LINKING DATA, BUSINESS INTUITION, AND COMPUTER SIMULATION FOR SUPPLY CHAIN STRATEGIC DECISIONS

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LINKING DATA, BUSINESS INTUITION, AND COMPUTER SIMULATION

FOR SUPPLY CHAIN STRATEGIC DECISIONS

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To my all-time supportive

husband and my conscientious daughter

for enabling this effort.

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ABSTRACT

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In today’s global manufacturing environment, world-class companies are aiming to standardize their operations in which their product is built using the same assembly “formula” across all the manufacturing sites. To that end, companies are geared up to a profitable partnership with their supply chain that provides flexibility and responsiveness to the market changes. A large amount of risks associated with product standardization are due to the hidden supply chain costs. If business owners knew them ahead of time, or had the right analysis tools, they could make better decisions regarding globalizing products. This study attempts to show how discrete

event simulation can help to identify and mitigate ‘hidden costs’ in the supply chain network suffered from un-predicable events. Unpredictable events such as delays in shipments due to custom, or variability in the lead-time have a significant effect on productivity and hinder efforts of standardization.

CHAPTER I

INTRODUCTION

<u>Background</u>

In today's manufacturing environment, companies attempt to standardize and simplify their manufacturing and supply chain (SC) operations, seeking to differentiate themselves from competitors. Standardized and simplified manufacturing drives lower cycle times and cost reductions since products are easier to build due to repeatable and predictable manufacturing/assembly processes. *Standardization* is the use of common components, processes and methods across all product lines. Designs and the manufacturing/assembly formulas are evaluated to streamline acquisition, staging, and ease of assembly of components. Standard components, and pre-shaped work pieces are used when possible. *Simplification* minimizes the amount of parts or components required to build the product, removing operational inefficiencies and variances between assembly methods of all the manufacturing sites. As a result of standardization and simplification, a common ground across all global sites is established in order to reduce the company's operational variability.

A global "assembly formula" provides clear and detailed information such that little interpretation is required regardless of the language or skill level of the operator. Nonetheless, when the SC is dispersed around the world, maintaining a simplified approach is a challenge even with a highly standardized and well-designed assembly process. Ren *et* al. (2006) indicated that global supply chains are difficult to optimize as these systems are typically complex, adaptive, and dynamic, with nonlinearities, delays, and network feedback loops. In spite of having non-divertive, standard, and clear assembly instructions to help reduce variability, it is difficult to maintain a simplified formula that maintains variability to a minimum. Cultural and language differences may cause conflicting interpretations of the information transferred causing an increasing effect to the process variability. For that reason is that simulation represents the most functional method to understand the behavior of the SC. Simulation models are capable of capturing the effects of factors that act against simplification and standardization and contribute to variation; resulting in higher operational cost.

There are other works of literature that have used simulation modeling to understand cost implication and to help represent behavior of different segments of the SC. Most of the literature focuses on the logistics aspect, which helps companies maintain inventory levels low and to reduce material cost. These are certainly important pieces of the SC puzzle; however most fail to assimilate the impact to operational cost (the cost to build a product) due to unpredictable behavior within the factory. This literature agrees with most management concepts of measuring manufacturing economic performance; the major concentration (and where most data is available, both academically and in industry) is around standard cost of manufacturing.

Companies focus on measuring and improving mainstream outflow measurements such as labor and material, machine utilization and inventory. However, managers lack tools that help them understand hidden cost in operations due to events and activities at isolated points along the SC. Typically, business decision makers look at SC chain cost from the total cost point of view of material, labor, and overhead. In a typical profit and loss (P&L) statement, the section allocated for operational cost is composed of cost due to sourcing of materials, labor (benefits, payroll taxes), and overhead (human resources, legal team, engineering, insurance, office space, sales, marketing). The first two cost components are variable, whereas the overhead cost (also called overall burden) is fixed. However, there are other costs within the P&L that are hidden and uncontrollable and highly unpredictable. Zhang *et* al. (2009) identified uncontrollable and "hidden" retractors in the SC due to global distances, transportation, cultural differences and variation. They developed a mixed-integer programming model to simulate and optimize different relocation sites. Recognizing that these retractors are valid, there are other factors or events that add to the SC cost in the form of operational variability. Factors such as demand variation and part shortages represent hidden operational costs that the literature does not acknowledge. Even when efforts of standardization and simplification of assembly methods are realized in factories, these events inhibit and make the financial success negligible.

Problem Statement and Research Purpose

The purpose of this study is to identify and analyze through discrete event simulation the SC deterrents that are decreasing efficiency of the operation in a simplified and standardized assembly line. Even in a highly standardized manufacturing assembly process, any non-planned disturbance to the flow has potential to generate other unexpected activities that have cost associated. These events are sporadic in nature and typically involve quick response from management and very little analysis. In terms of the SC chain, these costs affect productivity, create additional work, and increase the cost of the SC; however, they are required in order to recover from such disruption. Accounting for these costs is very difficult for most companies mostly because of the lack of data collection tools.

This thesis will also underline and evaluate some of the factors that negatively impact the bottom line and impinge on standardization and simplification efforts. The novel contribution here is to understand interactions of factors that contribute directly to the operational variability. The malfunction is in terms of suppliers defaulting on their delivery timeline promise, and any delays associated with delivery of raw material. The intention of this research is to test an operational model (of a hypothetical assembly line) using a simulation approach and measure the impact the SC performance make to the bottom line.

Proposed Procedure

We propose to model a highly standardized, manual assembly process recreated using a discrete event agent-based simulation using SIMIO™ software, (Simio 2012). The study is done using a focused framework of the SC and the operations; thus, a simplified operational model using bounded rationality is used. The operational model is a terminating simulation that ends after one year (52 weeks) and it is composed of an assembly line divided into seven departments, each department is modeled as a server and has a resource (operator) with limited capacity. The orders coming from the customer enter the assembly line as an entity and initiate the assembly process; inventory policy of a min/max for selected raw material is modeled with a minimum inventory levels and with a monitoring process that has a threshold (reorder quantity) value for each part; crossing the threshold in the negative direction triggers an order. The order activity follows an order process where there's set supplier's lead-time. One selected sub-assembly (HB-Sub1) is modeled to consume material from a BOM (bill of materials), with each part type having different attributes such as cost, minimum inventory levels, and lead-times.

Orders modeled as entities enter the system following a statistical distribution for inter-arrival times; these orders trigger production of sub-assemblies and the line is designed to stop if any of the needed components are not available. The assembly times are modeled using a triangular distribution, it includes operators, which are either dedicated or shared between operations. A triangular distribution was used because the product of interest is a new product and historical data is not available. However, the high and low values are known as well as the averages of the times, from time studies obtained from laboratory data from prototype builds. These operators and the entire model are on a 24-hour schedule; no breaks, holidays, or vacations are considered. A baseline of the model has been established by maximizing the line capacity in terms of throughput, an optimal min/max inventory policy is set up, and an ideal situation is created such that there is no part delays, quality issues, or part shortages. The experiments include introducing delays due to SC impairment, lead-time variability, and changing the inventory policy to identify effects. The simulation model will enable visibility to identify contributors to the cost of the sourcing which combined with production of the product, make up a substantial part of the total operational cost. The measurements provided by the simulation include of which they will be explained later:

1. Throughput
2. Inventory Cost
3. Utilization

Organization of the Thesis

The organization of the remainder part of the thesis is as follows. Chapter 2, entitled "Literature Review" provides a comprehensive overview of the supply chain studies using simulation. It provides previous research on useful strategies to identify cost in the SC, such as Total Landed Cost, as well as methods used by other studies to discover and manipulate different aspects of the SC using either mathematical or discrete event simulation models.

Chapter 3 entitled "Operational Model" describes the system of interest and the simulation model.

Chapter 4 entitled "Experimentation" provides information on the design of experiments, description of factors and levels and discussion of results as well as lessons learned.

Chapter 5 entitled "Conclusion and Future Research" presents the conclusions of this research effort and its contribution to the research literature. It also discusses suggested future research work.

CHAPTER II

LITERATURE REVIEW

Attitudes in Business for Decision-Making

Inarguably, research shows that most companies use approaches to perform risk assessment based on some percentage of non-scientific methods such as business intuition, when making strategic SC decisions. Christopher *et al.* (2011) reckon that companies do not possess a systematic method of mitigating risk when it comes to supply chain decisions. They identified risk in five different areas of the SC: process, control, demand, supply, and environmental and illustrated how some companies, for example, use tactics such as building close relationships with critical suppliers, or no relationship and many suppliers as a technique to spread risk. Other companies use optimization methods using extensive Excel spreadsheets to analyze SC. However, Ingalls *et al.* (1999) states spreadsheet-based modeling is not an effective method due to its inability to handle complex problems dealing with stochastic behaviors in the SC. All organizations have a foundation for making decisions. This foundation should be planned in a dynamic fashion because it befalls the organization's strategy. This strategy dictates the activities, priorities, and policies (Hopp 2008). Simulation provides better options for strategy-related decision-making, especially for supply and process risk. North *et al.* (2007)

affirm that simulation offers information (in the form of historical trace or path) that help managers understand interaction and behaviors of the system being studied; because simulation can be carried out in different frameworks and for different reasons, the researcher is able to decide the degree of complexity and simulate different scenarios where potential risk may exist prior to experiencing any malfunctions in the SC.

