

Synthetic data analysis by way of system dynamics

A corporate case

by
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Thesis
Submitted to the Department of Geography
in Partial Fulfillment of the Requirements for the Degree of
Master of Philosophy in System Dynamics



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Summer 2017

Acknowledgements

First and for most, I want to appreciate my supervisor, Professor Pål Davidsen, this thesis would never have been completed without his support, encouragement and help. I also want to thank all the members in the system dynamics group in Bergen University, it is not only the knowledge I gained during these two years of studying system dynamics. Most importantly I learned the way of thinking and analyzing issues, which can be applied to different fields in the future. I achieved a lot during these two years of study in Bergen University.

I would also want to thank my husband Saerda Halifu and my three beautiful children Ruya, Ruhsar and Yanar .

Thank you!

Abstract

An organization can be seen as a system that is a collection of subsystems integrated to achieve set of desired goals. Policies within the business organization are decision rules proposed based on strategy developers' and policy designers' understanding of the system they are managing. The behavior of the system, governed by existing policy, may not be understood without studying the policies governing that behavior, - policies designed and implemented by such managers and based on their understanding. Systems are often large, multifunctional and complicated. Therefore, the discrepancies in dynamic complexities between a real-world system and the managerial mental models will affect policy development in the social system. In this thesis, the behavior of the system will be studied by considering how two mental models leads to different implementations of policies in the system. A method is developed and illustrated in this thesis to study how mental models shape policies that govern decision-making. Mental models are simplified representations of our complex reality formed after the fact (based on experience). The system behavior (dynamics) is governed by the strategies developed, the policies designed and the decision made ultimately based on the mental models formed.

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1. Introduction

In this thesis we will illustrate how organizational policies and decision making may be affected by differences between a company structured and the way that structure is perceived, and how that shapes mental models, policy design and decision making. A precondition for effective policy design and decision making in a complex organization is a valid, coherent and consistent mental models of the structure underlying its behavior (Sterman, 1989). Cyert and March (1963) argued that the behavior of the firm, cannot be understood and described without considering the actions of important actors within the firm, those that, based on their mental models shape policies and make decisions. Several researchers have demonstrated that managerial mental models are simplified version of the real-system structures (Gary and Wood 2010). In this thesis we will study how mental model affect policy design, decision making and, ultimately, the behavior (dynamics) of such system (Hauge, 2004). Moreover, it is assumed that the execution of policies in the form of decision making results systems dynamics that, subsequently cause modifications of the mental models, policies and decision making through adaptation and learning (Sterman, 2000). In order to understand, describe and analyze a social system, we will consider at least two decision-makers' mental processes in the system. First we will present a system dynamics model of reality as a foundation for information acquisition conducted by decision-makers. Then a model will be developed to represent the mental perception of that reality. Finally, the two models will be made to interact to study the dynamic consequences of the resulting decision making and how adaption and learning affects the policy design and decision making process.

The thesis will describe, analyze and propose the system dynamics method to conduct synthetic data experiments so as to investigate how the formation of mental models shape policy design and decision making in their social system. In this introductory chapter, the method that we use to conduct the experiment will be described first. Secondly, the motivation for choosing this thesis topic will be discussed. Finally, the general set-up of the synthetic data experiment will be discussed so as to illustrate how the method will be applied in the thesis.

1.1 Experiment Design

In this section, first, the process of linking a real-world system dynamics model with another model – represent the decision-makers' perception of that reality will be explained. Second, how this particular experimental method is designed will be discussed. The system dynamics modeling method provides a tool to understand how the structure of complex systems creates their behavior. By understanding the structure in the system, model users would be able to explain the origin that generates undesired behavior and design more effective policies and strategies for greater success. Decision makers might often misperceive the feedback loops within the system because they are not fully understood the nature and significance of the causal structure of the system they are managing. The poor performance of a particular system must be sought in the interactions between the decision rule and the feedback structure of the simulated system (Sterman, 1989).

In a multifunctional, large social system, the process by which information is delivered often contains multiple feedback loops, time delays, and non-linear relationships within the system it operates. All decisions are based on models of the system dynamics, usually mental models, which include our beliefs about the causes and effects that describe how a system operates (Forrester, 1961). Policy resistance arises often because we do not fully understand the range of all the possible relationships operating in the system (Sterman, 2000). Various effects are produced from every decision within a system, and unanticipated effects may trigger the system to operate in an undesired way, which is a sign to show that our understanding of the system is not perfect or at least narrow. The information feedback from the real-world system does not only form the decision rules within the system itself, but it also feeds back to alter our mental model.

When a mental model accepts changes from information feedback, decision-makers change the structure of systems, adjust existing policies and design new strategies (figure 1). Therefore, if we can test various effects on a corporate system when decision-makers have less complicated mental models, and then we can study the dynamics of the mental models. According to Argyris and Schon (1978) that mental models also change over time based on decision makers' prior experience and through their developments of their mental model by learning techniques.

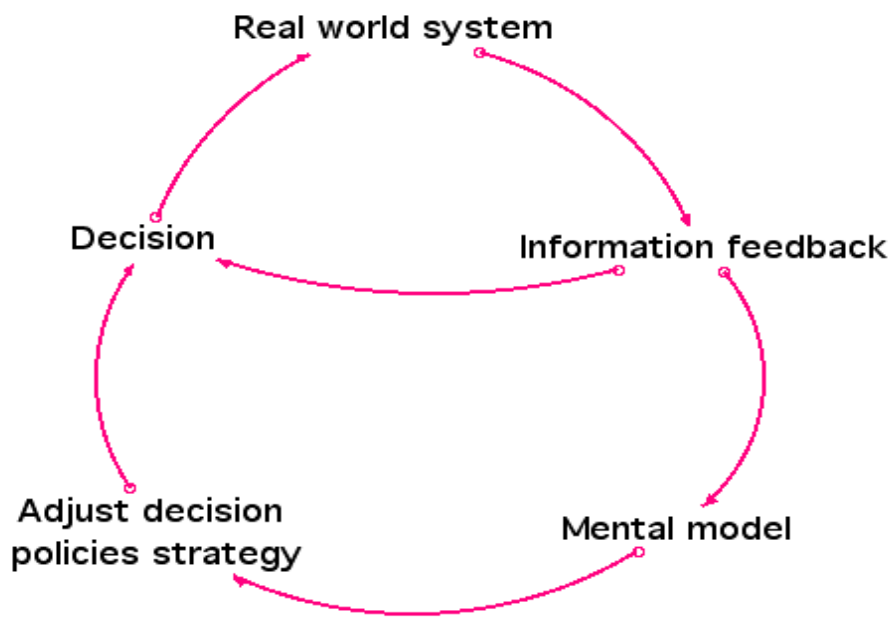


Figure 1-the learning feedback loop

Where information feedback from real world causes mental models to change. Mental model would have new goals and new policies as a result of a learning process.

The structure of a system generates its behavior in a social system (Güneralp, 2007). Thus, in order to have the most appropriate policy system in an organization, a perfect mental model should have exactly same structural complexities as the real-world system so that daily decisions would have direct effects in the real world system. However, decision-makers' mental models do not contain all the complex information as in the real-world system (Sterman, 1989).

For example, in a large manufacturing company, a temporary changes in the market would cause company to have longer effects in their system if decision makers cannot perceive the changes on time or he takes long time to recognize the new information.

The longer delay in perceiving new information by decision-makers would cause a delay in changing ordering policy, so the longer inappropriate policies is using in the system would cause longer side-effect to company. A decision maker with a long perception delay might be less effective compared to its competitor who has a more effective way to communicate with their system. Normally, customers will choose to have their products to be delivered faster according to their changing demand, so they might choose a competing company that has a shorter delivery time for its product. When a decision-maker did not realize the feedbacks from market described above and rather choose to invest money on marketing instead of having better understanding their system, that company would move further away from its sales and profit goals.

The method developed in this thesis can help us to synthetically experiment the effects of policy design and decision making in a company if managers misperceive the structure of system complexities (Hauge, 2004). In this thesis, two models will be developed. Firstly, a real-world model is built by using an already existing model developed by Lyneis (1982). Then, a mental model is used to synthetically test various effects on the real-world system when decision-makers continuously misperceive the implications of different dynamic complexities. Finally, the interacted two models will help decision makers to discover that the existing governing policies are inappropriate and therefore decision makers making policy adjustments when they improve their perception for the system every time.

1.2 Motivation for selecting the chosen topic

The purpose for selecting the chosen topic is to examine how decisions are formed in a large, multifunctional business and to study how the managers make day-to-day decisions according to their perceptions of the dynamic system. This thesis assumes that through simulation techniques, people could improve their understanding of how policies are changed over time. In addition, according to Cyert and March (1963), policy development cannot be understood without considering the dynamics of decision-making within the social system. Therefore, I became interested in studying how the differences in dynamic complexities between a mental model and a real-world model affect policy development in a complex multifunctional organization. In order to study this, I proposed a method to help decision-makers improve their understanding of a complex system through learning activities from perceived behavior that diverged from their expectations. Another important point of choosing the particular thesis topic is that the study of policy development is fairly important because studies of policy developments in the system is the study of how decisions are formed within the organizations. So, each policy or decision that made in the system would affect their interrelated members who are working in the system and society. It is also recognized that there have not been many studies modeling the decision-making process with its effects on the social system and exploring how decision makers can learn from unexpected behavior from decision- makers that is made based on perceived system structure. Finally, during literature review within the System Dynamics field, there were not many papers in the last decade analyzing policy developments using synthetic data experiment methods.

1.3 Introduction to the synthetic data experiment

The method allows policy-designers to assess the behavioral effects of possible misperceptions (or misinterpretation) of information about the systems that their policies are intended to operate within. Such an assessment is important under two different circumstances: When investigating the root cause of a problem behavior exhibited by a system, one may hypothesize that the policies governing a system is based upon a misperception or that the decision resulting from such policies may be based on information of inferior quality. When designing new policies, one would typically test the robustness of policies and the resilience of the system governed by such policies. In that case one may assume that the information upon which policies and decisions are made, diverge from reality so as to investigate the behavioral consequences of such a divergence. A synthetic data experiment may help policy designers understand the consequences of difference sources of such a divergence. This experimental approach is adapted from a traditional synthetic data experiment (figure 2). Such a synthetic data experiment involves two system dynamics models; – (i) one model that represents a real-world system; and (ii) a model portraying the current perception of the real world system (as represented by the first of these models). For short, we will call the first one the *real-world model* and the second one the *mental model* (representing a perception). In the real-world model data will be generated to be sampled by the mental model. The mental model may be used to identify (estimate) important parameter values that characterizes elements of a real-world model so as to, potentially, form the basis for decision making. Since the “true” structure, initial conditions and parameter values of the real-world model are known, we can perform controlled experiments to test the ability of mental model and associated techniques to

identify the real-world model (Crawford, Andersen, Richardson, 1989). Such identification must rely on a variety of techniques such as comparison between the behavior of the two models, statistical sampling and estimation, the adoption of structural assumptions in the form of learning etc, - all serving the improvement of the mental model.

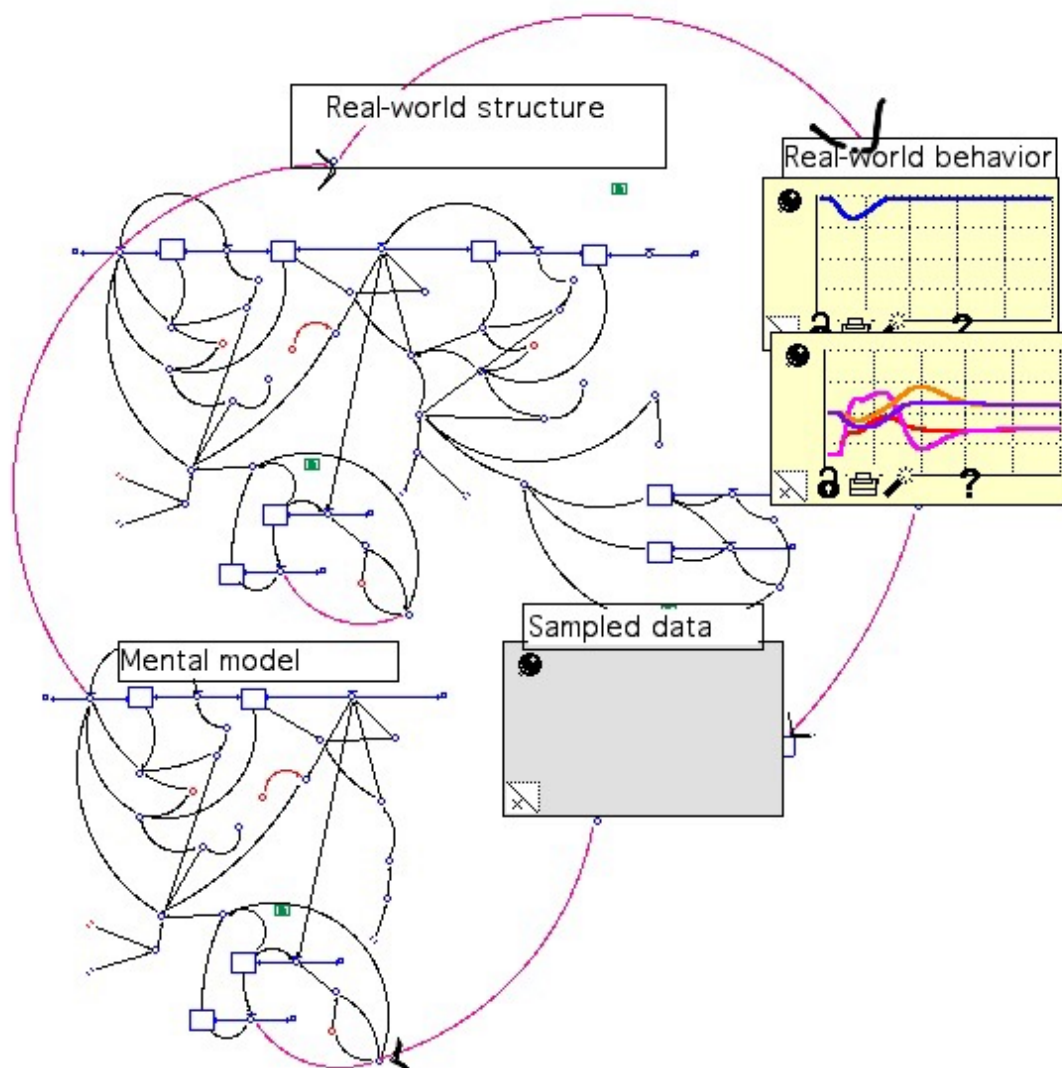


Figure 2- the link between the real-world structure and the mental model

Consequently, we assume that policy design and decision making in the social system can also be studied by using synthetic data experiment (Hauge, 2004). The real-world model is to represent the structural aspects of a multi-functional organization, implying that it encompasses a variety of interrelated domains, each governed by a specific policy. The mental model receives information (feedback) from the real-world model and then governs decision making in accordance with existing policies. Through adaptation (learning) these policies may be adjusted in view of a comparison between the “actual” behavior exhibited by the real-world model and the expected behavior produced by the mental model (figure 3). This approach provides full experimental control and allows us to investigate how perceptions, formal information sampling, information handling, and learning shaping policy design and implementation (decision making) may affect systems behavior (Crawford, Andersen, Richardson, 1989).

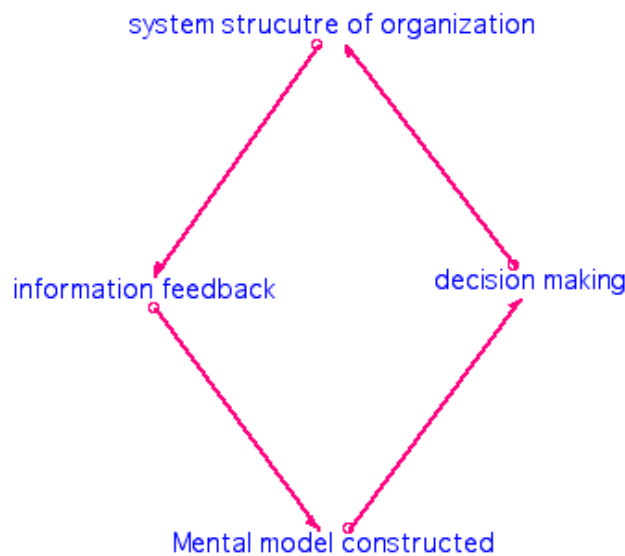


Figure 3 A representation of an organizational structure by focusing on information feedback through real-world model and mental model, where it is also address double loop learning- including the design of policies that govern decision making.

In this section, we introduced the synthetic data experiment and how to apply this technique in our study of policy design and decision making. Mainly, the decision-makers form in their minds a perception (mental model) of the structural of their environment (the real system), based on structural hypotheses (the mental model structure) and information feedback reflecting the behavior (dynamics) of the real system. Decision-makers normally construct simplified structural maps (mental model structures) in their minds to identify the structural components that are most important determinants of behavior and the ones they should concentrate on in their policy design and implementation (in the form of decision making. Our experiments allow us to test out synthetically how the real system would respond to decision resulting from policies that are based on simplified mental representations. The details of experimental set-up will be documented in section 4.

2. Literature review

System dynamics often portrays the causal structure of a system and serves as a tool for decision-makers to get a better understanding of complex social systems (Sterman, 2002). Forrester (1961,1975) stated that most complex social systems are composed of accumulations, multiple feedback loops, time delays and nonlinearities to create dynamic behavior. Moreover, Cyert and March (1963) argue that interactions of several goals in the social system increase the complexities of the system. A system dynamics model can be seen as a data-generating model that can be simulated to represent some aspects of a real-world system (Crawford, Andersen, Richardson, 1989). Policy design within an organization are affected by the development of the mental model of decision-makers.

Most decision-makers have limited, simple mental models (Simon, 1957). According to Doyle and Ford (1998, 1999), a mental model of a dynamic system is “a relatively enduring and accessible, but limited, internal conceptual representation of an external system (historical, existing, or projected) whose structure is analogous to the perceived structure of that system”. Due to limitations in the human information-processing system, decision-makers need to understand and control social systems by using simplified representations in their mind, that are able to mimic the behavior of the actual system in order to communicate with the system (Johnson-Laird, 1983; Norman, 1981; Simon, 1981). Decision-makers often fail to realize that their current mental models are flawed until a crisis has occurred within the system itself.

Mental models are also dynamic, which means they change over time. Mental models are developed as to reflect decision-makers' previous experiences and observations. The development of mental models can be improved through learning of the social system, which improves decision-makers' understanding of the complex dynamic environment. According to Cyert and March (1963), human beings often modify, replace and create control structures based on their short-term feedbacks and combined with ignorance of dynamic complexity in their system. When they ignore the complexities of the dynamic system, their mental model will only be sufficient in the short-term, and the system will thus tend to oscillate or to overshoot and collapse in the long run (Hauge, 2004).

Decision-makers are using their perceived knowledge about their organizational systems to form decision rules (Cyert and March, 1963). According to Hauge (2004), perception is the process by which people obtain, transfer, and transform impressions about the world into knowledge represented in their mental models. The sufficiency of our mental model is determined by how well we can observe our environment and our system (Wickens, 1987). Interestingly, due to limitations of our mental models, even though decision-makers may sometimes observe the correct parts of their system sufficiently, they might not always recognize correct information available to them (Johnson-Laird, 1983, Einhorn, 1982).

Policy designers and decision-makers would be able to learn from interactions between

their mental model and the real world behavior because their structural understanding of the system can be changed through changed behavior of the real world system (Argyris and Schon, 1978). Johanssen (2006) emphasizes that the simulation model can be a mind tool for the decision makers' mental model, and argued that the simulation model can play an important role in helping individuals develop productive and useful mental models which could facilitate learning and improve performance. The traditional learning activities often result after several simulations have occurred. According to Davidsen and Spector (2015), learning can occur between runs of a simulation model. Learning through simulation would improve the performance of the firms as the improved understanding of the system. In the thesis, the idea of learning through simulations will be advanced to address the various impacts of discrepancies between mental model and simulation model on policy adjustment in organizations.

A synthetic data experiment is conducted to test the effects of decision-makers' learning activities throughout the simulation. The origins of applying synthetic data experiments to study the social system in terms of estimating parameters can be traced back to the early 1970s. Brunner and Brewer (1971) applied synthetic data experiments on a formal model "modernization and mass politics" to investigate a series of implications of public policies in Turkey and the Philippines. There are also a number of experiments using synthetic data experiments within system dynamics conducted more recently. For example, Forrester (1979) tested the effects of several misperceptions in system dynamics stock evaluation models. And Crawford (1988) tested the effects of misperceived feedback loops in the design of statistical cross-sectional evaluations of government programs (Crawford, Andersen, Richardson, 1989).

3. Introduction to the real-world model

The purpose of the thesis is to represent the process of decision-making based on the mental models of managers and to study how they improve their policies according to the perceived performance in the social system that they are managing. The thesis is built on an already existing model, - a model that constitutes the basis for our experimental study, documented in Lyneis (1982)'s book: "Corporate Planning and Policy Design: a system dynamics approach". In the book, the "real-world" model that we use in our synthetic data experiment is carefully documented for the purpose of building a better understanding of all aspects of corporate behavior (i.e. dynamics). A system dynamics model enables managers to effectively understand the underlying structure causing the behavior of a real world system. Such an understanding is considered a prerequisite in the design of policies to control corporate behavior. This particular model contains typical aspects of a corporate structure of relevance to policy design (Lyneis, 1982). The complete model contains four sections: production, employment, finances, and the market-clearing sections. These corporate sections ultimately affect the attractiveness of the products produced. An organization that maintain a higher product attractiveness will typically grow faster and more smoothly than competing companies (Lyneis, 1982). Below, we will explicitly introduce the structure and behavior of each section.

