UNIVERSITY OF VAASA

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Bimo Bramantyo Murti

THE IMPROVEMENT OF SUPPLY CHAIN PERFORMANCES THROUGH PROCESS MODELING AND MULTIVARIATE ANALYSIS

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Symbols and abbreviation

ANOVA	Analysis of variance
API	Active Pharmaceutical Ingredients
BPR	Business Process Reengineering
BPS	Business Process Simulation
DES	Discrete Event Simulation
DOE	Design of Experiments
DRS	Discrete Rate Simulation
ERP	Enterprise Resource Planning
FG	Finish Goods
FGI	Finish Goods Inventory
FIFO	First In First Out
IM	Imported Material
KPI	Key Performance Indicators
LIFO	Last In First Out
MANOVA	Multi analysis of variance
PM	Packaging Material
RM	Raw Material
SCM	Supply Chain Management
SCOR	Supply Chain Operation References

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UNIVERSITY OF VAASA
Faculty of Technology
Author: Bimo Bramantyo Murti
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ABSTRACT:

In the supply chain management (SCM), the ability to fulfill the highly fluctuative demand in the most efficient way without compromising the product and/or service quality is seen as a strong value added that can contribute to the organization's financial performance and reputation. This study will explore the significance of the fluctuative demand towards the supply chain KPI performances. As an industry that is prone to demand fluctuation, a pharmaceutical case study company will be used as part of the empirical study.

The method will be implemented through business process modeling and simulation using ExtendSim 9 scenario analysis, followed by multivariate analysis using SAS. The objective is to understand how the seasonal demand fluctuation statistically impacts the SCM system and how can it be handled better to sustain and improve the SCM performance level.

The results for this study is that both demand and process variation have statistically shown significance in affecting the KPI performances. It furthermore shows that both production methods that are done within the organization's internal location are more sustainable against the demand increase in comparison to the toll out manufacturing system.

The minimization use for toll out manufacturing is seen as strongly beneficial in the long run as the system has shown high vulnerability, and an investment to increase the in-house production capacity is seen as pivotal move in order to provide a greater manufacturing flexibility in the long run.

KEYWORDS: Supply Chain Management, Business Process Modeling, Process Simulation, Multivariate Analysis, Correlation

1 INTRODUCTION

The importance of supply chain within an organization is pivotal. Understanding and exercising SCM have become an important prerequisite for staying within the global competition and to excel profitably (Li, Rao & Ragu-Nathan, 2005: 618). SCM involves many areas and activities that require a high level of coordination and system integration in order to achieve the objectives of the organization in the most efficient ways.

Cousineau, Lauer & Peacock (2004: 110) discuss that the operation within the supply chain system extends more than just cross-functional departments, but even more to between firms, which can be difficult to manage due to the great amount of human resources and process involved, as well as the necessary changes in the system that can be accepted, implemented and coordinated between entities in an efficient and effective manner.

Each supply chain is unique. It has its own characteristics, different process routings and various lead times. One of the important steps to understand the supply chain system is to streamline its business process. By having the visual representation of its business process, it opens the possibility to explore a wide range of scenarios and modifications that can provide a better platform for a more efficient and effective supply chain. This study will explore those possibility in the form of process simulation and scenario analysis.

The first chapter of this study will provide a brief introduction regarding the main topic as a groundwork for further exploration in terms of the method and analysis. It will also include the objectives, research questions and its scope as well as contribution of this study.

The subsequent chapter will provide a more comprehensive literature on the range of subjects that are involved within this study, e.g. business process, process simulation, and multivariate analysis. The knowledge can then be used as a foundation of the empirical research that will be applied into the case study on the third chapter.

The third chapter will comprise the method and empirical part of this thesis. A case study will be used to provide a groundwork in terms of its supply chain business process. The simulation model will be developed to depict the business process. It will be explained in depth, and the simulation results will be used as the input for the multivariate statistical analysis, which will be covered in chapter four.

In the fourth chapter, the multivariate statistical analysis and correlation testing will be performed to analyze the various significance degree of the input factors towards the output responses. Its results will be revealed and analyzed.

Fifth chapter will cover the discussion section, in which all the findings will be interpreted, highlighted and evaluated. The sixth chapter will covers the conclusion part, which is the summary from all the findings and discussion regarding the results. It will also include the managerial implication, in which solutions will be proposed as a list of measures that can be further explored by the manager, study limitation and suggestion for further study.

1.1 Objectives

This thesis will undertake an empirical study in regards to the demand effect. The demand is the key element that generates the needs for the SCM to function. The achievement on fulfilling the demand in the most efficient way without compromising the quality contributes a strong value added to the organization's financial performance and reputation.

As any other entity in business world, demand is nothing but steady. The fluctuation is always an issue in which its occurrence happens frequently in the rapidly changing market. Prevention measurement and the ability to handle such issue that results in a better performing and a more sustainable supply chain system is what this study is striving to achieve.

Taken into considerations all the aforementioned discussions, the following points are addressed as research questions for this study:

1. Shock test: What happens to the product availability, delivery cycle time and forecast accuracy when demand fluctuation is introduced?
2. Process variation: How does the process variation on the production lead time affects the product availability, delivery cycle time, and forecast accuracy?
3. KPI correlation: How do product availability, delivery cycle time and forecast accuracy correlate with each other in the tested demand scenarios?

This thesis will use a case study of a supply chain management system from a pharmaceutical industry as a groundwork for its empirical study and analysis. Therefore, the objectives that are manifested within this study are to first analyze the significance of demand increase towards the key performance indicator (KPI) of the supply chain, which leads to the evaluation of the system sustainability against the demand fluctuation.

The second purpose is to additionally analyze the significance of process variation towards the KPI performances. The analysis will be in combination with the demand fluctuation and thus will provide a broad overview of the sustainability of the current supply chain system. The last and third purpose is to explore the correlation between KPI to achieve better understanding on how a behavior of an indicator may explain the performance on its surrounding indicators.

By the end of the study, the author hopes to provide a comprehensive understanding on how to develop a high sustainable SCM system against the demand increase in order to maintain, and further improve, the current system performances which eventually leads to a better financial performances and reputation towards customers and global.

1.2 Research scope

This study will undertake the development of simulation model and scenario analysis using ExtendSim 9, which will be followed by the multivariate statistical analysis using SAS. The scope of this thesis will be the significance degree analysis on the effect of the demand fluctuation and process variation towards the SCM performances through its key performance indicators. In the empirical research, the simulation model will be built in accordance to the SCM system of the case study company.

The empirical part of this study is bounded towards the perspective of supply chain management business process model, specifically in terms of material management. Thus, it will not include any economical factor nor labor resources in its analysis.

Since the test will focus on the effect of demand fluctuation and process variation of the production lead time, any additional variation in other entities will be limited and not taken into consideration during the multivariate statistical analysis.

1.3 Research contribution

The method of discrete event simulation has been acknowledged in terms of its importance in the application for a variety of industry (Kristianto, Helo & Takala, 2010; Pawlewski & Greenwood, 2014; Persson & Olhager, 2002). This study takes the example from the real world pharmaceutical manufacturing industry, in which its supply chain system will be used as a groundwork for the development of the business process and the simulation model.

The simulation model itself will give an insight on how the SCM process model is constructed in the pharmaceutical industry, what are the characteristics of its process model, production types, along with the typical various issues and challenges in its activities and process.

Seasonal demand fluctuation has always been a recurrent issue in the pharmaceutical industry, as well as many others. This study acknowledges the phenomenon and provides an understanding of its significance, along with the combination of the process variation, towards the supply chain performances.

This study, in addition, has also provided an understanding on how a performance indicators may correlate with each other, and how strong do they correlate in the scenario of demand fluctuation and high process variation. This provides the platform of consideration during the decision making process in respect to what and how much effect it may cause when attempting to make an alteration that can impact the performance indicators of the system.

The study has resulted in the development of solution to anticipate better the demand fluctuation for different production types and supply chain system in the pharmaceutical industry, followed by the proposal on which path or approach will be the most beneficial to take in order to enhance the organization's performance in the long run, particularly in its supply chain system.

2 LITERATURE REVIEW

This chapter will consist of various literatures that are considered relevant for this study and its empirical research. This chapter aims to familiarize the readers of the fundamental concepts of supply chain, its challenges and various issues surrounding it. Furthermore, it will covers the literature in respect of the decision support tool for this study, the concept of business process modeling, process simulation and statistical analysis.

2.1 Supply chain

In today's highly competitive and rapidly changing industry, many argue that the competition is now more about supply chain rather than between firms. Having an efficient and effective supply chain system has emerged as a valuable way to gain the competitive advantages for an organization, in which furthermore will improve the organizational performances (Li et al. 2005: 618).

Higher transparency and liberal market have resulted in the steep increase of global competitiveness. When combining those factors with an advance progress in the field of information technology and system, they have become the main force to a faster development of a more complex and integrated supply chain (van der Zee & van der Vorst 2005: 65).

There are several definitions of SCM that will be introduced in this paper. The first definition is taken from van der Zee et al. (2005: 66) that define SCM as the incorporation between planning, control, and coordination of all the logistic activities and process with the aim of providing the highest consumer value at less cost without compromising the requirements of the stakeholders within the supply chain.

Elgazzar, Tipi, Hubbard & Leach (2012: 276) mention that achieving the competitiveness edge in today's industry require the excellent ability to find the balance between the cost reduction, quality improvement and productivity, as they typically go against one another.

Second definition of SCM can be taken from the same study of Egazzar et al. (2012), who define the supply chain as a set of an organization’s entire activities, process and operations which are interconnected, both directly and indirectly, in order to transform the inputs into outputs before being delivered to the final customer. A higher integration and transparent system is known to optimize the output and contribute a higher value added to the customers.

The last definition of SCM can be adapted from the book Operations Management (Russel & Taylor III, 1998: 371) that define SCM as the coordination of all the activities that include planning and managing supply and demand; warehousing; material sourcing; scheduling the product and/or service; manufacturing; inventory control and distribution; delivery and customer service, with the objective to serve the customers with reliable service of high quality products at less cost.

Li et al. (2005: 618) acknowledges the importance of SCM on supporting the strategic cooperation between organization with the objectives of achieving a performance improvement on the entire supply chain. It is within the goals of SCM to offer the highest quality of sourcing, manufacturing and delivery process across the organizational supply chain as a competitive tool.

Supply chain is oftentimes considered a key player for an organizational competitive advantage in a market that increases rapidly. According to Simchi-Levi (2011: 52-55), higher inventory, more push strategies and rethinking off shoring strategy are some of the changes that has been pushed forward in the global organization when dealing with volatility and increasing demand.

The emerging of technologies in today's IT industry has also played a part in the SCM efficiency. Helo, Xiao & Jiao (2006: 1063) discuss the importance of strategic IT tools such as Enterprise Resource Planning (ERP), Warehouse Management System (WMS) and Transport Management System (TMS) as a powerful tool for process coordination within the organization, and Agile Supply Demand Network (ASDN) as an integration tool for collaboration with the various external members of supply chain.

Lee (2004: 3) defines the three distinct characteristics that a great supply chain system has, in which they are known as the triple A's: agile, adapt and align. Agility is defined as a factor that is important to be obtained due to the high possibility of fluctuation in demands and sales over times. Demand shock can cause significant negative impact to the organizational performance if not responded properly. The ability to respond the short term changes in demand or supply quickly is considered a great agility. Supply Chain Operation Reference (SCOR) model defines agility in 3 measurements, which are upside supply chain flexibility, upside and downside supply chain adaptability (SCC, 2008: 12).

Adaptability factor represents the notion of flexibility. It is considered as the ability to adjust the supply chain design in order to meet the structural changes in market. It is essential to recognize the structural shift, possibly before it occurs, by obtaining the latest data and analyzing key patterns. Adapting accordingly to those shifts can keep the competitiveness edge high. Pawlewski et al. (2014: 127) states that flexibility can be obtained both internally e.g. shift arrangement, additional resources of personnel and equipment, and externally by policies and relationship between suppliers.

The relationship between suppliers, and organization, brings the discussion to the third concept, which is alignment. The importance of alignment is essential due to the acceptance that every organization tries to maximize only its own interest. Thus, the lack of alignment will likely to cause disruption in many areas of the supply chain practices. Method such as redefining relationship terms in favor to risk sharing and rewards is an example of a great alignment between firms or internal department within the supply chain process. Kristianto, Ajmal & Helo (2011: 113) mentions that the strategic inventory and replenishment alignment offer significant contribution to SCM network planning with respect to inventory value, the reduction in lead time and the maximization of profit.

Beamon (1999: 280) discusses that cost has always been considered as an integral part of SCM measurement. The heavy reliance on cost as a main performance measurement is seen as inadequate and oftentimes inconsistent with organization's strategic goals, and it lacks of consideration regarding the effect of uncertainty. He therefore suggests the incorporation aspect of resources, output and flexibility as part of the performance measurement indicators. Brief description of the concepts can be illustrated in table 1 below.

Table 1. Goals of performance measure (Beamon 1999).

Performance measure	Goal	Purpose
Resources	High level of efficiency	It critically leads to profitability
Output	High level of customer service	To avoid customers turning into other supply chains
Flexibility	Rapid response towards changing environment	In an uncertain environment, it is critical for supply chain to be highly adaptable and able to respond

Beamon (1999: 282) further describes more detail factors within these three elements. The measurements in resources typically include the level of inventory, personnel requirements, and utilization level of the equipment, energy and cost. The general objective for supply chain is to achieve the resource minimization with the most optimum output. Specific examples may include total cost of supply chain resources, distribution, manufacturing, inventory (investment, obsolescence, work-in-process, finish goods), and return on investment.

The measures of output include customer responsiveness, quality and quantity of the final product. The measurement of output should be able to associate to both organization's strategic goals and customer's goals and values. Specific examples may include profit margin, sales, fill rate, on-time deliveries, backorder, customer response time, manufacturing lead time, shipping errors and customer complaints (Beamon 1999: 283).

Flexibility measures the organization's ability to restructure its operations and strategy alignment in order to accommodate the uncertainty from both internal and external environment whilst still able to maintain the high performances (Li & Qi, 2008: 13). Hence, flexibility plays a vital role in an industry with high uncertainty. It functions to accommodate volume and schedule fluctuations from partners, e.g. suppliers, customers and manufacturers. Several flexibility measurement in the supply chain are the ability to respond and accommodate factors like demand variations (e.g. seasonality), machine downtime, new market segments, increasing competitors, among others.

As supply chain can be a significantly integrated business process with the amount of complexities that may increase over times, Beamon (1999: 275) states that designating appropriate performance measures for supply chain analysis is pivotal. Further suggestion is made that at least one individual measure, representing each of the aforementioned elements (Table 1), is incorporated within the supply chain performance measurement system.

The analysis on performance measurements, also known as key performance indicators (KPI) is increasingly becoming more important subject due to various beneficial effects that it offers with respect to the improvement of the supply chain. Chae (2009: 427) states that the role of KPI is to serve as a platform of feedback to the current supply chain system, and that observing those indicators will enhance the visibility on the gap that may have existed between planning and execution. Given the information from all relevant KPI will help identify and open the doors for possible correction and improvement on the potential issues.

Illustrated below (Fig. 1) is the supply chain that represents an overview network that contains series of process and decision-making activities which are interrelated by the flow of material and information across the boundaries between firms and organization (van der Zee et al. 2005:67).

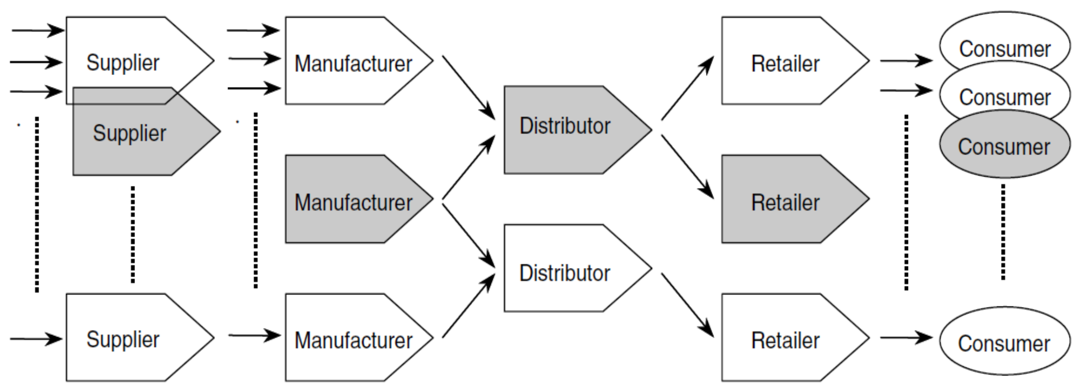

Figure 1. A generic supply chain (shaded) (van der Zee et al. 2005: 68).

Beamon (1998: 285) discusses that in a conventional way, analysis and study has been done in respect to individual stages of the bigger network of supply chain. It evolves as time goes by into focusing more to integration and comprehensive method of manufacturing system design which results in supply chain framework being recognized as an important entity.

2.1.1 Flexibility

In a rapidly changing market and volatile demand environment, the factor of flexibility is closely correlated with competitive advantage and key to survive. Not only in certain part of the organization, but rather at the various level of the business process. Duclos, Vokurka & Lummus (2003: 448) describes manufacturing flexibility as a multi-dimensional paradigm rather than a single entity or variable.

Russell et al. (1998: 32) defines the factor of flexibility as competitive weapon. It is described as the manufacturing ability to introduce and produce wide ranges of products, quickly modify existing products, and respond to customer needs. This is align with the previous literature of Lee (2004) and Beamon (1999) about supply chain flexibility.

SCOR 9 model (SCC, 2008: 63) adopts the concept of flexibility in its agility matrix. It integrates the aspect of upside supply chain flexibility, which is defined as the number of days that is needed to have an unplanned increase of quantities delivered as much as 20%. The 20% increase concept is then extended to the matrix of upside flexibility of sourcing, manufacturing, and return.

Lenz (1989) discusses the advantages that a production process can have by having a higher degree of flexibility, which is the lower inventory with less balanced station loads, and the ability to maximize production output with shorter and more consistent lead time.

2.2 Decision support system

In respect to computer-based information system, in which oftentimes used as a tool to facilitate organizational process and to support decision making process, a simulation is considered as an ideal starting point. In his dissertation, Page (1994: 156) states that a simulation is, first and foremost, a tool for decision support.

Particularly in discrete event simulation (DES), it has been extensively utilized in numerous industrial applications (e.g. manufacturing, supply chain system) as a simulation tool of assembly lines, distribution system, and other system alike. Albrecht (2010: 76) describes the classical approach of DES is in the simulation and modeling of a system.

As part of the powerful simulation tool, ExtendSIM will be utilized to build the simulation of the case study supply chain system in this thesis. The result of the simulation will be an abundance of statistical data and scenarios, in which further analysis will need to be done in order to extract the information from those data.

Statistical analysis is considered as the appropriate method to accommodate the study, in which the analytical ability of data mining will be used by the utilization of SAS. The analysis will involve the function of multivariate analysis of variance in order to gain the relevant understanding on the significance of the demand and/or process variation, as well as correlation between variables.

2.3 Business process modeling

Harrington (1991) mentions the functions of business process as a tool to support the organization’s objectives by serving a platform of logically interconnected set of tasks and activities that uses the organization’s resources to provide the beneficial results to organization’s development. As the development in the area of technology is increasing in higher pace than ever before, the needs to integrate the use of technology into the business processes and activities emerge significantly.

Becker, Rosemann & Uthmann (2000: 31) describe process modeling as an instrument that can be utilized to cope with the level of complexity that the process planning and controlling can offer. Business process has gained importance in many business areas. Desel & Erwin (2000: 129) state that the ability to effectively streamline the organization's business process in the most flexible way has become one of the most competitive factors for the success of today's competitive industry.

Min & Zhou (2002: 233) states that given the broad range of complexities and scale, there is no model that is able to capture all characteristics of supply chain business processes. Thus, it is important to be able to model the relevant scopes of the supply chain system that reflects the key points in the real-world dimension but yet still calculable and quantifiable within its analytic process. Obtaining the relevant KPI with a deep understanding of how to measure them is an important foundation of the decision making process.

According to Beamon (1998), the attention on the importance of the supply chain performances, design and analysis has increased due to various factors such as rising production cost, the shorter length of product life cycle, and the globalization of market economies. Laguna & Marklund (2013) discuss the importance of appropriately designing business process for internal efficiency and external effectiveness.

Van der Vorst, Beulens & Beek (2000: 356) defines the modeling method to be based on the concepts of business process of all parties in the supply chain network, design variables at both configuration and operational management level, relevant performance indicators and business entities.

The need to accommodate the use of business process has generated the need to have the necessary and suitable tools and techniques for the identification, analysis and simulation. Business process modeling is known to be the basis for this concern (Desel et al., 2000: 129). The model of business processes plays a significant role in many phases of business process reengineering (BPR).

Figure 2 below shows the phase of when the business process modeling is utilized. It is an important tool when an organization is attempting to reconstruct or reevaluate its current process model to achieve a better performance. The business process model is shown to be used during the design phase, which always happens after the analysis and before the implementation phase.

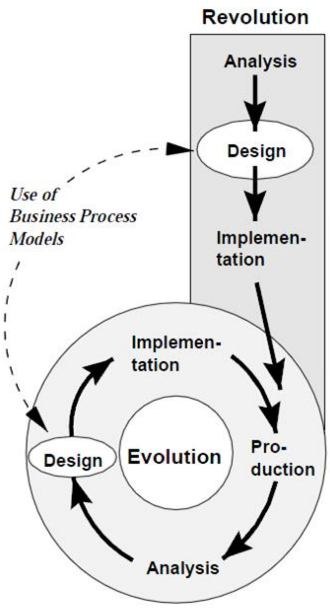

Figure 2. Revolutionary phases of BPR (Desel et al. 2000)

It has, at times, happened that the business process is designed mainly by experience or feelings. However, it is desirable to provide additional factors to the considerations of decision making process with some facts by building and evaluating business process model instead (Desel et al., 2000: 130).

Tumay (1995: 55) mentions that the reengineering of the business process starts with the basic hypothesis that the current hierarchical structure is flawed, hence the emerging need to do reinvention is considered of worth in order to provide a value-added process that the organization needs in order to maintain its competitiveness and survive the competition. Some of the typical examples of business processes are:

- Product development process
  Product design, testing, configuration, and documentation
- Order management processes
  Purchasing, receiving, storage, materials management

- Financial management processes
  Payroll, audit, accounts receivable, accounts payable
- Information management processes
  Database management, networking, client-server applications
- Human resources processes
  Hiring, placement, personnel services, training

SCM is closely related to the order management processes. Starting with the purchasing, all the way to materials management and later added to the delivery service, it has become important part of the business processes that can be integrated to the value-added competitive advantage for an organization.

Tumay (1995: 55) states that the reengineering of the current business process has the goal of one or several of the followings:

- Increase service level
- Reduce total process cycle time
- Increase throughput
- Reduce waiting time
- Reduce activity cost
- Reduce inventory cost

With many of those objectives above being applicable to the supply chain business process, the outcome will much likely be an infinite number of scenarios that makes it impossible or extremely hard to comprehend and evaluate without the help of a computer simulation.