Interactions Between the SC and the Operations

In the SC network, there are different types of organizations that if well established, when an organization optimizes their local objectives, the overall system is by default sub-optimized as well, Hopp, W. (2008). Interactions between operations and SC require careful coordination between the factory and the suppliers; different stocking strategies, part presentation locations and definition, information exchange flows, and inventory policies are some of the possible variants. Layouts are constantly calibrated to account to changes to production scenarios that take into consideration internal and external influences. Beham, et *al*. (2009) used process simulation and met heuristics to optimize the location of machines in a production floor in order to minimize material transport cost. Although this is somewhat similar to the purpose in this research, they fail to integrate the operational (facility) with the sourcing segment, which is to include the optimal location of drop zones for material coming from the suppliers. Ming, H, *et al.* (2002) affirm that a key component for a meaningful simulation of SC and the operations (the factory) includes the "product availability" feature, that measures variables such as inventory days of supply and order fill rate, and studying scenarios such as demand fluctuations in the demand pattern that often end in an unfulfilled order to the customer.

Supply Chain Modeling Techniques

A different approach found in the literature was an analytical model from Dayama et. *al.* (2009) for a multi-strategy supplier selection. Different to Prakash *et al.* (2010), this study considers logistics and material cost, in addition to inventory cost; some variables such as cost of oil cost variation between less than truckload (LTL) and inventory cost are also used as their parameters for their model. This approach is in a form of an optimization model that allows managers make the decision of selecting a supplier based on material, logistics, and inventory cost. The input for the material cost is the part cost quote presented by the supplier who is bidding for the business, the logistics and inventory cost is dictated by distances of the suppliers in reference to the factory and the inventory carried in warehouses. This model looks at two alternatives and picks the best based on the situation; for suppliers located far away and one for those close to the factory. For suppliers located at long distances, the factory will have a hub or warehouse where inventory will be held; for short distances, the supplier closest to the factory will deliver using carriers.

Shipping cost is measured in terms of miles and in- transit time from the selected carriers. The tool compares ordering cost to inventory cost and provides the most economical selection; ordering cost is the cost for machine set-up at the supplier plus receiving and inspection of the part at the factory. All this information is fed into the tool and the supplier combined with the inventory strategy is selected such that the total landed cost s minimized for the procured parts. The tool works in three stages, first, it selects the best option between distant suppliers: it picks the lowest cost between in-transit inventory cost and shipping cost, and then it looks at the best number (lowest) between order cost and inventory holding cost. And finally, it combines the entire transportation cost with the part cost and provides a total landed cost per part. By using this tool, managers are able to decide from a group of suppliers and parts, when and how to order.

Computer simulation modeling has aid in the development of SC strategies, in the areas of inventory planning, managing business objectives, and relocation decisions. Some work has been done in understanding the effect of customer behavior on the distribution network using discrete-event simulation. Kumar, *et al*. (2009) introduced an innovative use for simulation; they build a network model for one factory, three distribution centers, and three customers. They were able to mimic customer behavior based on six criteria (order quantity, order frequency, days to enter an order, days from order entry to order release, days to complete order, and days in transit). Six different part numbers were used and high, mid, and low runners were identified to build a standard inventory policy. One interesting measurement they took was customer performance measurements for each distributor in study. Their main objective with their study was to forecast supply chain performance.

Researches use simulation techniques to develop SC policy. Prakash *et al.* (2010) suggest in their study that the best strategy for companies to stay competitive in the global scale and to keep supply cost down is to create a horizontal integration with the suppliers. Their approach is to create a conceptual model of a four-stage (supplier-manufacturer-distributor-retailer), multi-node flexible SC for a single product using ARENA simulation software. Their research provides a method for full visibility of the SC such that direct communication is enabled between the manufacturer, the retailer, and distributor; they all respond to a specified inventory policy, the retailer carries the inventory and replenishes it as the product is consumed, the order rules ensure that the order size is always within the inventory capacity of the retailer so there is no risk of carrying too much inventory.

Inventory strategies are developed in this study using computational analysis for which the distributor makes decisions based on the manufacturing's inventory plan in an effort to keep cost down (in the form of backorder or inventory holding cost). Each of the contributors to the SC has shared information in the form of inventory levels, lead time, and cost; they are also able to see the impact of another contributor to the total cost: the ordering cost; it increases as reorder quantity increases. Although this study presents a novel tool for operation managers to make strategic decisions on how to reduce inventory-related cost of SC, the study fails to include many other inherent costs of logistics. According to the authors, winning companies reduce costs and become more flexible. However, there must be more than a simulation model and data; some intangibles must be present between factory and supplier: trust, senior management commitment, flexibility, teamwork, and patience.

Ren, *et al.* (2006) study highlight the gap between business objectives and SC operations using qualitative (cause-and-effect diagrams) and quantitative methods such as Systems Dynamics Simulation and optimization tools to compare business strategies to operational activities related to SC as a way of measuring performance. They defined the strategic objectives and translated them to KPIs (key process indicators) using qualitatively strategy map and metric networking; then they use system dynamics simulation to quantitatively show managers options for decision-making. They claim that although performance metrics help uncover existing problems in the SC, it doesn't help to find the root cause nor does it help managers find solutions to such problems. This emphasizes the fact that the SC problem is extensive due to the many variables and companies do not have the correct, structured data to make the right decisions.

Zang *et al.* (2009) developed a mathematical model using Mixed Integer Programming (MIP) where they attempted to include the total landed cost (TLC) of a product in order to make decisions for relocation for international markets. This study included more information related to cost that any other study found; its TLC was highly encompassing and inclusive of some variables such as exchange rate, tax rebate adjustments, and industry policy adjustments which is novel in the literature. This model provided light into what managers should be looking at when making decisions to relocate a product; their parameters selected are extensive and very detailed. They compared options of sourcing raw material locally vs. imported; they also made an attempt to compare the impact of SC cost to the operational cost; which the other studies did not. Nonetheless, the study had some limitations mostly because of the way the data was collected. Data was not collected from direct observation; all data came from governmental websites, which inevitably will be politicized in some way, removing in some way science validity.

CHAPTER III

OPERATIONAL MODEL OF THE ASSEMBLY LINE

This chapter provides a comprehensive description of the operational model used for the simulation purpose. It is organized as follows: introduction to the assembly line, setup of the model, and factors to be studied.

Introduction to the Assembly Line

The company under study is a multi-national manufacturer of gas pumps. The manufacturing of the product is highly manual and the part count of a dispenser typically is in the hundreds. Since this operation will be replicated across factories and implemented in the same fashion, we assume that the operational cost (plus a percentage allotted for inefficiencies) will remain constant.

The assembly process flow below represents the analog model of the product's manual assembly process. The product is built in a progressive fashion, where one operator attaches parts manually as the unit moves down the assembly line in a straight-line flow. The sequence of events for parts attachment is defined such that the build is done from the bottom-up and from inside out. The main line is divided into seven departments: the hydraulics, electronics, hoses, test, quality control, exterior, and shipping departments. Two departments have sub-assemblies that are built outside the line and brought into the line as needed (see Figure 1). The sub-assemblies are built on demand as each unit moves out of the previous station.

