Fuzzy Logic Decision Making in Supply Chain Systems; An Approach to Mitigate the Bullwhip Effect

Case study of ISACO

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Abstract

The bullwhip effect has been known and existed for many years as an undesirable characteristic in supply chain. This phenomenon negatively impacts the performance of supply chain particularly in keeping stable inventory level. Therefore, any effort to reduce the effect would be beneficial. Enormous number of studies have been focused on the cause and solutions for the bullwhip effect and there has been many of successfully tested experiments to dampen the effect. However, the feasibility of such studies and the actual contributions for supply chain performance are yet up for debate. While the theory and knowledge of the bullwhip effect is well established, there is still lack of holistic engineering framework and method to analyze the problem, diagnose its causes and offer functional remedies.

This research work aims to fill this gap by providing a holistic system-based perspective to the bullwhip effect identification and diagnosis and proposing a novel approach to mitigate such effect. The supply chain structure in this study and behavioral features are accomplished by means of system dynamics modeling and fuzzy logic approach.

The contribution of the thesis relies not only on the fuzzy logic implementation in system dynamics realm but also improvement in dampening the bullwhip effect with the employed fuzzy logic framework.

This research portrays the application of fuzzy set theory in supply chain systems in a case study that exposes the approach, analysis and results to the real-world problem.

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Chapter One: Introduction

This chapter attempts to briefly introduce the context for this research and to sketch the motivation for carrying out this study, including the major deficiencies of previous studies on supply chain systems and bullwhip effect as well as theoretical reasoning for conducting this study. Detailed explanation of key variables and players in the research area and comprehensive review of previous research has been carried out in the literature review chapter. Subsequently, the research question in accordance to the gap in literature will be presented and finally the overall structure of the thesis is outlined to illustrate the procedures for conducting this thesis and answering the research question.

Research motivation/problem

In today's competitive world, success of a business is dependent on its supply chain's performance. In the last few years, successful industries have been shifted from mass production to make-to-stock and customization. Thus, their approaches have moved from product-oriented to market-driven strategies (Datta, Christopher, & Allen, 2007). In such environment, competitive advantage is considered as a function of fully-unified supply chain systems (Bhamra, Dani, & Burnard, 2011). Moreover, due to globalization, complexity of supply chain systems is on the rise and therefore exposed to disturbances more than ever (Christopher & Peck, 2004). In order to optimize supply chain systems, managers have been trying to cut down on-hand inventories, reducing the number of suppliers and outsourcing non-critical activities. These decisions have mostly been made based on the assumption that marketplace is an unchanging and foreseeable environment (Kearney, 2003). However, in complicated business situation that we live in, the importance of risk management associated with supply chain is inevitable. These risks are the result of consumers' demand variability in a global market which originates from competitive business environment. In addition to that, lack of manufacturer's and supplier's responsive action to change have significantly increased the potential risks involved in incongruity between supply and demand.

Due to the current uncertain and complex environment, managers are reexamining their strategies so that they can be ahead of competitors in delivering value to the clients.

Numerous studies have focused on the bullwhip effect for the past few decades, attempting to identify the cause and negative impacts of such phenomenon on different level of supply chain systems. The bullwhip effect, also known as Demand Amplification, Whip-lash or Whip-saw (Lee, Padmanabhan, & Whang, 1997) implies that the order variability increases along a supply chain. According to Lee (1997), bullwhip effect occurs when the variance of orders received by the manufacturer and supplier is much greater that of customer's demand i.e. from downstream to upstream demand amplification. The four major causes of bullwhip effect are traced in price fluctuations, order batching, rationing and demand forecast updating. Walker (2005) argues that technological, process and relationship core competencies are essential factors for an organization to compete in a market. The bullwhip effect exhibits the core competency's performance of the process and relationship competencies in which might cause unintended costs, waste resources and consequently losing market share.

It is important to note that bullwhip effect is perceived by both academics and industry. Fisher, Hammond &Raman (1997) revealed a real-world case where price change stimulated bullwhip effect in Campbell's Soup supply chain. Further examples of bullwhip effect have been identified by Lee, Padmanabhan & Whang (2004) in Procter & Gamble (P&G) and HP companies.

Several studies have attempted modeling and exploring the bullwhip effect in order to pinpoint the possible causes or develop strategies which would reduce the effect. Forrester (1961) confirmed the empirical evidence of bullwhip effect and stated the difficulties in information feedback loop between organizations as a major cause of the bullwhip effect. Sterman (1989) presented "Beer Distribution Game" to prove the bullwhip effect and then attributed the effect to "misperception of feedback".

Furthermore, many studies are dedicated on quantifying the bullwhip effect (Chen, Drezner, Ryan, & Simchi-Levi, 2000) and investigating (Disney & Towill, 2003) the solutions for it. Although, the literature suggests many different methods to reduce bullwhip effect, this phenomenon still occurs in reality. The reason for this contradiction would be the difficulties in employing the outcome from academic studies which analyze the bullwhip effect in an extremely simplified models into a multi-level multi-product complicated supply chain system. Besides, many of the analyses on the bullwhip effect are entitled to limited assumptions which justifies the use of simple models.

Grounded on the previous studies, the overall objective of this thesis is to deeply understand the bullwhip effect across the supply chain in real-world case study where a three-echelon supply chain of an automobile spare part industry is examined in order to grasp the underlying mechanism of bullwhip effect and subsequently implement a fuzzy logic policy design in the supply chain structure to test out the effect under fuzzy decision scenarios. The benefit of system dynamics is that the behavior of a system originates from its structure. Thus, system dynamics gives us the opportunity to define the rules and policies in the structure and observe the behavior.

Scope of the research

This research aims to develop a customized simulation model based on system dynamics approach and Fuzzy rule-based inference system for evaluating the bullwhip effect in a single-product, multi-stage supply chain. The proposed model allows users to quantify the bullwhip effect as well as modifying the variables to observe the impacts on the bullwhip effect. The fuzzy rule-based system is firstly constructed in MathWorks MATLAB® software and then implemented into Vensim®. MATLAB's great feature, Fuzzy Inference System (FIS) would assist us in developing a fuzzy-based decision system which then can be utilized in system dynamics model. The following presents the major aspects of this research:

- A standard supply chain simulation model based on system dynamics approach for quantifying the bullwhip effect in multi-stage supply chain is developed.
- The system dynamics simulation model is based on a generic retailer-distributor-manufacturer system with customization tailored for the case study of Iran Khodro Spare Parts and After-Sale Services Co (ISACO). Orders for goods move from a downstream customer to an upstream provider, and the products are shipped in an opposite way.

- The model is divided into three main echelons; retailer, distributor and manufacturer. Each level has its stock management and re-ordering decision system. The period of simulation is 157 weeks with Euler integration method.
- Fuzzy inference systems (FIS) is constructed for decisions on replenishments policies based on the inventory level and incoming demand at each level.
- The fuzzy inference system is then translated into a system dynamics structure and implemented to the main supply chain simulation model.

Research question

In summary, two major gaps in the literature have been identified. The first one lies within the dynamics of a supply chain and the need to investigate the bullwhip effect phenomenon analytically to gain more insights on the role of conventional forecasting on the bullwhip effect. The second gap concerns the application of fuzzy set theory in the supply chain dynamics and how to deal with uncertainties and vagueness in dynamic models which might be a major cause in generating the bullwhip effect.

Hence, the following research questions have been formulated and are sought to be answered in this study:

1. What are the main causes of the bullwhip effect in a real-world supply chain (Case study of ISACO)?
2. How fuzzy set theory could help the supply chain systems to mitigate the bullwhip effect?

This thesis intends to answer these two main questions that primarily rooted in the research motivation and literature review.

Research structure

This thesis is organized into six chapters and its contents can be summarized as following:

Chapter 1: *Introduction*; presents an overall introduction to the study, motivation for undertaking the research, scope of the research work and formulated research questions based on the existing gaps that have been discovered in the literature.

Chapter 2: *Literature review*; delivers an overview of the previous literature on related areas to the research. It mainly covers the topics in supply chain dynamic systems, the bullwhip effect and fuzzy logic theory. In addition, the idea of integrating fuzzy logic and system dynamics is described in this chapter.

Chapter 3: *Research methodology*; outlines the methodology used to conduct this study including research design and methods. This chapter argues the different choices for carrying out the research and the reasoning why system dynamics is an appropriate option based on the type of simulation, nonlinearities and time delays. The choice of case study is also explained in this chapter.

Chapter 4: *Model explanation & case description;* describes the development of the simulation model for analyzing the bullwhip effect in a multi-stage supply chain. This chapter includes model assumptions and detailed model structure and sub-models. Moreover, case study background and specifications, customizations made to the generic model and procedures for constructing fuzzy inference systems (FIS) structure are presented in this chapter.

Chapter 5: *Research model analysis and results*; provides case study simulation results. It contains analysis of the implemented fuzzy policy design and the impact of new policy on the bullwhip effect. In addition, this chapter demonstrate model calibration and verification in accordance to the reference mode and model validation based on boundary adequacy test, extreme condition test and integration error test.

Chapter 6: *Conclusion*; summarize the objectives and outcomes of the research and the contributions of this study. It also presents the potential ideas for future studies.

Chapter Two: Literature review

This chapter provides a comprehensive overview of the previous research carried out in the field of supply chain management. Emphasis is particularly given to the conceptual and empirical research that outline the bullwhip effect and quantitative studies that have been trying to measure supply chain bullwhip effect. This review also pinpoints the gaps in the literature that resulted in formulation of the research question.

Supply chain systems

There are several discussions going on among scholars and practitioners about a suitable definition of supply chain (Mentzer, et al., 2001). Supply chain is defined as the network of enterprises that are connected through upstream and downstream links and are involved in different tasks and processes that delivers values in form of products and services to the final consumers (Christopher, 1992). The upstream and downstream relationships happen via material and information feedback flows (Towill, 1997).

In another definition, supply chain is defined as a network of facilities and distribution options that perform in the procurement of materials, transforming raw supplies into intermediate and finished goods and distribution of final products to the consumers. Supply chain management (SCM) is an approach through which the incorporation of abovementioned functions can be accomplished (Shapiro, 2002).

In the past, before the existence of supply chain managers, each echelon in the supply chain would operate independently. Managers at each level made decisions based on the requirements and objectives of their particular activities with only slight attention to the constraints imposed by the neighboring echelons. As a consequence, each echelon tried to optimize its own operations and as we know a sequence of locally optimized systems does not necessarily establish a global optimum. For instance, logistics and production are normally beneficial in large batch sizes but retailing stores tend to run with low level of inventory to minimize costs and preserve flexibility to change product lines. These competitions in different echelons can only be settled by considering supply chain as a single entity.

The emergence of computer systems in the 1970s allowed enterprises to analyze and modernize their assembly and production processes using data-driven material requirement planning (MRP) and manufacturing requirement planning (MRP II). Then in the 80s, the rise of attractive management viewpoints such as Just-In-Time (JIT) promoted improved system with zero on-site inventory (Cook & Rogowski, 1996).

Today, supply chain is the key in developing an integrated policy which tries to address the following topics;

1. Identifying and quantifying demand features with regards to price fluctuations, service consistency and lead time.
2. Degree of logistics in manufacturing process that might impact service quality.
3. Managing the flow of information among different echelons in supply chain.
4. Decisions on demand forecasting.
5. Placement of optimum inventory level along supply chain to maintain acceptable level of customer service.
6. Handling interruptions such as machine breakdowns etc.

Customers today are demanding a vast variety of goods than ever. The unpredictable nature of such demands suggests shorter product life cycle and greater demand variability. The challenge is to maintain service reliability while keeping the costs low throughout the supply chain.

Supply chain management

According to Christopher (1992), supply chain management encompasses all the processes from raw material supplier to distributor and ultimately the end consumer. Supply chain management employs industrial dynamics approach to handle physical distribution and logistics operations (Houlihan, 1987). Perhaps the more accurate definition of supply chain management is defined by Thomas and Griffin (1996) which denotes supply chain management as information and material flow management within and between corporations. Stevens (1989) defines supply chain management from information point of view which is a combination of supply, inventory, capacity and customer service grounded in material and information flow and feedbacks. This definition has been adapted by Lambert, Cooper and Pagh (1998) to include cash and ownership flows as well. Therefore, the objective of managing the supply chain is to synchronize the requirements of the clients with materials flow from suppliers in order to make a balance between customer service, low inventory investment and low unit cost or in other words, meeting demand with supply in the most effective and efficient way.

Supply chain network structure and members

Supply chain network includes all the companies contributing in value creation and production chain, providing services from raw material to the end customers and linkages among them. According to Lambert (2000), this structure is comprised of central organization and several of its links such as suppliers and customers. Based on this definition, the size of a supply chain is described by its length and the number of suppliers and customers at each level. However, Cooper et al. (1997) argue that supply chain does not perform as such, but rather operates like tree branches where roots and branches symbolize a network. The decision on managing number of these roots and branches depends on product complexity, number of suppliers and raw material availability (Lambert & Cooper, 2000).

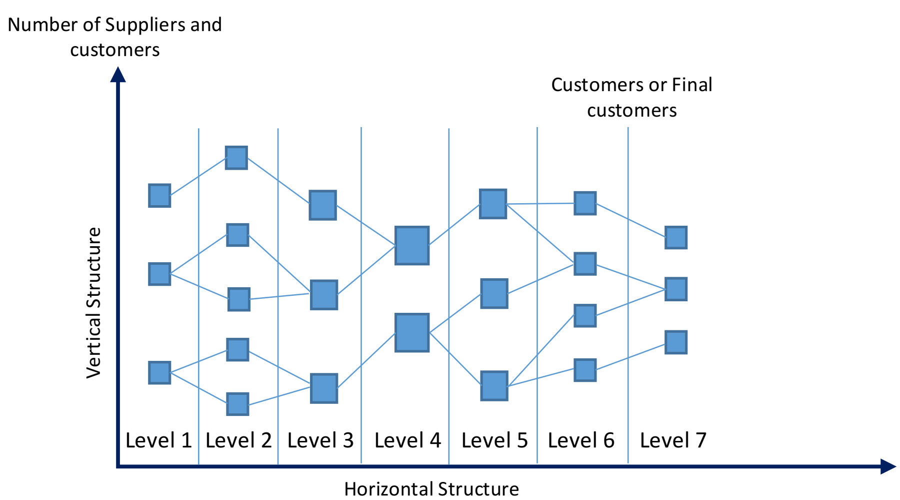

Figure 1, Network structural dimensions, Source: Lambert et al. (2000)

In order to determine the network structure, it is critical to recognize supply chain members and classify them by level and how fundamental they are for the company's success. Moreover, coordination and integration process between the members are often complex and most of the time counterproductive (Cooper, Ellram, Gardner, & Hanks, 1997). Hence, it is important to identify primary members from support members (Davenport, 1993). Primary members are independent companies that perform activities with added value or operate in a process which generates output for a specific market or client. In contrast, support members are those which supply resources, knowledge and tools for primary members. Transportation companies, production equipment companies, banks, storage facilities etc. are all examples of support companies. It is also worth mentioning that distinguishing primary and support firms is not so easy in all cases (Campuzano & Mula, 2011).

Supply chain management needs constant flow of information to produce the most efficient products flow towards the customers. Responding to regularly changing customer's demand requires a precise and sufficient information of processes.

Supply chain bullwhip effect

The bullwhip effect, also known as Demand amplification, Whip-saw or Whip-lash effect, refers to a phenomenon in which orders received by suppliers amplifies much higher than that of the retailer. Forrester (1958) investigated a supply chain and notices how a small change in consumer's demand leads to larger fluctuations as it travels through distribution, production for replenishment process. At each level in supply chain, the aberration becomes greater as the orders move upstream. This is due to unsatisfactory supply chain management which is also known as Forrester effect. Forrester (1961) examined this effect in his book "Industrial dynamics" and concludes the bullwhip effect is a result of non-zero lead time and imprecise forecasting by different supply chain partners when facing demand variability.

The Forrester Effect, which has also been called The Law of Industrial Dynamics (Burbidge J. L., 1984) is attributed to a combination of factors but a typical chain of events that results in demand variation is described as follow; amplifications in demand create a perceived shortage at some point along the supply chain that could falsely indicates that the inventory level is lower than desired inventory. A company which does not have a clear understanding of the supply chain may order excessively to shield against possible demand variations. This upsurge in order sends incorrect signals to the next echelon which creates a delusion of real higher orders which in turn triggers another over-order for protection (Riddalls, Bennett, & Tipi, 2000).

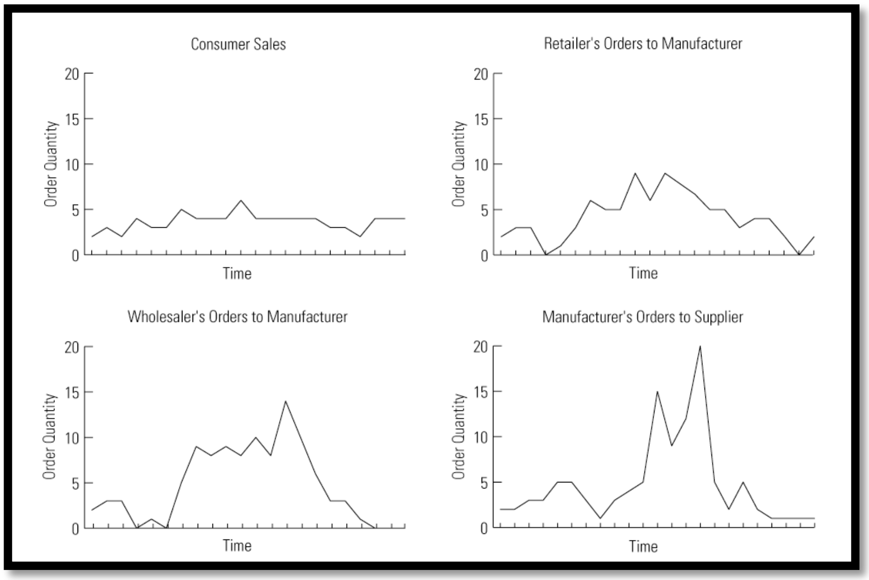

Figure 2, Bullwhip effect in a supply chain

The literature reveals that the bullwhip effect has increasingly been at the center of research topics for the past couple of decades. Below depicts the research area in four different categories since 1950s up until now.

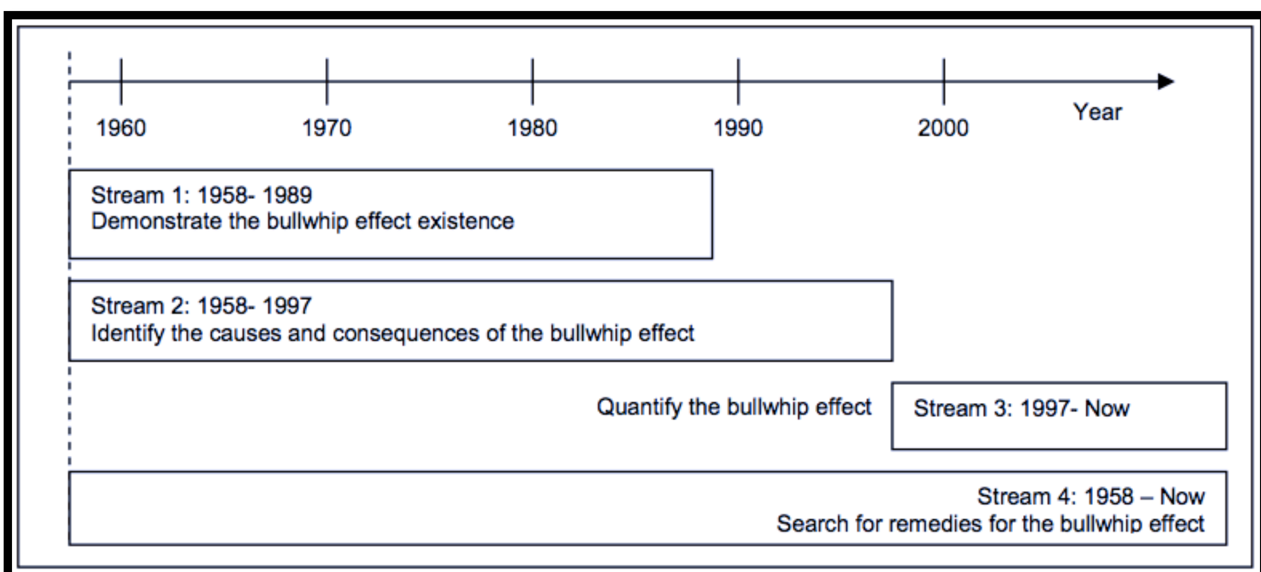

Figure 3, bullwhip effect literature stream

At first, researchers tried to prove the existence of bullwhip effect (Forrester J. W., 1961) and identify the causes and consequences of it (Sterman, 1989). At the present time, research focus has been shifted toward quantifying the effect (Metters, 1997) and investigating for remedies (Zhang, 2005) by employing range of techniques such as analytical approaches (Warburton, 2004), simulation (Chatfield, Kim, Harrison, & Hayya, 2004) and control theory (Disney & Towill, 2003).

The bullwhip effect occurs not only between supply chain members but also between the subdivisions or workstations that have autonomy in ordering decisions (Taylor D. , 1999).
There are number of examples of bullwhip effect in the literature. Towill and MacCullen (1999) analyzed the bullwhip effect in a textile supply chain while Holmström (1997) identified the demand variation in a case of grocery retailer’s industry. However, perhaps the best example of bullwhip effect has been demonstrated by Sterman (1989) using a famous business game called “Beer Game”. The beer distribution game attempted to examine how human misperceptions can impact the simulated supply chain. The author concluded that the bullwhip effect occurs due to lack of information transparency across the supply chain and uncontrolled increase or decrease in orders without attention to real orders. Figure 4 depicts the bullwhip effect in a beer game.

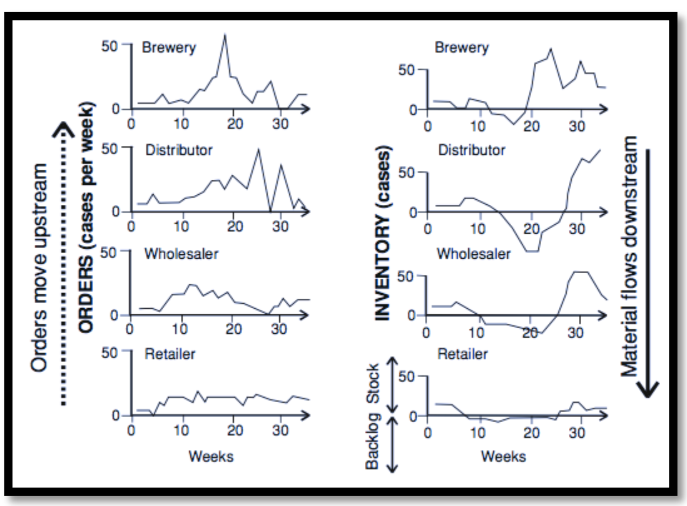

Figure 4, The bullwhip effect in beer game. Source: Sterman (1989)

According to Lee et al. (1997), four common causes of bullwhip effect are attributed to demand signal processing and non-zero lead time, order lot sizing, price fluctuations and shortage gaming.

1. ***Demand signal processing and non-zero lead time (Forrester effect)***

   Demand signal processing refers to distortion in information which can spread out in the entire supply chain when only local information is used for decision making (Miragliotta, 2006). It is also called "demand amplification" or "Forrester effect". Organizations in a supply chain normally perform forecasting for scheduling, inventory management and capacity planning. Forecasting is usually based on historical data from instant customers, for example, the retailer's forecast is based on previous consumer's demand while the distributor uses retailer's demand data.

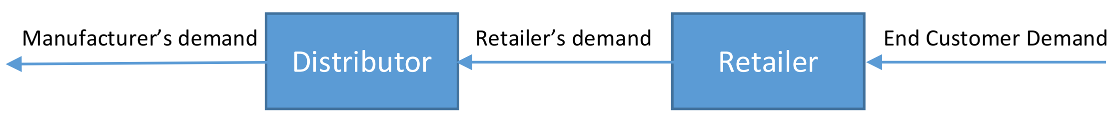

Figure 5, Information for demand forecasting

   Lee et al. (1997) argues that the bullwhip effect occurs when supply chain members base their forecasts on the demand input from their neighboring member in the supply chain. As for the forecasting, a simple method of exponential smoothing is normally used by the retailer to predict incoming customer demand. On the other hand, the demand sent by retailer to distributor indicates the amount of inventory replenishment from the retailer for future demand and desired safety stock. Hence, the oscillations in distributor's demand becomes greater than the retailer's demand. Consequently, demand amplification grows over the entire supply chain. Furthermore, lengthy lead time can worsen the situation due to the fact that, the longer the lead time, the higher the safety stock needed for replenishment and the greater the fluctuations.

2. ***Order lot sizing, order batching or Burbidge effect*** (1991)

   Throughout the supply chain, members usually accumulate demands before issuing an order to the upstream and not necessarily place an immediate order (Lee H. , 1997). The main challenge with this policy is economics of scale and ordering cost reduction related to packaging and transportation (Potter & Disney, 2006) and also to benefit from sales incentives. Promotions often result in forward buying to take advantage of lower prices. Placing orders in larger quantities would cause longer order processing and hence the irregularity from the bullwhip effect would be higher.

3. ***Price fluctuations, Promotion effect***

   It is quite common at distributor's and manufacturer's echelons to offer promotions in forms of price discounts, quantity discounts and rebates. These promotional campaigns lead to price variability which results in scattered ordering behavior. Larger orders at a lower price postpones the next order until the current inventory is depleted (Fisher, 1997). Therefore, the customer's purchasing pattern does not reveal its consumption behavior because the variations in purchasing rate is greater than consumption rate (Lee H. , 1997). Thus, the bullwhip effect happens even though the demand pattern is quite stable. In an experimental study by Rinks (2002), data structure of the Beer Game is used to demonstrate that it takes more than 20 intervals for the system to stabilize after a price fluctuation is initiated.

4. ***Rationing and shortage gaming, Houlihan effect*** (1987)

   Cyclical industries usually face irregular periods of excessive supply and undersupply. When consumers know that a shortage is imminent and rationing is going to occur, they will often increase the size of their orders to ensure that they get what they need. In practice when supply delivery time increases, buyers place multiple orders with the same supplier to get higher priority allocation and with different suppliers to get possible delivery. These multiple orders further overload capacity and stretch lead time. As a result, the bullwhip effect increases accordingly.

The abovementioned factors are widely accepted as the causes for bullwhip effect. However, Taylor (2000) argues that machine dependability, process capability and supply inconsistency could also be the possible reasons for the bullwhip effect. Companies face tremendous challenges when dealing with bullwhip effect. The common indicators of such effect would be extreme level of inventory, unsatisfactory forecasts, scarce or excessive capacities, substandard consumer service, uncertain production planning and control due to accumulated backlogs and overdue shipments (Ingalls, Foote, & Krishnamoorthy, 2005).

Solutions for the bullwhip effect

Understanding the causes of the bullwhip effect can assist us to mitigate it. To counter bullwhip effect, enterprises normally increase their safety stock inventories in an attempt to level production rate. However, holding expensive level of inventory against demand amplification would not be the most effective way. Furthermore, stocking up high level of inventory adds more to the misperception of any real demand variations. Burbidge (1961) presented a model for inventory and production control which traced to the bullwhip effect. The model proved that the traditional stock control by using Economic Order Quantity (EOQ) method tends to increase demand amplification along the supply chain.

According to Johnson (1998), information sharing, channel placement for swapping decision rights, decreasing order lead time and eradicating forecast updates can be used to mitigate the bullwhip effect. Wikner, Towill & Naim (1991), proposed series of actions to ease up the bullwhip effect including: enhancement of decision rules at each level of supply chain, time delays reduction, eliminating part of distribution echelons, developing rules among different echelons and improvement in information sharing throughout the supply chain.

Lee et al. (1997) also indicated the following coordination mechanism for reducing the bullwhip effect which are in line with the four major causes of the bullwhip effect: information sharing, operational efficiency and supply chain alignment.

Campuzano et al. (2011) suggest five strategies to lessen the bullwhip effect:

1. Disregarding demand forecast updates but instead renew the supply chain structure into a system where:
    - Demand data are available at all supply chain echelons by using Electronic Point of Sales (EPOS) system.

- Using Vendor Managed Inventory (VMI) structure for sharing demand and inventory level information throughout the supply chain.
- Direct sales to the final customers using e-commerce structure.

2. Avoid lot sizing
   - Just in Time (JIT) inventory system would be an effective and fast stock replenishment tool.
3. Stable pricing
   - Reducing the discounts frequency.
   - Everyday Low Price (EDLP); the pricing strategy promising consumers a low price without the need to wait for sale price events or comparison shopping.
   - Continuous Replenishment Program (CRP) strategies; a process by which a supplier is informed on a daily basis of actual sales or warehouse shipments and commits to replenishing these sales without stock outs and without receiving replenishment orders.
   - Activity-based costing (ABC) systems to assign the cost of each activity with resources to all products and services according to the actual consumption by each.
4. Eradicate rationing
   - Information sharing regarding inventory and capacity levels across the supply chain.
   - Communicating with customers to expand the production for seasonal offers.
5. Other policies
   - Employing Information Systems (IS)
   - Implementing incentive systems

Many other researchers have tried to explore the bullwhip effect from different perspectives and bring feasible solutions to dampen the effect. Table below displays the most relevant researches attempted to analyze the bullwhip effect and propose remedies for it. In most of the studies, the focus has been made on specific causes and solutions in specific aspects.

Table 1, Researches conducted on the bullwhip effect remedies

Author	Supply chain features	The bullwhip effect cause	Solutions
Baganha & Cohen (1998)	Single product, n retailers and one distributor	Demand signal processing	A centralized distribution system tends to reduce the bullwhip effect
Cachon (1999)	Single product, one supplier and n retailers	Order batching	Schedule ordering policy can reduce the bullwhip effect when the retailer order intervals are lengthened or when the retailer's batch size is reduced
Kelle & Milne (1999)	Single product, one supplier and n retailers	Order batching	Bullwhip effect can be reduced by reducing batch sizes, and by placing small frequent orders
Gavirneni, Kapuscinski, & Tayus (1999)	Single product, one retailer and one supplier	Demand signal processing	Information sharing is expected to be most beneficial when 1) the variance of customer demand is low 2) the difference between s and S is low and 3) the capacity of supplier is high
Cachon & Fisher (2000)	Single product, one supplier and n retailers	Demand signal processing	Information sharing via EDI can improve operational efficiency by reducing lead time and decreasing batches
Chen et al. (2000)	Single product, Linear four stage supply chain	Demand signal processing	The bullwhip effect can be partially reduced by centralizing demand information
Lee et al. (2000)	Single product, one retailer and one supplier	Demand signal processing	The value of demand information sharing can be high for manufacturer when demands are significantly correlated over time, the demand variance with each time is high and the lead time are long
Riddalls & Bennett (2001)	Single product, single stage	Order batching	1) The bullwhip effect is proportional to the remainder of the quotient (average demand/batch size) 2) Setting batch size at or near a divisor of the average demand rate can reduce the bullwhip effect

Disney and Towill (2003)	Single product, two stage supply chain	Demand signal processing	Increase the average age of forecasts and reduce the rate at which inventory and WIP correction can reduce the bullwhip effect
Warburton (2004)	Single product, one supplier, one retailer	Order batching	The correct parameterization of the inventory model can allow a reduction in the bullwhip effect
Chatfield (2004)	Single product, Linear multi-stage supply chain	Demand signal processing	1. Information quality for updating forecast demand is an important factor. The better information quality can reduce bullwhip effect 2. Information sharing reduce the bullwhip effect
Potter & Disney (2006)	Single product, two stage supply chain	Demand signal processing	The bullwhip effect levels from batching can be reduced if the batch size is a multiple of average demand
Ouyang (2007)	Multi linear supply chain	Demand signal processing	Information sharing can reduce the bullwhip effect. However, it cannot completely eliminate it.

Based on the literature review, the bullwhip effect solution studies can be classified in two groups. One type of solution is concentrating on each individual echelon and trying to improve efficiency and contributions with controllable policies which affect the ordering process for each supply chain unit (including forecasting policy and ordering policy) and the other one is improving the supply chain structure and relation which include eliminating supply chain units to reduce the delays or lead time and the information misrepresentation due to demand processing updates. Only after a decrease in demand processing updates and non-zero order lead time, the bullwhip effect can be weakened.

System dynamics and artificial intelligence

Modeling with soft variable is considered to be one of the reasons for unreliable results in system dynamics simulations. That is why researchers attempt to improve the models' accuracy by using artificial intelligence (Wang J. , 2001).

Artificial intelligence (AI) emerged as a computer science discipline in the mid-1950s for complex real world problems that would normally require human intelligence. Since then, number of tools has been introduced which perform excellently well in soft variables, including fuzzy logic, neuro fuzzy system, neural networks and so on. Fuzzy logic and neural networks are the major methodologies used in artificial intelligence (Jang, Sun, & Mizutani, 1997). These techniques are general function approximators which can be employed in modeling soft variables. Fuzzy logic enables us to identify the variables relationships by using linguistic data (Nauck, Klawonn, & Kruse, 1997). The main feature of a fuzzy system is the fuzzy rules to represent the input-output relationships (Babuska & Verbruggen, 2003). Nonetheless, there is no standard method for converting human knowledge or experience into the rule-based fuzzy system (Jang, 1993). On the other hand, neural networks are able to learn from data to estimate an input-output function. Neural networks method does not require a mathematical model but the result formulation is not explicitly given and are coded in the network and its parameters. Therefore, it is hard to recognize if the solutions are practical (Mitra & Hayashi, 2000). Since fuzzy logic is the main technique in this thesis, it will be elaborated in details in the next part.

Expert system concept

Expert system is a division of artificial intelligence that makes extensive use of particular knowledge in order to come up with human-level solutions. Typical expert system consists of six elements; knowledge-base (rules), inference engine (agenda), user interface, working memory (facts), explanation and knowledge acquisition facilities. In rule-based expert systems, the necessary information for solving problems must be "coded" in form of rules. These rules are conditional statements which comprise of an antecedent and consequent parts. For instance, a fuzzy rule can be articulated as follows:

IF *quality* is "HIGH" **THEN** *maintenance cost* becomes "VERY LOW".

Fuzzy rules are based on linguistic variables that exist in the real world and most of the time is vague, imprecise, uncertain and ambiguous in nature. This is specifically important due to the fact that classical theory struggles to answer some real world problems. The use of fuzzy expert system can help us solving these sort of problems with imprecise information.

Classical theory vs. Fuzzy set theory

The classical logic describes distinct crisp sets, for example, the number of students registered for an exam, or the names starting with K in a given phone book. It also defines relations between sets called propositions. For instance, consider two sets; zebras and mammals, a simple proposition could be stated that all zebras are mammals, that is Z⊂M, where Z is the zebra set and M is the mammals set; ⊂ means included in. The classical logic proposition is either true or false.

Fuzzy logic was introduced by Zadeh (1965) as an extension of classical set theory. The fuzzy logic was constructed based on fuzzy sets or membership functions. It gives us the opportunity to express ambiguity, vague and subjective relationships with mathematical formulations. It is specifically an appropriate method for representing input space to an output space by using fuzzy sets. The membership degree can be between zero and one, one when an element belongs to the set and zero when does not. Any number between zero and one shows the degree that an element belongs to the set. Figure 6 illustrates an example to show the difference between fuzzy sets and classical sets.