According to van der Zee et al. (2005: 66), the outcome of SCM should result in the selection of process scenarios that give a firm representation on how the supply chain should perform in terms of its production, distribution and coordination.

Furthermore, the article mentions the existing needs for theory building and the development of the appropriate tools and methods to achieve a successful SCM practices, in particular a modeling language to describe the dynamic analysis of supply chain scenarios with the objectives of sustaining the decision making within the organizational supply chain.

Beamon (1998: 282) categorizes the modeling approach of the multi-stage models in SCM process design, which are deterministic analytical model, stochastic analytical model, economic model, and simulation model. The study mentions that simulation technique is used to analyze and evaluate the effect of various SCM strategies in respect to demand fluctuation.

According to Tumay (1995: 56) in regards of business process model, there are four basic building blocks that are typically used; flow objects/entities, resources, activities and routings. By applying these four basic blocks with the combination of the supply chain KPI in the business process of an organization, this can be considered as an appropriate method in order to gain the objectives of this thesis study.

The modeling phase in the business process is a crucial step towards reaching a comprehensive understanding in the supply chain business process that is going to be understudied within this paper. Simatupang & Sridharan (2005: 258) mention the integrated supply chain process as part of the five features of collaboration. By knowing and trying to integrate the business process of the supply chain partner within the simulation model, it can provide a better representation and simulation outcome which leads to a better interpreted results and analysis.

Van der Zee et al. (2005: 69) classifies the requirement for modeling a business process based on the following:

- Model elements and relationships

  The integration of each process element with specific set of relationship and control policy. The clear concept of entities, roles, policies, processes and flow is essential to be included within the supply chain process model.
- Model dynamics

  It is important to provide the information about the dynamic effects in the model. Given that many entities are involved within the business process, several requirements to achieve the model dynamic include the ability to determine system state, calculate the value of several KPI in any given time, and designate the appropriate KPI to the relevant model and stages
- User interfaces

  The level of understanding from users towards the simulation model is an essential element. The participation of supply chain partners to the development of the business process model will be the key to achieve the shared and well-represented decision variables in the particular business model that will benefit to the analysis that are made towards it. There are two reasons in particular to which the joint participation is required in the simulation study:
    - Create trust in the solution and among the parties/entities involved, hence increasing the chance of better acceptance to the outcomes of the analysis
    - Increase the model quality, the solution, and the supply chain scenarios
- Ease of modeling scenario

  The complexity of the supply chain business process and the substantial amount of possible scenarios that can be constructed has called on the needs for a simple and transparent *what-if* analysis. It is specifically related to the selection within the model and the required time for tailoring them according to the preferable format.

As stated by Laguna et al. (2013), the essence of business process design is how to do things in a good way by achieving the process efficiency and effectiveness to satisfy the customer's needs. A well-designed process is to do the right things in a right ways.

2.4 Process simulation

Fripp (1997: 138) discusses the important roles that the business simulation plays in the development of management activities. It furthermore claims that business process simulation (BPS) can represent more of a reality in comparison to other tools and methods that have a similar objectives of capturing the real world activity. Simulation can be used in a general or tailor-made purpose to a particular case, areas, or industry. The values that derive from the simulation design can be used as an experiential learning device.

Tumay (1995: 56) describes the process simulation as a method that allows the process, activities, people and technology to be represented in a dynamic computer model, in which it is essentially divided into four steps:

- Model building
- Running a model
- Analyzing performance measurements
- Evaluating alternative scenarios

Lyons, Nemat & Rowe (2000: 107) have stated that modern BPS tools and techniques have potentially given the necessity to handle various industrial challenges that leads to the improvement in efficiency, increased profit and reduction in cost. O’Kane, Papadoukakis & Hunter (2007: 515) mention that simulation has been argued to be one of the major tools to assist improvement on the business effectiveness and performances.

Furthermore, O'Kane et al. (2007: 516) describe that simulation can demonstrate how the process operation may respond when the influencing variables are added, modified or withdrawn within the design system. Imagine That Inc. (2013: 55) mentions the needs to understand the goal of the process modeling before start building a simulation model. It provides the following examples of specific goals in process modeling, such as:

- To interpret the system
- To analyze its behavior
- To manage/control/operate it to achieve the desired outcomes
- To test hypotheses against the system
- To design/improve/modify the system
- To forecast the response and outcome under varying conditions

O'Kane et al. (2007: 516) also describe the other benefit of simulation, which it to identify the bottlenecks within the system that often cause high inventory level, low resource and low machine utilization. The related study also acknowledges the benefit of simulation in respect to contribute to the achievement of continuous improvement through the evaluation and analysis of the *what-if* scenario.

Furthermore, in the book of Imagine That Inc. (2013: 55), it breaks down the following steps for establishing a better simulation model. Building a simulation model is an iterative process that require analysis, refinement and comparison in its development. The steps are:

- Formulate the problem
- Determine the information flow
- Build and test
- Acquire the data
- Run the model
- Verify the simulation results
- Validate the model
- Result analysis
- Conduct experiments
- Documentation of the simulation and results
- Implement the decisions

Jansen-Vullers & Netjes (2006) explain that the simulation helps in obtaining a better understanding in analyzing and designing process. Introducing a dynamic aspect in this context can also provide a value added to the process. Evaluation can be done through multiple iterations of the simulation model in which various scenarios will emerge and can be compared, analyzed, drawn conclusion from and assessed for continuous improvement.

By experimenting the estimated future changes in the process design will help supporting the decision making and contribute to the improvement for a better understanding of the business process modeling (Aguilar, Rautert & Pater, 1999: 1383). The area of application in the simulation is very broad, starting from production/operation planning, financial analysis, healthcare, banking, and system information, among others.

Simulation is highly useful in measuring and analyzing the process performance, as well as serving as a strong platform for developing an improved and innovative process design. Implementation and feedback are the important points when following the development of the new process design. Figure 3 on the next page illustrates the usage of simulation within the development of process center management.

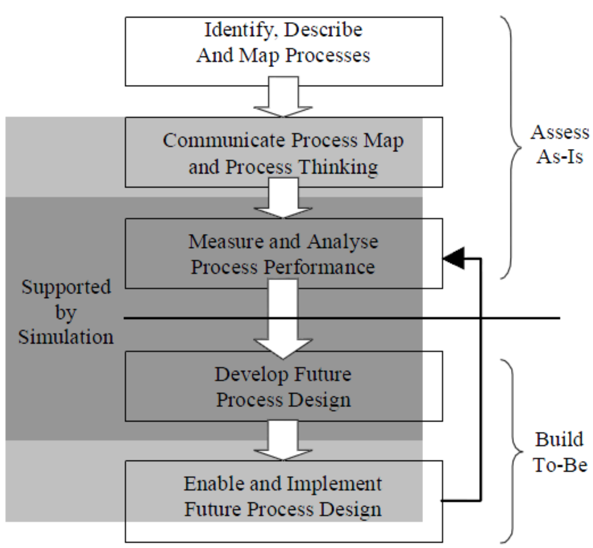

Figure 3. Building process centered management (Aguilar et al. 1999)

As stated by Laguna et al. (2013), simulation can be an attractive alternative for modeling tools due to its ability in offering the flexible and most powerful systemic tool in comparison to the strategy implementation that is done through pilot project which will most likely consume large amount of time and resources.

Russell et al. (1995: 618) argue that the popularity of simulation is largely due to the flexibility that it offers in its system analysis when comparing it to a more restrictive analytical technique. It also provides an excellent platform for experimental process that can be performed within a laboratory environment.,

Kalnins, Kalnina & Kalis (1998: 25) specify the general scheme of achieving goals in the typical current measures of performances (e.g. cost, service, speed and quality) that integrates the usage of simulation in the area of business process reengineering, which is described as follow:

- The current *as-is* model is built that includes aspects of the system such as:
    - Main business functionality
    - Organizational structure of the system
    - The workflow and the exact internal behavior of the system
    - General business principles and goals of the system
    - Low-level economic criteria of the system
- The *as-is* model is analyzed and improvements are proposed
- The proposed system improvements are documented as *to-be* model
- The *to-be* model is compared with logical equation, static analysis and dynamic simulation
- The best *to-be* model is implemented within the business process

Simulation can address the issue of bottleneck and enhance the system performance by introducing several dynamic parameters into the process, e.g. lead time, capacities and volumes. Those parameters can then able to provide a better overview in respect to the dynamic performance in comparison to a statistic analysis (Aguilar et al.1999: 1386).

One of the other benefits of BPS is that it provides the platform of communication and redirects people to the most important objective of achieving an improvement process performance (Aguilar et al. 1999: 1386). Kellner, Madachy & Raffo (1999: 93) state that the common purposes of process simulation modeling are to present a foundation for system experimentation, behavior prediction and as a responds to the *what-if* questions.

Furthermore, Kellner et al. (1999) also combine the general purposes of doing simulation into several categories, which are:

- Strategic management
- Planning
- Control and operational management
- Process improvement and technology adoption
- Understanding
- Training and learning

Jansen-Vullers et al. (2006) point out that simulating business processes is overlapping with the simulation of discrete event system. There are many character similarities during the development of BPS with the discrete event system. The discrete-event based simulation tools, in which will be explained furthermore in the next section, is considered the most capable and powerful tools for business process simulation (Tumay 1995:59). Following section will further study the types of simulation and modeling methodology in which the relevant business process model can be applied into.

2.5 Modeling methodology

Within the business process simulation (BPS) context, there are several modeling methodologies that are used to specify how the system is termed. The system is constructed from several set of entities in which the relationship between each other will be formulated in accordance to the rules and operating policies within the system. The running time will be the abstraction of the real time, and as the clock advances, the changes and the behavior of the system in terms of its performance, reaction and response will be seen, calculated and presented in output.

Imagine That (2013: 43) categorizes the three major modeling methodology for the simulation modeling methodology, which are:

- Continuous
- Discrete event
- Discrete rate

2.5.1 Continuous

Continuous model is a type of methodology in which the time step is fixed at the beginning of simulation. It advances in equal increment whilst the values change based directly on changes in time. Figure 4 below illustrates the timeline flow in the continuous model. It represents the continuous time that advances incrementally from one step to the next.

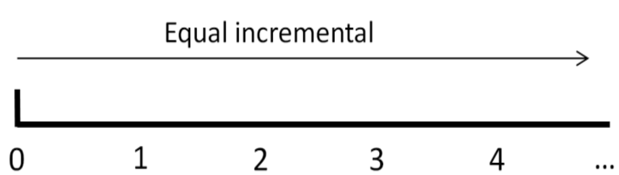

Figure 4. Timeline flow for continuous model

The typical examples that continuous model are an airplane flying that simulates the continuous system of its states (e.g. velocity, height, position), or a water/oil pipe that symbolizes the state of continually changing system represented in real numbers and may result in an infinite possibilities of numbers during the simulation.

The continuation phenomenon typically results in a fractional numbers and therefore may not always model the reality where things can oftentimes only be discrete (e.g. the sales number of cars in which it would be impossible to have 10 ½ cars being sold).

2.5.2 Discrete event

In the discrete event methodology, the system changes states when the discrete time-represented event occurs. The discrete event activity (Fig. 5) represents the time period is broken down into small discrete slices and the state is updated according to events happen in that particular slices. The individual items are the ones modeled using discrete-event.

The typical application for the DES is a factory or assembly system that manufactures entities of parts (e.g. cars, shoes, plastic products). The progress is represented in an integer numbers and therefore the results are countable (e.g. number of cars made per shift, number of ketchup bottled manufactured per hour). Another area of application may include traffic situation, people, data information, or network protocols.

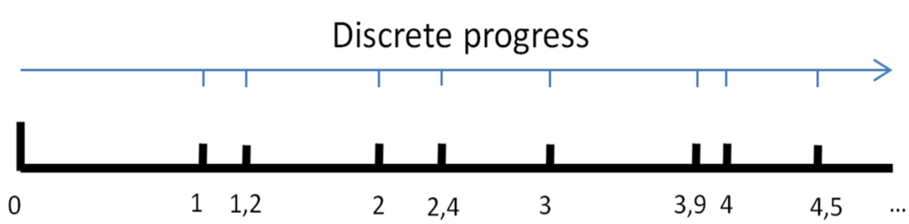

Figure 5. Timeline for discrete event

Persson et al. (2002: 234) state that DES is able to handle stochastic behavior of supply chain; thus it can accommodate the need to evaluate the phenomenon of queue system and similar activities that is dependent upon some level of uncertainty factors.

2.5.3 Discrete rate

A discrete-rate simulation (DRS) is a hybrid type that combines the methodology aspect of continuous with discrete-event. The method is typically used to simulate linear continuous process that concerns with the movement and flow routing. Hybrid system is used in a scenario where flow moves continually at incremental rates, similar to continuous methodology, but with the additional activities of discrete-event that is integrated within.

The timing that is represented in the simulation for the discrete rate activities is similar to the discrete event (Fig. 5), therefore the calculation of values and progress are made during the events that occur in specific time slices. Discrete event plays the fundamental role in building the discrete rate model, only the continuous activities are integrated within.

Typical application of the DRS includes those with rate-based flows of stuff. The example can be the pipeline of oil starting from the rig until the delivery process. When the oil is processed from the rig, it is counted as a discrete/integer number due to that it is transported per oil tanker. However, when the oil delivery process is going to be transported through the pipeline, the flow becomes continuous.

The comparison table below provides a better description of how each modeling methodology that is mentioned above is applied within the context of BPS. Adapted from Imagine That Inc. (2013: 45) and Kellner et al. (1999: 103), table 2 below will highlight several distinct characteristic differences between discrete event, continuous and discrete rate as follow:

Table 2. Differences between discrete event, continuous and discrete rate

Factor	Discrete Event	Continuous	Discrete Rate
What is modeled	Entities (items or things)	Values that flow within the model	Bulk flows of homogeneous item, or flows of otherwise distinct entities where sorting is unnecessary
The cause of state change	An event	Time	An event
Time steps	Interval between events is discrete	Interval between time steps is constant.	Interval between events is discrete
Characteristic of the model	Items has unique characteristics and can be tracked	Homogeneous flow	Homogeneous flow
Routing	By default, items are automatically routed to the first available branch	Values need to be explicitly routed by being turned off/on at a branch	Flow route is based on constraint rates and rules that are defined in the model
Statistical detail	General statistics, item can be tracked & counted, etc	General statistic: amount, efficiency, etc	In addition to general statistics, effective rates, cumulative amount
Queue system	FIFO, LIFO, priority, time delay or customized order	FIFO	FIFO
Typical usage	Manufacturing, service industries, business operations, systems engineering	Scientific (biology, chemistry, physics), electronics finance, system dynamics	Manufacturing of powders, fluids, and high speed, high volume processes, chemical processes
Advantages	1. CPU efficient due to time advances at events 2. Attributes allow entities to vary 3. Queues and interdependence capture resource constraints	Accurately captures the effects of feedback	Ability to handle sufficient complexity and breadth of mixes between discrete and continuous process

Factor	Discrete Event	Continuous	Discrete Rate
Disadvantages	1. Continuously changing variables not modeled accurately 2. No mechanism for states	1. Sequential activities are more difficult to represent 2. No ability to represent entities or attributes	Lack of technique development to understand the modeling and when to apply it in the real world application

2.6 Tools

Kellner et al. (1999: 91) discusses the increasing usage of software process simulation for the purpose of addressing variety of issues from the strategic management to supporting the process improvement in various degree of impact in the organization. Supply chain system has been a subject of improvement within many organization, and the simulation use in this field is considered a very beneficial, preventive and exploratory measures in regards of system improvement or policy implementation.

Many software tools have been developed for BPS within the last decade, in which most of them use a graphical symbols and objects as a representation of the business process model and the reflection of the relationships between them. Tumay (1995: 59) breaks down the three major categories for BPS tools, which are:

- Flow diagramming based simulation tools

  This method serves as the most basic level of simulation tool in which it uses flowchart to define process, activities and routings. The capabilities is limited in simulation analysis, but it is the most easy to use and learn. Example tools for this method are Optima and Process Charter

- System dynamics based simulation tools

  This tool is, in other words, the continuous simulation software which uses the methodology of system dynamics. The typical construction of this model includes levels, stacks, flows, converters and connectors. Example software tools are Ithink and Powersim
- Discrete event based simulation tools

  Stated as the most capable and powerful tools for BPS, DES system model serves as the representation of the modeling flow of the various entities which will allow the users to follow the process flow through the designated route. Examples of the tools are BPSimulator, Extend, and Simprocess.

Van der Zee et al. (2005: 66) state that DES is seen as a natural approach when analyzing the supply chain system considering its complexity that can highly limit the conventional method of analytic evaluation. This thesis case study, which will be explained in depth in the following chapter, will implement the most appropriate modeling methodology based on this literature for its simulation analysis to achieve its objectives.

As aforementioned in the chapter of decision support tool, DES has been widely used as a tool for decision support due to its ability to capture various types of system design within a broad range of industry. Designing the *as-is* system, performing experimental design process and establishing a strong foundation for a better, improved and innovative *to-be* system design are all part of the simulation process and objectives.

The DES tools can vary throughout many enterprises and may be specifically designed for certain type of industry. Kopytov & Muravjovs (2011), e.g., use the ExtendSim 8 for the study purpose of establishing a two-level inventory system with homogenous products that is characterized by random demand and lead-time for the product delivery. Other application area can include health industry, IT, financial institution, and food delivery service.

Many of the software developers put an effort to build the tool that are multi-purpose and may be used in wide range of industry that deals with complex problem areas. However, as stated by Zapata, Suresh & Reklaitis (2007: 2), those products that claim to be multi-purpose are typically developed initially to satisfy the need for more specific industries, thus leads to have numerous constraints that can be observed from its internal architecture.

Zapata et al. (2007) further explains the need for establishing a set of criteria and evaluation to various DES tools in order to get a better perspective during the utilization period of particular tool. Several evaluation criteria is then defined by the article for the tool comparison, some of which are highlighted below:

- Hierarchical model building
- Accessibility to elements
- Model reusability
- Modularity
- Interaction with spreadsheets and databases
- Dynamic updating of queuing policies
- Updating model structure at run time
- User defined routing
- Logic driven pre-emption
- Running multiple simulations
- Start from non-empty state
- Adaptability to model changes
- Animation layout development
- Quality of built-in elements

The DES packages that are used for the study evaluation are:

- eM Plant 7.6

- Flexsim 3.5
- Extend 7.0
- Micro Saint 2.2
- Quest 5 R17
- Sim Cad 7.2, and
- Workbench 5.2

The study reveals that eM Plant 7.6, Flexsim 3.5, and Extend 7, are amongst the finest candidates that addresses largest number of criteria. Another study of DES software comparison are identified by Albrecht (2010), in which a quantitative method of evaluation and ranking is done to four software simulation tool, which are:

- Arena
- Extend
- Sigma
- Ptolemy II

The article further elaborates the following factor of consideration that contributes to the evaluation, which covers seven major areas:

- Modeling Environment
- Model Documentation and Structure
- Verification & Validation
- Experimentation facilities
- Statistical facilities
- User support
- Financial and technical features

The study reveals the evaluation of the software in which Arena and Extend are considered the most comprehensive tools ready to use. Being commercial package, they are also known to hide more of the underpinnings (e.g. programming language, dialog editor, etc). ExtendSim has constantly proven its capability of modeling large and complex system that can to be applied in the most challenging simulation problems (Krahl, 2008: 220).

2.6.1 ExtendSim

This chapter will introduce the basic features of the ExtendSim simulation tool. This chapter is written for the purpose of familiarizing the simulation tool that will be used within this study. As previously written, ExtendSim has been acknowledged for its ability to perform a DES and can be used to simulate a wide ranges of industry application.

Krahl (2008: 215) mentions that the ExtendSim facilitates each phase of the simulation model during the designing stage which involves the development of the user interface that will allow other to analyze the visualization model of the system. The system will be modeled in accordance to the methodology explained earlier, which are continuous, discrete event or discrete rate.

In ExtendSim, it is the discrete event library Item.lix that provides the most needed features for modeling and simulation of business process (Laguna et al. 2013). Other library such as Plotter.lix and Value.lix also contains some of the needed features that can enhance the ability to simulate a business process.

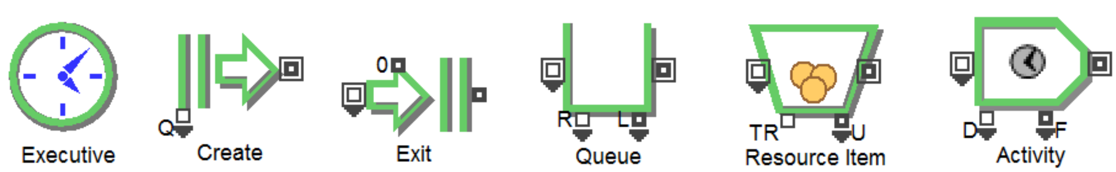

Figure 6. Basic blocks in ExtendSim 9

Laguna et al. (2013) describes a simulation model in ExtendSim as an interconnected set of blocks. It performs specific function such as being a queue buffer, or simulating a work or process activity. What will be tracked in the simulation is an item, which could resemble anything in regards of its application, e.g. documents, products, people or cars. Item can only be in one place at a time, and it can move according to the workflow that has been designed in the simulation model.

Laguna et al. (2013) defines the six basic blocks (Fig. 6) that can construct a simple simulation model, which are:

- The Executive block
  The Executive block controls and does event scheduling for discrete event model. Its use in a model is to change the timing so the simulation time advances from one event to the next instead of moving in a uniform intervals (Imagine That Inc. 2013)
- The Create block
  This block is used to create an item with a specific arrival times. The arrival time between an item can be specified in various ways, e.g. randomly, or using a specific distribution.
- The Exit block
  This block is used to represent the items that leave the process. Typically positioned as the final point, this block will record the amount of items that end here.
- The Queue block
  This is a block that serves as a holding area for an item. Similar to a queue system, item stays in this block while waiting to be processed in the next block.
- The Resource Item block
  This block is similar to a holding area but it can contain an initial number of items. The number can be specified in the setting and it can be continually filled with another input item.

- The Activity block

  This block is used to simulate an activity. Be it the production process, assembly process, and any other type of activity. The activity is simulated by delaying the item to leave the block after it enters. The time takes for an item to be processed in this block can be defined in constant time or in a specific distribution.

Additional features (Fig. 7) that are commonly used in the simulation model may include:

- Batch and Unbatch

  The block can collect the items until certain quantity before it is released as a batch item into the next process. The Unbatch is simply the reverse, in which an item can enter and being released in a numerous quantity. The quantity can be determined either from the block's properties, or from other sources using connectors
- Information

  The Information block is the point in which various information can be revealed and recorded. One of the eminent function in this block is the calculation of cycle time from the designated point origin. This relates to the next block, which is set.
- Set

  This block records the item that passes through from the input connectors to the next block. One of the function it can utilize is being the point origin of an item in terms of time. It can then be connected with the information block to count the cycle time of an item between the point origin until it reaches the information block.