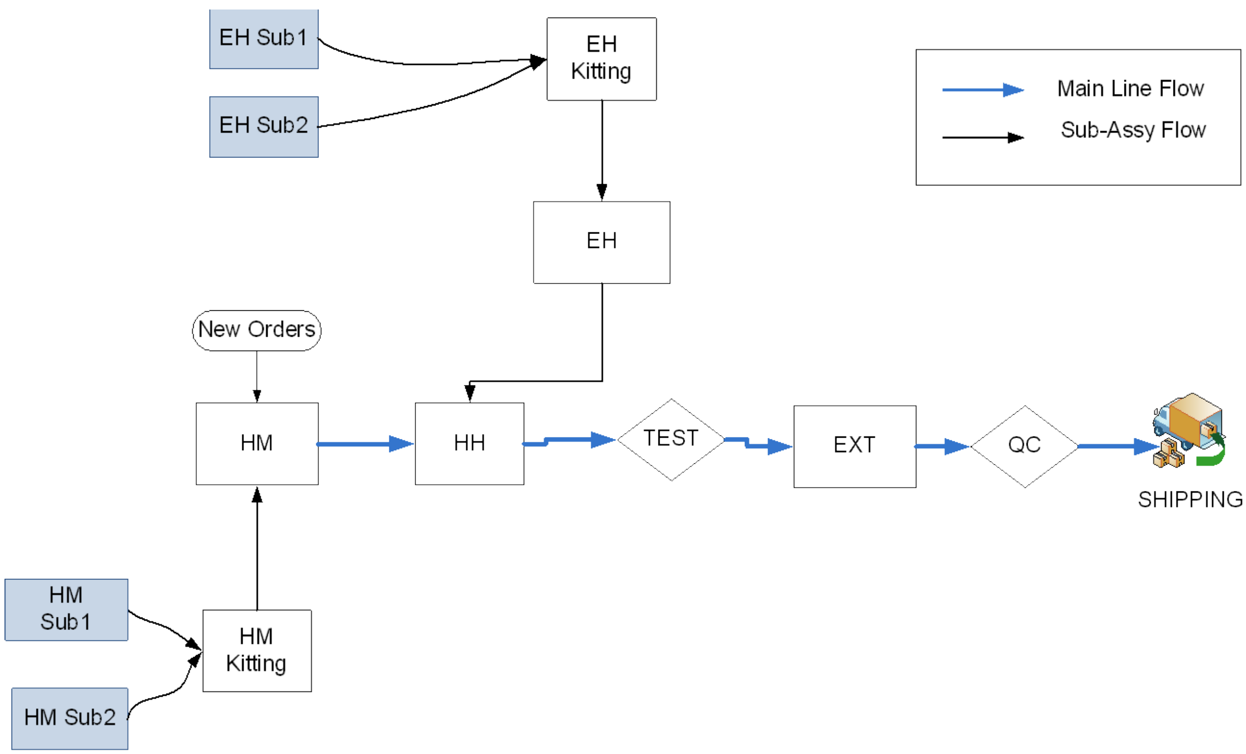

Figure 1 Assembly Process Flow

Model Setup

One operator is assigned to each department and one for each department's sub-assembly station. It is assumed that the same operator that builds the sub-assemblies also delivers them to the line. The walking distance from the sub-assemblies to the main line is considered negligible for the purpose of this study. Each department has one workstation that is enabled for two operators to work on each side of the unit if volumes increase; however, during low volumes, only one operator is assigned to each workstation.

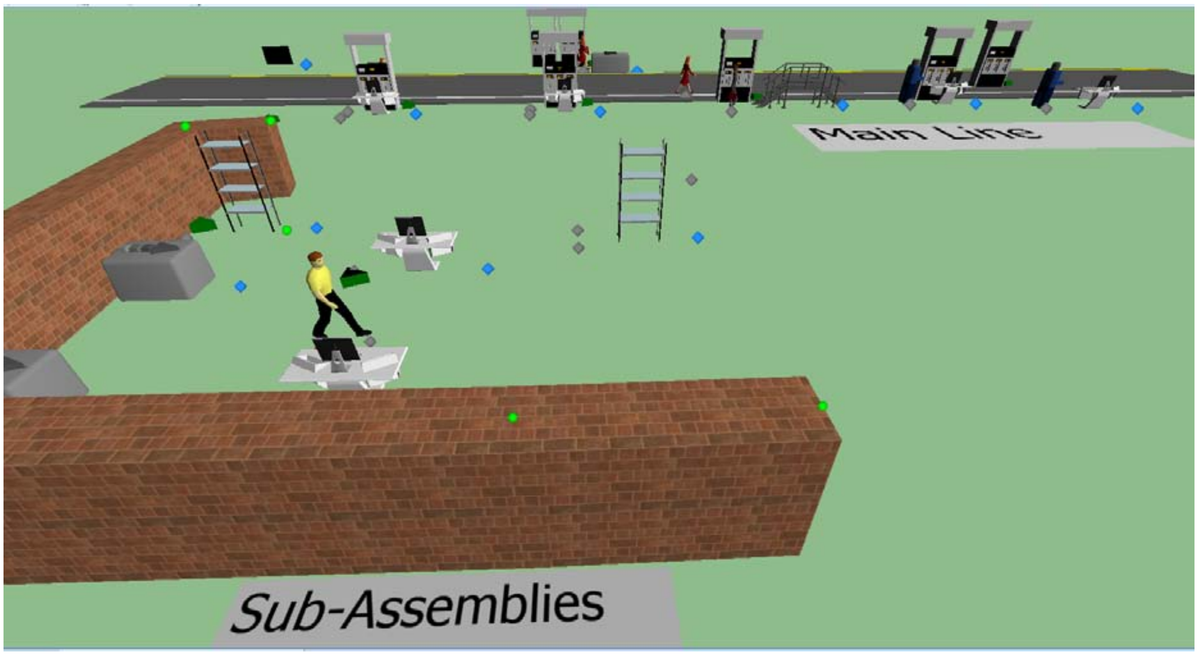

Figure 2 Operational model in Simio ™

Table 1 Processing times

DEPARTMENTS	Average Processing Times (min)	Distribution of Processing Times
HM	15	Triangular (11.75, 15,1 8.75)
EM	15	Triangular (11.75, 15, 18.75)
HM	10	Triangular (7.5, 10, 12.5)
TEST	15	Triangular (34, 45, 56)
EXT	15	Triangular (11.75, 15, 18.75)
QC	15	Triangular (11.75, 15, 18.75)
SHIPPING	10	Triangular (11.75, 15,1 8.75)
SUB-ASSEMBLIES	**Average Processing Times (min)**	**Distribution of Processing Times**
SUB1 for HM	7	Triangular (5.25, 7, 8.75)
SUB2 for HM	7	Triangular (5.25, 7, 8.75)
SUB1 for EH	7	Triangular (5.25, 7, 8.75)
SUB2 for EH	7	Triangular (5.25, 7, 8.75)

Each of the department has its own processing time and resources (operator and workstation). Processing time for each department includes operator acquiring and attaching the parts (see Table1). The input buffers for each department or workstation are pre-defined and not constricted. The assembly line is balanced and it uses single unit flow with the exception of the test departments, which has a capacity of 3 since its processing time is so long (shown in the graph below as balanced: 45min /3operators = 15m).

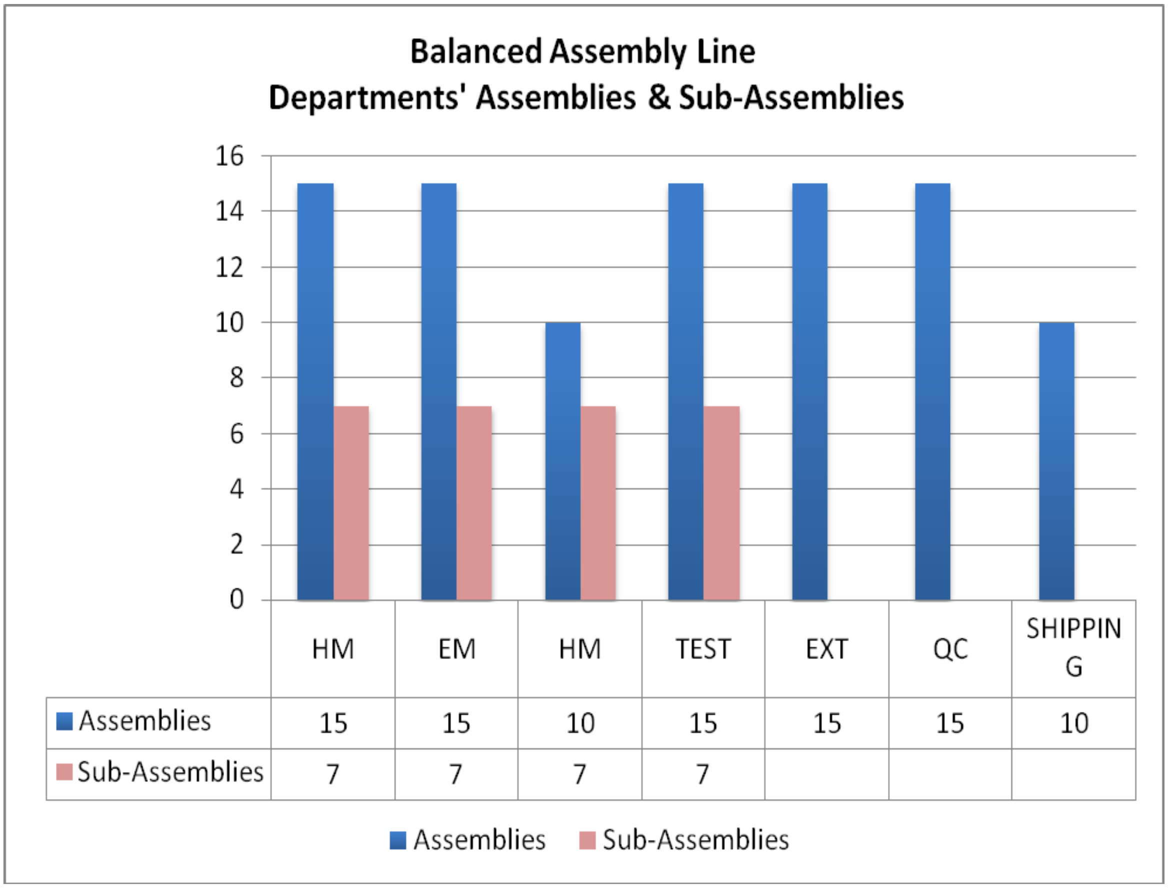

Figure 3 Balanced Assembly Lines

The parts for each department are staged at each workstation and are placed at hands reach of the operator. For simulation purposes, part acquisition time is small; therefore it is included in the processing time of the operation at each workstation. The parts follow a point of use (POU) part presentation, in other words the supplier delivers parts directly to the line.