The model has been developed to understand how an organization is operating in a dynamic environment, and how various policies affect the performance of the corporation. The book also includes various policy parameter sets to test the effects of management exhibiting various degrees of aggressiveness in their implementation of policies. In this particular synthetic data experiment, we have chosen to focus on the logistics of the system, including the interaction with company suppliers on the one hand and with customer and competitors on the other. In our context, we assume that the policy parameter values have been set so as to exercise aggressive policies (table 1).

<u>Policy Parameters</u>	TACOR	TCFI	TOCORG	TAPRPO	TCPI	TOPRGR
Aggressive	60 days	60 days	240 days	60 days	60 days	240 days

3.1 TABLE 1- POLICY PARAMENTERS SET

TACOR	Time to average customer order rate
TCFI	Time to correct finish inventory
TOCORG	Time to observe customer order rate growth
TAPRPO	Time to average production rate for parts ordering
TCPI	Time to correct parts inventory
TOPRGR	Time to observe production rate growth rate

3.2 TABLE 2- EXPLANATION OF POLICY PARAMETERS

3.1 The structure and behavior of the real-world model – the production section

First, the production and inventory section describe the structural origin of the instability of the inventory system and dynamics created by the interactions between the company and its suppliers. In this inventory system, a random step input (a 10 percent increase in customer order rate) causes the system to oscillate. In reality, such a system is influenced randomly and is thus destabilized, - typically returning towards equilibrium by way of oscillations (due to the underlying negative feedback loops, characterized by a variety of delays).

The model contains a two-stage inventory system (from parts on order to finished inventory), and an unexpected changes in market demand causes managers to exercise their parts order policy and the structure of the system, specifically the major negative feedback loops of the system (characterized by delays), causes the system to fluctuate (figure 3). As shipment rate depletes finished inventory, and “work in progress” is depleted by production completions, the resulting production rate must, together with adjustments for parts on order and parts inventory, determine the parts order rate that facilitates parts arrivals and production at the appropriate rate.

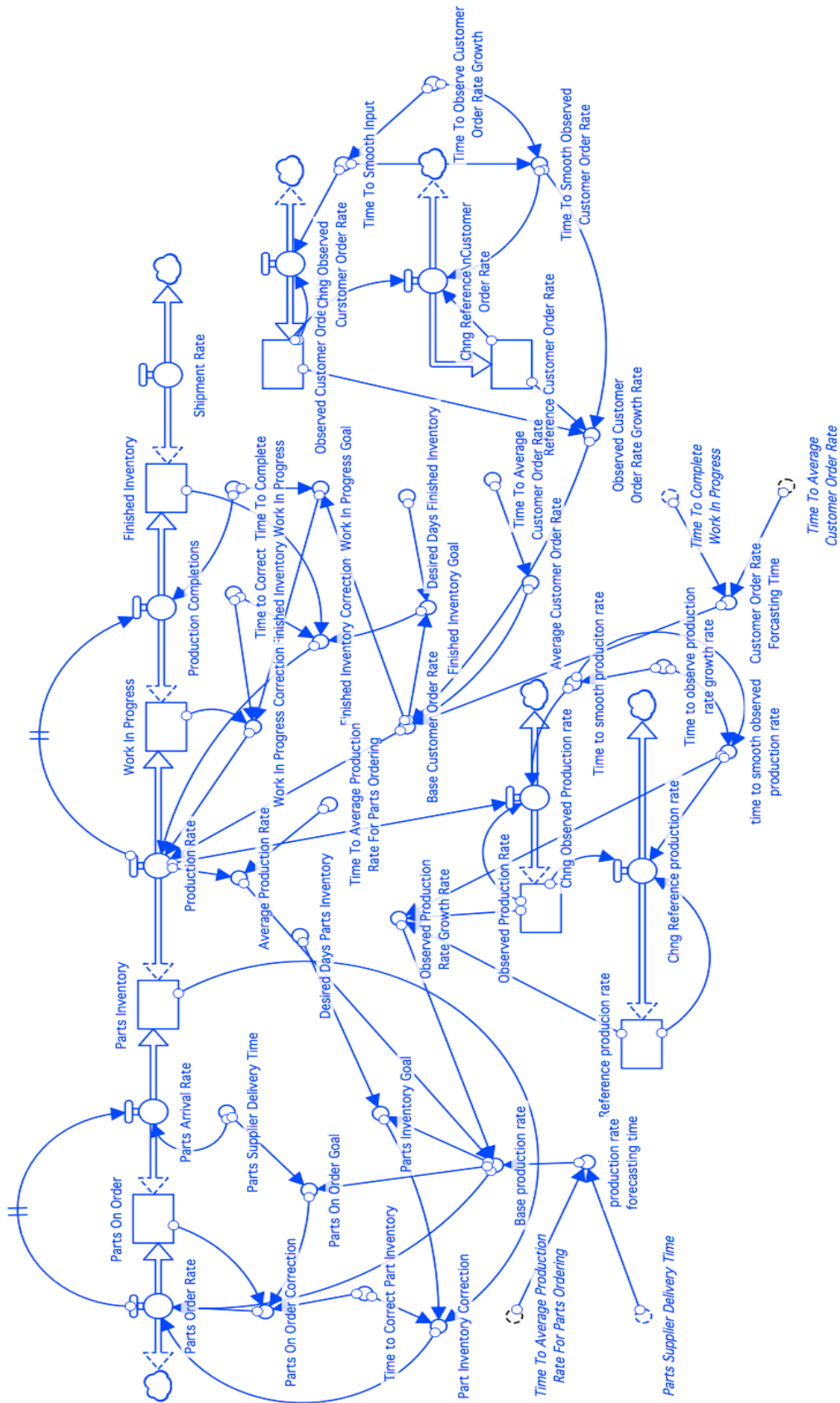


Figure 3- General model structure of the inventory system

However, the company suppliers also play an important role in a production line. Suppliers take time to produce raw materials and that may cause delays in its acquisition of raw materials of the company at hand. Decision makers need to understand how the dynamics of their suppliers will affect the behavior to their own company (and that of its market) when making decisions on parts order rate (figure 4). The suppliers structure in figure 4 indicate that an increase in order backlog temporarily lengthens parts supplier delivery time due to a sluggish adjustment of production capacity, so that the parts on order goal temporarily increases beyond its steady state. When the parts on order goal increases, the delivery delay apparently increases, and the loop is then closed by increased additional parts orders, i.e. phantoms orders. In the real-world model, company only orders materials from suppliers based on their desired usage of materials rather than their actual usage. The purpose is to prevent parts inventory shortage and to shorten the delivery time. Thus the inventory system, interacts with suppliers, to form negative feedback-loops that are intended to stabilize the system. (figure 5).

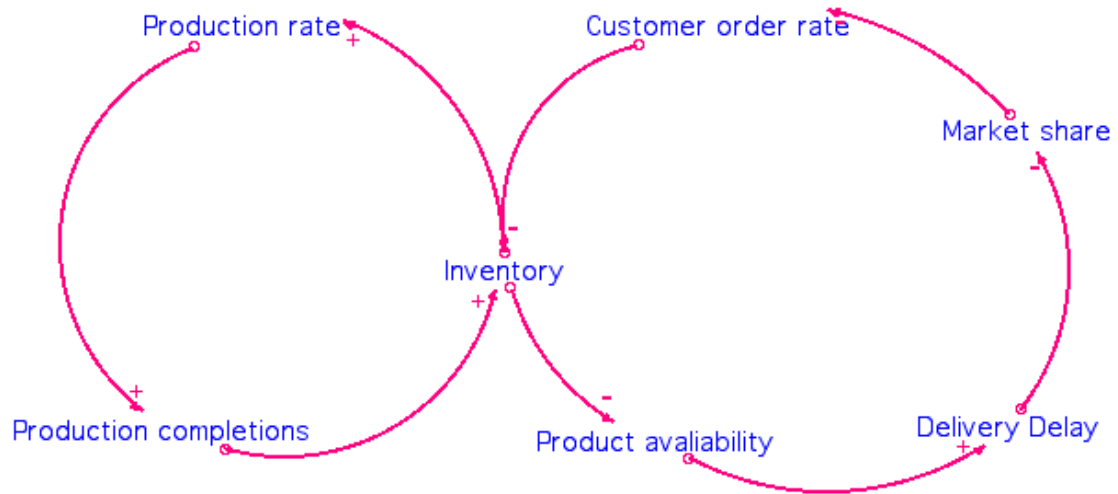


Figure 5- Negative feedback loop with major delays, which is intent to stabilize the inventory system

When there is a decrease in inventory caused by a step increase in customer demand, the production starts would increase, and after a suppliers' delivery delay and an additional production delay, the production completions and inventory will eventually increase. The production system in this feedback loop is trying to keep its inventory in tune with the company's goal for inventory. Another negative feedback loop introduced by market interactions in turn affects the stability of orders, production, and inventory as well as market share. When there is a decrease in inventory, there would be a decrease in availability of its production and an increase in its delivery delay to customers. Customers would decrease their demand since they receive orders less timely, - retracting from the value of the product.

The consequences of boom-and-bust cycles experienced by the inventory system would have both internal and external effects to the company. Firstly, because the parts inventory affects the production rate, and when there is a decrease in parts inventory, the production rate will be constrained so that finished inventory drops even lower. That causes the production rate to increase higher than the customer order rate. Another amplification is external to the company. When the system realizes the increase in customer demand, then the parts order rate increases dramatically, which is beyond the capacity of suppliers'. Thus, the suppliers' delivery time would increase and causes the parts inventory to drop lower than it otherwise would, and in turn causes an even larger increase in parts order rate. (Figure 6).

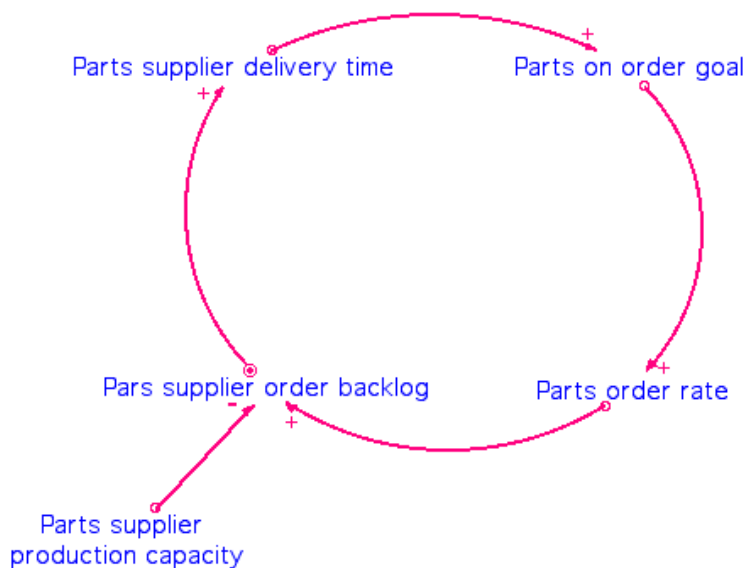


Figure 6- Positive feedback loop describe increased supplier delivery time increases level of oscillation within the system.

3.2 Structure and behavior of the real-world model – the labor section

Second, the model introduces dynamics created by interactions with labor and demonstrates how the production system is affected by employment instability. Labor is a human factor of production and is one of the most important resources to an organization. Companies experience large amplifications due to changing resource level adjustment times, including labor adjustment, in corporation with the production system (figure 7). In this thesis, however, the labor section is not included in our synthetic data analysis.. This is because the dynamics created by the system's interaction with the market are based on the inventory instability alone and do not take into consideration the employment instability in the real-world model itself. Due to the importance of employment instabilities to the company and its decision-making processes, we have chosen to introduce the dynamics created by interactions with the labor section as an illustration, but it is not included that aspect in the decision makers' mental model.

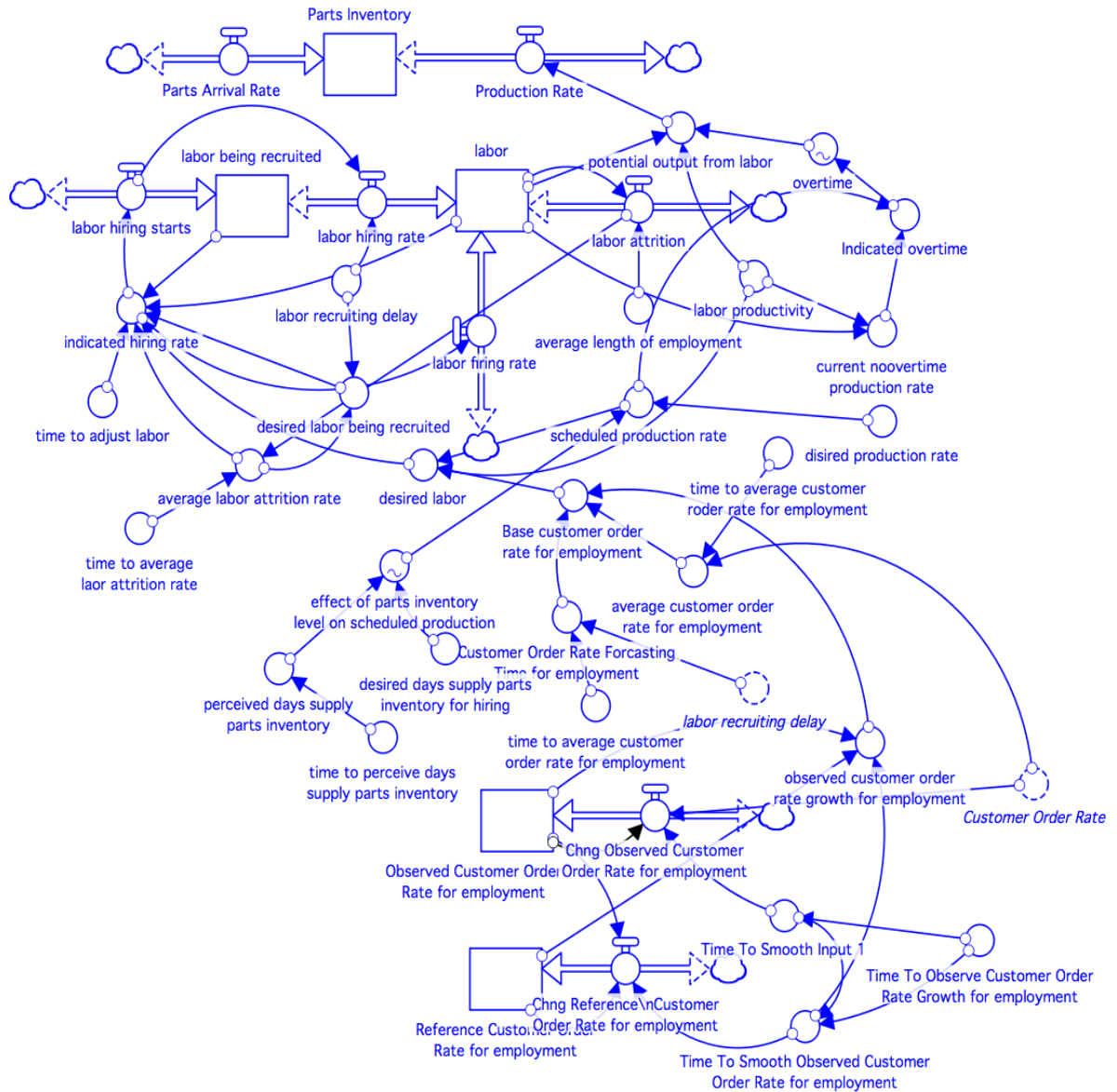


Figure 7- Dynamic structure of the labor section not included in the mental model as a demonstration.

From the structure in figure 7 we may conclude that decision-makers in large organizations normally need to decide how many new members of workforce to hire or fire, or whether to use over- or short-time policy in order to affect or alter their production rate. The production rate is assumed to be directly proportional to the level of labor employed at the company. When decision makers decide how much to produce, they need to take into consideration the productivity of the labor force together as well as the current inventory level.

When the production system takes into consideration the labor adjustment while coping with increased market demand, the system becomes more complex and dynamic. Decision-makers in most supply chain management tasks face similar problems almost every day. They only start to realize the company has sufficient workers when the actual production rate is larger than the desired production rate, whereupon they start to cut back on hiring and even may begin to lay off employees. The process of hiring and firing also takes time to execute, and the market demand might change once more during the labor adjustment period to cause even more instability in the system.

It is because organizations need advance notification of workers and additional time to schedule their production rate in accordance with the labor force, that the costs of labor instability typically cause companies to adjust labor more slowly than other production resources (Lyneis, 1982). As labor is one of the important means of production in companies, the labor levels exert a strong effect on the production rate. A company will face to pay extensively for their excess slack level and may, consequently, face financial problems if the system cannot adjust its resource (here workforce) levels swiftly because of long perception delays resulting from from decision-making. For

example, if labor resources do not match market demand, then the production rate would cause an undesirable change (increase or decrease) in the finished inventory and cause the desired production rate to fluctuate. The longer the adjustment time for labor, the greater amplification of stock values for the production system. Since labor is one of the most important resources within the production system, it is crucial for organizations to carefully adjust their policies when there is a crisis in system. The detailed functional aspect of the system will be examined in section 4.

3.3 Structure and behavior of the real-world model – the market-clearing section

An organization's inventory system is not only interacting with its own production system and that of the suppliers. Another important interaction takes place between the company and its social environment, - say when customers and the company's competitors, comprising the market, altogether influence the company performance and threaten the stability of the system (Lyneis, 1982). The structure of the market-clearing system encompasses the effect of the delivery delay, resulting from increased market demand and the resulting decreased inventory level, and feeds those effects back to market demand. Customers order goods from suppliers according to their demand (i.e in accordance with their preference for the company's products). The company provides its products based on customer's order rate as well as its own product availability. The company receives orders from the market according to market demand, and market orders goods from a company as a function of market demand and market share. The customer order rate in the model is no longer a simple step increase in customer order rate, but a function of market demand and market share. The model structure of the market-clearing mechanism as related to the inventory system is portrayed in figure 9.

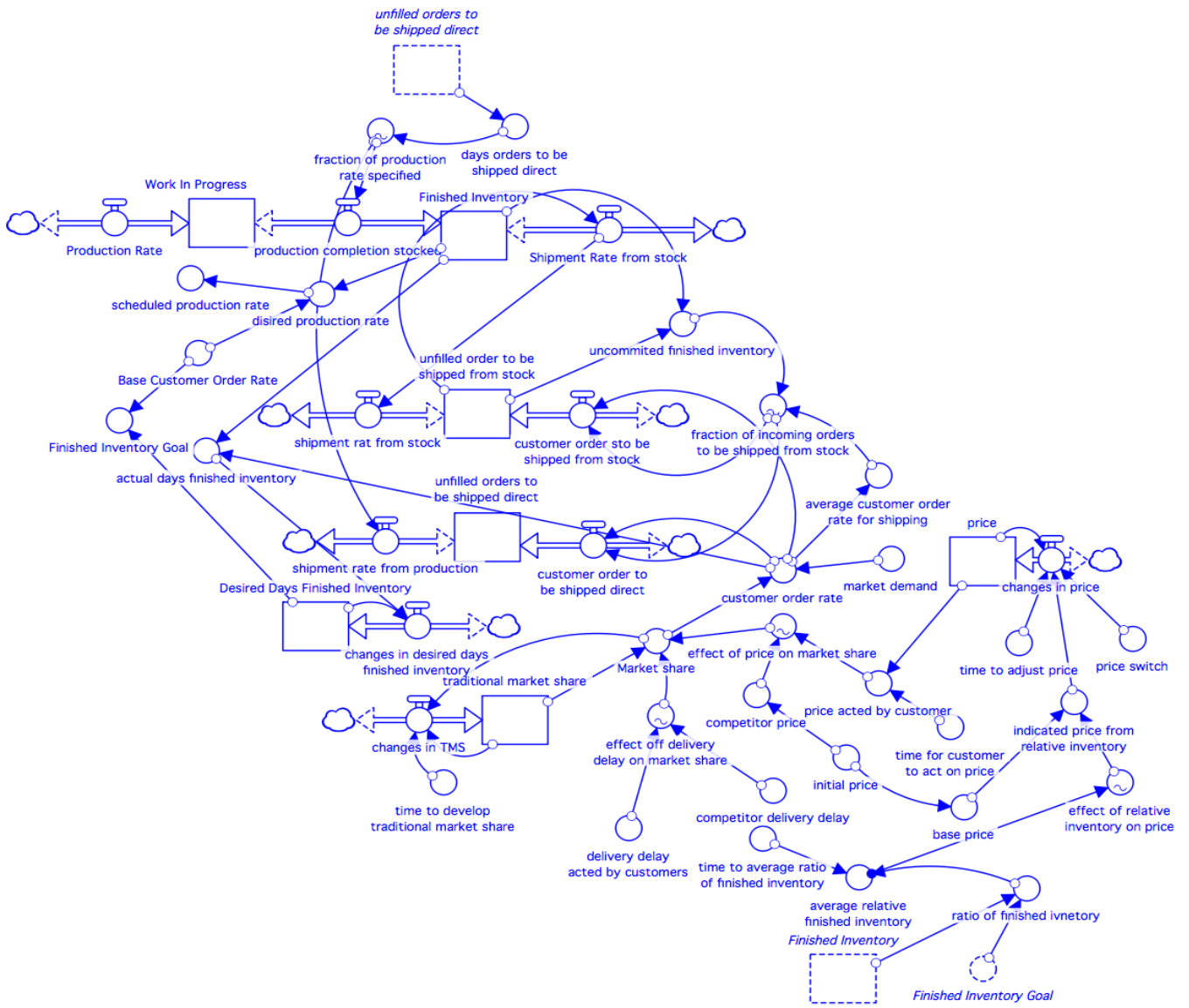


Figure 9- Dynamic structure of market-clearing system

Customers change their consumption preference according to product attractiveness that can be affected by the availability of products, price of products, quality, advertisement and services provided by the company. The company normally would change its short-term policies in an attempt to correct for any imbalance between the dynamic market demand and the supply of its products. The negative feedback loop portrayed in figure 10 from the market section controls the inventory system and affects the product attractiveness in terms of the availability / delivery delay of a product.