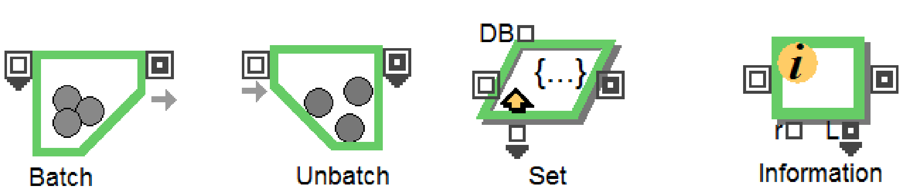

Figure 7. Additional basic blocks in ExtendSim 9

Random element

In the simulation of a business process, the model can be designed with fixed deterministic setting or with a certain level of randomness in the process. In the real world business process, constant process is something of a rarity. Variation in activities oftentimes happens in many level and process stages.

ExtendSim accommodates the situation by having several functions (Fig. 8) that can be used for integrating the element of randomness. Random processing time can easily be integrated in model such as Activity block, or Create block. The additional features of randomness that can be integrated are:

- Random block
  This is one of the prominent function of randomness element in the model. It can create a random number based on various distribution. The number can then be used to represent things such as, e.g., demand, item, processing time, etc.
- Select item in/out
  This block is used to separate the item based on the criteria of possibility. The Select Item In is able to distinguish the input from various sources and selecting one item out at a time. Inversely, the Select Item Out is used when an item that enters from an input can be transferred to several options in the next process.

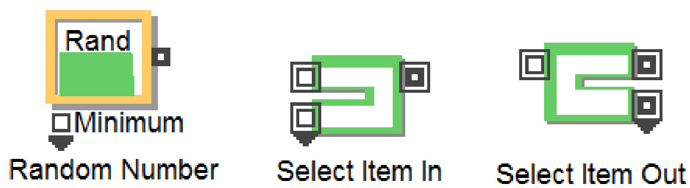

Figure 8. Blocks for random element

2.7 Statistical analysis

What is considered as the key element in the computer simulation is data analysis. Input and output data analysis is crucial in the establishment, development, and analysis of the simulation model and its results. A comprehensive analysis of the output data of simulation will provide a strong foundation of valid conclusions and suitable suggestions of improvement. An input data analysis is required to build a simulation, and simulation model will have less or no value without an output data analysis (Laguna et al., 2013: 345).

Peter (2001) articulates the use of statistics as a mathematical tool for quantitative data analysis by which numerous useful data information, e.g. experimental measurement, can be drawn from and interpreted. By having a right interpretation of data, the output can be used as considerable key points within the decision making process, as well as to deepen the understanding of the current system and the relationship between the variables within.

Naylor & Finger (1967: 98) highlighted several statistical tools that are considered the more important ones that are used to evaluate the goodness of fit of simulation model, in which some of it includes:

- Analysis of variance
- Chi-square Test
- Factor Analysis
- Regression analysis

Due to the nature of the business process that is rarely deterministic, the use of statistic is important to generally study and understand the pattern of the data that can either be used to build the simulation and/or analyze its results. Laguna et al. (2013: 345) describes the objectives of the analysis of output data, in which are the following:

- To understand the behavior of the current process
- To predict the behavior of the recommended process
- To compare the results from several simulated scenarios and determine the conditions under which the process is expected to perform most efficiently

Imagine That Inc. (2013: 624) mentions several factors that may define how statistically precise a simulation model is, which include the character of the problem, the risk possibility in the decision making, the importance of the decision, and the sensitivity of the model to the input data. There are various statistical methods available for different practices yet share the same purpose, which is to interpret data.

Law (2010) discusses the importance of analyzing the output data of simulation in a proper manner. It describes the likelihood of result misinterpretation that occurs when a lengthy and complex simulation model is only run once and the result is treated as the true characteristic that represents how the model works.

By doing only a single iteration in the simulation model, the effect for the analysis is that it could highly increase the chance of having a flawed understanding of the understudied process model. Therefore, having enough replication is seen as an approach to acquire a better output results that represents more of a true characteristics of the particular business process model.

The input value of a simulation business process model is an element that can determine the output of the simulation. Kelton (1997: 23) characterizes the simulation based on its input/output into two different types:

- DIDO (Deterministic In, Deterministic Out)
- RIRO (Random In, Random Out)

When deterministic input is used in the simulation model, the data output is likely to be highly predictable. Hence, replication is not needed in this type of simulation since each run will result in the exact output. This type of simulation is typically used when attempting to experiment several kinds of combinations in respect to the input parameters of the system in order to compare its result through a particular set of system.

But unlike the DIDO type, most simulation model is likely to involve some element of uncertainty and randomness. This type of simulation is also known as *stochastic* model, in which it involves a non-deterministic, or randomness, state within the model. Randomness is highlighted as an important element since if it is ignored, it may result on the possibility to obtain a misinterpretation of the simulation data output.

A simulation model that involves the element of randomness and non-deterministic value is certain to provide the result in a non-deterministic output data. It is categorized as RIRO, in which the purpose of developing such simulation model will be to study the effect of variety and randomness towards different kind of variables in the output data.

2.7.1 Hypothesis testing

The method of hypothesis testing is what will be used when attempting to find the significance from the sample. By having the comparison of two data sets, it is possible to explore if there is a significant differences between them in a form of hypothesis testing. The common practice of hypothesis testing is to first state the required two hypotheses:

- Null hypothesis (H_0)
- Alternative hypothesis (H_1)

The null hypothesis is the one being tested and judged in terms of its effect. When making the null hypothesis, it is conventionally assumed the two data sets are not interrelated and no effect is present between the two. In contrast, the alternative hypothesis is the one assumes that there is interconnection between two data sets, and that the data sets do have an effect to each other.

The null hypothesis will then be analyzed, and if the evidence does not show enough support for alternative hypothesis, then the null hypothesis is the one to be accepted; meaning that the data is proven to not having an interrelation to each other and that it does not have an effect to each other.

Conversely, if the evidence shows enough support for alternative hypothesis, and leads to the condition where null hypothesis is unlikely to be true, then the alternative hypothesis is the one to be accepted; meaning that the data is proven to be connected and having an effect to each other.

In its study, SPSS Inc (2010: 98) illustrates the concept of hypothesis testing to the phenomenon of the criminal justice system. The defendant is assumed to be innocence (e.g. null hypothesis is accepted) until there is enough evidence to support the hypothesis that the defendant is guilty beyond a reasonable doubt (e.g. the alternative hypothesis is accepted).

Alpha, p-values and confidence intervals

It is the nature of the hypothesis testing in the statistical analysis to involve the element of probability in its result. It is assessed by calculating the probability of finding the result, with the range of 0 to 1; representing 0% to 100%. Therefore, when analyzing the data in a statistical approach, it has to be provided by the criterion selection of acceptance or rejection of the null hypothesis. The criterion can also be known as the alpha level (α).

By using the alpha level (α) to judge the null hypothesis, it will also show the probability of a mistake that can happen when rejecting the null hypothesis (or judging the defendant is guilty). Therefore, the higher the alpha level is defined, the higher also the chance that a mistake can occur when rejecting the null hypothesis. The typical use of 5% alpha level (α) is common for data analysis (SPSS Inc, 2010: 99); meaning that when decision is made to reject the null hypothesis, there is a 5% chance that it is a wrong decision.

P-value is described as the likelihood of obtaining the equal or higher result than the data that has been obtained, assuming that the null hypothesis is true (Goodman 1999: 996). In other words, p-value illustrates the probability that the null hypothesis is true. It is in connection with the alpha level in a sense that: if p-value is lower than the alpha level (e.g. p-value of 0.04 and the alpha level of 0.05), meaning that there is immensely small probability (below the alpha level of 0.05) that the obtained data is in accordance to the null hypothesis; thus it is considered safe to reject the null hypothesis and accept the alternative hypothesis. Conversely, if p-value is larger than the alpha level (α), it essentially means that there is not enough evidence to reject the null hypothesis; thus it has to be accepted.

EPA (2006: 142) defines confidence interval as the estimate of range for the analyzed parameter of the population, in which its validity depends on factors such as the size of the sample, point estimate and confidence level. Confidence level is defined as the level of confidence that the parameters that are analyzed occur within the interval. It is often used in the decision making process and as a companion of hypothesis testing. Confidence level is also known as the complement of the alpha level (α), with the example of a 5% alpha level reflects a 95% confidence interval.

2.8 Analysis of variance

Analysis of variance, or also known as ANOVA, is a statistical method to draw conclusions in regards of differences in group means when it involves three or more comparison groups.

When involving two groups, the independent T test is used to analyze mean differences. However, when it involves more groups (e.g. 3), one-way ANOVA is the statistical method that can accommodate the situation (SPSS Inc. 2010: 169). Bolton & Bon (2004: 215) describes ANOVA as perhaps to be the most powerful tool of statistical method that can be utilized to analyze the data that is obtained from the designed experiments.

In the process of decision making, it is a crucial element to understand if two or more groups differ from each other, and if they are, how much statistically different are they. By understanding the significance differences between the group means, it avoids the decision making to be made with the incorrect perception.

Meyers, Gamst & Guarino (2009: 213) defines the three important elements within the ANOVA process, which are the number of independent variables, the number of levels contained in each independent variable, and the indication of the type of independent variables that are within the design.

ANOVA can be done as a one-way or two-way, with the difference being the number of independent variables that are involved in the design. One-way ANOVA is done with a single independent variable/factor, whereas two-way are done with two independent variables/factors in its analysis towards the dependent variables.

The independent variables can also have different number of levels, meaning that each variable may have several options. Therefore, in an example of 2 x 4 design, it means that there are two independent variables, hence considered a two-way ANOVA, in which the first variable has 2 different values (or levels) and the second variable has 4 different values (or levels). In total, the design can make up to 8 scenarios.

2.9 Multivariate analysis of variance

The differences in number of the independent variables determine the ANOVA method to be one-way or two-way. The similarity of those methods is that they only analyze a single dependent variable, also known as univariate ANOVA design. When the dependent variables are more than one, the analysis becomes what is called multivariate analysis of variance, or known as MANOVA.

Meyers et al. (2009: 313) describes the univariate ANOVA design to be highly useful with the emphasis on a single outcome measure. However, in many cases, the dependent variables can sometimes be several, in which correlations effect between the variables could be used to obtain a more in-depth understanding towards the particular research area.

They furthermore explain the argument of the possibility to perform a series of univariate ANOVA, one for each dependent measure. However, the downside of this approach is that it may increase the likelihood to obtain a false-positive result or correlation perception on at least one of the variables.

Therefore, the proper approach to avoid any downfall when performing an ANOVA design that involves one or two independent variables and several dependent variables are defined by Meyers et al (2009) as follow:

- The dependent variables are first combined together to form a composite dependent variable, known as a variate
- Evaluate group differences on the variate by means of a multivariate F ratio
- If the multivariate F ratio resulting from the MANOVA is statistically significant, continue the analysis to then examine the results of the univariate ANOVAs for each separate dependent variable

Meyers et al. (2009) furthermore recommends the use of Bonferroni-corrected alpha level that is obtained by dividing the traditional value of statistical significance of $\alpha = 0.05$ by the number of dependent variables that are involved within the statistic design. This will increase the possibility to avoid the mistake of rejecting the null hypothesis when it is true.

There are four multivariate testing that are commonly used, in which the Wilks' Lambda value is the most appropriate to use when dealing with data that has approximately equal sample sizes and variances that are comparable for the dependent variables across the groups (Meyers et al. 2009: 316). It is also the most widely used test statistics in various fields, including pharmaceutical industry and medical research (Patel & Bhavsar, 2013: 37). Therefore, Wilks' Lambda value is what will be considered within this study.

2.10 Correlation

Bolton et al. (2004) defines correlation as a commonly used procedure to quantitatively identify the relationships between variables. Exploring the correlation between them can provide a better understanding of the current business process model.

The outcome of this test is the degree measure of correlation; that is, how much a variable can be explained and predicted by the data knowledge of the other variable. The value that represents the test is known as the Pearson *r*, which is stated by Meyers et al. (2009) to be the most known and widely used measure of correlation. It is also the foundation of a more complex statistical procedure. The Pearson *r* represents the correlation coefficient with the value of -1 to +1. Value closer to 1 shows the better predictive power of the relationship.

Correlation testing is also often misunderstood in regards of its interpretation. It is often assumed that by having a strong correlation, the variable also has a causal effect, which is not always necessarily the case. Having a strong degree of correlation between variable simply means that those variables represent similar tendencies or trend rate in respect to its data.

2.11 Tools

According to Leeuw (2010), the acknowledgement of importance to the statistical software has changed drastically over the past 50 years. Some of the contributor factors to this phenomenon are the evolution of software and hardware within the computer devices in order to collect and store the data in high pace of increasing amount. These platforms of massive data collection are the drivers behind the increasing need to implement new techniques and to use statistical software for big data analysis.

On the general overview of the current statistical packages by Wegman & Solka (2005), SAS is being put as the top of the commercial statistical software industry, being referred as the Microsoft of the statistical software companies. It has included within its data analysis package the functionality to support univariate (ANOVA) and multivariate (MANOVA) analysis of variance, the testing method of regression, categorical, cluster data analysis and non-parametric analysis, among others.

With the emphasis on great integration of mathematical approach and statistical methodologies, along with the latest technology in database and business application, the software has been used in wide range of areas with its active software usage in various companies, government agencies and educational institution.

3 METHOD AND CASE STUDY

This chapter will focus on the utilization of the simulation tool to depict the supply chain system of the case study of a pharmaceutical manufacturing industry. The methodology that is proposed within this thesis is to develop a discrete event simulation based on the case study SCM process model in purpose of exploring the strength effect of seasonal demand fluctuation and process variation to the various performance indicators.

The decision support tool to conduct the design of experiments (DOE) of this study is ExtendSim scenario manager. The statistical multivariate analysis will be performed with SAS in the subsequent chapter.

The indicators of measurements, also noted as the Key Performance Indicators (KPI), in this study will be adjusted according to those considered the most relevant from the supply chain perspective of the case study practices, which are:

- Product availability
  The percentage measurement of the organization's ability to fulfill the incoming demand within a certain period
- Delivery cycle time
  The time it takes to deliver the finish product to the customer after the demand arrives
- Forecast accuracy
  The percentage comparison of the amount of goods produced with the incoming demand

DES is considered to be the most appropriate method for this study due its suitability to the case study of the SCM system in the manufacturing industry that produces discrete pharmaceutical products by which each item has its own unique characteristics that needs to be counted, tracked, and measured in terms of its cycle time and quantity.

This chapter will provide a comprehensive background of the case study and the simulation model that is developed based on its activities and business process. The model will be explained in detail for each of its activities, and the final result of the simulation will be mentioned at the end of this chapter.

3.1 Case description

The case study in this thesis will be taken from the perspective of supply chain department of a pharmaceutical manufacturing industry. The organization of the case study has over 600 employees in which 90% are designated within the factory area and 10% are spread within various departments in the main headquarter.

The organization has over 120 product lines with over 100 suppliers, both locally and internationally, and 5 manufacturing lines which are located both internal and external of the main office.

Over the years, one of the most occurring phenomenon within the pharmaceutical industry is the seasonal demand fluctuation in its product. Each medicine has its own market segment and dynamic environment in sales. As put by Song & Zipkin (1991: 351), demands for many products changes in responds to certain economic variables or summarize condition of the particular industry. For pharmaceutical industry in particular, other factors that impact the demand may include seasonal illness, upcoming virus, new products, government intervention and/or cooperation, new market segment, among others.

The inventory management, however, has very little information or control over such unpredictably changing factors. It is proceeding with standard inventory method of random demand projection, and it is oftentimes becoming increasingly difficult to cope with the dynamic environment of demand fluctuation, especially in times of demand amplification.

Thus, lost sales are often occurring in times of seasonal demand amplification. It also affects the SCM performances in regards of its ability to satisfy the demand with its determined target of lead time.

Other than having a fluctuating demand environment, the production method of the case study organization also has a limitation in terms of its capacity and equipment. Thus, in addition of producing in its own factory, it also uses the third party production process to cope with the current incoming demand. This is identified as the toll out manufacturing.

Despite the fact that the method of collaborative planning, forecasting and replenishment (CPFR) has been implemented, the utilization of toll out manufacturing still imposes certain risk of production delay and uncertainty due to the third party's capacity and labor constraint itself. Hence, it may at times inflict the ability to cope with the demand.

This study acknowledges these phenomenon and consider them as a knowledge gap with high importance that can further be explored in terms of its possible solution. The method, as aforementioned, will be to conduct the DOE in attempt to achieve a great understanding of the effect of demand amplification and process variation to the SCM performances and propose a suitable solution for these issues.

Within this case study, the SCM department handles all the supply chain activities from sourcing until delivery. The business process of the supply chain management involves several entities outside the department, i.e. the suppliers, quality department, and manufacturing department.

For reasons of time efficiency when performing the simulation run and statistical analysis, the original business process has been modified in several aspects with neither change in the business process nor the information flow.

The example of the changes is the reduction of production lines from five to four due to high similarity. Each of the line will be represented by a product, which adds to total four products. The lead time of production, quality testing and delivery remain the same.

The entities that are involved in the business process are:

- Supplier
- Quality department
- Manufacturing sites/lines
    - In-house
    - Repackaging
    - Third party (toll out manufacturing)
- Warehouse
- Customer

Supplier is in charge of providing the required materials to manufacture the finish goods **(FG)**. The materials are categorized into three, which are:

- Raw Material **(RM)**
- Packaging Material **(PM)**
- Imported Material **(IM)**

RM is the material that serves as the main substance of the FG. It may include pharmaceutical powder, active pharmaceutical ingredients (API), additives, e.g., sugar, minerals, vitamins, flavor enhancers, liquid ingredients and effervescent.

PM includes carton packaging, bottle, bottle-cap, paper, plastic bag, among others. IM is the finish product that is imported from abroad, in which it will be repackaged and relabeled before being delivered to the local customers.

The delivery lead time for RM and PM are relatively short due to the supplier's nearby location and high material availability. In contrast, IM product takes the longest due to shipping duration, supplier export capacity, and immigration paperwork.

Quality department play an eminent role that defines the continuity of a production process and/or delivery process. Its role is to do a lab quality check to all the incoming materials (RM, PM and IM) and outgoing materials (FG) and ensure that they have passed the compulsory prerequisites for standard quality of the organization

Manufacturing sites are the factory that runs around the clock with its role to manufacture the raw materials into finish products in accordance to the amount required by the production order. Within this study, the manufacturing sites are divided in three areas, which are:

- In-house
- Repackaging
- Toll out

In-house manufacturing is the production system that occurs in the organization’s own factory. Due to its integrated location, as well as involving organization's own human resource and schedule, the production lead time is relatively short, typically within a week.

Repackaging is the production type that has the shortest lead time but only applies to the imported material (IM). Once the IM has arrived and passed the requirement check, the repackaging lead time can take as short as three days. IM products have international barcodes, universal packaging and English-only instruction use, therefore all of them need to be localized for specific nation use, e.g. barcode from local food and drug national agency, additional local language in instruction use, etc.

Toll out manufacturing is the production system that uses the third party facility, warehouse, and resources; therefore the production lead time is much longer with high chances of delay. Toll out is done due to organization's equipment limitation and production capacity constraint. This study simulates two system of toll out with different lead times in its production.

Warehouse will be the place where all the arriving and departing materials are temporarily placed. The central warehouse is located alongside the factory and main office. Once the raw material arrives, the quality department will do the lab quality check in order to qualify the material for production. When the production is completed, the FG will be sent to the warehouse where it will undergo a quality test one last time in order to qualify for a customer delivery.

Customer in this context is not the final product users. The organization uses third party logistic service to deliver its products throughout nationwide, which includes pharmacies, hospitals, clinics and other health care services. The third party logistic service will serve as the only customer.

3.2 Workflow and simulation

The structure of the workflow for the supply chain process model is described in the following points:

1. Demand forecast is given in the beginning of the month
2. Given the forecast, the two activities will follow:
    a. Buyers will create order of RM/IM and PM from suppliers
    b. Supply planners will create the production plan and production order
3. Incoming materials (RM, PM, IM) are subject to laboratory check

4. Manufacturing process can begin once the production order has arrived and all incoming materials are available and passed the lab quality check
5. When the production is complete, it will undertake a lab quality check as FG before being qualified for delivery
6. Once qualified for delivery, the FG will be used to respond to the incoming demand. When both are met, the delivery can be completed

Figure 9 illustrates the workflow within the organization in respect to its supply chain perspective. Designed with the software *Aris Express*, this business process model illustrates the process step from the incoming forecast until the delivery process.

Afterwards, table 3 will provide the timeline activities of four different products that represent the four production lines. In addition, it will also show the average incoming demand and the batch size it needs for production. Within this empirical study, the daily demand will be used for the fluctuation shock test.

The delivery lead time for RM and PM are mostly constant due to high availability of suppliers, materials and nearby locations. However, production lead time may vary as numerous interventions that may happen during the process, e.g. machine breakdown, maintenance, failure in production, lack of documentation, etc.

The pharmaceutical industry has always faced the challenge of a seasonal demand fluctuation within a particular time of the year. During the period, demand may fluctuate in an unpredictable rate and may cause an effect on the performances of the supply chain. Bradley & Antzen (1999: 795) mention that seasonal demand is a factor that complicates the decision of how much capacity to install and inventory to hold for a manufacturing organization.

