
18	1	70	70	0	**99.4**	97.1
19	2	70	70	30	**96.1**	89.7
21	4	70	100	0	99.1	**99.2**
22	5	70	100	30	96.5	**97.5**
30	13	100	70	0	83.6	**93.1**
31	14	100	70	30	**95.1**	84.2
33	16	100	100	0	98.9	**99.1**
34	17	100	100	30	95.9	**97.0**
35	----	92.5	77.5	7.5	98.6	----
36	----	96.25	73.75	3.75	98.2	----

From a statistical perspective, each policy can be represented with a linear regression model as shown in Table 8-6. These models represent the coded experiments, where the lowest value for each factor is represented by –1, the moderate value is represented by 0, and the highest value is represented by 1. The table summarizes the intercept value, the coefficient values for all terms in the regression model, and the t-values for the intercept and coefficient terms.

Table 8-7 shows the R^2 values and p-values for the Lack-of-Fit test for each ordering policy. As shown in this table, both models have relatively high R^2 values, signifying that each model tends to fit the data well. Also, both models have p-values greater than 0.05, indicating that no statistically significant Lack-of-Fit is present in the model. Also evident in Table 8-6 is that demand has the only effect on the on-time delivery for the periodic-review model, while supplier on-time delivery appears to have the most significant effect for the inflated kanban model.

Table 8-6. Linear Regression Model for On-Time Delivery

Factors	Periodic-Review		Inflated Kanban	
	Coefficient	t-value	Coefficient	t-value
Intercept	97.58	637	94.79	442
Quality	----	----	-1.218	-4.35
Time	----	----	3.332	11.9
Demand	-1.48	-7.15	-2.646	-9.46
Quality * Time	----	----	1.107	3.54
Time * Demand	----	----	1.575	5.04

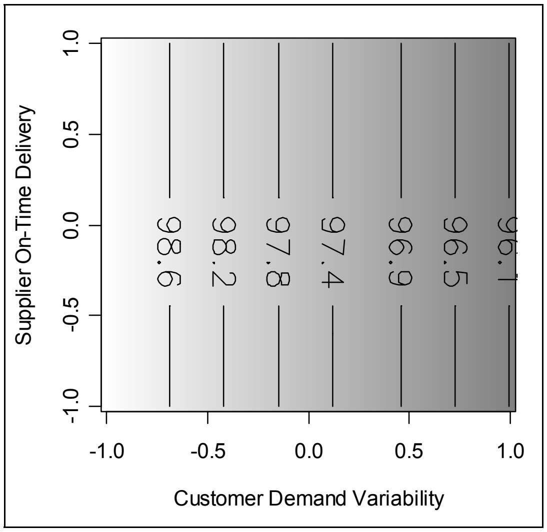
Table 8-7. Summary of Linear Regression Model for On-Time Delivery

	Periodic-Review	Inflated Kanban
R-Squared Value	0.7616	0.9632
Lack-of-Fit p-Value	0.876	0.268

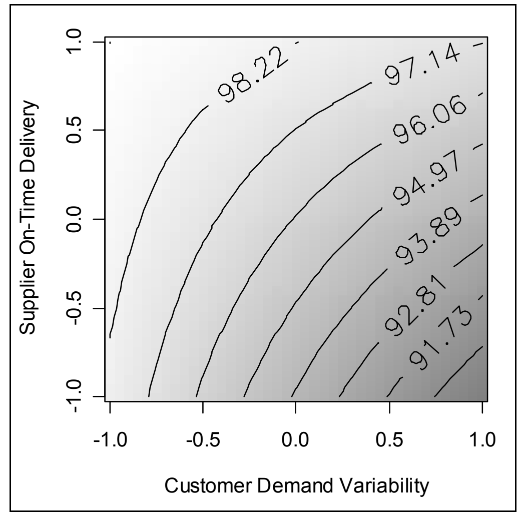
Contour plots have been generated from these models and are shown in Figure 8-2. Since the models are based on the coded experiments, the values on each axis represent the coded values. The plots illustrate the impact of supplier on-time delivery and customer demand variability on on-time delivery to the customer. For the periodic-review policy, only one plot is shown since supplier quality has no effect on on-time delivery, and the plots would be the same at any level of supplier quality. For the inflated kanban policy, different plots are shown for each of the three levels of supplier quality.

As shown in these graphs, the periodic-review policy appears to be more desirable than the inflated kanban policy in terms of on-time delivery performance to the customer for most levels of each factor. However, at high levels of supplier on-time delivery, the inflated kanban policy appears to be comparable in terms of the cell's OTD. For the periodic-review policy, shown in Figure 8-2a, the on-time delivery percentage to the customer tends to improve as the customer demand variability is reduced. For the inflated kanban policy, Figure 8-2b, c, and d, the on-time delivery performance of the manufacturing cell appears to improve as supplier quality levels decrease, supplier on-time delivery levels increase, or demand variability is reduced.

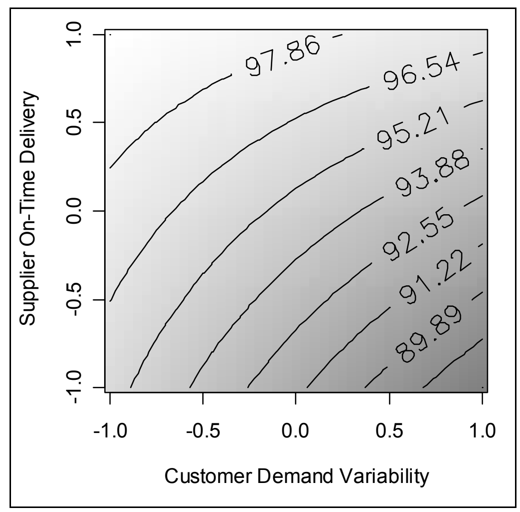
In summary, the periodic-review policy tends to outperform the inflated kanban policy in terms of on-time delivery performance to the customer for most levels of the factors. However, at high levels of supplier on-time delivery, the inflated kanban model achieves comparable on-time delivery. For the periodic-review model, customer demand appears to have the largest impact on the on-time delivery variable, and the on-time delivery tends to improve as customer demand variability is reduced. For the inflated kanban policy, supplier on-time delivery appears to have the largest impact on the value of on-time delivery, and on-time delivery to the customer tends to improve as supplier quality decreases, supplier on-time delivery increases, and demand variability decreases. Again, both the periodic-review policy and the inflated kanban policy are adjusted for supplier quality, which provides evidence for why the policies perform well for lower quality levels.



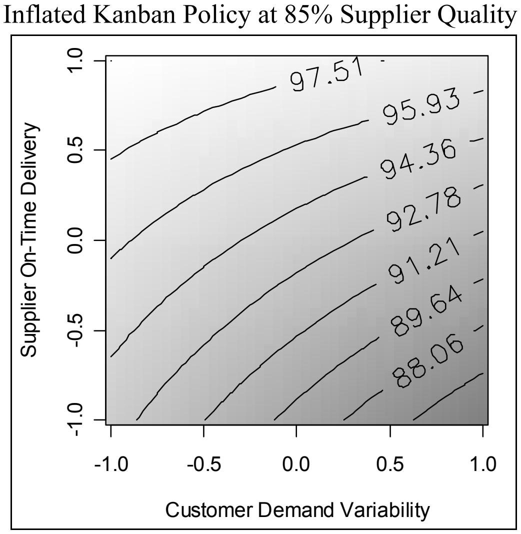
a) Periodic-Review Policy



b) Inflated Kanban Policy at 70% Supplier Quality



c) Inflated Kanban Policy at 85% Supplier Quality



d) Inflated Kanban Policy at 100% Supplier Quality

Figure 8-2. Contour Plots for the On-Time Delivery Variable

8.3. NUMBER OF MOTORS SHIPPED

The results for the number of motors shipped each week are summarized in Table 8-8. This table includes the levels for the factors supplier quality, supplier on-time delivery, and demand variability, and the number of motors shipped for each ordering policy for each of the experiments associated with that set of factor levels.

As shown in Table 8-8, the lowest NumShipped (119.6 motors) was achieved at the experiment signifying the periodic-review policy with 85% SQ, 85% SOTD, and 30% DV. The highest number of motors shipped (NumShipped) was achieved with a value of 119.9 motors per week at eight different experiments. These eight experiments are summarized in Table 8-9 as well.

From this data, it is unclear which of the policies is more preferable (has a higher number of motors shipped each week). Furthermore, since it appears that little difference exists in the value of the number of motors shipped for each ordering policy, little can be concluded in terms of how each factor affects this performance measure.

Table 8-8. NumShipped for Varying Levels of Factors for Each Policy

Experiment Number		Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)	Periodic-Review (#)	Inflated Kanban (#)
Periodic-Review	Inflated Kanban					
20	3	70	85	15	**119.9**	119.7
25, 26, 27	8, 9, 10	85	85	15	**119.8**	**119.8**
32	15	100	85	15	**119.9**	119.8
23	6	85	70	15	**119.9**	**119.9**
25, 26, 27	8, 9, 10	85	85	15	**119.8**	**119.8**
29	12	85	100	15	**119.9**	119.7
24	7	85	85	0	**119.8**	**119.8**
25, 26, 27	8, 9, 10	85	85	15	**119.8**	**119.8**
28	11	85	85	30	119.6	**119.8**
18	1	70	70	0	**119.8**	**119.8**
19	2	70	70	30	**119.8**	**119.8**
21	4	70	100	0	**119.8**	**119.8**
22	5	70	100	30	119.8	**119.9**
30	13	100	70	0	119.7	**119.8**
31	14	100	70	30	**119.9**	119.8
33	16	100	100	0	**119.8**	**119.8**
34	17	100	100	30	**119.9**	119.8
35	----	92.5	77.5	7.5	119.8	**----**
36	----	96.25	73.75	3.75	119.8	**----**

Table 8-9. Experiments with 119.9 Motors Shipped

Ordering Policy	Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)
Kanban Inflated	70	100	30
Kanban Inflated	85	70	15
Periodic-Review	70	85	15
Periodic-Review	100	85	15
Periodic-Review	85	70	15
Periodic-Review	85	100	15
Periodic-Review	100	70	30
Periodic-Review	100	100	30

From a statistical perspective, each policy can be represented with a linear regression model as shown in Table 8-10. These models represent the coded experiments, which means that the lowest value for each factor is represented by –1, the moderate value is represented by 0, and the highest value is represented by 1. The table summarizes the intercept value, the coefficient values for all terms in the regression model, and the t-values for the intercept and coefficient terms.

Table 8-11 shows the R^2 values and p-values for the Lack-of-Fit test for each ordering policy. As shown in this table, the periodic-review policy has a relatively low R^2 value, signifying that this model tends to fit the data poorly for the number of motors shipped each week. The R^2 value for the inflated kanban policy is not available because there are no coefficients associated with any of the factors. Also, both policies have p-values greater than 0.05, indicating that no statistically significant Lack-of-Fit is present in the model, most likely owing to the fact that the values for each of the experiments are so similar.

Due to the low R^2 values for these models and the relatively consistent values for all of the experiments, no additional analysis is conducted for the number of motors shipped each week. Also, since the difference in the number of motors shipped each week between the two policies is minimal, it makes little difference in the overall analysis of the manufacturing cell.

Table 8-10. Linear Regression Model for Motors Shipped

Factors	Periodic-Review		Inflated Kanban	
	Coefficient	**t-value**	**Coefficient**	**t-value**
Intercept	119.85	4085	119.98	----
Demand	0.004	0.15	----	----
Demand^2	-0.055	-1.34	----	----

Table 8-11. Summary of Linear Regression Model for Motors Shipped

	Periodic-Review	Inflated Kanban
R-Squared Value	0.1075	N/A
Lack-of-Fit p-value	0.8745	0.2346

8.4. WORK-IN-PROCESS INVENTORY

The results for the work-in-process inventory performance measure are summarized in Table 8-12. This table includes the levels for the factors supplier quality, supplier on-time delivery, and demand variability, and the amount of WIP for the each ordering policy for each of the experiments associated with that set of factor levels.

As shown, the lowest work-in-process inventory (47.1 motors) was achieved at three different experiments. These experiments are: the periodic-review policy with 70% SQ, 70% SOTD, and 0% DV, and with 70% SQ, 100% SOTD, and 0% DV; and the inflated kanban policy with 70% SQ, 100% SOTD, and 0% DV. The highest WIP (60.7 motors), on the other hand, was achieved at the experiment signifying the periodic-review policy with 100% SQ, 70% SOTD, and 0% DV.