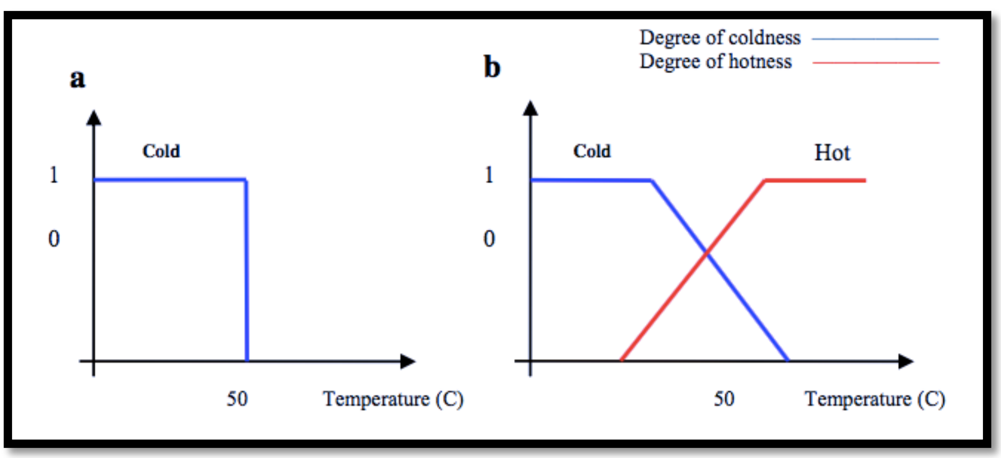

Figure 6, Classical sets (a) and Fuzzy sets (b)

In classical set theory, 40C is considered as cold while in the fuzzy set, the degree of coldness for 40C is 0.65 and the degree of hotness for 40C is 0.35, in other words, 40C is 65% cold and 35% hot.

Selecting the right membership function plays a critical role in designing a fuzzy logic controller. The shape of membership function could be defined based on efficiency, convenience and simplicity. Many different membership functions have been introduced in the literature, however, the commonly used membership functions are triangular, trapezoidal and Gaussaian (Youssefi, Nahaei, & Nematian, 2011). Trapezoidal membership function is represented in the previous example (Figure 6). Moreover, sets in fuzzy logic do not have sharp boundaries; hence, there is always a degree of vagueness.

Fuzzy rule based has been developed to relate the input variables to the output variables by if-then logical rules. The values for these variables are defined on universe of discourse and determine the degree of element which belongs to the membership functions. In fuzzy logic, given particular values of the input variables, the degree of fulfillment of a rule is obtained by aggregating the membership degrees of these input values into the respective fuzzy sets. The fuzzy output is determined by the degree of fulfillment and the consequent part of the rules. The most common techniques to modify the output fuzzy set are truncation using *min* function or scaling using *prod* (product) function (Youssefi, Nahaei, & Nematian, 2011).

Fuzzy Inference System (FIS)

Fuzzy inference is a process of formulating the mapping of inputs to an output by using fuzzy logic. The mapping delivers a basis from which a decision can be made. Fuzzy inference system is used to evaluating fuzzy linguistic descriptions by employing membership functions, fuzzy logic operators and if-then rules (Tsoukalas & Uhrig, 1997). Fuzzy inference systems (FIS) are also termed in different names such as fuzzy expert systems, fuzzy modeling, fuzzy logic controller, fuzzy associative memory and simple fuzzy systems. The two main types of FIS are mamdani and sugeno which determine how the output is generated (Al-Najjar & Alsyouf, 2003). In this research mamdani type of FIS is being used. Mamdani method is among the first fuzzy control systems. It was proposed by Ebrahim Mamdani in order to control a steam engine and boiler combination by using a set of linguistic rules attained from human experience. The mamdani fuzzy logic operator works as follows:

$$f\big(\mu(\mathrm{x}), \mu(\mathrm{y})\big) = \mu(x) \wedge \mu(y)$$

where $\mu(x)$ represents the membership function of x.

In mamdani FIS, the "or" connective in a rule is substituted with "max" operator and the "and" connective is replaced with "min" operator. All the outputs in mamdani FIS are aggregated using aggregation methods such as maximum(max) function, probabilistic OR, sum of the outputs and customized methods.

The output of a fuzzy process can be the logical union of two or more fuzzy membership functions that are defined on the universe of discourse of the output variable (Usenik J. , 2012). The process of nonlinear mapping of crisp input vector $X^T = (x^1, x^2, x^3, \dots\ x^n)$ to a crisp output vector $Z^T = (z^1, z^2, z^3, \dots\ z^m)$ based on fuzzy rules is depicted in the Figure 7. The process has been extended into a three-stage process in Figure 8.

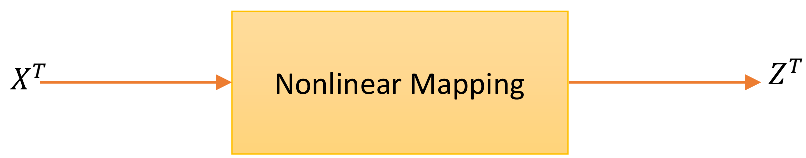

Figure 7, Rule-based inference

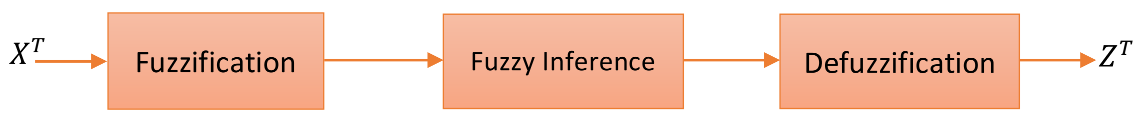

Figure 8, Extended fuzzy rule based system process

1. **Fuzzification**

Fuzzification maps the crisp input data vector to the vector of corresponding input linguistic variables. In this stage, all the fuzzy variables including input and output and their membership functions are defined (Usenik J. , 2012). For each component of input vector X^T, there is one verbal variable $x^i \rightarrow A^i$, $i = 1,2, \dots, n$, with linguistic values $A^i = \left\{A_1^i, A_2^i, \dots, A_j^i\right\}$ that are defined on the universe of discourse of the input variables. Membership functions are then assigned to each linguistic value $\mu_{A_l^i}(x), i = 1, \dots, n; l = 1, \dots, j$. Therefore, fuzzification maps the crisp values of each component of an input to a set of membership values;

$$x^i \rightarrow \left\{\mu_{A_l^i}\left(x^i\right)\right\};\ i = 1, \dots, n\ ; l = 1, \dots, j$$

2. Fuzzy Inference

In the next stage, a specific conclusion is derived from a set of fuzzy statements (Usenik J. , 2012). This stage is the core of a fuzzy system where a set of rules are established that reveals the knowledge about the object of concern. Conditional if-then statements are used for presenting this knowledge (Ross, 2007). Such rules demonstrate the implication of antecedent to the conclusion. The "if-then" rule in form of "if x is A, then z is B" where A is a fuzzy set indicating "antecedent" part and B is a fuzzy set representing "consequent" part of the statement. The term "x is A" is assessed to $\mu_A(x)$.

Antecedents can be in a form of multiple conjunctive: "x^1 *is* A_p^1 *and* x^2 is A_f^2 ….. *and* x^n *is* A_g^n"

which is determined by:

$$\alpha = \min\{\mu_{A_p^1}(x^1), \mu_{A_p^2}(x^2), \ldots.\mu_{A_g^n}(x^n)\}$$

or in a form of disjunctive: "x^1 *is* A_p^1 *and* x^2 is A_f^2 ….. *and* x^n *is* A_g^n"

which is evaluated to:

$$\alpha = \max\left\{\mu_{A_p^1}(x^1), \mu_{A_p^2}(x^2), \ldots.\mu_{A_g^n}(x^n)\right\}, \alpha \in [0,1]$$

the membership value of the antecedent α defines the membership function of the conclusion. A simple method to do so is an α-cut or clipping method. It returns the membership function of consequent as a cut at the value of $\alpha, \alpha \in [0,1]$. α-cut method modifies the fuzzy subset of the output which is illustrated in Figure 9.

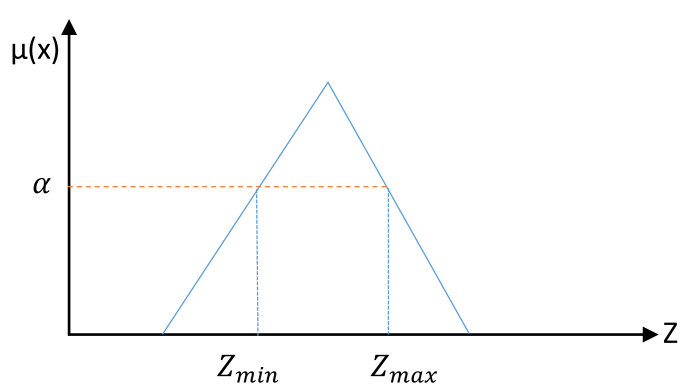

Figure 9, a-cut method

The conclusion is defined in a multiple form:

Z^1 is B_p^1 , Z^2 is B_p^2 , … Z^m is B_l^m. B_l^i is the linguistic value l of the output variable Z^i. The membership functions of consequent are cut at the α value of the antecedent.

In a fuzzy inference system with r rules and m output linguistic variables, the antecedents are considered as $\alpha_1, \alpha_2, \ldots, \alpha_r$, $\alpha_i \in [0,1]$, $i = 1,2, \ldots, r$.

For every linguistic variable in the consequent, one rule contributes. In order to combine all these conclusions for specific linguistic values into one conclusion, the disjunction of the α values that the verbal value has been cut is usually used. For example, linguistic values B_l^i is cut in rule k at the value α_k and the rule i at the value α_i, therefore, B_l^i are cut at the value of $max[\alpha_k, \alpha_i]$. The conclusion of the rules concerning one output variable must be combined into general conclusion for this variable which is an "aggregation" process in fuzzy logic. The final result of fuzzy inference system is the integrated output fuzzy set for each output variable with their membership functions $\mu(Z^i), i = 1,2, \ldots, m$. Figure 10 shows the aggregation process in fuzzy inference systems.

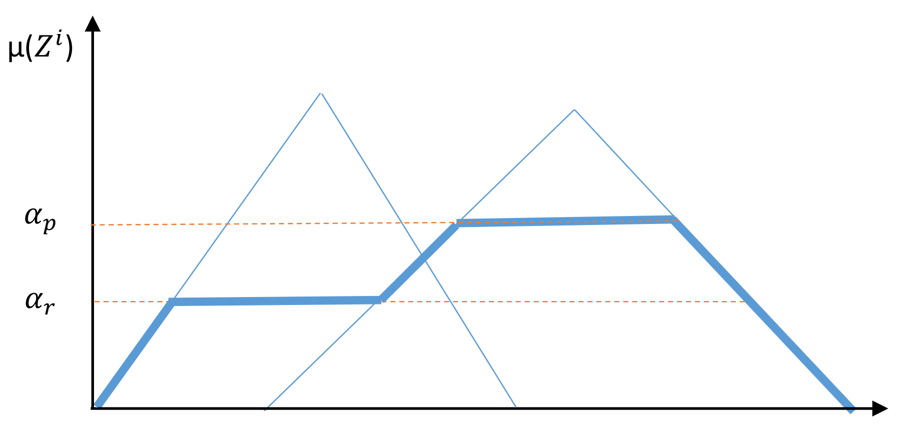

Figure 10, FIS Aggregation process

3. Defuzzification

The final step is defuzzification process of the fuzzy output variables. Defuzzification maps the fuzzy variables to the crisp values i.e. the crisp output vector. Different defuzzification process can give different results. However, the most commonly used methods are "First of the maximum", "Largest of the maximum", "Mean of the maximum", "Height method", "Center of the maximum" and "Center of gravity" (Ross, 2007). In this research Height method is used due to simplicity of calculations and ease of implementation in system dynamics.

The defuzzified value of Z_c^i of the fuzzy Z^i is the weighted average of maximum:

$$Z_c^i = \frac{\sum_l \mu_{B_l^i}^i(Z^i).Z_{B_l^i MAX}^i}{\sum_l \mu_{B_l^i}^i(Z)}$$

where:

$l = 1,2, \dots, k$ is the number of linguistic values for the output variables Z^i .

$\mu_{B_l^i}^i(Z^i)$ is the membership value of the output variable Z^i where the membership function is cut.

$Z_{B_l^i MAX}^i$ is the crisp value of output variable Z^i at the maximum of its membership function.

In order to implement the rule-based fuzzy model in the system dynamics, the entire fuzzy logic system that has been created in MathWorks MATLAB® software is replicated in the system dynamics environment. Detailed procedure of implementation is explained in the model explanation and case description chapter.

Setting up a Fuzzy Logic System

In order to create a fuzzy logic system, Harris (2000) suggests five steps as illustrated in the Figure 11. First step is to identify and recognize the parameters that constitute the antecedents and the conclusions, ranking and prioritizing them. The second step includes identifying knowledge and frameworks, which needs to be established by conceptual models and processes. Moreover, expert opinions on local knowledge must be exerted wherever needed. The next step is formulating the knowledge into fuzzy format which is creating the proper propositions and the style of presentation. In the fourth step, in order to embody in the fuzzy logic framework, inputs and outputs need to be normalized, universe of discourse must be defined, inputs and outputs are required to be fuzzified/defuzzified and finally the information manipulation processes should be formed. Testing and validating are the last steps in creating a fuzzy logic system to ensure the stability and validity of the input. Pilot studies are also necessary to guarantee the quality of the results and acceptability of the range.

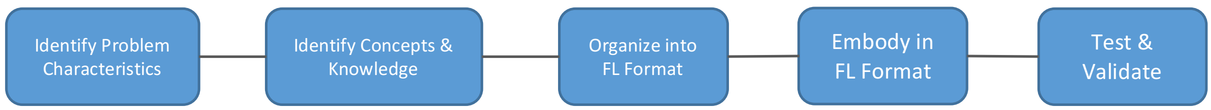

Figure 11, Creating a Fuzzy Logic System; Harris (2000)

System dynamics & fuzzy logic

Traditionally, Fuzzy logic approach is being used for language processing and imprecise knowledge in expert systems, process control and pattern recognition (Karavezyris, Timpe, & Marzi, 2002). On the other hand, system dynamics literature covers wide area of studies, from environmental problems to socioeconomic and administrative issues. The first authors to integrate these two approaches were Pankaj & Sushil (1994) who suggested a method for qualitative analysis of causal loops using fuzzy logic to integrate the perceptions of the modelers. Their reasoning for proposing such integration was the idea that humans' mental models are best when expressed in natural language and in order to construct such mental models, fuzzy logic would give us the best tool.

Many studies have been trying to bridge fuzzy logic and system dynamics. Most of the available researches in fuzzy logic and system dynamics integration attempted to use fuzzy variables when data is unavailable or specific variables demonstrate uncertainties.

Levary (1990) proposed applying fuzzy sets concept to deal with imprecision and vagueness in system dynamics modeling. The author then exemplifies a case where fuzzy arithmetic operations can be implemented in the level, rate and auxiliary equations and proposes using conditional statements that include fuzzy variables or fuzzy algorithms instead of regular relationships in the dynamic modeling.

Maeda, Asaoka & Murakami (1996) argued that fuzzy reasoning methodologies have not come up with a solution for utilizing a time delay between premise and consequent. They suggested a cognitive method that integrates a vague time delay into fuzzy conditional rules and define a time variable to denote an event and its fuzzy time interval. Later, Maeda & Nobsada (1998) proposed a new approach based on the previous work called “Multi-fold Multi-stage Approximate Reasoning” (MMAR) using real data to predict Japan’s population growth until 2025.

Fuzzy logic and system dynamics have been used by Ortega, Sallum & Massad (2000) in order to deal with uncertainties and ambiguities in epidemic problems such as vagueness in risk factors, contact patterns, infected conditions and hazards. They used Mamdani’s Max-Min inference method for Multiple-input Multiple-output (MIMO) model and the Center of Area (COA) defuzzification method was employed for calculating the crisp output. However, the detailed implementation of COA in system dynamics modeling has not been provided by the authors. It has been then concluded that using MIMO model delivers acceptable results when the number of parameters and control variables are restricted. Due to the fact that the membership functions for fuzzy variables and the behavior of key factors in the model have not been specified in their research, the success of fuzzy logic implementation in system dynamics modeling would be hard to assess.

In another study, Polat & Bozdag (2002) made a comparison of crisp and fuzzy rules in a system dynamics simulation model for a simple heating system. The comparison illustrates the relationship between the temperature and speed of heating machine under different scenarios consisting crisp or fuzzy, discrete or continuous, linear or non-linear parameters. The fuzzy rules were defined for describing the relationship between the perceptions on desired speed of heating machine and the temperature of environment. However, the authors did not consider scenarios with different fuzzy variables in their study.

Chang, Pai, Lin & Wu (2006) illustrated the fuzzy arithmetic applications in system dynamics modeling and evaluated the results for customer-producer-employment model. Fuzzy logic was used in their model for “order quantity receiving rate” and “labor productivity” variables with triangular membership functions. However, these fuzzy variables were not interacting with each other in the model and the combination of fuzzy variables were not reflected in their research.

In the most relevant research, Campuzano, Mula & Peidro (2010) used different approach to exhibit the application of possibility theory and fuzzy numbers for demand and orders estimation in a supply chain system dynamics model. They demonstrated that using fuzzy approach would be beneficial when demand is uncertain due to incompleteness and unattainability of historical data in a dynamic environment. The authors proved that despite the increase in complexity of model formulations, the results are improved in connection with dampening the bullwhip effect and oscillations in the inventory. Nevertheless, it is suggested to enhance the model to n-stage and n-item of the supply chain.

Kunsch & Springael (2008) employed fuzzy logic in a carbon tax design system dynamics model. The goal was to demonstrate how to aggregate external data driving the model. They used two external data sets that are fuzzified using triangular membership functions. Since each variable has five characteristics, ten fuzzy rules were generated. Despite detailed calculations, the authors did not provide complete aspects of fuzzy implementation nor described the behavior of fuzzy parameters during the simulation.

The approach of integration between system dynamics and Fuzzy Inference Systems (FIS) for the analysis of supply chain models is a novel method that has permitted a better qualitative understanding of model (Guzmán & Andrade, 2009). More application of fuzzy logic has developed by Ghazanfari (2006) in which causal diagrams are proposed with fuzzy relations.

Xu & Li (2011) proposed a conceptual model using system dynamics and fuzzy optimization for initial, flow and level variable. The authors then performed parameter optimization with genetic algorithms. Furthermore, Carvalho (2000) conducted a study on fuzzy cognitive maps and qualitative relation in system dynamics models. The use of genetic algorithms as a method of integrated solution for system dynamics is proposed by Li & Wang (2010), Lian & Jia (2012) and Ng, Khirudeen, Halim & Chia (2009) for inventory optimization. On the other hand, Skoglund & Dejmek (2007) introduce the term “fuzzy traceability”, demonstrating the difficulty in tracing the raw material used in the production process in a liquid food factory. They utilized fuzzy optimization and system dynamics to address the issue of fuzzy traceability.

Finally, Herrera, Becerra, Romero & Orjuela (2014) developed an approach in dealing with fuzzy logic and system dynamics modeling integration. The integration favors the process of decision making due to complexity of system dynamics and uncertainty in parameters of simulation. The relationship between system dynamics and fuzzy inference system is shown in the Figure 12. In a complex system, decisions are normally made by actors in a system dynamics models or experts in a fuzzy rule based. By integrating these two, decision rules of a simulation model can be related to the knowledge based fuzzy logic system.

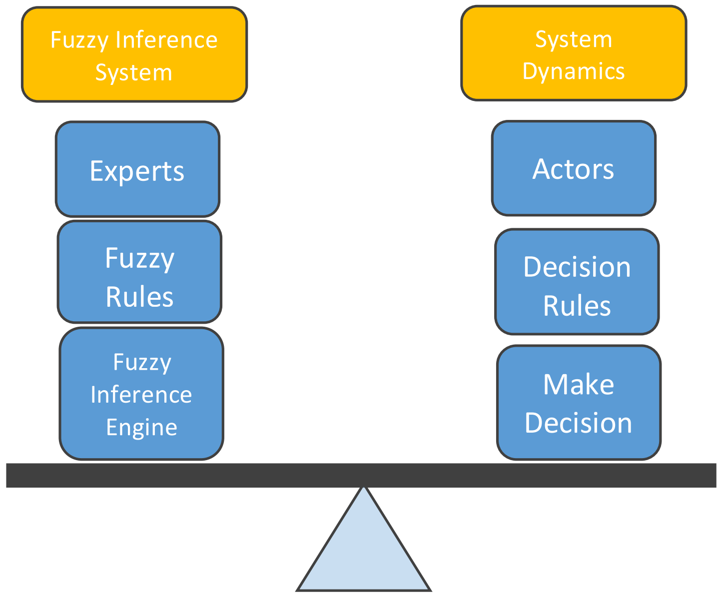

Figure 12, Fuzzy Inference Systems and System Dynamics relationship; Source: Herrera et al. (2014)

The integration procedure is then expanded in the flowchart below.

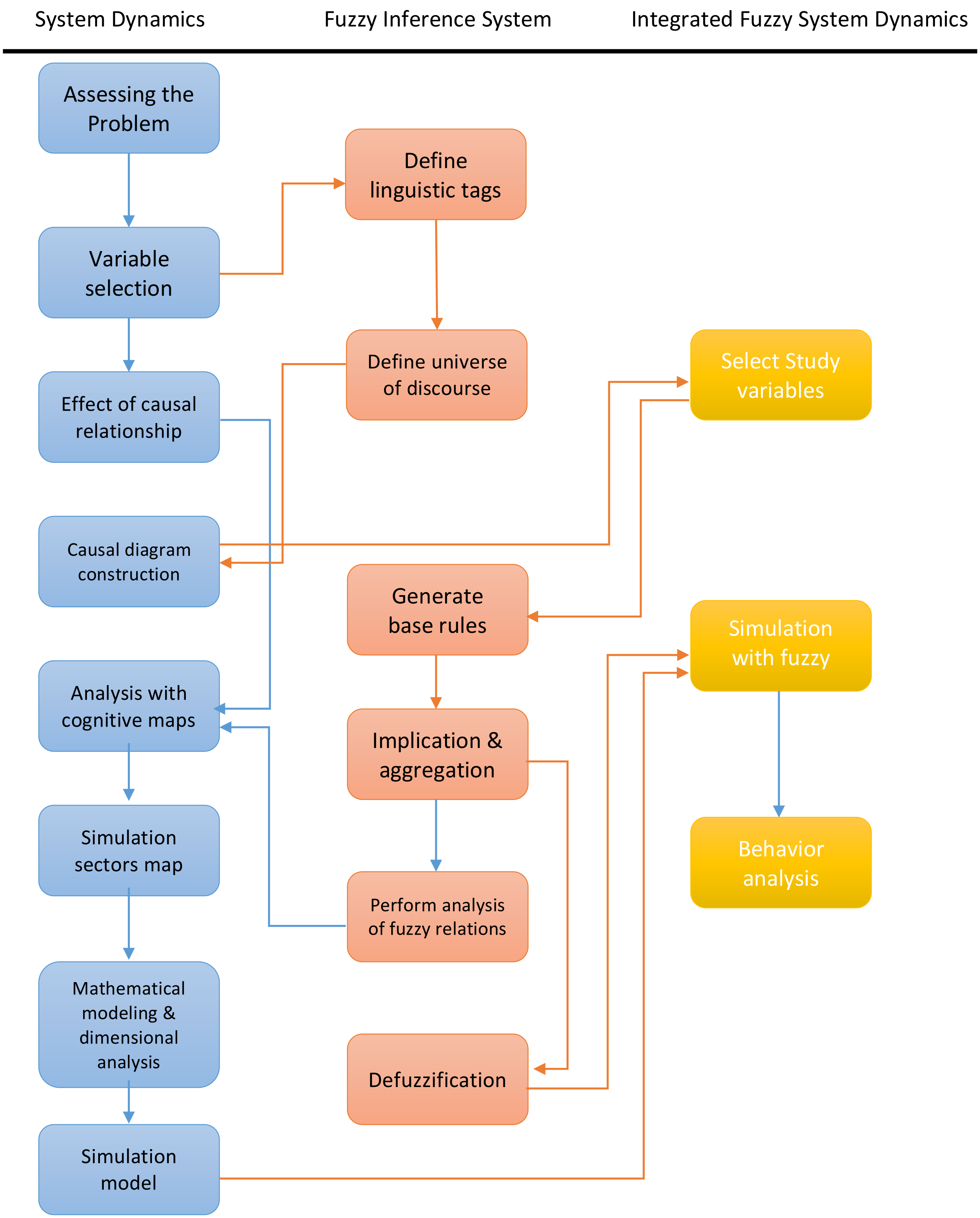

Figure 13, Fuzzy System Dynamics Integration; Herrera et al. (2014)

To sum up the literature review in this chapter, only limited number of studies have been found that actually addressed fuzzy logic in supply chain dynamics. Moreover, these studies do not explicitly provide a comprehensive approach and details on how to incorporate fuzzy logic method into system dynamics frameworks.

Chapter three: Research Methodology

The previous chapter discussed the relevant topics in supply chin bullwhip effect and the applications of fuzzy logic in system dynamics and supply chain systems. Moreover, the relevant gaps in the literature have been highlighted. This chapter demonstrate the research method for carrying out this study with regards to ontological and epistemological position, research design and methods.

Any research paradigm entails an ontology, an epistemology and methodology (Blanche, Durrheim, & Painter, 2007). Ontology shows the relationship between the concepts and categories in the subject area and consists a set of assumptions regarding the nature of reality or the nature of knowledge. Essentially, ontology questions the occurrence of reality, whether it happens naturally or is a result of social interactions between individuals. Epistemology is related to the theory of knowledge particularly with regards to its methods validity and scope; in other words, epistemology refers to the assumptions made about the ways that knowledge of reality is attained (Saunders, Lewis, & Thornhill, 2009). Methodology is then influenced by ontological and epistemological assumptions. Methodology is defined as the foundation and reasoning behind the selection of methods and collection of concepts, ideas and theories (Bryman & Bell, 2007). It is important to understand the choice of epistemological considerations and the selected methods as there is always trade-offs between generalization, realism and control in social sciences. Quantitative methods try to optimize generalization and control and gain external validity, whereas qualitative research methods attempt to maximize realism and obtain internal validity (Golicic, Davis, & McCarthy, 2005).

As for the case of supply chain management research strategy and its ontological and epistemological positions, the literature has been thoroughly investigated. Considering the importance of supply chain management in the realm of business research, there are different opinions on philosophical nature of this field. However, the academic debate on the supply chain management research paradigm and theory is still considerably limited (Wolf, 2008). Moreover, supply chain research is such a wide area that encompasses various research streams including logistics, leadership, information systems, marketing, strategic management etc (Burgess, Singh, & Koroglu, 2006).

In order to identify the most relevant methodology for this research, the existing research design and methodology in supply chain management is used for debate.

Some scholars applied the exiting frameworks established in other research fields to identify supply chain management paradigm. For example, Meredith et al. (1989) used Meredith model for identifying and analyzing logistics models. Dunn, Seaker & Waller (1994) argue that supply chain and logistics research can be characterized into three fields: description of variables, understanding of informant impressions and rebuilding the reality. Burgess et al. (2006) investigated a total number of hundred articles in supply chain management research and tried to group them based on descriptive features, definitional issues, theoretical concerns and research approaches. The author then categorized the research methodologies in supply chain management research to the two ends of paradigmatic spectrum, positivist and non-positivist approaches.

Different studies have also focused on the research methods used in logistics research or supply chain management research. Mentzer & Kahn (1995) found out that normative research and exploratory studies were mainly the mainstream of research method during the period when most articles in logistics were published. This shows that researchers had found substantial justification for further study but limited theory for developing and testing. A decade later, Sacha & Datta (2005) assessed the situation of supply chain management research development and realized that survey methods were still the most common tools for conducting the researches even though supply chain management research trend had been shifting from exploratory research to model building and testing.

It has been argued that logistics research is primarily based on objective and external perspective methods, such as experiments, surveys, literature studies etc. This indicates a gap in understanding logistics with an involved, subjective and cognitive perspective (Frankel, Naslund, & Bolumole, 2005). Näslund (2002) argued the need for qualitative anti-positivist research in supply chain management research. Therefore, supply chain management study methods can be categorized into objectivity versus subjectivity, quantitative versus qualitative, deduction versus induction and positivism versus non-positivism.

Positivism states that only verifiable allegations based on observation and experience could be considered genuine knowledge (Patton, 2002). The term positivism was first coined by a French philosopher Auguste Comte in nineteenth century. Positivists believe that social science phenomena should be studied in the same way of mindset as one studies natural sciences (Durkheim, 1964). Positivism carries the following features: objectivity or independence, causality, hypothetico-deductive, operationalization, cross-sectional analysis, reductionism and generalization (Easterby-Smith, Thorpe, & Lowe, 1991) and chiefly qualitative methods and broad research strategies are used (Duberley & Johnson, 2005).

Kovács & Spens (2005) looked for a new reasoning approach for supply chain management research and found out that abductive approach suits best. Abductive approach combines the elements of inductive, deductive, rationalism and empiricism terms (Samuels, 2000). The abductive approach begins as the inductive approach starts but it makes a loop between the real-life observation and the theoretical framework process and after defining the research questions, the abductive process ends like deductive approach by applying or testing the hypothesis (H) or propositions (P) and contributing to the new knowledge and theory. Figure 14 illustrates the reasoning paths in inductive, deductive and abductive approaches.

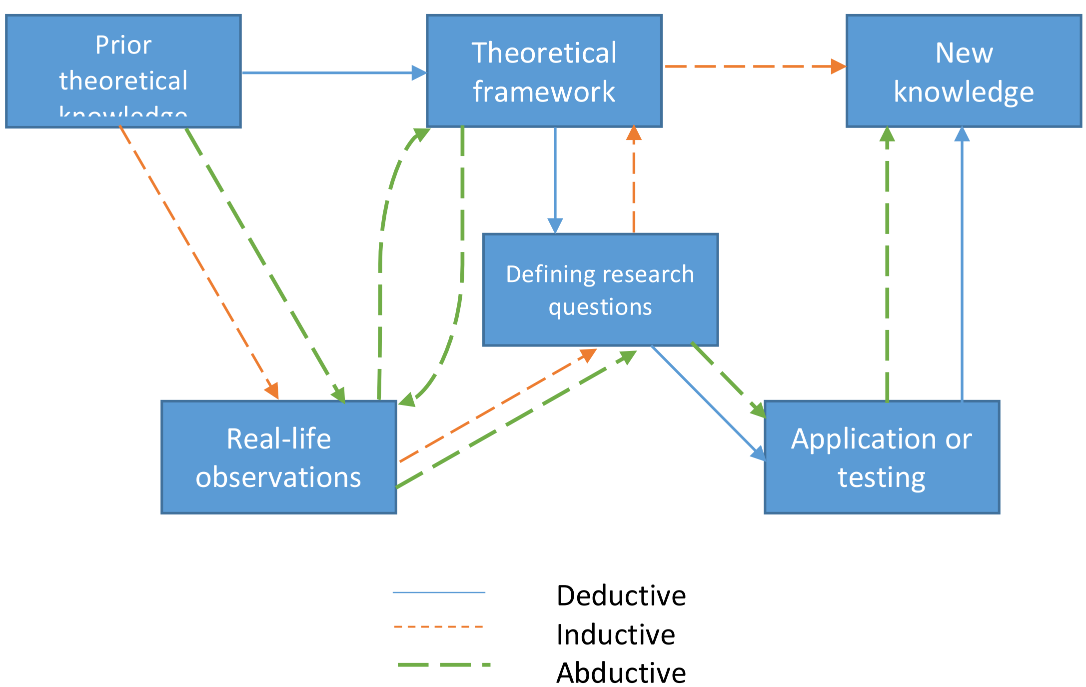

Figure 14, Deductive, inductive and abductive research process. Source: Kovacs & Spens (2005)

In another study within logistics research, Gammelgaard (2004) categorized existing supply chain management research into three groups: analytical, systems and actors' approaches. Based on analytical approach, hypothesis development and testing can be studied by making the objective reality into smaller elements. In system approach in logistics, researchers strive for a holistic understanding of system parts, links, goals and feedback mechanism in order to improve the system. Finally, actors' approaches suggest that reality is the result of social constructions and not an objective phenomenon, thus, knowledge creation depends on researcher's interpretation and social actors and since all these happen within a context, qualitative and inductive approach seem more appropriate. The methodological framework for supply chain management research is shown in Table 2.

Table 2, Methodological Framework for supply chain management research, Source: Gammelgaard (2004)

	Analytical approach	Systems approach	Actors' approach
Theory type	Determining cause-effect relationships. Explanations, predictions. Universal, time and value free laws	Models. Recommendations, normative aspects. Knowledge about concrete systems.	Interpretations, understanding. Contextual knowledge
Preferred method	Quantitative (Qualitative research only for validation)	Simulation and case studies (Qualitative and Quantitative)	Qualitative
Unit of analysis	Concepts and their relations	Concepts and their relations	People and their interaction
Data analysis	Description, hypothesis testing	Mapping, modeling	Interpretation
Position of the researcher	Outside	Preferably outside	Inside as part of the process

Since the research question in this study involves the causality between different elements such as demand, delays, stocks level production rate, capacity as well as the mechanisms in the structure; the system approach from Gammelgaard (2004) is much suitable. However, the system thinking approach is not clearly recognized as part of any social science school of thought. Besides, the system approach is theory-driven but this theory is rather contextual than universal and lastly, the reality is objective and is prone to be influenced, so it is preferable that the researcher stay outside the research object. Moreover, the ontological assumption of this research is considered objective since the author believes that the supply chain phenomenon exists independently of his perception and interpretation.

Supply chain dynamics and system thinking

According to Gammelgaard (2004), supply chain management field can be related to system thinking approach because of its interdependencies between the different elements of supply chain. In system thinking approach, data collection and theory construction seem to happen simultaneously. Nonetheless, the reality is considered to be objective and hence it exists independently from human thoughts or beliefs.

The system approach enables the analysis of complex, dynamic feedback systems by understanding the dynamic behavior of its elements and their interactions (Wolf, 2008). Feedbacks in this context means that one component of the system might influence another. For a holistic system analysis, it is crucial to take into account these feedback loops (Forrester J. W., 1961).

Supply chain dynamics traditionally proposes and tests theories and consequently provides data for establishing scientific laws. This is in line with the principle of positivism (Bailey, 1994). Systems approach encompasses the components of positivism school of thought and particularly in this thesis, an objective and holistic view has been taken into consideration.

Research Method and tools

Research Strategy

According to Wolf (2008), research strategy can be categorized into conceptual and empirical groups whether the data is obtained for theory generation or not. Conceptual research strategy persuades theoretical debates and encourages for further empirical research. The main objective in conceptual research is to increase reliability and validity of concept rather than reliance of empirical field data (Bowen & Sparks, 1998). For example, in order to make theoretical models for research analysis more precise, simulation and mathematical modeling could be used to produce artificial data (Wolf, 2008). Moreover, in exploratory research method, where the main goal is to look at phenomena from a different angel or look for new insights, the research approach needs to be carried out by investigating the literature (Adams & Schavaneveldt, 1991). Different research methodologies are categorized in the Figure 15 based on research strategy and research analysis.