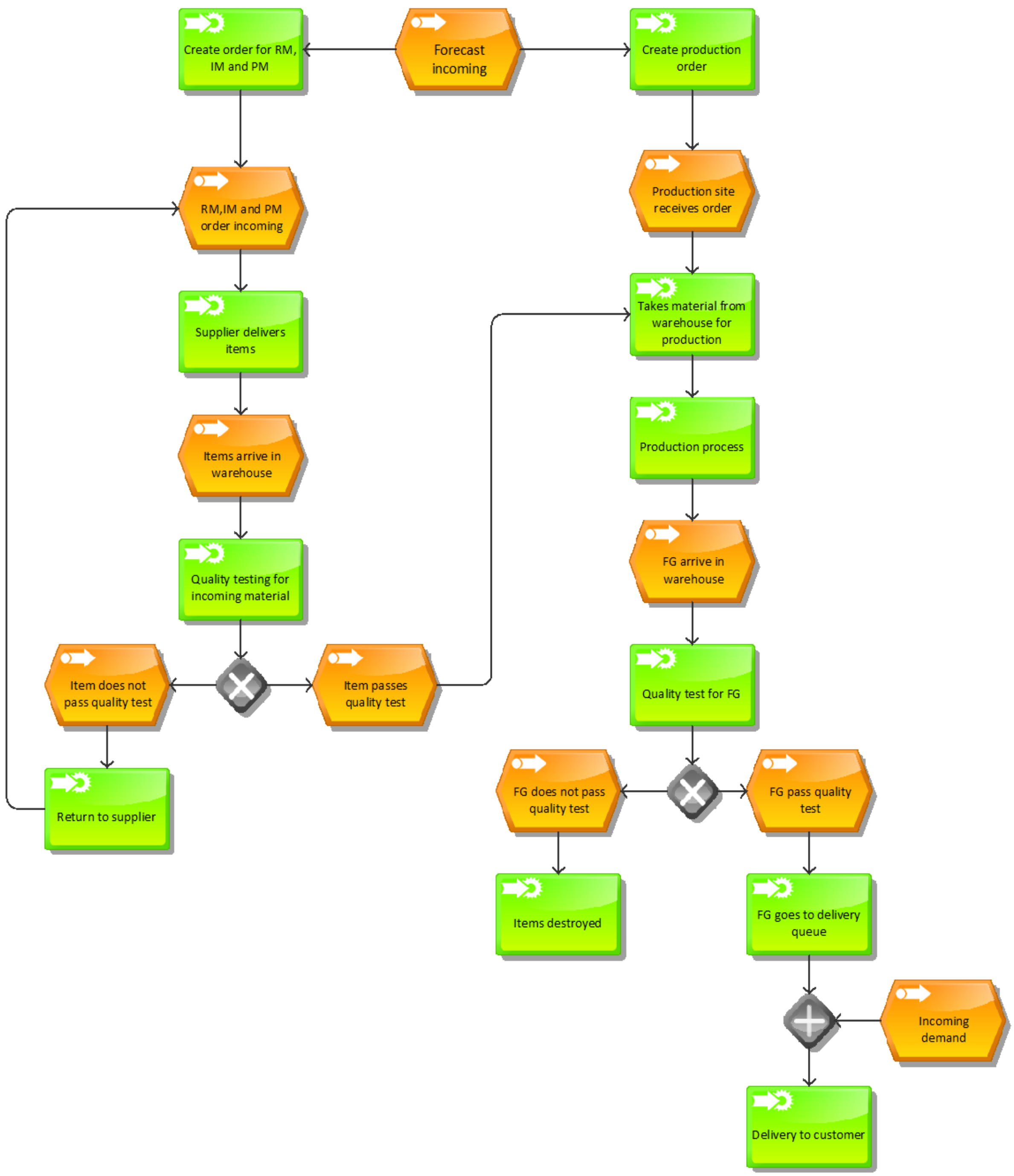

Figure 9. Business process model of the case study

Table 3. Product information

Product No	Product 1	Product 2	Product 3	Product 4
Production Type	In-house	Repackaging	Toll-Out	Toll-Out
Delivery Lead-Time				
Raw/Import Material	7 days	60 days	7 days	7 days
Packaging Material	3 days	3 days	5 days	5 days
Quality Check				
Raw/Import Material	14 days	14 days	14 days	14 days
Packaging Material	7 days	7 days	7 days	7 days
Production Lead-Time	7 days	3 days	60 days	30 days
Quality Check				
Finish Goods	4 days	4 days	4 days	4 days
Average Last Year Demand				
Monthly (+/-)	3200 pcs	1300 pcs	2400 pcs	2800 pcs
Daily Demand (+/-)	108 pcs	44 pcs	80 pcs	92 pcs
Batch Size	400 pcs	800 pcs	500 pcs	800 pcs

The following figure 10 is the simulation model that is developed for this case study. This model represents the supply chain activities and processes from the initial point of sourcing until the final point of delivery. The sub activities in the model will be broken down and explained in great depth within this chapter.

The model (Fig. 10) will be duplicated four times to represent the four simulation model of different production types. Each production type, as shown in table 3, will have its own parameters in regards of time and quantity. In total, four simulations will be performed and analyzed within this study.

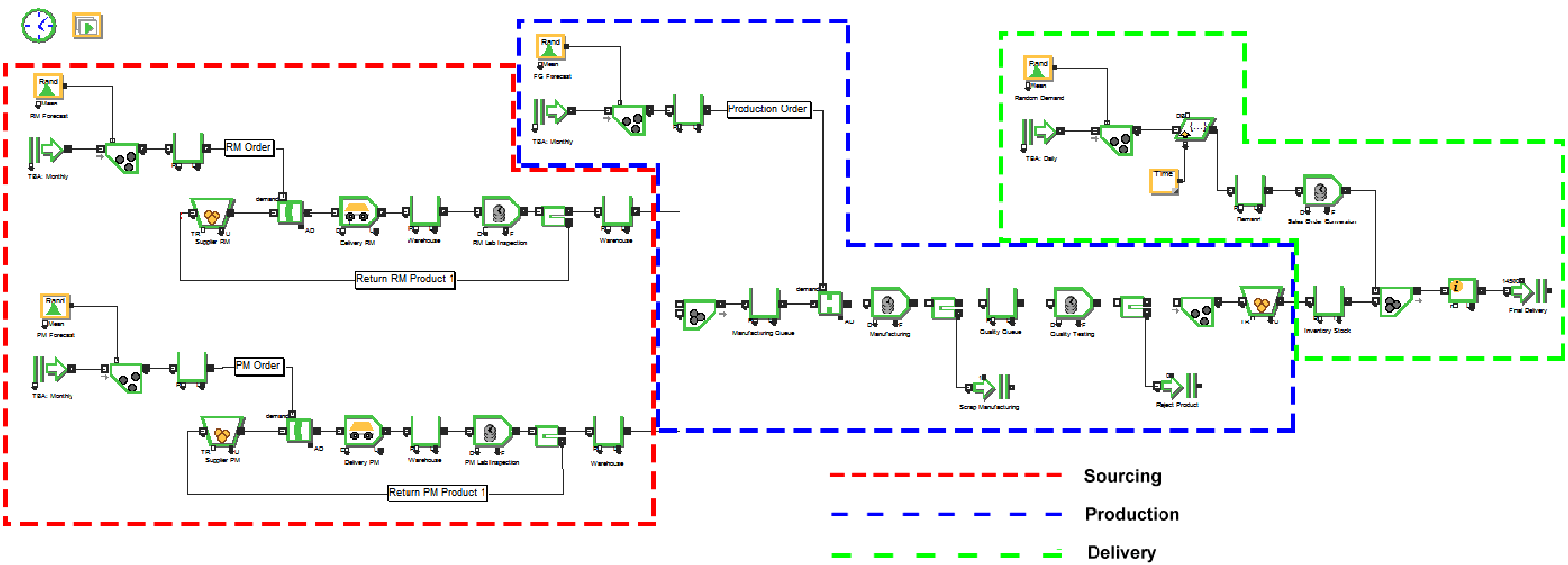

Figure 10. The ExtendSim simulation model for the case study

The simulation model will be broken down in order to present a better explanation on each of its sub activity. The sub activities for this simulation model are:

- Sourcing
- Manufacturing
- Delivery

3.2.1 Sourcing

Figure 11 illustrates the sourcing activity, which is the activity that is done to acquire the necessary materials, RM/IM and PM. Therefore, both activities will share the same model but with different lead times in delivery and lab quality testing.

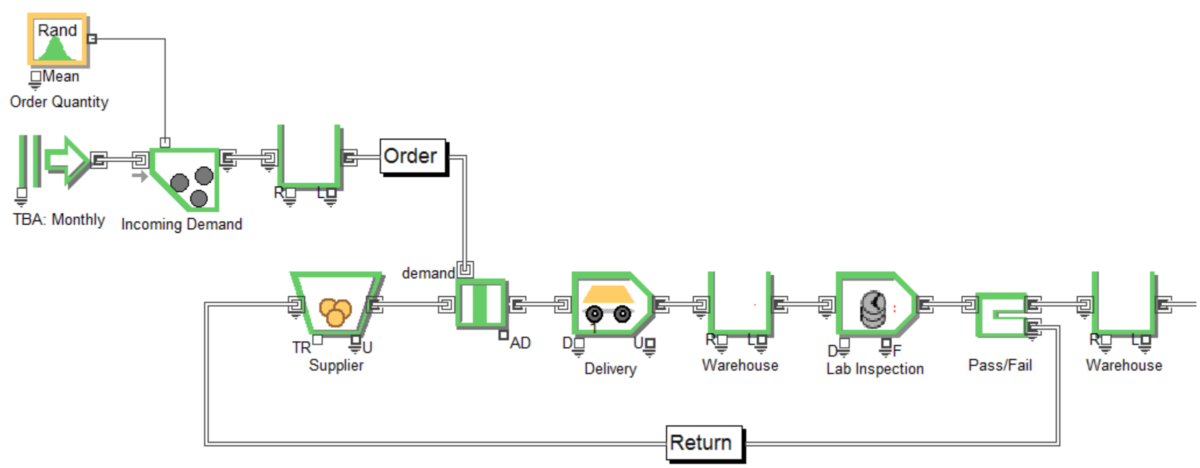

Figure 11. Sub activity: Sourcing

In this figure, the forecasted demand is created in the *order quantity* Random block. It will generate a range of numbers with an average value for the monthly forecast. The *Create* block is set up to create an item once a month, in which the item will then be converted by the *Unbatch* block into quantity that *Random* block has determined. This system will result in having the integer random number of material demand that comes in a monthly basis.

The material order will go to the *Get* block, in which it will then ask the material from the suppliers. This model assumes that no material availability issue occurs in the supplier; hence material will always be delivered when the order comes. The delivery will be done in batches, and will be delivered to the warehouse. It will then undergo the lab inspection by the quality department when it arrives.

With a 5% failure chance, the rejected material will be sent back to the supplier for a replacement. Those that fulfill the requirement will be sent further to the warehouse as a ready-to-use material for production. The lead time for delivery and quality testing are shown below (Fig. 12 and 13, respectively). The lead time for delivery and quality check is designed to be steady with no capacity constraint.

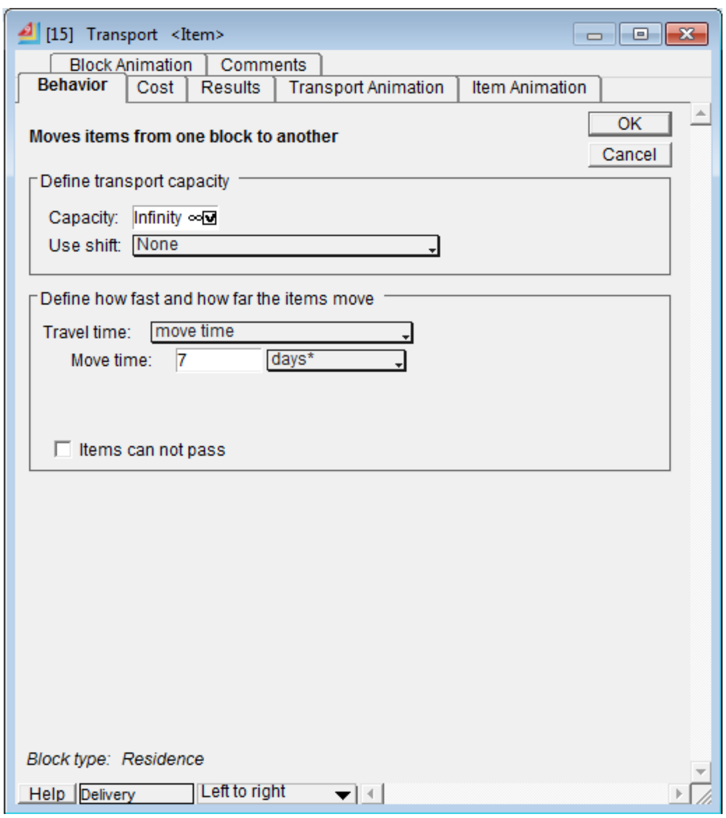

Figure 12. Sub activity: Delivery lead time

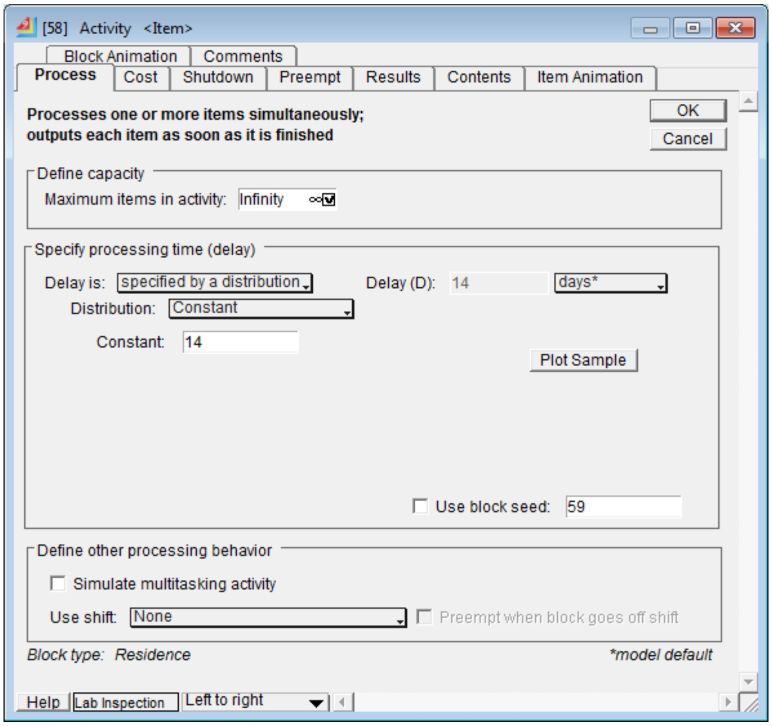

Figure 13. Sub activity: Lab inspection lead time

3.2.2 Production

The process of production begins with the production order (Fig. 14). The production order is created through the *Random* block that serves as a forecast. In the model, the *Random* block will generate numbers with an average value that is in accordance with the average monthly demand in order to cope with the ordinary situation.

The *Create* block will determine the timing for the production order to come in a monthly basis (Fig. 15). The created item will then be converted by the *Unbatch* block in accordance to the number that is generated by *Random* block. The converted item will go through the *queue* block and come out as a production order. This setup will result in having a random integer number of production order that comes in a monthly basis.

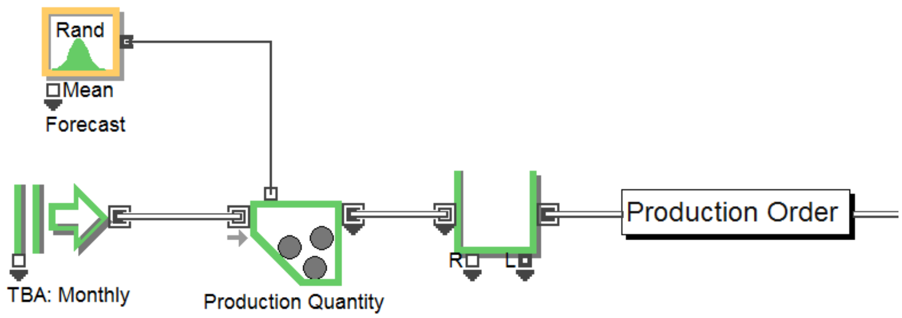

Figure 14. Sub activity: Production order

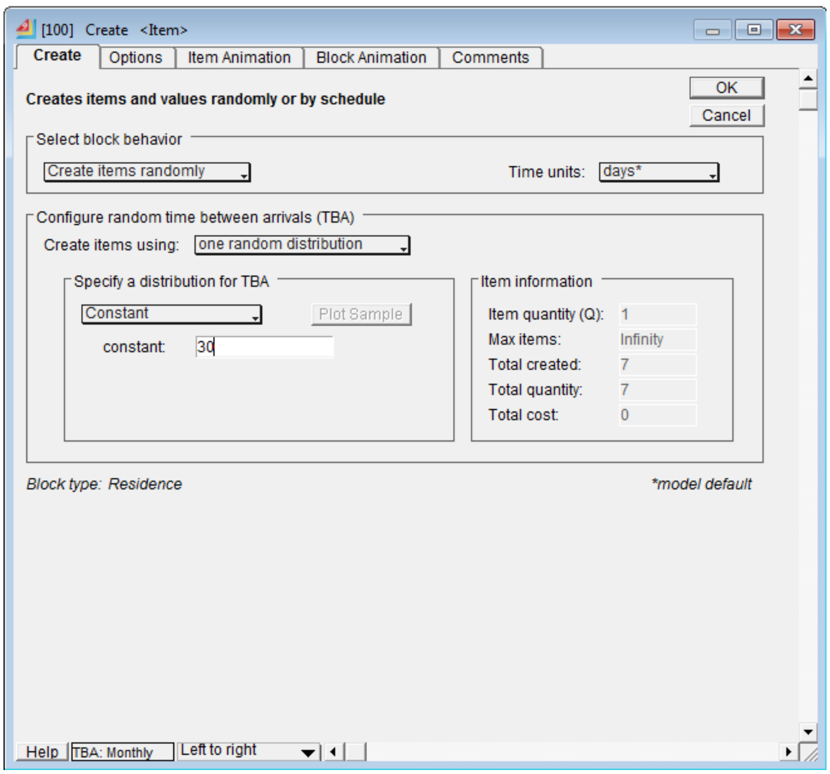

Figure 15. Sub activity: Monthly item for production order creation

Similar to sourcing activity, the order will be counted in batches. It will be sent to the *Get* block, in which the manufacturing queue will be ready to fulfill the order (Fig. 16). The manufacturing queue block is where both the RM and PM is batched and stored in order to fulfill the production order.

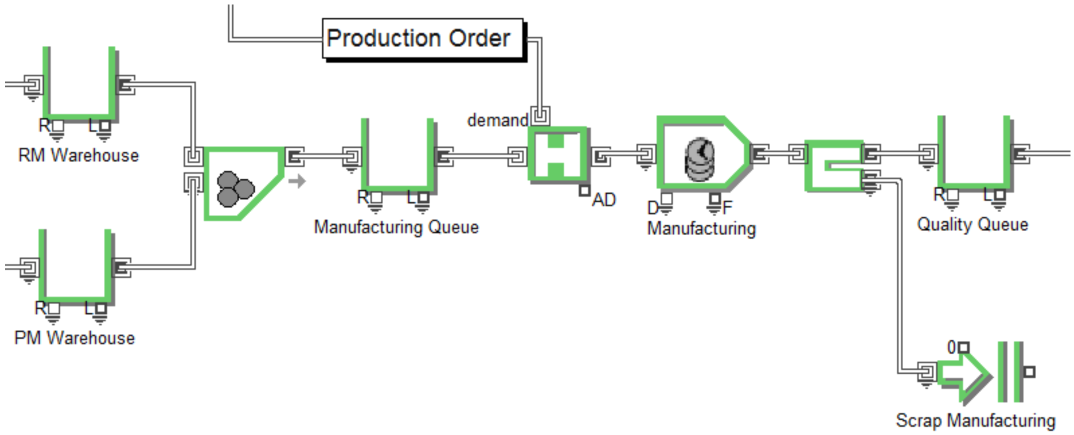

Figure 16. Sub activity: Production

When production order comes and the batches are ready, the production will begin. The *Activity* block will simulate the production with a time delay according to the production system. With a failure chance of 5%, the rejected manufacturing product will be sent as scrap, in which they will be destroyed in a standardized manner for a pharmaceutical industry, typically burned down.

Those that are successfully manufactured will be sent as FG to further undergo the quality testing (Fig. 17). With a 5% chance of failure, the FG that passes the quality requirement will be passed to the warehouse as a ready-to-delivery material. Before arriving, it will be unbatched in order to respond the demand that comes in various quantity in a daily basis.

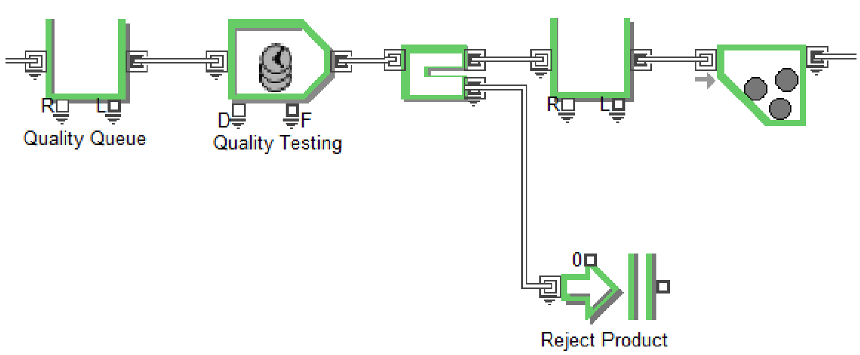

Figure 17. Sub activity: Quality testing and Unbatched

One of the empirical test in this study is to see the effect of process variation to all the KPI. The process variation will be set up by having an increase in production lead time to double its duration. It will then be analyzed in terms of its influence to the KPI performances.

3.2.3 Delivery

The delivery process starts with the incoming daily demand (Fig. 18). One of the KPI in this study is product availability, which represents the ability to deliver the product according to the incoming demand. Hence, a good performance of product availability means that the total delivery is align with the quantity of incoming demand.

The inventory level, represented in *warehouse* queue block (Fig. 22), is an entity that supplies the material when responding to the demand, thus it represents the ability to cope with the demand. Low inventory level will result in lower ability to meet the demand, hence resulting in lower product availability and the increase of delivery cycle time.

The demand itself is established by *Random* block (Fig. 18). The *Create* block will set the timing of incoming demand to be in a daily basis, which is done by having an item created once a day (Fig. 19). The *Random* block for the demand will have an average value that, with a given standard deviation, will fluctuate everyday (Fig. 20).

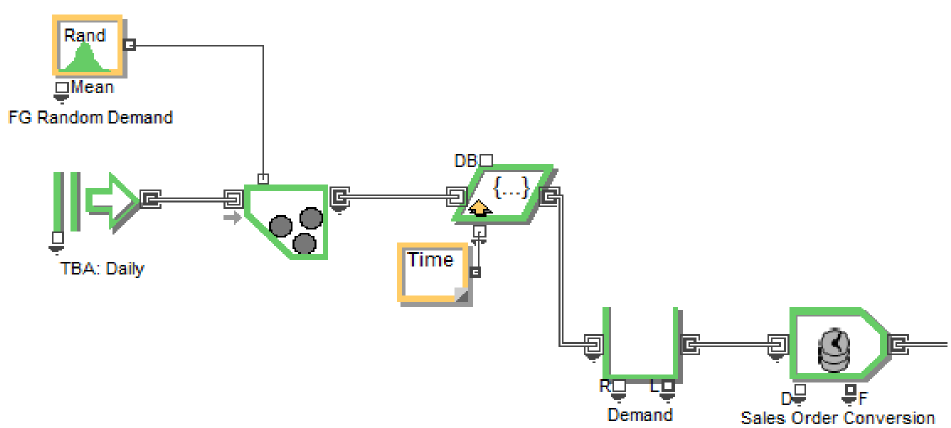

Figure 18. Sub activity: Incoming demand

The *Set* block is placed after the demand has been created with the purpose of the delivery cycle time (Fig. 18). It serves as a starting point of the demand arrival. The final point will be an *Information* block that is placed just before the final delivery (Fig. 22). Therefore, the delivery cycle time will be the amount of time it takes from the time the demand arrives until it is ready in the final delivery point.