In general, the periodic-review model tends to outperform the inflated kanban model with respect to WIP levels, where a lower value is more desirable. Within the periodic-review policy, little can be derived from the data, with the exception of having extremely high levels of WIP for the experiment signifying 100% SQ, 70% SOTD, and 0% DV. Finally, it appears that for the inflated kanban policy, WIP levels appear to improve as supplier quality decreases, supplier on-time delivery improves, and demand variability decreases.

Table 8-12. WIP Inventories for Varying Levels of Factors for Each Policy

Experiment Number		Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)	Periodic-Review (# of Motors)	Inflated Kanban (# of Motors)
Periodic-Review	Inflated Kanban					
20	3	70	85	15	**47.2**	48.9
25, 26, 27	8, 9, 10	85	85	15	**47.2**	50.3
32	15	100	85	15	**48.2**	51.1
23	6	85	70	15	**47.2**	53.2
25, 26, 27	8, 9, 10	85	85	15	**47.2**	50.3
29	12	85	100	15	**47.2**	**47.2**
24	7	85	85	0	**47.3**	49.4
25, 26, 27	8, 9, 10	85	85	15	**47.2**	50.3
28	11	85	85	30	**47.3**	52.5
18	1	70	70	0	**47.1**	48.8
19	2	70	70	30	**47.3**	53.2
21	4	70	100	0	**47.1**	**47.1**
22	5	70	100	30	**47.3**	47.4
30	13	100	70	0	60.7	**53.2**
31	14	100	70	30	**47.9**	59.7
33	16	100	100	0	**47.2**	**47.2**
34	17	100	100	30	**47.4**	**47.4**
35	----	92.5	77.5	7.5	47.5	----
36	----	96.25	73.75	3.75	47.7	----

From a statistical perspective, each policy can be represented with a linear regression model as shown in Table 8-13. These models represent the coded experiments, which means that the lowest value for each factor is represented by –1, the moderate value is represented by 0, and the highest value is represented by 1. The table summarizes the intercept value, the coefficient values for all terms in the regression model, and the t-values for the intercept and coefficient terms.

Table 8-14 shows the R^2 values and p-values for the Lack-of-Fit test for each ordering policy. As shown in this table, both models have high R^2 values, signifying that each model tends to fit the data well. The low p-value for the periodic-review policy, however, signifies that the model exhibits Lack-of-Fit, meaning the model does not contain enough terms to completely represent the policy. To decrease this Lack-of-Fit, higher order terms must be added to the regression model. However, it was determined that a 2nd-order Taylor Series is an appropriate approximation for this analysis, so higher terms were not added to this model. The inflated kanban model, on the other hand, has a p-value greater than 0.05, indicating that no statistically significant Lack-of-Fit is present in the model. Also evident in Table 8-13 is that supplier quality appears to have the most significant effect on the WIP for the periodic-review model, while supplier on-time delivery appears to have the most significant effect for the inflated kanban model.

Table 8-13. Linear Regression Model for WIP

Factors	Periodic-Review		Inflated Kanban	
	Coefficient	t-value	Coefficient	t-value
Intercept	47.28	635	50.41	435
Quality	0.263	4.6	1.315	8.7
Time	-0.123	-2.15	-3.19	-21.1
Demand	0.057	1	1.45	9.6
$Quality^2$	0.347	3.21	0	---
$Time^2$	-0.153	-1.41	0	---
$Demand^2$	-0.053	-0.49	0	---
Quality * Time	-0.155	-2.33	-1.364	-8.07
Quality * Demand	-0.03	-0.45	0	---
Time * Demand	0.03	0.45	-1.317	-7.8

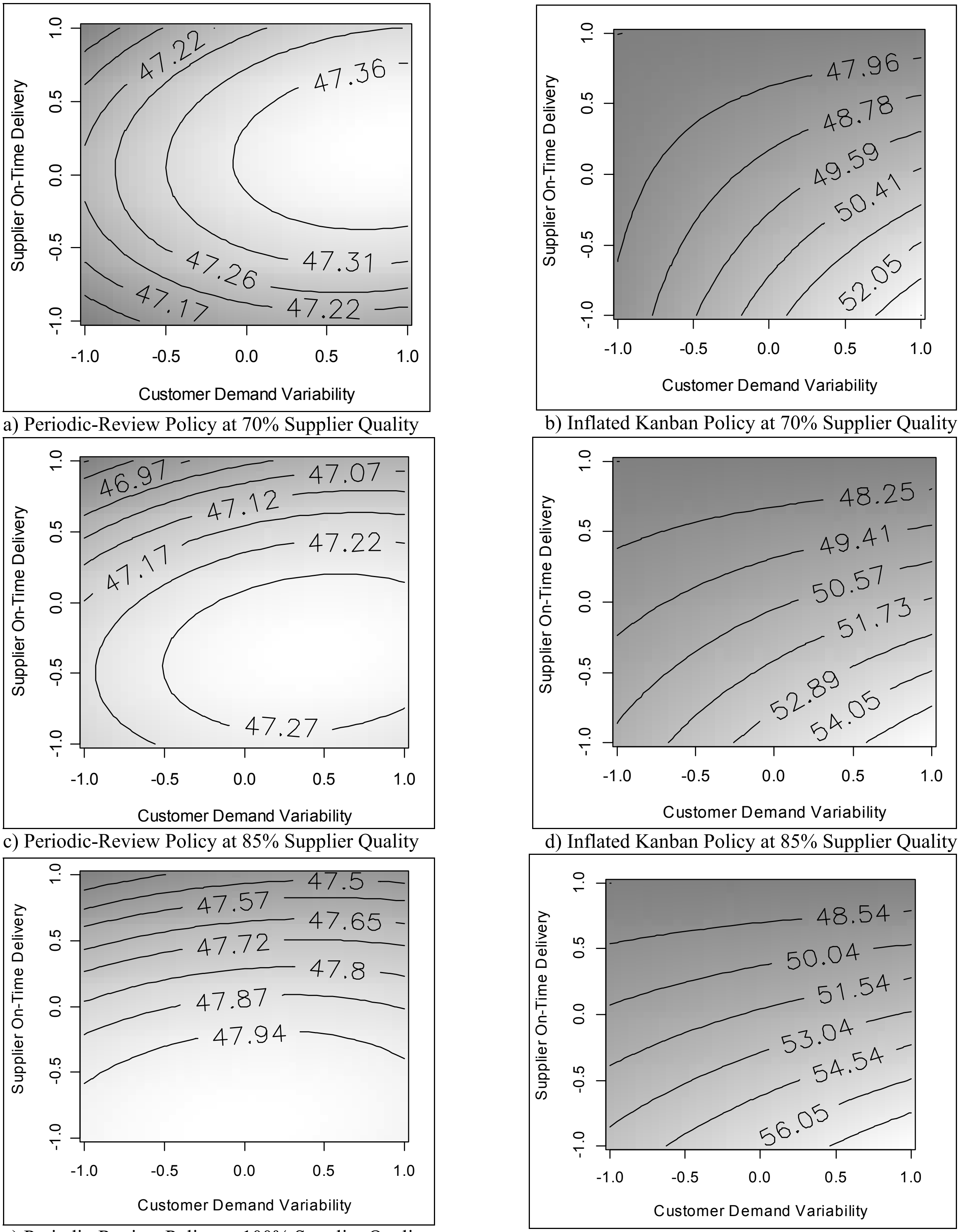
Table 8-14. Summary of Linear Regression Model for WIP

	Periodic-Review	Inflated Kanban
R-Squared Value	0.8311	0.9853
Lack-of-Fit p-value	<.0001	0.2004

Contour plots have been generated from these regression models and are shown in Figure 8-3. Individual plots are shown for each ordering policy for each of the three supplier quality levels. Since the models are based on the coded experiments, the values on each axis represent the coded values. It is necessary to use three different contour plots for each policy because the contour plots only show two factors, meaning one factor must be held constant. The plots illustrate the impact of supplier on-time delivery and customer demand variability on WIP levels. For each ordering policy, three different plots are shown for the different levels of supplier quality.

From these plots it appears that the periodic-review policy is preferable in terms of the amount of work-in process inventory in the manufacturing cell. Furthermore, for the periodic-review policy, shown in Figure 8-3a, c, and e, the amount of work-in process inventory tends to be more preferable if supplier quality is below 100. For the inflated kanban policy, shown in Figure 8-3b, d, and f, the amount of WIP tends to improve as supplier quality decreases, supplier on-time delivery improves, and demand variability is reduced.

In summary, the periodic-review policy tends to outperform the inflated kanban policy in terms of the amount of WIP in the cell for most levels of the factors. For the periodic-review model, supplier quality appears to have the largest impact on the amount of WIP, and the amount of WIP tends to be more preferable if supplier quality is less than 100%. For the inflated kanban policy, supplier on-time delivery appears to have the largest impact on the amount of WIP, and the amount of WIP tends to improve as supplier quality decreases, supplier on-time delivery increases, and demand variability decreases. Again, both the periodic-review and the inflated kanban policies are adjusted for supplier quality, which provides evidence for why the policies perform well for lower quality levels.



a) Periodic-Review Policy at 70% Supplier Quality

b) Inflated Kanban Policy at 70% Supplier Quality

c) Periodic-Review Policy at 85% Supplier Quality

d) Inflated Kanban Policy at 85% Supplier Quality

e) Periodic-Review Policy at 100% Supplier Quality

f) Inflated Kanban Policy at 100% Supplier Quality

Figure 8-3. Contour Plots for the Work-in-Process Inventory Variable

8.5. STOCKOUT FACTOR

The results for the stockout factor performance measure are summarized in Table 8-15. This table includes the levels for the factors supplier quality, supplier on-time delivery, and demand variability, the stockout factor for each ordering policy for each of the experiments associated with that set of factor levels.

As shown, the lowest Stockout Factor (SOF) was achieved for eight different experiments at 0%, which are shown in Table 8-15 and also summarized in Table 8-16. While Table 8-15 shows more than eight experiments with a stockout factor of 0.0%, not all are truly 0%, as some of the experiments have a few stockouts, yet the overall stockout factor rounds to 0.0%. The experiments shown in Table 8-16, however, have no recorded stockouts throughout the simulated time. The highest SOF (14.1%), on the other hand, was achieved at the experiment signifying the inflated kanban policy with 100% SQ, 70% SOTD, and 30% DV.

In general, the periodic-review model tends to outperform the inflated kanban model with respect to the stockout factor, where a lower value is more desirable. Within the periodic-review policy, the SOF tends to be improved if the supplier quality is below 100%, the supplier on-time delivery level is above 70%, and the demand variability is greater than 0%. Finally, it appears that for the Inflated Kanban policy, the SOF improves as supplier quality decreases, supplier on-time delivery improves, and demand variability decreases.

Table 8-15. SOF for Varying Levels of Factors for Each Policy

Experiment Number		Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)	Periodic-Review (%)	Inflated Kanban (%)
Periodic-Review	Inflated Kanban					
20	3	70	85	15	**0.0**	4.6
25, 26, 27	8, 9, 10	85	85	15	**0.0**	7.6
32	15	100	85	15	**1.6**	8.3
23	6	85	70	15	**0.0**	12.9
25, 26, 27	8, 9, 10	85	85	15	**0.0**	7.6
29	12	85	100	15	**0.0**	**0.0**
24	7	85	85	0	**0.6**	6.5
25, 26, 27	8, 9, 10	85	85	15	**0.0**	7.6
28	11	85	85	30	**0.0**	9.6
18	1	70	70	0	**0.0**	4.9
19	2	70	70	30	**0.0**	10.0
21	4	70	100	0	**0.0**	**0.0**
22	5	70	100	30	**0.0**	**0.0**
30	13	100	70	0	14.1	**12.8**
31	14	100	70	30	**1.0**	18.4
33	16	100	100	0	0.2	**0.0**
34	17	100	100	30	**0.0**	0.1
35	----	92.5	77.5	7.5	1.6	----
36	----	96.25	73.75	3.75	2.8	----

Table 8-16. Experiments with a Stockout Factor of 0%

Ordering Policy	Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)
Inflated Kanban	70	100	0
Inflated Kanban	100	100	0
Periodic-Review	70	70	0
Periodic-Review	70	70	30
Periodic-Review	70	85	15
Periodic-Review	70	100	0
Periodic-Review	70	100	30
Periodic-Review	85	100	15

From a statistical perspective, each policy can be represented with a linear regression model as shown in Table 8-17. These models represent the coded experiments, which means that the lowest value for each factor is represented by –1, the moderate value is represented by 0, and the highest value is represented by 1. The table summarizes the intercept value, the coefficient values for all terms in the regression model, and the t-values for the intercept and coefficient terms.