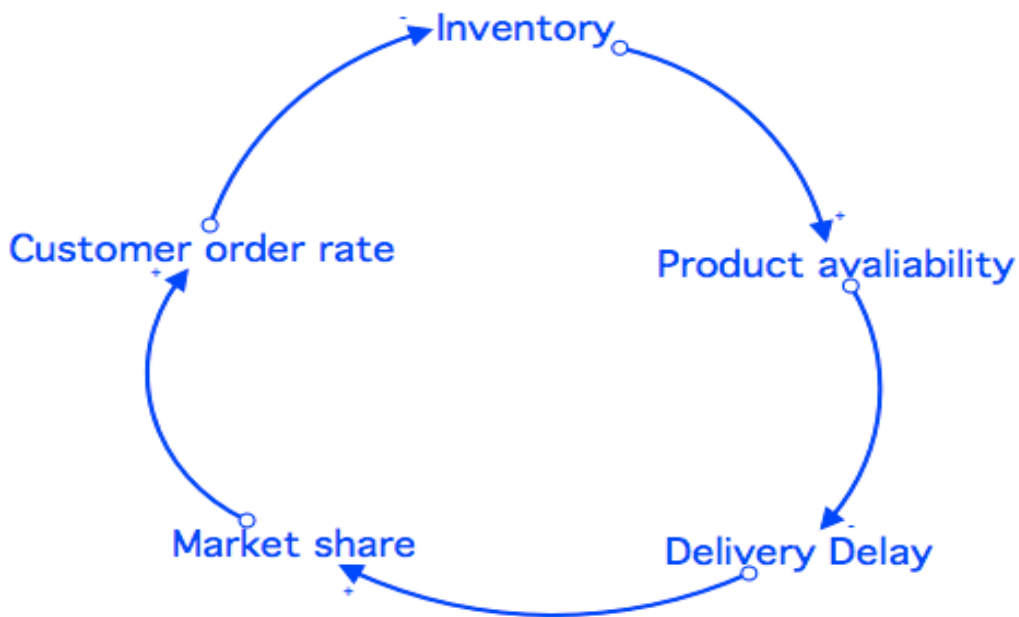


Figure 10- The market section controls the company inventory through negative feedback loop.

Decision-makers should have a clear picture in mind re. the changing stock levels and delivery times characterizing their system so as to make efficient decisions on order and production rates. If a sudden increase in customer order rate reduces the inventory level, then the company would order more from its suppliers to rebuild its inventory. On the other hand, the customer perceives the decreased availability level and thus reduces their demand (i.e. order rate) to match the lower production capacity. The production rate will not increase immediately after the manager orders more from their suppliers due to the increased customer order rate earlier on.

The behavior of the inventory system resulting from the interaction between the three sections discussed above is illustrated in figure 11 and 12.

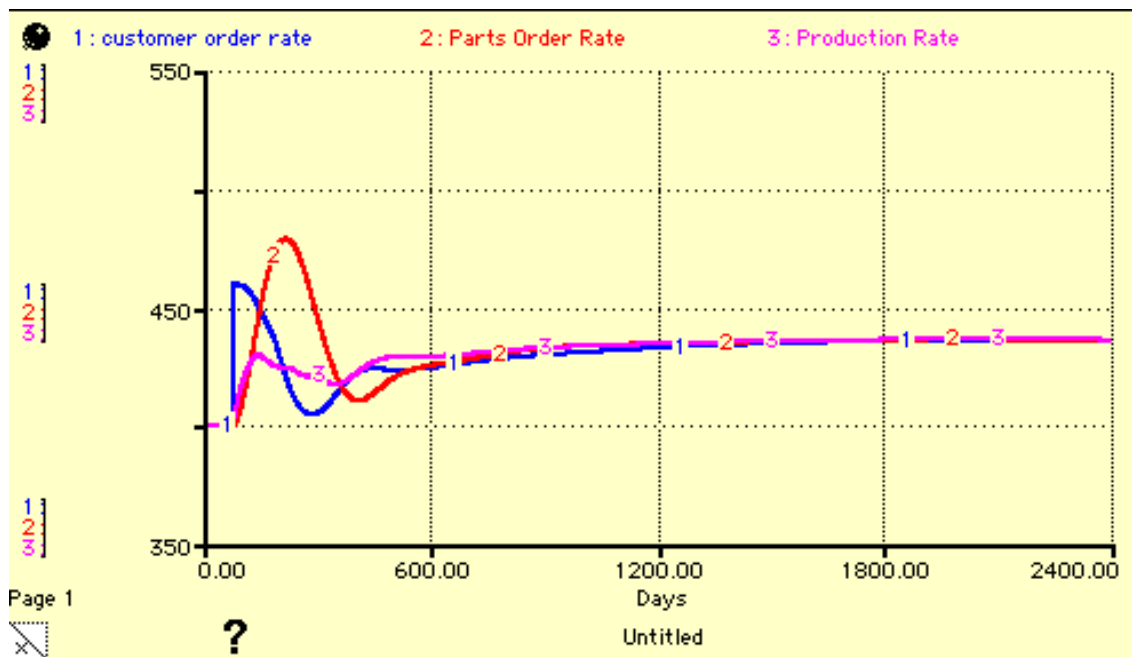


Figure 11- Customer order rate; parts order rate and production rate response to a 15% step increase in market demand

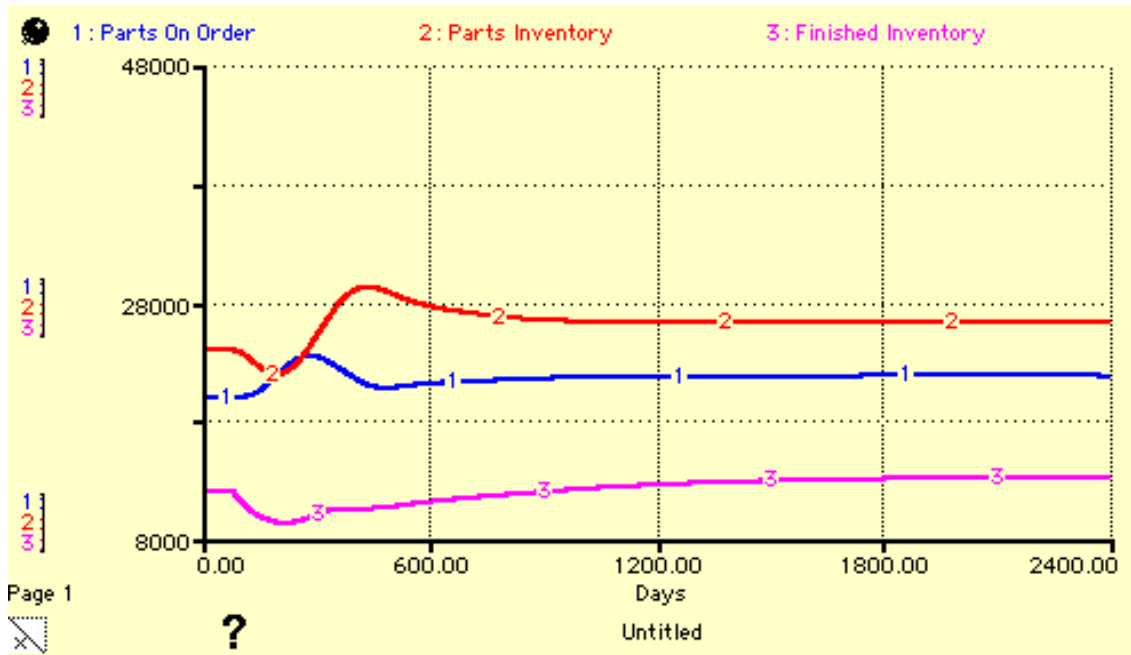


Figure 12- Parts on order, parts inventory and finished inventory response to a 15% step increase in market demand

The customer order rate increased 15% from day 60. Then, parts order rate start to increase above customer demand from day 80 because of the parts suppliers and production delays. In the meantime, production rate did not keep up with customer demand because there is not enough raw materials for production. The customer order rate then declined under the parts order rate and production rate, because the system experienced insufficient production to satisfy market demand. The inventory therefore experienced instability when customer increased their demand suddenly. Parts inventory and finished inventory declined first from day 60, then, they start to rise to stable level as long as parts order rate and production rate keep up with constant customer order rate after day 750.

4. The experiment set-up

4.1 Decision processes in each department in the inventory system

In this section, we will first describe how perception, formation of estimates and structural misunderstanding by decision-makers can be represented in the model.

4.1.1 Perception

By perception we mean how mental models are formed based on real world observations, i.e. the link between real world facts presented to us and the representation of those facts that form the basis for our decisions. The information transmitted to us through observations is interpreted in light of our existing mental models and forms the basis for a reformation of those models. The result of observation, interpretation and reformation what we define as perception, - how we “see” reality. Needless to point out, that “vision” of reality, - our mental models then become part of our reality. The way we think about reality is, in fact, reality itself through a different part of reality than the one we form mental models of. A first-order information delay can be represented as a perception of information process for managers (Serman, 1986); (Beer,1975) (Figure 15). In this thesis, I will adopt that perspective. In our models, decision-makers are make and execute decisions in the reality that they are managing based on their perceptions of that reality, - the real world

systems they observe and act in. All the variables that represent the perception of reality are modeled as the decision-makers' mental model and are colored dark green.

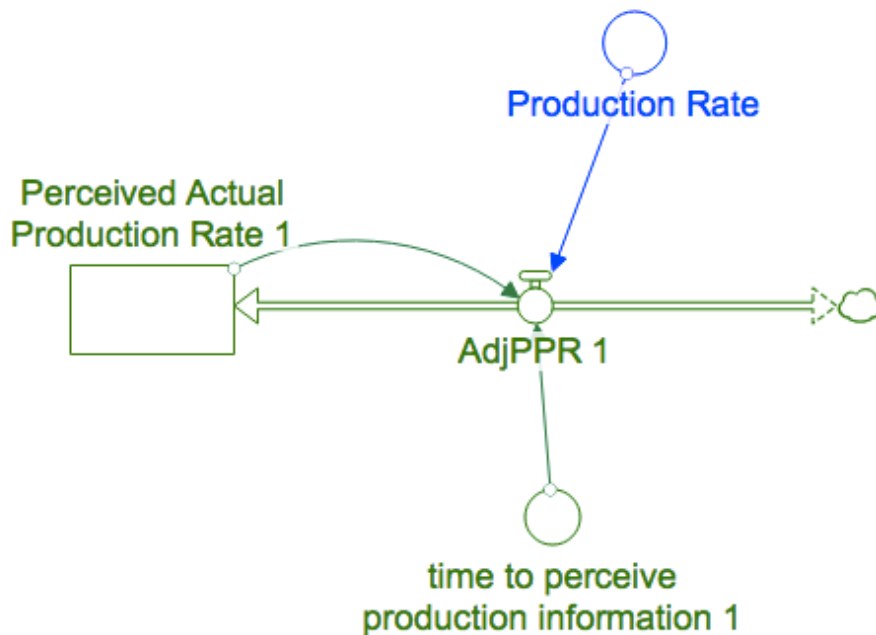


Figure 15 – Stock-and-flow representation of perception of information from real world

In Figure 15, the actual production rate with blue color is the real world fact that people observe and form a perception (mental model) about. People make new observations about the production rate on a continuous basis and, based thereupon, modify their mental models. In this thesis, these modifications (perceptions) are assumed to be taking place in the form of a first order exponential delay as the one described above. The time to perceive production information (the time to form a perception) may be considered a function of the level of development of the decision-makers' mental model that characterizes his/her willingness and ability to modify their mental models so as to accurately represent the actual production rate.

Traditionally, the stock and rate equations associated with the structure portrayed in figure 15 are presented as follows:

$$\text{Perceived_Actual_Production_Rate_1}(t) = \text{Perceived_Actual_Production_Rate_1}(t - dt) + (\text{AdjPPR_1}(t-dt, t)) * dt$$

$$\text{AdjPPR_1}(t-dt, t) = (\text{Production_Rate_1}(t) - \text{Perceived_Actual_Production_Rate_1}(t-dt)) / \text{time_to_perceive_production_information_1}(t)$$

The interpretation of this set of equations is, typically, that the perception (mental model formation) process each time period is aiming at closing the gap between the former perception (*Perceived_actual_Production_Rate_1*(*t - dt*)) and the (observation made of) reality (*Production_Rate_1*(*t*)) over the perception time (*Time_to_Perceive_production_information_1*(*t*)). This is, to many, a fuzzy interpretation. An alternative may be obtained by merging the two equations to:

$$\text{Perceived_Actual_Production_Rate_1}(t) = \text{Perceived_Actual_Production_Rate_1}(t - dt) + (\text{Production_Rate_1}(t) - \text{Perceived_Actual_Production_Rate_1}(t-dt)) / \text{time_to_perceive_production_information_1} * dt$$

and rearrange by defining;

$$ALFA = 1 / \text{time_to_perceive_production_information_1}$$

resulting in

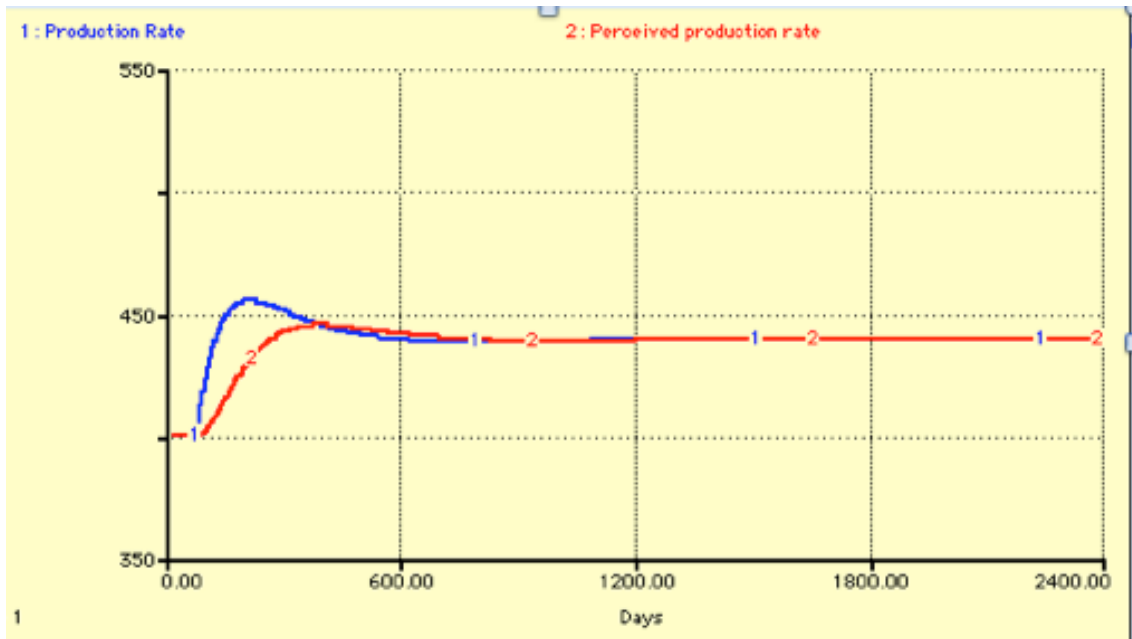
$$\begin{aligned} \text{Perceived_Actual_Production_Rate_I}(t) = & \text{Production_Rate_I}(t) * \text{ALFA} * dt + \\ & \text{Perceived_Actual_Production_Rate_I}(t - dt) * (1 - \text{ALFA} * dt) \end{aligned}$$

By interpreting ALFA as the weight assigned to a new observation over a model time period, the resulting equation may be interpreted as follows:

The perception formed after a new observation over a model time period is the weighed average of the new observation, assigned the weight ALFA, and the old perception, assigned the weight (1-ALFA). In the case that the perception (mental model formation process) takes place more frequently, - say every dt of the model time period, then the reality has been observed over a shorter period of time and the new observation should, consequently be assigned a correspondingly smaller weight, - ALFA * dt. Thus the equation above.

Graph 1 represents the typical behavior of the first order perception structure.

Decision-makers have perfect knowledge of the actual production rate from the time 0, and then the customer order rate suddenly increases by 10% on day 60, resulting in a gradual increase in the production rate as of day 67. But decision-makers are not willing or able to adjust immediately their perception of that increase in reality. A decision-maker would, over time, only update his/her mental model of the actual production rate in accordance with his/her willingness and ability to perceive that reality, represented by the relative weight assigned to the new observation. After 1163 days, the perceived production rate is, finally representing the actual production rate, with only a marginal inaccuracy, a perception of reality with a major delay.



Graph 1- Behavior of typical perception process of production rate

4.1.2. Estimation

Another important structure associated with the modeling of decision processes based on mental models is the estimation processing made by decision makers to calibrate their mental models. Typically, in the daily decision making associated with supply chain management, the decision makers need to rely on estimates. For example, it takes time for suppliers to deliver the materials to the company after they have received new orders. Managers might know that there will be a delay from parts are ordered until they arrive. However, how this affects the relationship between the order rate and the delivery rate is not always obvious and needs to be estimated based upon observations (experience). Depending on the assumptions underlying such estimation, this relationship may be subject to misperception. Managers may e.g. under- or over-estimate the need for new orders because they under- or over-estimate the delivery delay generated by their suppliers (Sterman,1989). Decision makers also estimate how long it takes for customers to have their orders fulfilled by the company. If, say, the deliveries are restricted as a consequence of a low finished inventory level, then, unless the decision makes have an appropriate mental model of such a mechanism, the delivery time may be under- or over-estimated. The typical estimation process is represented in figure 16.

Normally, decision makers cannot predict precisely the delivery rate generated by their suppliers in response to the parts order rate. They do not have sufficient insights into how their suppliers operate. Therefore, they estimate the parts suppliers' arrival (i.e. delivery) rate based on the perceived suppliers delivery time and parts order rate, both represented in their mental model.

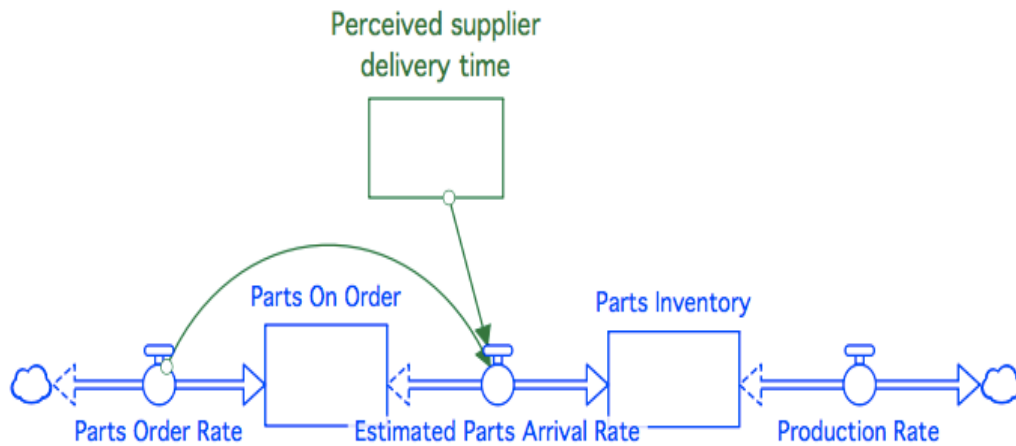


Figure 16- Estimation process of delivery rate based on perceived variables in mental model.

When representing the perception structure, the value of the perceived variable lags behind the value of the variable represented in the real world. However, when representing the estimated variable as in figure 16, the two perceived variables are used as inputs in the estimation of the parts arrival rate. Therefore, the estimated part arrival rate will typically be a delayed representation of the real parts arrival rate. Consequently, the values of the parts on order and parts inventory may develop differently than their real counterparts.

4.1.3. Structural misperception

In the previous two sections, we introduced the typical perception structure and estimation process that represent decision processes in the mental model structure. In this section, we discuss how decision makers may misperceive the effect of feedback when they partially or totally ignore the link between two variables in a feedback loop.