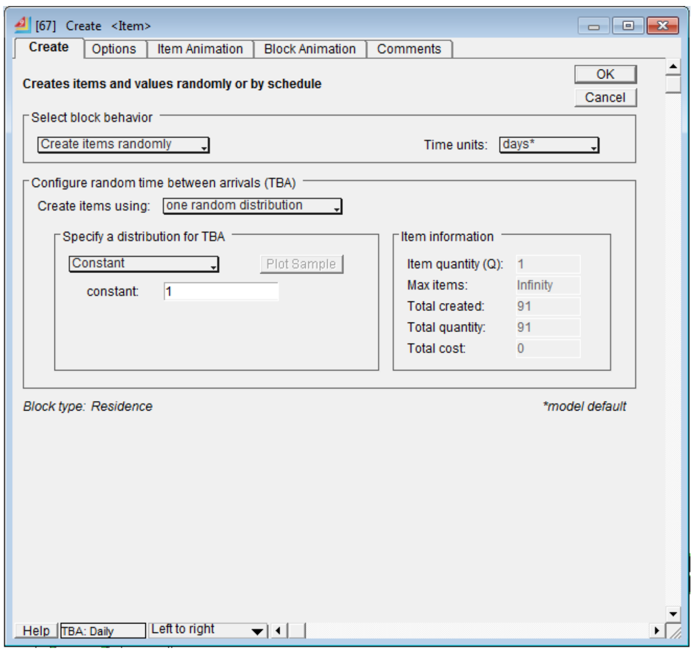

Figure 19. Sub activity: Demand timing setting

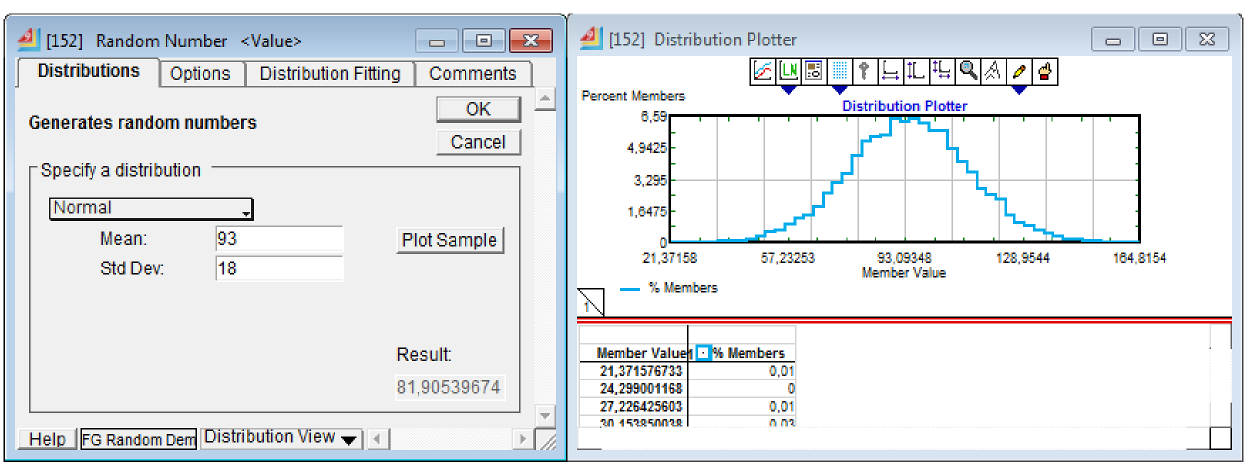

Figure 20. Sub activity: Random number setting for demand

After the demand has been created, it needs to be converted into sales order by the administration office. The average time of conversion is 1 day, with the possibility of delay due to administrative tasks. Therefore, the exponential distribution will be the timing duration when converting the demand into sales order (Fig. 21).

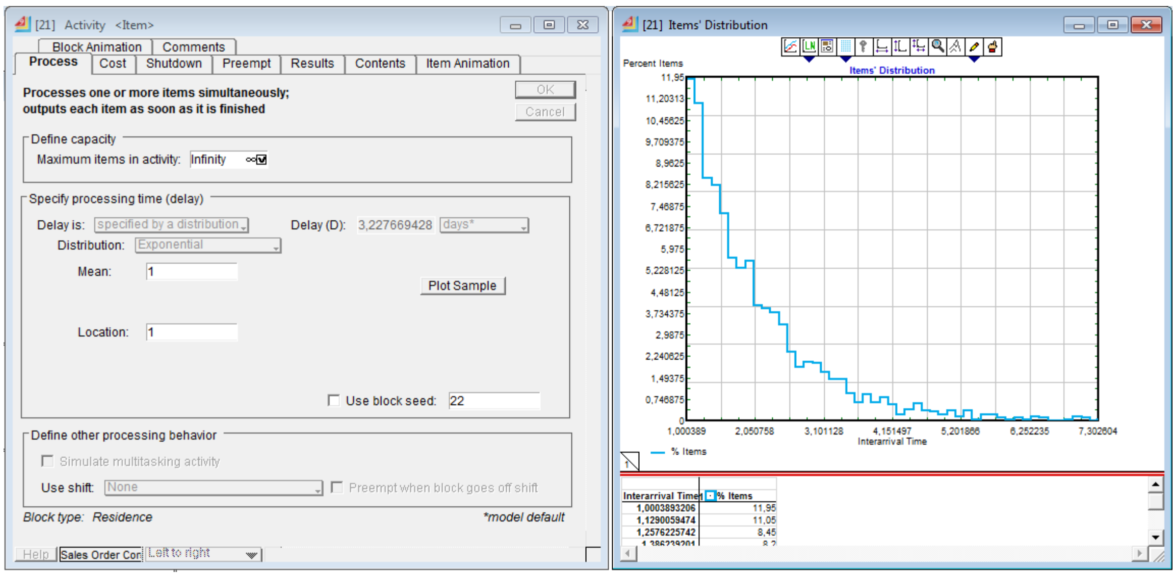

Figure 21. Sub activity: Timing setting for sales order conversion

After the sales order is created, it will then be unified with the inventory stock of FG material from the warehouse using *Batch* block and together it will be sent to the final delivery point (Fig. 22). The *Batch* block is used due to its ability to let the item pass without removing its timing attribute so the delivery cycle time can be tracked using the *Information* block that is placed subsequent to it (Fig. 23).

The case study has a preferable safety stock policy of 2 months. Hence, in this simulation, each production type will have a finish goods ready that is equivalent to the amount of 2 months of its average monthly demand. Hence, the demand can start to be fulfilled already on day 1.

As previously mentioned, the *Information block* is placed as the end point to track cycle time, and the point origin is the *Set block* that is placed right after the demand arrives (Fig. 18).

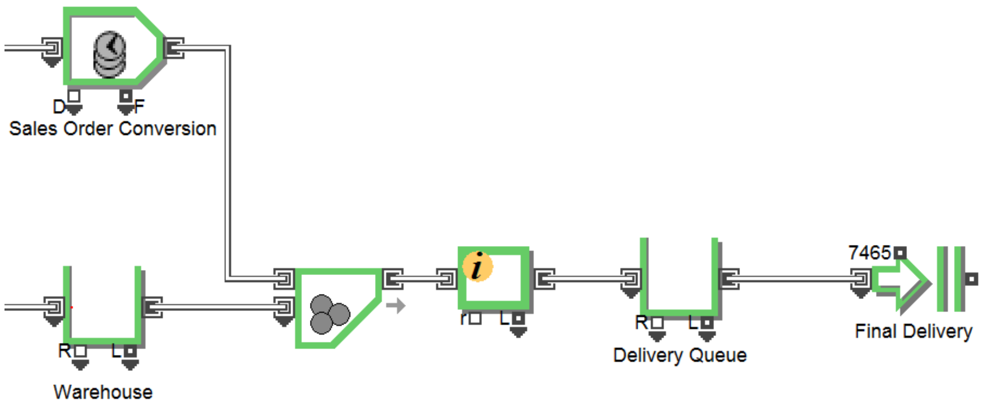

Figure 22. Sub activity: Delivery

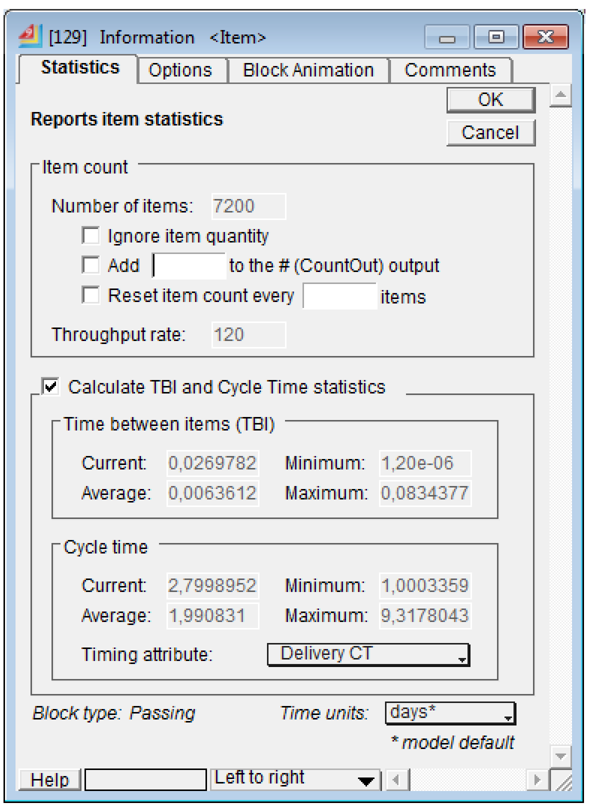

Figure 23. Sub activity: Information block on cycle time

3.3 Design of Experiments

In response to the research questions that are mentioned in the introductory chapter, this thesis will conduct an empirical study that is designed to test the significance of demand amplification and process variation in its impact to the SCM performance indicators of the case study.

The variation that is given in the demand and process of the model will result in a numerous scenarios. These scenarios can then be recorded and analyzed to examine the various effects that the variation has and further correlations of between indicators.

In ExtendSim 9, scenario analysis is a method that is utilized to strategically and systemically examine the outcome of various configurations of the model, with the purpose of supporting the exploration and analysis of alternatives, as well as gaining understanding on why the system behaves the way it does and how can it be improved (Imagine That Inc. 2013). This is what will be used as a tool for the DOE of this thesis study.

What the scenario manager (Fig. 24) provides to the simulation model is the ability to design the experiments in the evaluation of an unlimited number of possible scenarios that can be configured from the model inputs or factors. The input factors will be given a range of minimum and maximum value, which will then create a scenario.

The simulation will be run in numerous iterations to lessen the possibility of a bias results. This provides the platform to explore the effect of the input factors towards the designated various outcomes of the model, and see how the model behaves under different conditions.

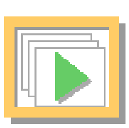

Figure 24. Scenario manager in ExtendSim

Table 4 shows the list of the independent and dependent variables that will be explored in the DOE of this study. The demand fluctuation and the process variation will be introduced in the simulation, and the responses of the KPI will be recorded and analyzed to see if there is any significance that it brings to the performances of the current supply chain system.

The three main KPI that will be evaluated as an indicator for SCM performances are product availability, forecast accuracy, and delivery cycle time. The additional responses of total delivery and inventory stock will also be added for the purpose of providing better explanation during result observation.

Table 4. Factors and responses in DOE

Factor (Model Input)	Responses (Model Result)
Demand fluctuation **Process variation**	**Major KPI** • Delivery Cycle Time • Product Availability • Forecast Accuracy **Additional KPI** • Total Delivery • FGI Stock

The table 5 illustrates the variation factors with their associated minimum and maximum value. The two factors that are assigned in this simulation model are the daily demand and production lead time. Four production types, each represented by a product on its own, will be tested and evaluated in terms of its performance.

The incline step defines how much increase will the value has in each step. The demand fluctuation, for example, will be introduced in 5 steps, which are the current average value, then followed by 25%, 50%, 75% and eventually 100% increase.

Table 5. DOE variation factors and their associated level

Factor	Production Type	Min Value	Max Value	Incline Step
Daily Demand (pcs)	In-House	108	216	27
	Repackaging	44	88	11
	Toll Out 1	80	160	20
	Toll Out 2	92	184	23
Production Lead Time (days)	In-House	7	14	7
	Repackaging	3	6	3
	Toll Out 1	60	90	30
	Toll Out 2	30	60	30

Once the variation factors have been defined, scenarios can then be constructed in terms of their minimum and maximum value. Table 6 shows the scenario analysis on product 1, which represents the in-house system.

Table 6. DOE scenario analysis of input factors

Scenario Analysis	Daily Demand	Production Lead Time
Scenario 1	108	7
Scenario 2	108	14
Scenario 3	135	7
Scenario 4	135	14
Scenario 5	162	7
Scenario 6	162	14
Scenario 7	189	7
Scenario 8	189	14
Scenario 9	216	7
Scenario 10	216	14

Table 7 shows how the simulation setting is defined. As illustrated, the 3 month seasonal period will be simulated in 50 iteration for each of the 10 constructed scenarios with 95% confidence interval. The full factorial implies that all scenarios will be executed.

Table 7. Scenario analysis setup

Scenario analysis setup	
DOE method	Full factorial
Runs per scenario	50
Simulation start time	0
Simulation end time	90
Confidence interval	95 %

In respect to the responses (output result), table 8 will show the target line for the major KPI, which will be used as benchmark for the evaluation on its sustainability in the following chapter and as indicator of how well the supply chain performs within a certain period of time, e.g. monthly or seasonally.

Table 8. Target line of KPI

KPI	Target Limit
Delivery Cycle Time	< 5 days
Product Availability	> 90%
Forecast Accuracy	> 70%

The inventory level has a stock policy of *2 months*. Thus, an FGI stock equivalent with 2 months of its average demand will be provided at the beginning of the simulation. Table 9 to 12 will show the simulation result of the average value from the 50 iterations of its simulation run. The red shading table highlights the point where the target line has been unfulfilled.

Table 9. Scenario analysis - Product 1: In-house manufacturing

Scenario Analysis	Daily Demand	Production Lead Time	Product Availability	Forecast Accuracy	Delivery Cycle Time
Scenario 1	108	7	97%	100%	2,5
Scenario 2	108	14	97%	100%	2,5
Scenario 3	135	7	97%	89%	2,5
Scenario 4	135	14	97%	88%	2,6
Scenario 5	162	7	97%	73%	2,6
Scenario 6	162	14	97%	74%	2,5
Scenario 7	189	7	94%	63%	2
Scenario 8	189	14	94%	63%	2,4
Scenario 9	216	7	83%	55%	3,1
Scenario 10	216	14	83%	55%	9

Table 10. Scenario analysis - Product 2: Repackaging

Scenario Analysis	Daily Demand	Production Lead Time	Product Availability	Forecast Accuracy	Delivery Cycle Time
Scenario 1	44	3	97%	91%	2,4
Scenario 2	44	6	97%	94%	2,5
Scenario 3	55	3	97%	82%	2,8
Scenario 4	55	6	97%	80%	2,7
Scenario 5	66	3	95%	70%	2,4
Scenario 6	66	6	96%	67%	2,3
Scenario 7	77	3	93%	59%	2,6
Scenario 8	77	6	90%	56%	4,5
Scenario 9	88	3	82%	49%	6,6
Scenario 10	88	6	83%	49%	8,7

Table 11. Scenario analysis - Product 3: Toll out manufacturing 1

Scenario Analysis	Daily Demand	Production Lead Time	Product Availability	Forecast Accuracy	Delivery Cycle Time
Scenario 1	80	60	97%	100%	2,2
Scenario 2	80	90	97%	100%	2,6
Scenario 3	100	60	97%	97%	2,6
Scenario 4	100	90	83%	98%	1,9
Scenario 5	120	60	94%	83%	2,2
Scenario 6	120	90	70%	82%	2,9
Scenario 7	140	60	82%	71%	1,7
Scenario 8	140	90	61%	71%	9,6
Scenario 9	160	60	72%	62%	2,4
Scenario 10	160	90	52%	63%	16,8

Table 12. Scenario analysis - Product 4: Toll out manufacturing 2

Scenario Analysis	Daily Demand	Production Lead Time	Product Availability	Forecast Accuracy	Delivery Cycle Time
Scenario 1	92	30	97%	100%	2,5
Scenario 2	92	60	97%	100%	2,6
Scenario 3	115	30	97%	92%	2,5
Scenario 4	115	60	91%	91%	3,5
Scenario 5	138	30	97%	77%	2,3
Scenario 6	138	60	78%	76%	12,5
Scenario 7	161	30	92%	66%	4,4
Scenario 8	161	60	67%	67%	23,5
Scenario 9	184	30	81%	57%	11,4
Scenario 10	184	60	58%	58%	32,2

The four table above shows the scenarios in which the sustainability of the system is reflected on. The increase of demand, combined with the increase of production lead time as a process variation, provides different results in each of the production line in different degrees. The significance degree that the two input factors bring to the KPI is what will be understudied in the following chapter.

The following chapter will discuss more of the statistical analysis of the above shown results. In respect to the first and the second research question on the introduction chapter, the multivariate analysis is the method that will explore the possible significance effect from the demand amplification and process variation to all the KPI.

In respect to the third research question, the further correlation testing will be performed as well in the following chapter in purpose of exploring the relationship between each KPI and obtaining a better understanding of how the behavior of a KPI can be correlated with the performance of its surroundings.

4 RESULTS

This chapter will cover the statistical analysis that will be performed in order to get a better interpretation and understanding of the current business process model under the empirical study of an increasing demand and variation within the production lead time. The effect towards the KPI of the supply chain will be revealed and analyzed.

As aforementioned in the previous chapter, the responses (KPI) that will be recorded for this empirical study is product availability, forecast accuracy, and delivery cycle time. An addition of total delivery and FGI stock will be included for general observation.

With the utilization of SAS as the statistical software in this study, the MANOVA analysis testing is the most appropriate method to analyze this type of design. The step of the analysis will be explained in the following:

1. To perform the MANOVA testing to all the KPI under the shock test of demand amplification. In SAS, the responses are called discriminant variable; hence the name of the test, discriminant analysis. This test will result in better understanding on the statistical significance that the demand increases has towards the KPI.
2. In addition to demand variation, the MANOVA will also test the effect of process variation; that is, the increase lead time for production process. This will result in better understanding of the significance the process variation may have to the KPI.
3. To perform a correlation test to explore the possible relationship between KPI. This test will result in a better representation of how the behavior from one KPI may be associated with the performance of the others.

Based on the observation of the statistical outcome and the plotter graph, this study will evaluate the sustainability of the current system. Suggestions can be drawn up from the empirical study on how to improve the performance level in a comprehensive point of view.

4.1 Product 1: In-House Manufacturing

This product represents the system of in-house manufacturing with local suppliers of both RM and PM. This production system has relatively short lead time duration due to its in-house location and production process that is done with own resources, schedule and labor.

Demand Variation

The effect of demand fluctuation can be explored using the multivariate test of Wilks' Lambda. Figure 25 shows the value of Wilks' Lambda (Λ) to be 0.0004; representing 0.04% of variances that are unaccounted for in this testing. Hence, it shows that most variances are accounted for in the test.

With the F Value of 735.69, it has a p-value (Pr>F) of below the significance alpha level (α) of 0.05. Therefore, it is safe to conclude that the demand increase is a statistically significance variable to affect the KPI.

Multivariate Statistics and F Approximations					
S=4 M=0 N=244.5					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.00047758	735.69	20	1629.4	<.0001
Pillai's Trace	1.92984926	92.10	20	1976	<.0001
Hotelling-Lawley Trace	364.09819112	8918.83	20	1072.8	<.0001
Roy's Greatest Root	359.89076816	35557.2	5	494	<.0001
NOTE: F Statistic for Roy's Greatest Root is an upper bound.					

Figure 25. MANOVA - Demand variation - Product 1

The next step is to look at how the significance affects each of the responses. It can be seen from the univariate test result (Fig. 26) for each variable during the same discriminant analysis testing. The relevant values to be considered are the R-Square, F Value and p-value (Pr > F). R-Square provides an approximation of the strength effect that the demand has to each individual responses.

When evaluating the univariate results, Bonferroni-corrected alpha level is used by dividing the alpha (α) of 0.05 with the amount of the dependent variables (in this case, 5). Therefore, the corrected Bonferroni significance alpha (α) for univariate testing is α = 0.01

Univariate Test Statistics							
F Statistics, Num DF=4, Den DF=495							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.0589	0.0220	0.0611	0.8621	6.2534	773.86	<.0001
Forecast Accuracy	0.1666	0.0248	0.1840	0.9781	44.6346	5523.53	<.0001
Delivery Cycle Time	2.4804	2.0259	1.6112	0.3382	0.5111	63.25	<.0001
Total Delivery	2636	429.1152	2905	0.9737	37.0377	4583.42	<.0001
FGI Stock	2641	582.2051	2878	0.9518	19.7474	2443.74	<.0001

Figure 26. Univariate - Demand variation - Product 1

Using the Bonferroni alpha level, the significance test result can be seen on the p-value of each KPI. Figure 26 shows that all KPI have the p-value lower than 0.01, indicating that all KPI are statistically affected by the demand increase. Therefore, on the basis of R-Square, the hypothesis result can be written as such:

> In the environment of in-house manufacturing, the demand increase yields a considerable impact towards the KPI (Fig.25). The impact (Fig. 26) approximately accounts for 86% of product availability, 98% of forecast accuracy, 34% of delivery cycle time, 97% of total delivery and 95% of FGI stock

The evaluation of sustainability against the demand increase will visualize how this significance degree affects the performances of each of the variable (Fig. 33 to 36).

Process Variation

In addition to demand shock test, the multivariate testing of process variation will also explore the possible effect it has towards the KPI. The process variation in this model is the increase of production lead time on the DOE. In this in-house production type, the increase is from 7 days to 14 days, representing the moderate occurrence of production delay in the manufacturing process due to various technical factors.

Multivariate Statistics and Exact F Statistics					
S=1 M=1.5 N=246					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.87718177	13.83	5	494	<.0001
Pillai's Trace	0.12281823	13.83	5	494	<.0001
Hotelling-Lawley Trace	0.14001457	13.83	5	494	<.0001
Roy's Greatest Root	0.14001457	13.83	5	494	<.0001

Figure 27. MANOVA - Process variation - Product 1

The multivariate testing of Wilks' Lambda (Fig.27) shows some significance for the variable; that is, by having the p-value lower than alpha level (α) of 0.05. However, notice that the Wilks' value is 0.87; representing the 87% of variances that are not accounted for. It indicates that the significance degree will be small compare to the previous multivariate test of demand increase. To confirm this, further analysis is taken to the univariate test statistics results (Fig. 28).

Univariate Test Statistics							
F Statistics, Num DF=1, Den DF=498							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.0589	0.0590	0.000602	0.0001	0.0001	0.03	0.8718
Forecast Accuracy	0.1666	0.1668	0.000304	0.0000	0.0000	0.00	0.9770
Delivery Cycle Time	2.4804	2.4005	0.8954	0.0653	0.0698	34.78	<.0001
Total Delivery	2636	2639	22.5737	0.0000	0.0000	0.02	0.8925
FGI Stock	2641	2644	6.8391	0.0000	0.0000	0.00	0.9674

Figure 28. Univariate - Process variation - Product 1

It confirms that from all the responses, only delivery cycle time has the p-value of below the Bonferroni alpha level (α) of 0.01. It indicates the only variable that is being affected by the process variation, as much as approximately 7%.