Table 8-18 shows the R^2 values and p-values for the Lack-of-Fit test for each ordering policy. As shown in this table, both models have high R^2 values, signifying that each model tends to fit the data well. The low p-value for the periodic-review policy, however, signifies that the model exhibits Lack-of-Fit, meaning the model does not contain enough terms to completely represent the policy. To decrease this Lack-of-Fit, higher order terms must be added to the regression model. However, it was determined that a 2nd-order Taylor Series is an appropriate approximation for this analysis, so higher terms were not added to this model. The inflated kanban model, on the other hand, has a p-value greater than 0.05, indicating that no statistically significant Lack-of-Fit is present in the model. Also evident in Table 8-17 is that supplier quality appears to have the most significant effect on the stockout factor for the periodic-review model, whereas the inflated kanban model appears to be most affected by the supplier on-time delivery factor.

Table 8-17. Linear Regression Model for Stockout Factor

Factors	Periodic-Review		Inflated Kanban	
	Coefficient	t-value	Coefficient	t-value
Intercept	0.002	0.93	0.077	43.1
Quality	0.007	4.46	0.02	14.6
Time	-0.005	-3.13	-0.059	-43
Demand	-0.004	-2.47	0.014	10.1
$Quality^2$	0.006	2.04	-0.01	-4.06
$Time^2$	-0.002	-0.77	-0.01	-3.91
$Demand^2$	0.001	0.29	0	---
Quality * Time	-0.006	-3.24	-0.02	-13.2
Quality * Demand	-0.004	-2.1	0	---
Time * Demand	0.003	1.82	-0.013	-8.58

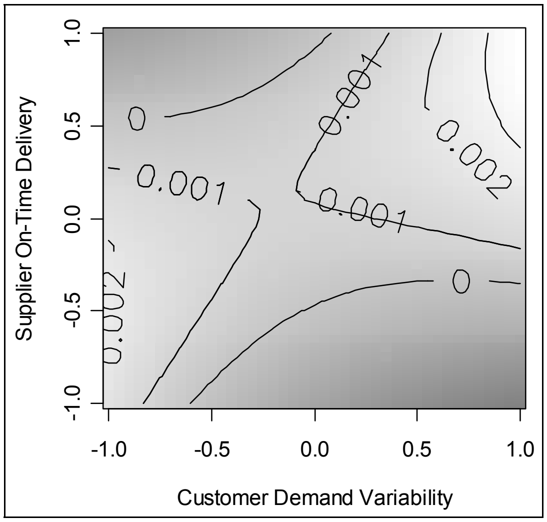
Table 8-18. Summary of Linear Regression Model for Stockout Factor

	Periodic-Review	Inflated Kanban
R-Squared Value	0.8439	0.9964
Lack-of-Fit p-value	<.0001	0.213

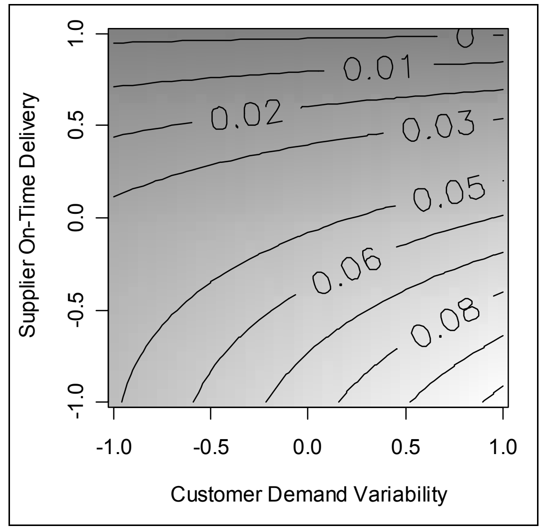
Contour plots have been generated from these regression models and are shown in Figure 8-4. Individual plots are shown for each ordering policy for each of the three supplier quality levels. Since the models are based on the coded experiments, the values on each axis represent the coded values. The contours for these plots represent the decimal value for the stockout factor, not the percent value, meaning that a contour with a value of 0.002, has a SOF of 0.2%. The plots illustrate the impact of supplier on-time delivery and customer demand variability on the stockout factor.

As shown in these plots, the periodic-review policy appears to outperform the inflated kanban policy. For the periodic-review policy, shown in Figure 8-4a, c, and e, the stockout factor tends to improve as supplier quality decreases, as supplier on-time delivery performance increases, and demand variability increases. For the inflated kanban policy, shown in Figure 8-4b, d, and f, the stockout factor appears to improve as supplier quality decreases, supplier on-time delivery performance improves, and as demand variability decreases.

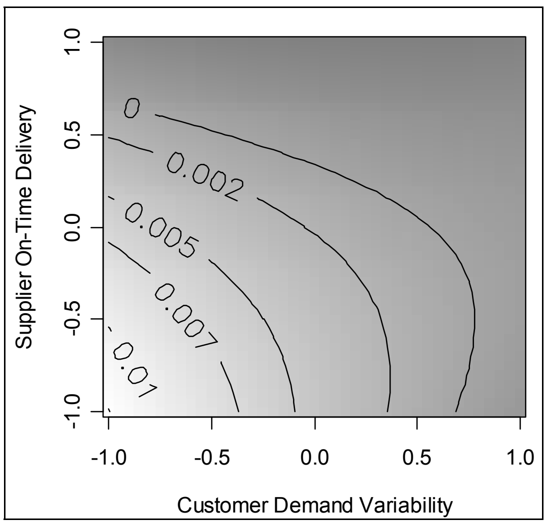
In summary, the periodic-review policy tends to outperform the inflated kanban policy in terms of the amount of time the cell is stocked out for most levels of the factors. For the periodic-review model, supplier quality appears to have the most significant affect on the SOF, and the number of stockouts tends to improve as supplier quality decreases, supplier on-time delivery performance increases, and demand variability increases. For the inflated kanban policy, supplier on-time delivery appears to have the largest impact on the stockout factor, and the number of stockouts tends to improve as supplier quality decreases, supplier on-time delivery performance improves, and demand variability decreases. Again, both the periodic-review policy and the inflated kanban policy are adjusted for supplier quality, which provides evidence for why the policies perform well for lower quality levels.



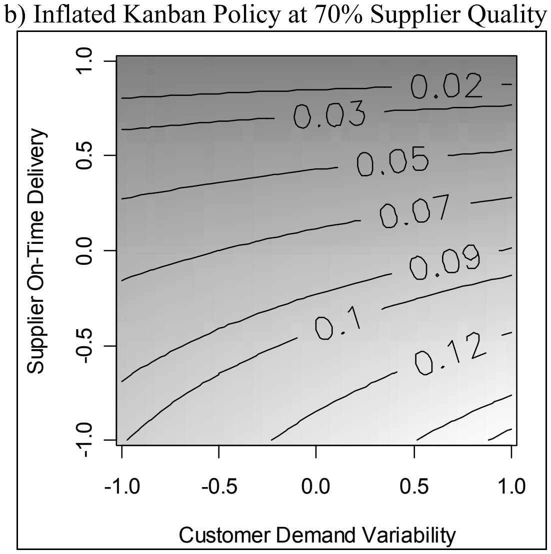
a) Periodic-Review Policy at 70% Supplier Quality



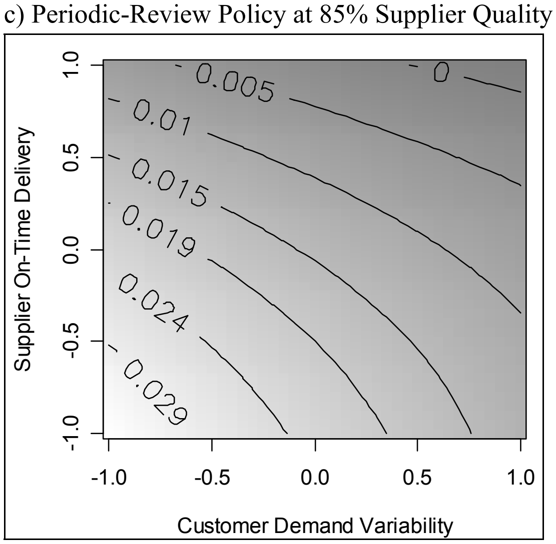
b) Inflated Kanban Policy at 70% Supplier Quality



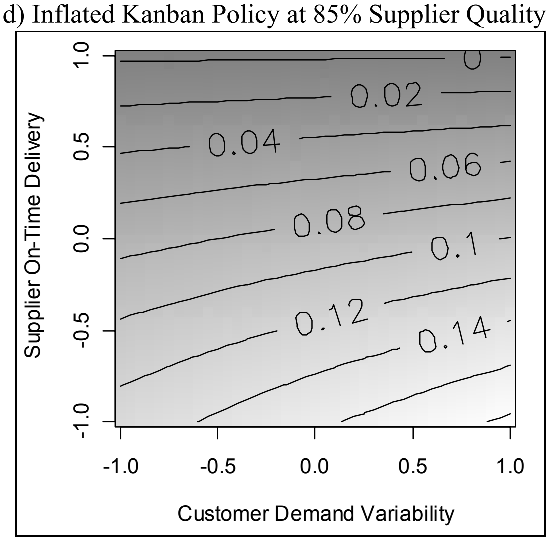
c) Periodic-Review Policy at 85% Supplier Quality



d) Inflated Kanban Policy at 85% Supplier Quality



e) Periodic-Review Policy at 100% Supplier Quality



f) Inflated Kanban Policy at 100% Supplier Quality

Figure 8-4. Contour Plots for the Stockout Factor Variable

8.6. SUPPLIED PART INVENTORY FACTOR

The results for the supplied part inventory factor performance measure are summarized in Table 8-19. This table includes the levels for the factors supplier quality, supplier on-time delivery, and demand variability, and the inventory factor for each ordering policy for each of the experiments associated with that set of factor levels.

As shown, the lowest supplied part inventory factor (InvFac) was achieved at 139 motors at the experiment signifying the inflated kanban policy with 85% SQ, 70% SOTD, and 15% DV. The highest inventory factor (1398 motors), on the other hand, was achieved at two experiments, signifying the periodic-review policy with 70% SQ, 70% SOTD, and 30% DV, and with 70% SQ, 100% SOTD, and 30% DV.

In general, the inflated kanban model appears to outperform the periodic-review model with respect to the supplied part inventory factor, where a lower value is more desirable. Furthermore, for the periodic-review policy, the inventory factor tends to improve as supplier quality increases, supplier on-time delivery decreases, and demand variability decreases. Finally, it appears that for the Inflated Kanban policy, the inventory factor is more desirable if supplier quality is above 70%, and improves as supplier on-time delivery decreases.

Table 8-19. Inventory Factor for Varying Levels of Factors for Each Policy

Experiment Number		Supplier Quality (%)	Supplier OTD (%)	Demand Var. (%)	Periodic-Review (# of Motors)	Inflated Kanban (# of Motors)
Periodic-Review	Inflated Kanban					
20	3	70	85	15	1086	**152**
25, 26, 27	8, 9, 10	85	85	15	856	**140**
32	15	100	85	15	711	**142**
23	6	85	70	15	845	**139**
25, 26, 27	8, 9, 10	85	85	15	856	**140**
29	12	85	100	15	867	**142**
24	7	85	85	0	530	**141**
25, 26, 27	8, 9, 10	85	85	15	856	**140**
28	11	85	85	30	1095	**140**
18	1	70	70	0	673	**152**
19	2	70	70	30	1398	**151**
21	4	70	100	0	673	**153**
22	5	70	100	30	1398	**153**
30	13	100	70	0	433	**141**
31	14	100	70	30	881	**140**
33	16	100	100	0	453	**144**
34	17	100	100	30	904	**144**
35	----	92.5	77.5	7.5	656	**----**
36	----	96.25	73.75	3.75	584	**----**

From a statistical perspective, each policy can be represented with a linear regression model as shown in Table 8-20. These models represent the coded experiments, which means that the lowest value for each factor is represented by –1, the moderate value is represented by 0, and the highest value is represented by 1. The table summarizes the intercept value, the coefficient values for all terms in the regression model, and the t-values for the intercept and coefficient terms.

Table 8-21 shows the R^2 values and p-values for the Lack-of-Fit test for each ordering policy. As shown in this table, both models have high R^2 values, signifying that each model tends to fit the data well. The low p-value for the periodic-review policy, however, signifies that the model exhibits Lack-of-Fit, meaning the model does not contain enough terms to completely represent the policy. To decrease this Lack-of-Fit, higher order terms must be added to the regression model. However, it was determined that a 2nd-order Taylor Series is an appropriate approximation for this analysis, so higher terms were not added to this model. The inflated kanban model, on the other hand, has a p-value greater than 0.05, indicating that no statistically significant Lack-of-Fit is present in the model. Also evident in Table 8-20 is that supplier on-time delivery appears to have the least significant effect on the inventory factor for the periodic-review model, while supplier quality appears to have the most significant effect for the inflated kanban model.