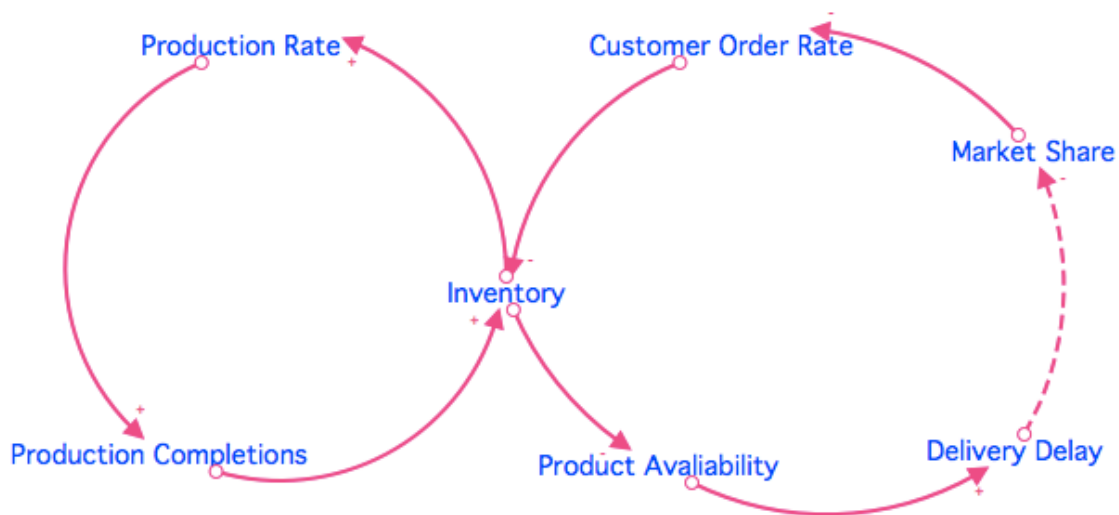


Figure 17- Illustration of how to ignore the effect of delivery delay to the customer order rate.

As illustrated in figure 17, the inventory is controlled by two negative feedback loops in the real-world system. The “long” and delayed feedback loop that includes the link from delivery delay to the customer order rate is likely to be ignored or misperceived in a complex inventory system. Delivery delay is increased when product availability decreases. That causes market share to decrease and result in a potential drop in customer demand for products. Decision makers might ignore or underestimate the

effect of delivery delay on the market demand due to the delayed feedback or, merely, because the loop extends beyond the boundary of the company or their domain. .

Market_Share=

Traditional_Market_Share

**Effect_Of_Delivery_Delay_On_Market_Share*Effect_Of_Price_On_Market_Share*

Customer_Order_Rate =

*Market_Demand*Market_Share*

When managers ignore the delivery delay from the system, they are assuming there is no delay from the time when customer ordered products to the time they actually receive their orders. Therefore, managers assuming that customers having higher expectation about the company's performance because they are expecting they can receive their orders immediately after they have place an order. However, if the production line does not operate effectively, there might exist a delay from the time company receives customer orders until they actually deliver the products ordered. Thus, when the managers do not expect that thee customer order rate be affected by delivery delays, they will not consider measures to improve delivery times for the purpose of boosting the customer order rate. Moreover, as they will not attribute a change in the customer order rate to their delivery delay, they will, rather, attribute it to price! Thus they will over-emphasize the effect of price on customer order rate. This will influence managers' choice of policy: Price alone will be used as policy instrument and that instrument to influence (increase) customer order rate will work less

effectively than expected because there is also the unrecognized, effect of delivery delays.

Another typical misperception of the structure of an inventory system occurs when decision makers underestimate the significance of the material delay in a supply chain system. Material delay is different from information delay. Material delay represents a physical flow while as information delay represent perception delay (Albin, 1998). In the decision makers' mental model that we represent in this thesis, a misperceived structure of material delay is represented in the mental model behavior. In our example, we illustrate how managers misperceive a third-order delay to be a first-order delay. In Figure 18a and b, two stock-and-flow diagrams represent the generic structure of a first-order delay and a third-order delay and their behavior are compared in Figure 19.

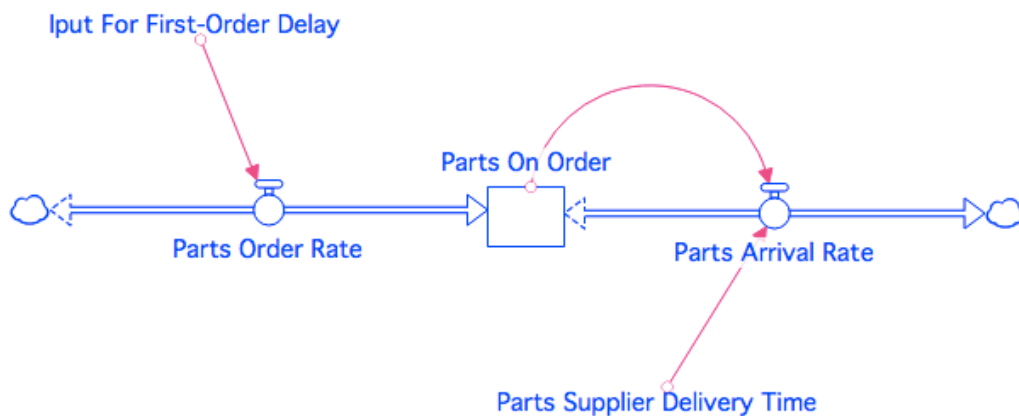


Figure 18a- Stock-and-flow diagram of a first-order material delay structure

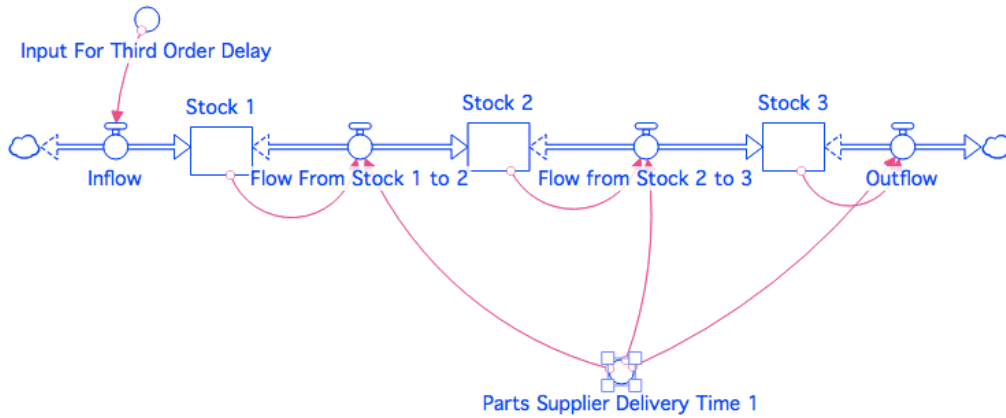


Figure 18.b Stock-and-flow diagram of a third-order material delay structure

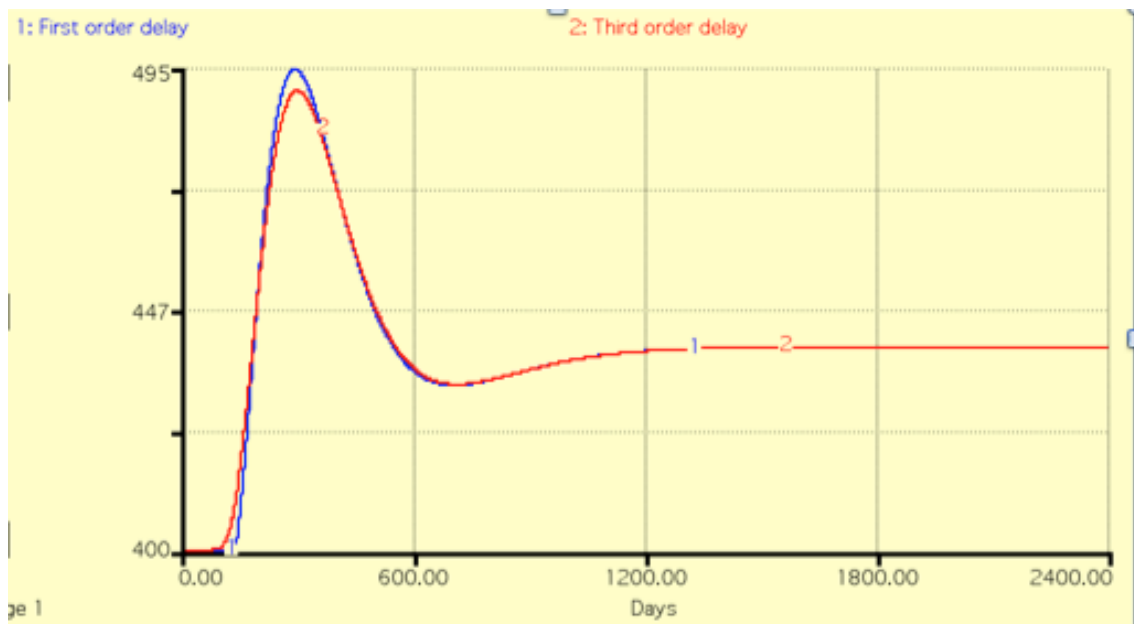


Figure 19- Behavior of the first and third order delay

A third-order material delay is used in the real-world inventory model in our thesis to represent the parts arrival rate from suppliers. When managers estimate the delivery time characterizing their suppliers, they are likely to misperceive the structure of the actual delay function. They may well assume the arrival rate is a first-order delay of the parts order rate is in place. Therefore, decision makers would estimate that much more items are delivered earlier than average in their first-order delay structure, and some are

delivered much later. When decision makers making order rate decision, they are likely anticipating much higher suppliers' delivery rate at the early stage of average time than the real world delivery rate (which is fewer items are delivered earlier than average). It will cause managers to have different ordering policy if they are assuming their system have a first-order delivery delay structure.

In the next section, we will examine how policy designers and decision-makers make operating decisions and change their policies based on their perceived structure of the system. In addition, we will examine how these decisions affect the behavior of the real-world system when these decisions are based on the following perception processes: (i) ignorance of the feedback loops and (ii) estimation based on misperceived structure of the delay function.

5. Decision-makers' mental model

5.1. Decision variables implemented in the real-world system based on misperceptions of structures, represented in the decision-makers' mental model

In this section, we will analyze the misperceived mental structure of a decision maker. Decision-makers' mental model is a result of a delayed perception of real-world information, may reflect the ignorance of structural elements that constitute feedback loops and estimations based on misperceived systems structures. We will describe five decision variables, which are representations of the decision-making activities in their social environment. The chosen decision variables are input parameters to the real-world social system. There are five decision variables that are implemented in the real-world system and that are colored blue in the real-world model. Each of these decision variables is being described in the sections below.

5.1.1. Parts order rate

First, parts order rate is a crucial decision variable. The policy (structure) governing this variable contributes significantly to the (oscillatory) behavior of the system. While as an abundance of raw material is undesirable for cost reasons, shortages of such materials slow the assembly line and contribute to insufficient production. Consequently, decision makers increase or decrease their orders from suppliers based on their perception of the production rate and the actual inventory levels of parts on order and parts inventory. The stock of parts on order is an “invisible” inventory level that accounts for how many parts have been ordered from suppliers, but that have not been received yet. The parts inventory is the raw materials, which have already been received by the company through deliveries. The parts order rate is easy to miscalculate by decision makers because of the fluctuation of the production rate and the delivery delay from the suppliers. It consists of three components:

Parts Order Rate =

Base Production Rate + Parts Inventory Correction + Parts On Order Correction

The parts order rate is anchored in the perception of the production rate and corrected for the parts inventory level and the parts on order level. Every time managers place new orders, they identify their perceived production rate (colored dark green to represent their perception process). In the mental model component, the production rate is represented as a perception. We assume that managers cannot perceive instantaneously the production rate at any point in time. And since the inventory system

typically exhibits fluctuations as a result of the delivery delays, the perceived values will be off the real ones (figure 21).

Base Production Rate defined in the original real-world model incorporates trend extrapolation method. Base Production Rate equals 1.0 plus Production Rate Forecasting Time multiplied by Observed (Perceived) Production Rate Growth Rate, all multiplied by Perceived Actual Production Rate. By forecasting variations of actual production rate, decision makers would be able to adjust their production in advance so that production more nearly match shipments so that inventory will fluctuate little.

In decision makers' mental model, we assume managers cannot observe the accurate production rate, so perceived actual production rate is used in decision makers' mental model.

Base Production Rate =

$$(1 + \text{Production_Rate_Forecasting_Time_1} * \text{Perceived_Production_Rate_Growth_Rate_1}) * \text{Perceived_Actual_Production_Rate}$$

The Production Rate Forecasting Time is the sum of Time To Perceive Production Information and the Perceived Parts Supplier's Delivery Time:

$$\text{Production_Rate_Forecasting_Time_1} = \text{Time_To_Perceive_Production_Information} + \text{Perceived_Parts_Supplier_Delivery_Time_1}$$

$$\text{Time_To_Perceive_Production_Information} = 60 \text{ days}$$

The Perceived Parts Supplier Delivery Time is the sum of the production delay and observed time to schedule supplier's production:

$$\text{Perceived_Parts_Supplier_Delivery_Time_1} = \text{Parts_Supplier_Production_Delay_1} + \text{Perceived_Parts_Supplier_Scheduling_Delay_1}$$

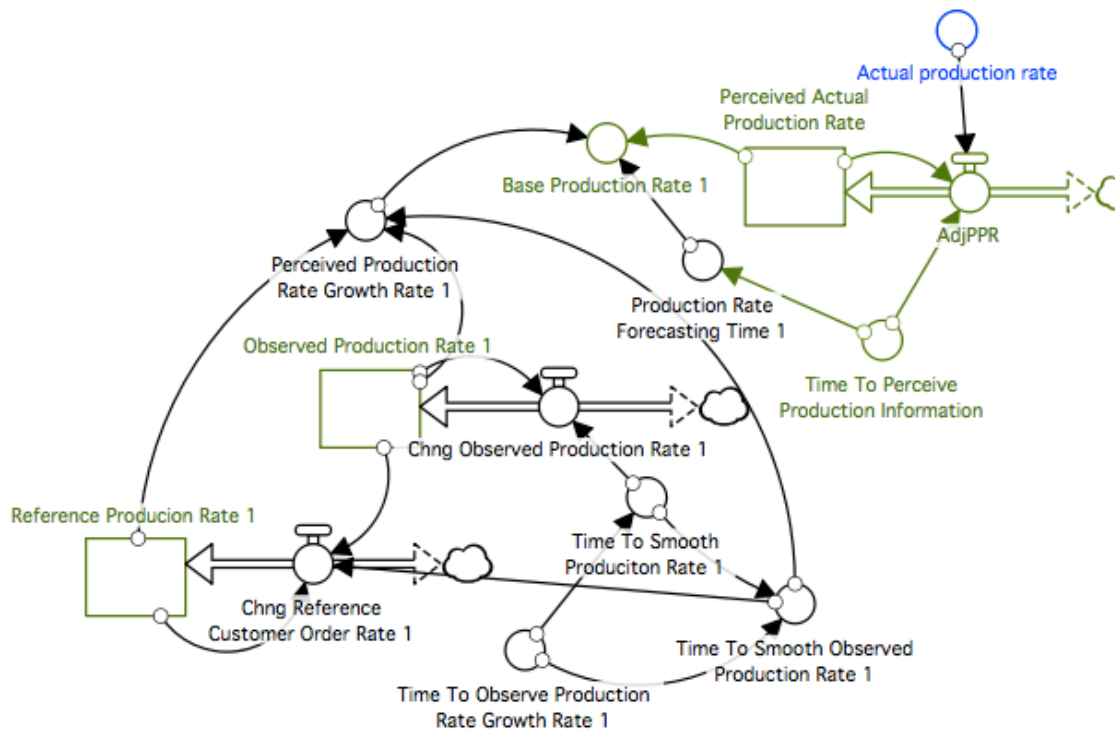


Figure 21- Representation of Base Production Rate 1 that is based on Perceived Actual Production Rate in mental model.

Parts_Supplier_Production_Delay_1= 50 days

The production might be constrained by supplier's production capacity, so the scheduling delay reflects any increase in lead-time caused by parts orders in excess of supplier's capacity. It is defined as:

$$\text{Perceived_Parts_Supplier_Scheduling_Delay}_1 = \frac{\text{Parts_Supplier_Order_Backlog}_1}{\text{Perceived_Parts_Supplier_Production_Starts}}$$

The Parts Supplier Order Backlog is a level variable that is increased Parts Order Rate and decreased by Parts Supplier Production Starts, which is initialized by supplier's minimum scheduling delay (10days) by constant customer order rate (400 units/day):

$$\text{Parts_Supplier_Order_Backlog_1} = \text{Parts_Supplier_Order_Backlog_1}(t - dt) + (\text{Potential_Parts_Order_Rate_1} - \text{Parts_Supplier_Production_Starts_1}) * dt$$

$$\text{Parts_Supplier_Minimum_Scheduling_Delay_1} = 10 \text{ days}$$

$$\text{Constant_Customer_Order_Rate_1} = 400 \text{ Units/day}$$

The Parts Supplier Production Starts is the outflow of supplier's backlog, which is constrained by parts supplier's production capacity. Managers might not directly observe the actual supplier's capacity and the rate of their production. This particular variable will be analyzed in the next section.

The following equations are process of how decision makers forecasting the Production

Rate Growth Rate:

Perceived Production Rate Growth Rate=

$$\frac{(\text{Observed_Production_Rate_1} - \text{Reference_Production_Rate_1})}{(\text{Reference_Production_Rate_1} * \text{Time_To_Smooth_Observed_Production_Rate_1})}$$

$$\text{Observed_Production_Rate_1} = \frac{\text{Perceived_Actual_Production_Rate}}{(1 + \text{Time_To_Smooth_Production_Rate_1} * \text{Initial_Production_Rate_Growth_Rate_1})}$$

$$\text{Chng Observed Production Rate 1} = \frac{(\text{Disired_Production_Rate_1} - \text{Observed_Production_Rate_1})}{\text{Time_To_Smooth_Production_Rate_1}}$$

$$\text{Reference_Production_Rate_1} = \frac{\text{Observed_Production_Rate_1}}{(1 + \text{Time_To_Smooth_Observed_Production_Rate_1} * \text{Initial_Production_Rate_Growth_Rate_1})}$$

$$\text{Chng Reference Production Rate 1} = \frac{(\text{Observed_Production_Rate_1} - \text{Reference_Production_Rate_1})}{\text{Time_To_Smooth_Observed_Production_Rate_1}}$$

$$\begin{aligned} \text{Time_To_Smooth_Observed_Production_Rate_1} = \\ \text{Time_To_Observe_Production_Rate_Growth_Rate_1} - \\ \text{Time_To_Smooth_Production_Rate_1} \end{aligned}$$

$$\text{Initial_Production_Rate_Growth_Rate_1} = 0 \text{ day}$$

$$\begin{aligned} \text{Time_To_Smooth_Production_Rate_1} = \\ 0.4 * \text{Time_To_Observe_Production_Rate_Growth_Rate_1} \end{aligned}$$

$$\text{Time_To_Observe_Production_Rate_Growth_Rate_1} = 480 \text{ days}$$

The perceived actual production rate is a information updating process in managers' mental model by observing the actual production rate. The perceived actual production rate is defined as:

$$\text{Perceived Actual Production Rate} = \text{Perceived_Actual_Production_Rate}(t - dt) + (\text{AdjPPR}) * dt$$

$$\text{AdjPPR} = (\text{Potential_Production_Rate_1} - \text{Perceived_Actual_Production_Rate}) / \text{Time_To_Perceive_Production_Information}$$

$$\text{Time_To_Perceive_Production_Information} = 60 \text{ days}$$

Decision makers also adjusting the current inventory levels with its desired level every 240 days when they are ordering new raw materials. Parts on order correction is defined as:

$$\begin{aligned} \text{Parts_On_Order_Correction} = \\ (\text{Parts_On_Order_Goal} - \text{Parts_On_Order}) / \text{Time_to_Correct_Part_Inventory_1} \end{aligned}$$

The desired level of parts on order is 50 days of suppliers' production delay multiply the observed production rate by managers:

$$\begin{aligned} \text{Parts_On_Order_Goal} = \\ \text{Parts_Supplier_Production_Delay_1} * \text{Base_Production_Rate_1} \end{aligned}$$

$$\text{Parts_On_Order} = \text{Parts_On_Order}(t - dt) + (\text{Parts_Supplier_Production_Delay}_1 * \text{Constant_Customer_Order_Rate}_1) * dt$$

$$\text{Parts_On_Order}(\text{Init}) = \text{Parts_Supplier_Production_Delay}_1 * \text{Constant_Customer_Order_Rate}_1$$

$$\text{Constant_Customer_Order_Rate}_1 = 400 \text{ Units/day}$$

$$\text{Parts_Supplier_Production_Delay}_1 = 50 \text{ days}$$

$$\text{Constant_Customer_Order_Rate}_1 = 400 \text{ Units/day}$$

$$\text{Time_to_Correct_Part_Inventory}_1 = 240 \text{ days}$$

The Parts Inventory Correction is defined as:

$$\text{Part_Inventory_Correction} =$$

$$(\text{Parts_Inventory_Goal} - \text{Parts_Inventory}) / \text{Time_to_Correct_Part_Inventory}_1$$

The desired level of parts inventory is defined as:

$$\text{Parts_Inventory_Goal} = \text{Desired_Days_Parts_Inventory_PV} * \text{Base_Production_Rate}_1$$

$$\text{Parts Inventory} = \text{Parts_Inventory}(t - dt) + (\text{Parts_Arrival_Rate} - \text{Production_Rate}) * dt$$

$$\text{Parts Inventory (Init)} =$$

$$\text{Desired_Days_Parts_Inventory_PV} * \text{Constant_Customer_Order_Rate}_1$$

$$\text{Desired_Days_Parts_Inventory} = 60 \text{ days}$$

5.1.2. Potential parts supplier capacity utilization rate

The dynamic structure represented in figure 22 illustrates how managers modeling the parts supplier capacity utilization rate in their mental model. The potential parts supplier capacity utilization rate is colored blue in order to represent it as the decision variable, which will be later implemented in the real-world structure. The utilization rate is a non-linear function of parts supplier desired production rate divided by the perceived parts supplier production capacity. We are assuming that decision makers have distorted picture of the accurate supplier's production capacity. The Potential Parts Supplier Capacity Utilization Rate is defined as:

Potential_Parts_Supplier_Capacity_Utilization_Rate (PPSPCUR)=
 GRAPH(Parts_Supplier_Desired_Production_Rate(PSDPR)/Perceived_Parts_Supplier
 _Production_Capacity(PSPC))
 (0.00, 0.00), (0.25, 0.25), (0.5, 0.5), (0.75, 0.75), (1.00, 1.00), (1.25, 1.15), (1.50, 1.25),
 (1.75, 1.30), (2.00, 1.30)

The potential parts supplier capacity utilization rate equation defined the relationship between desired production rate and the observed production capacity. The supplier would cut back utilization rate proportionately when desired production rate falls below perceived production capacity. The supplier then increases its utilization rate less than proportionately when desired production rate exceeds production capacity (figure 23). The suppliers' utilization rate then affects how efficient the supplier's production is to achieve company's new order for raw materials.