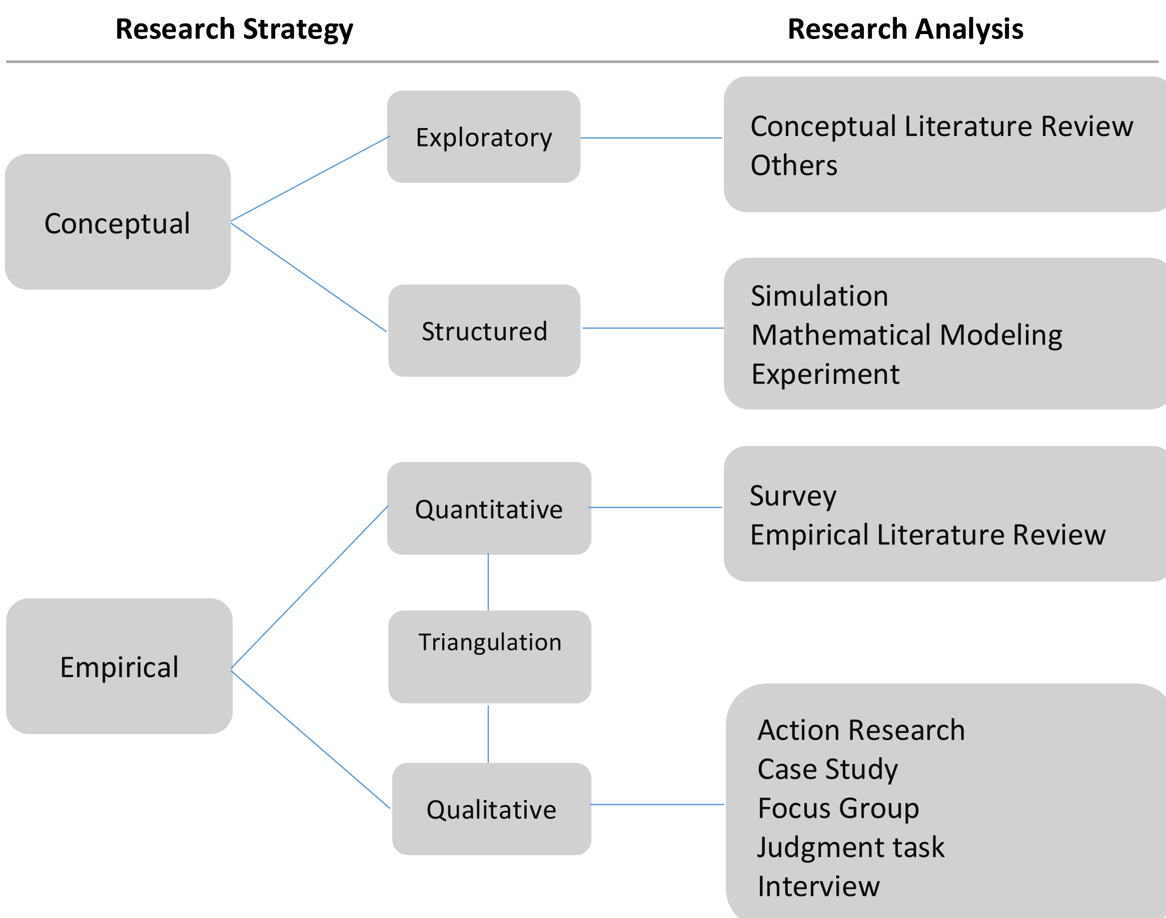

Figure 15, Hierarchy in Research Methodologies, Source: Wolf (2008)

In conceptual research strategy, the research analysis can be done via simulation, mathematical modeling, experiment and conceptual literature review. The purpose of conceptual literature review is to use the knowledge for model conceptualization that can further be empirically tested in a structured conceptual analysis (Denyer & Tranfield, 2006). Mathematical modeling technique can be used in order to explain the behavior of a system (Cameron & Price, 2009). Simulation is beneficial when the reaction of a model needs to be tested against manipulation of variables in an artificial environment (Wolf, 2008). Experiment and simulation share similarities in a way that the researcher manipulate variables to see different results. Although, experiments occur in a natural environment (Saunders, Lewis, & Thornhill, 2009).

This thesis is conducted with structured and exploratory conceptual research strategies. The exploratory strategy is used for investigating the literature for the bullwhip effect phenomenon in supply chain systems so that a qualitative framework for analysis can be formulated. In addition to that, a qualitative empirical research strategy in the form of a case study is applied to test out the findings from the conceptual framework.

Case Study

Case study delivers rich and deep evidence that can be used for discovery of a theory. Qualitative case study methodology can aid researchers to examine complex phenomena within their contexts. Yin (2003) suggests that a case study design should be used when the focus of the research is to answer “how” and “why” questions or when the researcher cannot manipulate the behavior of those involved in the case or when the researcher favors protecting contextual environments because they are relevant to the case study. Robson (2002), suggests that an exploratory study is a useful tool for finding “what is happening”, “to seek new insight” and “to assess phenomena in a new light”. Since this thesis needs to clarify the understanding of a problem and investigate a new phenomenon, exploratory study is conducted.

Robson (2002) describes case study as a strategy of conducting a research that contains an empirical investigation of a specific contemporary phenomenon, which occurs in real life context. Moreover, according to Yin (2009), there are two goals in studying a case;

1. The researcher has no control of the events
2. The focus is on contemporary experience in a real life

These reasons fit perfectly to this research. Therefore, a case study is an appropriate way to conduct this research.

Every case study can be grouped based on two discrete dimensions: single case versus multiple case, and holistic case against embedded case. A single case is often used because it provides an opportunity to observe and analyze a phenomenon that few have considered before. An important reason for using a single case is defining the actual case (Yin, 2003). On the other hand, the rationale for using multiple cases is to observe whether the findings in one case happen in another i.e. the need for generalizing. The second dimension refers to the unit of analysis. If a research concerns only with one organization as a whole, then the research is a holistic case study. Embedded case study occurs when one wishes to examine a number of sub-units within an organization, such as departments or work groups (Yin, 2003).

Moreover, generalizations from cases are analytical and based on reasoning. There are three principles for reasoning: deductive, inductive and abductive. When generalization is based on deductive approach, a hypothesis is expressed and testable consequences are resulted by deduction. Then the findings, which derived from theory and the case, are compared with empirical findings to accept or reject the hypothesis. The second type of generalization is reached through induction. This can be achieved through conceptualization, which is based on data gathered from the case. The inductive theory generation results in developing a set of related concepts. The third type of generalization is called abduction; a combination of deductive and inductive approach. Abduction is the process of encountering an unforeseen fact, employing some rules and as a result hypothesizing a case that maybe valid (Baxter & Jack, 2008).

Mathematical modeling

For modeling dynamic, time-dependent and feedback systems, mathematical modeling is a useful tool for replicating reality. Differential equations and control theory are the commonly used mathematical methods. Control theory is a division of engineering and mathematics that mainly employed by dynamical systems. A system is defined as a set of components related with each other with information and physical links (Leigh, 2004). Control theory enables us to evaluate feedback systems systematically and identify the causal relationships and hence it is a great tool for studying supply chain systems (Towill, Naim, & Wikner, 1992). There are number of techniques in analyzing dynamical systems including: block diagram manipulation, state space, difference and differential equations etc.

Discrete, Continuous and hybrid modeling

Variables in any dynamical system can change discretely or continuously over time and sometimes combination of both. An inventory control system either operates continuously where the inventory and order replenishment is reviewed continuously, or discretely for periodic inventory review.

A handful of studies has been done in discrete and continuous production control. Simon (1952) applied continuous control theory for inventory related problems. Winkner et al. (1992) formulated Forrester's differential equations of the industrial dynamics model into block diagram depiction in the Laplace domain. Grubbström & Huynh (2006) analyzed MRP systems for ordering strategies such as Fixed Order Quantity, Fixed Period Requirement and Lot-for-Lot by using Laplace transform. However, there are some issues in continuous dynamic modeling when dealing with discrete variables that frequently happen in forms of scheduling and time delays (Naim, Disney, & Towill, 2004). Both continuous and discrete time modeling can be used to study supply chains, despite the discrepancies in results their qualitative nature is essentially the same (Disney, Towill, & Warburton, 2006).

Linear and nonlinear models

A system is linear if the system's response to a given input signal of *X+Y* is the sum of the behavior in subsequent signals of magnitude *X* and *Y* applied separately (Towill, 1970). Two basic tests of linearity are homogeneity and additivity. Homogeneity implies that the output functions in the same behavior as the input. Additivity in linear system is explained as the measured response of the output is the sum of its input responses individually. A system that satisfy both homogeneity and additivity is considered linear. These two rules are often called as the principle of superposition.

There is an extensive range of techniques in the literature for describing and analyzing linear systems. The literature in linear control theory has been widely used in supply chain dynamics.

On the contrary, nonlinear system is described as a system which its behavior does not follow the principle of superposition. This implies that the output in nonlinear systems is not proportional to the input (Atherton, 1975).

System dynamics has been greatly used in analysis of supply chain systems with nonlinear behavior, however, the application of quantitative approaches have been mostly limited to linear supply chain systems. Therefore, experimental simulation method is mainly used in the literature for analyzing supply chain dynamics (Forrester J. W., 1958; Sterman, 1989; Shukla, Naim, & Yaseen, 2009; Poles, 2013) or to develop linearized approximation models and use the exact method for nonlinear systems (Towill, 1982; John, Naim, & Towill, 1994; Disney & Towill, 2005; Gaalman & Disney, 2009; Zhou, Disney, & Towill, 2010).

It is quite important to classify nonlinearities in supply chain dynamics models due to the fact that the possible nonlinearities in such systems are countless and hence, the method of analysis is largely dependent on the type of nonlinearity. Mohapatra (1980) identified three types of nonlinearities in business dynamics modeling: limiting functions, table functions and product operators. The author then suggests techniques to deal with such features in nonlinear models including: removing unnecessary functions, linearization through averaging, best-fit line approximations and small perturbation theory. Nonlinearities are comprehensively classified in control systems literature into six groups: intentional or inherent; single-valued or multiple valued and continuous or discontinuous (Towill, 1970; Graham & McRuer, 1961; Vukic, Kuljaca, Donlagic, & Tesaknjak, 2003) as it is demonstrated in Figure 16.

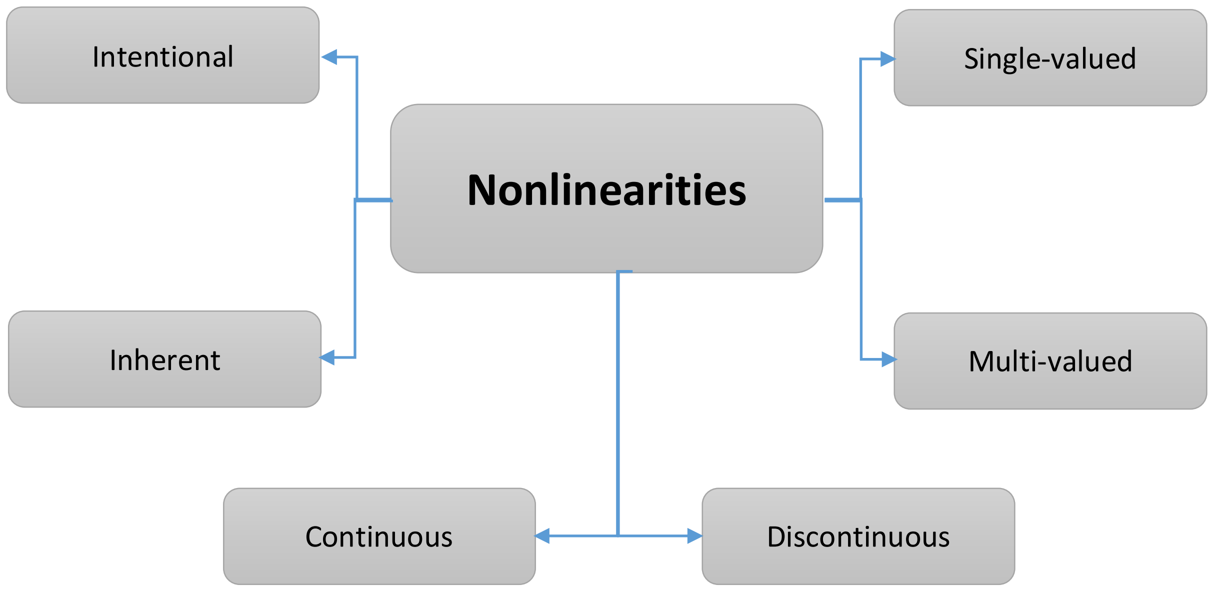

Figure 16, Different types of nonlinearities

Inherent nonlinearities derive from the nature of the system and are usually unfavorable and therefore need to be identified and compensated by the modeler. Intentional nonlinearities, on the other hand, are introduced to the system by the modeler in order to improve the performance of the system (Cook, 1986). In supply chain dynamics, nonlinearities exist due to the model constraints such as physical, financial or capacity constraints. Depending on the degree of accuracy and complexity of the supply chain system, the nonlinearities might be considered or disregarded. Moreover, supply chain modelers might also be interested in implementing nonlinearities that do not exist in reality for enhancing the performance measures. These types of nonlinearities have been applied in the following studies: "demand amplification versus service level" by Evans & Naim (1994), "complexity of the production plan versus production cost" by Grübbstrom & Wang (2000), "lead time expectations versus dynamics behavior in the system" by Wikner, Naim, & Rudberg (2007).

Continuous and discontinuous nonlinearities are concerned with the relationship in between the inputs and output. In continuous functions, output can be smooth enough to have convergent expansions at all points and hence can be linearized (Cook, 1986). Forester's industrial dynamics model referred to this by showing the delay in filling orders and the gap between actual and desired inventory. Sudden changes of output values indicate discontinuity. Piecewise linear functions are the most common type of continuous nonlinearity. They include a series of linear relations for different regions. Most efforts in supply chain dynamics has been given in understanding the chaotic behaviors and their causes and subsequently in forming stability regions of discontinuous and piecewise linear supply chain systems (Larsen, Morecroft, & Thomsen, 1999; Mosekilde & Laugesen, 2007; Wang & Disney, 2012).

Single-valued nonlinearities implies that the output value is not dependent on the history of the input which is also called memory-less (Cook, 1986). Multi-valued functions are mostly used in business studies and economics (Göcke, 2002), for example between buying/selling and price (Cross, Grinfeld, & Lamba, 2009) or unemployment and economy growth rate (Lang & de Peretti, 2009). However, multi-valued nonlinearities are not commonly used in supply chain research. The application of multi-valued nonlinearities in supply chain dynamics modeling is limited to certain operational strategies that are reliant on cost directions. For instance, investigation on global sourcing (Kouvelis, 1998) and manufacturing strategies (Kogut & Kulatilaka, 1994) based on foreign exchange rate directions. In production-inventory control system, multi-valued nonlinearities have not ordinarily been used due to the fact that the order placement to the supplier or sent to consumers will always match demand regardless of demand growing direction. Nonetheless, taking variable capacity into account, these outputs can demonstrate a complex multi-valued nonlinear behavior.

Dealing with nonlinearities and nonlinear systems can be challenging and there are number of methods for analyzing nonlinear systems. The first approach is linearization due to availability of different methods in linear system theory (Kolk & Lerman, 1992). However, due to limited literature on the nonlinear control systems and analysis techniques, finding the existing techniques and their applicability for nonlinear system is extremely difficult. Table below demonstrates the existing methods that have been adequately acknowledged in the literature.

Table 3, Summary of techniques used for analyzing nonlinear systems

	Method of Analysis	Applications	Considerations
Linearization methods	Small perturbation theory with Taylor series expansion	Continuous single-valued	Assumption that the amplitude of the excitation signal is small. Local stability analysis only.
	Describing function	Continuous, Discontinuous single-valued, Multi-valued	Less accurate when nonlinearities contain higher harmonics. Analysis of systems with periodic or Gaussian random input only.
	Small perturbation theory with Volterra/Wiener series expansion	Continuous multi-valued	Assumption that the amplitude of the excitation signal is small. Difficulty in calculating the kernels and operators of the system, making it impractical for high order systems.
	Averaging and best0fit line approximations	Continuous, Discontinuous Single-valued, Multi-valued	Gross approximation of real responses. Only when better estimates are not possible.
Graphical and Simple methods	Phase plane and graphical solutions	Continuous, Discontinuous Single-valued, Multi-valued	Limited to 1^{st} and 2^{nd} order systems only.
	Point transformation method	Discontinuous Single-valued, Multi-valued	Piecewise linear systems only. For high order systems, automated numerical methods must be employed.

Exact solutions	Direct solution	Continuous Single-valued	Limited to a finite number of equations.
Stability method	Lyapunov-based stability analysis for piecewise-linear systems	Discontinuous Only single-valued examples were found	Piecewise linear systems only. Computation can be complex de- pending on the system.
Simulation	Numerical and simulation solution	Continuous, Discontinuous Single-valued, Multi-valued	Can be time consuming. Dependent on computer and soft- ware calculations capacity.

Different methods for linearization of nonlinear systems such as perturbation theory, describing function and averaging enables the nonlinear system to be tested through successive approximations in the form of power series (Kolk & Lerman, 1992). The system can be approximated using perturbation theory only when it can be characterized by the Taylor series or Volterra series (Odame & Hasler, 2010). The describing function is denoted as quasi-linearization because of its representation of the linear system for particular inputs. For instance, sinusoidal inputs are often used since the frequency response approach is a solid tool for analysis (Graham & McRuer, 1961; Towill, 1970; Atherton, 1975). In order to understand the complex systems, averaging and best-fit approaches serve as decent tools (Mohapatra, 1980). However, if reliability and accuracy are the main concerns, these methods should not be used (Cook, 1986). The phase plane analysis is a graphical method and is only restricted to second order systems (Graham & McRuer, 1961; Towill, 1970; Atherton, 1975). Simulation technique is quite useful tool for complementing the other analytical methods. Using simulation for exploratory analysis can be expensive and time consuming (Atherton, 1975).

Simulation & System Dynamics

Simulation offers a middle ground between mathematical modeling, empirical observation and experiments for strategic issues in supply chain research (Größler & Schieritz, 2005). There are several advantages in using simulation such as not needing particular mathematical calculations chiefly because simulation proceed step-for-step using numerical approximation methods for an optimal solution. Furthermore, simulation approach enables modelers and system designers to estimate the parameters that are difficult to measure such as soft variables (Wolf, 2008).

Many simulation techniques have been developed to assess dynamic systems; system dynamics, discrete-event and agent-based simulations are few examples. Agent-based simulation deals with actions and interactions of independent agents and assumes that there is no a global system control (Größler & Schieritz, 2005). This type of simulation would not be useful for the sake of this research since the control systems are the subject of this study and also because it has been assumed that supply chain actors i.e. managers and employees accept standardized processes before making any decisions.

Discrete-event simulation is beneficial in modeling the discrete sequence of sample paths (Fishman, 2001). Discrete-event simulation can be used in understanding the system's behavior and assist decision makers on resource allocation and job assignment (Allen, 2011). For example, decisions on the number of operators and equipment to deal with upcoming demand. Discrete-event simulation therefore would not be considered as proper tool for conducting this research.

System dynamics simulation is useful when coping with situations where feedback loops play a critical role in understanding the system's behavior (Akkermans & Dellaert, 2005). System dynamics has been developed by Forrester (1961) and includes constructing the relationships between variables using causal loop diagrams (CLDs), translating these relations into differential equations, exposing the system to a disturbance and then analyzing the output responses to recognize the cause and effect relationships.

When formulating system dynamics simulation models, four major elements should be taken into account; levels (stocks), flows, information channels and decision functions (Forrester J. W., 1961). Levels represents the accumulations within the system and also the existing value of the parameters. Level's value depends on the inflow and outflow rates. For instance, inventories in production control systems are level variables and the production rate and delivery rate determine the value of the inventory (inventory level) at any given point in time. Flow rates are considered instantaneous flows in the system which run between levels. As an example, production rate moves production items from raw material supplier stock level to the finished goods inventory stock. In order to control the rates between different levels, decision functions are used in forms of differential or algebraic equations. Lastly, information channels transfer the information about the stock levels for the decision functions. For example, inventory level and work in progress information need to be available to regulate the order rate.

It has been argued by many scholars that system dynamics is only capable of continuous modeling and simulation. However, assuming $\Delta t = 1$, continuous equations can be discretized into difference equations. This type of simulation is also known as hybrid simulation. The benefit of discretization is time reduction due to the fact that less points are required for numerical calculations. In this thesis, a hybrid simulation is employed to analyze the supply chain dynamics as well as the impact of fuzzy decision policy on the bullwhip effect.

There are various tools and software packages available to conduct simulation and help mathematical analysis of system dynamics models. Each and every one of them has advantages and disadvantages. In this study Vensim® package from Ventana Systems has been used as the main modeling tool for demonstrating supply chain dynamics. Vensim® is a powerful tool for hybrid (discrete and continuous) simulation. Moreover, MATLAB® software from MathWorks has been employed for undertaking fuzzy logic modeling and constructing fuzzy inference system (FIS). Later on, the fuzzy structure built in MATLAB® is incorporated into Vensim® software for the ease of use and interaction with the main supply chain structure.

Forrester's industrial dynamics model

Up until 1950s, most of the work done in operation research and optimization was based on open loop processes, in a sense that inputs to a system were considered exogenous and not affected by the system (Forrester J. , 1968). Advances in computers and technology as well as the opportunity to conduct low-cost computer simulations, enabled a team of academics at

Massachusetts Institute of Technology (MIT) to introduce the concept of feedback loops from engineering into social science (Richardson, 2011).

The Forrester's industrial model of a production-distribution system was built to illustrate the unstable behavior and fluctuations coming from organizational relationships and management policies at the manufacturer, distributor and retailer (Forrester J. W., 1961). In his model, the author demonstrated the information and material time delays, policies for inventory replenishment, forecasting and trend investigation through stocks (levels), flows (rates) and decision functions. Although Forrester's industrial model is considered as a benchmark of supply chain that represents the bullwhip effect, it is an oversimplified model of reality.

The modeling of this thesis is grounded on the Forrester's industrial dynamics model and customized for the case study in this research.

Chapter four: Model Explanation & Case study description

This chapter demonstrates the modeling process for screening the bullwhip effect in an actual supply chain case by means of system dynamics as well as fuzzy logic policy design implemented in the main model. The case study is a spare part manufacturing supply chain composed of three echelons: manufacturer, distributor and retailer. In this chapter, model formulation is extended using Vensim® simulation tool from Ventana Systems.

Case study background

The company being studied, Iran Khodro Spare Parts and After-Sale Service Co. (ISACO), is a large-sized commercial and service company located in the west side of Tehran, Iran. The company was founded in 1977 in an area of 80,000 square meters consisting offices and central warehouses. ISACO's major activities are supplying automobiles parts and services, customer services and after-sale services for all the automobiles manufactured by Iran Khodro; the largest automotive manufacturer in the middle east. ISACO has been declared the best after-sales service provider in the country for three consecutive years. The company received the highest scores in quality promotions and customer satisfaction by Iran Standards and Quality Inspection Company (ISQIC). ISACO's headquarter is responsible for managing the product diversity and its representative offices across the country.

In the recent years, the company have experienced market disturbance due to emergence of Asian competitors and occasionally third party products in the market. In response to this situation, and specially for the sake of local market, the company has taken a defensive strategy to maintain its market share and regain customer loyalty by differentiating its proposition against competitors based on high quality products with flawless delivery compliance. However, in reality the execution of this strategy has not been a great success as the company struggles to meet promised delivery times for the large group of products. Besides, the company's major cash flow depends significantly on delivering parts to Iran Khodro assembly line which gives it the highest priority and hence, signifies a high risk for company's vulnerability to successfully meet local market demand. In addition, international sanctions against Iran has substantially depreciated the currency exchange rate and consequently impacted the imported raw materials which has led to price fluctuations. Competing in this market environment has made the management of the company a complicated task.

Primary observations of ISACO inventory sheets had showed that the company exhibits symptoms of the bullwhip effect in their main line of products. The company regularly struggled estimating the market demand for their products and subsequently had difficulties with operational planning. The auditing was performed only at the manufacturing echelon and did not include other levels of supply chain which possibly experienced disturbance in their demand signals as well. Therefore, ISACO was chosen as a main candidate for the case study of bullwhip effect. The selected product for this study is oxygen sensor for wide range of Peugeot automobiles. This product line is one of the bestselling and most importantly a product with prominent contribution in company's overall performance.

ISACO exhibits typical processes of a push production system. Customers receive their monthly needs from inventory which results from the balance of demand and production outcome. ISACO's production planning estimates are based on a monthly forecast, firm's budget, orders in place and safety stock margin. As in classic pushed-based environments, ISACO operation policies, product design and hardware are dedicated to economies of scale through mass production. Production plan serves as an input for calculating the replenishment plan.

The company's delivery time is one week for distributors and varies for assembly line consumption, depending on availability of raw materials, production capacity, demanded amount and desired delivery date. In this case study, the company's policy is to undertake only orders that have been placed two weeks in advance.

Distribution channel plays an important role. They have been authorized and licensed by the company to be the official distributor of ISACO (In this research called Agents) and hence are in the front line to deal with customers and retailers. Distributors operate independently with regards to their inventory level and replenishment policy. They also have decision autonomy in selling the products to the retailers or direct sales to the end customers. However, distributors in this case study perform the combination of both. Delivery performance is influenced by the delivery policy such as volume discount deal offered to all distributors. Such policies might exert pressure on the distributors to increase warehouse capacity or impose financial constraints.

Retailing operation replicates the distributor's role on a smaller scale. They both share similar shortcomings in their forecasting techniques and hence face difficulties in keeping a stable inventory.

Model description

In this section, the developed system dynamics model is explained to analyze the bullwhip effect of the case study. In addition to that, the detailed fuzzy logic structure which serves as a policy design system is demonstrated in this chapter.

Model assumptions

There are number of assumptions regarding the presented supply chain model that are addressed thoroughly as follows;

1. The model is divided into three main divisions where each individual company is represented in a separate echelon. Although, these companies are affiliated with the main company (ISACO), they have full autonomy in inventory policy and replenishments. The retailer and distributor echelons are in aggregated form which represent total sum of all retailers and distributors.
2. The demand from the customers and supply of the materials are considered exogenous variables to the model.
3. There are no major constraints in capacity, labor force and quality control (defective products). Available inventory defines the order fulfillment rate and therefore it is the only constraint in this study. The reasoning behind this assumption is due to fairly short time period for this research. It would be fair to assume that manufacturing capacity and labor availability do not change over the course of this study.
4. Make-to-stock versus make-to-order policy; the chosen company in this study follows the traditional production strategy of Make to stock (MTS) that is used to match production and inventory with consumer forecasts. The make to stock policy however, requires a precise forecast of demand in order to determine how much product needed for manufacturing.

5. The effectiveness of a make-to-stock policy is largely reliant on the ability of a company to predict the future demand. In this study, moving average is used by the manufacturer which is extremely useful for forecasting long-term trends. Moving average is an average of any subset of numbers. For example, sales data for a twenty-week period can be calculated by a five-week moving average, a four-week moving average and so on.
6. The experimental company manufactures multiple products. Though, due to model size reduction and feasibility of this study, multiple products are aggregated into a single item so that we can build up a functioning model without excessive expansion. To tackle the issue of multiple product aggregation, a formula for order fulfillment as a function of inventory is used. According to Sterman (2000), a company ships what it wants to ship or what it can ship, whichever is less. That is the logic for the formula:

   Shipment Rate = MIN (Desired Shipment Rate, Maximum Shipment Rate)

   However, this rule only makes sense when a single product or stock keeping unit (SKU) is considered. Most models usually demonstrate companies with multiple SKUs, and very often hundreds of different products. Yet, it is not always ideal to model each SKU independently. Therefore, inventory level in such models are the sum total of all SKUs. The problem arises when some items are out of stock due to random customer demands even though the aggregate desired shipment rate and maximum shipment rate are equal. To address this problem, Table for Order fulfillment is used to correct the aggregate SKUs. By using the Table function, Order fulfillment ratio will be adjusted. The table function is adopted from "Order fulfillment as a function of inventory" graph from Sterman (2000) as illustrated in the figure below. SR, DSR and MSR stand for shipment rate, desired shipment rate and maximum shipment rate, respectively. The horizontal line where order fulfillment ratio equals 1 represents the case that shipments always equal desired shipments. If the shipment rate goes below, then shipment rate equals maximum shipment rate (SR=MSR). In reality, the actual relationship happens in the area to the right and below those reference lines. When the company has plenty of inventories, the maximum aggregate shipment rate is much bigger than desired shipment rate. Therefore, chances of any single item being out of stock is trivial (Order fulfillment ratio= 1). On the other hand, the order fulfillment ratio will be less than 1 when the aggregate maximum shipment rate equals desired shipment rate. Since the generic product could be any item, its possibility for stockout should be higher. The table function that adjust the amount of shipments, regardless of extreme inventories for all SKUs in order to balance the stockout situation of a single SKU is shown in figure 18.

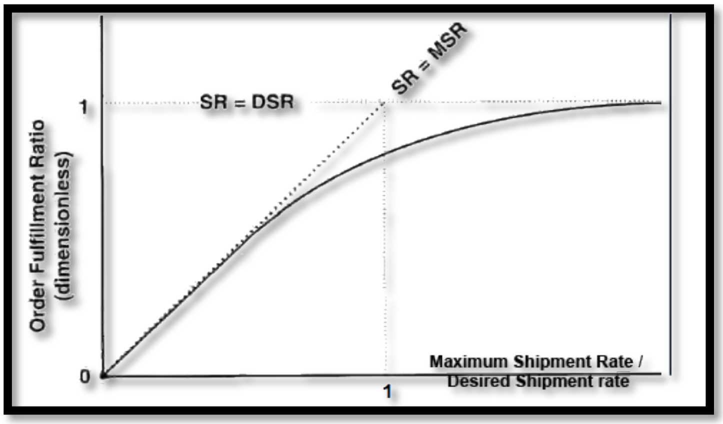

Figure 17, Order fulfillment as a function of inventory, Sterman (2000)

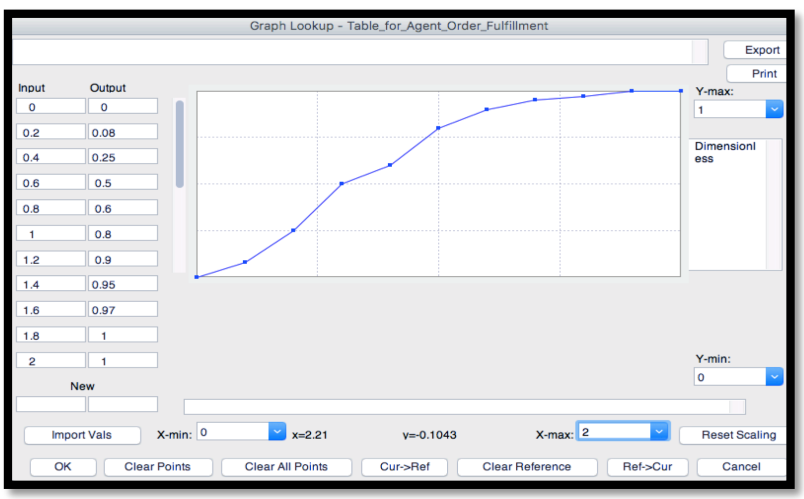

Figure 18, Table for Order Fulfillment Correction

7. The model includes flows of information and material. Financial constraints only affect the manufacturing echelon as a payment delay.

Model Explanation

A supply chain model is a combination of several nodes and can be created by aggregating multiple generic echelon models (Sterman, 2000). Every node in supply chain represents different company and therefore requires a degree of customization. In this case study, a generic system dynamics model is used for each echelon as a template which has further been customized to the specific configuration of the case study (Forrester J. W., 1961; Olivia, 1996). The proposed supply chain model is shown in Figure 19 which includes three echelons; Retailer, Distributor and Manufacturer. The demonstrated model provides an overall structure with organizational subunits and decision milestones. It also delivers the main feedback loops as well as the important stocks and flows.

From the right hand side of the model, Retailer echelon receives orders from consumers. Orders then triggers the order fulfillment process. Ordering process and forecasting influence the retailer's product flow decisions with on-hand inventory considerations. This simplified assumption is due to the fact that the retailer is affiliated to the distributor, even though they are individual companies.

The needed items from the retailer are received by the distributor as incoming orders. Most of the rules and logics considered in retailer's echelon is also applied for the distributor and manufacturer. For example, Order Fulfillment process which is influenced by inventory and backlog, is only different in the parameters in each echelon. However, in the distributor's echelon, procurement process is needed in order to adjust the in-transit flow of products. Multiple feedback mechanisms between on-hand and backlogged products, forecasted demand and lead times regulate the in-line product flow.

The left rectangular represents the manufacturer model which includes order fulfillment, production and procurement processes. The manufacturer's supplier is considered exogenous variable and out the scope of this thesis. The simulation model consists of information and material flows. Financial flow is only considered when dealing with material supply performance.

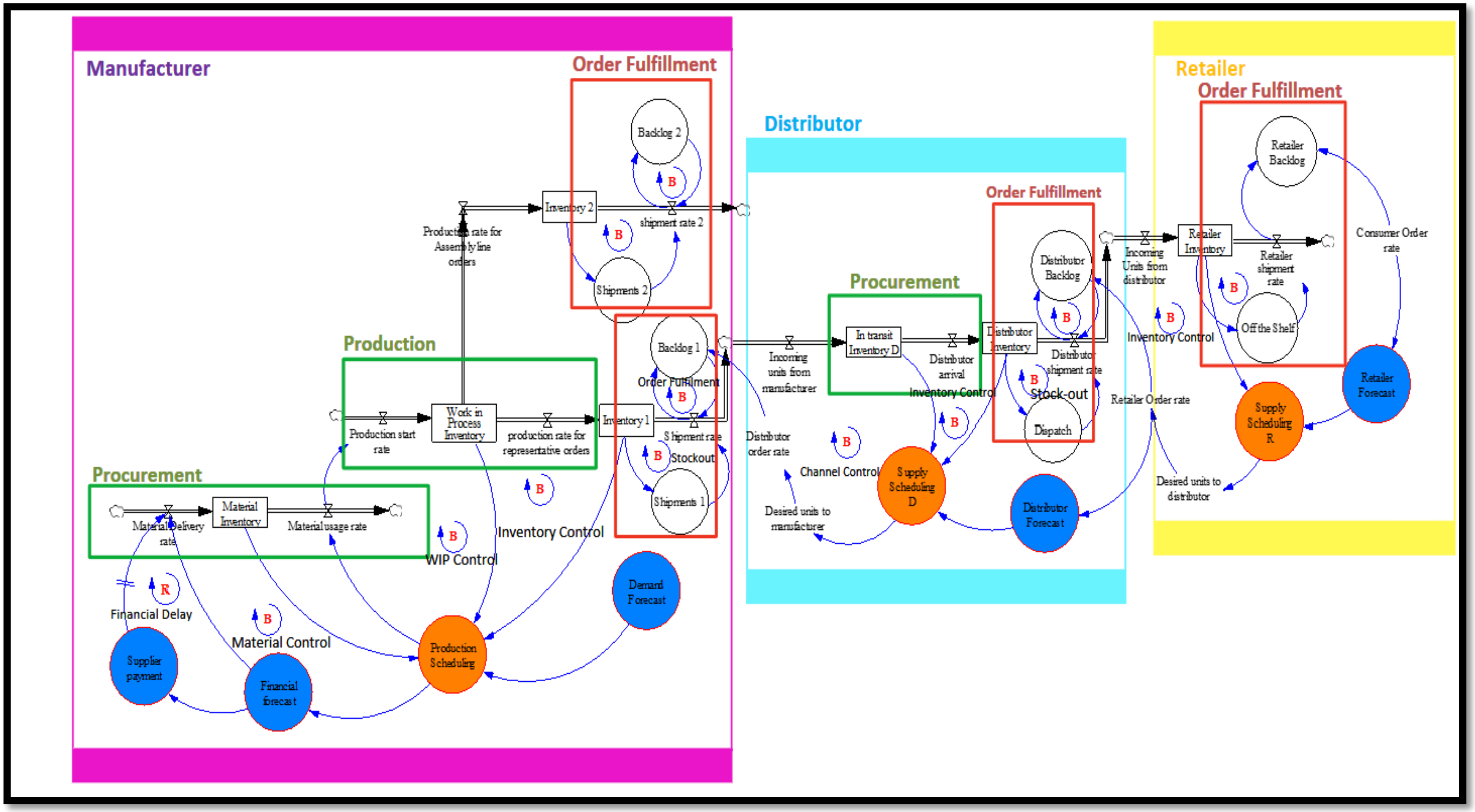

Figure 19, Overview of the proposed three-echelon supply chain model

Supply Chain Model Components

Manufacturer echelon

Figure 20 shows the manufacturing echelon in detail; describing the key variables and components as well as causal feedback loops. There are two major parts in manufacturing echelon; one is the pipeline for orders from distributor and the other is the pipeline for assembly line orders. Although the two pipelines perform in the same mechanism for order fulfillment and reaching to a desirable level, the forecasting and inventory processes are notably different.