KPI Correlations

This multivariate correlation test is a further test in order to acquire a better understanding on the relationship between KPI that may explain their behavior. By looking at the Pearson correlation testing (Fig. 29), it shows that all major KPI factors are statistically correlated with each other in different degrees.

Pearson Correlation Coefficients, N = 500 Prob > |r| under H0: Rho=0			
	Product Availability	Forecast Accuracy	Delivery Cycle Time
Product Availability	1.00000	0.70476	-0.64312
		<.0001	<.0001
Forecast Accuracy	0.70476	1.00000	-0.35712
	<.0001		<.0001
Delivery Cycle Time	-0.64312	-0.35712	1.00000
	<.0001	<.0001	

Figure 29. Pearson correlation - KPI - Product 1

The 3 figures below illustrates the relationship plot of the KPI performances during the simulation. Figure 30 shows the strong relationship between product availability and forecast accuracy. With Pearson *r* coefficient of 0.70, it shows that the strong performance of product availability is correlated with high forecast accuracy.

It applies the *inverse* correlation with the delivery cycle time. In figure 31, it shows that a lower delivery cycle time is correlated with a higher product availability. As shown, most entities that passes over 5 days of delivery cycle time only happen in the middle and lower part of the product availability performance.

Figure 32 also shows the similar correlation with forecast accuracy but in a smaller degree. Although quite dispersed, it still however has the same trend in a way that a higher delivery cycle time only appears in the area of lower forecast accuracy, typically below the 0,7 (70%) point. The low delivery cycle time correlates with better performance of forecast accuracy.

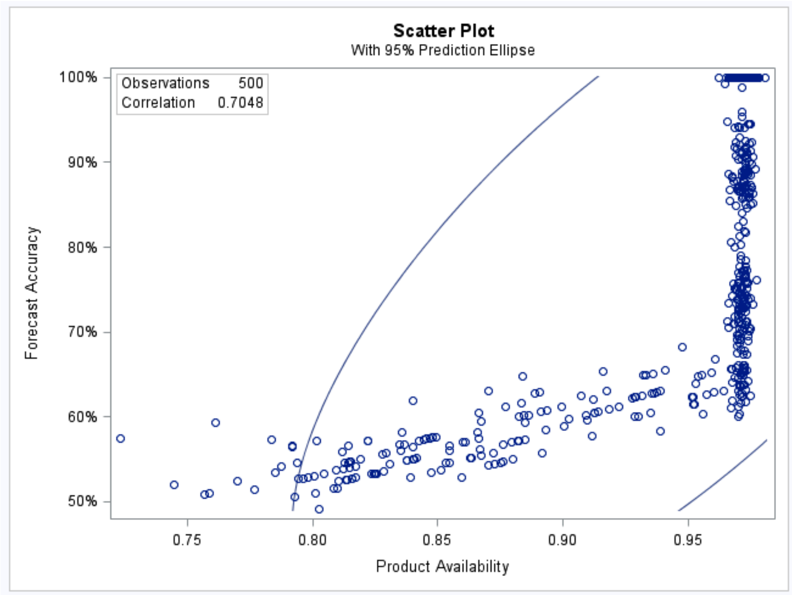

Figure 30. Scatter plot - Product Availability - Forecast accuracy - Product 1

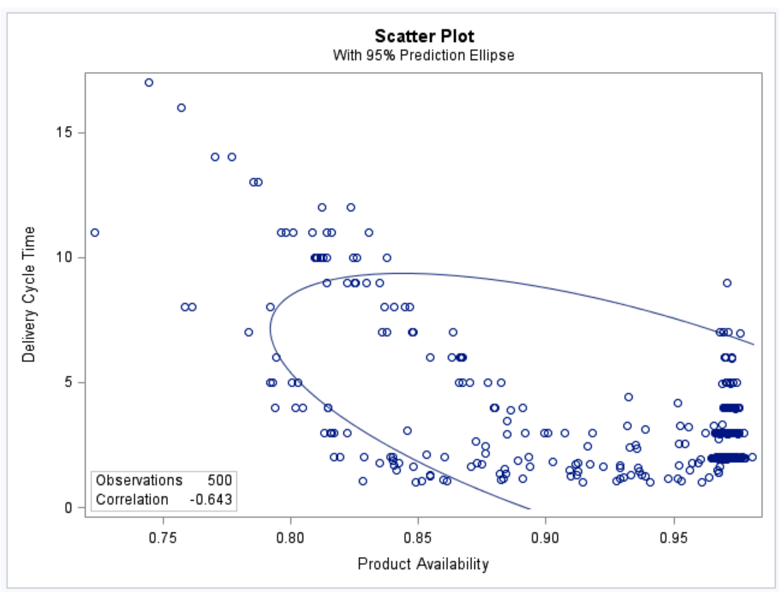

Figure 31. Scatter plot - Product Availability - Delivery cycle time - Product 1

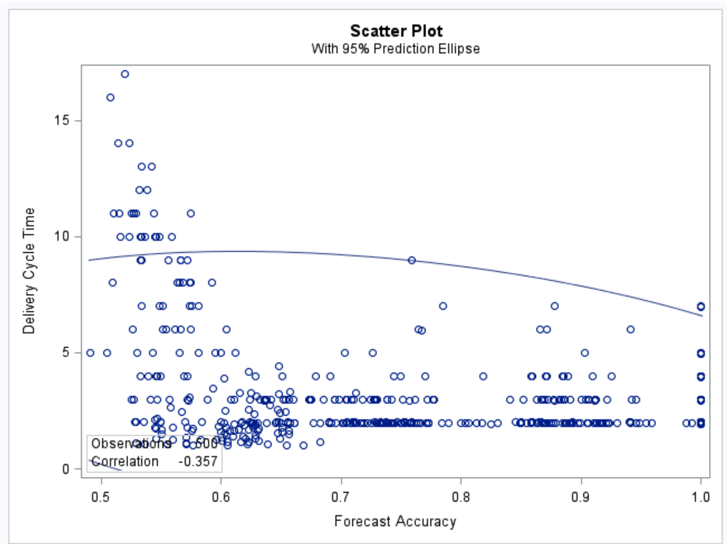

Figure 32. Scatter plot - Forecast accuracy - Delivery cycle time - Product 1

Sustainability

The plotter graphs (Fig. 33 to 35) are shown to evaluate the sustainability level of the KPI against the demand increase. These graphs are the visualization of the value from the DOE scenario analysis (Table 9) of the previous chapter. The red line represents the target line of the particular KPI, as illustrated in table 8.

As shown below, the KPI will start to fall below target line approximately after the 4th phase of 75% demand increase for product availability (Fig. 33), the 3rd phase of 50% demand increase for forecast accuracy (Fig. 34) and 100% demand increase for delivery cycle time (Fig. 35). Hence, the evaluation considers that the current system has a relatively high sustainability against demand increase.

The phenomenon that occurs in these graphs is dispersion, which indicates the high disparity in the performances. The graphs show that high dispersion most notably happen in the 4th phase of 75% demand increase for product availability (Fig. 33), in which its effect can directly be seen in the stagnant trend rate for total delivery after the 4th phase (Fig. 36).

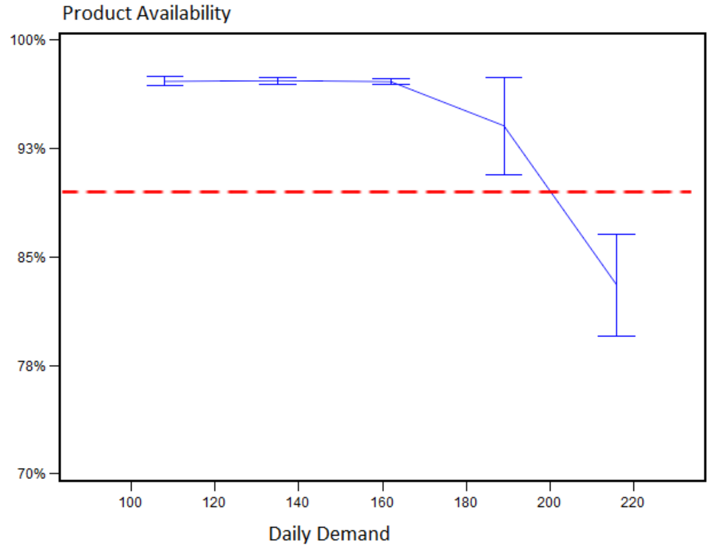

Figure 33. Demand - Product availability - Product 1

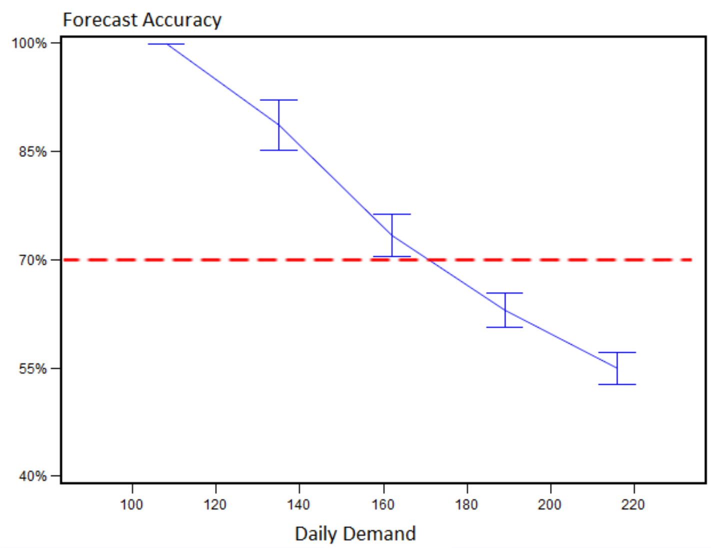

Figure 34. Demand - Forecast accuracy - Product 1

The figure 35 represents the delivery cycle time performance, which indicates its strong sustainability against the demand increase and process variation. It shows that the current system and FGI stock are still able to satisfy the demand within the target line of below 5 days despite of the spike increase of demand and production delay.

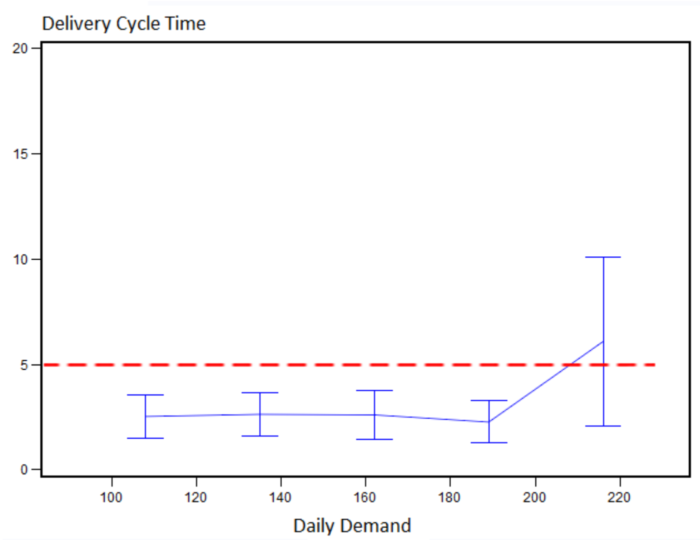

Figure 35. Demand - Delivery cycle time - Product 1

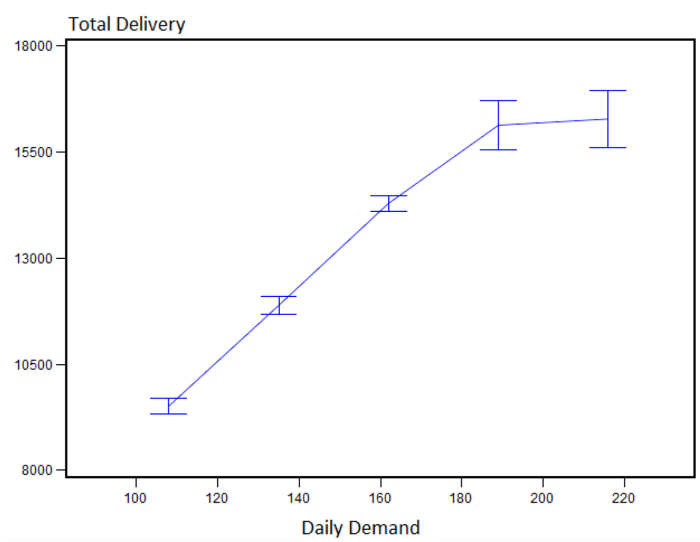

Figure 36. Demand - Total delivery - Product 1

4.2 Product 2: Repackaging

Product 2 represents the medicine that is imported from abroad (IM) which needs to be repackaged before being delivered to local customers. Although the repackaging time can be very short, the shipping delivery is known to be lengthy. This, similar with the first product, is a production process that is done within the organization's own factory.

Demand Variation

Figure 37 shows the multivariate result for the demand variation. The Wilks' Lambda (Λ) is 0.001, meaning that most variances are accounted for in this test. With the p-value of less than 0.05 (column Pr > F), it shows that the demand variation does have a significance in affecting the KPI results.

Multivariate Statistics and F Approximations					
S=4 M=0 N=244.5					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.00134622	516.40	20	1629.4	<.0001
Pillai's Trace	1.49965201	59.26	20	1976	<.0001
Hotelling-Lawley Trace	377.91089660	9257.18	20	1072.8	<.0001
Roy's Greatest Root	376.96745673	37244.4	5	494	<.0001
NOTE: F Statistic for Roy's Greatest Root is an upper bound.					

Figure 37. MANOVA - Demand variation - Product 2

The univariate test result for each KPI is recorded in figure 38. The F Value shows the demand significance to each particular KPI, and with all the p-value (Pr > F) shows less than the Bonferroni alpha level (α) of 0.01, it can be concluded that the demand increase contributes considerable impact to all of the designated KPI. Hence, based on the R-Square value, the following hypothesis can be written as such:

> Within the repackaging production system, the demand increase statistically yields significant impact to all the KPI (Fig. 37). The impact based on (Fig. 38) approximately accounts for 42% of product availability, 65% of forecast accuracy, 23% of delivery cycle time, 82% of total delivery and 71% of FGI stock

Univariate Test Statistics							
F Statistics, Num DF=4, Den DF=495							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.0845	0.0644	0.0614	0.4236	0.7350	90.96	<.0001
Forecast Accuracy	0.1949	0.1151	0.1761	0.6542	1.8918	234.12	<.0001
Delivery Cycle Time	4.1716	3.6722	2.2408	0.2313	0.3009	37.24	<.0001
Total Delivery	1123	475.3854	1137	0.8221	4.6222	572.00	<.0001
FGI Stock	1200	646.7203	1130	0.7117	2.4685	305.47	<.0001

Figure 38. Univariate - Demand variation - Product 2

Process Variation

The multivariate result for process variation is shown in figure 39. The Wilks' Lambda (Λ) shows some significance in the process with p-value below the alpha level (α) of 0.05. However, the univariate test result shows that among the KPI, only delivery cycle time yields a mere 6% of its variances accounted for by the process variation.

Univariate Test Statistics							
F Statistics, Num DF=1, Den DF=498							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.0825	0.0825	0.001261	0.0001	0.0001	0.06	0.8092
Forecast Accuracy	0.1223	0.1223	0.007784	0.0020	0.0020	1.01	0.3147
Delivery Cycle Time	5.5148	5.3489	1.9267	0.0612	0.0651	32.44	<.0001
Total Delivery	1103	1104	11.5485	0.0001	0.0001	0.03	0.8687
FGI Stock	0.8323	0.8331	0.007869	0.0000	0.0000	0.02	0.8813

Average R-Square	
Unweighted	0.0126801
Weighted by Variance	0.0000564

Multivariate Statistics and Exact F Statistics					
S=1 M=1.5 N=246					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.16898666	485.86	5	494	<.0001
Pillai's Trace	0.83101334	485.86	5	494	<.0001
Hotelling-Lawley Trace	4.91762671	485.86	5	494	<.0001
Roy's Greatest Root	4.91762671	485.86	5	494	<.0001

Figure 39. MANOVA - Process variation - Product 2

KPI Correlation

Figure 40 shows a similar relationship with the previous system. A relatively strong positive correlation between product availability and forecast accuracy is observed. Given a Pearson *r* coefficient of 0.65, figure 41 shows that higher performance of product availability is correlated with good performance of forecast accuracy. Delivery cycle time, on the other hand, correlates in the *inverse* direction with both factors (Fig. 42 and 43).

Pearson Correlation Coefficients, N = 500 Prob > |r| under H0: Rho=0			
	Product Availability	Forecast Accuracy	Delivery Cycle Time
Product Availability	1.00000	0.65287	-0.76838
		<.0001	<.0001
Forecast Accuracy	0.65287	1.00000	-0.40471
	<.0001		<.0001
Delivery Cycle Time	-0.76838	-0.40471	1.00000
	<.0001	<.0001	

Figure 40. Pearson correlation - KPI - Product 2

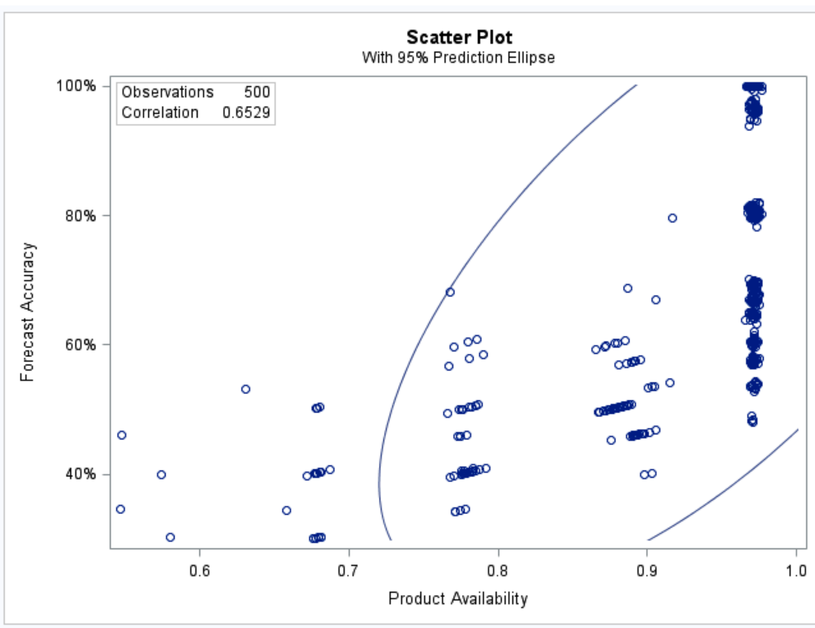

Figure 41. Scatter plot - Product availability - Forecast accuracy - Product 2

The correlation in figure 42 and 43 shows that the higher delivery cycle time correlates with low performance of product availability and forecast accuracy. The correlation is weaker in forecast accuracy (Fig. 43), thus explains the more scattered result in its plot compare to the plot in product availability (Fig. 42).

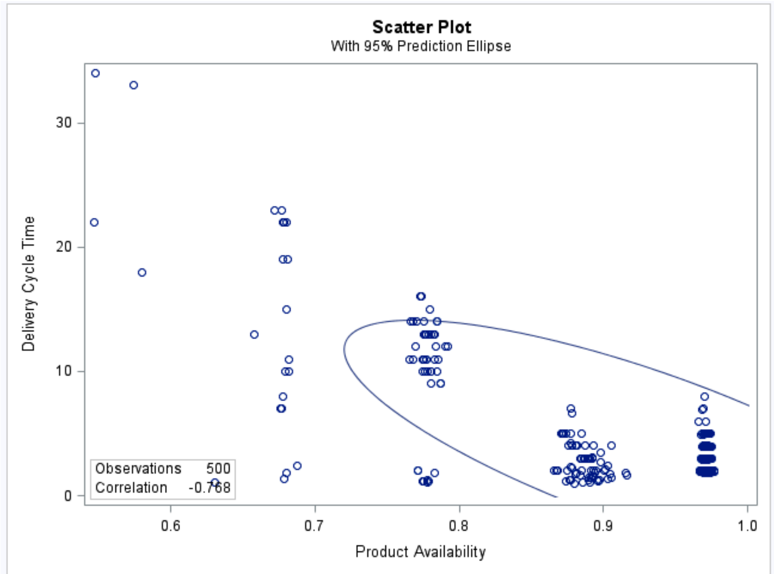

Figure 42. Scatter plot - Product availability - Delivery cycle time - Product 2

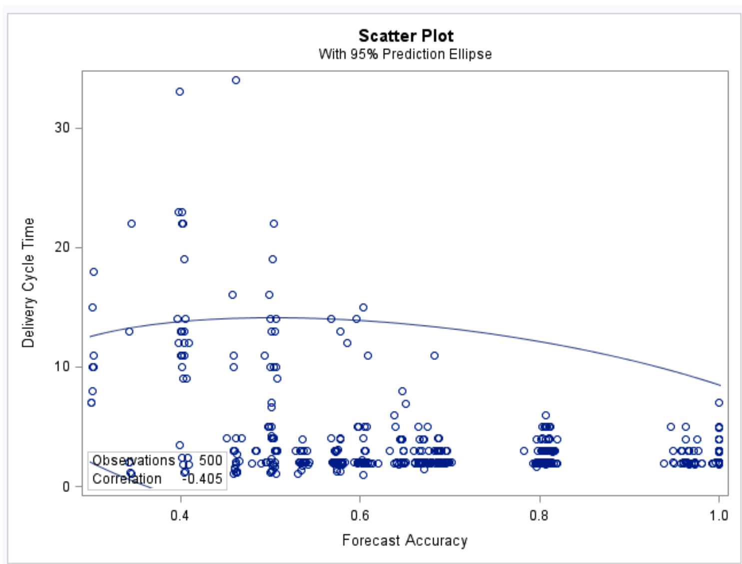

Figure 43. Scatter plot - Forecast accuracy - Delivery cycle time - Product 2

Sustainability

Based on figure 44 to 46, and evaluating the DOE scenario analysis for the repackaging production system (Table 10), it shows that the sustainability against the demand increase falls below target on the 4th phase of 75% demand increase for product availability (Fig. 44) and delivery cycle time (Fig. 46), and on the 3rd phase of 50% demand increase for forecast accuracy (Fig. 45).

The phenomenon of dispersion is seen increasing for product availability and total delivery (Fig. 44 and 47, respectively). The dispersion in product availability represents the inability to fulfill the demand as it rises, which then results in the dispersed performance in total delivery. This shows that the trend in the performance availability directly represents the performance level in total delivery.