The parts supplier desired production rate is the sum of observed supplier's parts order rate and adjustment of supplier's backlog, it is defined as:

$$\text{Parts Supplier Desired Production Rate} = \text{Perceived_Parts_Supplier_Average_Parts_Order_Rate}_1 + \text{Parts_Supplier_Order_Backlog_Correction}_1$$

The perceived parts supplier average parts order rate is an exponential average of potential parts order rate, which can be defined as perception process of how suppliers perceive the actual parts order rate. This perception process is presented in the real-model model. It is defined as:

$$\text{Perceived_Parts_Supplier_Average_Parts_Order_Rate} = \text{Perceived_Parts_Supplier_Average_Parts_Order_Rate}_1(t - dt) + (\text{AdjPSAPOR}_1) * dt$$

$$\text{Perceived_Parts_Supplier_Average_Parts_Order_Rate}_1(\text{Init}) = \text{Constant_Customer_Order_Rate}_1$$

$$\text{Adjustment of Parts Supplier Average Parts Order Rate} = (\text{Potential_Parts_Order_Rate}_1 - \text{Perceived_Parts_Supplier_Average_Parts_Order_Rate}_1) / \text{Time_To_Perceive_Parts_Supplier_Average_Parts_Orders}_1$$

The parts supplier order backlog correction (PSOBC) is a negative inventory, which gives the supplier feedback control over the backlog. When order backlog is greater than its desired level, the desired production rate increases above average parts order rate; when the backlog is less than desired backlog level, the average parts order rate increases above the desired production rate. The equation showed the difference between parts supplier order backlog (PSOB) and parts supplier desired order backlog (PSDOB), divided by parts supplier time to correct order backlog (PSTCOB):

$$\text{PSOBC} = (\text{Parts_Supplier_Order_Backlog}_1 - \text{Parts_Supplier_Desired_Order_Backlog}_1) / \text{Parts_Supplier_Time_To_Correct_Order_Backlog}_1$$

The potential production rate is the inflow of parts supplier order backlog, which is analyzed in the last section. The outflow of parts supplier order backlog is parts supplier production starts, which defines the efficiency of supplier's production that is constrained by perceived supplier's production capacity.

Parts Supplier Production starts =
 $\text{Perceived_Parts_Supplier_Production_Capacity} * \text{Potential_Parts_Supplier_Capacity_Utilization_Rate_1}$

When decision makers modeling the supplier's capacity, they compare between their perceived parts order rate (perceived parts order rate is the supplier desired production capacity) with their current capacity. Decision makers have not directly perceive the actual Parts Order Rate, they misperceived the accurate parts order rate. So, we are assuming that decision makers cannot have perfect knowledge of the suppliers current capacity level because they have distorted picture of parts order rate. The perceived parts supplier production capacity is defined as:

Perceived Parts Supplier Production Capacity=
 $\text{Perceived_Parts_Supplier_Production_Capacity}(t - dt) + (\text{Adj_PPSPC}) * dt$

Perceived_Parts_Supplier_Production_Capacity(Init) =
 $\text{Parts_Supplier_Production_Capacity_1}$

Adjustment Of Perceived Parts Supplier Production Capacity=
 $(\text{Parts_Supplier_Production_Capacity_1} - \text{Perceived_Parts_Supplier_Production_Capacity}) / \text{Time_To_Perceive_Production_Information}$

In decision maker's mental model, we replace the parts supplier production capacity with perceived parts supplier production capacity in equation of parts suppliers desired order backlog:

$\text{PSDOB} = \text{Perceived_Parts_Supplier_Production_Capacity} * \text{Parts_Supplier_Minimum_Scheduling_Delay_1}$

$\text{Parts_Supplier_Minimum_Scheduling_Delay_1} = 10 \text{ days}$

5.1.3. Estimated parts arrival rate

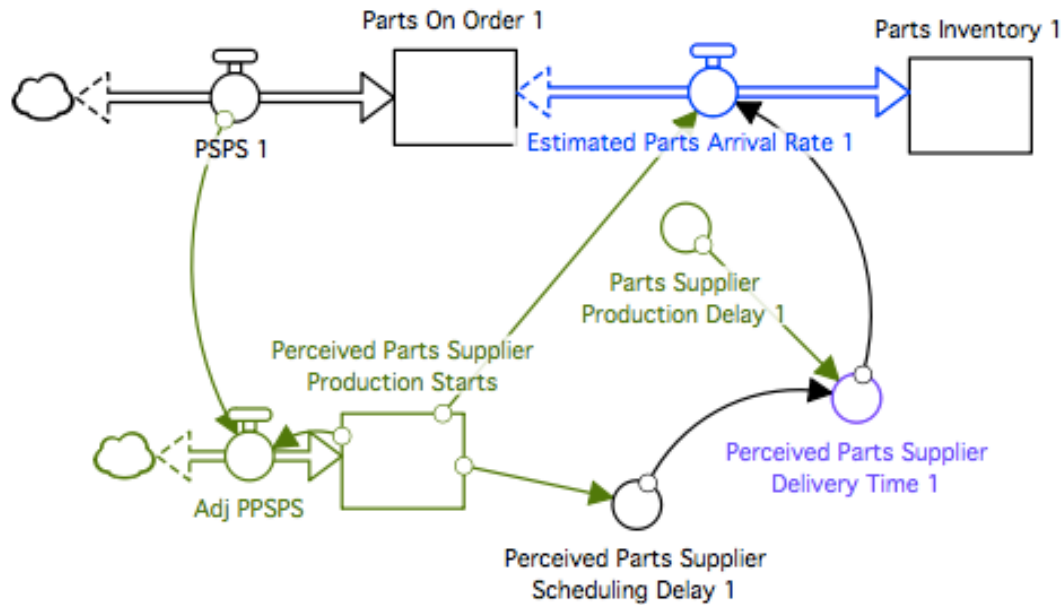


Figure 23- Stock-and-flow structure of Estimated Parts Arrival Rate in decision makers' mental model

Estimated_Parts_Arrival_Rate_1=
 DELAY1(Perceived_Parts_Supplier_Production_Starts,
 Perceived_Parts_Supplier_Delivery_Time_1)

The estimated parts arrival rate in decision makers' mental model is defined as first-order delay function of perceived parts supplier production starts and perceived parts supplier delivery time (figure 23). We assume that decision makers cannot accurately observe the rate of parts supplier production starts, so perceived parts supplier production starts is used to estimate the arrival rate. We also assume that managers misperceive the structure of the delay function and used a first-order delay function on estimation rather than a third-order delay function. In addition, the perceived parts supplier delivery time is used rather than parts supplier production delay in mental model.

$$\text{Perceived_Parts_Supplier_Production_Starts}(t) = \text{Perceived_Parts_Supplier_Production_Starts}(t - dt) + (\text{Adj_PPSPS}) * dt$$

$$\text{Perceived_Parts_Supplier_Production_Starts (Init)} = \text{Parts_Supplier_Production_Starts_1}$$

$$\text{Adj_PPSPS} = (\text{Parts_Supplier_Production_Starts_1} - \text{Perceived_Parts_Supplier_Production_Starts}) / \text{Time_To_Perceive_Production_Information}$$

The Perceived Parts Supplier Delivery Time is the sum of supplier's production delay and supplier's scheduling delay:

$$\text{Perceived_Parts_Supplier_Delivery_Time_1} = \text{Parts_Supplier_Production_Delay} + \text{Perceived_Parts_Supplier_Scheduling_Delay}$$

The parts supplier production delay is a constant number of 50 days.

The perceived parts supplier scheduling delay is calculated by parts supplier order backlog divide the perceived parts supplier production starts.

$$\text{Perceived_Parts_Supplier_Scheduling_Delay_1} = \text{Parts_Supplier_Order_Backlog_1} / \text{Perceived_Parts_Supplier_Production_Starts}$$

5.1.4. Potential production rate

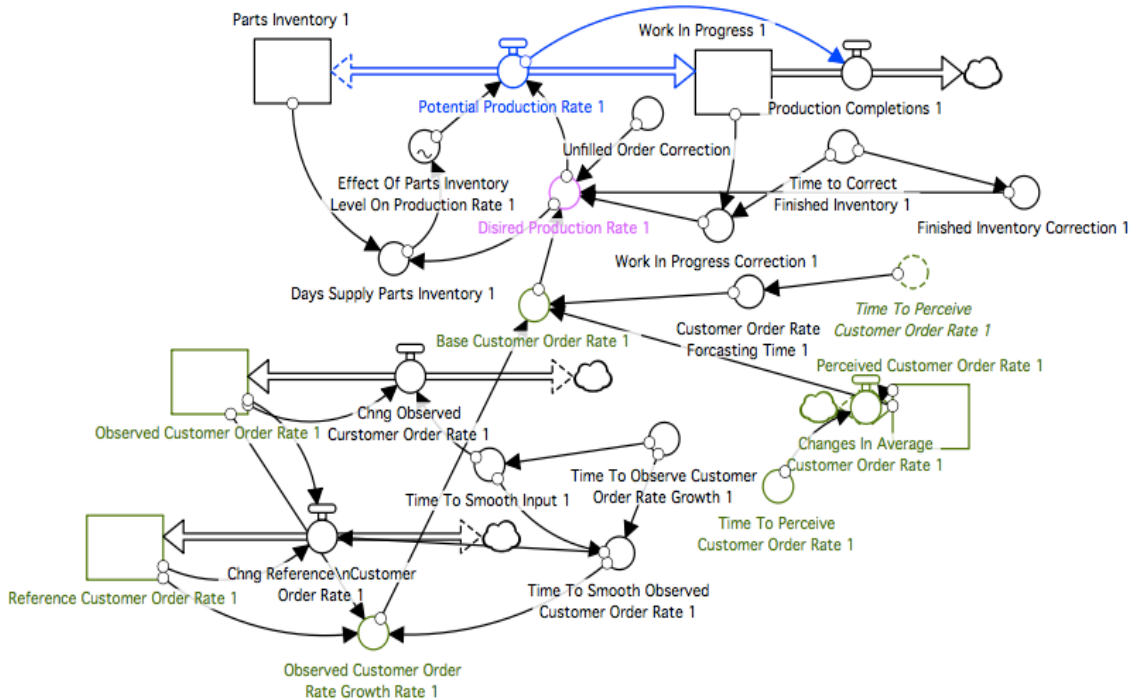


Figure 24- Stock-and-flow structure of potential production rate

Decision makers in a multiple inventory system need to have an efficient policy on the production rate to control their system. The sufficient policy would be to balance its inventory level and customer demand. However, when decision makers misperceive the underlying structure of the system, then compose policy decision according to their misperceived understanding about their system, the fluctuation of their inventory system would increase, and thus cause unstable capacity. So, the supply line would experience periods of insufficient production and lost orders. Production rate can be distorted and miscalculated by decision makers when they have several supply chains functioning at the same time. Figure 24 illustrates the potential production rate based on the desired production rate and the level of the parts inventory. The desired production

rate is taking consideration of the work in progress level, finished inventory level and unfilled orders plus the perceived changing customer order rates.

$$\text{Potential_Production_Rate} = \frac{\text{Effect_Of_Parts_Inventory_Level_On_Production_Rate} * \text{Disired_Production_Rate}}{1}$$

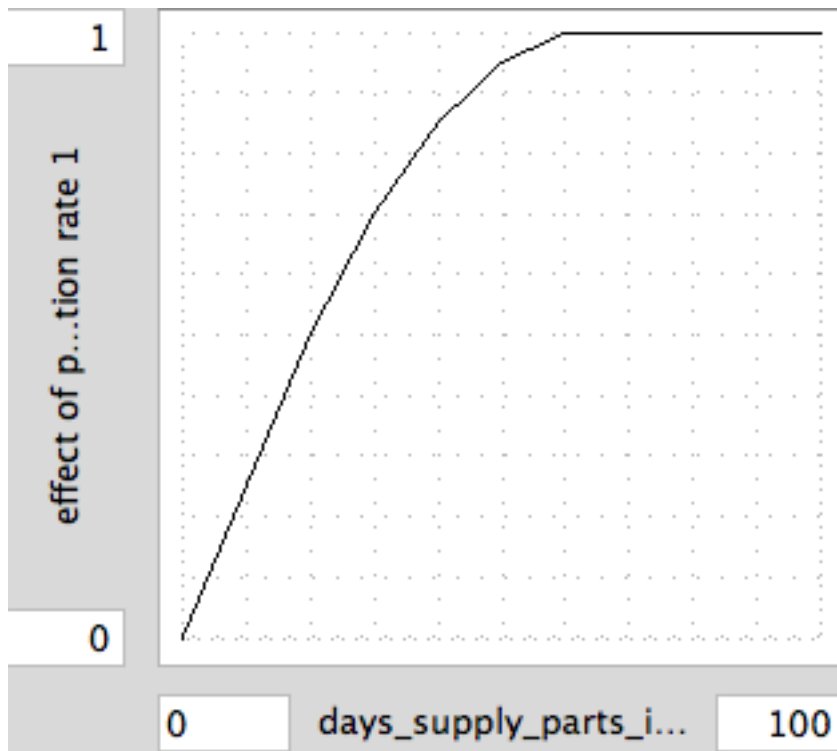


Figure 25- the graphical function of Effect Of Parts Inventory Level On Production Rate

The following equation defines the effect of parts inventory level on production rate (EPILPR) as a function of days supply parts inventory(DSPI). When DSPI is 60 days or more, EPILPR is 1.0 so the production rate is equal to desired production rate. When DSPI is less than 60 days, EPILPR drops below 1,0, slower at the beginning but more rapidly as DSPI falls below 40 days:

Effect_Of_Parts_Inventory_Level_On_Production_Rate= =

GRAPH(Days_Supply_Parts_Inventory)

(0,0, 0,000), (10,0, 0,250), (20,0, 0,500), (30,0, 0,700), (40,0, 0,850), (50,0, 0,950),
(60,0, 1,000), (70,0, 1,000), (80,0, 1,000), (90,0, 1,000), (100,0, 1,000)

When deciding how much to produce in the production line, decision makers are assuming when there is non-parts inventory, so the production is impossible (figure 25).

When parts inventory increasing, the production rate increases with diminishing returns.

Days Supply Of Parts Inventory is modeled as Parts Inventory divided by Desired Production Rate:

Days_Supply_Parts_Inventory = Parts_Inventory_1/Disired_Production_Rate_1

Parts Inventory is a stock variable, which is increased by Parts Arrival Rate and decreased by Production Rate:

Parts_Inventory(t) = Parts_Inventory(t - dt) + (Parts_Arrival_Rate - Production_Rate) * dt

Parts_Inventory(Init) =
Desired_Days_Parts_Inventory*Constant_Customer_Order_Rate

Desired production rate is the sum of base customer order rate, finished inventory correction and work in progress correction as well as unfilled orders corrections:

Desired_Production_Rate=
Base_Customer_Order_Rate+Finished_Inventory_Correction+Work_In_Progress_Correction+Unfilled_Orders_Correction

The base customer order rate is a forecasting method that managers use to estimate their current customer demand. In decision makers' mental model, we are assuming that decision makers updating their knowledge of current customer order rate with a

delay, so perceived customer order rate is used to represent the observed customer order rate in mental model.

$$\text{Base Customer Order Rate} = (1 + \text{Customer_Order_Rate_Forecasting_Time_1} * \text{Observed_Customer_Order_Rate_Growth_Rate_1}) * \text{Perceived_Customer_Order_Rate_1}$$

Where the:

$$\text{Customer_Order_Rate_Forecasting_Time_1} = \text{Time_To_Perceive_Customer_Order_Rate_1} + \text{Time_To_Complete_Work_In_Progress_1}$$

$$\text{Observed Customer Order Rate Growth Rate} = \frac{(\text{Observed_Customer_Order_Rate_1} - \text{Reference_Customer_Order_Rate_1})}{(\text{Reference_Customer_Order_Rate_1} * \text{Time_To_Smooth_Observed_Customer_Order_Rate_1})}$$

$$\text{Perceived_Customer_Order_Rate_1}(t) = \text{Perceived_Customer_Order_Rate_1}(t - dt) + (\text{Changes_In_Average_Customer_Order_Rate_1}) * dt$$

$$\text{Perceived_Customer_Order_Rate_1}(\text{Init}) = 400 \text{ Units/day}$$

$$\text{Changes_In_Average_Customer_Order_Rate_1} = (\text{Customer_Order_Rate_1} - \text{Perceived_Customer_Order_Rate_1}) / \text{Time_To_Perceive_Customer_Order_Rate_1}$$

$$\text{Time_To_Perceive_Customer_Order_Rate_1} = 60 \text{ days}$$

5.1.5. Potential market share

The customer order rate is represented as market demand for company.. In the inventory system, the customer order rate is modeled as the product of market demand and market share. The market share would fluctuate when there are changes in production attractiveness due to the effect of delivery delay on market share and effect of price on market share. As a result, managers might have a distorted understanding of market share when managers misperceive the effect of the delivery delay on market share (figure 27). In this section, we are going to analyze the variable of potential market share when managers misperceive the delivery delay on market share. The potential market share is defined as:

$$\text{Potential_Market_share} = \text{Traditional_Market_Share_1} * \text{Estimated_Effect_Of_Delivery_Delay_On_Market_Share_1} * \text{Effect_Of_Price_On_Market_Share_1}$$

Traditional market share is represented as a level variable that adjusted by changes in traditional market share:

$$\begin{aligned} \text{Traditional_Market_Share_1}(t) &= \text{Traditional_Market_Share_1}(t-dt) + \\ &(\text{Changes_In_TMS_1}) * dt \\ \text{Traditional_Market_Share_1}(\text{Init}) &= 1 \end{aligned}$$

$$\text{Changes_In_TMS_1} = (\text{Potential_Market_share} - \text{Traditional_Market_Share_1}) / \text{Time_To_Develop_Traditional_Market_Share_1}$$

Time to develop traditional market share reflects the loyalty of customers to their suppliers, which is 4 years in this case. It also implies customer have higher brand loyalty in this case:

$$\text{Time_To_Develop_Traditional_Market_Share_1} = 960 \text{ days}$$

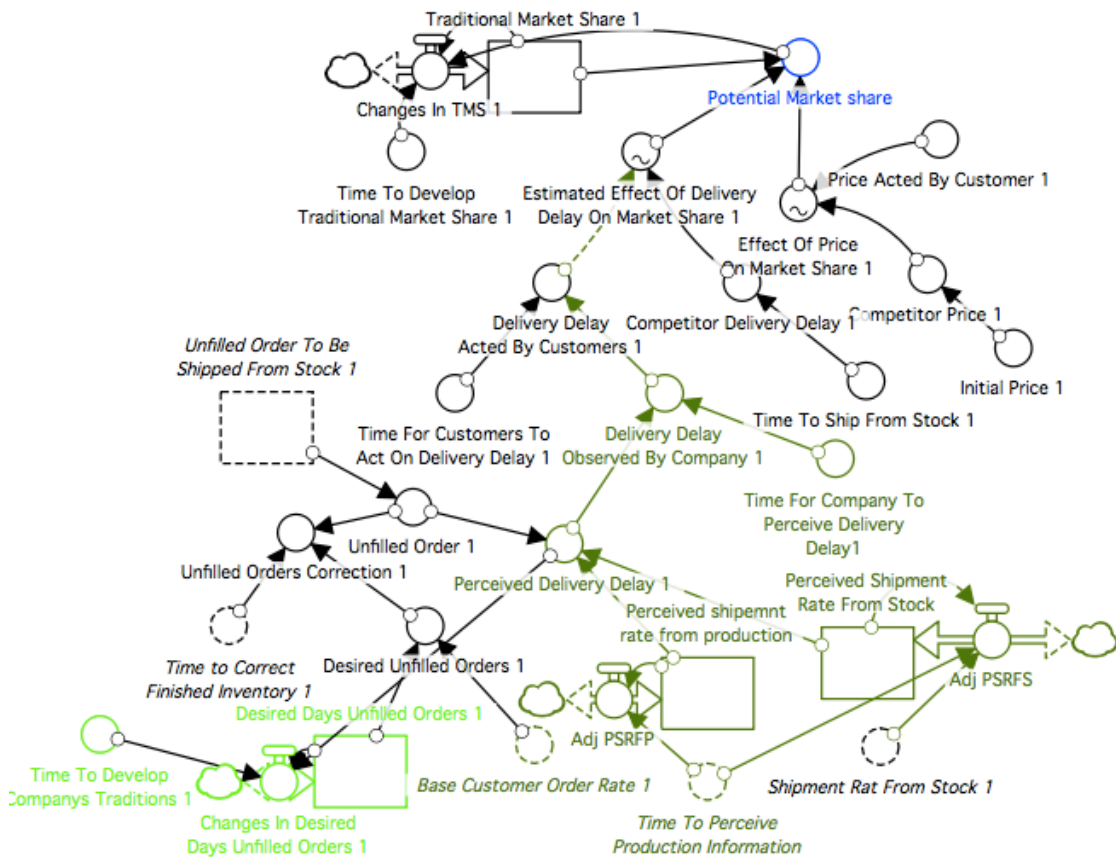


Figure 27- The dynamic structure to model Potential Market Share in mental model

The estimated effect of delivery delay on market share in decision makers’ mental model is a nonlinear function of delivery delay acted by customers relative to competitor delivery delay (figure 28).