Table 8-20. Linear Regression Model for Inventory Factor

Factors	Periodic-Review		Inflated Kanban	
	Coefficient	t-value	Coefficient	t-value
Intercept	857	145	140.3	960
Quality	-177	-39.1	-5.05	-41.3
Time	-0.95	-0.2	1.303	10.7
Demand	284	62.7	0	---
$Quality^2$	43.8	5.1	6.864	36
$Time^2$	1.29	0.2	0	---
$Demand^2$	-42.2	-4.9	0	---
Quality * Time	-3.28	-0.6	0.49	3.58
Quality * Demand	-77.5	-14.7	0	---
Time * Demand	9.03	1.7	0	---

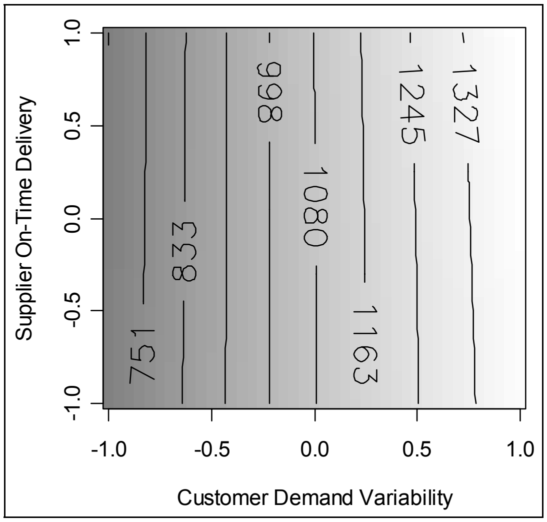
Table 8-21. Summary of Linear Regression Model for Inventory Factor

	Periodic-Review	Inflated Kanban
R-Squared Value	0.9987	0.9962
Lack-of-Fit p-value	0.0013	0.4341

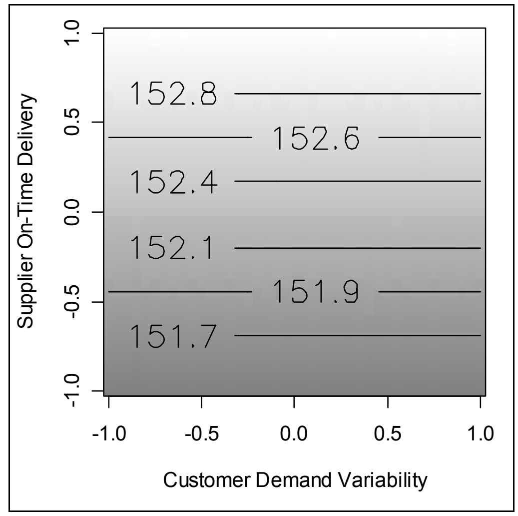
Contour plots have been generated from these regression models and are shown in Figure 8-5. Individual plots are shown for each ordering policy for each of the three supplier quality levels. Since the models are based on the coded experiments, the values on each axis represent the coded values. The plots illustrate the impact of supplier on-time delivery and customer demand variability on the supplied part inventory factor.

As shown in these plots the inflated kanban policy appears to dominate the periodic-review policy in terms of the required amount of supplied part inventory. For the periodic-review policy, shown in Figure 8-5a, c, and e, the inventory factor tends to improve as the supplier quality increases and demand variability decreases. For the inflated kanban policy, shown in Figure 8-5b, d, and f, the inventory factor appears to be more preferable if the supplier quality is greater than 70%, and appears to improve as supplier on-time delivery levels decrease.

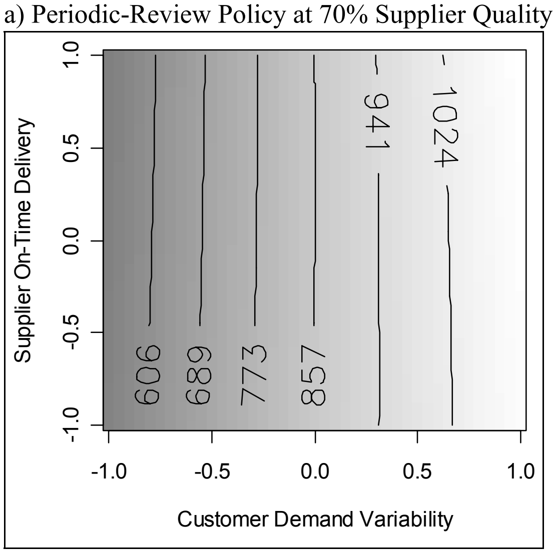
In summary, the inflated kanban policy appears to outperform the periodic-review policy in terms of the amount of supplied part inventory in the cell for most levels of the factors. For the periodic-review model, supplier on-time delivery has the least impact on the inventory factor, and the amount of supplied part inventory in the cell improves as the supplier quality increases and demand variability decreases. For the inflated kanban policy, supplier quality appears to have the largest impact on the inventory factor, and the amount of supplied part inventory appears to be more preferable if the supplier quality is greater than 70%, and appears to improve as supplier on-time delivery levels decrease. Again, both the periodic-review policy and the inflated kanban policy are adjusted for supplier quality, which provides evidence for why the policies perform worst for the inventory factor performance measure at lower quality levels.



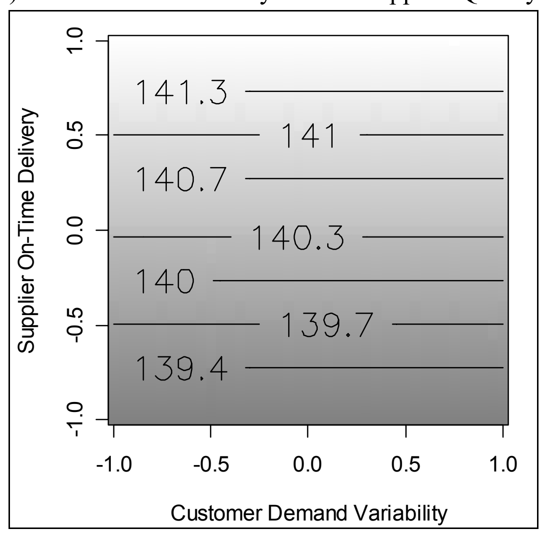
a) Periodic-Review Policy at 70% Supplier Quality



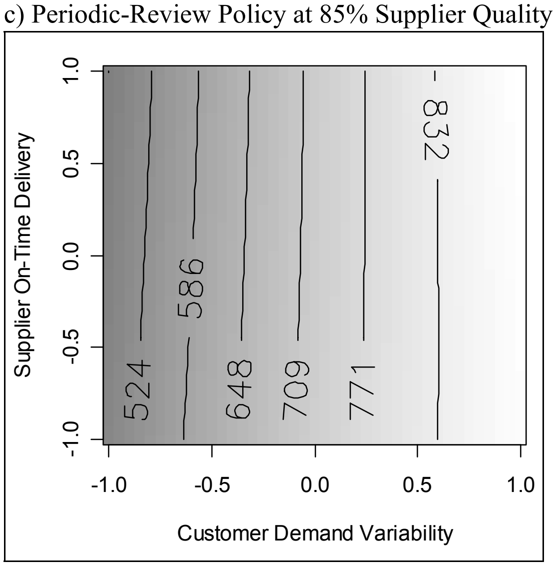
b) Inflated Kanban Policy at 70% Supplier Quality



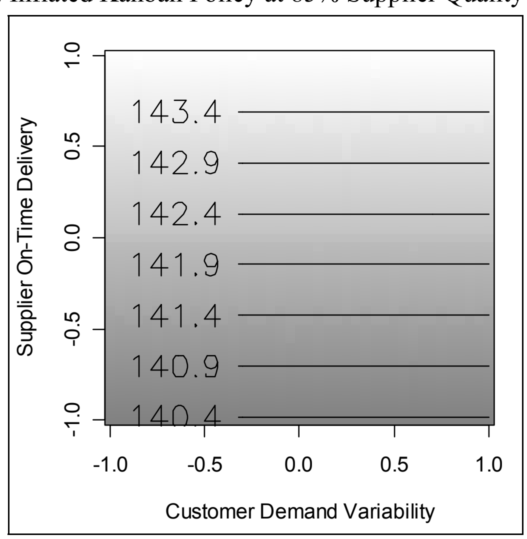
c) Periodic-Review Policy at 85% Supplier Quality



d) Inflated Kanban Policy at 85% Supplier Quality



e) Periodic-Review Policy at 100% Supplier Quality



f) Inflated Kanban Policy at 100% Supplier Quality

Figure 8-5. Contour Plots for the Inventory Factor Variable

8.7. RESULTS SUMMARY

Based on the results from each of the six performance measures, the periodic-review policy appears to outperform the inflated kanban model with respect to flowtime, on-time delivery to the customer, work-in-process inventory levels, and stockout factor. However, the inflated kanban model appears to dominate the periodic-review policy with respect to the supplied part inventory factor. In addition, the inflated kanban model tends to perform reasonably well at high levels of supplier on-time delivery and low levels of demand variability for the other four performance measures.

The two factors with the largest effect on the performance of the cell for the periodic-review policy tended to be supplier quality and demand variability. The factor with the largest effect on the performance of the cell for the inflated kanban policy tended to be supplier on-time delivery. Both the periodic-review policy and the inflated kanban policy are adjusted for supplier quality levels, which provides evidence for why the policies perform well at lower quality levels.

CHAPTER IX

SUMMARY AND CONCLUSIONS

The purpose of this research was to determine the effect of the ordering policy for supplied parts on the performance of a manufacturing cell under conditions of variable customer demand and supplier performance levels. Specifically the factors of interest were:

- Ordering policy (periodic-review, uninflated kanban, and inflated kanban);
- Supplier quality (70%, 85%, and 100%);
- Supplier on-time delivery (70%, 85%, and 100%); and
- Demand variability (0%, 15%, and 30%).

The effect of the factors on the performance of a manufacturing cell was analyzed using an augmented central composite design and a detailed simulation model. The performance of the manufacturing cell was measured by:

- Flowtime;
- On-time delivery to the customer;
- Work-in-process inventory;
- Stockout factor; and
- Inventory factor.

The results obtained from this study suggest that the preferred ordering policy for supplied parts is the periodic-review policy for most levels of the three other factors. However, this policy results in high levels of supplied part inventory, which is the reason for the high performance for most response variables. This increased inventory is in direct conflict with one of the key principles of Lean Production, waste reduction.

Furthermore, the inflated kanban policy tends to perform well at high levels of supplier on-time delivery and low levels of customer demand variability. These results are consistent with the proper conditions under which to implement Lean Production: good supplier performance and level customer demand.

This study also shows that if the number of kanban cards utilized in a manufacturing system is not inflated by the quality levels of the supplier, the system will not perform well. This is contrary to most kanban calculations shown in journal articles or textbooks (Olhager, 1995; Nahmias, 1997; Sipper and Bulfin, 1997). If the number of kanban cards for a supplier with poor quality is not inflated, the performance of a manufacturing cell transitioning to lean production may be negatively impacted.

Since both the periodic-review policy and the inflated kanban policy are inflated for lower supplier quality levels, both policies tend to perform well for lower quality levels. In fact, when on-time delivery is low and customer demand variability is high, both policies perform better at lower levels of supplier quality than higher levels. Inflating for supplier quality levels results in increased inventory levels, which allows more flexibility for lower supplier on-time delivery levels and increases in demand variability.

Comparing this analysis to the literature reviewed in Chapter 3 is difficult, as the analyses use different factors, levels, and performance measures. However, some comparisons can be made with the reviewed literature, and are promising. For instance, both this analysis and the analysis completed by Yang (1998) determine that the reorder point policy with continuous review requires more inventory to achieve the same performance for the manufacturing cell. Also, both this analysis and Bassok and Akella (1991) conclude that sizeable gains can be achieved using Just-in-Time policies. Finally, both this analysis and Savasor and Al-Jawini (1995) agree that manufacturing cells are highly affected by the variability in demand.

The positive results from inflating the policies for lower supplier quality may also support including an inflation factor for the supplier on-time delivery level in the kanban calculation. Since the on-time delivery of the suppliers has a significant impact on the performance of the manufacturing cell, the effect of including an inflation factor for the supplier on-time delivery percentage is an area for further research. Further research should also be conducted on the manufacturing cell to determine how its performance would be affected by changes in the current factors or by new factors added to the analysis. One change of interest is to place a restriction on the amount of supplied part inventory the manufacturing cell can hold, allowing for a more realistic analysis of the periodic-review policy. Another change to the current analysis is to expand the types of demand profiles analyzed. This research focuses on demand variation around an average level of demand. Other demand profiles include linearly increasing, linearly decreasing, and cyclical demand. A third change of interest is to look at the effect of a flexibile kanban system, with the demand known several weeks in advance. A flexible kanban system is established in a manufacturing cell with widely varying demand, where production leveling is difficult. In this system, the number of kanban cards throughout the manufacturing cell can be adjusted depending on the demand for a specific product. This general area of research on improving the performance of a manufacturing cell during the transition to a Lean Production environment is an area of importance for both researcher and practitioners.