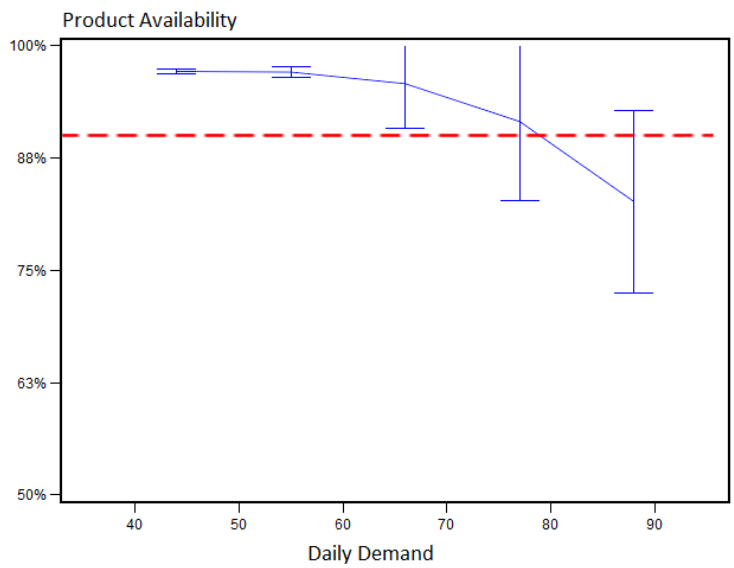

Figure 44. Demand - Product availability - Product 2

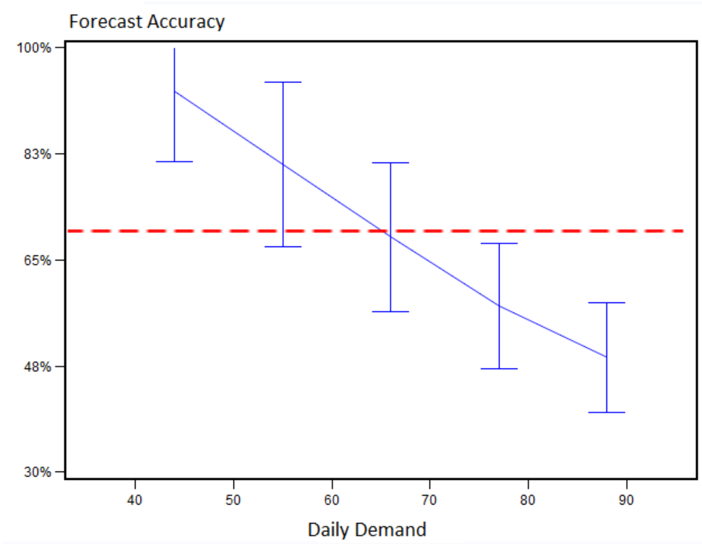

Figure 45. Demand - Forecast accuracy - Product 2

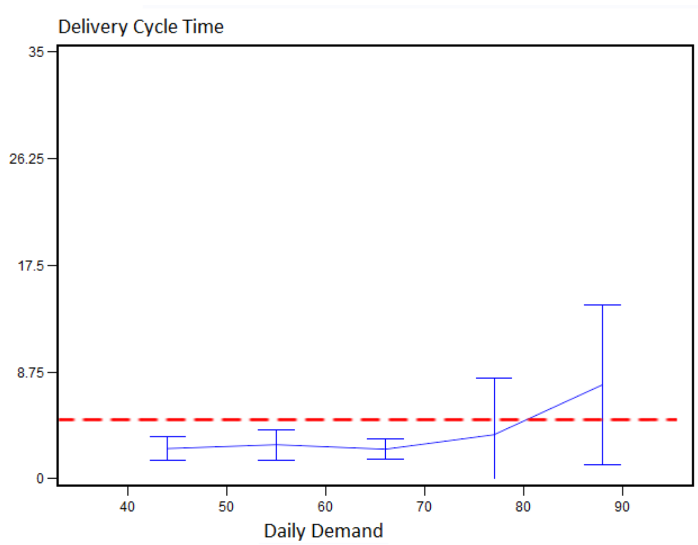

Figure 46. Demand - Delivery cycle time - Product 2

Overall, the sustainability level for the repackaging system is still considered relatively strong against the demand increase. The process variation does not yield significant changes in the performance result, and the resistance that has been observed against the demand increase shows that during a seasonal time of demand amplification, the system can still perform to deliver a performance that fulfills the indicators target line.

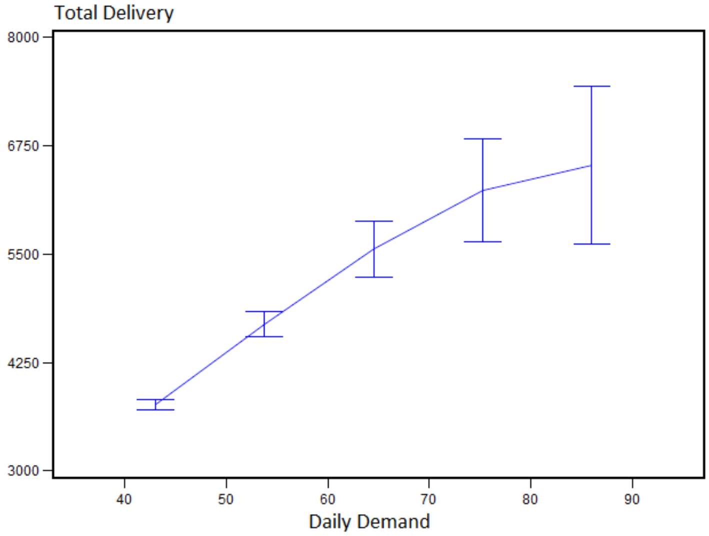

Figure 47. Demand - Delivery cycle time - Product 2

4.3 Product 3: Toll Out Manufacturing 1

This product represents the process model of the first premise of toll out manufacturing. Due to capacity issue of the third party, the production lead time is very lengthy and it imposes risk of delay up to 90 days at times. However, on the other hand, this option helps to accommodate the internal issue of production capacity and limited equipment that the case study organization faces in its internal factory.

Demand Variation

The result (Fig. 48) of multivariate Wilks' Lambda test shows the value of 0.01, indicating there are only small variances that are unaccounted for. With the p-value below the alpha level of 0.05 in column Pr > F, it can be stated that the demand increase brings significance on the impact towards the KPI performances. The univariate test that exemplifies the degree significance in each KPI performances will be shown afterwards (Fig. 49).

Multivariate Statistics and F Approximations					
S=4 M=0 N=244.5					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.01004520	244.69	20	1629.4	<.0001
Pillai's Trace	1.38243682	52.18	20	1976	<.0001
Hotelling-Lawley Trace	59.63428576	1460.78	20	1072.8	<.0001
Roy's Greatest Root	58.97712622	5826.94	5	494	<.0001
NOTE: F Statistic for Roy's Greatest Root is an upper bound.					

Figure 48. MANOVA - Demand variation - Product 3

The univariate test result (Fig.49) shows the significance of demand increase to each KPI. Looking at the p-value of all KPI, it shows that all KPI have it below the Bonferroni alpha level (α) of 0.01. Hence, it can be understood that all KPI are statistically impacted by the demand variation. By looking at the R-Square value, it can be written as hypothesis below:

> In the setting of the first premise of toll out manufacturing, the demand increases statistically yields differences (Fig. 48) to all KPI, and based on (Fig. 49), it approximately affects 63% of product availability, 95% of forecast accuracy, 33% of delivery cycle time, 31% of total delivery and 51% of FGI stock

Univariate Test Statistics							
F Statistics, Num DF=4, Den DF=495							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.1570	0.0954	0.1396	0.6336	1.7294	214.01	<.0001
Forecast Accuracy	0.1505	0.0336	0.1639	0.9506	19.2343	2380.24	<.0001
Delivery Cycle Time	4.9067	4.0261	3.1584	0.3321	0.4973	61.54	<.0001
Total Delivery	1395	1159	874.0408	0.3147	0.4592	56.83	<.0001
FGI Stock	1086	764.2677	865.7258	0.5091	1.0369	128.31	<.0001

Figure 49. Univariate - Demand variation - Product 3

Process Variations

The result of the multivariate test for the process variation is shown below (Fig. 50). Based on the Wilks' Lambda, the p-value is below the alpha level (α) of 0.05, indicating that the process variation yields a significance towards the KPI. The value is shown to be 0.09, indicating that most variances are accounted for within this multivariate statistics test.

Multivariate Statistics and Exact F Statistics					
S=1 M=1.5 N=246					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.09865651	902.65	5	494	<.0001
Pillai's Trace	0.90134349	902.65	5	494	<.0001
Hotelling-Lawley Trace	9.13617846	902.65	5	494	<.0001
Roy's Greatest Root	9.13617846	902.65	5	494	<.0001

Figure 50. MANOVA - Process variation - Product 3

Figure 51 shows the significance degree of process variation. Based on the p-value that is below the Bonferroni alpha level (α) of 0.01, it shows that all KPI but forecast accuracy yield significant changes in response to the increase of production lead time.

Unlike the previous 2 production system of in-house and repackaging, in the first premise of toll out manufacturing the process variation brings a moderate impact to most of the KPI performance. The largest goes to total delivery with 46% significance degree.

The forecast accuracy in the test (Fig. 51) shows no significance at all. This finding also resonates with the previous finding (Fig. 49) that concludes the forecast accuracy is largely affected, as high as 95%, by the demand fluctuation instead.

Univariate Test Statistics							
F Statistics, Num DF=1, Den DF=498							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.1570	0.1357	0.1119	0.2545	0.3413	169.98	<.0001
Forecast Accuracy	0.1505	0.1506	0.001147	0.0000	0.0000	0.01	0.9042
Delivery Cycle Time	4.9067	4.3569	3.2004	0.2131	0.2709	134.90	<.0001
Total Delivery	1395	1025	1338	0.4612	0.8560	426.27	<.0001
FGI Stock	1086	991.1909	631.3785	0.1692	0.2037	101.44	<.0001

Figure 51. Univariate - Process variation - Product 3

Thus, based on the multivariate analysis test result (Fig.50) and the R-square value (Fig. 51) for process variation, the hypothesis can be written as such:

> Within the setting on the first premise of toll out manufacturing, the process variation statistically yields impact on most of the KPI, particularly on the changes in 25% of product availability, 21% of delivery cycle time, 46% of total delivery and 17% of FGI stock

KPI Correlation

The Pearson correlation testing for product 3 show similar pattern of relationship from the two previous testing but with a higher degree of correlation. Product availability and forecast accuracy shows an eminently strong positive correlation with each other (Fig. 52), given a coefficient value of 0.77. Figure 53 shows the correlation between the two, which shows how the two has similar trend rate.

Delivery cycle time, on the other hand, has a negative correlation with both product availability and forecast accuracy (Fig. 54 and 55, respectively). Hence it indicates that the higher delivery cycle time is correlated with a lower performance in product availability and forecast accuracy. Figure 54 shows the correlation between delivery cycle time and product availability.

Pearson Correlation Coefficients, N = 500 Prob > |r| under H0: Rho=0			
	Product Availability	Forecast Accuracy	Delivery Cycle Time
Product Availability	1.00000	0.77973	-0.74213
		<.0001	<.0001
Forecast Accuracy	0.77973	1.00000	-0.50532
	<.0001		<.0001
Delivery Cycle Time	-0.74213	-0.50532	1.00000
	<.0001	<.0001	

Figure 52. Pearson correlation - KPI - Product 3

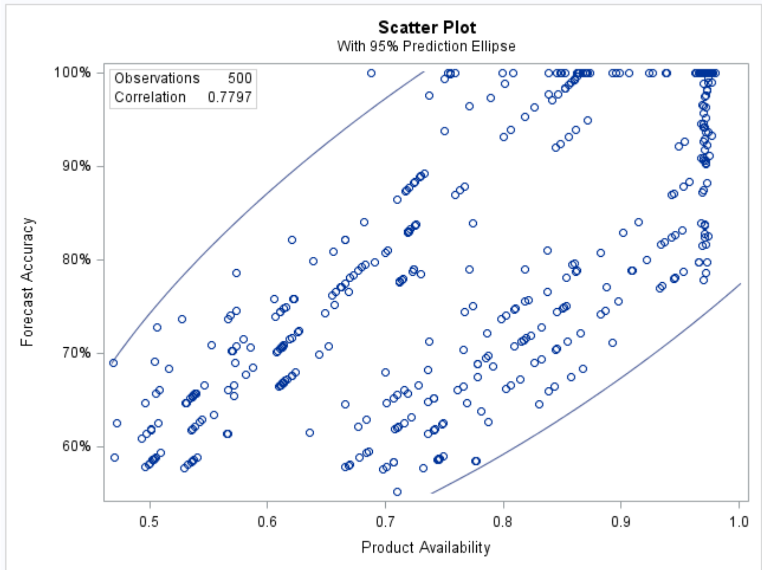

Figure 53. Scatter plot - Product availability - Forecast accuracy - Product 3

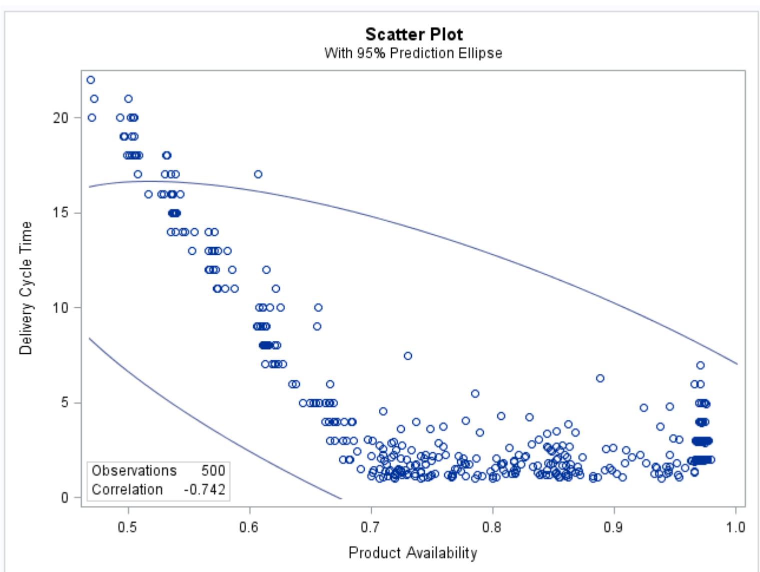

Figure 54. Scatter plot - Product availability - Delivery cycle time - Product 3

Figure 55 shows the correlation between delivery cycle time and forecast accuracy. Although looks dispersed, it still has similar trend with its correlation with product availability (Fig. 54).

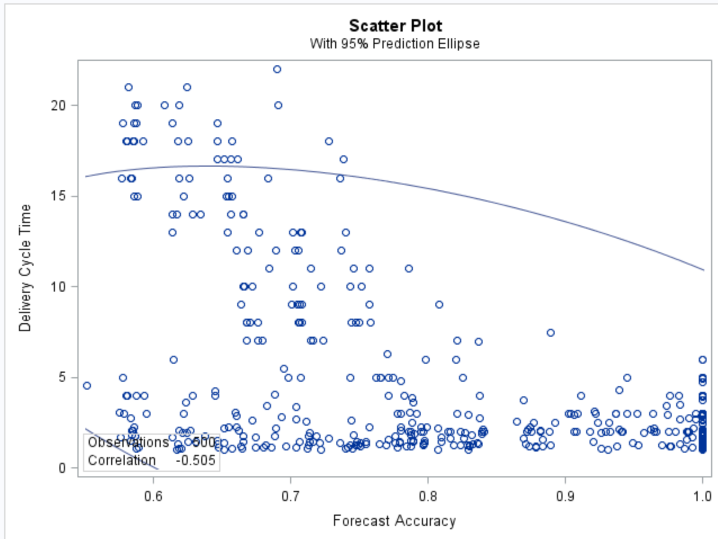

Figure 55. Scatter plot - Forecast accuracy - Delivery cycle time - Product 3

Sustainability

The plotter graphs (Fig. 56 to 58) and the DOE scenario analysis for product 3 (Table 11) provides a better data and visual understanding of the system sustainability level. The data shows that the KPI performance will fall behind the target line approximately on the point of 25% demand increase for product availability (Fig. 56), 75% demand increase for forecast accuracy (Fig. 57) and delivery cycle time (Fig. 58).

Large disparity can be observed in the product availability, and its impact is directly seen on the total delivery that has reached a plateau after the 2nd phase (Fig. 59). It indicates that the system is no longer able to deliver more products than the demand requires. This also resonates with the performance of delivery cycle time that spikes up after the 3rd phase, indicating that the FGI stock is empty so the product can no longer be delivered on time.

As shown in the MANOVA testing result for demand fluctuation process variation (Fig. 49 and 51, respectively), this performance of total delivery can be concluded that it is 31% affected by the demand and 46% by the increase of production lead time. Hence, in this production system, unlike the previous system of in-house and repackaging, the production delay from 60 days to 90 days in the toll out manufacturing setting does contribute a significant negative impact to the KPI performances.

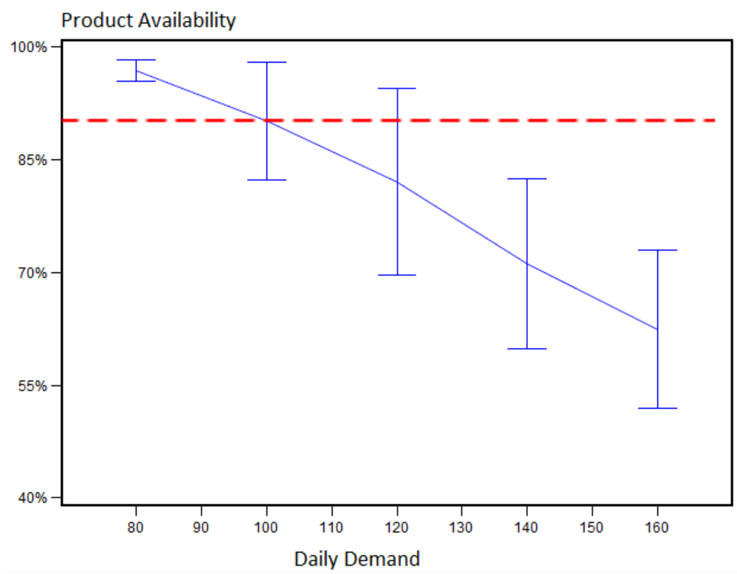

Figure 56. Demand - Product availability - Product 3

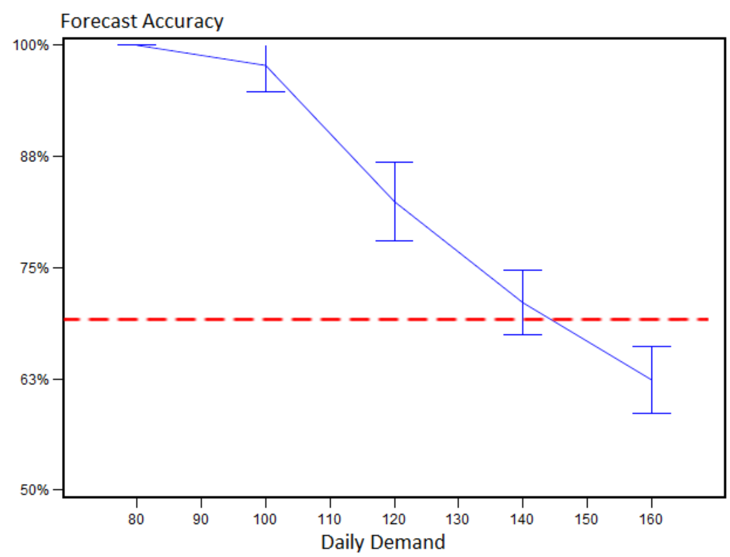

Figure 57. Demand - Forecast accuracy - Product 3

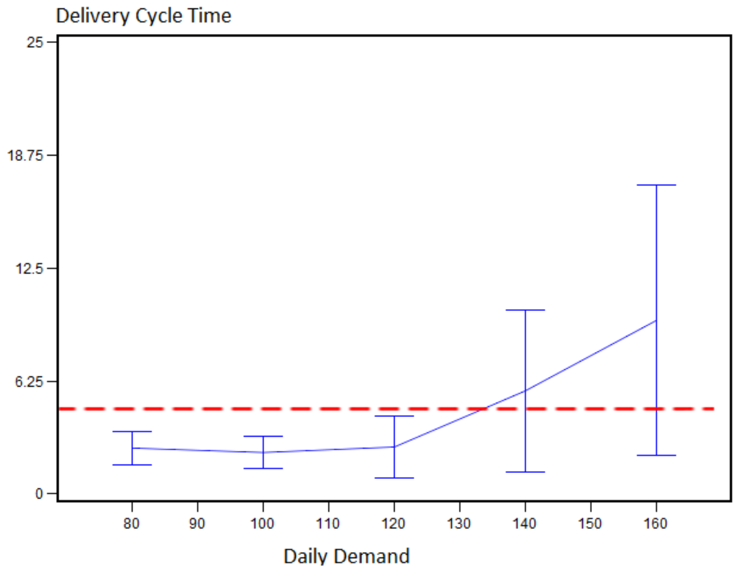

Figure 58. Demand - Delivery cycle time - Product 3

Figure 59. Demand - Total delivery - Product 3

Overall, the sustainability in this production system is considered very low and weak. It indicates that this production system is highly vulnerable when facing the demand fluctuation, especially when combined with delay in process variation. The stagnant of the total delivery shows a highly inefficient performance with plenty of lost sales.

4.4 Product 4: Toll Out Manufacturing 2

This product resembles the supply chain process model from the second premise of toll out manufacturing. In this system, the production lead time is relatively shorter than the previous premise due to the third party's larger production capacity. However, chance of delay are still possible.

Demand Variation

The multivariate result for the demand fluctuation is shown below (Fig. 60). Wilks' Lambda (Λ) value is 0.003; indicating that most variances are accounted for within the test. The F Value is 366.46 and the p-value is below the alpha level (α) of 0.05. It is therefore safe to conclude that the demand increase yields a significant impact on the KPI performances.

It is then followed by having a closer look on the degree significance it has to each KPI variable in the univariate test result (Fig. 61).

Multivariate Statistics and F Approximations					
S=4 M=0 N=244.5					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.00350745	366.46	20	1629.4	<.0001
Pillai's Trace	1.27968458	46.48	20	1976	<.0001
Hotelling-Lawley Trace	207.43601359	5081.28	20	1072.8	<.0001
Roy's Greatest Root	207.08550702	20460.0	5	494	<.0001
NOTE: F Statistic for Roy's Greatest Root is an upper bound.					