Estimated Effect of Delivery Delay on Market Share=

GRAPH (Delivery_Delay_Acted_By_Customers_1/Competitor_Delivery_Delay_1)
 (0,000, 1,000), (0,250, 1,000), (0,500, 1,000), (0,750, 1,000), (1,000, 1,000), (1,250, 0,950), (1,500, 0,850), (1,750, 7,000), (2,000, 0,500), (2,250, 0,350), (2,500, 0,250), (2,750, 0,150), (3,000, 0,100), (3,250, 0,050), (3,500, 0,000), (3,750, 0,000), (4,000, 0,000)

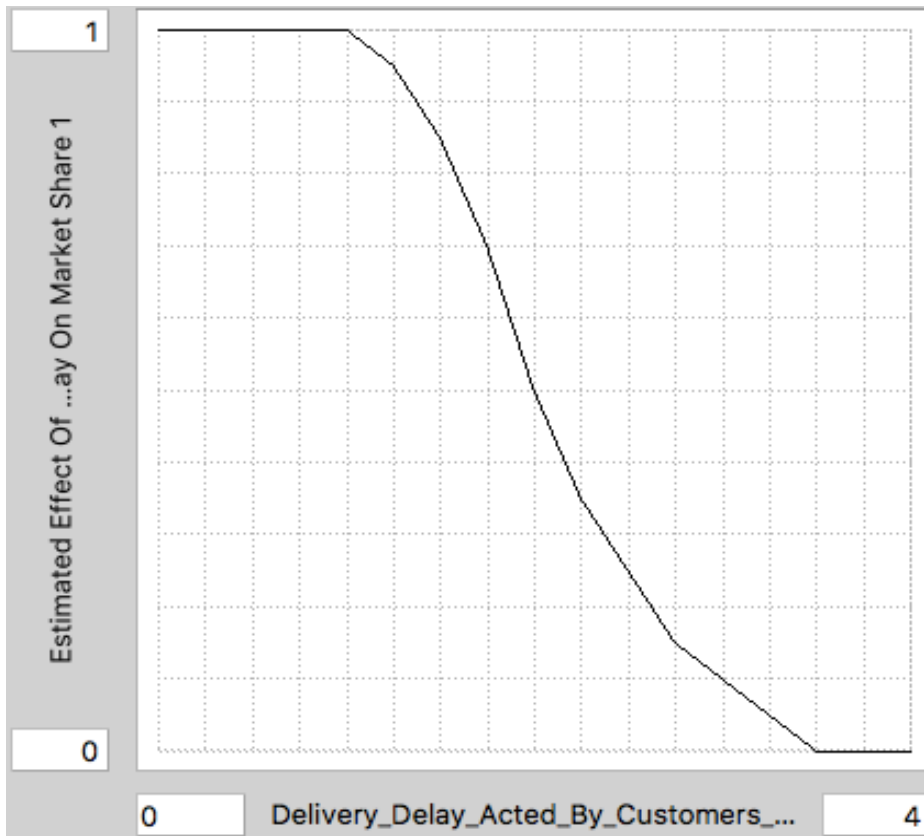


Figure 28- Graphical illustration of Estimated Effect Of Delivery Delay On Market Share

The graphical illustration implies that when delivery delay acted by customers (DDAC) is equal to or less than competitor delivery delay (COMDD), the estimated effect of delivery delay on market share (EEODDOMS) equals 1.0. EEODDOMS begins to fall when DDAC increases above COMDD. The slope increases as DDAC increase but the decrease is gradual at first.

Delivery delay acted by customers is represented as an exponential average of delivery delay observed by company:

$$\text{Delivery_Delay_Acted_By_Customers}_1 = \text{SMTH1}(\text{Delivery_Delay_Observed_By_Company}_1, \text{Time_For_Customers_To_Act_On_Delivery_Delay}_1)$$

Delivery delay observed by company is represented by an exponential average of perceived delivery delay, this is a perception process included in the real-world model:

$$\text{Delivery_Delay_Observed_By_Company}_1 = \text{SMTH1}(\text{Perceived_Delivery_Delay}_1, \text{Time_For_Company_To_Perceive_Delivery_Delay}_1)$$

$\text{Time_For_Customers_To_Act_On_Delivery_Delay}_1 = 60$ days

$\text{Time_For_Company_To_Perceive_Delivery_Delay}_1 = 20$ days

When modeling the expected delivery delay in decision-makers' mental model, the shipment rates from production and from finished inventory are modeled as perception processes because we are assuming it can be difficult for managers to directly observe the exact shipment rates on daily basis. Their perception of delivery delay is based on their perceived shipment rate from production and perceived shipment rate from stock. These two shipment rates are outflows from production line and finished inventory stock in the social system (real-world system). The perceived delivery delay is modeled to represent the average time needed for customers to received their products, which is unfilled orders divided by the sum of perceived shipment rate from stock and perceived shipment rate from production:

$$\text{Perceived Delivery Delay}_1 = \frac{\text{Unfilled_Order}_1}{(\text{Perceived_Shipment_Rate_From_Stock} + \text{Perceived_shipment_rate_from_production})}$$

Unfilled Orders are the orders that company has not delivered to its customers, it is defined as:

Unfilled_Orders=

Unfilled_Order_To_Be_Shipped_From_Stock_1+Unfilled_Orders_To_Be_Shipped_Direct_1

Unfilled order to be shipped from stock is a level variable, which is increased by customer orders to be shipped from stock and decreased by shipment rate from stock:

Unfilled_Order_To_Be_Shipped_From_Stock_1(t)=

Unfilled_Order_To_Be_Shipped_From_Stock_1(t-dt)+

(Customer_Orders_To_Be_Shipped_From_Stock_1 - Shipment_Rat_From_Stock_1) * dt

Unfilled_Order_To_Be_Shipped_From_Stock_1(Init)=

Time_To_Ship_From_Stock_1*Constant_Customer_Order_Rate_1

Unfilled orders to be shipped direct is a level variable that is increased by customer orders to be shipped direct and decreased by shipment rate from production:

Unfilled_Orders_To_Be_Shipped_Direct(t)=

Unfilled_Orders_To_Be_Shipped_Direct(t-dt)+

(Customer_Order_To_Be_Shipped_Direct - Shipment_Rate_From_Production) * dt

Unfilled_Orders_To_Be_Shipped_Direct (Init)= 0

Perceived shipment rate from stock is a perception process in decision maker's mental model to represent how managers updating their knowledge about the shipment rate, we are assuming that managers cannot directly calculate their shipment rates on the daily basis, so they are gradually updating their perception according to the shipment rates from social system:

Perceived_Shipment_Rate_From_Stock(t) = Perceived_Shipment_Rate_From_Stock(t - dt) + (Adjustment Of Perceived Shipment Rate From Stock) * dt

Perceived_Shipment_Rate_From_Stock (Init)= Shipment_Rate_from_stock_

Adjustment Of Perceived Shipment Rate From Stock= $(\text{Shipment_Rate_From_Stock}_1 - \text{Perceived_Shipment_Rate_From_Stock}) / \text{Time_To_Perceive_Production_Information}$

Time_To_Perceive_Production_Information = 60 days

In addition, perceived shipment rate is another perception process modeled in decision maker's mental model:

Perceived_Shipment_Rate_From_Production(t)=
 $\text{Perceived_Shipment_Rate_From_Production}(t - dt) + (\text{Adjustment Of Perceived Shipment Rate From Production}) * dt$
 Perceived_Shipment_Rate_From_Production(Init)=
 Shipment_Rate_From_Production_1

Adjustment Of Perceived Shipment Rate From Production= $(\text{Shipment Rate From Production} - \text{Perceived_shipment_rate_from_production}) / \text{Time_To_Perceive_Production_Information}$

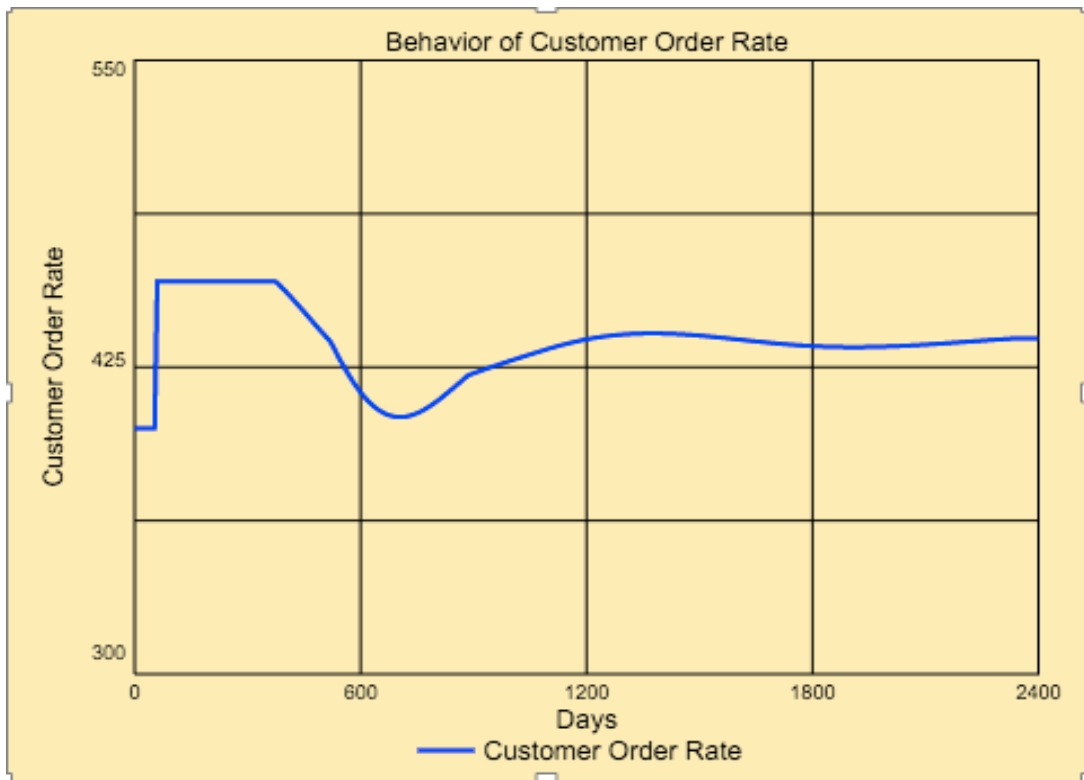
In this section, we have presented the model structure of decision-makers' mental model and how the decision variables are constructed based on their perceived structure of the real-world system. There are five decision variables that will be implemented in the real-world model. They are: *Potential Parts Order Rate*, *Potential Parts Suppliers Capacity Utilization Rate*, *Potential Production Rate*, and *Estimated Parts Arrival Rate*, *Potential Market Share*. In the next section, we will examine the behavior of the real-world inventory system when decision makers are implementing their decisions based on their mental model.

6. The implementation

In this chapter, behavior in the real-world system will be analyzed in accordance with implementing “misperceived decision variables” as input to the real-world system. There are five decision variables that are formulated based on decision makers’ misperceived structure of their system. We will first explain how a social environment will behave when a single decision variable is implemented to the real-world system. Then, we will explain how would the system react with all five misperceived decision variables interacted with the real-world system. We have chosen “Customer Order Rate” as a main real-world behavior indicator to represent customers’ feedbacks from company’s performance. The Finished Inventory; Production Rate and Parts Inventory are also presented to compare with their desired level as performance indicators.

The graphs 5.1(1) to 5.1(4) illustrate the behavior of the inventory system without implementing the decision variables from the decision-makers’ mental model. There are four performance indicators that represent the system’s behavior. The customer order rate is a representation of company’s performance regarding to the market demand. Finished inventory is compared with its goal as a representation to show how the company is performing in terms of managing its finished products. The production rate with its desired level is illustrated as a performance indicator to test whether the production line is productive enough to have stable production. The parts on order inventory with its expected level are compared to show how the company is capable of managing its orders to have healthy inventory level for production.

6.1 Real-world behavior



Graph 5.1.(1) – Behavior of Customer Order Rate without implementation of decision variables from mental model

Graph 5.1(1) showed the behavior of customer order rate in the social system without any misperceived system structures. There was a 15% step increase in customer demand from day 60. The sudden increase in customer order rate above production causes finished inventory to decrease below its desired level. Therefore, in order to match the higher market demand and to rebuild inventory, company increased its desired production rate. Around day 120, the actual parts inventory and finished inventory level started to increase to their desired level, and the desired production rate began to decrease to reach its stable level (graph 5.1(2) and graph 5.1(3)). At the same time, as a result of delivery delay increases, which causes the customer order rate to fall.

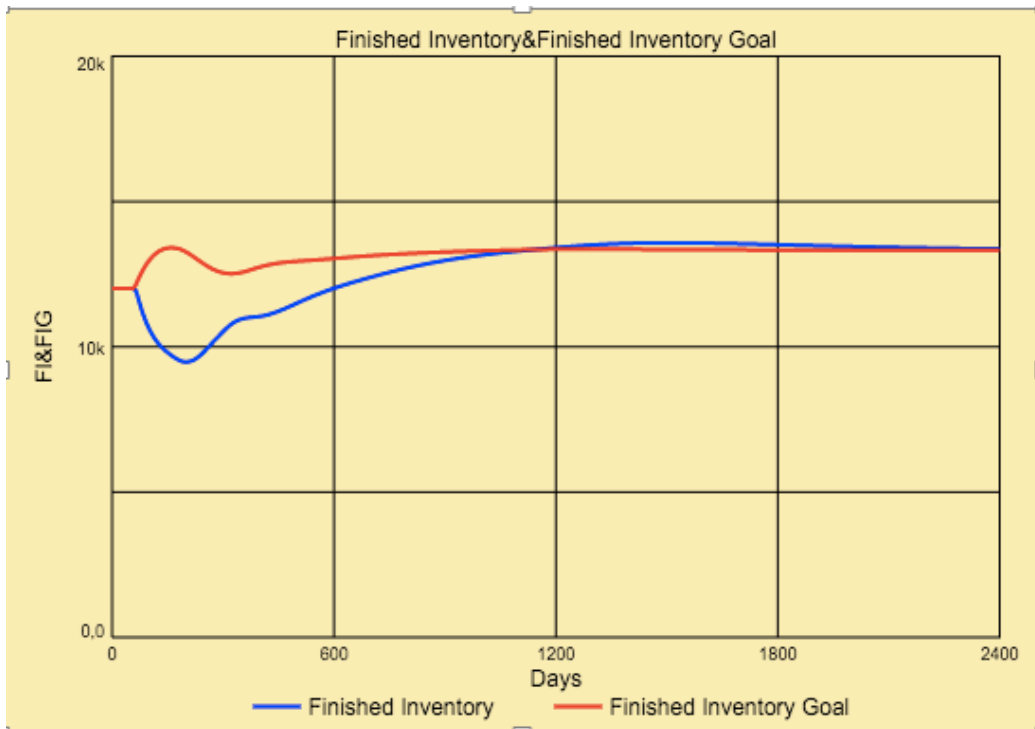


Figure 5.1.(2)- Behavior of Finished Inventory with finished inventory goal without any decision variables from mental model implemented

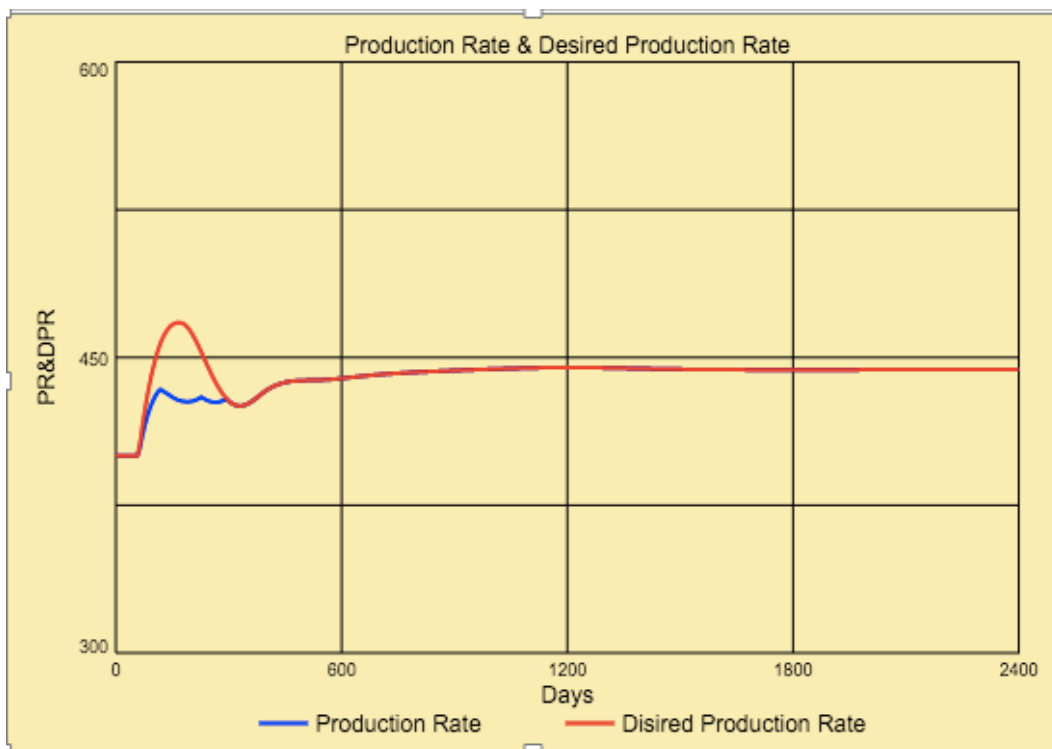


Figure 5.1.(3)- Behavior of Production Rate with desired production rate without any decision variables from mental model implemented

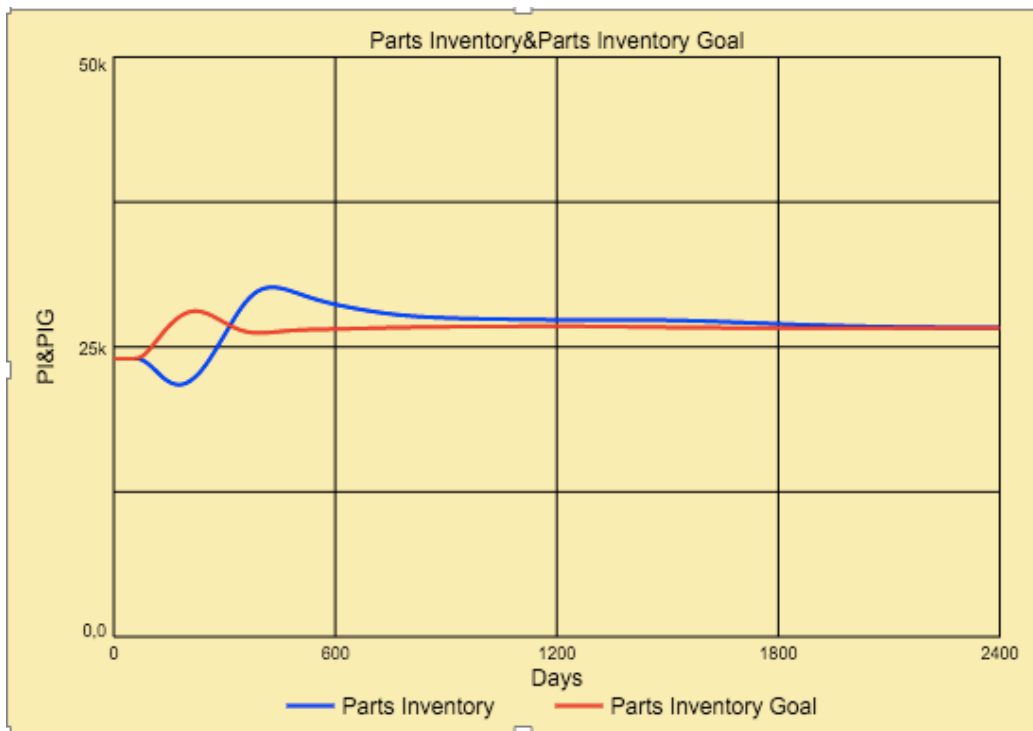


Figure 5.1.(4)- Behavior of Parts Inventory and expected parts inventory without any decision variables from mental model implemented

Parts inventory level in graph 5.1(4) dropped firstly because sudden increase in customer order rate from day 60. Parts inventory level started to diverge from its desired level from day 60 because of delayed information process in the system. Around day 264, when parts inventory level increased sufficiently for production (the effect of parts inventory level on production rate is 1), the customer order rate decreased below production rate. Then parts inventory level began to increase above its desired level around day 336 because of delay. Company did not recognize the overloaded parts inventory level until day 450, so the actual parts inventory level is above its goal. From day 460, parts inventory decreases again to stabilized to match its desired level.