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APPENDIX A

EXPERIMENTAL DESIGNS

Table A-1. Complete Experimental Design

Experiment #	Ordering Policy	Supplier Quality	Supplier On-Time Delivery	Demand Variability
1	Inflated Kanban	70%	70%	0%
2	Inflated Kanban	70%	70%	30%
3	Inflated Kanban	70%	85%	15%
4	Inflated Kanban	70%	100%	0%
5	Inflated Kanban	70%	100%	30%
6	Inflated Kanban	85%	70%	15%
7	Inflated Kanban	85%	85%	0%
8	Inflated Kanban	85%	85%	15%
9	Inflated Kanban	85%	85%	15%
10	Inflated Kanban	85%	85%	15%
11	Inflated Kanban	85%	85%	30%
12	Inflated Kanban	85%	100%	15%
13	Inflated Kanban	100%	70%	0%
14	Inflated Kanban	100%	70%	30%
15	Inflated Kanban	100%	85%	15%
16	Inflated Kanban	100%	100%	0%
17	Inflated Kanban	100%	100%	30%
18	Periodic-Review	70%	70%	0%
19	Periodic-Review	70%	70%	30%
20	Periodic-Review	70%	85%	15%
21	Periodic-Review	70%	100%	0%
22	Periodic-Review	70%	100%	30%
23	Periodic-Review	85%	70%	15%
24	Periodic-Review	85%	85%	0%
25	Periodic-Review	85%	85%	15%
26	Periodic-Review	85%	85%	15%
27	Periodic-Review	85%	85%	15%
28	Periodic-Review	85%	85%	30%
29	Periodic-Review	85%	100%	15%
30	Periodic-Review	100%	70%	0%
31	Periodic-Review	100%	70%	30%
32	Periodic-Review	100%	85%	15%
33	Periodic-Review	100%	100%	0%
34	Periodic-Review	100%	100%	30%

Table A-1. Complete Experimental Design

(continued from previous page)

Experiment #	Ordering Policy	Supplier Quality	Supplier On-Time Delivery	Demand Variability
35	Non-Inflated Kanban	70%	70%	0%
36	Non-Inflated Kanban	70%	70%	30%
37	Non-Inflated Kanban	70%	85%	15%
38	Non-Inflated Kanban	70%	100%	0%
39	Non-Inflated Kanban	70%	100%	30%
40	Non-Inflated Kanban	85%	70%	15%
41	Non-Inflated Kanban	85%	85%	0%
42	Non-Inflated Kanban	85%	85%	15%
43	Non-Inflated Kanban	85%	85%	15%
44	Non-Inflated Kanban	85%	85%	15%
45	Non-Inflated Kanban	85%	85%	30%
46	Non-Inflated Kanban	85%	100%	15%
47	Non-Inflated Kanban	100%	70%	0%
48	Non-Inflated Kanban	100%	70%	30%
49	Non-Inflated Kanban	100%	85%	15%
50	Non-Inflated Kanban	100%	100%	0%
51	Non-Inflated Kanban	100%	100%	30%

Table A-2. Complete Coded Experimental Design

Factor	Level –1	Level 0	Level 1
Supplier Quality	70	85	100
Supplier On-Time Delivery	70	85	100
Demand Variability	0	15	30

Table A-3. Complete Coded Experimental Design

Experiment #	Ordering Policy	Supplier Quality	Supplier On-Time Delivery	Demand Variability
1	Inflated Kanban	-1	-1	-1
2	Inflated Kanban	-1	-1	1
3	Inflated Kanban	-1	0	0
4	Inflated Kanban	-1	1	-1
5	Inflated Kanban	-1	1	1
6	Inflated Kanban	0	-1	0
7	Inflated Kanban	0	0	-1
8	Inflated Kanban	0	0	0
9	Inflated Kanban	0	0	0
10	Inflated Kanban	0	0	0
11	Inflated Kanban	0	0	1
12	Inflated Kanban	0	1	0
13	Inflated Kanban	1	-1	-1
14	Inflated Kanban	1	-1	1
15	Inflated Kanban	1	0	0
16	Inflated Kanban	1	1	-1
17	Inflated Kanban	1	1	1
18	Periodic-Review	-1	-1	-1
19	Periodic-Review	-1	-1	1
20	Periodic-Review	-1	0	0
21	Periodic-Review	-1	1	-1
22	Periodic-Review	-1	1	1
23	Periodic-Review	0	-1	0
24	Periodic-Review	0	0	-1
25	Periodic-Review	0	0	0
26	Periodic-Review	0	0	0
27	Periodic-Review	0	0	0
28	Periodic-Review	0	0	1
29	Periodic-Review	0	1	0
30	Periodic-Review	1	-1	-1
31	Periodic-Review	1	-1	1
32	Periodic-Review	1	0	0
33	Periodic-Review	1	1	-1
34	Periodic-Review	1	1	1

Table A-3. Complete Coded Experimental Design

(continued from previous page)

Experiment #	Ordering Policy	Supplier Quality	Supplier On-Time Delivery	Demand Variability
35	Non-Inflated Kanban	-1	-1	-1
36	Non-Inflated Kanban	-1	-1	1
37	Non-Inflated Kanban	-1	0	0
38	Non-Inflated Kanban	-1	1	-1
39	Non-Inflated Kanban	-1	1	1
40	Non-Inflated Kanban	0	-1	0
41	Non-Inflated Kanban	0	0	-1
42	Non-Inflated Kanban	0	0	0
43	Non-Inflated Kanban	0	0	0
44	Non-Inflated Kanban	0	0	0
45	Non-Inflated Kanban	0	0	1
46	Non-Inflated Kanban	0	1	0
47	Non-Inflated Kanban	1	-1	-1
48	Non-Inflated Kanban	1	-1	1
49	Non-Inflated Kanban	1	0	0
50	Non-Inflated Kanban	1	1	-1
51	Non-Inflated Kanban	1	1	1

APPENDIX B

KANBAN STARTING VALUES

To determine the number of kanbans at each of the three locations at the beginning of the simulation the following computations were made:

1) To determine the number of cards at the manufacturing cell (K_{Cell}) take the total number of kanbans in the system (K_{Total}) and subtract from that the number of kanbans required for safety stock, which is found by dividing the number of parts in safety stock (SS) by the container quantity for that part (*C*). Then divide this result by three, add back in the number of kanban cards used for safety stock, and round the answer up to the nearest whole number. A mathematical representation of the process is shown as follows:

$$K_{Cell} = \left\lceil \frac{K_{Total} - \frac{SS}{C}}{3} + \frac{SS}{C} \right\rceil \tag{B.1}$$

2) To determine the number of cards at the supplier (KSupplier), take the total number of kanban cards in the system (KTotal), and subtract the number of kanban cards required at the manufacturing cell (KCell). Then divide the result by two and round it up to the nearest whole number. A mathematical representation of the process is shown as follows:

$$K_{Supplier} = \left\lceil \frac{K_{Total} - K_{Cell}}{2} \right\rceil \tag{B.2}$$

3) To determine the number of cards en-route (K_{Route}), take the total number of kanban cards for the system (K_{Total}) and subtract the number of cards at the manufacturing cell (K_{Cell}) and those at the supplier ($K_{Supplier}$). A mathematical representation of the process is shown as follows:

$$K_{Route} = K_{Total} - (K_{Cell} + K_{Supplier}) \tag{B.3}$$

APPENDIX C

WARM-UP PERIOD GRAPHS

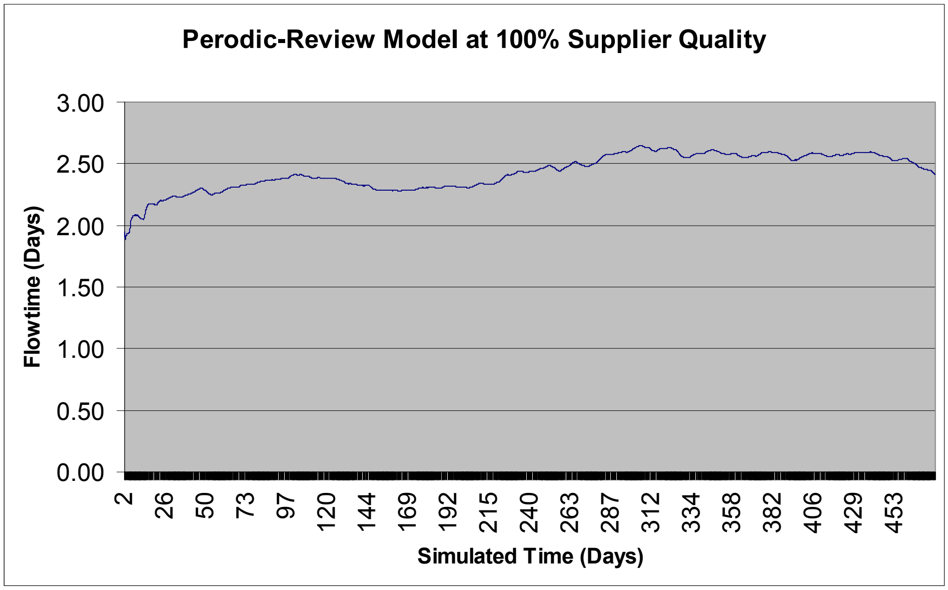

Figure C-1. Moving Average of Flowtime for Periodic-Review Policy at 100% Supplier Quality, 70% Supplier On-Time Delivery, and 0% Demand Variability

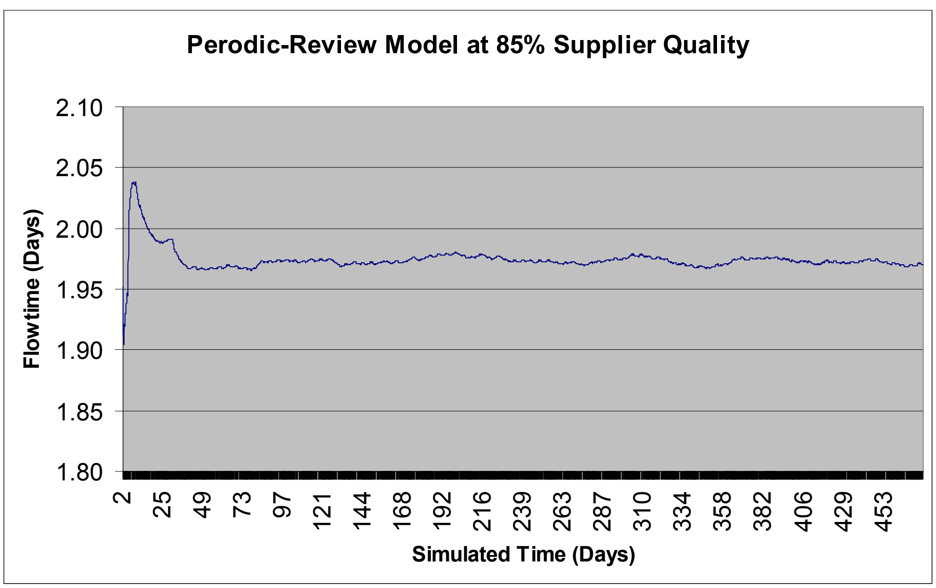

Figure C-2. Moving Average of Flowtime for Periodic-Review Policy at 85% Supplier Quality, 70% Supplier On-Time Delivery, and 0% Demand Variability

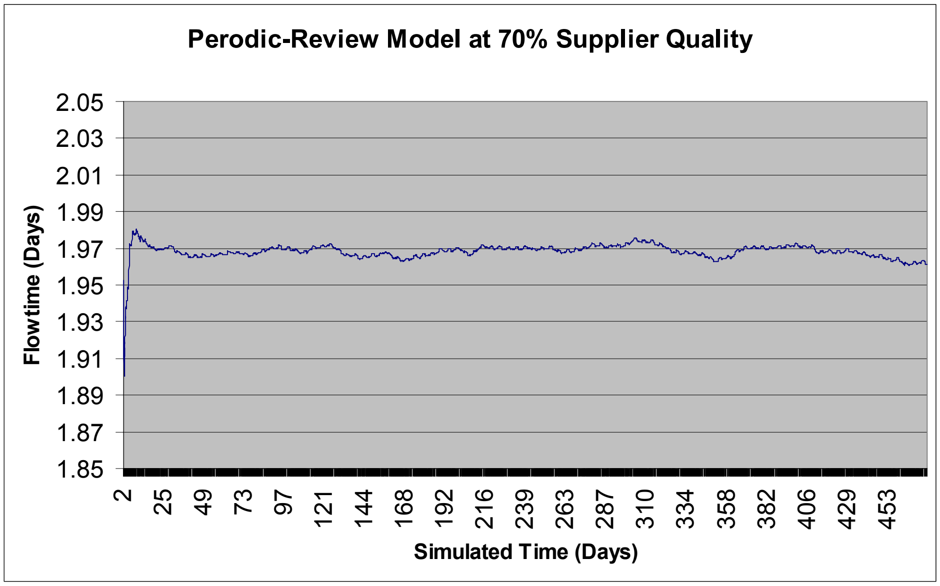

Figure C-3. Moving Average of Flowtime for Periodic-Review Policy at 70% Supplier Quality, 70% Supplier On-Time Delivery, and 0% Demand Variability