Manufacturing echelon follows a typical pushed-based production policy where the forecasting system and perceived sales determines the amount to be produced. This strategy of pushed-based production requires procurement policy which has been shown on the left side of the model. Moreover, the material forecasting process and payment delay are independently added to the push-based system to demonstrate the financial constraints in the model.

There are two different order fulfillment processes in the manufacturer echelon. The fulfillment process for distributors pushes inventory stock after forecast, while assembly line does not have a forecasting mechanism and also does not hold stock. Apart from these differences, the formula and logic for both fulfillment processes are similar.

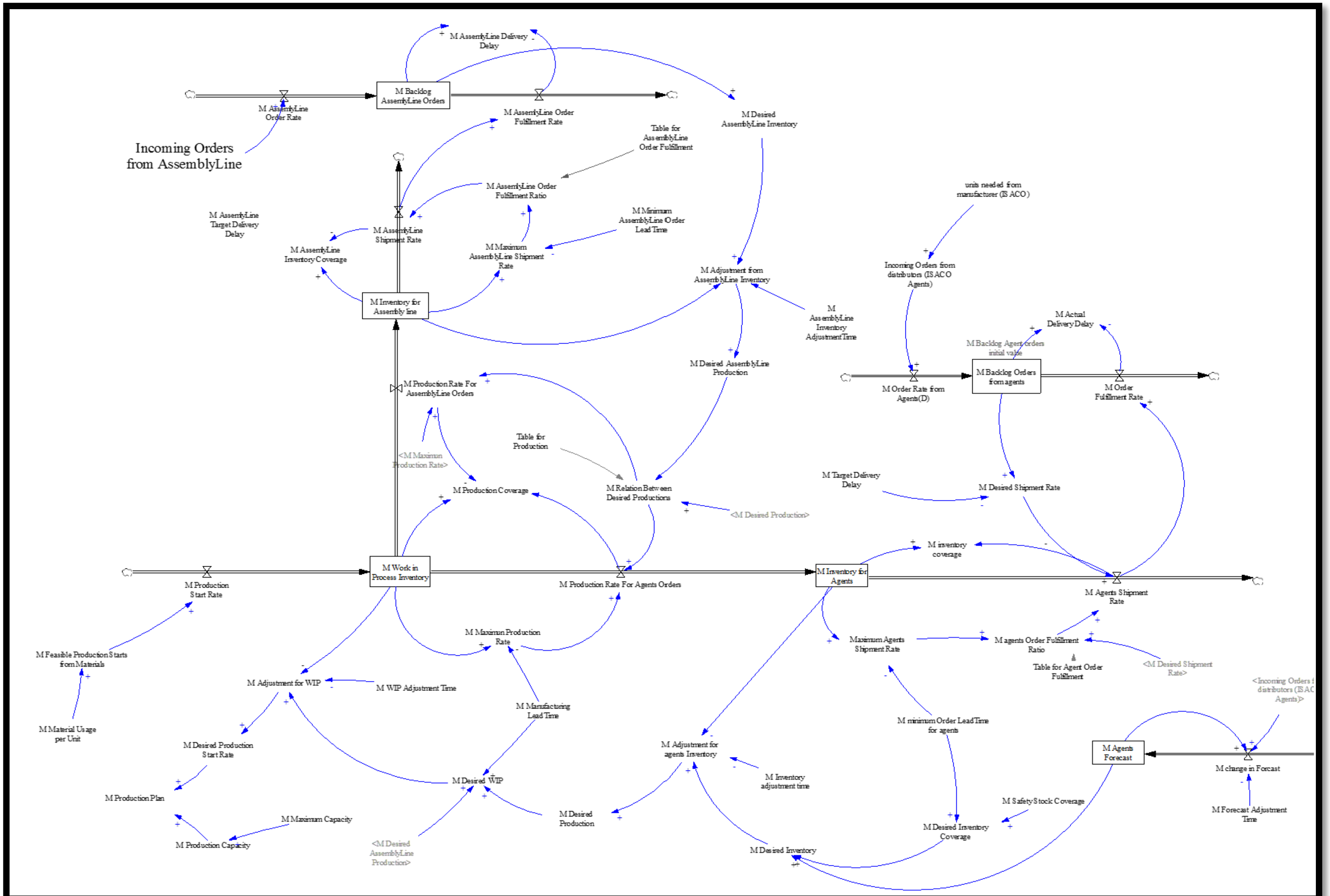

Figure 20, Stock & Flow Diagram of Manufacturer Echelon

The variable Order Rate from Agents shows the incoming orders from the distributor and therefore it is not an exogenous variable to the model. Since the order rate represents the incoming orders to the system and are not supposed to be fulfilled right away, they become Backlog Orders and stay in the stock variable until they are served. Order fulfillment rate releases the pending orders from the backlog at the same pace as the Agents Shipment Rate variable. Therefor the equation would be:

$$(d/dt)Backlog\ Orders = Order\ Rate - Order\ Fulfillment\ Rate$$
$$Agents\ Shipment\ Rate = Order\ Fulfillemnt\ Rate$$

Target Delivery Delay is defined as the intervals which orders are fulfilled by manufacturer once they are place by the distributor. The Desired Shipment Rate variable is weekly number of items waiting for the promised delivery time;

$$Desired\ Shipment\ Rate = Backlog\ Orders\ /\ Target\ Delivery\ Delay$$

The Actual Delivery Delay is calculated based on on-hand Backlog and Order Fulfillment rate and is similar to the previous equation;

$$Actual\ Delivery\ Delay = Backlog\ Orders / Order\ Fulfillment\ rate$$

In order to regulate the shipments, Stock-out loop performs with regards to the Inventory for Agents level. The Inventory for Agents stock receives the finished products form an input flow, Production Rate for Agent Orders, and is depleted by the Shipment Rate output flow. Therefore;

$$(d/dt)Inventory\ for\ Agents = Production\ Rate\ for\ Agent\ Orders - Shipment\ Rate$$

The Maximum Shipment Rate for Agents indicates the highest feasible delivery and is calculated based on the level of Inventory and the Minimum Order Lead time for Agents which is the time for processing and delivering an order;

$$
\begin{aligned}
&Maximum\ Shipment\ Rate\ for\ Agents \\
&\qquad = Inventory\ forAgents/Minimum\ Order\ Lead\ time
\end{aligned}
$$

From the previous equations, it can be concluded that when there is enough Inventory, the actual Shipment Rate should equal desired Shipment Rate, otherwise it should follow the Maximum Shipment Rate for Agents formula. This logic works well when the distributors order a single item. However, in reality customers order multiple items and even when the number of available and demanded orders are identical, there might be a chance that some orders cannot be fulfilled due to inventory shortage for one single item. To address this issue, Order Fulfillment Ratio has been used in the model. Order Fulfillment Ratio receives the Maximum Shipment Rate for Agents and Desired Shipment Rate values and delivers the output value by using the Table function for Order Fulfillment. The Order Fulfillment Ratio then is used to adjust the actual Shipment Rate;

$$
Shipment\ Rate = Desired\ Shipment\ Rate\ .Order\ Fulfillment\ Ratio
$$

The Table function for Order Fulfillment is shown in the graph below which takes the ratio of desired to actual Shipment Rates on the x-axis and returns the output value in the y-axis. The table function is adapted from Sterman (2000) which justifies the nonlinear nature of the Order Fulfillment Ratio.

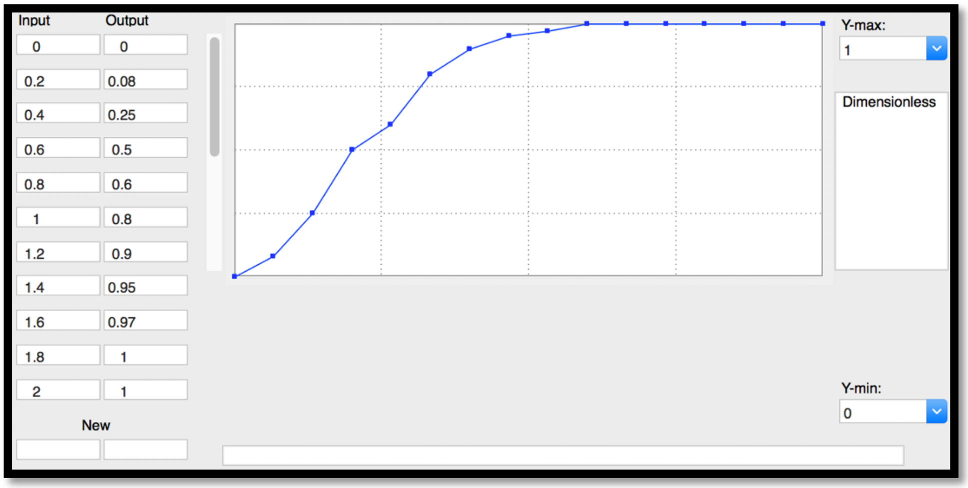

Figure 21, Table function for Order Fulfillment Ratio

The forecasting method used in this study is based on exponential smoothing technique and adaptive expectations presented by Sterman (2000). This forecasting method argues that it takes time for the company to perceive the change in demand and therefore, the firm's perception of the demand gradually adjusts to the actual demand whenever there is a gap between them. This is also referred as first order delay in the literature. The perceived demand then is calculated in accordance to the actual incoming demand and the current status of the demand within the review time as it is shown in the equation below;

$$(d/dt)Agents\ Forecast = \frac{Agents\ Forecast - Incoming\ Orders\ from\ Distributors}{Forecast\ Adjustment\ Time}$$

Production scheduling and replenishment of inventory are determined based on the demand forecast, inventory strategies and the inventory level. Desired Inventory variable is defined as the expected number of product that last over the Desired Inventory Coverage time. Therefore, Desired Inventory Coverage time must cover the Minimum Order Lead time which is the time to ship an order and also a Safety Stock Coverage as a time buffer.

$$Desired\ Inventory\ Coverage = Minimum\ Order\ Lead\ time + Safety\ Stock\ Coverage$$

$$Desired\ Inventoy = Forecast\ .Desired\ Inventory\ Coverage$$

When scheduling a production plan, it is vital to take the current Inventory level into consideration as it requires to reach to the desired level within each systematic review intervals (Inventory Adjustment Time). This is a simple fragment of the counteracting Inventory Control feedback loop which is formulated as;

$$Adjustment\ for\ Agents\ Inventory = \frac{Desired\ Inventory - Inventory\ for\ Agents}{Inventory\ Adjsutment\ time}$$

Since Adjustment for Agents Inventory can be positive or negative and orders cannot be negative, a solid formulation to translate Adjustment Inventory to Desired Production would be;

$$Desired\ Production\ for\ Agents = Max(0, Adjustment\ for\ Agents\ Inventory)$$

The abovementioned variables and formulas construct the main body of manufacturing echelon, covering Order Fulfillment for Agents, Forecasting and Production planning processes. Similar formulation is applied for the Assembly Line Orders. However, Assembly line Order Fulfillment lacks an official forecast, safety stock and inventory coverage. Thus, the Desired Assembly Line Inventory equals Backlog for Assembly Line Orders.

$$Desired\ Assembly\ line\ Inventory = Backlog\ for\ Assembly\ line\ Orders$$

Desired Work in Process represents the amount of product needed to keep steady production for Manufacturing Lead time, which is the time it takes to manufacture a product. Therefore, we have;

$$\begin{aligned} &Desired\ Work\ in\ Process \\ &\qquad = (Desired\ Production\ fot\ Agents \\ &\qquad + Desired\ Assembly\ Line\ Production).Manufacturing\ Lead\ time \end{aligned}$$

Similar to replenishment policy for Inventory for Agents is executed on WIP Inventory where Work in Process control loop regulates a stable flow to the stock. To achieve so, there is a need for Adjustment for Work in Process variable;

$$Adjustment\ for\ WIP = \frac{Desired\ WIP - WIP\ Inventory}{WIP\ Adjustment\ time}$$

Desired Production Start Rate is formulated in the same way as Production Rate;

$$Desired\ Production\ Start\ Rate = \max(0, Adjustment\ for\ WIP)$$

The real Production Start Rate however, transfers the items to be manufactured in Work in Process Inventory where the stock becomes depleted by the outflows of Production Rate for Agent Orders and Production Rate for Assembly Line Orders. Therefore;

$$\begin{aligned}(d/dt)&Work\ in\ Process\ Inventory \\ &= Production\ Start\ Rate - Production\ Rate\ for\ Agent\ Orders \\ &- Production\ Rate\ for\ Assembly\ Line\ Orders\end{aligned}$$

Maximum Production Rate indicates the available Work in Process Inventory that can be processed in Manufacturing Lead time. Hence, both production rates rely on Maximum Production Rate.

$$Maximum\ Production\ Rate = Work\ in\ Process\ Inventory/Manufacturing\ Leat\ time$$

Since demand fulfillment for assembly line orders receives greater priority over the agents, the variable Relation Between Desired Productions is introduced to the model to divide the capacity between Production Rate for Assembly Line Orders and Production Rate for Agent Orders. Hence,

$$Production\ Rate\ for\ Assembly\ Line\ Orders \\ = Maximum\ Production\ Rate * Relation\ Between\ Desired\ Productions$$

$$Production\ Rate\ for\ Agent\ Orders \\ = Maximum\ Production\ Rate \\ * (-Relation\ Between\ Desired\ Productions)$$

A nonlinear table function has been employed to replicate the allocation policy for actual production decisions. Table for Production variable is shown in the Figure 22 where demonstrates the importance of production for assembly line over the distributors (Agents). The table function takes Desired Assembly Line Production and Desired Production as inputs and gives an output policy through a nonlinear function. Relation Between Desired Production stays zero until the Desired Production is half of the Desired Assembly Line Production meaning all resources will be allocated to the assembly line. When they become equal, Relation between Desired Production just assigns 40 percent of resources to the distributor's orders. Only when the Desired Production has become five times greater, 100 percent the resources will be allocated to the agent's orders.

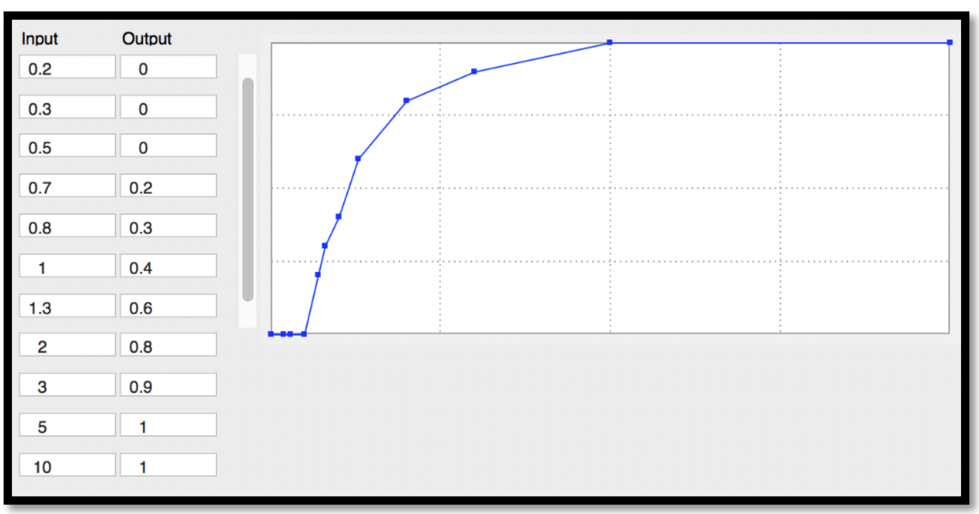

Figure 22, Table for Production for Relation Between Desired Productions

Thus far, the main Production structure of the model has been explained. However, the counteracting loops of Inventory Control and Work in Process Control should be closed when the desired and actual Production Start Rates are connected. Therefore, material availability as well as a linkage between products and materials flows need to be addressed.

Production Plan takes into account the Desired Production Start Rate and Maximum Production Capacity in the following logic;

$$Production\ Plan = \begin{cases} Maximum\ Production\ Capacity, MPC < DPSR \\ Desired\ Production\ Start\ Rate, \qquad Otherwise \end{cases}$$

Figure 23 demonstrates the procurement and material management structure. Material Delivery Rate and Material Usage Rate which are the inflow and outflow of receiving and dispatching materials for production, control the stock of Material Inventory. Hence;

$$(d\ /\ dt)\ \ Material\ Inventory = Material\ Delivery\ Rate - Material\ Usage\ Rate$$

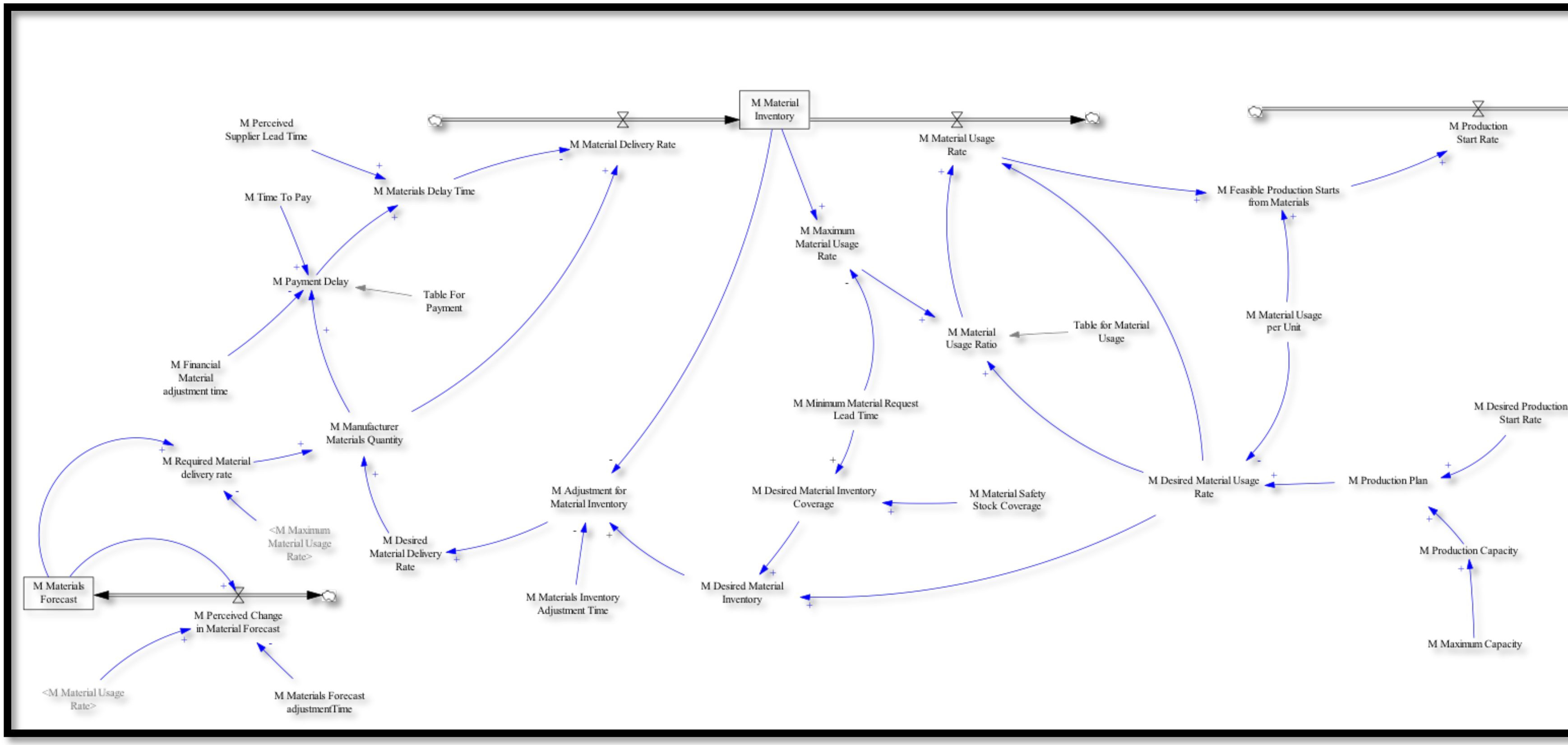

Figure 23, Procurement and Material Management Structure

For the sake of simplicity all general components that constitutes the end product is aggregated in Material Inventory. Therefore, Material Usage per Unit denotes the amount of materials that makes one unit of output. Thus, Desired Material Usage Rate is formulated as;

$$Desired\ Material\ Usage\ Rate = \max\left(0, Production\ Plan\ /\ Material\ Usage\ per\ Unit\right)$$

Considering the limitations in Materials Management due to limited availability of Material Inventory, Material Usage Ratio is expressed as the fraction of Desired Material Usage that material management is able to provide. In order to formulate this ratio, a nonlinear table function is used which takes the values of Maximum Material Usage Rate and Desired Material Usage Rate. The nonlinear function as well as Material Usage Ratio formula are shown as;

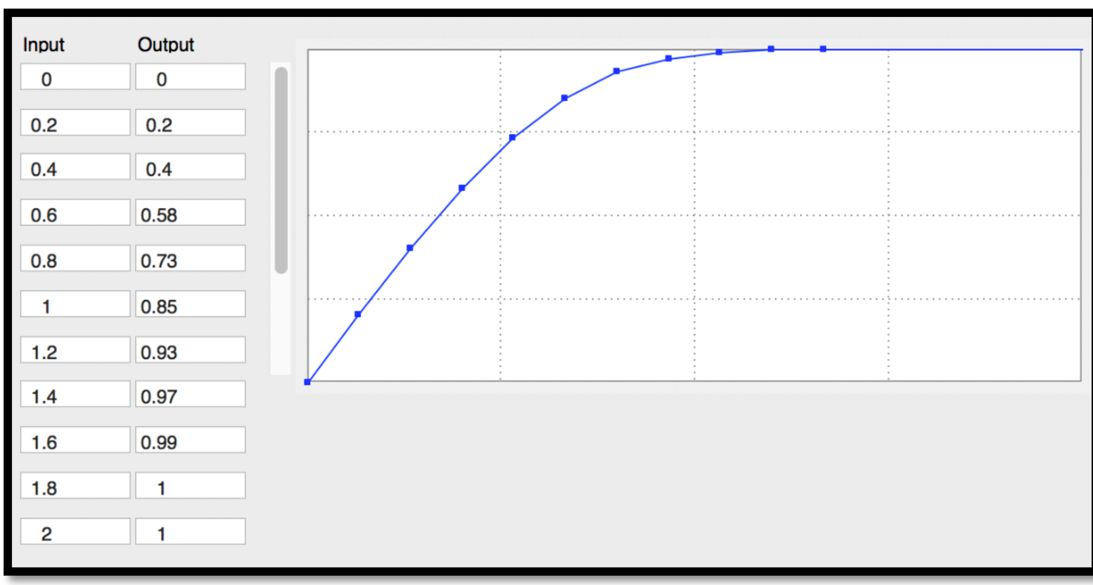

Figure 24, Nonlinear function for Material Usage Ratio

$$Material\ Usage\ Ratio$$
$$= Table\ for\ Material\ Usage(Maximum\ Material\ Usage\ Rate / Desired\ Material\ Usage\ Rate)$$

Moreover, Material Usage Rate is formulated as;

$$Material\ Usage\ Rate = Desired\ Material\ Usage\ Rate * Material\ Usage\ Ratio$$

Material Usage Rate is the amount of components provided to Production. To calculate the feasible number of items to start production or in other words the Production Start Rate, following formulation is used;

$$Feasible\ Production\ Start\ from\ Materials = Material\ Usage\ Rate\ * Material\ Usage\ per\ Unit$$

$$Feasible\ Production\ Start\ from\ Materials = Production\ Start\ Rate$$

The Material Control counteracting feedback loop is described by identifying Adjustment for Material Inventory which tries to close the gap between Desired Material Inventory and actual Material Inventory. Therefore;

$$Adjustment\ for\ Material\ Inventory = ((Desired\ Material\ Inventory - Material\ Inventory)) / Material\ Inventory\ Adjustment\ time$$

The Desired Material Inventory is defined by the Desired Material Inventory Coverage which is the time to deliver a demanded material and a safety amount of time for variations coverage. Therefore;

$$Desired\ Material\ Inventory\ Coverage = Minimum\ Material\ Request\ Lead\ time + Material\ Safety\ Stock\ Coverage$$

$$Desired\ Material\ Inventory = Desired\ Material\ Inventory\ Coverage * Desired\ Material\ Usage\ Rate$$

and so;

$$Desired\ Material\ Delivery\ Rate = \max(0, Adjustment\ for\ Material\ Inventory)$$

In order to make connection between the Desired Material Delivery Rate and the actual Material Delivery Rate, forecasting system and financial delays are introduced to the model.

By taking the historical consumption into account, the Required Material Delivery Rate can be determined by the Manufacturer. Moving Average is used as a way of forecasting method in Procurement.

Material Forecast accumulates the changes in every Material Forecast Adjustment time. The Perceived Change in Material Forecast is determined by comparing the current material consumption (Material Usage Rate) and the estimated material consumption (Material Forecast). Therefore;

$$(d/dt)Material\ Forecast = Perceived\ Change\ in\ Material\ Forecast$$

$$\begin{aligned} &Perceived\ Change\ in\ Material\ Forecast \\ &\qquad = ((Material\ Forecast - Material\ Usage\ Rate)) \\ &\qquad / \ Material\ Forecast\ Adjustment\ time \end{aligned}$$

The Required Material Delivery Rate is the difference between Material Forecast and the Maximum Material Usage Rate and must be nonnegative. Thus;

$$\begin{aligned} &Required\ Material\ Delivery\ Rate \\ &\qquad = \max(Material\ Forecast - Maximum\ Material\ Usage\ Rate, 0) \end{aligned}$$

According to two different sources of required material supply, namely Desired Material Delivery Rate and Required Material Delivery Rate; the larger number is selected;

$$\begin{aligned} &Manufacturers\ Materials\ Quantity \\ &= \max\ (Desired\ Material\ Delivery\ Rate, Required\ Material\ Delivery\ Rate) \end{aligned}$$

Manufacturer Materials Quantity represents a solid formulation for supplies under uncertainty and it eventually becomes the Material Delivery Rate after a delay for a down payment and the supplier’s ordering lead time.

The connection between manufacturer's ability to pay and the number of units is illustrated in the Figure 25. As the order size increases, it takes more time for manufacturer to do the payments. In order to formulate the financial constraints, a nonlinear table function for Payment Delay is introduced to the model. The function takes the Manufacturer Materials Quantity over the Financial Material Adjustment time to normalize the ratio. The output of the table function is a delay which needed to be used for Time to Pay variable. Therefore, Payment Delay can be understood as the estimated delay for a specific amount of orders.

$$\begin{aligned} &Payment\ Delay \\ &\qquad = Table\ for\ Payment(Manufacturer\ Materials\ Quantity \\ &\qquad\ / \ Financial\ MaterialAdjustment\ time).Time\ to\ Pay \end{aligned}$$

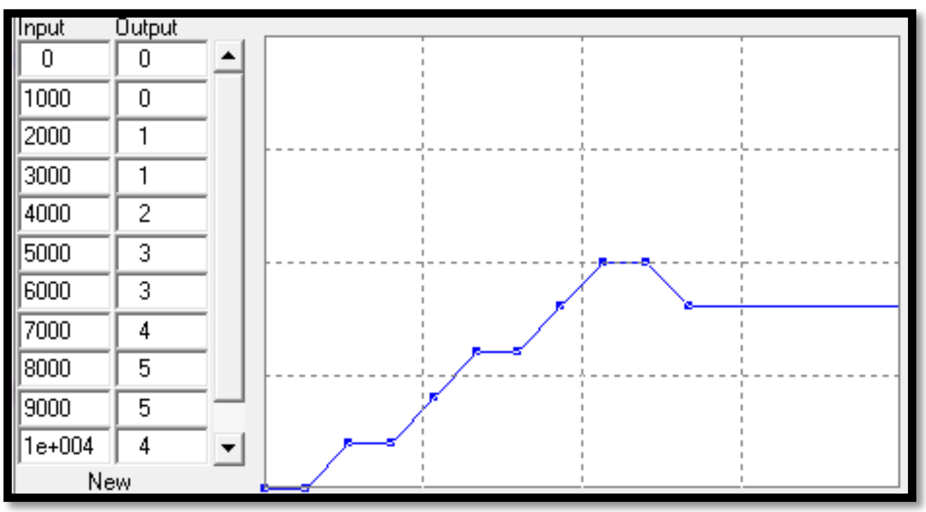

Figure 25, Table Function for Payment Delay

Moreover, Materials Delay Time is the total sum of Payment Delay and Perceived Supplier Lead Time;

$$Materials\ Delay\ Time = Payment\ Delay + Perceived\ Supplier\ Lead\ Time$$

Finally, Material Delivery Rate is formulated as a first order delayed of Manufacturer Materials Quantity. Therefore;

$$(d\ /\ dt) Material\ Delivery\ Rate = (Manufacturer\ Materials\ Quantity - Material\ Delivery\ Rate)\ /\ Material\ Delay\ Time$$

or

$$(d\ /\ dt) Material\ Delivery\ Rate = DELAY1(Manufacturer\ Materials\ Quantity, Material\ Delay\ Time)$$

Distributor Echelon

Similar to the Manufacturer, the Distributor follows a push-based policy and most of the processes and policies are the same. Figure 26 illustrates the Distributor structure which holds a lot of similarities to the Manufacturer, except that the distributor echelon lacks manufacturing process. In most cases, parameters of the Distributor model replicate the Manufacturer structure and follows similar logic and formulations.

The major processes in Distributor echelon are shown in the Figure 26 including Order Fulfillment and Procurement. Order Fulfillment process is the exactly the same as Manufacturer's process as previously described. Incoming orders from Retailers become the demand for the Distributor which are accumulated in as Backlog for Orders until they are fulfilled. On the other hand, Desired Replenishment Rate triggers the Procurement process. Considerations regarding the current orders, forecast, current stock and safety coverage have been made when formulating the Desired Replenishment Rate. Desired Replenishment Rate can be translated into Desired Incoming Units from the Manufacturer when Enlistment Time which is the time that the Manufacturer process and delivers an order has been taken into account. So it can be formulated as;

$$Desired\ Incoming\ Units = Desired\ Replenishment\ Rate * Enlistment\ Time$$

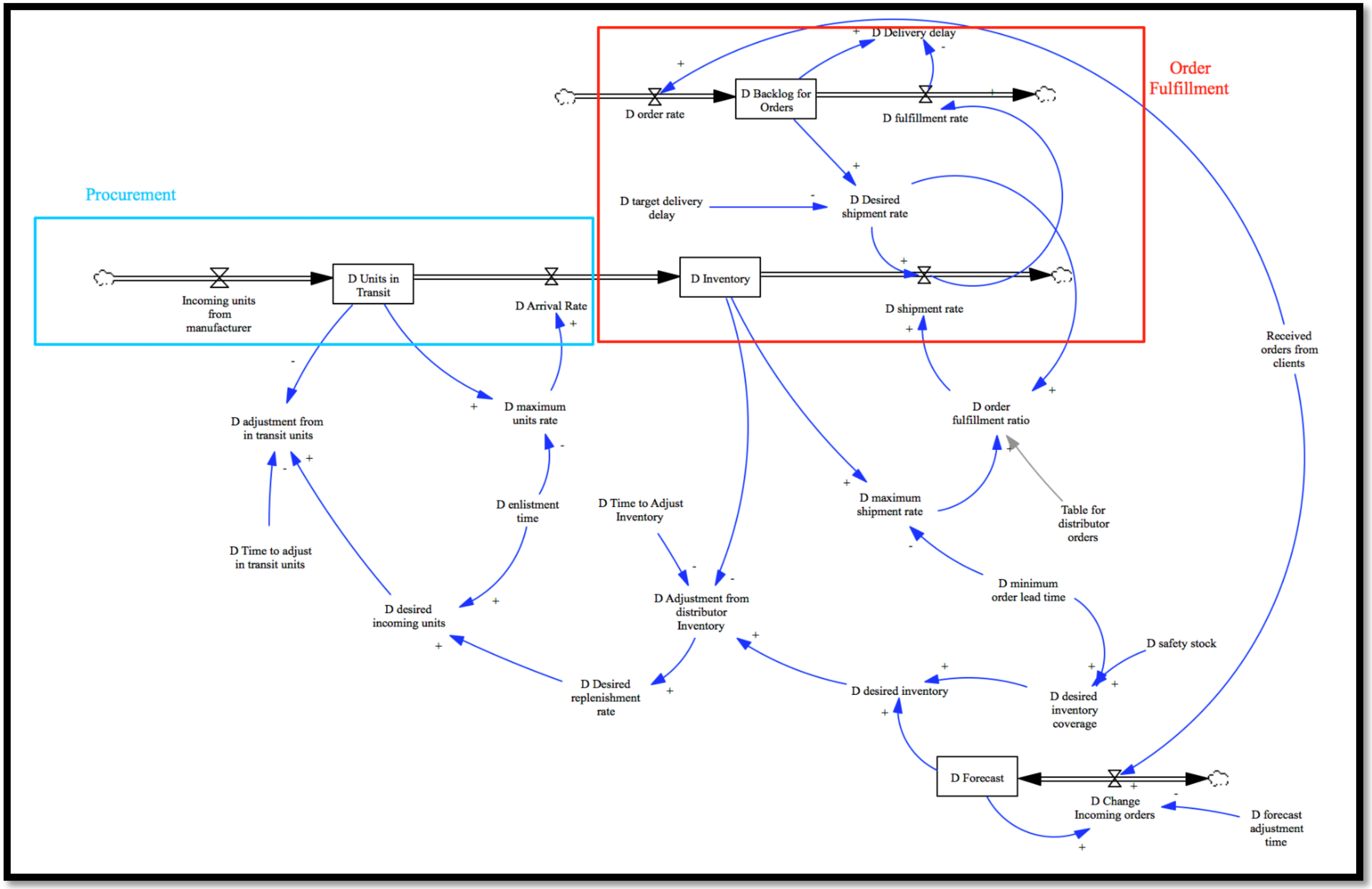

Figure 26, Distributor Echelon Structure

Desired Incoming Units gives us the ground for calculating the Desired In-Transit Units and after taking the Distributor's Units In-Transit and the Adjustment Time into consideration, the Adjustment from In-Transit Units can be attained. Thus;

$$Asjustment\ from\ InTransit\ Units = (Desired\ Incoming\ Units - Units\ inTransit) / Time\ to\ Adjust\ inTransit\ Units$$

The formulation above indicates the replenishment policy that considers the current in-transit units in the pipeline that subsequently forms the Distributor's Delivery Rate. This equation also performs as an input for the Manufacturer which is previously known as Order Rate from Agents (Distributors).

The stock of Units in-Transit implies the moving units from the Manufacturer to the Distributor and is served by the Incoming Units flow from the Manufacturer and depleted by the Distributor's Arrival Rate, articulated as;

$$(d\ /\ dt) Units\ InTransit = Incoming\ Units\ from\ Manufacturer - Distrinutor'\ s\ Arrival\ Rate$$

Retailer Echelon

The retailer echelon model also shares many similarities with the Distributor and Manufacturer echelon. The retailer in the case study is the spare parts outlets which are affiliated with the Distributor; yet, retailers have autonomy in their inventory replenishment decisions. In addition to that, pipeline inventory and Units in Transit are not reflected in the Retailer structure due to geographical accessibility and reliable delivery.

Figure 27 shows the Retailer structure of the model. Due to extreme similarities between the Retailer and Distributor sectors, equations and detail description of the variables in the Retailer division are not explained in this section. However, the input and output of the model are important for explanation. Incoming Demand is the input for both retailer and the entire supply chain system and the output of the Retailer model is Units Needed from Distributor which performs as an input for the Distributor echelon.