The baseline model was created using an ideal situation, where assembly line is near maximum capability. Resources are set such that they do not created limitations, and part deliveries have zero probability for delays. In order to find the levels at which the inventory for each part does not deplete to zero, the baseline model was run using several iterations, incrementing the minimum quantity until ideal levels where reached. Following the central limit theorem and the notion that as number of replications approach infinity, the mean of the population becomes more normal, we executed sixty replications. This optimization was done to find the inventory levels that ensure the parts would never backordered. Statistical analysis was used for this study using a 95% confidence interval evaluation.

Factors to be Studied

This study narrows down to one workstation: *HM Sub1*, the workstation that builds and delivers one of the subassembly for department HM. This assembly has a bill of materials composed of components coming from three categories (A, B, and C) based on attributes such as the type of supplier, the cost of the unit price, and the lead-times. The parts ordering or replenishment system is based on a min/max inventory policy for which a specified quantity is set for each of the component/parts evaluated here. The component/parts have been grouped based on the parts pricing as follows:

Table 2 Component Characterizations

Part Type	Cost/ unit ($)
A	$500
B	$50
C	$1.50

When each of the two evaluated parts' inventory levels reaches the reorder points, an event called "place order" is generated. This even includes the following activities, which are incorporated in the lead-time:

- Supplier receives the order
- Order is shipped
- Order is received

In searching the minimum inventory levels, it was evident that for the part C category it was advantageous to be excluded from the model due to a limiting variant; this because these type parts were so inexpensive and the volumes needed so large, that it made more sense to consider them commodity parts. Initially, the minimum reorder quantities were determined using the following information from the company being studied here: part A requires a minimum of 1 week of min inventory and part B requires a minimum of 2 weeks of inventory plus safety stock. These inventory levels were used to optimize the line at the ideal situation (no delays, no variability). Demand was set at 1 order arriving every 20 minutes or 72 orders/day.

The model replenishes these components once a corresponding reorder point value is reached. The model is set up such that it uses first the parts located in the workstation (within hands reach of the operator); these parts follow a pull system that is triggered by orders entering the department for which this sub-assembly will be used. In this case, it is the department HM. As the workstation parts are depleted, orders are placed when they reach a minimum level; if the order doesn't arrive on time, the parts from the safety stock will be consumed until the order arrives. If the safety stock inventory is depleted before the order arrives (this does not occur in the baseline model), then the line has to stop until the order arrives. As part of the experimentation, a decision step (based on probability) was added to the process to incorporate delays in addition to variability in the lead-time. This will be explained in more detail in chapter IV.

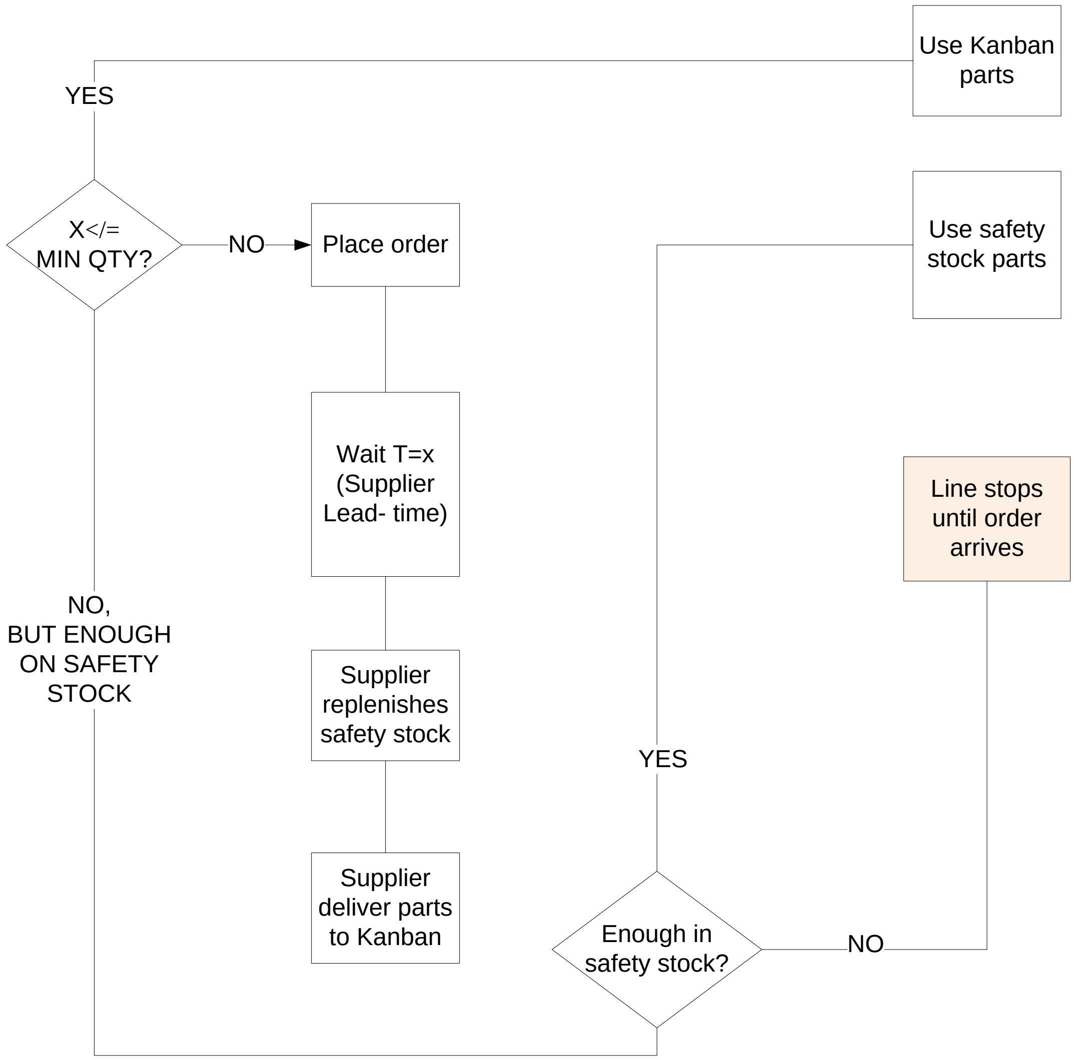

Figure 4 Part Replenishment/Ordering Rule

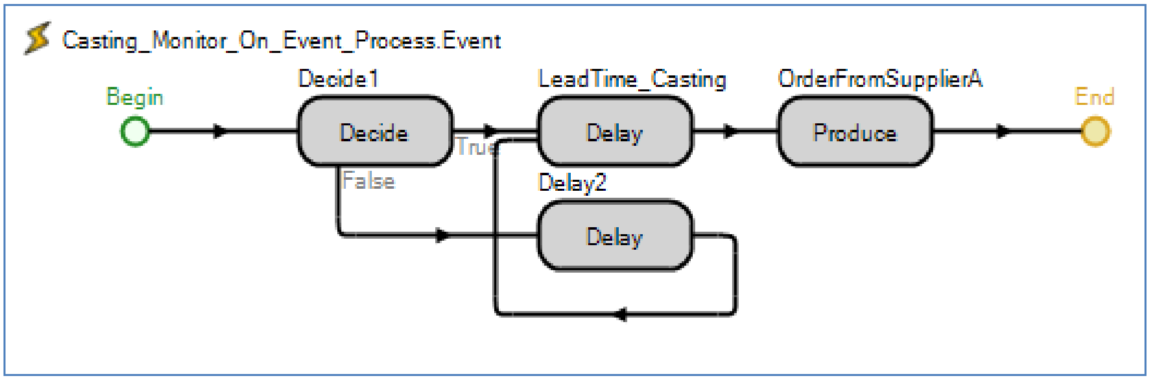

Figure 5 Ordering Event for Part Type A

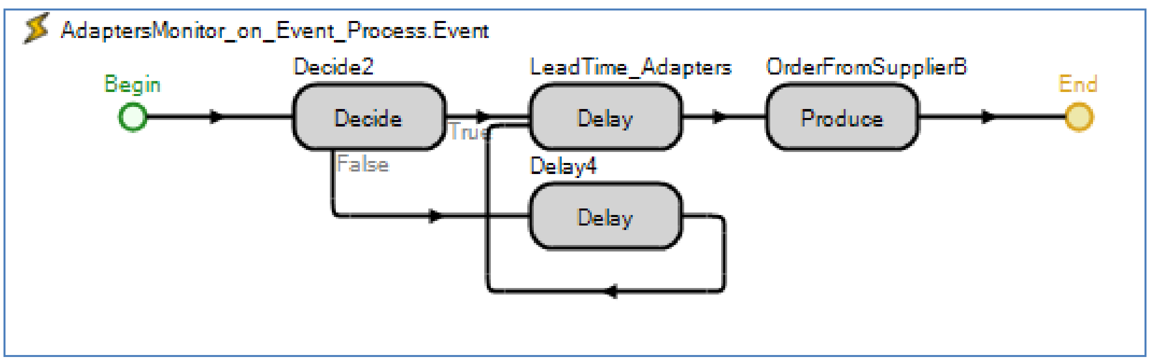

Figure 6 Ordering Event for Part Type B

CHAPTER IV

EXPERIMENTATION

The simulation experiment is explained in this chapter. SIMIO ™ version 6.46 is used to conduct the experiments and to perform the statistical analysis. The total simulation run was set to one year and two separate experiments were set: one for setting the baseline using 12 different cases (see table 3) and the best case scenario, in terms of reorder levels such that they never deplete even at the longest delay of 72 hours. The second experiment was set to evaluate the effects variability in the lead-time from the suppliers, knowing the preferred inventory levels for each part type. These simulations were run for one year (8,736 hours) and 15 replications. The reason for the 15 replication is that once we achieved the results within the 95% confidence interval, we decided the number of runs was sufficient since the simulation of one year is long enough.