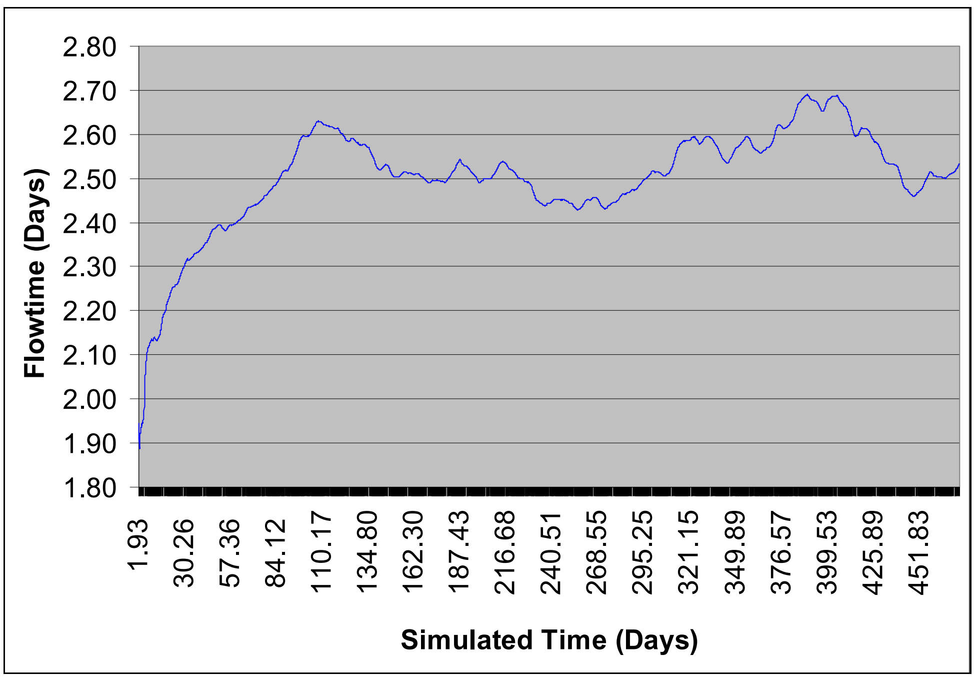

Figure C-4. Moving Average of Flowtime for Inflated Kanban Policy at 100% Supplier Quality, 70% Supplier On-Time Delivery, and 30% Demand Variability

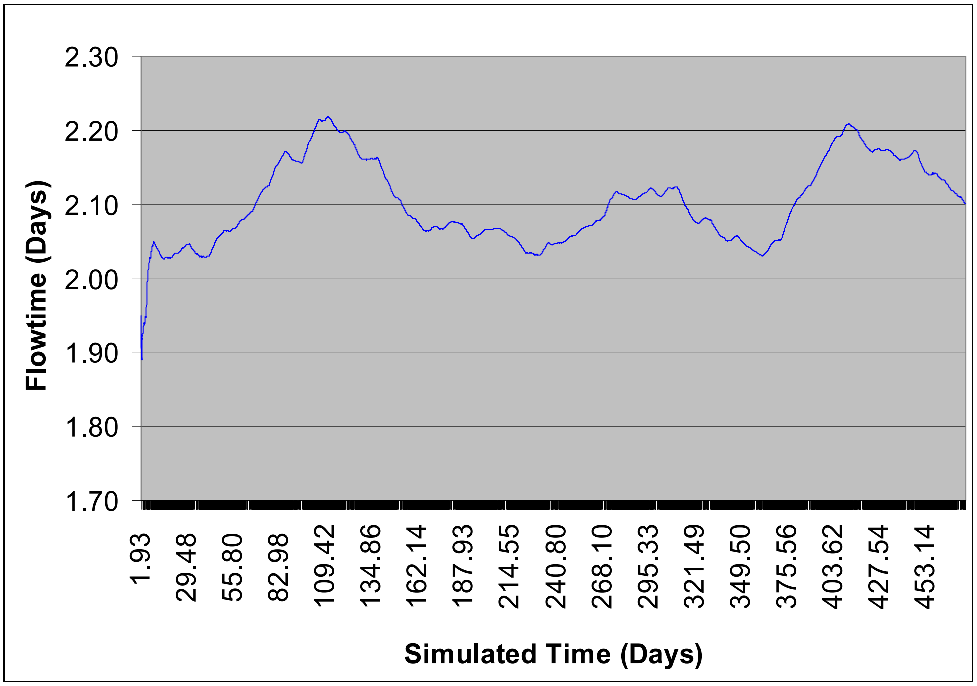

Figure C-5. Moving Average of Flowtime for Inflated Kanban Policy at 85% Supplier Quality, 70% Supplier On-Time Delivery, and 30% Demand Variability

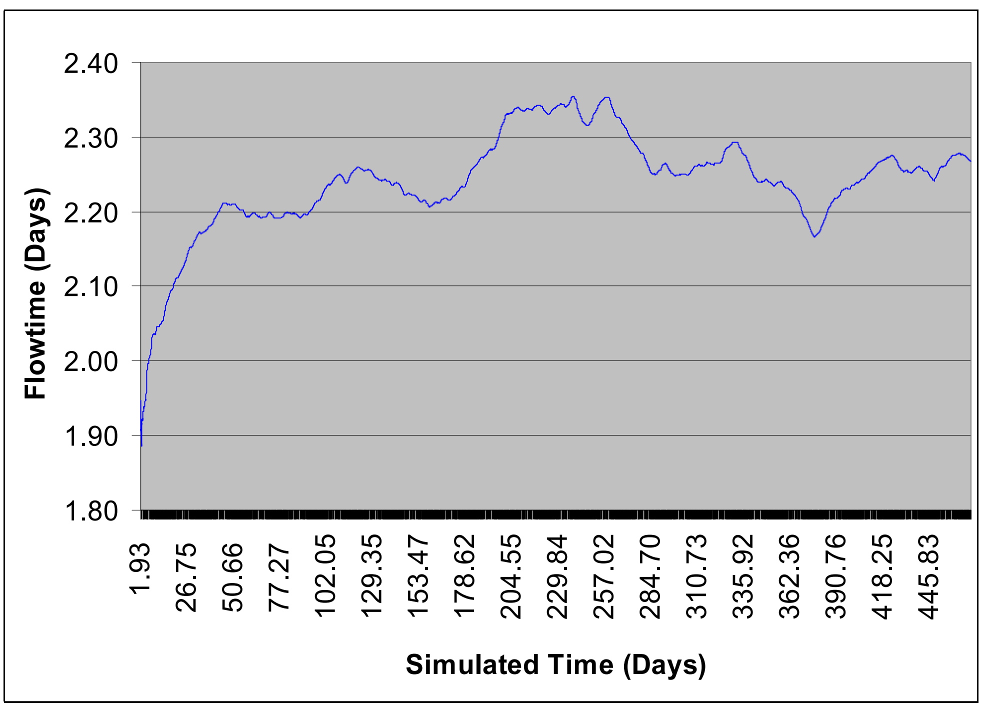

Figure C-6. Moving Average of Flowtime for Inflated Kanban Policy at 70% Supplier Quality, 70% Supplier On-Time Delivery, and 30% Demand Variability

APPENDIX D

NON-INFLATED KANBAN POLICY WARM-UP PERIOD GRAPHS

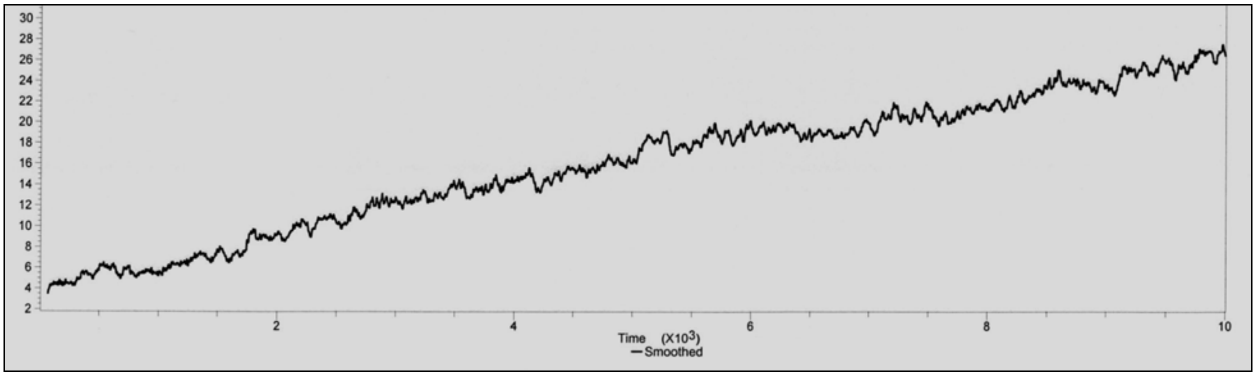

Figure D-1. Moving Average Plot for 70% Supplier Quality, 70% Supplier On-Time Delivery, and 0% Demand Variability

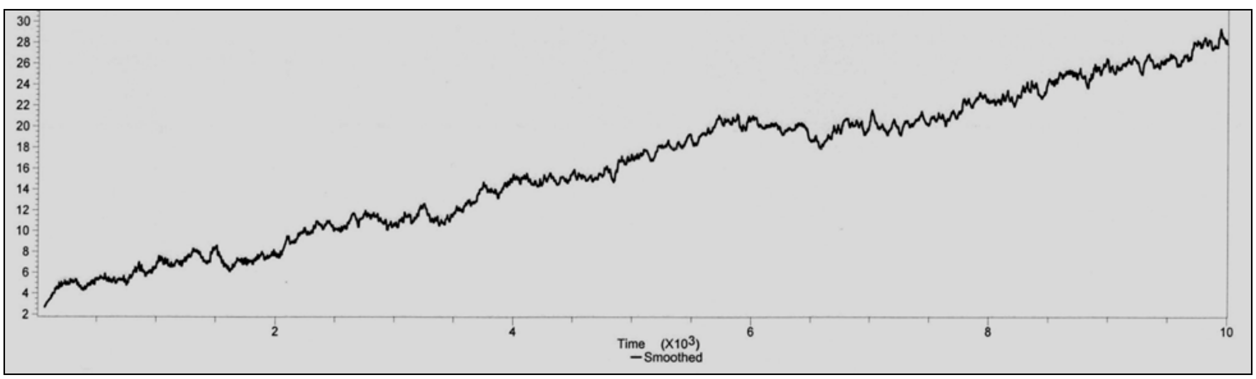

Figure D-2. Moving Average Plot for 70% Supplier Quality, 70% Supplier On-Time Delivery, and 0% Demand Variability

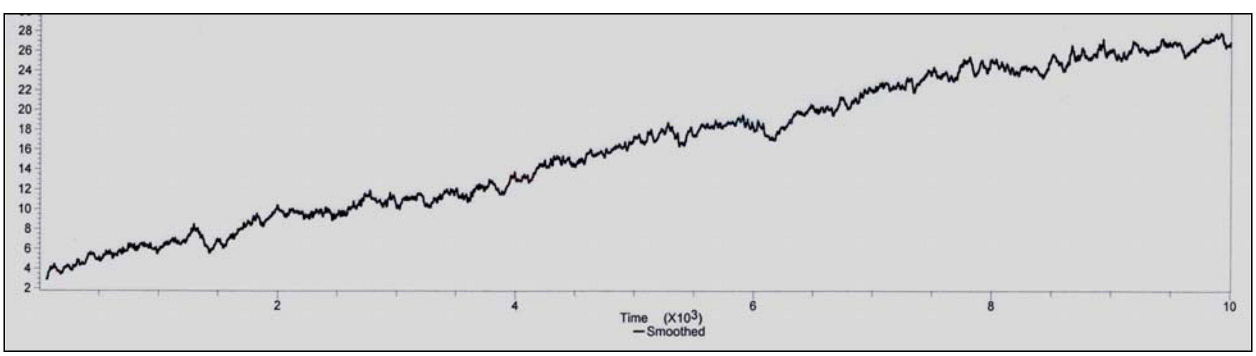

Figure D-3. Moving Average Plot for 70% Supplier Quality, 70% Supplier On-Time Delivery, and 30% Demand Variability