6.1.1 Decision variables as input in real-world system: Potential Parts Order Rate; Potential Parts Supplier Capacity Utilization Rate

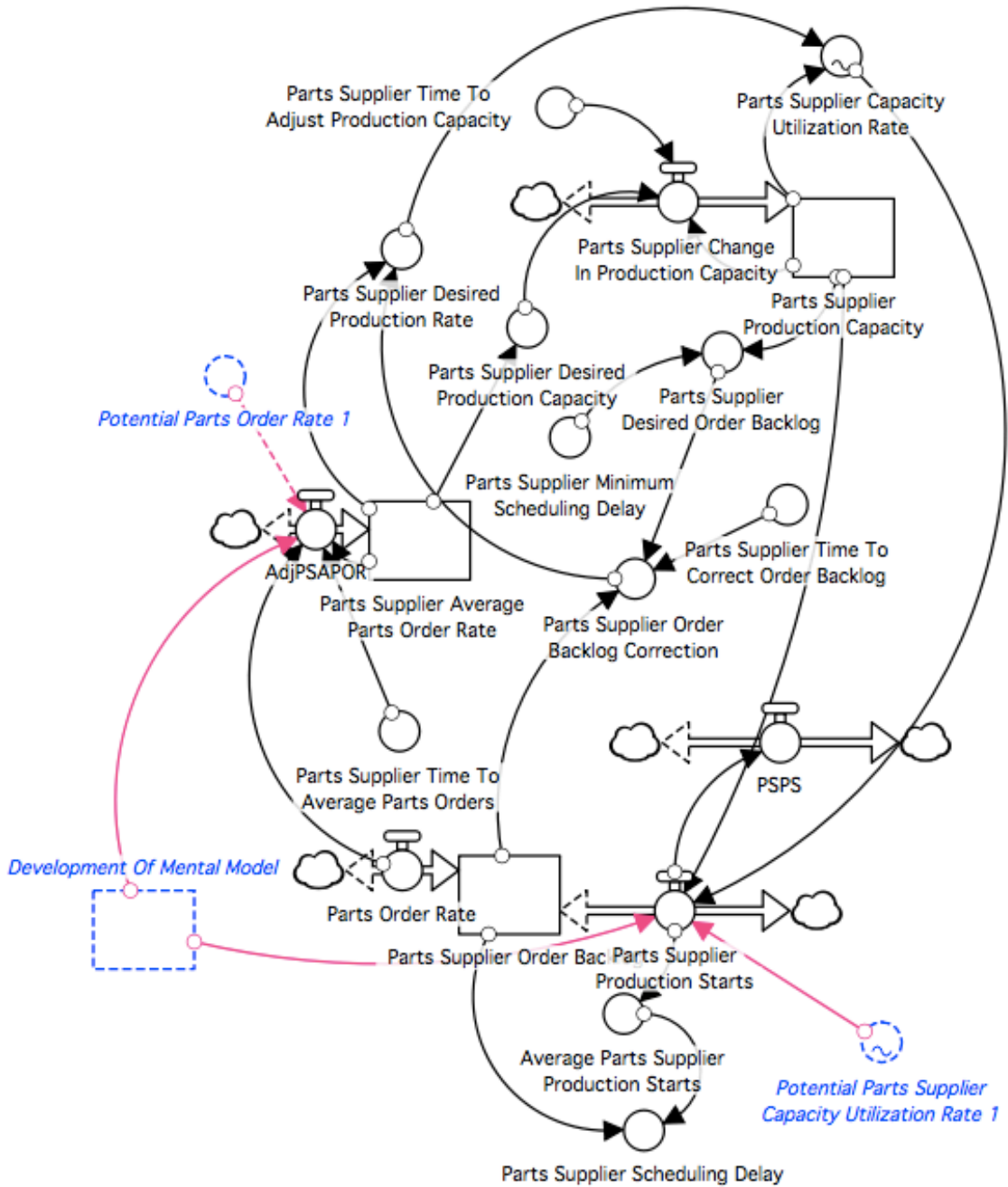


Figure 30- Potential Parts Order Rate and Potential Parts Supplier Capacity Utilization Rate as decision variables to the real-world system

Figure 30 shows the potential parts order rate as well as the potential parts supplier capacity utilization rate as decision variables that are implemented into the real-world system. The potential parts order rate used in variable “ Adjustment of Parts Supplier Average Parts Order Rate” as inflow to the stock of parts supplier average parts order rate. The stock of parts suppliers average parts order rate is modeled as first-order information delay to represent a perception process of decision makers to capture the movements of actual parts order rate. The parts order rate switch is equal to 1. The purpose of adding “switch” as input to the system is to compare effects of each “misperceived decision variables” to the real-world system. For example, when parts on order switch if off, the “misperceived parts order rate” is not implemented into the real-world system, only the actual parts order rate is used. The equations are defined as:

$$\text{Parts_Supplier_Average_Parts_Order_Rate}(t) =$$

$$\text{Parts_Supplier_Average_Parts_Order_Rate}(t - dt) + (\text{AdjPSAPOR}) * dt$$

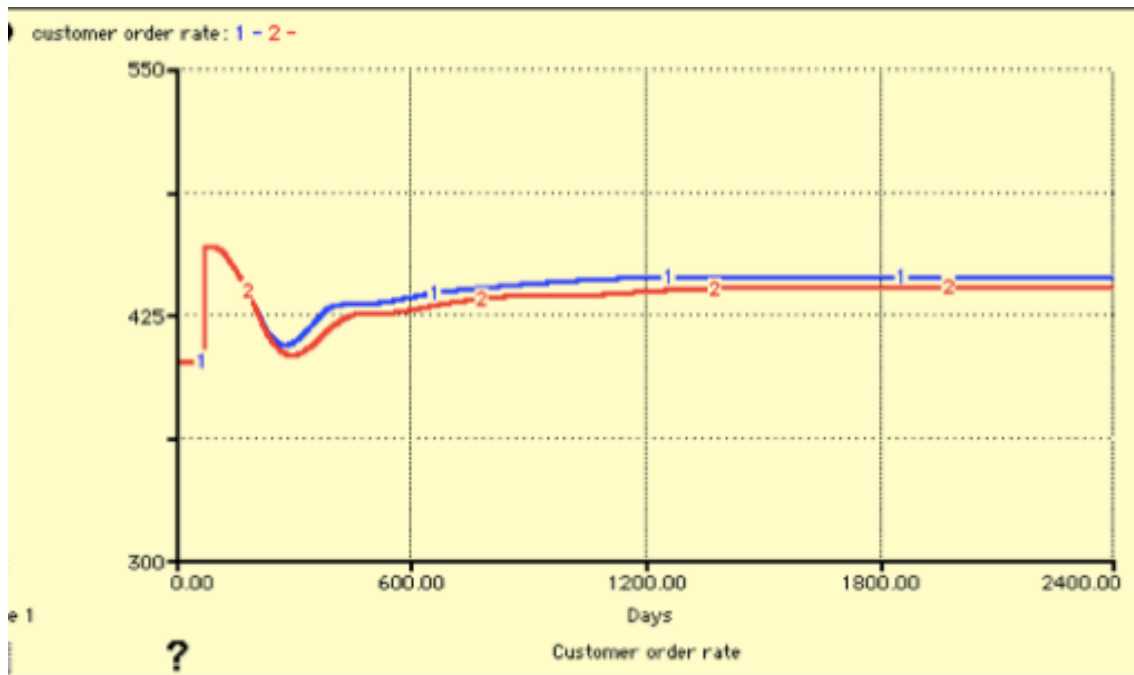
$$\text{INIT Parts_Supplier_Average_Parts_Order_Rate} =$$

$$\text{Constant_Customer_Order_Rate}$$

$$\text{AdjPSAPOR} =$$

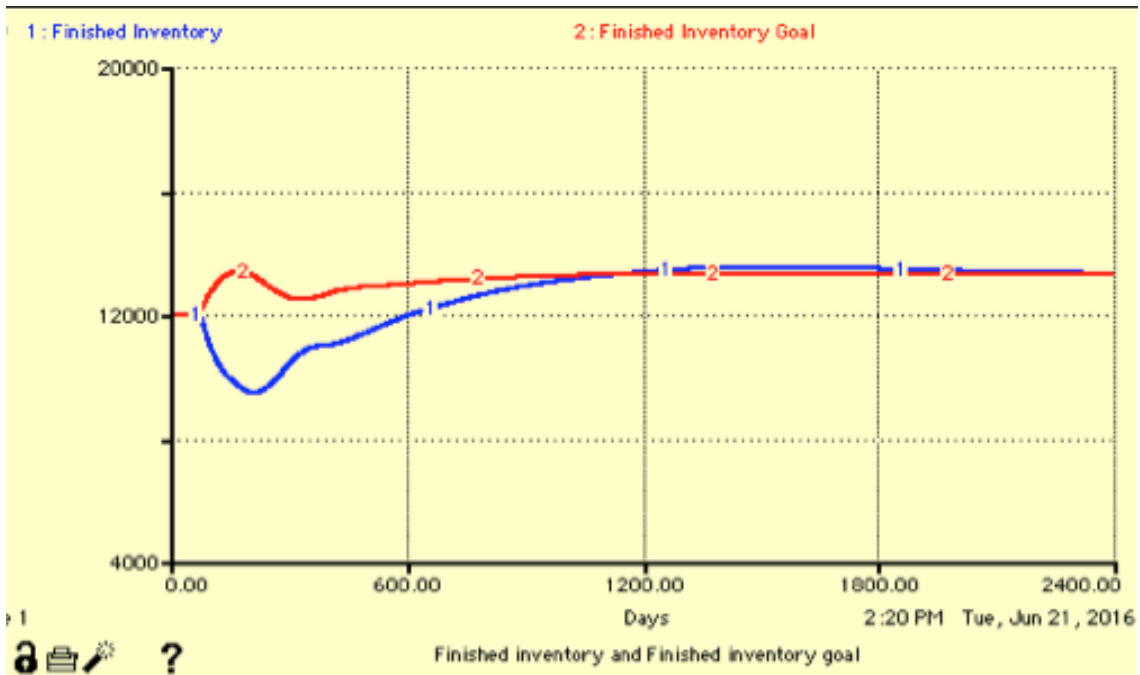
$$\text{if}(\text{PORswitch}) \quad \text{then} \quad ((\text{Potential Parts Order Rate} - \text{Parts_Supplier_Average_Parts_Order_Rate}) / \text{Parts_Supplier_Time_To_Average_Parts_Orders})$$

$$\text{else}((\text{Parts_Order_Rate} - \text{Parts_Supplier_Average_Parts_Order_Rate}) / \text{Parts_Supplier_Time_To_Average_Parts_Orders})$$

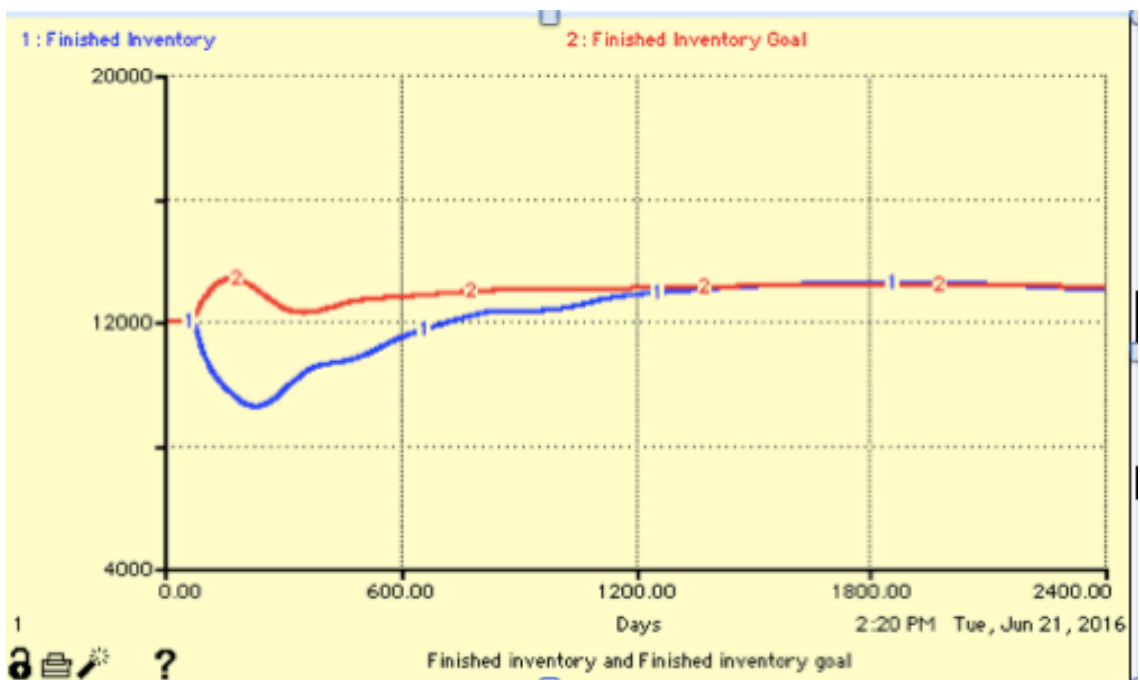


Graph 5.1.1(1) – Compared behavior of Customer Order Rate when Potential Parts Order Rate is implemented

Graph 5.1.1(1) compared the behavior of customer order rate when potential parts order rate is used as input to the real-world system. The blue line is the original customer order rate without any misperceived input. The red line showed, the customer order rate is decreased below the original value when decision makers make orders from suppliers based on their misperceived structure of the real-world system. The company would underperform and experience a loss in customer base when decision makers are misperceiving the structure of the real-world system.



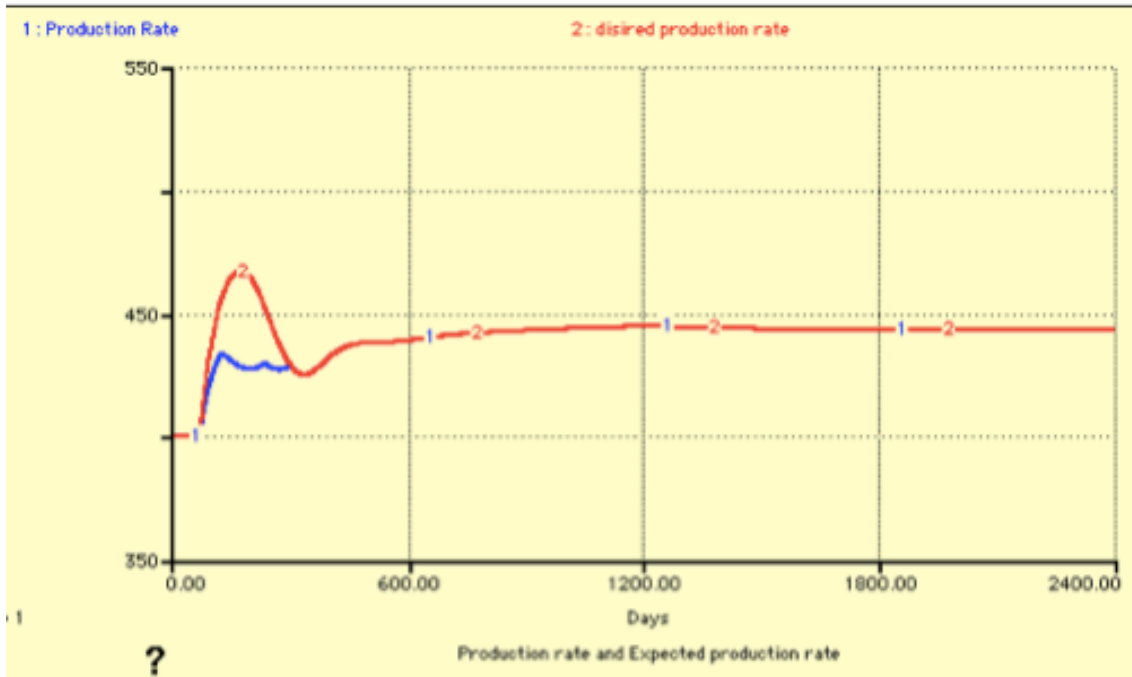
Graph 5.1.1(2) Behavior of Finished Inventory with Finished Inventory Goal in the real-world system without any misperception



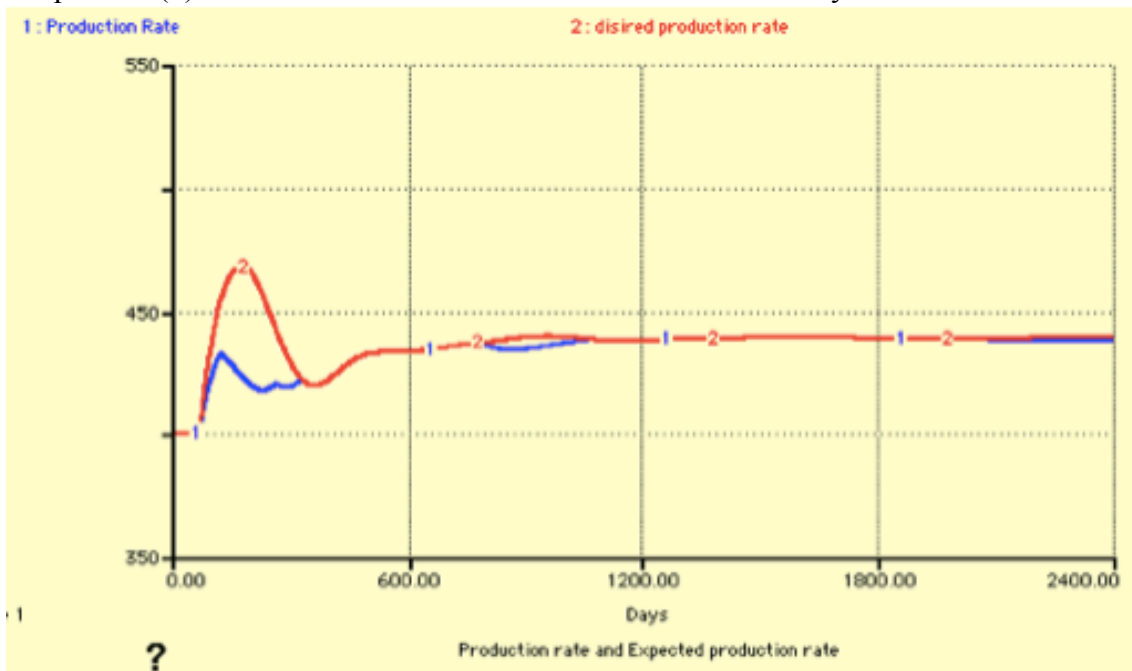
Graph 5.1.1(3) - Behavior of Finished Inventory when Potential Parts On Order Rate is implemented

When we compare the behavior from 5.1.1(2) to 5.1.1(3), the finished inventory had the similar behavior as the original model after the misperceived decision variable is implemented. However, finished inventory started to move towards its desired level

sooner in the real-world model, around day 800 the actual finished inventory is moving to its desired level. When managers misperceive the structure of the system, the finished inventory level start to reach its goal from day 1000, a bit slower.