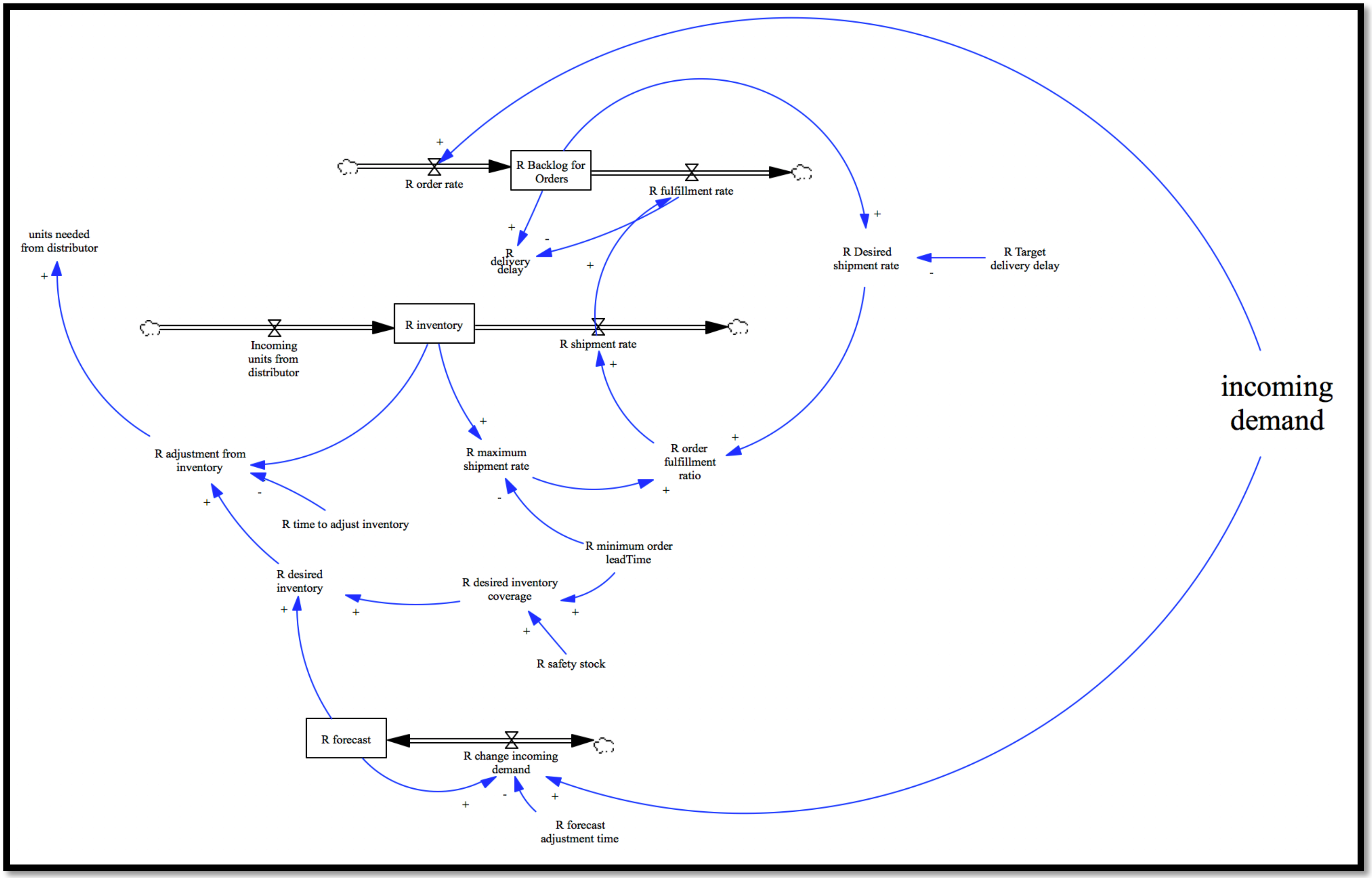

Figure 27, Retailer Echelon Structure

Model Calibration

Calibration in system dynamics models is a procedure in which the model parameters are estimated for a statistical coincidence between simulated and observed behavior. This means, generating a desired model behavior by manipulating parameters in the model structure under certain restrictions. When dealing with undetermined parameters in system dynamics, modelers trust the model to adjust its response to a known system response by changing the unset variables and not collecting more data from reality. The model structure receives higher confidence as a valid representation of reality when such model can reproduce the observed behavior without assigning excessive values for the calibrated inputs (Barlas, 1996; Olivia, 2003). Nonetheless, calibration has some limitations. The calibration process is merely a partial test of the model where a model is made of series of equations and parameters. Therefore, it is probable that a set of parameters with unrealistic formulations produce realistic behavior. Thus, for solid validation of the model structure, a comprehensive structure test is required (Olivia, 2003; Randers, 1976).

The model calibration can be executed automatically or manually. The manual model calibration is normally done by examining the the discrepancies between the simulated and observed data, detecting the possible reasons for the differences and finally adjusting the parameters of the model by hand to correct these discrepancies. The process of parameters adjustments and estimations in manual calibration is based on the modeler's experience and expert's opinions (Lyneis & Pugh, 1996). On the other hand, statistical analysis can be used to make parameter estimation process more robust. Two major approaches that have been adopted for a better parameter estimations are: full information maximum likelihood through optimal filtering (FIMLOF) and model reference optimization (MRO) which is based on nonlinear optimization algorithms (Olivia, 2003). Since these approaches are vastly reliant on data and extensive computations, many simulation software offer automated calibration (AC) features.

For the sake of simplicity, manual calibration is selected in this research model with the following steps; Defining the calibration reference variable, Identifying the known variables with their estimated values from real data, selecting variables to be calibrated with an acceptable range of values, Running the model with the calibrated parameters, Assessing the reference variable fit to the actual value.

The preferred calibration reference variable for each echelon is the Inventory level due to the fact that data comparison is simpler and the historical data is readily available. The model's auxiliary variables and their estimated values from real data is listed in the Table 4. Moreover, the parameters to be calibrated with the fitted values are also listed in the Table 5.

Table 4, Auxiliary Variables and the inputs

Parameters	Values	Parameters	Values
Target Delivery Delay (Weeks)	1	Distributor Order Lead time (Weeks)	1
Assembly Line Target Delivery Delay (Weeks)	5	Distributor Target Delivery Delay (Weeks)	1
Minimum Order Lead time (Weeks)	1	Manufacturer Order Lead time (Weeks)	1
Minimum Material Request Lead time (Weeks)	1	Distributor in-Transit Units Adjustment time (Weeks)	1
Time to Pay (Weeks)	1	Retailer Minimum Order Lead time (Weeks)	1
Material Usage per Item (Units/Component)	325		
Maximum Production Capacity	3600000		
Minimum Manufacturing Lead time (Weeks)	1		

Table 5, Parameters to be Calibrated

Echelon	Parameters to be calibrated	Fitted value
Manufacturer	Assembly Line Adjustment time (Weeks)	1.268
	Inventory for Agents Adjustment time (Weeks)	1.591
	Safety Stock Coverage (Weeks)	4.214
	Material Forecast Adjustment time (Weeks)	4
	Material Inventory Adjustment time (Weeks)	1.57
	Material Safety Stock Coverage (Weeks)	3.82
	Minimum Order Lead time for Assembly Line (Weeks)	1.5
	Perceived Supplier Lead time (Weeks)	12

Distributor	Work-in-Process Adjustment time (Weeks)	1
	Time to Adjust Distributor Inventory (Weeks)	1.4
	Distributor Forecast Adjustment time (Weeks)	4
	Distributor Safety Stock (Weeks)	3
Retailer	Time to Adjust Retailer Inventory (Weeks)	2.4
	Retailer Forecast Adjustment time (Weeks)	2
	Retailer Safety Stock (Weeks)	2.7

In order to analyze the model calibration, the manufacturer inventory level is tested compared to the historical data from the case study. As it is depicted in the Figure 28, the model delivers a decent graphical fit to the actual data with the calibrated parameters. The degree of adjustment seems to be adequate. However, for detailed statistical analysis of the calibration, numerical results using r-squared (R^2) is required.

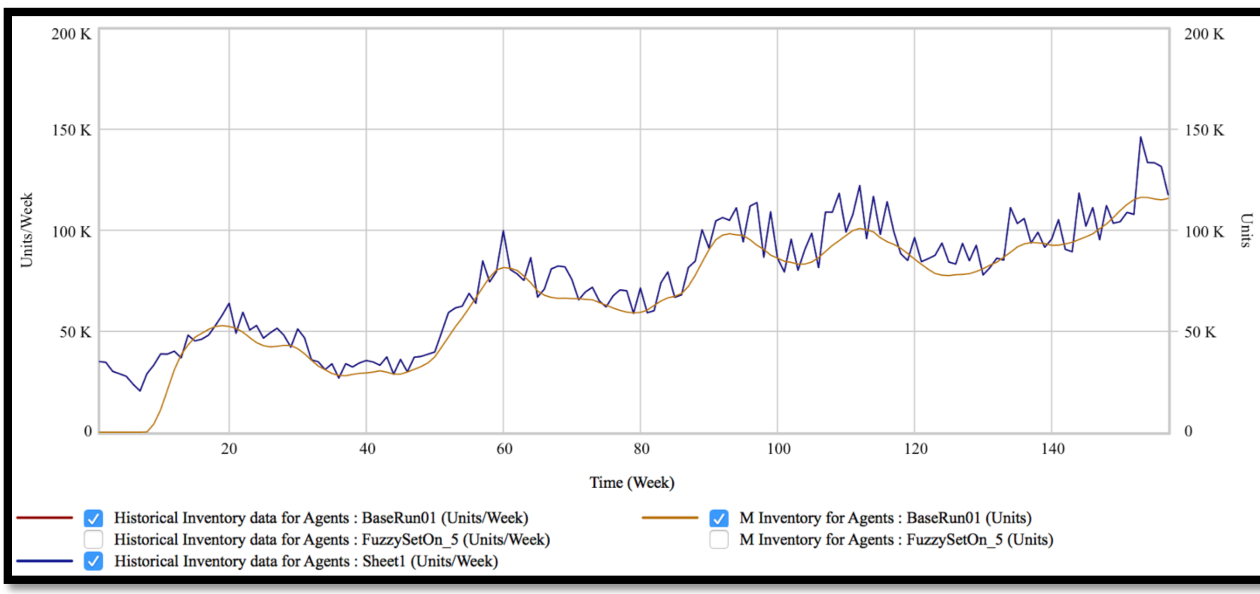

Figure 28, Manufacturer Inventory for Agents; Graphical Fit with the Reference Mode

Model Validation

Model validation is crucial to build confidence in the practicality and effectiveness of the model for its envisioned purpose. To examine the validity of the supply chain model, some of the in-depth validation guideline presented by Sterman (2000) has been used as follows;

1. *Boundary Adequacy tests*

Boundary adequacy tests examine the relevance of the model boundary for the purpose of research, meaning that the critical variables of the model to address the problem are endogenous to the model. Sterman (2000) suggests the stock and flow maps, interviews, workshops to request expert opinion, literature review and direct inspection of model equations as useful tools for model boundary determination.

In this study, boundary adequacy is achieved through careful examination of model equations, direct interviews with supply chain experts to attain their opinions and approval and more importantly, comprehensively reviewing the literature in supply chain dynamics for model construction. The outcome of boundary adequacy tests resulted in having only two exogenous parameters to the model, namely Incoming Demand and Incoming Orders from Assembly line as previously depicted in Figure 20 and Figure 27.

2. *Structure Assessment tests*

Structure assessment tests investigate whether the constructed model is consistent with relevant knowledge of the system. It emphasizes on the appropriateness of aggregation level, the conformance of the model to the basic physical realities such as conservation laws and the behavior of actors in decision rules. Sterman (2000) suggests procedures for conducting structure assessment tests including causal diagrams, stock and flow diagrams, partial model tests of the intended rationality of decision rules.

In this research, in addition to inspections for model behavior under different scenarios, the rationality of the model has also been checked with the supply chain experts in the company. Partial model tests have been performed for rationality of the individual rules. For instance, the manufacturing echelon is individually tested by eliminating the links from/to distributor and supplier to examine the functionality of the manufacturing level. The results for partial model test in manufacturing echelon are shown in the Figure below. In this particular test, the following variables have been assumed to be constant;

$$unit\ needed\ from\ manufacturer = 10000$$

$$feasible\ production\ starts\ from\ materials = 10000$$

$$Incoming\ Orders\ from\ Assembly\ Line = 0$$

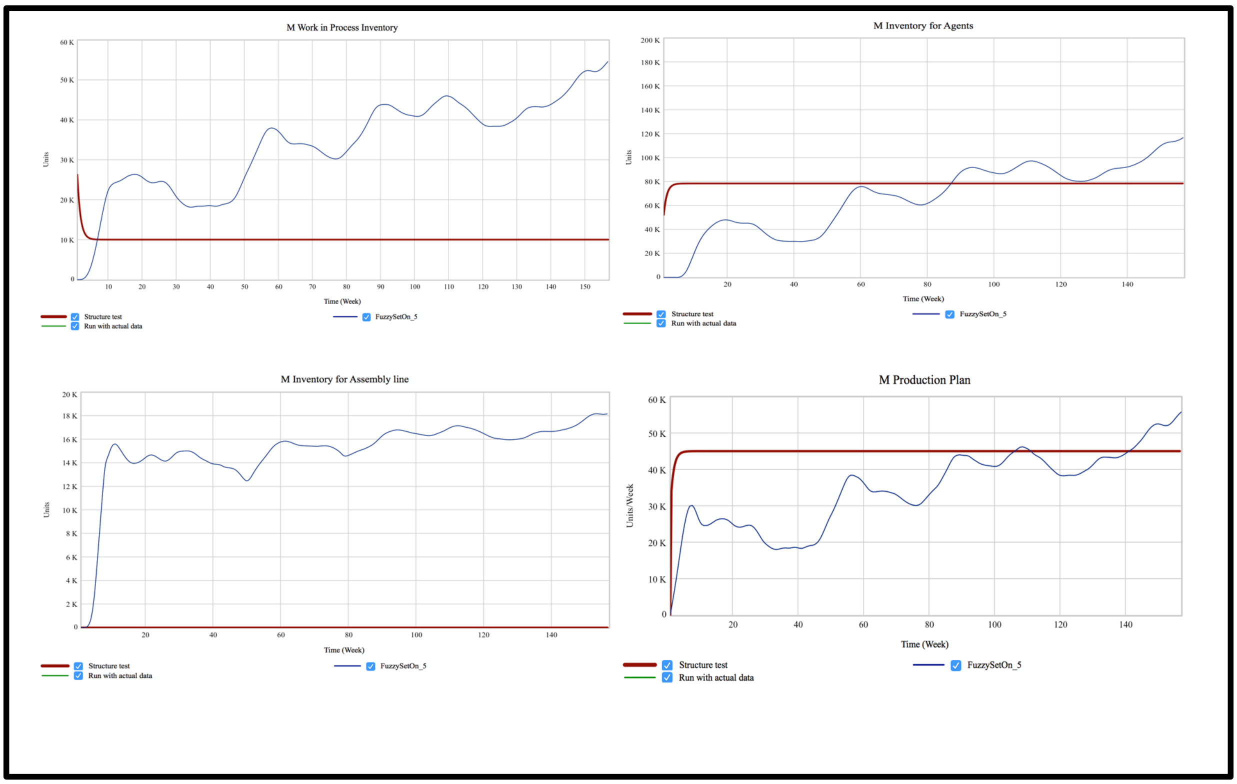

Figure 29, Results from Partial tests

As it is illustrated in the graphs, for constant "inflow" and "outflow" to the manufacturer echelon (isolating one sector), the partial test verifies that the model performs rationally.

3. Dimensional Consistency

Dimensional consistency is considered one the rudimentary tests which makes sure that each equation in the model is dimensionally consistent with their meaning in the reality.

Dimensional analysis in the studied model has been done using Units Check in Vensim®.

4. Parameter Assessment

Firstly, it is critical to make sure every constant parameter in the model has a clear, real-life meaning. In other words, all the parameters need to have real world counterparts. Secondly, decision on the values of each parameter must be made in a logical manner. According to Sterman (2000), judgment methods based on interviews, expert opinion and statistical methods to estimate parameters can be used for parameter assessment.

In this thesis, parameters have been chosen based on their actual existence in reality and the value of each parameter has been estimated in accordance to the numerical data or expert's opinions. Moreover, individual parameters have been validated with the supply chain specialists in the company.

5. Extreme Condition Tests

The idea of extreme condition test is to measure the robustness of the model in different scenarios. It indicates the strength of a model when extreme inputs or imposed policies do not alter the model behavior. A prominent example of extreme condition test is dealing with inventories. Inventories can never become less than zero no matter how large the demand might be, or the demand for goods should always become zero when the price increases sufficiently. Therefore, it is vital that each equation makes sense even when its inputs take intense values and the model responds rationally when subjected to extreme conditions. The simulation model has been exposed to extreme values for inputs in each supply chain echelon and the model responded in a rational way. Two major extreme condition tests has been conducted in the Manufacturing echelon. The reason for choosing Manufacturing echelon is that the Retailer and Distributor echelons have essentially the same model structure as the Manufacturer's and therefore, extreme tests in Manufacturing echelon may validate the whole model.

5.1 Extreme condition test on Incoming Orders from Assembly Line

The purpose of performing this test is to evaluate a condition where there are no orders from the assembly line ($Incoming\ Orders\ from\ Assembly\ Line = 0$) and hence, the entire production system serves the spare part's market (Distributors and Retailers). The expected results for Material Inventory, Inventory for Agents and Inventory for Assembly Line are shown in the Figures 30.

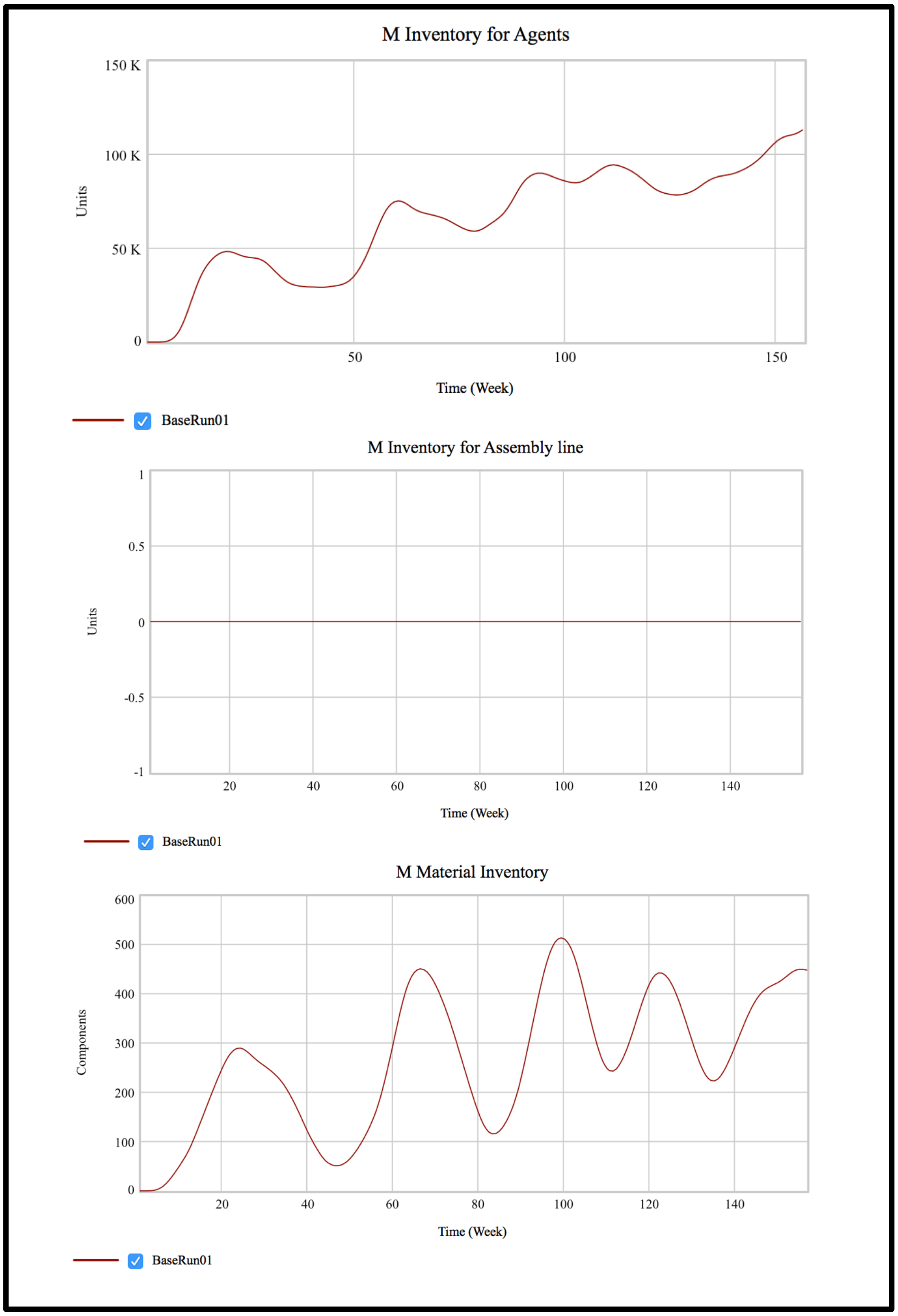

Figure 30, Extreme Condition Tests; Test 1 Results

Inventory for Agents stock oscillates in order to keep the Desired Inventory fulfilled for the time of simulation. Inventory for Assembly Line follows the make-to-stock policy and therefore, equals to zero during the simulation. Material Inventory demonstrates the bullwhip behavior because of the received order batches from the production line for the Agents.

5.2 *Extreme condition test on both Incoming Assembly Line Orders and Incoming Orders from Distributor*

The aim of this test is to evaluate the Manufacturer response when there is no demand at all. The expected response from ISACO is to have all the level variables at zero. The results are illustrated in the Figure 31.

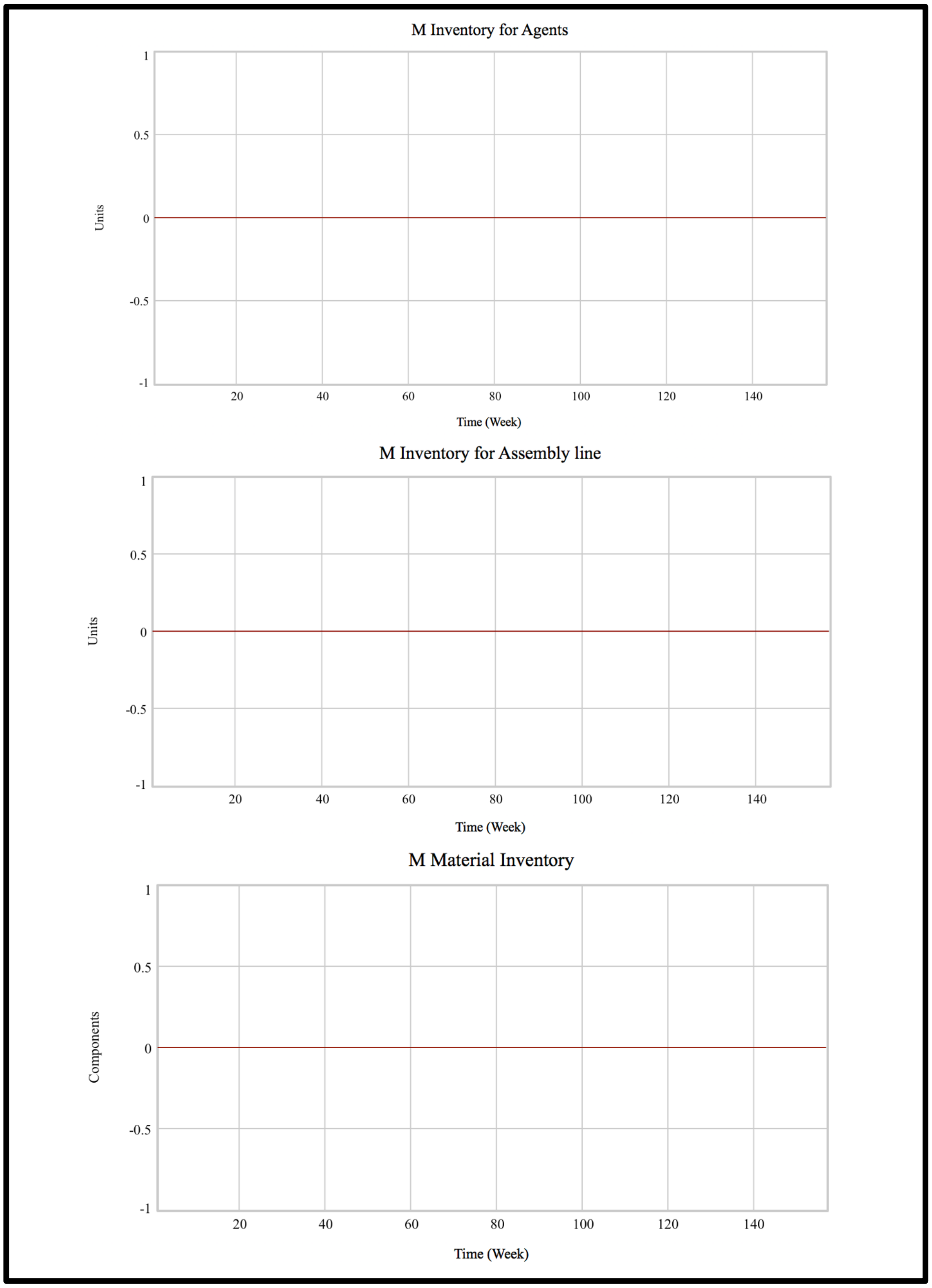

Figure 31, Extreme Condition Tests; Test 2 Results

6. Integration Error Tests

Integration error tests refer to modeling formulations and selecting an appropriate method of integration and time unit in a sense that the outcome of the simulation model should not be sensitive to the choice of time step or integration method.

The case study model has been tested for different time steps (DTs) and the results stayed identical. Figure below demonstrates the results for three time steps as follows;

$TIME\ STEP = 0.25$

$TIME\ STEP = 0.125$

$TIME\ STEP = 0.0625$

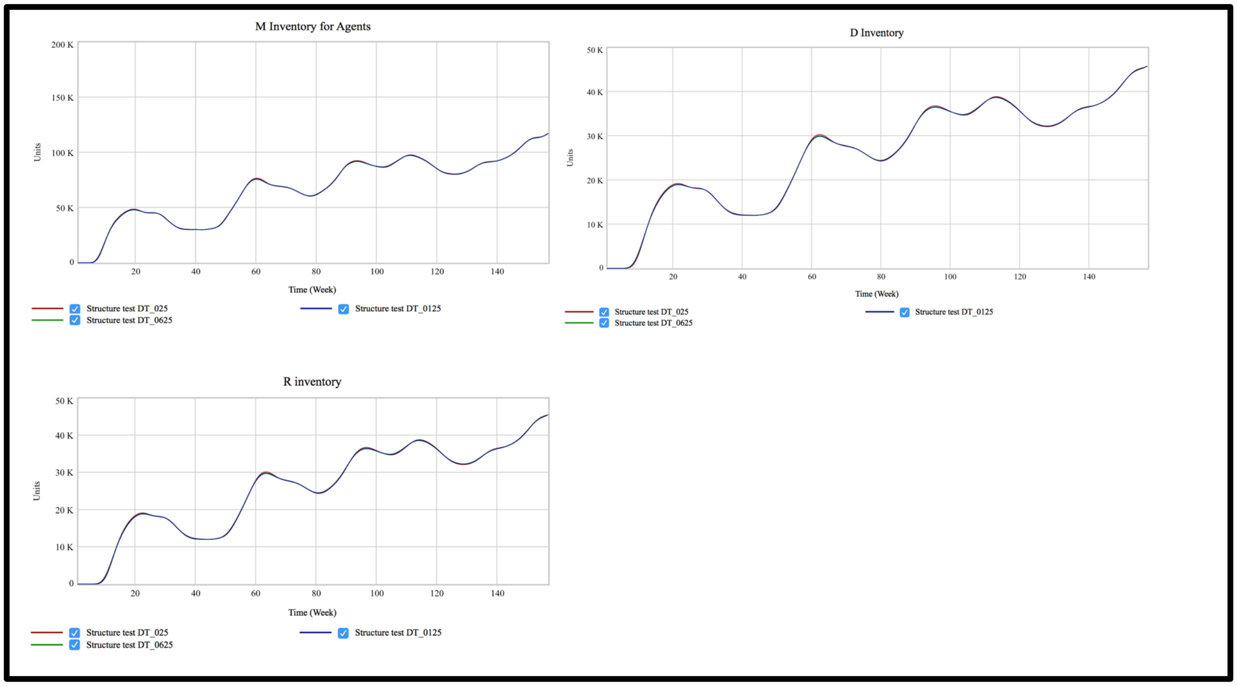

Figure 32, Results for Integration Error Tests, DT= 0.25, 0.125, 0.0625

7. *Behavior Reproduction Tests*

Although the validity and reliability of a model can not be measured with behavior reproduction tests, but the objective of modeling is to regenerate the behavior of interest in the system, both qualitatively and quantitatively. The appropriate use of the behavior reproduction test is to identify weaknesses in the structure or variables of the model and evaluate whether they matter to the purpose.

As it is previously illustrated in the graphical analysis, the calibrated model fits well compared to actual system behavior, particularly with regards to the bullwhip effect demonstration. The model was also compared with actual data in terms of behavior modes, variables' shape, relative amplitudes and phasing. Figure 33 shows the decent fit resulted from model behavior reproduction.

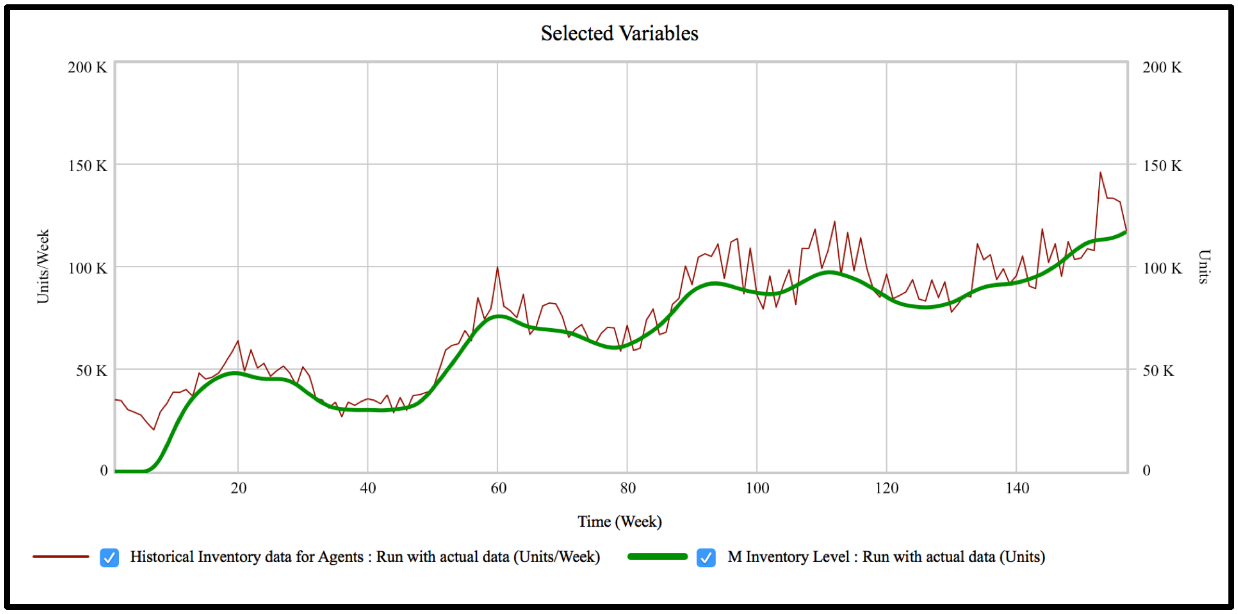

Figure 33, Results from Behavior Reproduction Tests

8. Sensitivity Analysis

Sensitivity analysis tests the robustness of the conclusions against uncertainties in the model assumptions. There are different types of sensitivity. Numerical sensitivity deals with the fact that changing assumptions would change the numerical values of the results. Behavior mode sensitivity refers to behavior pattern changes due to a change in the assumptions and finally Policy sensitivity appears when a change in assumptions reverse the effects of a suggested policy. The types of sensitivity in any project depend on the goal of the model. In case of business models, the goal is not to predict the sales or future profit but rather designing policies to aid the company become profitable. Therefore, behavior mode sensitivity and policy sensitivity are the most relevant. In the case of ISACO supply chain model, Univariate and Multivariate sensitivity analysis have been performed for the parameters of $Safety\ Stock\ Coverage$ in the retailer, distributor and manufacturer. This test indicates how sensitive the $Inventory$ stocks are for random changes in safety stocks. The results are shown in the Figure 34 down below with the following assumptions;

$$Retailer\ Safety\ Stock = (0{,}2) Random\ Uniform\ Distribution$$

$$Distributor\ Safety\ Stock = (2{,}3) Random\ Uniform\ Distribution$$

$$Manufacturer\ Safety\ Stock = (4{,}6) Random\ Uniform\ Distribution$$

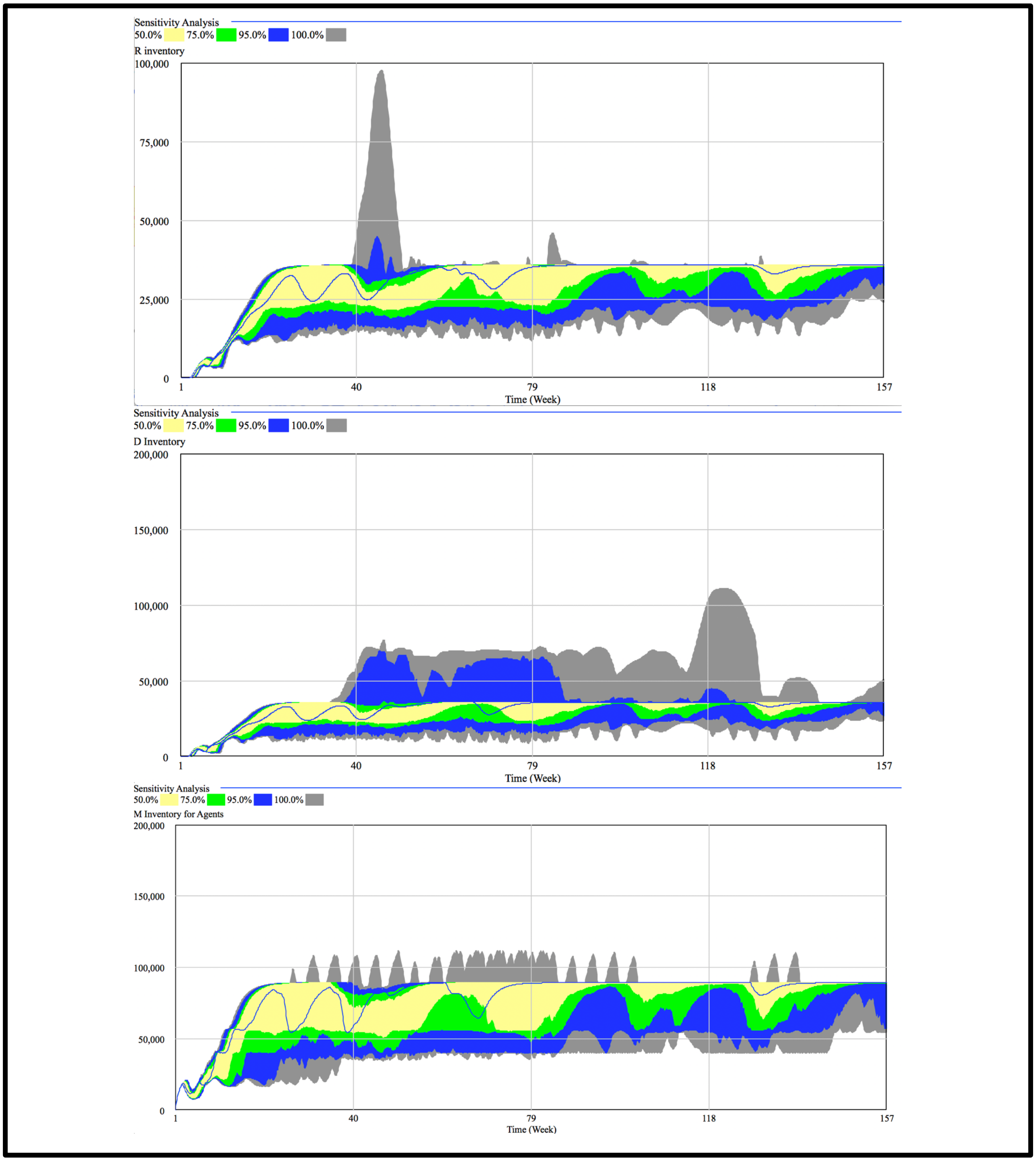

Figure 34, Results from sensitivity analysis

Fuzzy Logic Structure

The supply chain model uses the judgment of the decision makers for replenishment policies which is considered as a soft variable. There are two major phases in modeling a soft variable with fuzzy logic in the proposed simulation model. The first phase is to find relation between input and output which can be presented as a fuzzy inference system in MATLAB® and define fuzzy rules. The second phase is to transform the fuzzy inference system (FIS) into the form of a mathematical representation which can be implemented in the constructed simulation model in Vensim®.