The baseline serves as a gauge point for comparisons once the experiments have been carried out. This baseline model establishes the minimum inventories quantities for these parts such that they are never depleted nor have a negative effect on the throughput:

- Part (type A) = 510 units
- Part (type B) = 1015 units

Design and Analysis of Experiment

The experiment is carried out by manipulating the following variables for both of the part types and creating scenarios to investigate the effects of delays and different inventory levels. The following represent a matrix of the manipulated variables:

- Part's minimum inventory quantities,
- Delivery delays per part (in hours).

Table 3 Experimental Cases

Experiments	Part Delay A	Min. Qty A	Part Delay B	Min. Qty B	No. of Runs
Baseline	**0**	**510**	**0**	**1015**	**60**
Case A	72	510	0	1015	10
Case B	72	525	0	1015	10
Case C	72	550	0	1015	10
Case D	72	600	0	1015	10
Case E	72	650	0	1015	10
Case F	72	700	0	1015	10
Case G	72	730	0	1015	10
Case H	0	510	72	1015	10
Case I	0	510	72	1025	10
Case J	0	510	72	1050	10
Case K	0	510	72	1100	10
Case L	0	510	72	1150	10
Case M	0	510	72	1200	10
Case N	0	510	72	1280	10
Case O	**72**	**730**	**72**	**1280**	**10**
Case P	72	730	72	1015	10
Case Q	72	510	72	1280	10
Case R	72	510	72	1015	10

The ways the cases are set up are as follows:

- ***Case A through G:*** Delay on part A for different values of min qty of A.

B is maintained at low levels

- ***Case H through N***: Delay on part B for different values of min qty of B.

A is maintained at low levels

- ***Case O***: Max delay on both parts, max min qty for both
- ***Case P***: Max delay on both parts, max qty for A, min qty for B
- ***Case Q***: Max delay on both parts, min qty A, max qty for B
- ***Case R***: Max delay on both parts, min qty for both

After the execution of these cases (or trials), we were able to determine a secondary baseline, one that provides the best-case scenario for inventory levels of each part once presented with a maximum delay (worst-case scenario for delays). From simulation runs, it was determined that case O represents the preferred inventory levels, such that depletion was never evident, given the 72-hour delay (equivalent to 3 days). The parts delays follow a probability of 15% each time an order is placed. See Figure 7 and 8 below.

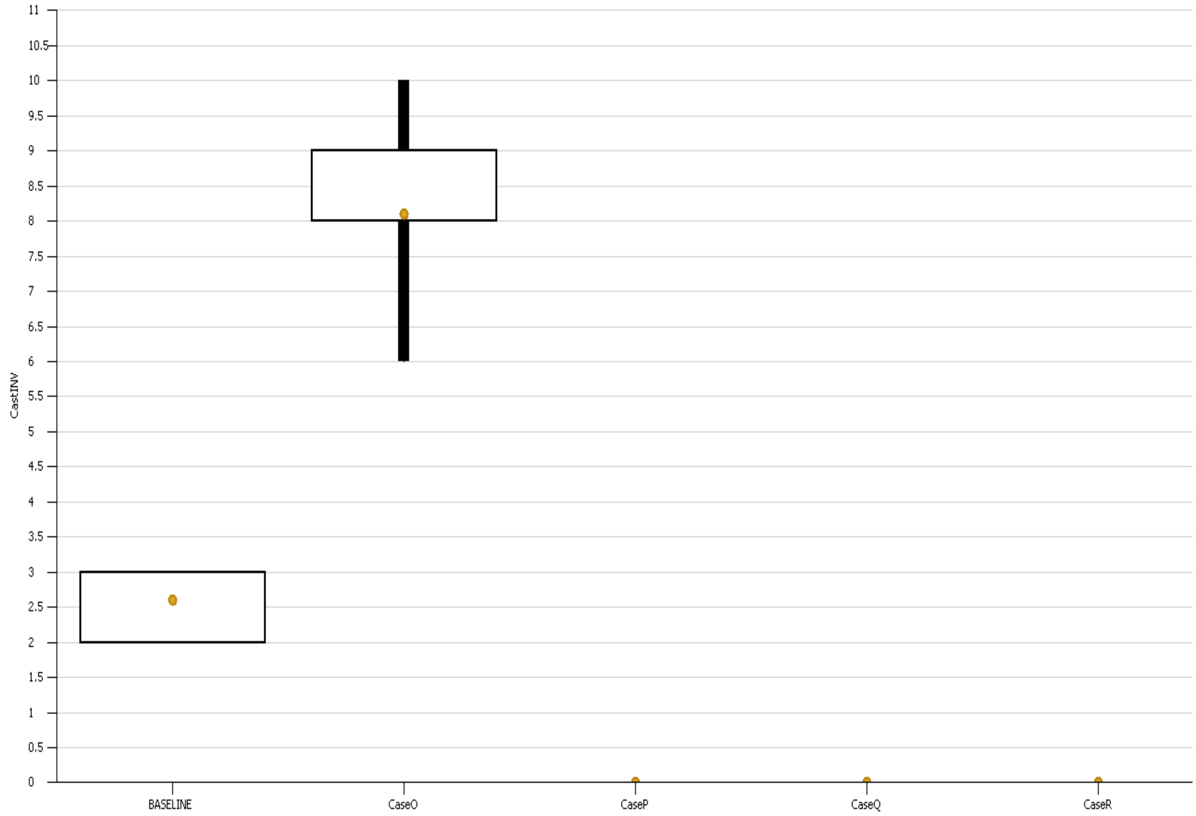

Figure 7 Comparisons of (Part Type A) Inventory Levels with Baseline

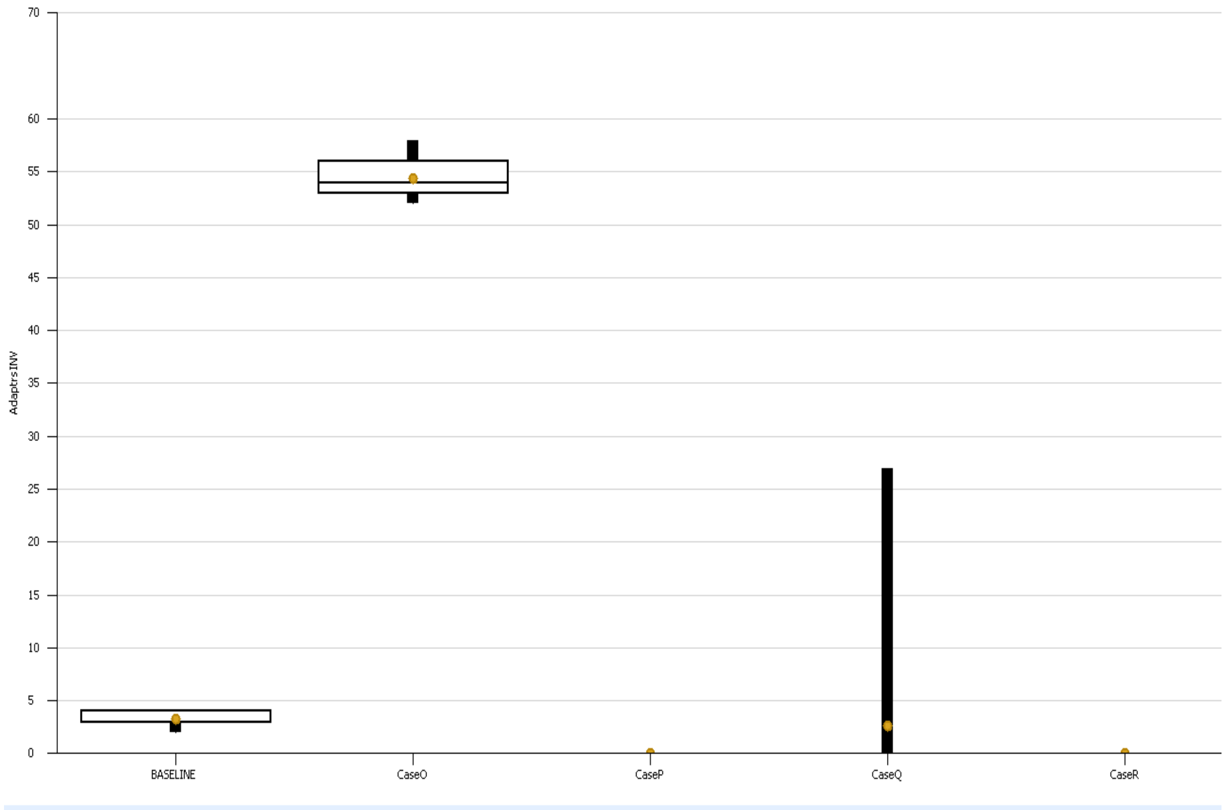

Figure 8 Comparisons of (Part Type B) Inventory Levels with Baseline

After obtaining the results of the baseline and the best case scenario (for parts), we then manipulated the inventory minimum reorder quantities to understand the effect that different levels of delays would have on the productivity (in terms of throughput). The distribution of the delays was changed from only 15% to an exponential distribution, which represents a more realistic scenario. The following represents the factors manipulated during the second experiment:

Table 4 Factors for Second Experiment

		Levels		
Factors	**Type**	**Low**	**Mid**	**High**
1	Part Delays	24	48	72
2	Minimum Reorder Quantity (Part A)	510	N/A	730
3	Minimum Reorder Quantity (Part B)	1015	N/A	1280

Results

The same scenarios or cases as portrayed above for baseline characterization are examined in this section; however the response is measured in terms of line performance and not the inventory depletion. The idea here is to understand the effects that unpredictable events such as a 3-day part delay due to transportation would have on the overall productivity.

Although the operational model created here is of a standardized assembly line, the activities of the SC are not. Transportation of parts, especially in a global environment, is prone to introducing the variability to the process. One of the events that create hidden cost is during transportation. When documents are not aligned, shipments are delayed due to this. The results characterized here represent the delays (in hours) when parts are held up in customs. Similar to Dayama *et al.* (2009) study, where he used simulation to calculate cost of parts due to transportation cost, this experiment will calculate effects, in terms of productivity that an occurrence like this will have on the operations.

Performance Analysis of Due to Specific Part Shortage (15% Chance for Delay)

Figure 9 represents the effect on throughput using different reorder levels for A type parts (Cases A through G) and delays of 72-hours. Cases A, B, and C reveal a significant reduction in production; their throughput numbers are lower than the baseline, whereas D, E, F, and G seemed like the production was able to recover in spite of depletion of inventory. Case G was not expected to show production reduction since the minimum reorder quantity was set such that inventory was never fully depleted in spite of the delays to the controlled part. Figure 10 show that case G throughput values are very similar to the baseline. It is also observed that cases D through F do not show significant production loss in spite of both parts reaching zero inventory levels during simulation. This is due to the ability of the system to recover due to excess capacity and increase utilization once the parts arrive. Cases A through C show an increasing trend in production as we increase part A type components.

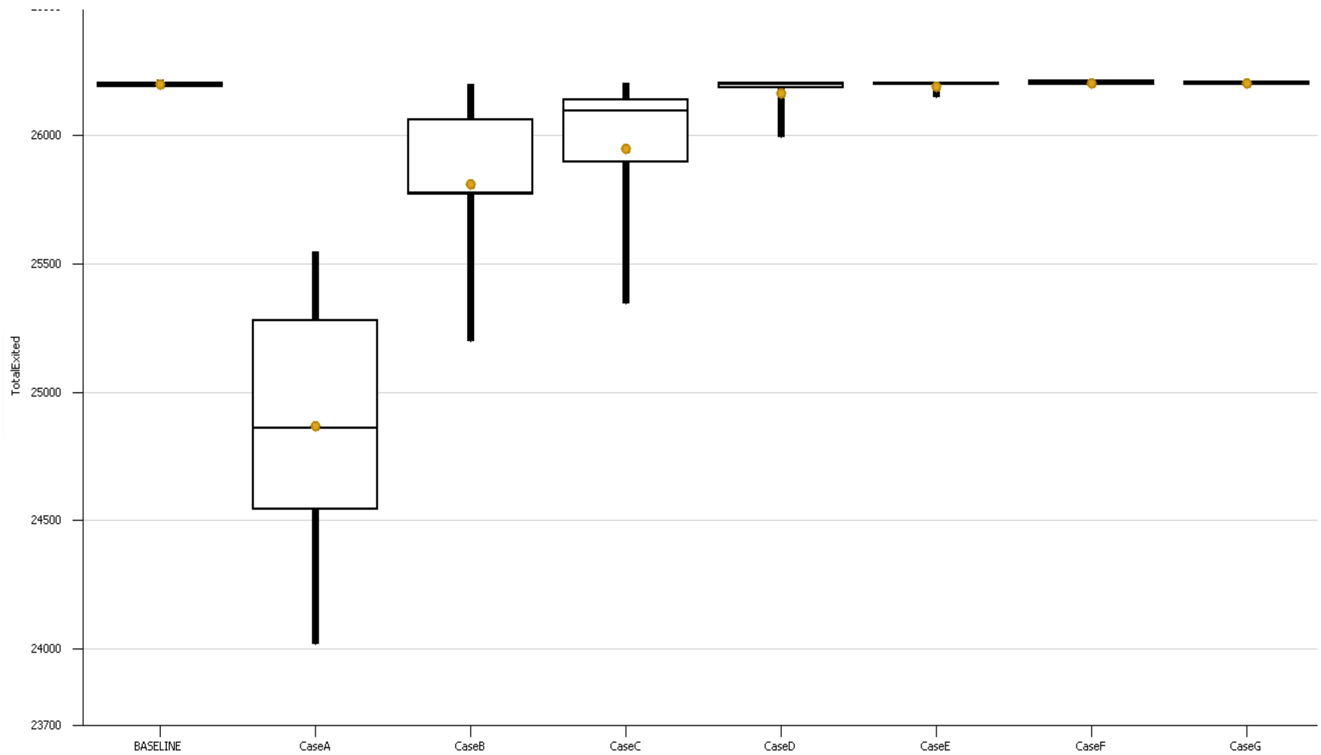

Figure 9 Throughput for Cases A through G – Effects Due to Type A parts

<u>72-hour Delay on Part B for Different Values of Minimum Reorder Quantity of B. A is Maintained at Low Levels (15% Chance of Delay)</u>

Figure 10 below represents the effect on throughput using different reorder levels for B type parts (Cases H through N) and delays of 72-hours. (Cases H through N). It is observed in this graph that the production loss is less than Figure 10, which presented production losses due to type A parts effects; this is explainable by the fact that the lead times for type B parts is longer than for type A parts. These cases show the same pattern as in Figure 12. Like for case G, case N was not expected to show production reduction since the min quantity was set at the level at which the inventory was never fully depleted in spite of the delays to the controlled part. This results also present the criticality type A part have over type B; in other words, type A parts should never be late and special effort should be made to ensure no occurrence of out-of-stock.