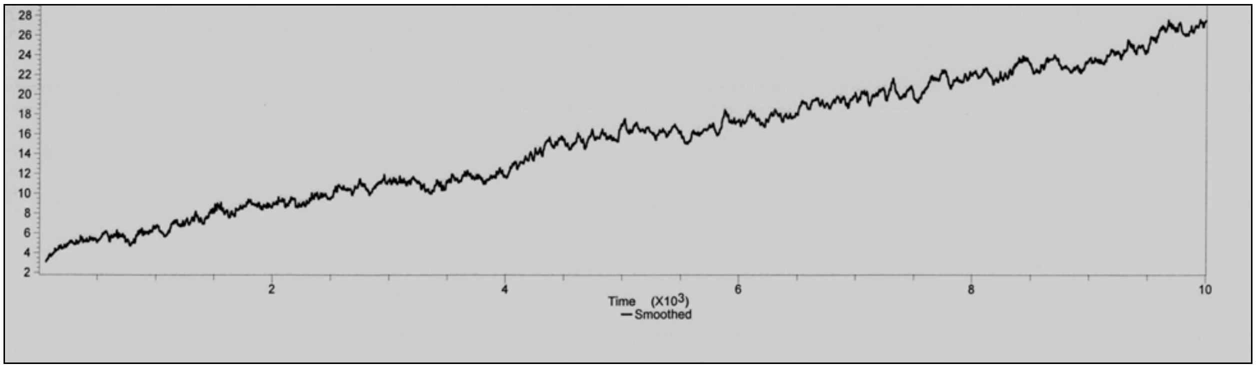

Figure D-4. Moving Average Plot for 70% Supplier Quality, 70% Supplier On-Time Delivery, and 30% Demand Variability

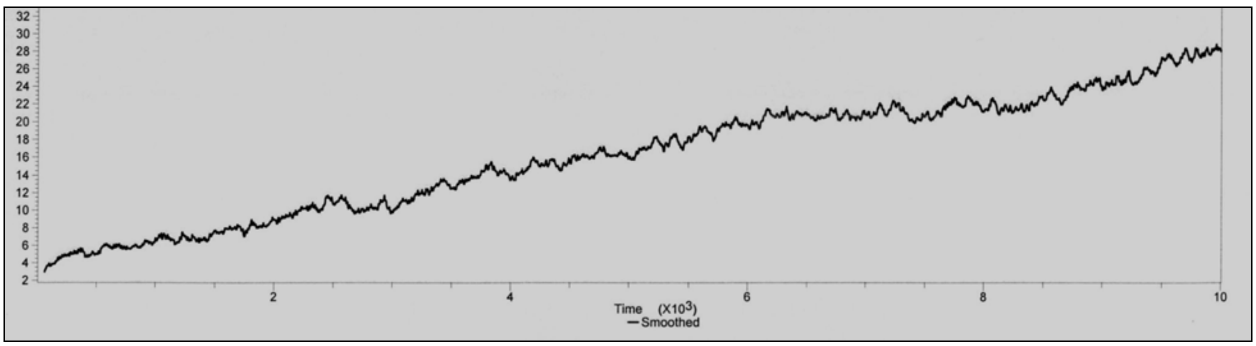

Figure D-5. Moving Average Plot for 70% Supplier Quality, 85% Supplier On-Time Delivery, and 15% Demand Variability

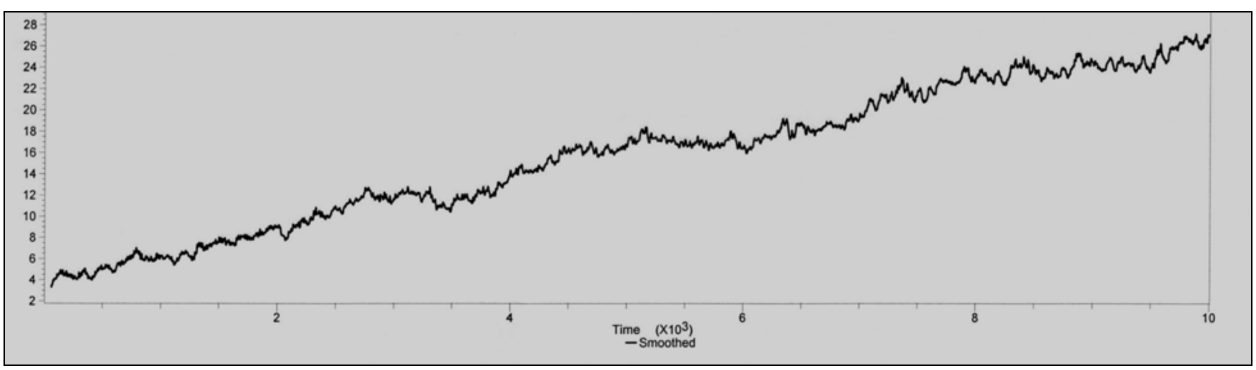

Figure D-6. Moving Average Plot for 70% Supplier Quality, 85% Supplier On-Time Delivery, and 15% Demand Variability

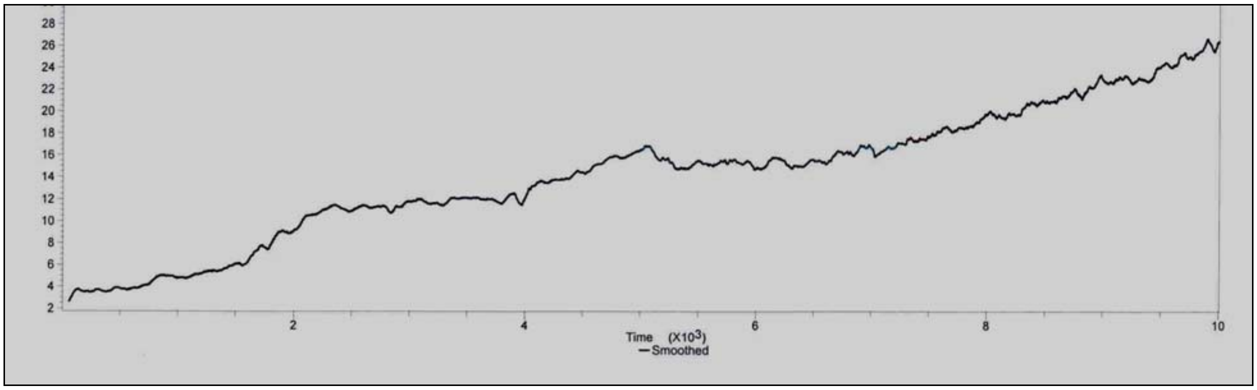

Figure D-7. Moving Average Plot for 70% Supplier Quality, 100% Supplier On-Time Delivery, and 30% Demand Variability

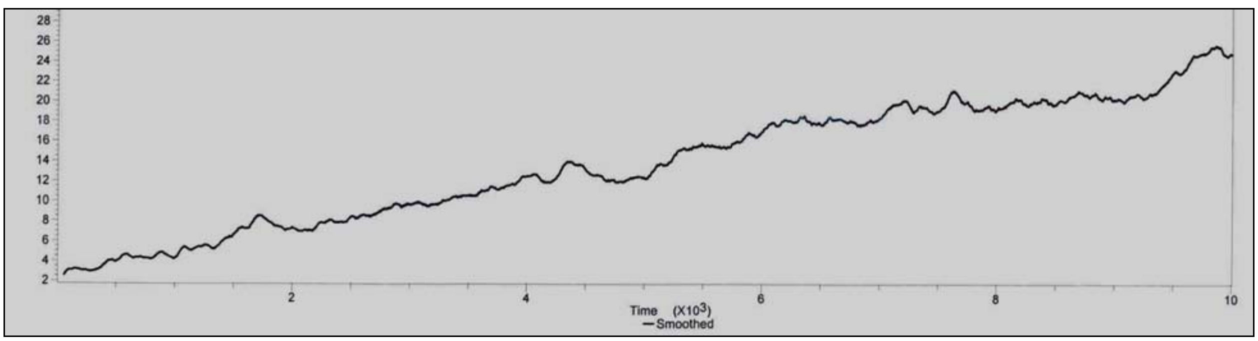

Figure D-8. Moving Average Plot for 70% Supplier Quality, 100% Supplier On-Time Delivery, and 30% Demand Variability

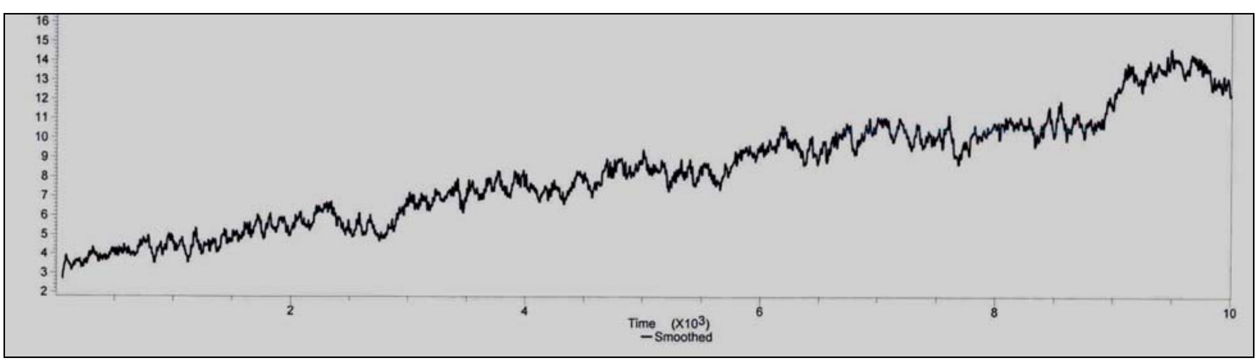

Figure D-9. Moving Average Plot for 85% Supplier Quality, 70% Supplier On-Time Delivery, and 15% Demand Variability

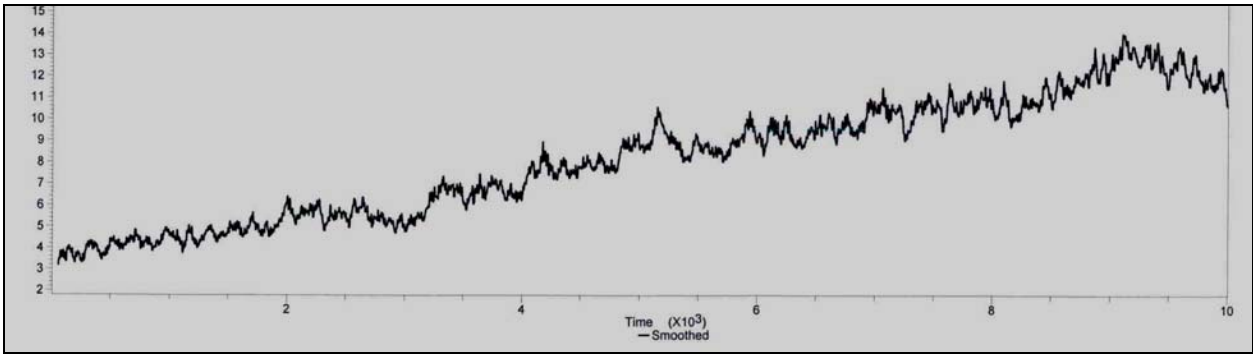

Figure D-10. Moving Average Plot for 85% Supplier Quality, 70% Supplier On-Time Delivery, and 15% Demand Variability

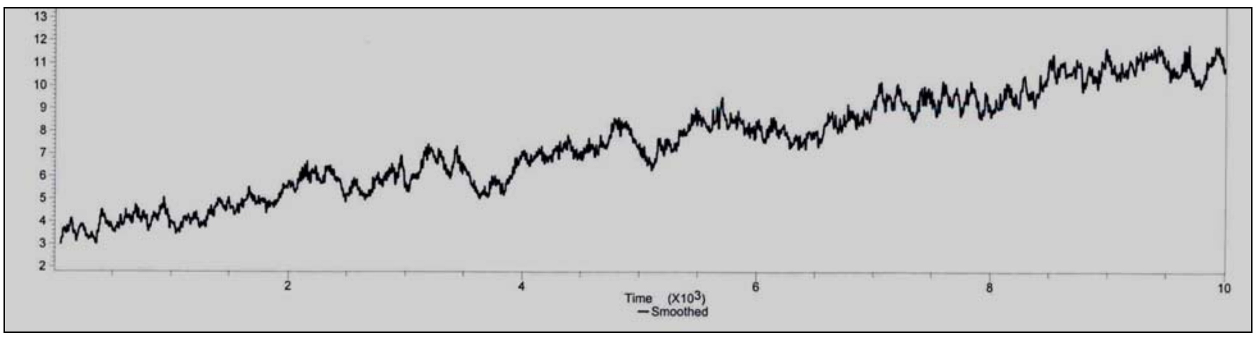

Figure D-11. Moving Average Plot for 85% Supplier Quality, 85% Supplier On-Time Delivery, and 0% Demand Variability