- *Phase 1: Creating a fuzzy inference system (FIS) in MATLAB®*

This study benefits one of the most useful programming languages, MATLAB fuzzy logic toolbox, for crafting fuzzy inference system (FIS). Two inputs have been identified in this regard which are Inventory level and Incoming Demand (which after considering Forecasting and Desired Inventory coverage translates into Desired Inventory). These two inputs have been used for each echelon while the output is the decision on "Units Needed" or in other words, Received Orders from another echelon. Figure 35 illustrates the overall fuzzy inference system in MATLAB®.

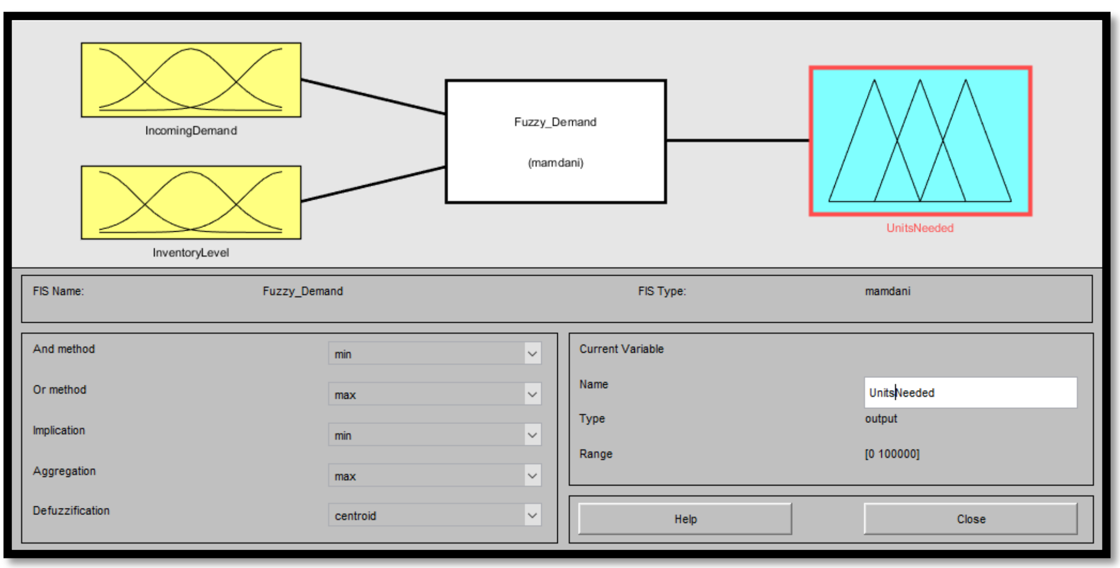

Figure 35, Fuzzy Inference System in MATLAB

The next step is to define membership functions for Inventory level, Incoming Demand and the Units Needed. Expert's opinions have been used in this regard for defining the fuzzy variables and their membership functions. A total number of five membership functions have been outlined for each input and output including: Extremely Low, Low, Average, High and Extremely High. Triangular and trapezoidal types of membership functions are employed for defining fuzzy variables. Figures 36, 37 and 38 shows the membership functions for the inputs/output.

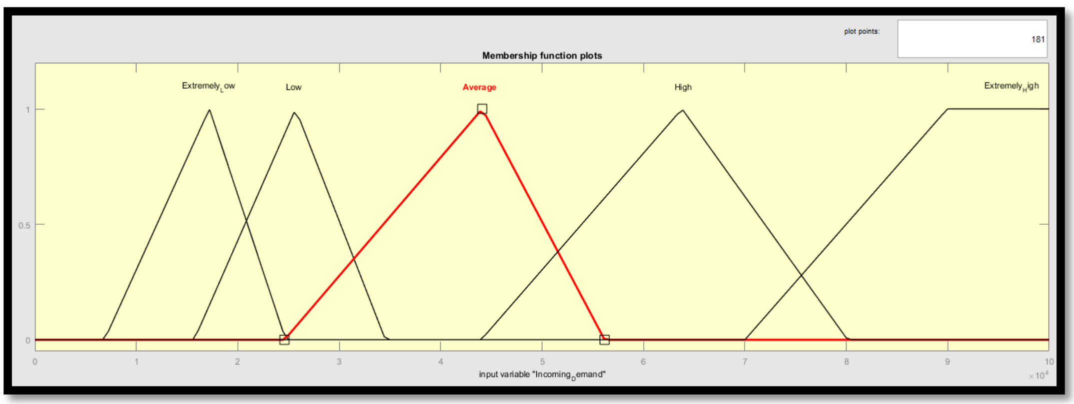

Figure 36, Membership Function for Incoming Demand (Input)

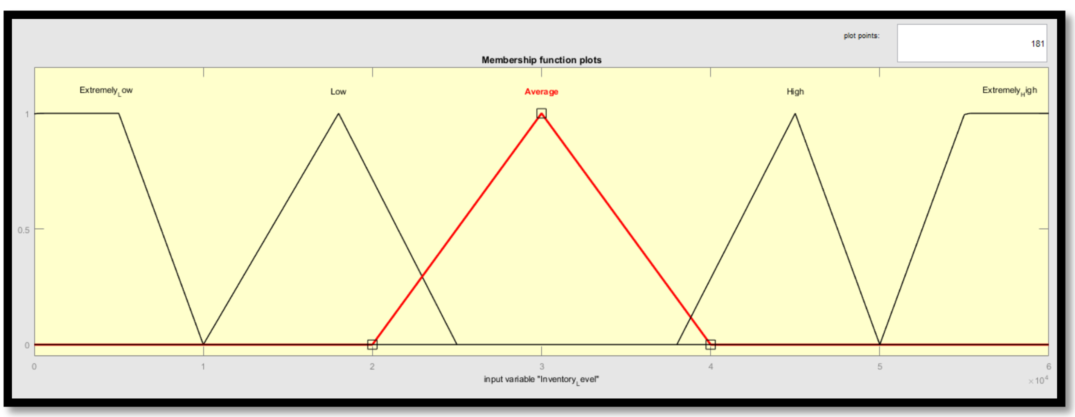

Figure 37, Membership Function for Inventory Level (Input)

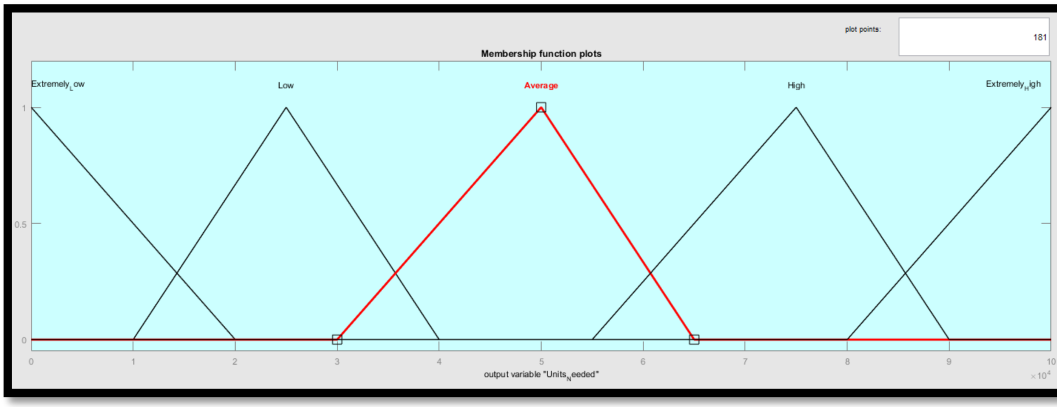

Figure 38, Membership Function for Units Needed (Output)

Once again, the membership functions and the degrees of membership are based on spare parts supply chain expert's opinions and hence, might be different from one business to another.

Next step is to define the fuzzy rules in a logical way. Twenty-five logical rules have been set via IF THEN commands consisting five membership functions for Inventory level and five membership functions for Incoming Demand (Desired Inventory). Figure 39 depicts the logical rules used in MATLAB® Rule-Editor.

1. If (Incoming_Demand is Extremely_Low) and (Inventory_Level is Extremely_Low) then (Units_Needed is Low) (1)
2. If (Incoming_Demand is Extremely_Low) and (Inventory_Level is Low) then (Units_Needed is Low) (1)
3. If (Incoming_Demand is Extremely_Low) and (Inventory_Level is Average) then (Units_Needed is Average) (1)
4. If (Incoming_Demand is Extremely_Low) and (Inventory_Level is High) then (Units_Needed is Low) (1)
5. If (Incoming_Demand is Extremely_Low) and (Inventory_Level is Extremely_High) then (Units_Needed is Extremely_Low) (1)
6. If (Incoming_Demand is Low) and (Inventory_Level is Extremely_Low) then (Units_Needed is Average) (1)
7. If (Incoming_Demand is Low) and (Inventory_Level is Low) then (Units_Needed is Low) (1)
8. If (Incoming_Demand is Low) and (Inventory_Level is Average) then (Units_Needed is Average) (1)
9. If (Incoming_Demand is Low) and (Inventory_Level is High) then (Units_Needed is Low) (1)
10. If (Incoming_Demand is Low) and (Inventory_Level is Extremely_High) then (Units_Needed is Extremely_Low) (1)
11. If (Incoming_Demand is Average) and (Inventory_Level is Extremely_Low) then (Units_Needed is High) (1)
12. If (Incoming_Demand is Average) and (Inventory_Level is Low) then (Units_Needed is Average) (1)
13. If (Incoming_Demand is Average) and (Inventory_Level is Average) then (Units_Needed is Extremely_Low) (1)
14. If (Incoming_Demand is Average) and (Inventory_Level is High) then (Units_Needed is Extremely_Low) (1)
15. If (Incoming_Demand is Average) and (Inventory_Level is Extremely_High) then (Units_Needed is Extremely_Low) (1)
16. If (Incoming_Demand is High) and (Inventory_Level is Extremely_Low) then (Units_Needed is Extremely_High) (1)
17. If (Incoming_Demand is High) and (Inventory_Level is Low) then (Units_Needed is Extremely_High) (1)
18. If (Incoming_Demand is High) and (Inventory_Level is Average) then (Units_Needed is High) (1)
19. If (Incoming_Demand is High) and (Inventory_Level is High) then (Units_Needed is Low) (1)
20. If (Incoming_Demand is High) and (Inventory_Level is Extremely_High) then (Units_Needed is Extremely_Low) (1)
21. If (Incoming_Demand is Extremely_High) and (Inventory_Level is Extremely_Low) then (Units_Needed is Extremely_High) (1)
22. If (Incoming_Demand is Extremely_High) and (Inventory_Level is Low) then (Units_Needed is Extremely_High) (1)
23. If (Incoming_Demand is Extremely_High) and (Inventory_Level is Average) then (Units_Needed is High) (1)
24. If (Incoming_Demand is Extremely_High) and (Inventory_Level is High) then (Units_Needed is High) (1)
25. If (Incoming_Demand is Extremely_High) and (Inventory_Level is Extremely_High) then (Units_Needed is Average) (1)

Figure 39, Logical Rules between Inputs and Output

And lastly, defuzzification process where the outcome of the fuzzy inference system (FIS) is generated in crisp values. The Surface illustration of fuzzy inference system with inputs/output value representations are demonstrated in the Figure 40. The Surface indicates the the crisp value for output for any given inputs.

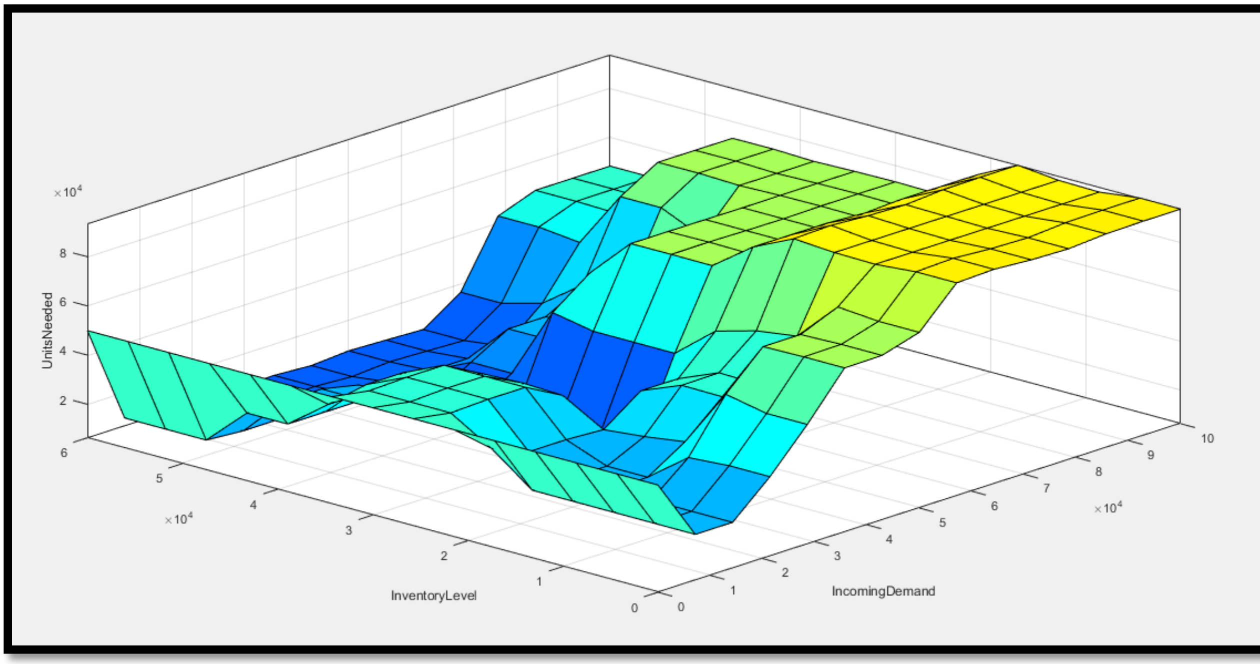

Figure 40, Surface illustration of fuzzy inference system

For better depiction of FIS based on different rules, “Rule-viewer” is used to show if any of the rules is fulfilled for each input. Since all membership functions have a degree of membership, at any given crisp input, some rules could be either partially or completely fulfilled. For instance, for the input $Incoming\ Demand = 5e + 04$, rules *11, 12, 13, 14* and *15* are almost 70% fulfilled while rules *16, 17, 18, 19* and *20* are about 30% fulfilled or for the input $Inventory\ Level = 3e + 04$, rules *3, 8, 13, 18* and *23* are fully fulfilled as it is shown in the Figure 41.

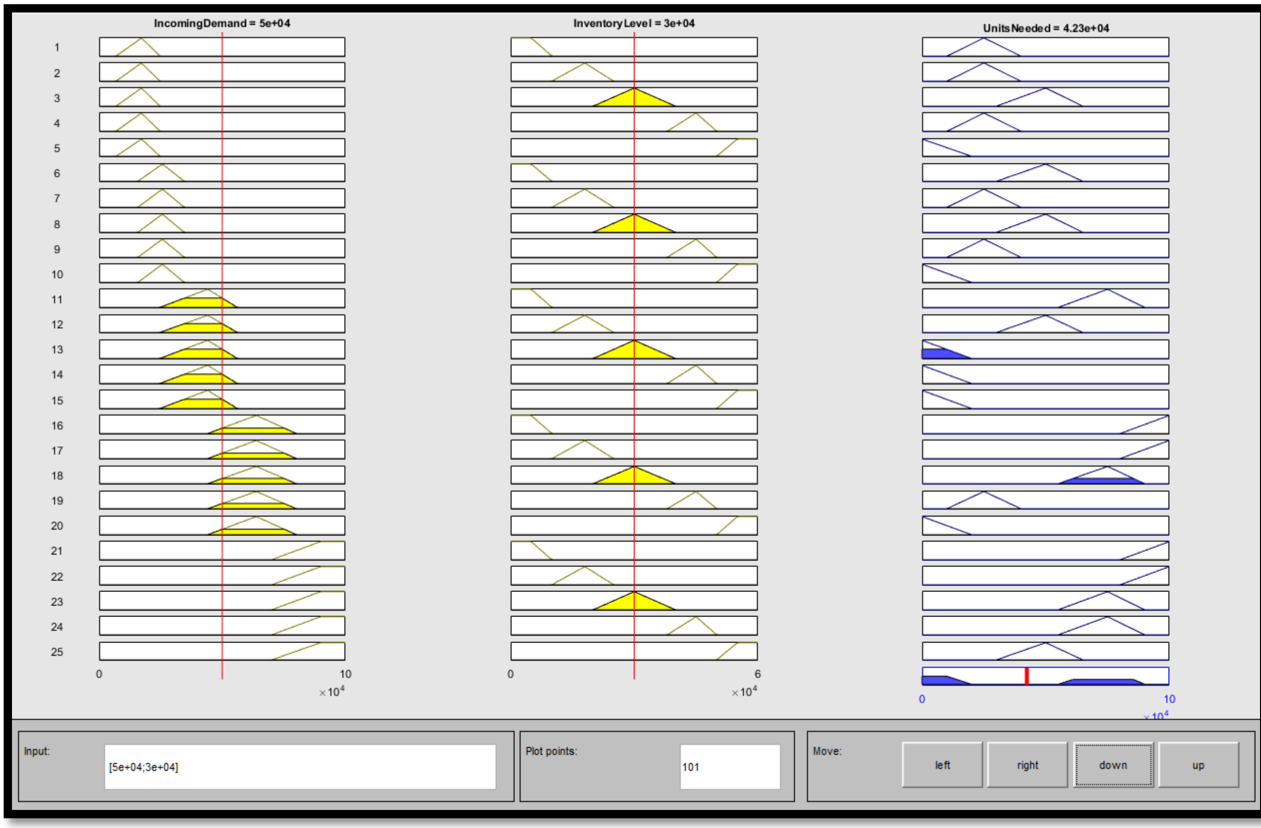

Figure 41, Rule-viewer and Fulfilled Rules for given values

- *Phase 2: Modelling the fuzzy inference system (FIS) in system dynamics model*

After an optimized fuzzy inference system is generated, the nest step is to transform this developed FIS into the form of mathematical representation that can be used in system dynamics model. As it is previously discussed in chapter 2, three main steps for fuzzy rule-based system process are Fuzzification, which maps the crisp input data vector to the vector of corresponding input linguistic variables; Fuzzy Inference, which a specific conclusion is derived from a set of fuzzy statements and lastly Defuzzification which maps the fuzzy variables to the crisp values (crisp output vector).

An extended process of transforming fuzzy inference system is adopted from Usenik & Turnsek (2013) which is portrayed in Figure 44 . The process begins with receiving the crisp input variable and fuzzification based on their membership functions, then applying antecedent conclusions for different scenarios. Every rule contributes one conclusion for each linguistic variable included in the consequent. To combine all of the conclusions for certain verbal values into one conclusion, the disjunction of the α values at which the verbal value has been cut is used. This process is called "Aggregation". As for defuzzification, there are many defuzzification methods which can give different results. However, the most frequently used methods are "Largest of the maximum", "Mean of the maximum", "First of the maximum", "Center of the maximum", "Height method" and "Center of gravity" (Ross, 2007). In this study, Height method is used due to simplicity and ease of use in system dynamics modeling which finally returns the crisp output value.

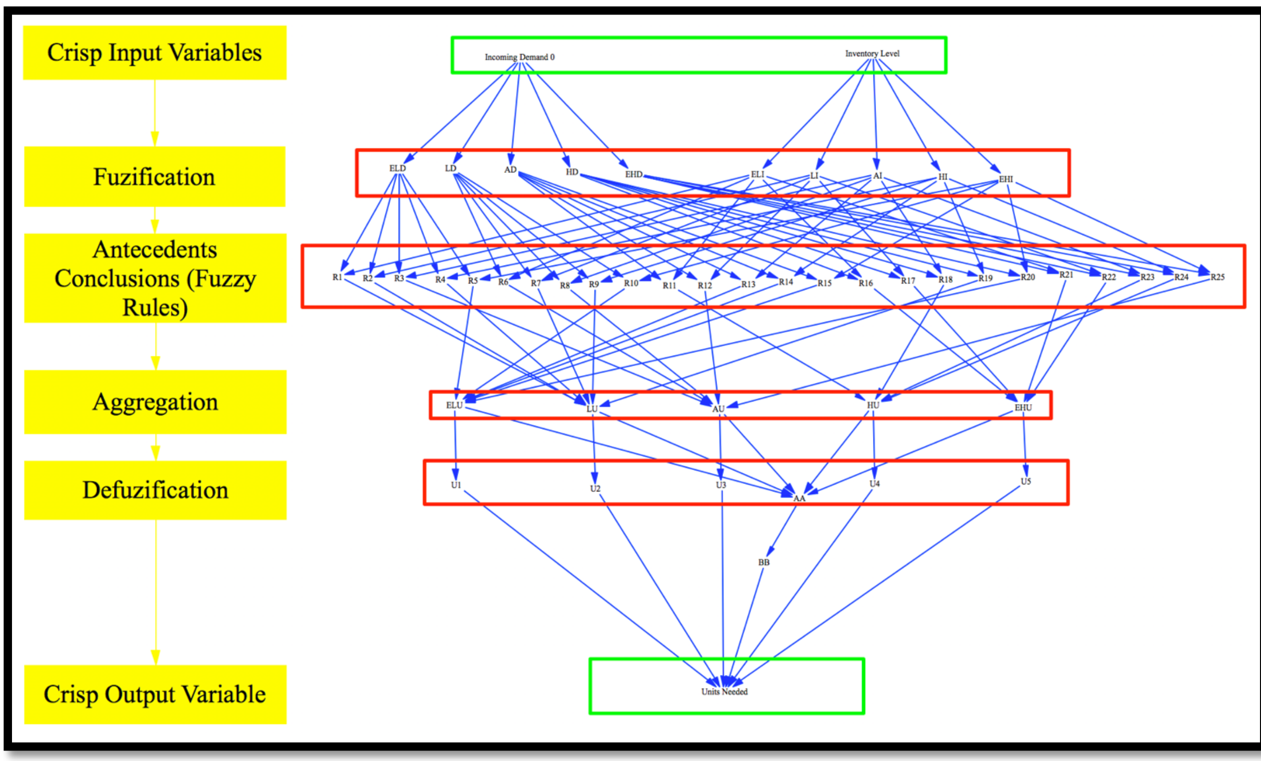

Figure 42, Fuzzy Inference System transformed into System Dynamics model

Variables ELD to EHD are abbreviations for "Extremely Low Demand" and "Extremely High Demand". Similar contractions apply for ELI to EHI as "Extremely Low Inventory" and "Extremely High Inventory". The formulation used in Fuzzification process attempts to mimic the fuzzy membership functions illustrated in Figures 36 and 37. For instance, to reproduce the Extremely Low Demand (ELD) membership function, the following formulation is used;

$$ELD = IF\ THEN\ ELSE(\ 10000 <= Incoming\ Demand\ 0 \colon AND \colon Incoming\ Demand\ 0 < 25000, 1\ , IF\ THEN\ ELSE(\ 25000 <= Incoming\ Demand\ 0 \colon AND \colon Incoming\ Demand\ 0 < 50000, (50000 - Incoming\ Demand\ 0)/(50000 - 25000), 0\ ))$$

Similarly, Extremely Low Inventory (ELI) is defined as:

$$ELI = IF\ THEN\ ELSE(Inventory\ Level < 25000, 1, IF\ THEN\ ELSE(25000 <= Inventory\ Level \colon AND \colon Inventory\ Level < 35000, (35000 - Inventory\ Level)/(35000 - 25000), 0))$$

R1 to R25 represent the fuzzy rules which employ MIN function for each fuzzy pair. Max function is used for Aggregation of all the conclusions for certain values into one conclusion, as for example ELU (Extremely Low Unit):

$$ELU = MAX(\ MAX(\ R5\ , R10\ )\ , MAX(\ R13\ , MAX(\ R14\ , MAX(\ R15\ , R20\ )\ )\ )\ )$$

Finally, Defuzzification based on Height Method returns the crisp value for “Units Needed” as in the case of U1;

$$U1 = IF\ THEN\ ELSE(\ 0 < ELU\ , ELU * C1\ , 0\ )$$

and so;

$$Units\ Needed = (U1 + U2 + U3 + U4 + U5)/BB$$

The fuzzy structure has been incorporated with rest of the supply chain model and gets initiated via a Switch variable in order to observe the effect of fuzzy re-ordering policy on the bullwhip effect and compare it with business as usual. Next chapter will analyze the bullwhip effect and the fuzzy policy design in depth.

Chapter Five: Model Results and Analysis

This chapter presents the results of model simulation under two different scenarios. Firstly, the model is run in equilibrium where the incoming demand is constant. This scenario is meant to assess the model performance in its calibrated settings and also to investigate the model response to single exogenous shock input. The second scenario involves analysis of the model behavior with fuzzy decision policy and how the possible bullwhip effect can be modified with the use of fuzzy logic.

The Bullwhip Effect Analysis

In order to identify where bullwhip effect occurs in the supply chain system due to demand input signal distortion, the model must be initialized in equilibrium. This type of test is necessary to expose the model to a shock input and analyze the bullwhip effect.

Model testing is process of controlled investigation. Therefore, it is crucial to initialize the model in "balance" equilibrium for a crystal clear observation. Equilibrium implies that all stocks in the model are unchanging which requires all net flows in the system to be zero. A balanced equilibrium refers to a situation where all the stocks in the system are equal to their desired values (Sterman, 2000). Moreover, a proper shock input to the system should stress the model to produce the effect of interest, allowing to detect the bullwhip effect.

The supply chain model is initiated with a constant Incoming Demand of 1000 units per week and the following modifications have been executed to the model for balanced equilibrium.

a. <u>Initial values of the stocks</u>

$$Intitial\ value(Retailer\ Backlog\ for\ Orders) = RetailerDesired\ Inventory$$

$$Initial\ value\ (Retailer\ Inventory) = Retailer\ Desired\ Inventory$$

$$Initial\ value\ (Retailer\ Forecast) = Retailer\ Order\ Rate$$

$$Initial\ value\ (Distributor\ Inventory) = Distributor\ Desired\ Inventory$$

$$\begin{aligned} &Initial\ value\ (Distributor\ Backlog\ for\ Orders) \\ &\qquad = Distributor\ Order\ Rate * Distributor\ Target\ Delivery\ Delay \end{aligned}$$

$$Initial\ value\ (Distributor\ Forecast) = Distributor\ Order\ Rate$$

$$Initial\ value\ (Distributor\ Units\ in\ Transit) = Distributor\ Desired\ Incoming\ Units$$

$Initial\ value\ (Manufacturer\ Inventory\ for\ Assembly\ Line)$
$= Manufacturer\ Desired\ Assembly\ Line\ Inventory$

$Initial\ value\ (Manufacturer\ Inventory\ for\ Agents) = Manufacturer\ Desired\ Inventory$

$Initial\ value\ (Manufacturer\ Backlog\ from\ Assembly\ Line\ Orders)$
$= Manufacturer\ Assembly\ Line\ Order\ Rate$
$* Manufacturer\ Assembly\ Line\ Target\ Delivery\ Delay$

$Initial\ value\ (Manufacturer\ Backlog\ from\ Agents\ Orders)$
$= Manufacturer\ Order\ Rate\ from\ Agents * Manufactruer\ Target\ Delivery\ Delay$

$Initial\ value(Manufacturer\ Forecast) = Manufacturer\ Order\ Rate\ from\ Agents$

$Initial\ value(Material\ Forecast) = Material\ Usage\ Rate$

$Initial\ value(Manufacturer\ Work\ in\ Process\ Inventory) = Manufacturer\ Desired\ WIP$

$Initial\ value(Material\ Inventory) = Desired\ Material\ Inventory$

b. Modified Equations

$Units\ Needed\ from\ the\ Distributor = Max(0, Retailer\ Adjustment\ from\ Inventory + Retailer\ Forecast)$

$Distributor\ Desired\ Replenishment\ Rate$
$= Max(0, Distributor\ Adjustment\ from\ Inventory + Distributor\ Forecast)$

$Units\ Needed\ from\ Manufacturer$
$= Max(0, Distributor\ Adjustment\ from\ inTransit\ Units + Desired\ Replenishment\ Rate)$

$Desired\ Assembly\ Line\ Production$
$= Max(0, Adjustment\ from\ Assembly\ Line\ Inventory$
$+ Maximum\ Assembly\ Line\ Shipment\ Rate)$

$Manufacturer\ Desired\ Production$
$= Max(0, Manufacturer\ Adjustment\ for\ Agents\ Inventory$
$+ Manufacturer\ Forecast\ for\ Agents)$

$Manufacturer\ Desired\ Production\ Start\ Rate$
$= Max(0, Manufacturer\ Adjustment\ for\ WIP + Desired\ Assembly\ Line\ Production$
$+ Desired\ Agents\ Production)$

$Desired\ Material\ Delivery\ Rate$
$= Max(0, Adjustment\ for\ Material\ Inventory + Desired\ Material\ Usage\ Rate)$

The model behavior for balanced equilibrium with constant $Incoming\ Demand = 1000$, indicates unchanged stock variables which shown in the Figure 43. The stock values keep the same as the initial values throughout the simulation time period.

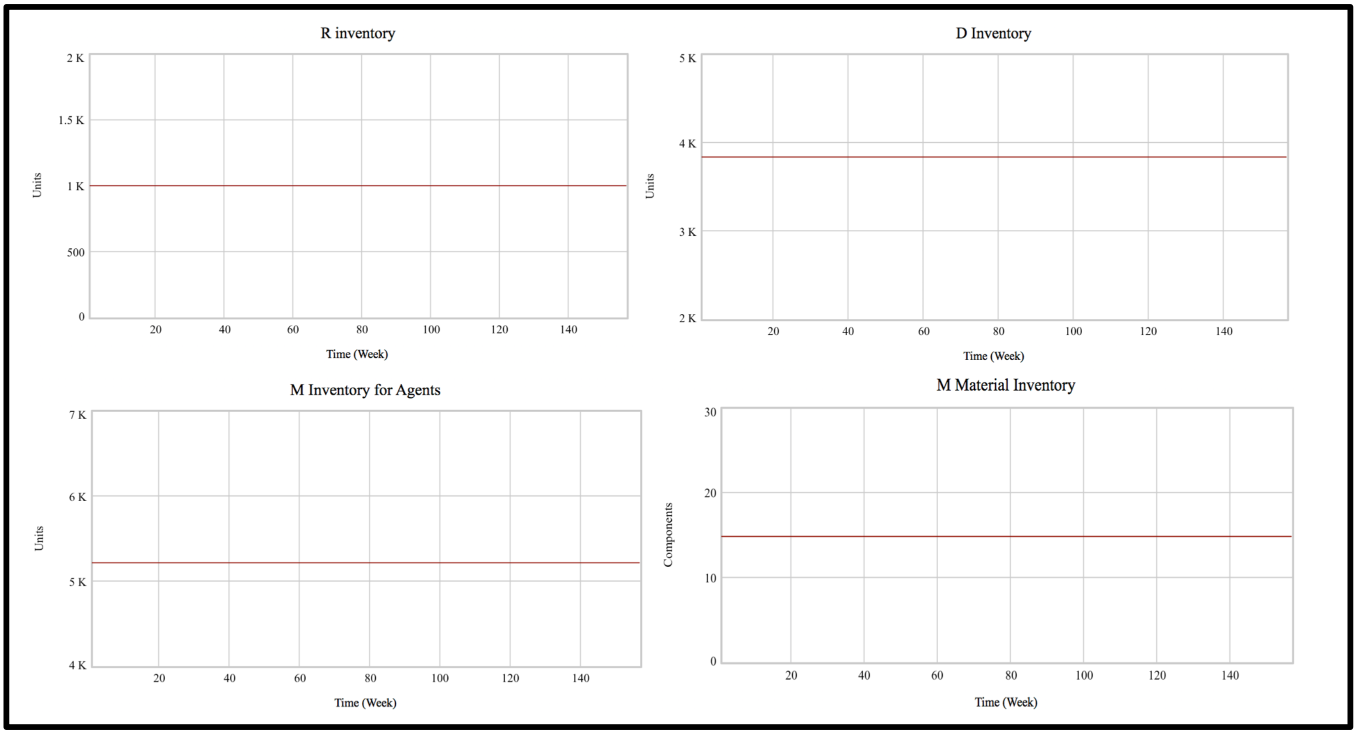

Figure 43, Model Response in Balanced Equilibrium

In the next test, STEP function is used to impose a shock to the system. A sudden increase of 20% to the Incoming Demand in week 40 forces the stable supply chain system to respond. As the step input travels upstream in the model, the response of the model gets amplified. Figures 44 and 45 demonstrate the step in Incoming Demand and inventory level at each echelon as well as the material inventory when facing a 20% increase in demand in the week 40. So;

$$Incoming\ Demand = 1000 + STEP(200, 40)$$

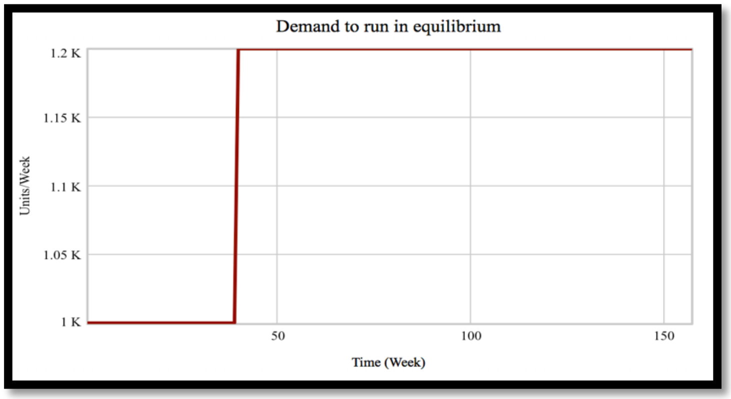

Figure 44, 20% step increase in Demand

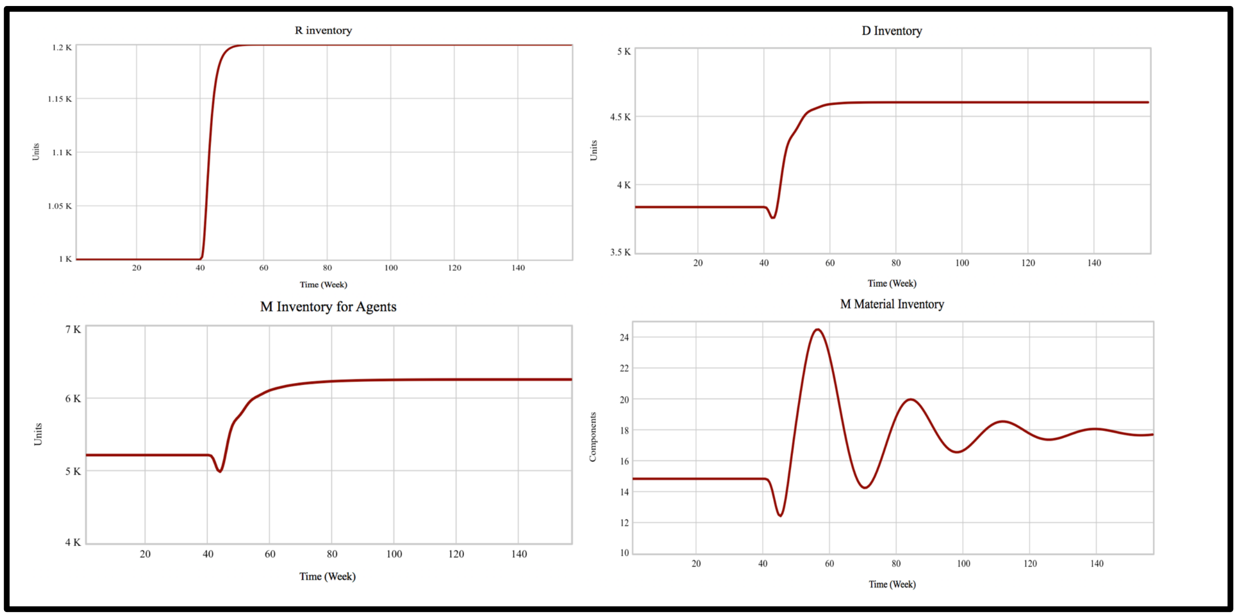

Figure 45, The model response to 20% pulse in Demand

Thus far, the Incoming Orders for Assembly Line is considered constant and zero. The next analysis involves taking the demand for assembly line into consideration. The results for 20% increase in Incoming Demand to the supply chain and 20% increase in Incoming Orders for Assembly Line are shown in the Figures 46 and 47. The formulations for two demands are as;