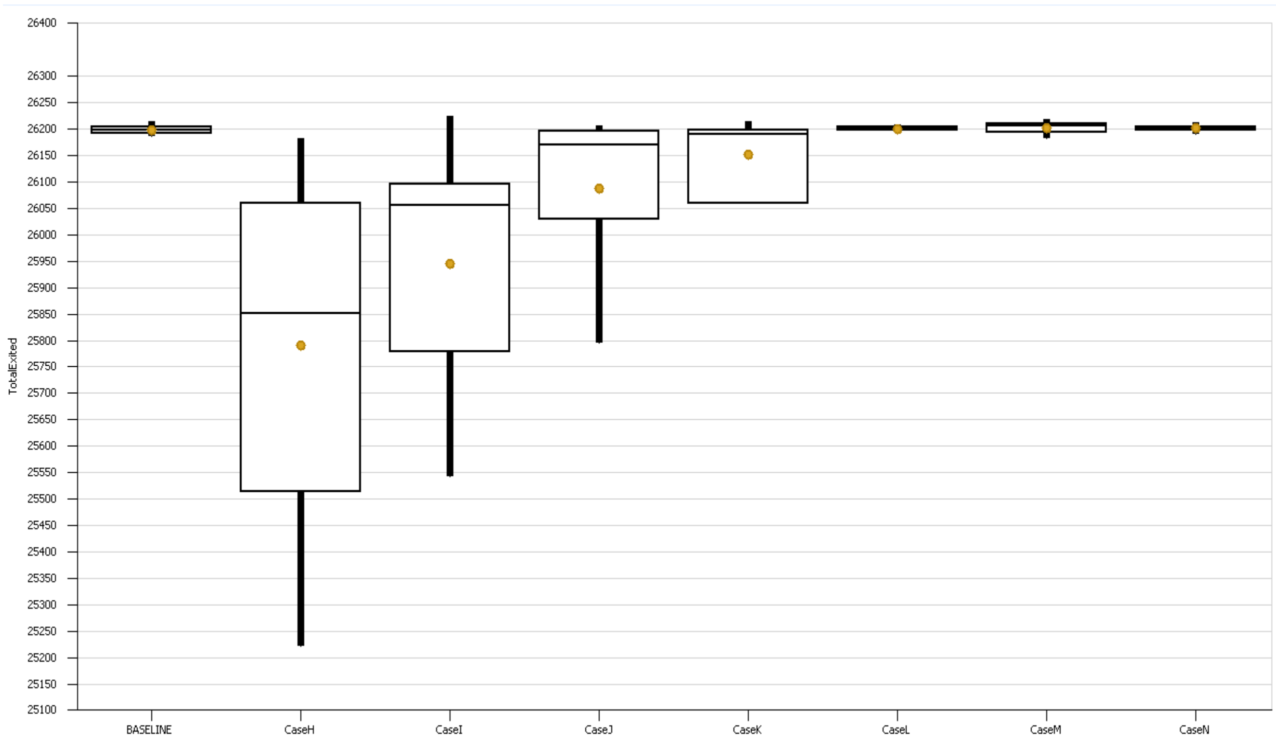

Figure 10 Throughput for Cases H Through N – Effects Due to Type B parts

In figure 11, it is shown that case O is pretty much identical to the baseline because both part types (A & B) min reorder quantities are set at high levels, therefore inventory depletion are not expected. All cases show the effects of varying min reorder levels for each part type; however part min levels for type A parts seem to have a more significant effect on the productivity. Case P has higher throughput results than any of the other cases. Case P is where type A parts have high min reorder levels and type B have low reorder levels; even though case Q has type A low min levels and high type B and the throughput is lower.   This can be explained by the fact that the 3 day (72-hour) delay time represents a larger proportion for type A parts than for type B parts; thus making a delay on part type A more significant than for type B parts.

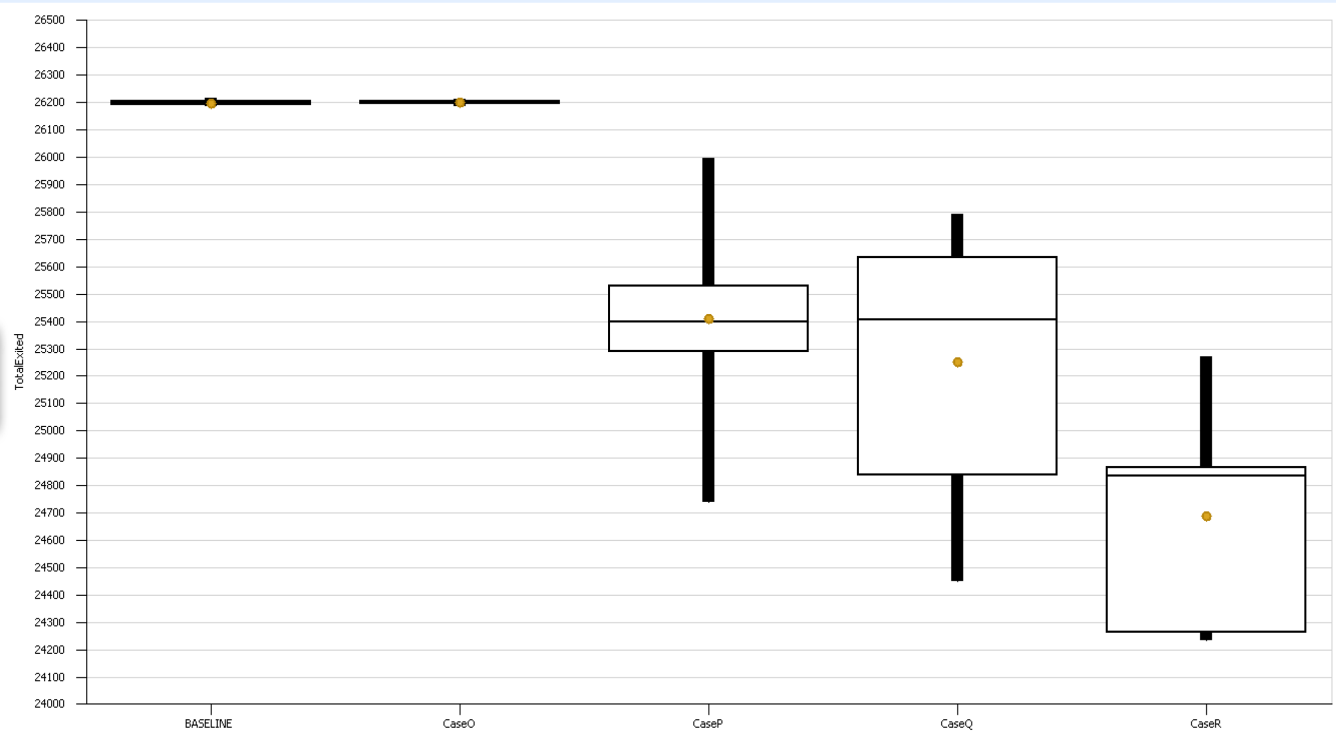

Figure 11 Throughput for Cases O Through R – Effects Due to Type A & B Parts

<u>Effects on Productivity due to Variation in Lead-Time Using Exponential Distributions</u>

The following are the results from the experiments performed with lead-time variation using an exponential distribution. The objective here is to identify effects of lead-time variations in the productivity (throughput) and utilization of the resources for the specified sub-assembly (HM-Sub1) for different delays and parts levels.

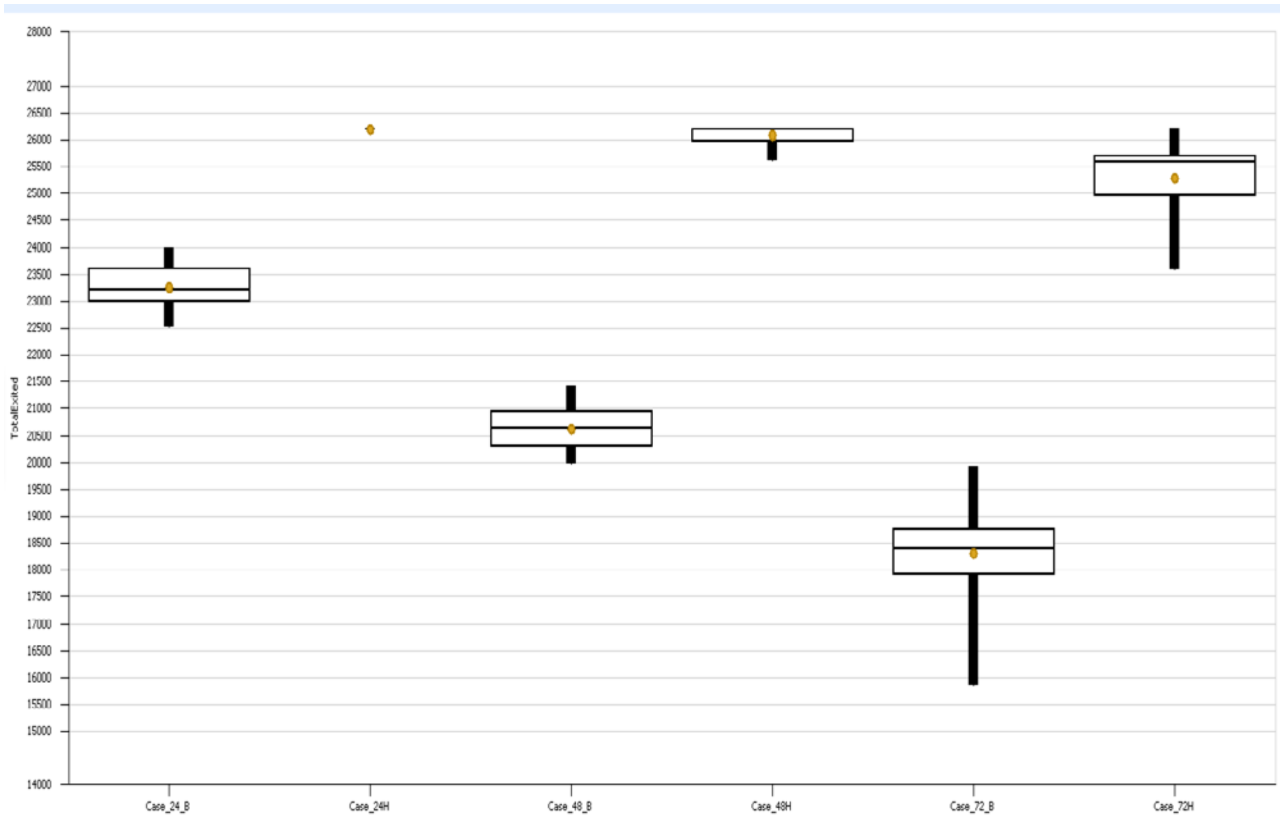

Figure 12 Throughput for Both Part Types Under Baseline and Max Reorder Quantities

Table 5 Results of Throughput

Scenario	Reorder Levels for Part A	Reorder Levels for Part B	Part Delay Variable (Hours)	Throughput (Mean)	Mean Confidence Interval Start	Mean Confidence Interval End	Total Reduction in Throughput	Reduction in Throughput (per month)	Decrease in Sales (per Month)
BASELINE	*510*	*1015*	*0*	*26203*	*26199*	*26208*	-----	-----	-----
Case_24_B	510	1015	exp(24)	23259	23015	23503	*2704*	89	$535,541
Case_48_B	510	1015	exp(48)	20629	20403	20855	*5353*	177	$1,059,904
Case_72_B	510	1015	exp(72)	18306	17813	18800	*7407*	244	$1,466,825
Case_24H	730	1280	exp(24)	26202	26197	26206	*2*	0	$0
Case_48H	730	1280	exp(48)	26084	25977	26192	*16*	0.51	$3,077
Case_72H	730	1280	exp(72)	25284	24867	25701	*507*	17	$100,376

It is evident from inspection of Figure 12 and Table 5 that the throughput reduction is more dramatic when parts are held at baseline levels (510 and 1015 for Part types A & B respectively). In other words, variability in lead-times does have a negative effect on productivity of the assembly line, which may cause missing orders. However, if the reorder quantities are dynamically set using a simulation tool, such as this model, the problem can be mitigated. In other words, using a simulation tool to define optimal levels of reorder quantities reduced the negative effects (in terms of throughput) of variation in the SC and reduces cost due to the decrease in monthly sales.