Figure 60. MANOVA - Demand variation - Product 4

By looking at the p-value (Pr > F) of the KPI variables (Fig. 61) that are lower than 0.01 Bonferroni alpha level (α), it shows that the effect is in a considerable size of impacting most of the KPI performances. Thus, based on the R-Square value from the same figure, the following hypothesis can be written as such:

Within the setting on the second premise of toll out manufacturing, the demand increase yields a statistical impact on approximately 52% of product availability, 94% of forecast accuracy, 48% of delivery cycle time, 47% of total delivery and 51% of FGI stock

Univariate Test Statistics							
F Statistics, Num DF=4, Den DF=495							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.1391	0.0966	0.1122	0.5218	1.0910	135.01	<.0001
Forecast Accuracy	0.1610	0.0398	0.1743	0.9394	15.4943	1917.42	<.0001
Delivery Cycle Time	10.5159	7.6018	8.1513	0.4816	0.9291	114.98	<.0001
Total Delivery	1950	1432	1485	0.4650	0.8692	107.56	<.0001
FGI Stock	1920	1355	1526	0.5063	1.0255	126.91	<.0001

Figure 61. Univariate - Demand variation - Product 4

Process variation

The multivariate result for the process variation is shown below (Fig. 62). The Wilks' Lambda (Λ) value of 0.11 shows that only approximately 11% of variances are unaccounted for. With the p-value (Pr > F) below 0.05, the MANOVA test can conclude that the variation in production lead time yields some significance to the changes in the KPI performances. The univariate test afterwards will show the significance degree it has towards each indicators (Fig. 63).

Multivariate Statistics and Exact F Statistics					
S=1 M=1.5 N=246					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.11732974	743.27	5	494	<.0001
Pillai's Trace	0.88267026	743.27	5	494	<.0001
Hotelling-Lawley Trace	7.52298813	743.27	5	494	<.0001
Roy's Greatest Root	7.52298813	743.27	5	494	<.0001

Figure 62. MANOVA - Process variation - Product 4

Univariate Test Statistics							
F Statistics, Num DF=1, Den DF=498							
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
Product Availability	0.1391	0.1181	0.1042	0.2812	0.3911	194.78	<.0001
Forecast Accuracy	0.1610	0.1611	0.000525	0.0000	0.0000	0.00	0.9589
Delivery Cycle Time	10.5159	9.1982	7.2244	0.2365	0.3097	154.22	<.0001
Total Delivery	1950	1632	1510	0.3004	0.4293	213.81	<.0001
FGI Stock	1920	1699	1269	0.2187	0.2800	139.44	<.0001

Figure 63. Univariate - Process variation - Product 4

Based on the univariate test statistics (Fig. 63), it shows that all but forecast accuracy are affected by the process variation. This resonates with the previous finding (Fig. 61) which concludes that demand variation affects 94% of the forecast accuracy. Based on the R-square value for this test, following hypothesis can be written as such:

> Within the setting of toll out manufacturing for the second premise, the process variation plays an eminent role in affecting the KPI performances, most notably accounts for 28% of product availability, 24% of delivery cycle time, 30% of total delivery and 22% of FGI stock

KPI correlation

The Pearson correlation testing (Fig. 64) and its scatter plots (Fig. 65 to 67) provide a better explanation on the relationship between the KPI. It shows another strong positive relationship between product availability and forecast accuracy with Pearson *r* coefficient of 0.69. It can be seen in figure 65 that both variables have the same upwards trend rate.

The delivery cycle time, on the other hand, shows a stronger inverse correlation with both factors compare to the correlation testing of the previous system. It indicates that the increase of the delivery cycle time is strongly correlated with a declining performance of product availability (Fig. 66) and forecast accuracy (Fig. 67).

Pearson Correlation Coefficients, N = 500 Prob > |r| under H0: Rho=0			
	Product Availability	Forecast Accuracy	Delivery Cycle Time
Product Availability	1.00000	0.69610	-0.94507
		<.0001	<.0001
Forecast Accuracy	0.69610	1.00000	-0.63634
	<.0001		<.0001
Delivery Cycle Time	-0.94507	-0.63634	1.00000
	<.0001	<.0001	

Figure 64. Pearson correlation - KPI - Product 4

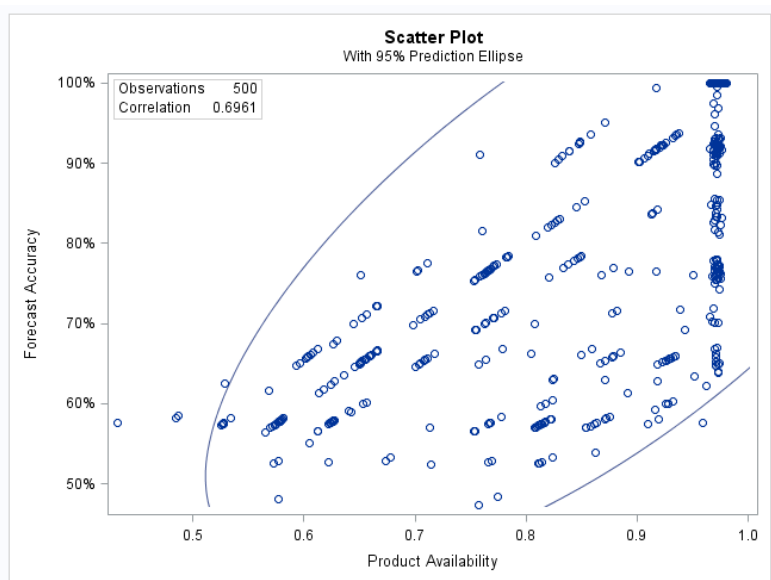

Figure 65. Scatter plot - Product Availability - Forecast accuracy - Product 4

The highest correlation can be seen happening with the delivery cycle time and product availability (Fig. 66). It shows that the low product availability performance leads to the inability of products to be delivered on time (below 5 days).

The correlation between delivery cycle time and forecast accuracy (Fig. 67) also shows a higher correlation than in previous system. The delivery cycle time performance, however, is immensely disappointing with cycle time of almost 50 days at the worst scenario.

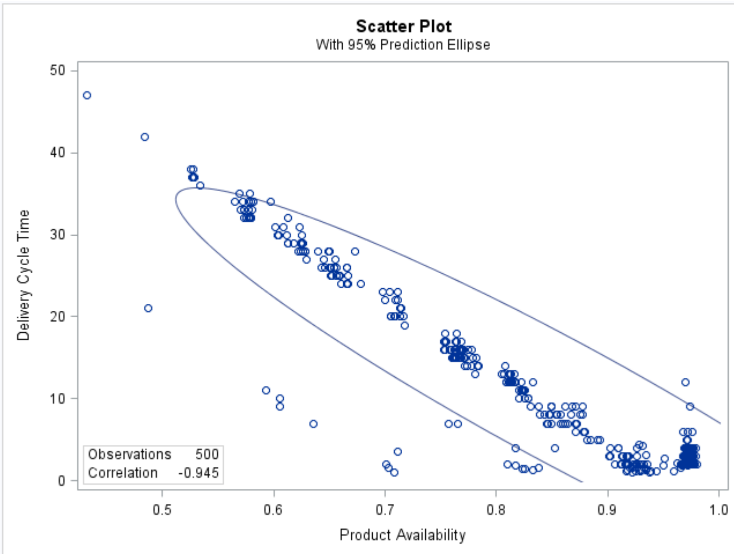

Figure 66. Scatter plot - Product Availability - Delivery cycle time - Product 4

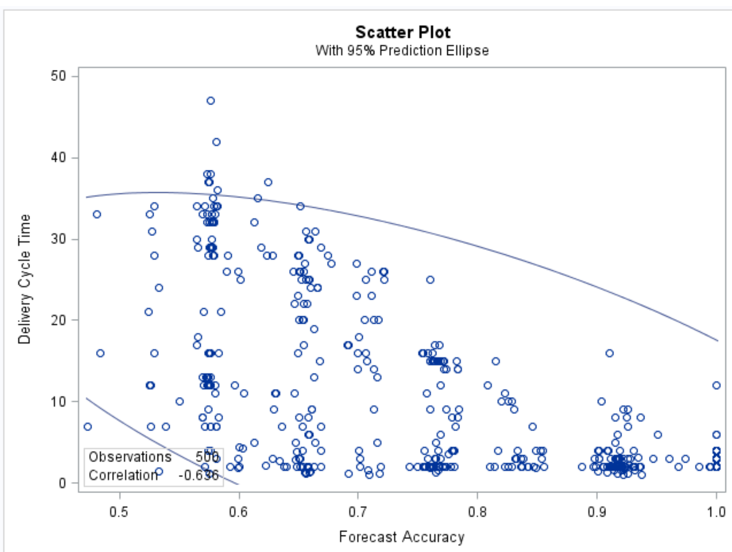

Figure 67. Scatter plot - Forecast accuracy - Delivery cycle time - Product 4

Sustainability

This last sub-chapter will be the observation of the current system stability against the demand increase. Based on the plotter graphs (Fig. 68 to 71) and the DOE scenario analysis result (Table 12), it can be evaluated that the sustainability level will fall behind the target line approximately on the 3rd phase of 50% demand increase for product availability and delivery cycle time (Fig 68 and 70, respectively), and on the 4th phase of 75% demand increase for forecast accuracy (Fig. 69).

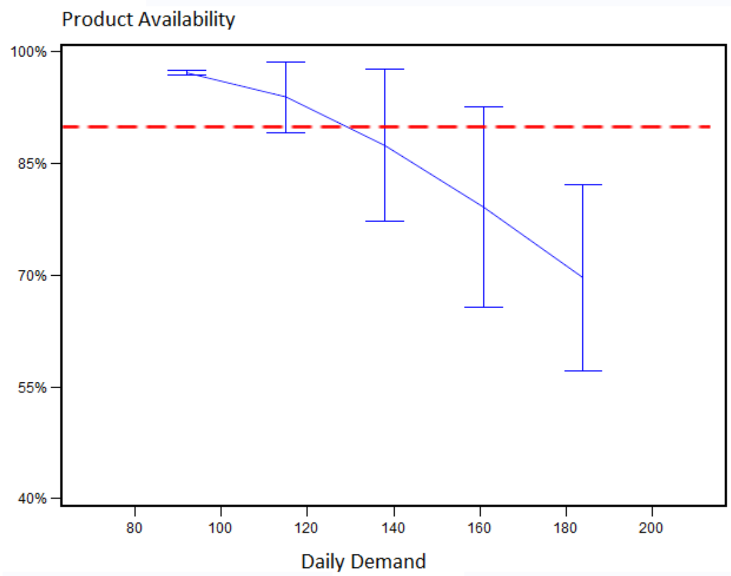

Figure 68. Demand - Product availability - Product 4

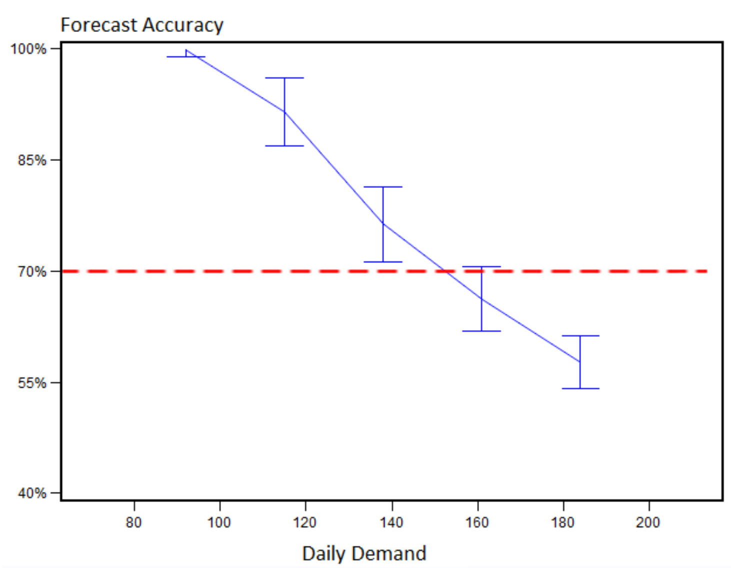

Figure 69. Demand - Forecast accuracy - Product 4

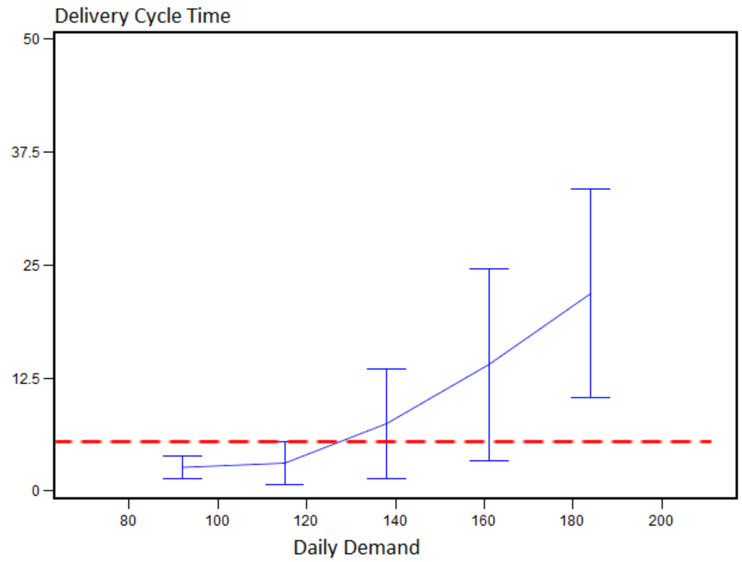

Figure 70. Demand - Delivery cycle time - Product 4

Figure 71. Demand - Total delivery - Product 4

The dispersion is eminently large for product availability, indicating that the system is barely able to cope with the demand as it increases. This results in the poor performance of the total delivery (Fig. 71), which has reached a stagnant growth rate on the 4th phase of demand increases.

The sustainability in the second premise of toll out manufacturing against the demand increase can be concluded to be very weak. Similar to the first system of toll out manufacturing (product 3), this system too is very vulnerable against the demand increase and the increase in production lead time.

The next chapter will highlight all the results that are mentioned in this chapter, and provide an interpretation and some suggested solution in regards of the phenomenon of these results.

5 DISCUSSION

This chapter will discuss all the findings that have been revealed in the previous chapter. The four products, which represent the four different production lines, have shown that each of them has its own response towards the variation study that have been performed.

In response to the first and the second research question in this study, both seasonal demand fluctuation and process variation have statistically shown some significance in affecting the KPI performances with a different degree of influence. Table 13 below summarizes the findings of all the empirical research that are done in chapter 4.

Table 13. MANOVA summary result

Multivariate analysis		**Degree of significance towards KPI**				
		Product Availability	**Forecast Accuracy**	**Delivery Cycle Time**	**Total Delivery**	**FGI Stock**
Demand variation	Product 1	86%	98%	34%	97%	95%
	Product 2	42%	65%	23%	82%	71%
	Product 3	63%	95%	33%	31%	51%
	Product 4	52%	94%	48%	47%	51%
Process variation	Product 1	~	~	7%	~	~
	Product 2	~	~	6%	~	~
	Product 3	25%	~	21%	46%	17%
	Product 4	28%	~	24%	30%	22%

The multivariate statistical result (Table 13) shows that seasonal demand fluctuation plays a significant role in affecting the performance level of all the designated KPI. This is true especially when considering the industry that is very prone to seasonal demand fluctuation for its product with numerous production lines.

Furthermore, the sustainability level of each KPI against the demand amplification is evaluated. Table 14 shows the highest level in which each KPI is able to maintain its performance above the target line under the shock test of demand fluctuation. By knowing the sustainability level of each KPI, it can serve as a consideration input during the decision making process about policies and measurement against further demand challenges.

Table 14. Sustainability level summary

Sustainability Evaluation	Demand Amplification			Average Sustainability Level
	Product Availability	Forecast Accuracy	Delivery Cycle Time	
Product 1: In-house	75%	50%	100%	75%
Product 2: Repackaging	75%	50%	75%	67%
Product 3: Toll out 1	25%	75%	75%	58%
Product 4: Toll out 2	50%	75%	50%	58%

This study shows that the effort to achieve a supply chain management system that can sustain the performance level against the increasing demand and process variation is considered as the key element to increase the competitive advantage for the organization.

Based on all aforementioned considerations, the proposed solution for this study will be to comprise a tailor-made assessment for every type of production process that is based on the projected demand fluctuation and the sustainability level of the particular production line.

The solution can start by acquiring the demand forecast for all the products. It is then followed by the classification of those products based on its production type and projected fluctuation level. If the forecasted demand for the particular product and production line is projected to fluctuate during seasonal time above its sustainability level, then a prevention measurement or alteration in its business process model may be worth undertaken.

5.1 In-house and repackaging

The first analysis is undertaken for *product 1* and *product 2*, representing both production system that are done in the organization's own factory with relatively short manufacturing lead time. Multivariate testing (Table 13) shows that demand fluctuation has a huge significance in affecting the KPI performance for those products.

However, table 14 shows that the two production system have a relatively high sustainability level against the demand fluctuation. It shows that *product availability* can still perform accordingly to its target line until approximately 75% of demand increase. Forecast accuracy falls below the target line after the 50% of demand increase. Hence, the improvement in forecast accuracy can have a positive impact on the overall sustainability level for in-house and repackaging production lines.

The improvement in forecast accuracy can be made by having a greater supply chain flexibility regarding its ability to respond to demand fluctuation. By quickly adapting to changes, the production can be adjusted accordingly and therefore increase the accuracy of the forecast performance during a volatile demand environment. This resonates to the study of Beamon (1999) and Lee (2004) which are earlier mentioned in the literature section.

For the in-house and repackaging production system, process variation of longer production lead time does not statistically yield major differences in KPI performances. It indicates that the current production lead time is still strongly able to sustain the demand increase.

5.2 Toll out manufacturing

The system of toll out manufacturing in both premises has shown a different observation result. In respect to demand fluctuation, multivariate testing (table 13) shows a similar trend with the previous system, which is that demand fluctuation plays a significant role in affecting the performance in each of the KPI.

In addition to demand fluctuation, unlike the in-house and repackaging production system, table 13 shows that process variation does yield a moderate impact to the KPI performances level. The effect can be seen in the performance of total delivery for product 3 (Fig. 61), in which it shows that it has reached a plateau state starting on the 3rd phase of demand increase; indicating that the system is unable to delivery more product that what the demand requires.

Thus, in the toll out manufacturing system, both demand and process variation is seen as a focal setback contributor to the system. It can be observed by the DOE scenario analysis for product 3 and 4 (Table 11 and 12) that the scenarios in which the production lead time is delayed contribute a negative impact to the KPI sustainability performance.

The proposed solution in order to increase the overall sustainability level of the KPI performances is to improve the process variation in terms of minimizing its production lead time and reduce the variation on the lead time through strategic sourcing between the case study organization with the toll out manufacturer. The objectives can be to have a higher production capacity, joint inventory replenishment and a more flexible manufacturing system to provide alternative paths during a volatile demand environment, and reduce the possible delay in overall production process.

By having a more pro-active collaborative interaction, the benefit that the case study company can get is to have a more flexible system in which will lead to a shorter and more consistent production lead time for its products. This is especially beneficial when dealing with fluctuative demand environment.

6 CONCLUSION

This study has successfully built a simulation model to depict the process model of the pharmaceutical manufacturing industry including its activities, routings and lead times, for four different production lines that are currently implemented within the organization. The empirical study is then performed on the simulation model to explore the significance of demand fluctuation and process variation towards the SCM performance indicators using the multivariate analysis as a statistical method for data analysis.

Simulation is found to be a highly useful tool in this study. It enables to expose the various issues and weaknesses that happen in the process model and increase visibility within the supply chain network. It resonates with the study of Fripp (1997) in respect of the simulation ability to capture real world environment and can be tailor-made to specific case study to be used as an experiential learning device.

Based on the discussions on the previous chapter, as well as statistical result (Table 13) and sustainability evaluation (Table 14), this study concludes that both production methods that are done internally have statistically higher sustainability against the demand fluctuation and process variation in comparison to the toll out manufacturing. The assessment of the sustainability level on each KPI for each production type can serve as an input for the future production planning. The summary of the discussion section will be implemented in the following managerial implication for the case study.

6.1 Managerial implication

This chapter will summarize the various discussion and conclusion for this study and form it in a list of measures and actions that can be taken by the managers of the case study company to be further considered as points to improve the current supply chain system.

This study considers that the most optimum way to improve the KPI performance level during the seasonal demand fluctuation for both *in-house* and *repackaging* manufacturing system is to improve the forecast accuracy by increasing its supply chain flexibility to achieve these objectives:

1. To be able to respond quicker to rapidly changing demand, so faster action can be taken either to increase or postpone production order
2. To have a real-time product demand from the customers and joint information system in order to better manage the current production order

For the *toll out manufacturing system*, both of them have proven to be very unsustainable against both demand increase and process variation. This is reflected in the poor performance of product availability along with high delivery cycle time and stagnant performance of total delivery. Thus, the managerial measure that can then be taken for these production types is to use the approach of strategic sourcing with the toll out manufacturing party to achieve these objectives:

1. To increase the production capacity and minimize the production lead time
2. To have a greater manufacturing flexibility system in order to provide more optional paths of production during seasonal and volatile demand environment
3. To have a better pro-active cooperation with the toll out manufacturer by being able to prioritize and/or postpone certain products in response to the demand situation at the moment

For the long run strategy, the minimization use for toll out manufacturing will be seen as a strongly beneficial move. In addition to that, the investment to increase the production capacity for *in-house* production system in order to provide an alternative path for toll out manufacturing and eventually allocate more production activity to this manufacturing system is seen as a pivotal move that can give more flexibility in the organization's production system, and increasing its competitive advantage to thrive in a volatile demand environment.

6.2 Result limitation

During the empirical research of developing the simulation model, DOE scenario analysis and multivariate statistical testing, there are several limitations that has bounded certain aspect of the result for this study. Those limitations may have given an impact on the proposed solution in terms of their relevancies and/or feasibility in the decision making process of the organization. Those limitations are:

1. The process model within this study is developed in accordance to the organizational SCM system, thus it does not represent the human variables in all its activities and process, e.g. man-made error, intervention, labor incompetency.
2. This study has simplified the business process in numerous aspects, most notably in regards of the amount of products, suppliers and production types. Hence it only represents a generalization to a more complex system, resources and variable interdependency.
3. The process variation that is experimented is limited on the lead time of production process, hence it does not represent the whole possible variation that may occur in the other area within the business process.

6.3 Further study

This study explores a closer look on the empirical study of demand increase and process variation to various SCM indicators. As aforementioned, the simulation model in this study assumes some level of certainty in its elements, e.g. supplier material availability, steady delivery lead time, amongst others. Thus, there are still some variations that are yet to be added to the process model. The further study can be done by extending the simulation model to have more entities and factors such as options of suppliers, higher fluctuation in the supplier material availability, and more detailed sub-activities, e.g. production shift.

Those variations will then lead to more factors to consider in the multivariate testing. Input factors such as supplier delivery lead time, quality testing lead time, or the supplier material availability, are still open for exploration in terms whether they too have a statistical significance towards the KPI.

In regards of the scenario analysis, it is also still open for more KPI responses. The KPI that is chosen for the future study can be extended into other area out of supply chain, i.e., production and sales. As aforementioned in the research scope, no economical factor or human labor activities are taken into consideration. However, all the process and activities in this model does involve certain aspect of the resource utilization of money and human labor. Those factors can be taken into consideration when making analysis of effect towards the KPI. It will then result into a more comprehensive and wide-ranged solution.

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