$$Incoming\ Demand = 1000 + STEP(200, 40)$$

$$Incoming\ Orders\ from\ Assembly\ Line = 100 + STEP(20, 100)$$

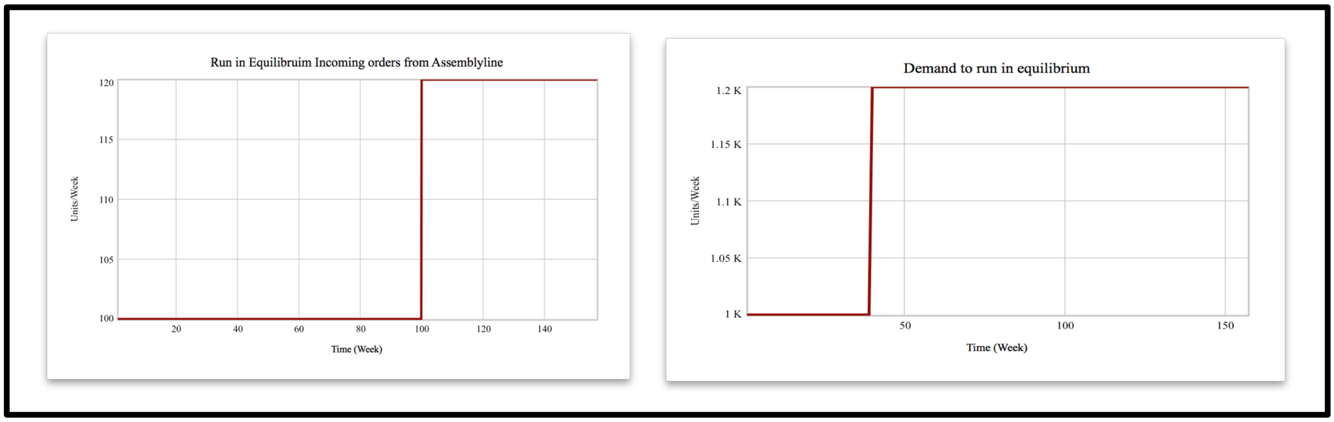

Figure 46, 20% increase in Incoming Demand & Incoming Assembly Line Orders

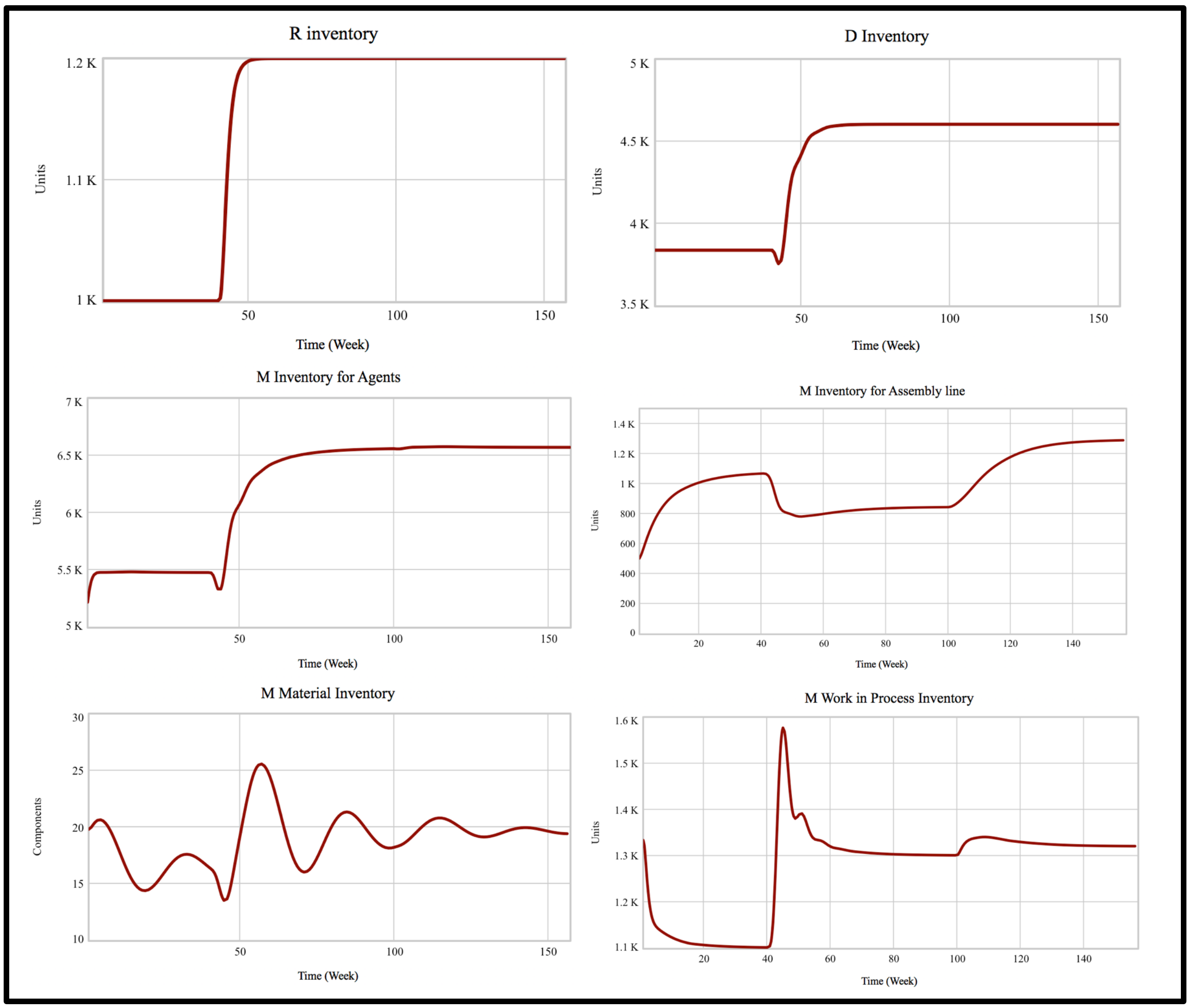

Figure 47, Model Response to 20% increase in Incoming Demand & Incoming Orders from Assembly Line

As it is clearly evident in the Figure 47, adding another step input into the system makes the model oscillate severer and hence the bullwhip effect in Material Inventory becomes more intense.

Furthermore, the impact of demand amplifications in Production Rate is noticeable. The amplification in Production Rate for Agent Orders is much greater as a result of fewer disparities in its input signal and substantial production inconsistency due to delayed scheduling initiated by lower priority of production for agents (Distributors). The comparison in between Production Rates for Assembly Line Orders and Agent Orders are depicted in the Figure 48.

Figure 48, Impact of Demand Amplifications on Production Rates

Moreover, Production Start Rate is magnified for the Production for Agents and dampened for Assembly Line Production due to lower priority of Production for Agents.

The most distinctive source of the bullwhip effect can be traced to material planning; featuring the largest amplifications in the supply chain. This is due to significant delays in financial constraints and supplier actions (Materials Forecast).

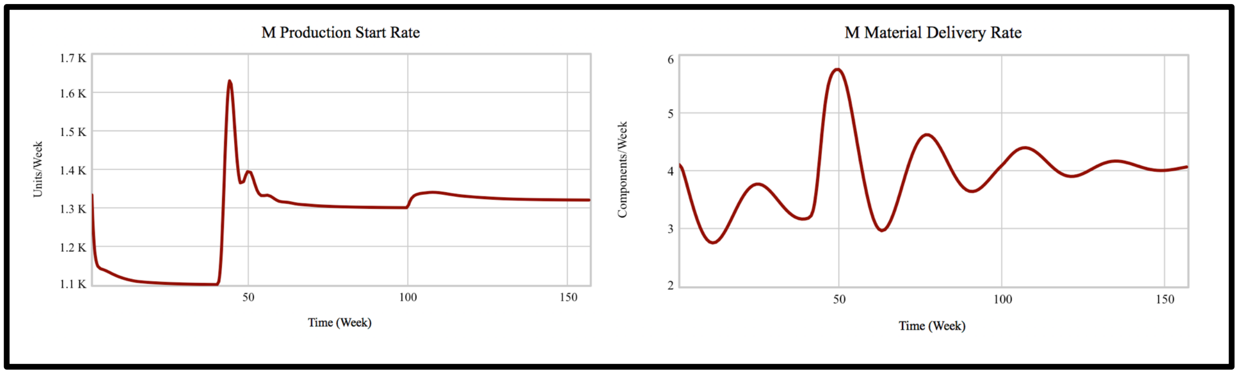

Figure 49, Impact of Demand Amplification on Production Start Rate & Material Delivery Rate

The focus of this study has been mainly on the Manufacturing echelon as well as supplier's behavior. The analysis and results indicates the existence of the bullwhip effect within the studied supply chain. Taking actual data into consideration, the results for major stocks and flows reaffirm the demand amplification throughout the ISACO supply chain. The observed model behavior for historical data Incoming Demand are illustrated in the Figures below.

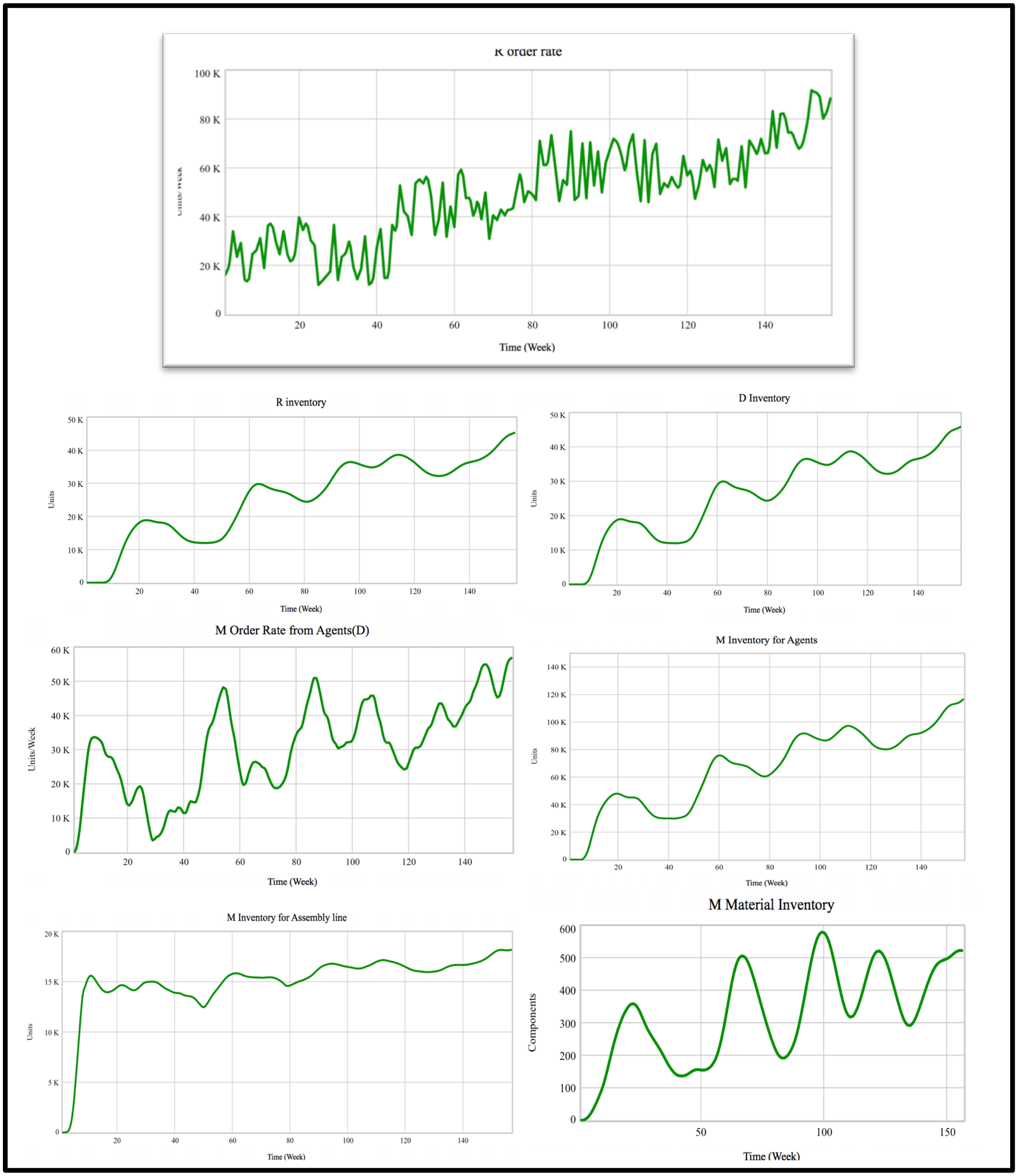

Figure 50, Model Response to Historical Demand Input

The reported bullwhip effect can be attributed to demand signal processing and non-zero lead time which previously called Forrester effect. Distortion in demand information has widely spread out throughout the supply chain which is used for decision making. In addition to that, forecasting has been the major tool for scheduling and inventory management in this model which is typically based on historical data from immediate customers. However, the demand sent by retailer to distributor indicates the amount of inventory replenishment from the retailer for future demand plus the desired safety stock. Therefore, the fluctuations in distributor's demand becomes greater than the retailer's demand. Subsequently, demand amplification grows over the entire supply chain. Furthermore, lengthy lead time worsen the situation due to the fact that, the longer the lead time, the higher the safety stock needed for replenishment and the greater the variations. These are the major causes of the described bullwhip effect in the system which are in line with the study by Lee et al. (1997) for the origin of the bullwhip effect.

To test out the causes of the bullwhip effect, first, the model is run with a 25 percent increase in Minimum Lead Times and then with a 25 percent increase in the safety stock. The results confirm the hypothesis that lengthy lead times and safety stock coverage worsen the demand amplification.

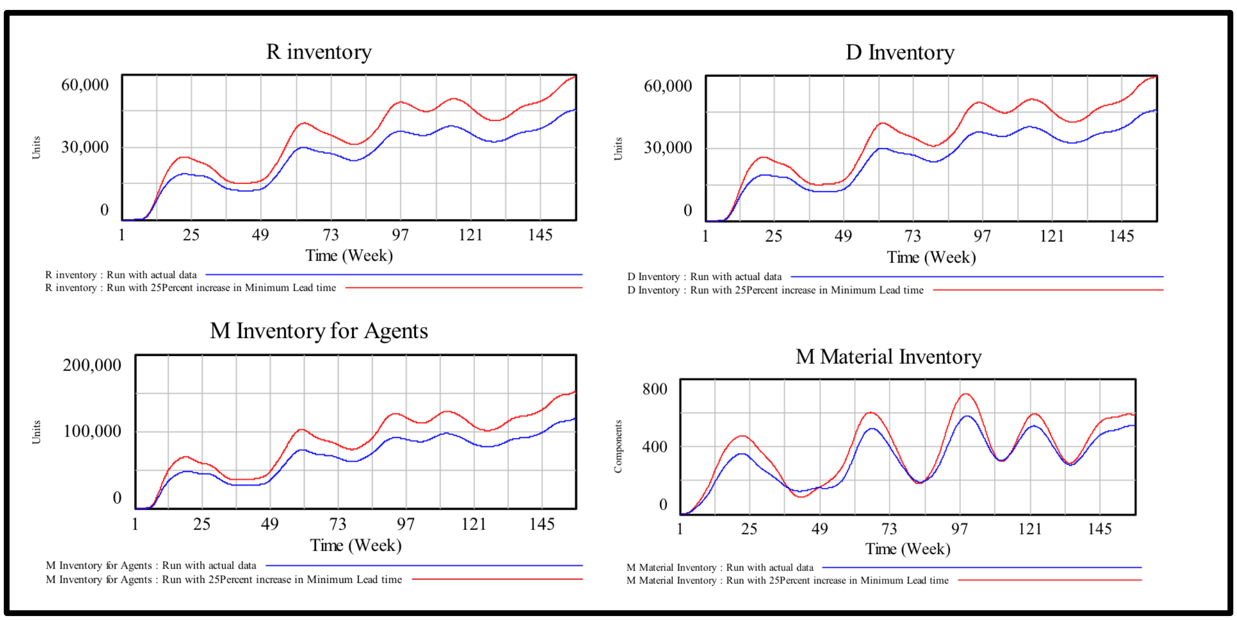

Figure 51, Results for 25% increase in Minimum Lead time

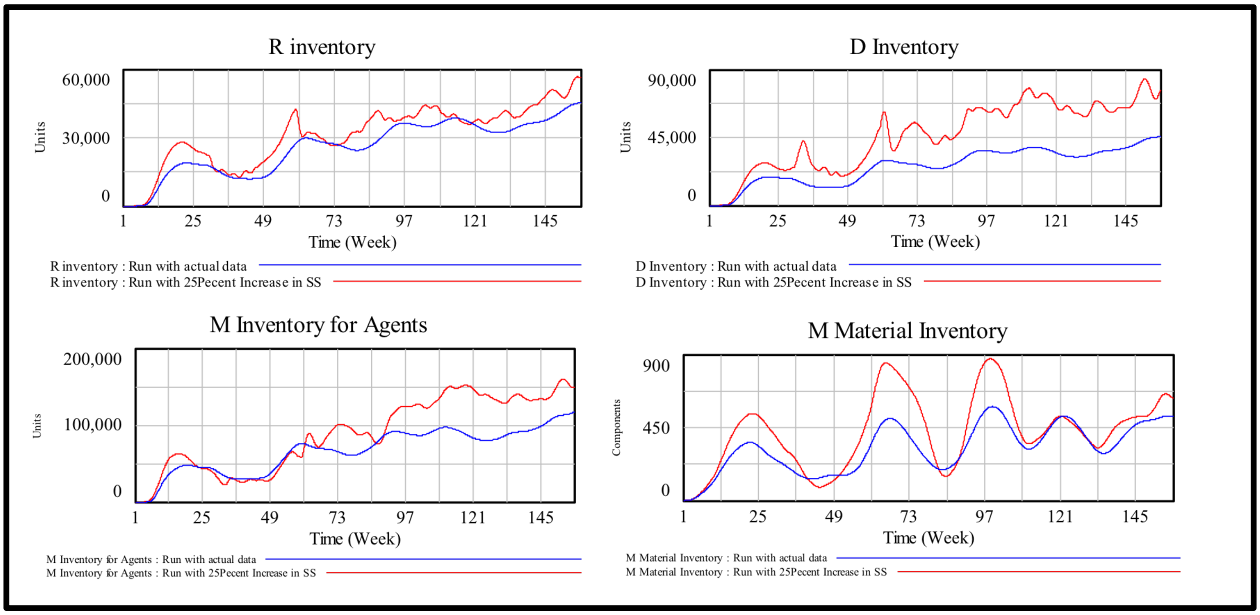

Figure 52, Results for 25% increase in Safety Stock

Supply Chain Bullwhip Effect under Fuzzy Logic Decision Making

In this section, the implemented fuzzy logic will be tested in order to observe the impact of fuzzy decision making policy on the overall supply chain system and particularly the bullwhip effect. Firstly, inputs for the fuzzy system at each echelon are the Inventory level and the Desired Inventory which performs as forecasted Incoming Demand plus the Desired Inventory Coverage. Therefore, the fuzzy policy does not replace any equations in the model and only operates as an alternative to the process of replenishment policy. The results of the fuzzy structure for major Inventory stocks are illustrated in the Figures below.

As it is clear in the model behavior, the fuzzy policy significantly reduces the noise in the behavior of the stocks. This is due to the fact that demand signal processing with fuzzy logic is categorized into a membership function with a degree of membership. This, along with the current level of inventory and its membership function, defines a logical rule to make decisions on the number of needed units from the upstream in the supply chain.

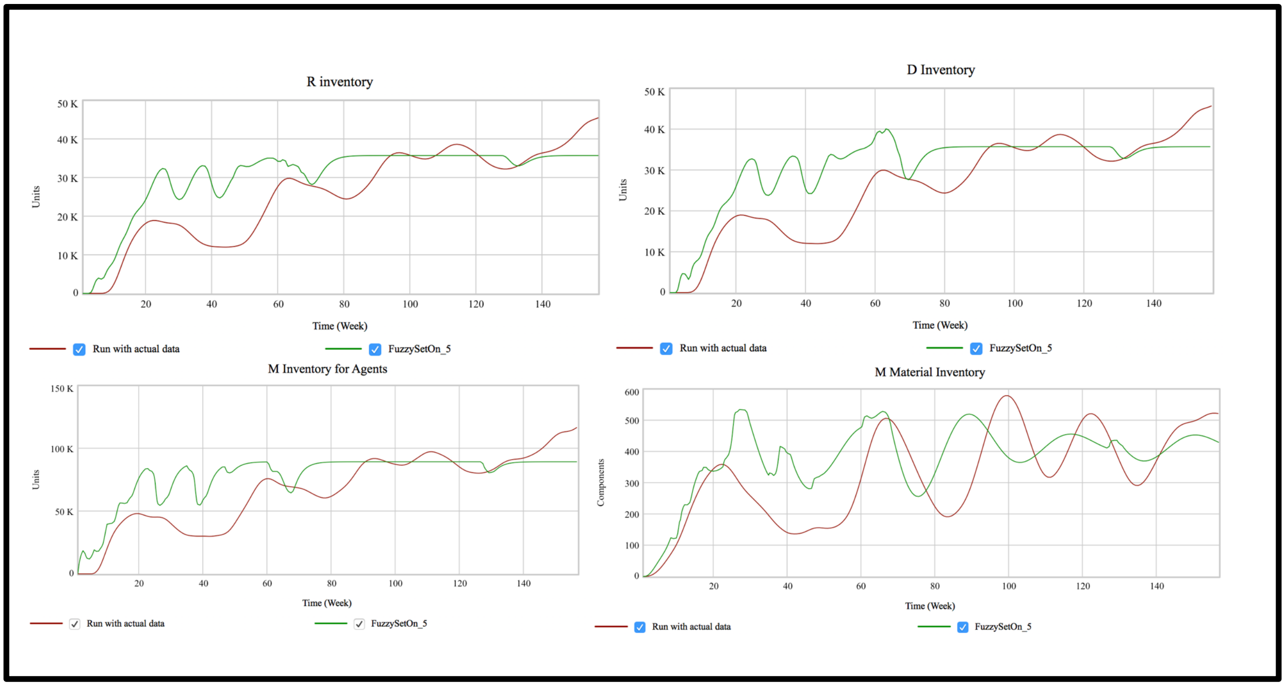

Figure 53, Major Inventory levels with & without Fuzzy Decision Policy

However, the downside of operating the model with fuzzy logic is the irrationality in performance of some of the variables. For instance, running the simulation model with fuzzy logic produces fierce distress in the behavior of Manufacturer Production Plan and consequently the Desired Material Inventory. This is due to the fuzzy decision making process which base judgment on the availability of products and the size of demand via a logical *If-Then* function. The fuzzy decisions occur locally and only consider two elements with respective membership functions which are not fully optimized and hence the needed units work as "pulses" signals to the upstream in supply chain. Therefore, the production plan experiences severe fluctuations in the beginning and as the inventory level stabilizes, production plan also alleviates.

In order to correct the undesirable behavior of production plan, using an Adaptive Network-based Fuzzy Inference System (ANFIS) learning algorithm is recommended, where the degree of memberships for each parameter is optimized to serve the purpose of the model. ANFIS can significantly escalate the accuracy of soft variables in system dynamics modeling. Figure 54 illustrates the behavior of Production Plan and Desired Material Inventory.

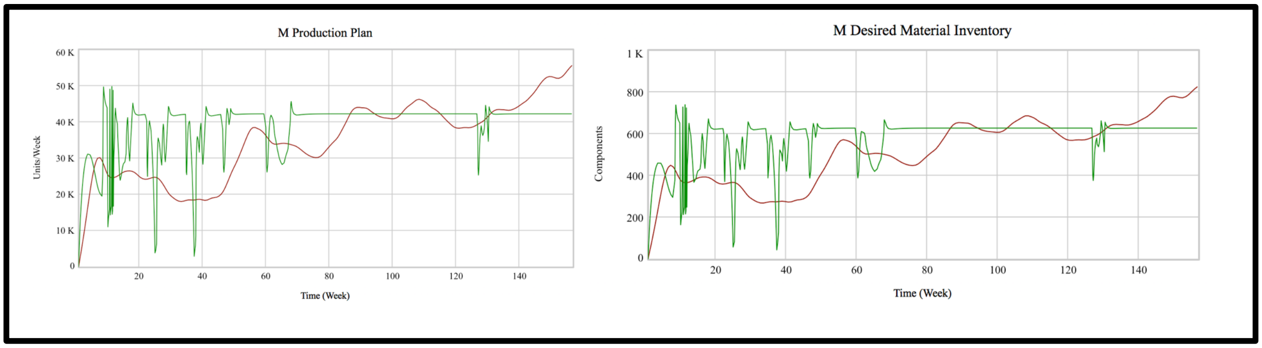

Figure 54, Simulation Behavior for Production Plan & Desired Material Inventory

Chapter Six: Conclusions

The bullwhip effect has been in the center of attentions in the supply chain studies for more than fifty years. The reason for such devotion to this topic is the fact that such undesirable effect is prevalent and capable of taking away up to 50% of profits (McCullen & Towill, 2002).

This thesis presented a case study simulation model for spare part supply chain company in Iran. The purpose of this study was to illustrate the existing bullwhip effect and possible solutions to mitigate the effect with the use of fuzzy logic decision making.

Although the theory around bullwhip effect has been well-developed in the literature and the body of knowledge is quite solid for both origin of the issue and the impacts on other levels in supply chain; the gap between theory and practice is still considerably wide. Moreover, the lack of a universal approach in dealing with such effect in different supply chain contexts is noticeable. Current literature is mainly focused on the bullwhip effect existence and analysis methods are based on typical principles that owe their success more to the expert's capability than to a systematic and organized approach to resolve the issue (Rene, 2011). Therefore, a customizable approach is necessary whenever the source of the bullwhip effect is vague and blurry. In addition, when modeling supply chain systems, in plenty of situations, information processing and decision making are required to deal with 'soft' variables. Even though system dynamics approach is well-recognized to be able to work with such variables via table functions, the accuracy and usability of these tools are up for debate. Furthermore, human judgment in the process of decision making cannot be exactly captured by simulation models; chiefly because human behavior follows fuzzy rules when tackling an issue and not necessarily process in a black-and-white type of judgment.

This research focused on developing a generic model based on system dynamics approach and fuzzy logic. The model structure was customized to suit the case study in hand and exemplify the bullwhip effect in a single-product, multi-stage supply chain system. The procedures and outcomes of this study are as follows:

1. *Developing a simulation model based on system dynamics approach for analyzing the bullwhip*

In order to analyze the bullwhip effect, a generic model based on system dynamics approach was constructed to identify the effect in a single-product, multi-stage supply chain system. The simulation structure was grounded on the Forrester's industrial dynamics model which is further customized for Iran Khodro Spare Parts and After-Sale Services (ISACO) company for the line of Oxygen Sensors in Peugeot automobiles. The proposed model consists of variable influencing the bullwhip effect including the forecasting method using exponential smoothing based on historical data, non-zero lead times, replenishment policy on safety stock coverage, information and material delays.

2. *Calibration and validation of the structure to increase the confidence and effectiveness of the simulation model.*

The manual model calibration was performed by setting the calibration reference variable, identifying the known variables with their estimated values and identifying the parameters to be calibrated. After running the simulation model for several times, the reference variable (Manufacturer Inventory) produced a decent fit to the actual pattern.

Moreover, validation tests including boundary adequacy, structure assessment, dimensional consistency, extreme condition tests and sensitivity analysis have been conducted to reassure the robustness of the model.

3. *Developing a fuzzy logic decision procedure to reduce the bullwhip effect in the proposed simulation model*

This study proposed a procedure to dampen the Forrester's effect by replacing the inventory replenishment decision making with fuzzy logic. Two main phases were designated in constructing the fuzzy decision policy. In phase one, the inputs and output of the fuzzy were identified. A fuzzy inference system (FIS) was created in MATLAB® fuzzy logic toolbox to apply the fuzzy rules on the inputs, output and their membership function. In the second phase, the constructed fuzzy model was transformed into the main system dynamics model in Vensim® to work with the supply chain model.

Research Contributions

The contributing value of this research are as follows;

- *Identifying the causes of the bullwhip effect*

In order to understand the causes of bullwhip effect in the supply chain simulation system, the behavior of the model was tested when exposed to shock inputs of 20% increase in Incoming Demand and 20% increase in Incoming Orders for Assembly Line. The results indicated that demand signal processing is one the main causes of the bullwhip effect in the system. This means that a slight change in demand sends incorrect signals to the next echelon which creates an illusion of higher orders which in turn triggers another over-order to shield against stock-out situation. Distortion in demand information then spread out throughout the supply chain and made an oscillatory behavior in major inventories. It is important to note that time delays in the form of financial constraints in supplier's material planning and poor forecasting mechanism in each level have been identified to be contributing to the bullwhip effect in the case study simulation model.

Moreover, non-zero lead time was found to be another causes of the bullwhip effect. The longer the lead time, the higher safety stock needed for replenishment and therefore the greater signal variations. The experimental model was tested with 25% increase in Minimum Lead times and also 25% increase in the Safety Stock Coverage. The results reaffirmed the hypothesis in which lengthy lead time and safety stock coverage would increase demand amplification.

Furthermore, price fluctuations, rationing and shortage gaming seem to have adverse effect on the bullwhip effect in supply chain, however, such financial impacts were out of the scope of this study and therefore have not been examined.

- *Effective and implementable use of fuzzy logic in system dynamics realm*

System dynamics depends heavily upon quantitative data to produce feedback models. Qualitative data and their analysis also play a key role in modeling process at various levels. Although the classical literature on system dynamics solidly support this argument, the procedures to integrate this information during the modeling process are not specified by most influential authors. Techniques for data collection such as interviews and focus groups, and techniques in qualitative data analysis such as grounded theory methodology and ethnographic decision models could have a strong, critical role in system dynamics methods. Additionally, in most cases, mathematical representations of problems and policy alternatives are not dependent upon numerical information, but qualitative data. For instance, Forrester (1994) suggests that the information sources for model building process can be qualitative data that exist in the mental database or actor's mind and can be in the form of written text. Furthermore, the author recognized the mental database as the most important source for modelers; both in terms of quantity and significance. However, the lack of an integrated procedures to obtain and analyze qualitative data creates a gap between the actual problem and the constructed model. This gap is more obvious when modeling involves the use of 'soft' variables, for example variables such as "customer satisfaction" or "perceived quality" which quantification and formulation of them are relatively challenging (Luna-Reyes & Andersen, 2003). Besides, in some cases the uncertainty associated with this quantification has made the professionals to assume that the results arising from simulations could be misleading or fragile (Coyle, 2000). As Sterman (2000) pointed out, individual's mental model is fuzzy, incomplete, vaguely defined and time dependent. Hence, each individual understands specific content differently and adapts the model in a different way.

By using fuzzy logic with clearly-stated verbal rules, all the hypotheses and decision-policies can be externalized. After all, natural language is one of the most formidable ways of transferring knowledge and information that human have regarding the problems and situations involving reasoning and decisions. The benefit of using fuzzy logic over other approaches to support decision making is that the language is flexible, simple and easy enough to understand (Salles, Neto, & Marujo, 2016).

This research employed fuzzy logic for the process of decision making in system dynamics environment. The ease of implementation and usability of the constructed model is one the main contributions of this thesis.

- *Mitigating the bullwhip effect in supply chain system*

It is known that the Forrester effect is one of the indicators of inefficient supply chain management. Forrester (1961) attested that this effect is the result of industrial dynamics and suggested a methodology for simulation of dynamic models. Generally speaking, the objective of system dynamics is to identify the structural cause of a system behavior. Demand signal processing, non-zero lead time, order lot sizing, product price fluctuation, rationing and forecasting are considered as major causes of the bullwhip effect. In this case study, the sources of bullwhip effect in manufacturing echelon is traced to input signal processing, poor forecasting, large batch sizes in pushed-based production and long lead times from the suppliers that consequently result in enlarged batch orders. Moreover, demand forecasting used in supply chain and production planning is considered fuzzy in nature due to its incompleteness and sometimes unattainability of the data which can be only acquired subjectively (Chen & Chang, 2006). In actual decision making process, market demands are normally ambiguous over the scope of planning. Thus, allocating a set of crisp values for such vague variables is not suitable (Torabi & Hassani, 2008).

In this research, the demand forecast was replaced with a fuzzy inference system to handle this naturally ambiguous phenomenon. The crisp values from the incoming demand forecasts along with the level of inventory were obtained and replaced with fuzzy numbers. A generic single-item, multi-echelon, multi-period supply chain was proposed to host the fuzzy inference implementation. The results showed an overall improvement in mitigating the bullwhip effect across the supply chain. The process of decision making based on fuzzy logic rules rationalize the demand signal processing by taking current inventory and incoming demand into consideration and hence enhancing the supply chain performance.

This research illustrated the usefulness and importance of fuzzy estimations based on expert's linguistically and logically defined parameters instead of relying merely on the traditional demand forecasting based on time series. Despite the increased complexity of the calculations and structure of the fuzzy model, the bullwhip effect has been considerably reduced.

Recommendation for further work

This research proposed a methodology for using fuzzy inference system in supply chain models to mitigate the bullwhip effect. At the core of the fuzzy inference system (FIS), expert's opinions have been adapted to define the fuzzy rules. Such contribution from professionals in the supply chain has several benefits but the downside is that the constructed model is only appropriate for a particular supply chain and sometimes just for a specific echelon in the supply chain. Therefore, future research work should focus on defining universal membership functions based on Adaptive Network-based Fuzzy Inference System (ANFIS) learning algorithm where the degree of memberships for each parameter is optimized to serve the purpose of the model. ANFIS can significantly escalate the accuracy of soft variables in system dynamics modeling.

Furthermore, the financial aspects of demand amplifications and specifically the bullwhip effect existence costs have not been focused on this research. It is assumed that demand variations increases the operational cost for the manufacturer due to excess setup of production line, idle time and labor recruitment or lay offs (Wang & Disney, 2015). Future research should consider the impact of bullwhip effect on the production cost and analyses of the proposed fuzzy logic decision policy from an economical point of view.