Utilization Results

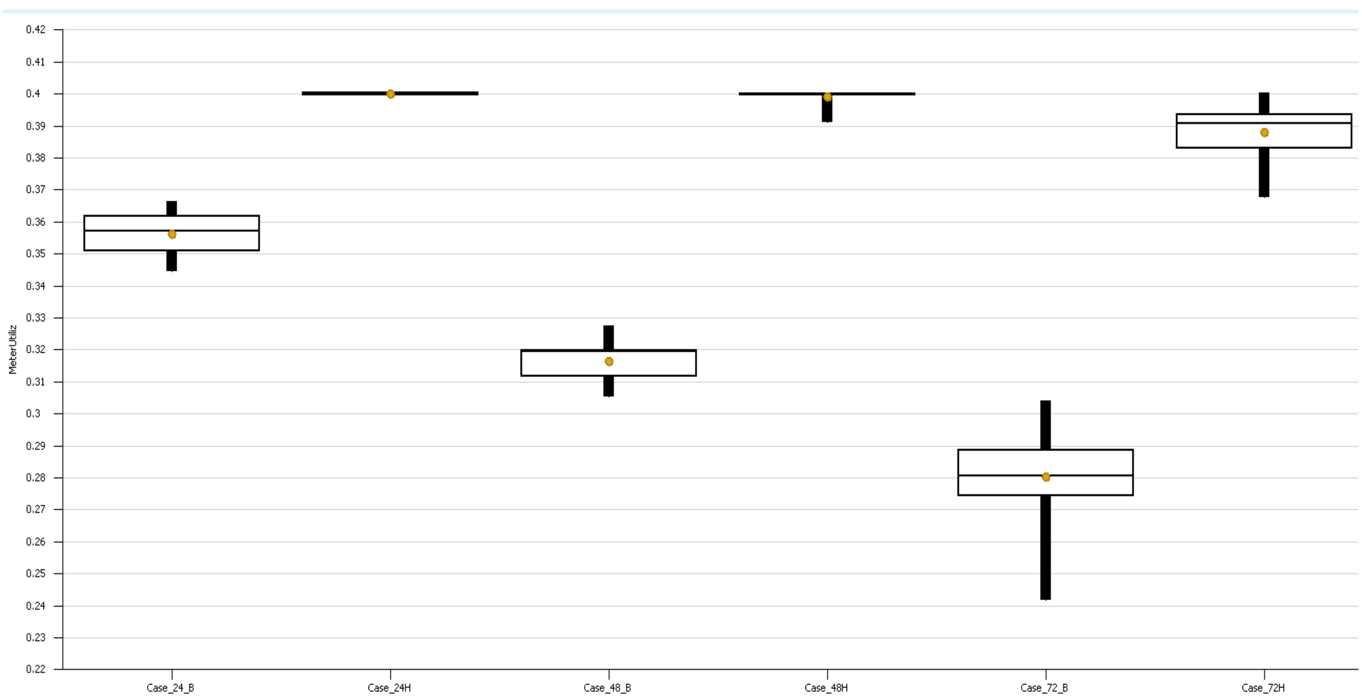

Figure 13 Resource Utilization for Sub-Assembly “HM-Sub1”

Figure 13 and Table 6 represent the effects of variability in lead-times for different parts have on the utilization of the resource where the sub-assembly HM-Sub1 is built. Utilization is measured in terms of the amount of time the station was busy building product. It is evident that the utilization is reduced when parts are depleted and the station remains idle until parts arrive. However, the optimized values found for case O (see Fig. 11) help mitigate variability problems and maintain the utilization levels very stable in spite of longer delays in the lead-time; utilization increases when the parts arrive and on average maintain stability. The statistical significance of these results was checked against 95% confidence intervals, to ensure the response were not due to noise in the system. (Comments from Jin: This sentence's meaning is not clear)

Table 6 Results of Sub-Assembly Utilization

Scenario	Reorder Levels for Part A	Reorder Levels for Part B	Part Delay Variable (Hours)	Utilization (Mean)	Mean Confidence Interval Start	Mean Confidence Interval End
BASELINE	*510*	*1015*	0	*40.01%*	*39.99%*	*40.02%*
Case_24_B	510	1015	exp(24)	35.62%	35.23%	36.00%
Case_48_B	510	1015	exp(48)	31.64%	31.31%	31.98%
Case_72_B	510	1015	exp(72)	28.04%	27.28%	28.79%
Case_24H	730	1280	exp(24)	40.00%	39.99%	40.02%
Case_48H	730	1280	exp(48)	39.91%	39.76%	40.05%
Case_72H	730	1280	exp(72)	38.82%	38.27%	39.37%

Table 7 shows the levels of inventory that had to be carried in the period of the simulation run (1 year) for reorder levels of: 730 and 1280 for part types A & B respectively. Part B had the maximum values of inventory held at some point, however, it is preferred to carry inventory for part type B since they are less expensive than part type A. The cost of inventory is insignificant compared to the opportunity cost from each due to the decrease in sales.

Table 7 Results of Parts Inventory Levels at High Reorder Levels

Scenario	Part Type	Mean	Median	Minimum	Maximum	Inventory Cost (per month)
Case_24H	A	0.2	0	0	3	$125
Case_24H	B	37	42	0	78	$325
Case_72H	A	0	0	0	0	$0
Case_72H	B	0	0	0	0	$0
Case_48H	A	0	0	0	0	$0
Case_48H	B	2.8	0	0	42	$175

CHAPTER V

CONCLUSION AND FUTURE RESEARCH

This research investigates the effects of SC behavior and business intuition that has on the productivity of an assembly line. It defines a standardized assembly process using a discrete event simulation running at required capacity in order to fulfill the specified orders and models different scenarios of SC malfunctions considering material transportation issues such as custom quarantines or wrong decision making in the form of reorder quantity settings for different parts. As mentioned previously, these events are erratic, unforeseen, and all represent deterrents to the standardization and simplification efforts. Consequently, they produce diminishing results in terms of productivity, create no-value add work, and increase the cost of operations.

By using simulation techniques, we were able to identify the preferred reorder quantities for different parts, taking into account production capacity and the effect that one part shortage would have on the other, as well as on the utilization of the workstation. In spite of a highly standardized assembly process, hidden costs in the form of missed orders and/or resource idling are staggeringly high if the SC and the operations are not systematically studied. A holistic approach is necessary when defining SC parameters such as min/max levels for reordering parts; this should be accompanied by the ability to measure “what if” scenarios that incorporate probabilistic events and accommodate for such (this is not clear by Jin). Based on the simulation outcome, we were able to understand the relations between the two parts; we were also able to discover that in this case, due to the latency in the process, production was able to recover from parts shortages. There were some intangibles found as a consequence of this study such as customer satisfactions that play in the overall success of the organization. These finding should be appropriately incorporated into the management decision process.

From our investigation, the simulation demonstrated that when there are part shortages, the entire assembly line is affected and utilization rates changes once parts re-enter the line. This utilization shifts consequently causes other parts to deplete faster than planned, creating disruptions to the line. Also, it was demonstrated that variability reduces productivity significantly and increases cost because companies will either increase the inventory of all the part as a method of lessening effects, creating high cost of inventory or lose money due to reduction in sales. This simulation model enabled us to understand the effects of variability in the lead-times from suppliers and provided a method of understanding preferred inventory levels without escalating the inventory costs.

Future research

Improvement of the model is desired which will include the development of analytical models for determining reordering points. This will help us to estimate order size using demand patters which will include variation in order placements using probabilistic theories.

Another improvement will be that the actual model does not include capacity and/or resource constraints; tightening resources will help us better understand effects of SC interactions and make better judgment on the minimum quantities required per part so that inventory levels are minimized.

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VITA

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