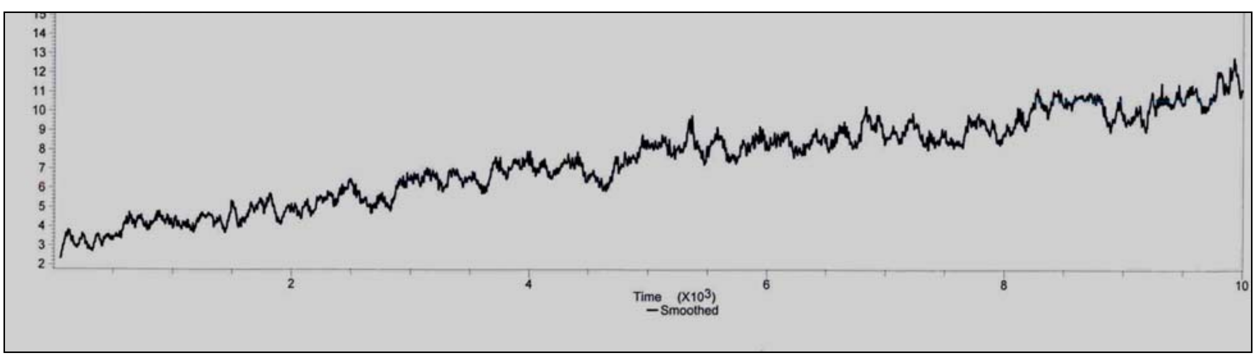

Figure D-12. Moving Average Plot for 85% Supplier Quality, 85% Supplier On-Time Delivery, and 0% Demand Variability

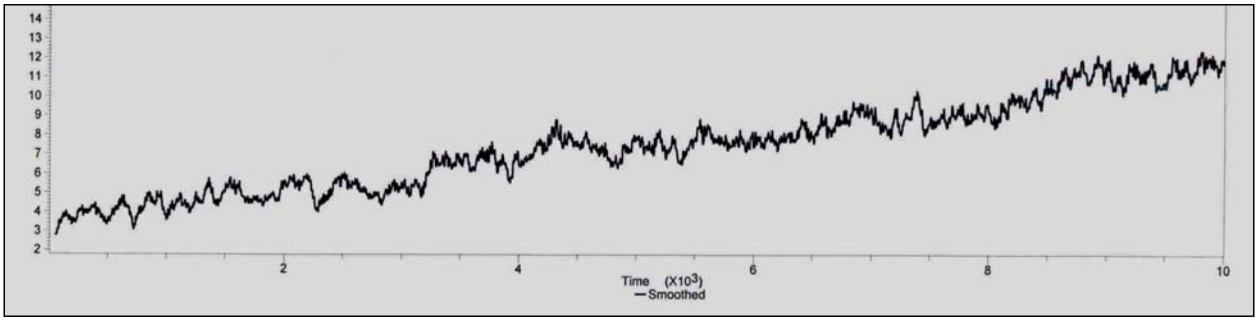

Figure D-13. Moving Average Plot for 85% Supplier Quality, 85% Supplier On-Time Delivery, and 15% Demand Variability

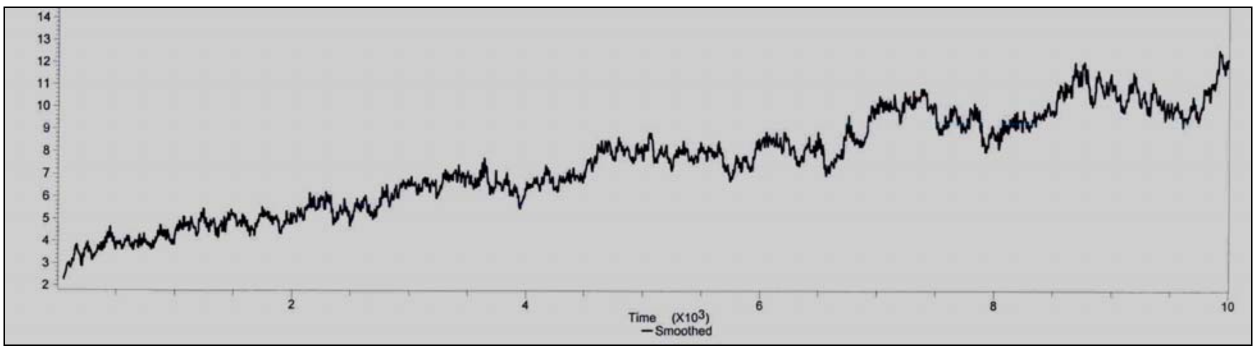

Figure D-14. Moving Average Plot for 85% Supplier Quality, 85% Supplier On-Time Delivery, and 15% Demand Variability

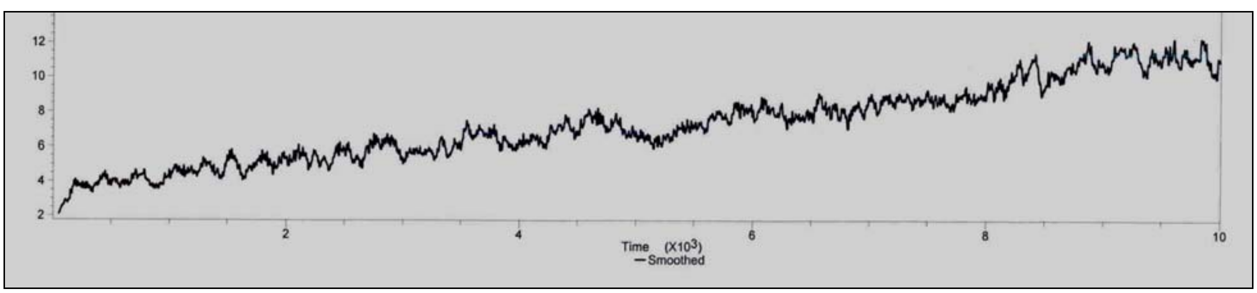

Figure D-15. Moving Average Plot for 85% Supplier Quality, 85% Supplier On-Time Delivery, and 30% Demand Variability

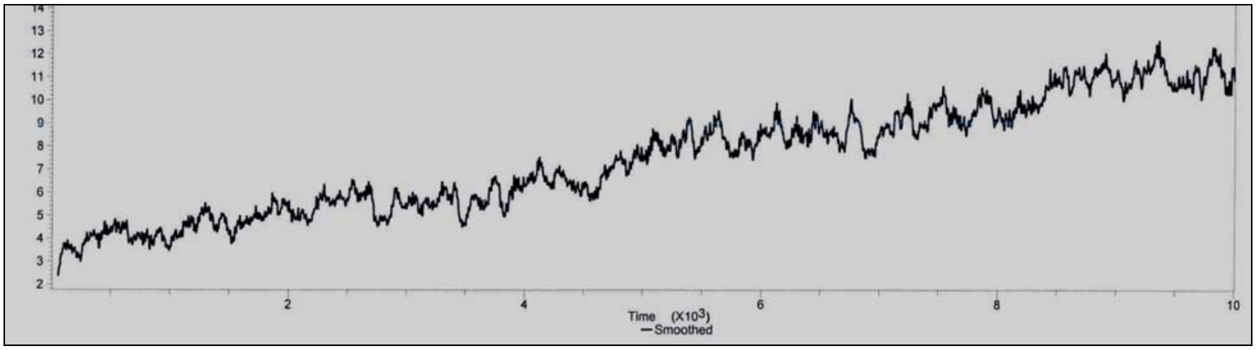

Figure D-16. Moving Average Plot for 85% Supplier Quality, 85% Supplier On-Time Delivery, and 30% Demand Variability

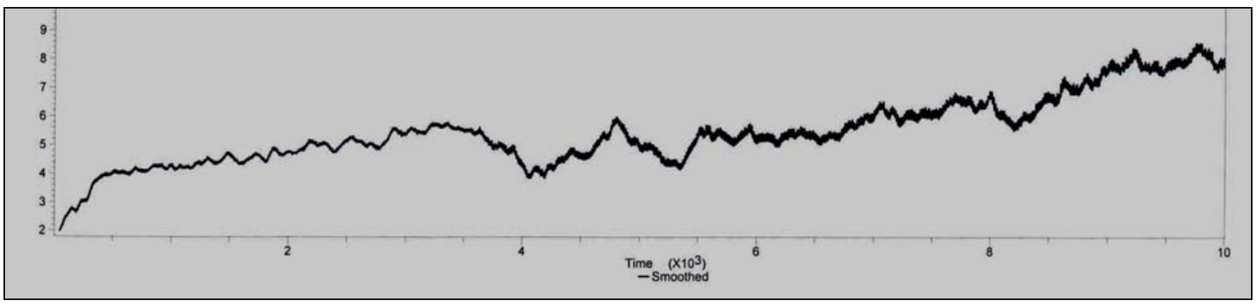

Figure D-17. Moving Average Plot for 85% Supplier Quality, 100% Supplier On-Time Delivery, and 15% Demand Variability

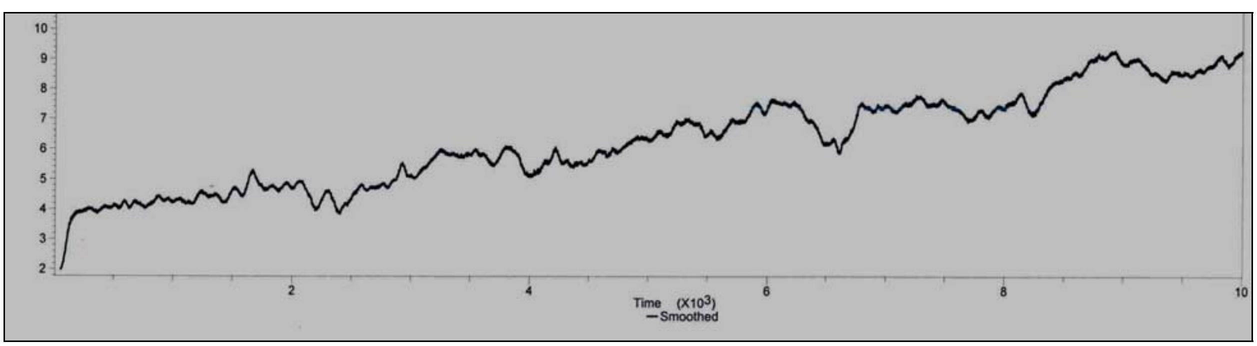

Figure D-18. Moving Average Plot for 85% Supplier Quality, 100% Supplier On-Time Delivery, and 15% Demand Variability

VITA

Alan D. Hafner was born to Gary and LeeAnn Hafner on October 24, 1978, in Salem, Oregon. He has a sister, Eileen, and grew up enjoying sports and raising cattle. He graduated with honors in 1996, belonging to the National Honor Society, and was an avid participant in the local FFA chapter, 4-H group, and the Oregon Junior Simmental Association.

After high school, Alan attended Oregon State University, studying Industrial Engineering, on a four-year scholarship from the Ford Family Foundation. He graduated Magna Cum Laude in 2000 with a Bachelor of Science degree in Industrial Engineering. While at Oregon State, Alan was involved in numerous extra-curricular activities, including the OSU Country/Western Dance Team that traveled to Knoxville, Tennessee to perform on Club Dance, a show formerly on TNN, and competed on the OSU Livestock Judging Team.

Alan is currently a graduate student at Virginia Polytechnic Institute and State University, aided by the extension of his Ford Family Foundation scholarship, and the Pratt Fellowship, awarded by Virginia Tech. At the end of his first year in graduate school, he was awarded the ASQ Ellis R. Ott Scholarship, and was awarded 2nd place in a regional technical writing contest sponsored by APICS. Alan will receive a Master of Science degree in Industrial and Systems Engineering in Spring, 2004. While completing his studies, Alan worked as a Graduate Teaching and Research Assistant, and instructed a course in Discrete-Event Simulation during the summer of 2001. He was also a member of INCOSE, and served as their Treasurer.

Alan is currently working as an Industrial Engineer at Layton Manufacturing, and lives in Salem with his wife, Jenny. Alan and Jenny are expecting their first child in March, 2004.