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Appendix: Model Equations

AA=AU+EHU+ELU+HU+LU
Units: Units

AD=IF THEN ELSE(70000<=Incoming Demand 0:AND:Incoming Demand 0<95000, (Incoming Demand 0-70000)/(95000-70000), IF THEN ELSE(95000<=Incoming Demand 0:AND:Incoming Demand 0 <120000, (120000-Incoming Demand 0)/(120000-95000), 0))
Units: Units

AI=IF THEN ELSE(35000<=Inventory Level:AND:Inventory Level<45000, (Inventory Level-35000)/(45000-35000), IF THEN ELSE(45000<=Inventory Level:AND:Inventory Level<60000, (60000-Inventory Level)/(60000-45000), 0))
Units: Units

AU=MAX(R3 , MAX(R6 , MAX(R8 , MAX(R12 , R25))))
Units: Units

BB=(IF THEN ELSE(AA>0 , AA , 1))/unitcon
Units: Dmnl

C1=10000
Units: Dmnl

C2=23620
Units: Dmnl

C3=22500
Units: Dmnl

C4=75000
Units: Dmnl

C5=90000
Units: Dmnl

D AA=D AU+D EHU+D ELU+D HU+D LU
Units: Units

D AD=IF THEN ELSE(50000<=D Incoming Demand 0:AND:D Incoming Demand 0<65000, (D Incoming Demand 0-50000)/(65000-50000), IF THEN ELSE(65000<=D Incoming Demand 0:AND:D Incoming Demand 0<80000, (80000-D Incoming Demand 0)/(80000-65000), 0))
Units: Units

D Adjustment from distributor Inventory=
(D desired inventory-D Inventory)/D Time to Adjust Inventory
Units: Units/Week

D adjustment from in transit units=
(D desired incoming units-D Units in Transit)/D Time to adjust in transit units

Units: Units/Week

D AI=
IF THEN ELSE(40000<=D Inventory Level:AND:D Inventory Level<50000, (D Inventory Level-40000)/(50000-40000), IF THEN ELSE(50000<=D Inventory Level:AND:D Inventory Level<60000, (60000-D Inventory Level)/(60000-50000), 0))
Units: Units

D Arrival Rate=
D maximum units rate
Units: Units/Week

D AU=MAX(D R3 , MAX(D R6 , MAX(D R8 , MAX(D R12 , D R25))))
Units: Units

D Backlog for Orders= INTEG (
D order rate-D fulfillment rate,
D Backlog For Orders initial value)
Units: Units

D Backlog For Orders initial value=
0
Units: Units

D BB=(IF THEN ELSE(D AA>0 , D AA , 1))/D unitcon
Units: Dmnl

D Change Incoming orders=
(Received orders from clients-D Forecast)/D forecast adjustment time
Units: Units/(Week*Week)

D Delivery delay=
ZIDZ(D Backlog for Orders , D fulfillment rate)
Units: weeks

D desired incoming units=
D Desired replenishment rate*D enlistment time
Units: Units

D desired inventory=
D Forecast*D desired inventory coverage
Units: Units

D desired inventory coverage=
D minimum order lead time+D safety stock
Units: weeks

D Desired replenishment rate=
MAX(0, D Adjustment from distributor Inventory)
Units: Units/Week

D Desired shipment rate=
D Backlog for Orders/D target delivery delay
Units: Units/Week

D EHD=
IF THEN ELSE(100000<=D Incoming Demand 0:AND:D Incoming Demand 0<130000, (
D Incoming Demand 0-100000)/(130000-100000), IF THEN ELSE(130000<=D Incoming Demand 0
, 1, 0))
Units: Units

D EHI=
IF THEN ELSE(70000<=D Inventory Level:AND:D Inventory Level<90000, (D Inventory Level
-70000)/(90000-70000), IF THEN ELSE(90000<=D Inventory Level, 1, 0))
Units: Units

D EHU=
MAX(D R16 , MAX(D R17 , MAX(D R21 , D R22)))
Units: Units

D ELD=
IF THEN ELSE(10000<=D Incoming Demand 0:AND:D Incoming Demand 0<20000, 1 , IF
THEN ELSE(20000<=D Incoming Demand 0:AND:D Incoming Demand 0<50000, (50000-D Incoming
Demand 0)/(50000-200000), 0))
Units: Units

D ELI=
IF THEN ELSE(D Inventory Level<20000, 1, IF THEN ELSE(20000<=D Inventory
Level:AND:D Inventory Level<32000, (32000-D Inventory Level)/(32000-20000), 0))
Units: Units

D ELU=
MAX(MAX(D R5 , D R10) , MAX(D R13 , MAX(D R14 , MAX(D R15 , D R20)
)))
Units: Units

D enlistment time=
1
Units: weeks

D Forecast= INTEG (
D Change Incoming orders,
Received orders from clients)
Units: Units/Week

D forecast adjustment time=
4
Units: weeks

D fulfillment rate=
D shipment rate
Units: Units/Week

D Fuzzy Review time=
1
Units: Week

D HD=
IF THEN ELSE(80000<=D Incoming Demand 0:AND:D Incoming Demand 0<90000, (D Incoming Demand 0-80000)/(90000-80000), IF THEN ELSE(90000<=D Incoming Demand 0:AND:D Incoming Demand 0<120000, (120000-D Incoming Demand 0)/(120000-90000), 0))
Units: Units

D HI=
IF THEN ELSE(50000<=D Inventory Level:AND:D Inventory Level<60000, (D Inventory Level -50000)/(60000-50000), IF THEN ELSE(60000<=D Inventory Level:AND:D Inventory Level<70000, (70000-D Inventory Level)/(70000-60000), 0))
Units: Units

D HU=
MAX(D R11 , MAX(D R18 , MAX(D R23 , D R24)))
Units: Units

D Incoming Demand 0=
D desired incoming units
Units: Units

D Inventory= INTEG (D Arrival Rate-D shipment rate,D desired inventory)
Units: Units

D Inventory Level=D Inventory
Units: Units

D LD=
IF THEN ELSE(40000<=D Incoming Demand 0:AND:D Incoming Demand 0<60000 , (D Incoming Demand 0-40000)/(60000-40000) , IF THEN ELSE(60000<=D Incoming Demand 0:AND:D Incoming Demand 0<70000 , (70000-D Incoming Demand 0)/(70000-60000) , 0))
Units: Units

D LI=
IF THEN ELSE(30000<=D Inventory Level:AND:D Inventory Level<40000, (D Inventory Level -30000)/(40000-30000), IF THEN ELSE(40000<=D Inventory Level:AND:D Inventory Level <50000, (50000-D Inventory Level)/(50000-40000), 0))
Units: Units

D LU=
MAX(MAX(D R1 , D R2) , MAX(D R4 , MAX(D R7 , MAX(D R9 , D R19)))
)
Units: Units

D maximum shipment rate=
D Inventory/D minimum order lead time
Units: Units/Week

D maximum units rate=
D Units in Transit/D enlistment time
Units: Units/Week

D minimum order lead time=
1
Units: weeks

D order fulfillment ratio=
Table for distributor orders(ZIDZ(D maximum shipment rate , D Desired shipment rate))
Units: Dmnl

D order rate=
Received orders from clients
Units: Units/Week

D R1=
MIN(D ELD , D ELI)
Units: Units

D R10=
MIN(D EHI , D LD)
Units: Units

D R11=
MIN(D AD , D ELI)
Units: Units

D R12=
MIN(D AD , D LI)
Units: Units

D R13=
MIN(D AD , D AI)
Units: Units

D R14=
MIN(D AD , D HI)
Units: Units

D R15=
MIN(D AD , D EHI)
Units: Units

D R16=
MIN(D ELI , D HD)
Units: Units

D R17=
MIN(D HD , D LI)

Units: Units

D R18=
MIN(D AI , D HD)
Units: Units

D R19=
MIN(D HD , D HI)
Units: Units

D R2=
MIN(D ELD , D LI)
Units: Units

D R20=
MIN(D EHI , D HD)
Units: Units

D R21=
MIN(D EHD , D ELI)
Units: Units

D R22=
MIN(D EHD , D LI)
Units: Units

D R23=
MIN(D AI , D EHD)
Units: Units

D R24=
MIN(D EHD , D HI)
Units: Units

D R25=
MIN(D EHD , D EHI)
Units: Units

D R3=
MIN(D AI , D ELD)
Units: Units

D R4=
MIN(D ELD , D HI)
Units: Units

D R5=
MIN(D EHI , D ELD)
Units: Units

D R6=

MIN(D ELI , D LD)
Units: Units

D R7=
MIN(D LD , D LI)
Units: Units

D R8=
MIN(D AI , D LD)
Units: Units

D R9=
MIN(D HI , D LD)
Units: Units

D safety stock=
2.8355
Units: weeks

D shipment rate=
D order fulfillment ratio*D Desired shipment rate
Units: Units/Week

D target delivery delay=
1
Units: weeks

D Time to adjust in transit units=
1
Units: weeks

D Time to Adjust Inventory=
1.4
Units: weeks

D U1=
IF THEN ELSE(0<D ELU , D ELU*P1 , 0)
Units: Units

D U2=
IF THEN ELSE(0<D LU , D LU*P2 , 0)
Units: Units

D U3=
IF THEN ELSE(0<D AU , D AU*P3 , 0)
Units: Units

D U4=
IF THEN ELSE(0<D HU , D HU*P4 , 0)
Units: Units

D U5=
IF THEN ELSE(0<D EHU , D EHU*P5 , 0)
Units: Units

D unitcon=
1
Units: Units

D Units in Transit= INTEG (
Incoming units from manufacturer-D Arrival Rate,
D desired incoming units)
Units: Units

D Units Needed=
(D U1+D U2+D U3+D U4+D U5)/D BB
Units: Units

Demand to run in equilibrium=
0
Units: Units/Week

EHD=
IF THEN ELSE(140000<=Incoming Demand 0:AND:Incoming Demand 0<160000, (Incoming Demand 0
-140000)/(160000-140000), IF THEN ELSE(160000<=Incoming Demand 0, 1, 0))
Units: Units

EHI=
IF THEN ELSE(80000<=Inventory Level:AND:Inventory Level<100000, (Inventory Level
-80000)/(100000-80000), IF THEN ELSE(100000<=Inventory Level, 1, 0))
Units: Units

EHU=
MAX(R16 , MAX(R17 , MAX(R21 , R22)))
Units: Units

ELD=
IF THEN ELSE(10000<=Incoming Demand 0:AND:Incoming Demand 0<25000, 1 , IF THEN ELSE
(25000<=Incoming Demand 0:AND:Incoming Demand 0<50000, (50000-Incoming Demand 0
)/(50000-25000), 0))
Units: Units

ELI=
IF THEN ELSE(Inventory Level<25000, 1, IF THEN ELSE(25000<=Inventory Level
:AND:Inventory Level<35000, (35000-Inventory Level)/(35000-25000), 0))
Units: Units

ELU=
MAX(MAX(R5 , R10) , MAX(R13 , MAX(R14 , MAX(R15 , R20))))
Units: Units

FINAL TIME 0 = 157
Units: Week
The final time for the simulation.

Fuzzy Adjusted Units Needed=
Units Needed/R Fuzzy Review time
Units: Units/Week

Fuzzy Adjusted Units Needed from Manufacturer=
D Units Needed/D Fuzzy Review time
Units: Units/Week

Fuzzy Desired Production=
M Units Needed/M Fuzzy Reviw Time
Units: Units/Week

FUZZY SWITCH 1ON=
1
Units: Dmnl

HD=
IF THEN ELSE(120000<=Incoming Demand 0:AND:Incoming Demand 0<135000, (Incoming Demand 0
-120000)/(135000-120000), IF THEN ELSE(135000<=Incoming Demand 0:AND:Incoming Demand 0
<150000, (150000-Incoming Demand 0)/(150000-135000), 0))
Units: Units

HI=
IF THEN ELSE(50000<=Inventory Level:AND:Inventory Level<65000, (Inventory Level
-50000)/(65000-50000), IF THEN ELSE(65000<=Inventory Level:AND:Inventory Level
<80000, (80000-Inventory Level)/(80000-65000), 0))
Units: Units

Historical Inventory data for Agents:INTERPOLATE:
Units: Units/Week

HU=
MAX(R11 , MAX(R18 , MAX(R23 , R24)))
Units: Units

incoming demand:INTERPOLATE:
Units: Units/Week

Incoming Demand 0=
R desired inventory
Units: Units

Incoming Orders from AssemblyLine=
6500
Units: Units/Week

"Incoming Orders from distributors (ISACO Agents)"=
"units needed from manufacturer (ISACO)"
Units: Units/Week

Incoming units from distributor=
D fulfillment rate
Units: Units/Week

Incoming units from manufacturer=
M Order Fulfillment Rate
Units: Units/Week

Initial Forecasted=
800000
Units: Units/Week

Inventory Level=
R inventory
Units: Units

k1=
10000
Units: Dmnl

k2=
22500
Units: Dmnl

k3=
55000
Units: Dmnl

k4=
60000
Units: Dmnl

k5=
90000
Units: Dmnl

LD=
IF THEN ELSE(40000<=Incoming Demand 0:AND:Incoming Demand 0<55000 , (Incoming Demand 0
-40000)/(55000-40000) , IF THEN ELSE(55000<=Incoming Demand 0:AND:Incoming Demand 0
<75000 , (75000-Incoming Demand 0)/(75000-40000) , 0))
Units: Units

LI=
IF THEN ELSE(30000<=Inventory Level:AND:Inventory Level<35000, (Inventory Level
-30000)/(35000-30000), IF THEN ELSE(35000<=Inventory Level:AND:Inventory Level

<40000, (40000-Inventory Level)/(40000-35000), 0))
Units: Units

LU=
MAX(MAX(R1 , R2) , MAX(R4 , MAX(R7 , MAX(R9 , R19))))
Units: Units

M AA=
M AU+M EHU+M ELU+M HU+M LU
Units: Units

M Actual Delivery Delay=
ZIDZ(M Backlog Orders from agents,M Order Fulfillment Rate)
Units: weeks

M AD=
IF THEN ELSE(140000<=M Incoming Demand 0:AND:M Incoming Demand 0<180000, (
M Incoming Demand 0-140000)/(180000-140000), IF THEN ELSE(180000<=M Incoming Demand 0
:AND:M Incoming Demand 0<225000, (225000-M Incoming Demand 0)/(225000-180000
), 0))
Units: Units

M Adjustment for agents Inventory=
(M Desired Inventory - M Inventory for Agents)/M Inventory adjustment time
Units: Units/Week

M Adjustment for Material Inventory=
(M Desired Material Inventory - M Material Inventory)/M Materials Inventory Adjustment Time
Units: Components/Week

M Adjustment for WIP=
(M Desired WIP - M Work in Process Inventory)/M WIP Adjustment Time
Units: Units/Week

M Adjustment from AssemblyLine Inventory=
(M Desired AssemblyLine Inventory - M Inventory for Assembly line)/M AssemblyLine
Inventory AdjustmentTime
Units: Units/Week

M Agents Forecast = INTEG (
M change in Forcast,
"Incoming Orders from distributors (ISACO Agents)")
Units: Units/Week

M agents Order Fulfillment Ratio=
Table for Agent Order Fulfillment(ZIDZ(Maximum Agents Shipment Rate,M Desired Shipment
Rate
))
Units: Dimensionless

M Agents Shipment Rate=

M agents Order Fulfillment Ratio*M Desired Shipment Rate
Units: Units/Week

M AI=
IF THEN ELSE(50000<=M Inventory Level:AND:M Inventory Level<75000, (M Inventory Level
-50000)/(75000-50000), IF THEN ELSE(75000<=M Inventory Level:AND:M Inventory Level
<100000, (100000-M Inventory Level)/(100000-75000), 0))
Units: Units

M AssemblyLine Inventory AdjustmentTime=
1.268
Units: weeks

M AssemlyLine Delivery Delay=
ZIDZ(M Backlog AssemlyLine Orders,M AssemlyLine Order Fulfillment Rate)
Units: weeks

M AssemlyLine Inventory Coverage=
ZIDZ(M Inventory for Assembly line,M AssemlyLine Shipment Rate)
Units: weeks

M AssemlyLine Order Fulfillment Rate=
M AssemlyLine Shipment Rate
Units: Units/Week

M AssemlyLine Order Fulfillment Ratio=
Table for AssemblyLine Order Fulfillment(ZIDZ(M Maximum AssemblyLine Shipment Rate
,M Desired AssemlyLine Shipment Rate)
)
Units: Dimensionless

M AssemlyLine Order Rate=
(Incoming Orders from AssemblyLine)*(1-Run the model in Equilibrium 1ON)+(
Run in Equilibruim Incoming orders from Assemblyline)*Run the model in Equilibrium 1ON
Units: Units/Week

M AssemlyLine Shipment Rate=
M AssemlyLine Order Fulfillment Ratio*M Desired AssemlyLine Shipment Rate
Units: Units/Week

M AssemlyLine Target Delivery Delay=
5
Units: weeks

M AU=
MAX(M R3 , MAX(M R6 , MAX(M R8 , MAX(M R12 , M R25))))
Units: Units

M Backlog Agent orders initial value=
0

Units: Units

M Backlog AssemlyLine Orders= INTEG (
M AssemlyLine Order Rate-M AssemlyLine Order Fulfillment Rate,
0)
Units: Units

M Backlog Orders from agents= INTEG (
"M Order Rate from Agents(D)"-M Order Fulfillment Rate,
M Backlog Agent orders initial value)
Units: Units

M BB=
(IF THEN ELSE(M AA>0 , M AA , 1))/M unitcon
Units: Dmnl

M change in Forcast=
("Incoming Orders from distributors (ISACO Agents)"-M Agents Forecast)/M Forecast Adjustment Time
Units: (Units/Week)/Week

M Desired AssemblyLine Inventory=
M Backlog AssemlyLine Orders
Units: Units

M Desired AssemblyLine Production=
MAX(0,M Adjustment from AssemblyLine Inventory)
Units: Units/Week

M Desired AssemlyLine Shipment Rate=
M Backlog AssemlyLine Orders/M AssemlyLine Target Delivery Delay
Units: Units/Week

M Desired Inventory=
(M Agents Forecast*M Desired Inventory Coverage)
Units: Units

M Desired Inventory Coverage=
M Safety Stock Coverage+M minimum Order LeadTime for agents
Units: weeks

M Desired Material Delivery Rate=
MAX(M Adjustment for Material Inventory, 0)
Units: Components/Week

M Desired Material Inventory=
M Desired Material Usage Rate*M Desired Material Inventory Coverage
Units: Components

M Desired Material Inventory Coverage=
M Material Safety Stock Coverage+M Minimum Material Request Lead Time

Units: weeks

M Desired Material Usage Rate=
MAX(0, M Production Plan/M Material Usage per Unit)
Units: Components/Week

M Desired Production=
(MAX(0,M Adjustment for agents Inventory))*(1-FUZZY SWITCH 1ON)+(Fuzzy Desired Production
)*(FUZZY SWITCH 1ON)
Units: Units/Week

M Desired Production Start Rate=
MAX(0, M Adjustment for WIP)
Units: Units/Week

M Desired Shipment Rate=
M Backlog Orders from agents/M Target Delivery Delay
Units: Units/Week

M Desired WIP=
M Manufacturing LeadTime*(M Desired Production+M Desired AssemblyLine Production
)
Units: Units

M EHD=
IF THEN ELSE(240000<=M Incoming Demand 0:AND:M Incoming Demand 0<275000, (
M Incoming Demand 0-240000)/(275000-240000), IF THEN ELSE(275000<=M Incoming Demand 0
, 1, 0))
Units: Units

M EHI=
IF THEN ELSE(100000<=M Inventory Level:AND:M Inventory Level<130000, (M Inventory Level
-100000)/(130000-100000), IF THEN ELSE(130000<=M Inventory Level, 1, 0))
Units: Units

M EHU=
MAX(M R16 , MAX(M R17 , MAX(M R21 , M R22)))
Units: Units

M ELD=
IF THEN ELSE(0<=M Incoming Demand 0:AND:M Incoming Demand 0<40000, 1 , IF THEN ELSE
(40000<=M Incoming Demand 0:AND:M Incoming Demand 0<75000, (75000-M Incoming Demand 0
)/(75000-40000), 0))
Units: Units

M ELI=
IF THEN ELSE(M Inventory Level<20000, 1, IF THEN ELSE(20000<=M Inventory Level
:AND:M Inventory Level<40000, (40000-M Inventory Level)/(40000-20000), 0))

Units: Units

M ELU=
MAX(MAX(M R5 , M R10) , MAX(M R13 , MAX(M R14 , MAX(M R15 , M R20)
)))
Units: Units

M Feasible Production Starts from Materials=
M Material Usage Rate*M Material Usage per Unit
Units: Units/Week

M Financial Material adjustment time =
1
Units: Components/Week

M Forecast Adjustment Time=
12
Units: weeks

M Fuzzy Reviw Time=
1
Units: Week

M HD=
IF THEN ELSE(200000<=M Incoming Demand 0:AND:M Incoming Demand 0<225000, (
M Incoming Demand 0-200000)/(225000-200000), IF THEN ELSE(225000<=M Incoming Demand 0
:AND:M Incoming Demand 0<250000, (250000-M Incoming Demand 0)/(250000-225000
), 0))
Units: Units

M HI=
IF THEN ELSE(80000<=M Inventory Level:AND:M Inventory Level<100000, (M Inventory
Level
-80000)/(100000-80000), IF THEN ELSE(100000<=M Inventory Level:AND:M Inventory Level
<120000, (120000-M Inventory Level)/(120000-100000), 0))
Units: Units

M HU=
MAX(M R11 , MAX(M R18 , MAX(M R23 , M R24)))
Units: Units

M Incoming Demand 0=
M Desired Inventory
Units: Units

M Inventory adjustment time=
1.591
Units: weeks

M inventory coverage=
ZIDZ(M Inventory for Agents , M Agents Shipment Rate)

Units: Week

M Inventory for Agents= INTEG (
M Production Rate For Agents Orders-M Agents Shipment Rate,
M Desired Inventory)
Units: Units

M Inventory for Assembly line= INTEG (
M Production Rate For AssemblyLine Orders-M AssemlyLine Shipment Rate,
M Desired AssemblyLine Inventory)
Units: Units

M Inventory Level=
M Inventory for Agents
Units: Units

M LD=
IF THEN ELSE(70000<=M Incoming Demand 0:AND:M Incoming Demand 0<110000 ,
(M Incoming Demand 0-70000)/(110000-70000) , IF THEN ELSE(110000<=M Incoming Demand 0
:AND:M Incoming Demand 0<150000 , (150000-M Incoming Demand 0)/(150000-110000
) , 0))
Units: Units

M LI=
IF THEN ELSE(40000<=M Inventory Level:AND:M Inventory Level<50000, (M Inventory
Level
-40000)/(50000-40000), IF THEN ELSE(50000<=M Inventory Level:AND:M Inventory Level
<60000, (60000-M Inventory Level)/(60000-50000), 0))
Units: Units

M LU=
MAX(MAX(M R1 , M R2) , MAX(M R4 , MAX(M R7 , MAX(M R9 , M R19)))
)
Units: Units

M Manufacturer Materials Quantity=
MAX(M Desired Material Delivery Rate, M Required Material delivery rate)
Units: Components/Week

M Manufacturing LeadTime=
1
Units: weeks

M Manufacturing Total Inventory=
M Inventory for Assembly line+M Inventory for Agents
Units: Units

M Material Delivery Rate=
DELAY1(M Manufacturer Materials Quantity, M Materials Delay Time)
Units: Components/Week

M Material Inventory= INTEG (
M Material Delivery Rate-M Material Usage Rate,
M Desired Material Inventory)
Units: Components

M Material Safety Stock Coverage=
3.82
Units: Week

M Material Usage per Unit=
325
Units: Units/Components

M Material Usage Rate=
M Material Usage Ratio*M Desired Material Usage Rate
Units: Components/Week

M Material Usage Ratio=
Table for Material Usage(ZIDZ(M Maximum Material Usage Rate, M Desired Material Usage Rate
))
Units: Dimensionless

M Materials Coverage=
ZIDZ(M Material Inventory, M Material Usage Rate)
Units: weeks

M Materials Delay Time=
M Payment Delay+M Perceived Supplier Lead Time
Units: weeks

M Materials Forecast= INTEG (
M Perceived Change in Material Forecast,
M Material Usage Rate)
Units: Components/Week

M Materials Forecast adjustmentTime=
4
Units: weeks

M Materials Inventory Adjustment Time=
1.57
Units: weeks

M Maximum AssemblyLine Shipment Rate=
M Inventory for Assembly line/M Minimum AssemblyLine Order LeadTime
Units: Units/Week

M Maximum Capacity=
3.1e+06
Units: Units/Week

M Maximum Material Usage Rate=
M Material Inventory/M Minimum Material Request Lead Time
Units: Components/Week

M Maximun Production Rate=
M Work in Process Inventory/M Manufacturing LeadTime
Units: Units/Week

M Minimum AssemblyLine Order LeadTime=
1.5
Units: weeks

M Minimum Material Request Lead Time=
1
Units: weeks

M minimum Order LeadTime for agents=
1
Units: weeks

M Order Fulfillment Rate=
M Agents Shipment Rate
Units: Units/Week

"M Order Rate from Agents(D)"=
"Incoming Orders from distributors (ISACO Agents)"
Units: Units/Week

M Payment Delay=
Table For Payment(M Manufacturer Materials Quantity/M Financial Material adjustment time)*M Time To Pay
Units: weeks

M Perceived Change in Material Forecast=
(M Material Usage Rate-M Materials Forecast)/M Materials Forecast adjustmentTime
Units: (Components/Week)/Week

M Perceived Supplier Lead Time=
12
Units: weeks

M Production Capacity=
M Maximum Capacity
Units: Units/Week

M Production Coverage=
ZIDZ(M Work in Process Inventory, (M Production Rate For Agents Orders+M Production Rate For AssemblyLine Orders
))
Units: weeks

M Production Plan=
IF THEN ELSE(M Desired Production Start Rate>=M Production Capacity, M Production Capacity
, M Desired Production Start Rate)
Units: Units/Week

M Production Rate For Agents Orders=
M Maximun Production Rate* M Relation Between Desired Productions
Units: Units/Week

M Production Rate For AssemblyLine Orders=
M Maximun Production Rate * (1 - M Relation Between Desired Productions)
Units: Units/Week

M Production Start Rate=
M Feasible Production Starts from Materials
Units: Units/Week

M R1=
MIN(M ELD , M ELI)
Units: Units

M R10=
MIN(M EHI , M LD)
Units: Units

M R11=
MIN(M AD , M ELI)
Units: Units

M R12=
MIN(M AD , M LI)
Units: Units

M R13=
MIN(M AD , M AI)
Units: Units

M R14=
MIN(M AD , M HI)
Units: Units

M R15=
MIN(M AD , M EHI)
Units: Units

M R16=
MIN(M ELI , M HD)
Units: Units

M R17=
MIN(M HD , M LI)
Units: Units

M R18=
MIN(M AI , M HD)
Units: Units

M R19=
MIN(M HD , M HI)
Units: Units

M R2=
MIN(M ELD , M LI)
Units: Units

M R20=
MIN(M EHI , M HD)
Units: Units

M R21=
MIN(M EHD , M ELI)
Units: Units

M R22=
MIN(M EHD , M LI)
Units: Units

M R23=
MIN(M AI , M EHD)
Units: Units

M R24=
MIN(M EHD , M HI)
Units: Units

M R25=
MIN(M EHD , M EHI)
Units: Units

M R3=
MIN(M AI , M ELD)
Units: Units

M R4=
MIN(M ELD , M HI)
Units: Units

M R5=
MIN(M EHI , M ELD)
Units: Units

M R6=
MIN(M ELI , M LD)
Units: Units

M R7=
MIN(M LD , M LI)
Units: Units

M R8=
MIN(M AI , M LD)
Units: Units

M R9=
MIN(M HI , M LD)
Units: Units

M Relation Between Desired Productions=
Table for Production(IF THEN ELSE(M Desired AssemblyLine Production <> 0
, M Desired Production/M Desired AssemblyLine Production
, 10))
Units: Dimensionless

M Required Material delivery rate=
MAX(M Materials Forecast-M Maximum Material Usage Rate, 0)
Units: Components/Week

M Safety Stock Coverage=
4.214
Units: weeks

M Target Delivery Delay=
1
Units: weeks

M Time To Pay=
1
Units: weeks

M Total Production=
M Production Rate For AssemblyLine Orders+M Production Rate For Agents Orders
Units: Units/Week

M U1=
IF THEN ELSE(0<M ELU , M ELU*k1 , 0)
Units: Units

M U2=
IF THEN ELSE(0<M LU , M LU*k2 , 0)
Units: Units

M U3=
IF THEN ELSE(0<M AU , M AU*k3 , 0)
Units: Units

M U4=
IF THEN ELSE(0<M HU , M HU*k4 , 0)
Units: Units

M U5=
IF THEN ELSE(0<M EHU , M EHU*k5 , 0)
Units: Units

M unitcon=
1
Units: Units

M Units Needed=
(M U1+M U2+M U3+M U4+M U5)/M BB
Units: Units

M WIP Adjustment Time=
1
Units: weeks

M Work in Process Inventory= INTEG (
M Production Start Rate-M Production Rate For Agents Orders-M Production Rate For AssemblyLine Orders
,
M Desired WIP)
Units: Units

Maximum Agents Shipment Rate=
M Inventory for Agents/M minimum Order LeadTime for agents
Units: Units/Week

P1=
10000
Units: Dmnl

P2=
22500
Units: Dmnl

P3=
67500
Units: Dmnl

P4=
75000
Units: Dmnl

P5=
100000
Units: Dmnl

R adjustment from inventory=
(R desired inventory-R inventory)/R time to adjust inventory
Units: Units/Week

R Backlog for Orders= INTEG (
R order rate-R fulfillment rate,
R Backlog for Orders initial value)
Units: Units

R Backlog for Orders initial value=
0
Units: Units

R change incoming demand=
(((incoming demand)-R forecast)/R forecast adjustment time)*(1-Run the model in Equilibrium
1ON
)+(((Demand to run in equilibrium-R forecast)/R forecast adjustment time))*
Run the model in Equilibrium 1ON
Units: Units/(Week*Week)

R delivery delay=
ZIDZ(R Backlog for Orders , R fulfillment rate)
Units: weeks

R desired inventory=
R forecast*R desired inventory coverage
Units: Units

R desired inventory coverage=
R minimum order leadTime+R safety stock
Units: weeks

R Desired shipment rate=
R Backlog for Orders/R Target delivery delay
Units: Units/Week

R forecast= INTEG (
R change incoming demand,
0)
Units: Units/Week

R forecast adjustment time=
2
Units: weeks

R fulfillment rate=
R shipment rate

Units: Units/Week

R Fuzzy Review time=
 1
Units: weeks

R inventory= INTEG (
 Incoming units from distributor-R shipment rate,
 R desired inventory)
Units: Units

R maximum shipment rate=
 R inventory/R minimum order leadTime
Units: Units/Week

R minimum order leadTime=
 1
Units: weeks

R order fulfillment ratio=
 IF THEN ELSE(R maximum shipment rate>=R Desired shipment rate , R Desired shipment rate
 , R maximum shipment rate
)
Units: Units/Week

R order rate=
 (incoming demand)*(1-Run the model in Equilibrium 1ON)+(Demand to run in equilibrium
)*Run the model in Equilibrium 1ON
Units: Units/Week

R safety stock=
 1
Units: weeks

R shipment rate=
 R order fulfillment ratio
Units: Units/Week

R Target delivery delay=
 1
Units: weeks

R time to adjust inventory=
 2.4
Units: Week

R1=
 MIN(ELD , ELI)
Units: Units

R10=

MIN(EHI , LD)
Units: Units

R11=
MIN(AD , ELI)
Units: Units

R12=
MIN(AD , LI)
Units: Units

R13=
MIN(AD , AI)
Units: Units

R14=
MIN(AD , HI)
Units: Units

R15=
MIN(AD , EHI)
Units: Units

R16=
MIN(ELI , HD)
Units: Units

R17=
MIN(HD , LI)
Units: Units

R18=
MIN(AI , HD)
Units: Units

R19=
MIN(HD , HI)
Units: Units

R2=
MIN(ELD , LI)
Units: Units

R20=
MIN(EHI , HD)
Units: Units

R21=
MIN(EHD , ELI)
Units: Units

R22=
MIN(EHD , LI)
Units: Units

R23=
MIN(AI , EHD)
Units: Units

R24=
MIN(EHD , HI)
Units: Units

R25=
MIN(EHD , EHI)
Units: Units

R3=
MIN(AI , ELD)
Units: Units

R4=
MIN(ELD , HI)
Units: Units

R5=
MIN(EHI , ELD)
Units: Units

R6=
MIN(ELI , LD)
Units: Units

R7=
MIN(LD , LI)
Units: Units

R8=
MIN(AI , LD)
Units: Units

R9=
MIN(HI , LD)
Units: Units

Received orders from clients=
units needed from distributor
Units: Units/Week

Run in Equilibruim Incoming orders from Assemblyline=
0
Units: Units/Week

Run the model in Equilibrium 1ON=
0
Units: Dmnl

SAVEPER 0 =
TIME STEP
Units: Week
The frequency with which output is stored.

Table for Agent Order Fulfillment(
[(0,0)-(600,1)],(0,0),(0.2,0.08),(0.4,0.25),(0.6,0.5),(0.8,0.6),(1,0.8),(1.2
,0.9),(1.4,0.95),(1.6,0.97),(1.8,1),(2,1),(2.2,1),(2.4,1),(2.6,1),(2.8,1),(
3,1),(4,1),(5,1),(10,1),(100,1),(500,1))
Units: Dimensionless

Table for AssemblyLine Order Fulfillment(
[(0,0)-(10,1)],(0,0),(0.2,0),(0.4,0.1),(0.6,0.2),(0.8,0.3),(1.1,0.5),(1.2,
0.8),(1.4,1),(2,1),(3,1),(4,1),(10,1))
Units: Dimensionless

Table for distributor orders(
[(0,0)-(600,1)],(0,0),(0.2,0.2),(0.4,0.4),(0.6,0.58),(0.8,0.7),(0.9,0.8),(
1,0.9),(1.2,1),(2,1),(3,1),(10,1),(500,1))
Units: Dmnl

Table for Material Usage(
[(0,0)-(10000,1)],(0,0),(0.2,0.2),(0.4,0.4),(0.6,0.58),(0.8,0.73),(1,0.85)
,(1.2,0.93),(1.4,0.97),(1.6,0.99),(1.8,1),(2,1),(10,1),(20,1),(100,1),(1000
,1), (10000,1))
Units: Dimensionless

Table For Payment(
[(0,0)-(8e+08,10)],(0,0),(1000,0),(2000,1),(3000,1),(4000,2),(5000,3),(6000
,3),(7000,4),(8000,5),(9000,5),(10000,4),(1e+06,4))
Units: Dimensionless

Table for Production(
[(0,0)-(100,1)],(0,0),(0.2,0),(0.3,0),(0.5,0),(0.7,0.2),(0.8,0.3),(1,0.4),
(1.3,0.6),(2,0.8),(3,0.9),(5,1),(10,1),(100,1))
Units: Dimensionless

TIME STEP = 0.125
Units: Week [0,?]
The time step for the simulation.

U1=
IF THEN ELSE(0<ELU , ELU*C1 , 0)
Units: Units

U2=

```
        IF THEN ELSE( 0<LU , LU*C2 , 0 )
Units: Units

U3=
        IF THEN ELSE( 0<AU , AU*C3 , 0 )
Units: Units

U4=
        IF THEN ELSE( 0<HU , HU*C4, 0 )
Units: Units

U5=
        IF THEN ELSE( 0<EHU , EHU*C5 , 0 )
Units: Units

Units Needed=
        (U1+U2+U3+U4+U5)/BB
Units: Units

units needed from distributor=
        ((MAX(0, R adjustment from inventory))*(1-FUZZY SWITCH 1ON))+(Fuzzy Adjusted Units
Needed
)*(FUZZY SWITCH 1ON)
Units: Units/Week

"units needed from manufacturer (ISACO)"=
        (MAX(D adjustment from in transit units,0))*(1-FUZZY SWITCH 1ON)+(Fuzzy Adjusted Units
Needed from Manufacturer
)*(FUZZY SWITCH 1ON
        )
Units: Units/Week
```