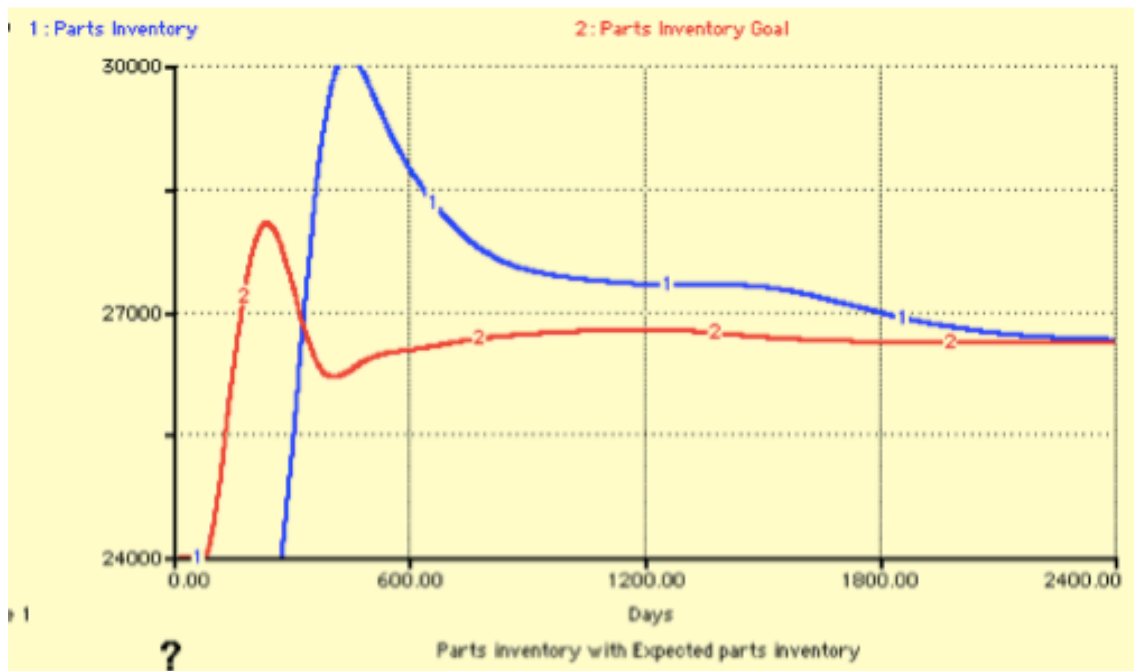


Graph 5.1.1(4) - Behavior of Production Rate in the real-world system



Graph 5.1.1(5) - Behavior of Production Rate when Potential Parts On Order Rate is implemented

There is not much difference between the production rates with its desired level after potential parts order rate is implemented. The production rate (with misperception) decreased slightly below its desired level around day 880. But it increased again after day 1062 try to match with its desired level. As we can see, the production rate started to decrease again after day 2400. It is suggested that in the long run, the behavior of the production rate might diverge from its desired level if managers are misperceiving their system structure over long time.



Graph 5.1.1(6) - Behavior of Parts Inventory with its desired level in the real-world system



Graph 5.1.1(7) - Behavior of Parts Inventory with its goal when Potential Parts On Order Rate is implemented

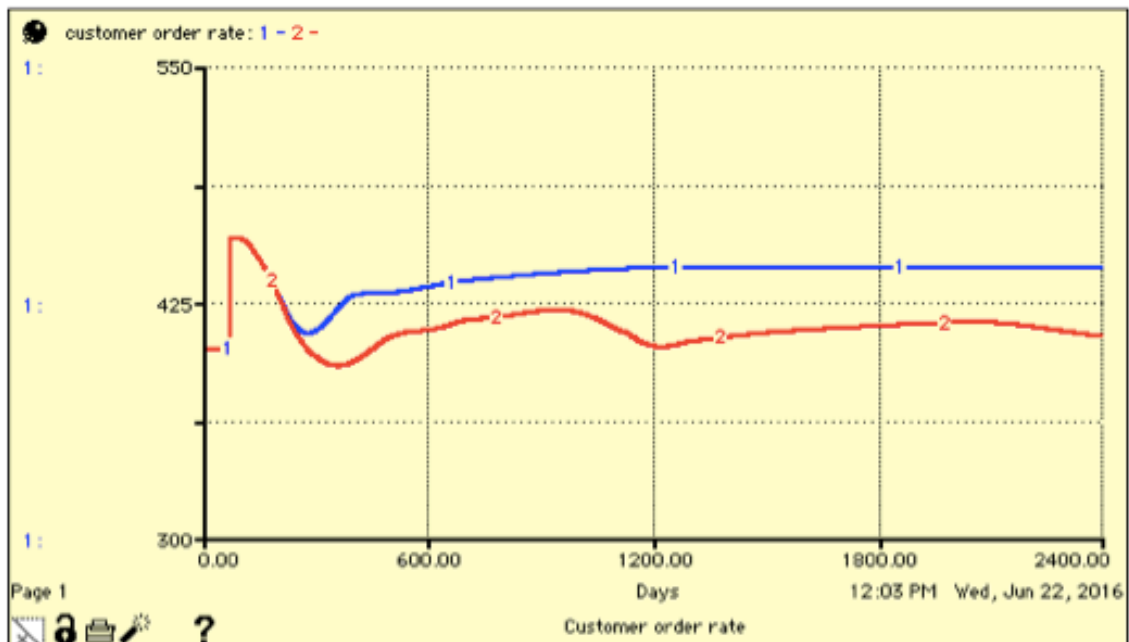
Parts inventory is the raw materials that have been delivered but have not entered the production line yet. When managers make decisions on order rates, the parts inventory level is affected by the potential parts order rate because of the delivery delay by suppliers. When we compare the behavior from graph 5.1.1(6) to 5.1.1(7), the parts inventory fluctuates a lot around its expected inventory level and then it diverges from its goal at the end of the simulation period at day 2400 when the potential parts order rate is implemented into the real-world model. In the long run, the rest of the production line might be affected since the parts inventory level has diverged from its expected value and fluctuated after 2400 days.

The potential parts supplier capacity utilization rate is the rate that state how much the suppliers produces as a percentage of what it can produce. The potential parts supplier capacity utilization rate then as a input variable to adjust the parts supplier production starts within the supply chain.

Parts_Supplier_Production_Starts =

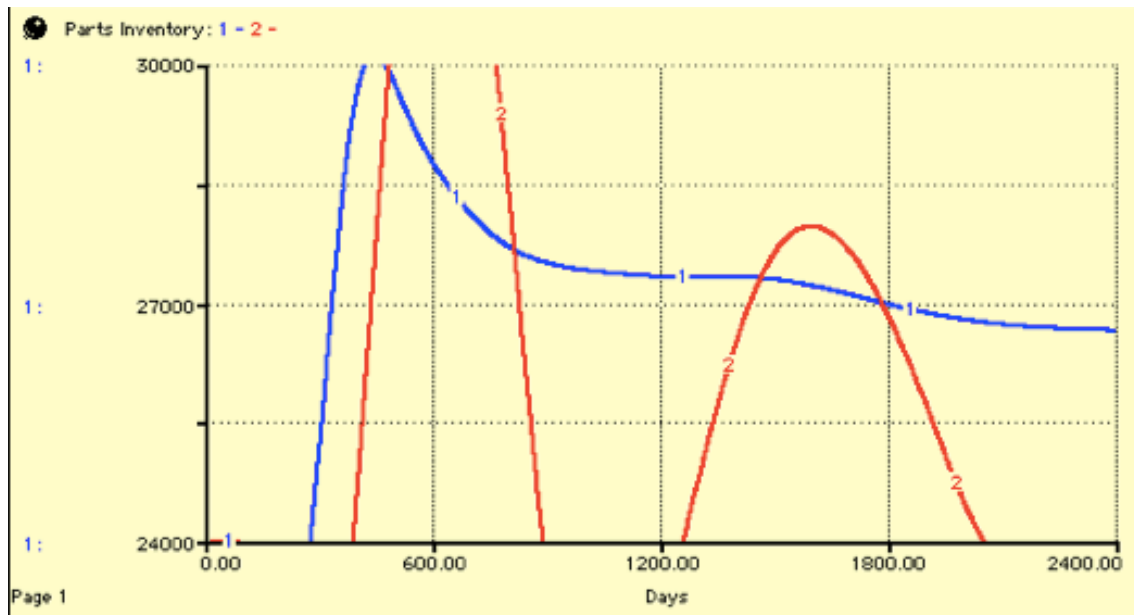
If(Utilization_switch)Then(Potential_Parts_Supplier_Capacity_Utilization_Rate_1*Parts_Supplier_Production_Capacity)
Else(Parts_Supplier_Capacity_Utilization_Rate*Parts_Supplier_Production_Capacity)

So, the parts supplier production starts determine how much raw materials is producing according to the perceived parts order rate by suppliers. The real-world behavior will be analyzed in the flowing graphs.



Graph 5.1.2(1)- Behavior of Customer Order Rate with Potential Suppliers Utilization Rate implemented into the real-world model

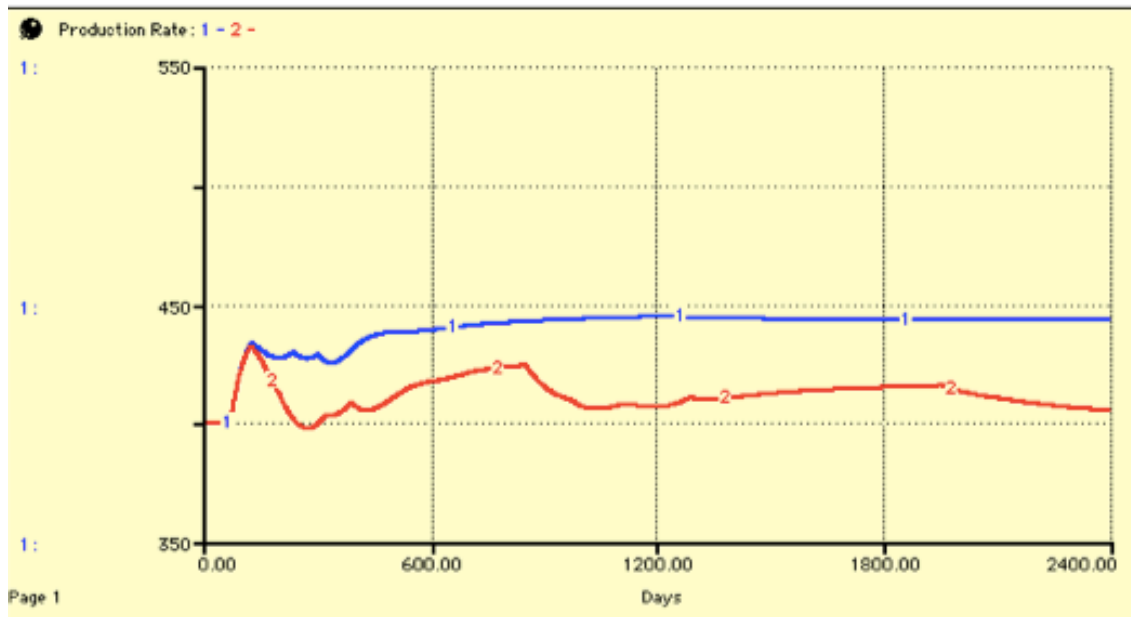
When decision makers misperceiving the structure of their system and conducting supplier's utilization rate, the behavior of customer order rate decreased about 10% compared with when managers are having perfect mental model. Customer order rate can be seen as an indicator of the performance of the company in the market, so in the long run, the decreased customer order rate would make company to loss its customer base and thus making lower average profit.



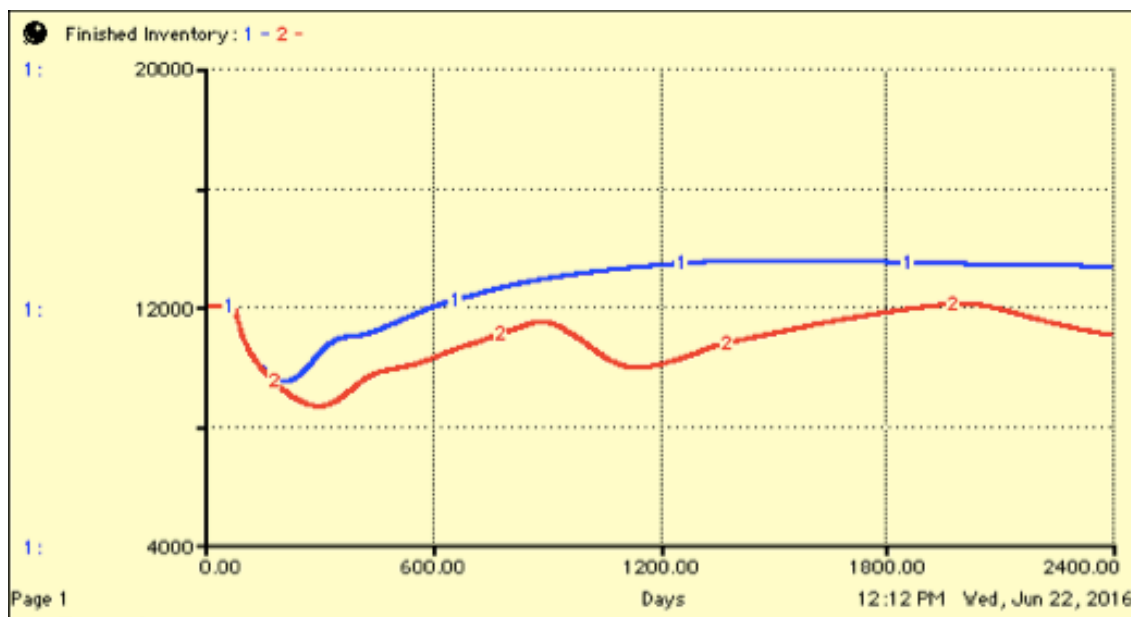
Graph 5.1.2(2)- Behavior of Parts Inventory with Potential Suppliers Utilization Rate implemented into the real-world model

The parts inventory level fluctuated a lot compare to normal real-world behavior (without any misperception involved) when Potential Suppliers Utilization Rate is used as input to the real-world system, and the system would not stabilize until end of the simulation period. The unstable parts inventory level would causes unstable production rate and thus causes insufficient finished inventory level as result in graph 5.1.2(3) and 5. 1. 2(4).

As a result, the fluctuated parts inventory level thus causes the production rate unable to stabilize and also decreased below its normal level. The unexpected low production rate would cause low finished inventory level and thus even lengthen the delivery delay and decrease customer order rate in the long run.



Graph 5.1.2(4)- Behavior of Production Rate with Potential Suppliers Utilization Rate implemented into the real-world model



Graph 5.1.2(2)- Behavior of Finished Inventory with Potential Suppliers Utilization Rate implemented into the real-world model

The finished inventory also underperformed when potential suppliers utilization rate is implemented into the real-world model. Therefore, the finished inventory level would not be sufficient to support the increased customer orders and thus company would not have been able to satisfy their customers in the short run and it might loss their loyal customer base in the long run even (graph 5.1.2(2)).

6.1.3 Decision variables as input to real-world system: Estimated Parts Arrival Rate

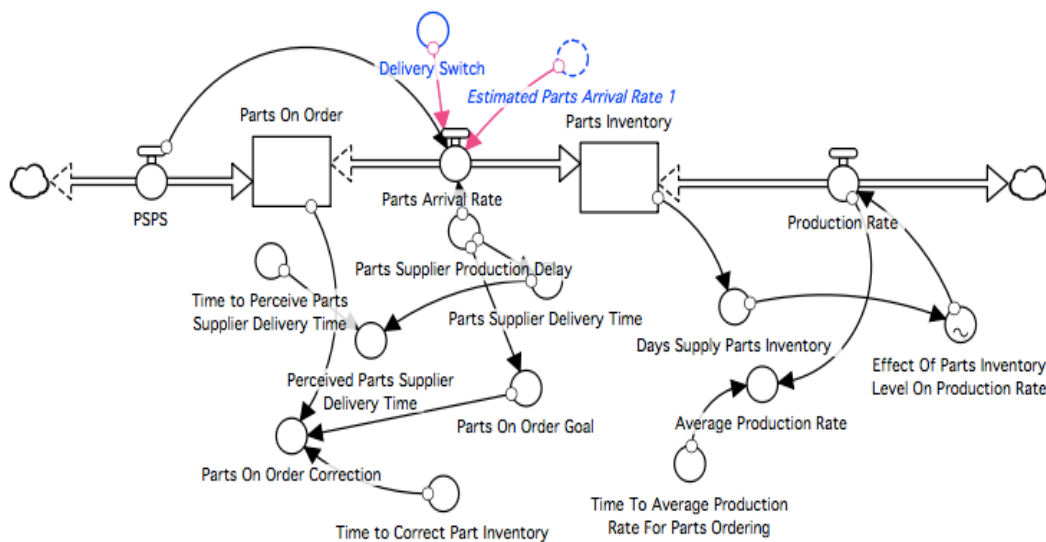
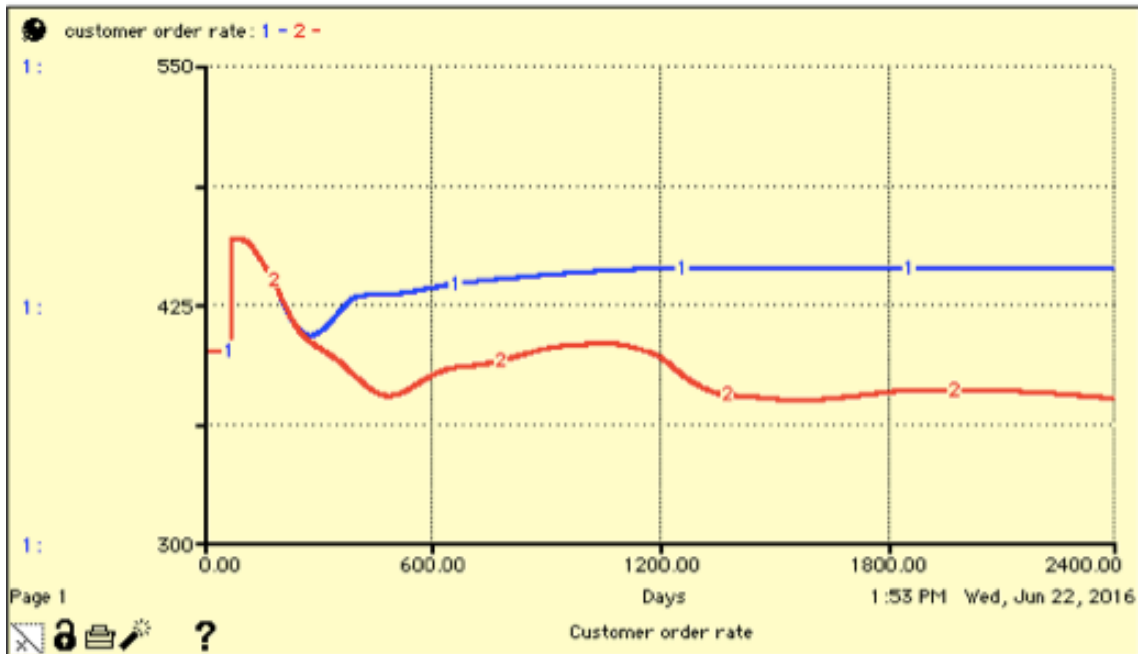


Figure 5.1.3(1)- Stock-and-flow structure of Estimated Parts Arrival Rate as decision variable implemented to the real-world system

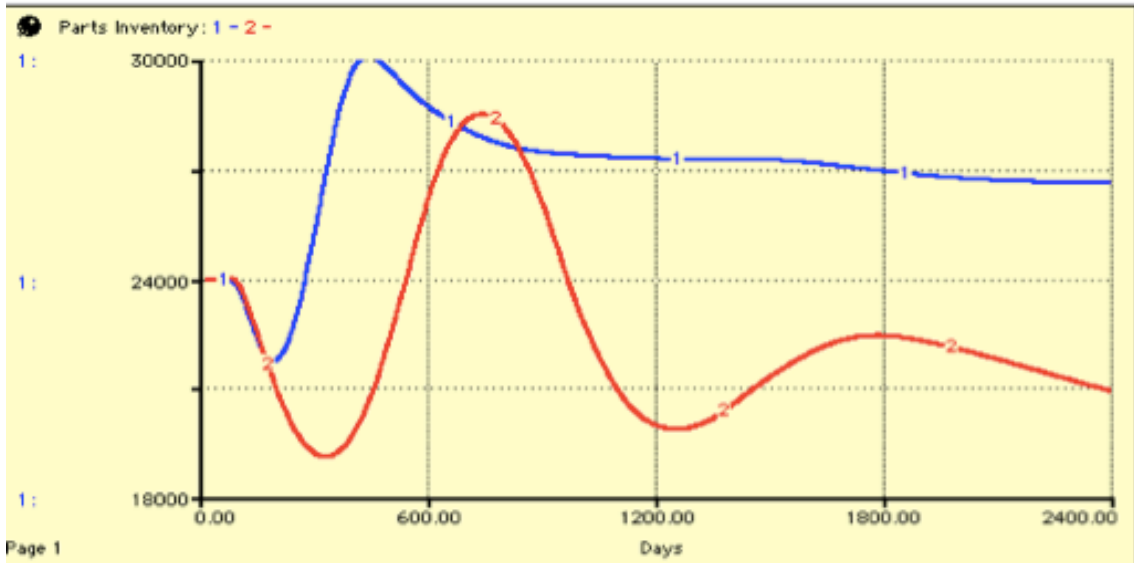
Parts Arrival Rate= IF(Delivery_Switch)THEN(Estimated_Parts_Arrival_Rate_1)ELSE
(DELAY3(PPSP, Parts_Supplier_Production_Delay))

The estimated parts arrival rate is the arrival rate of raw materials to be delivered to the company. The estimated parts arrival rate is a first-order delay function of perceived parts supplier production starts with perceived parts supplier delivery time.

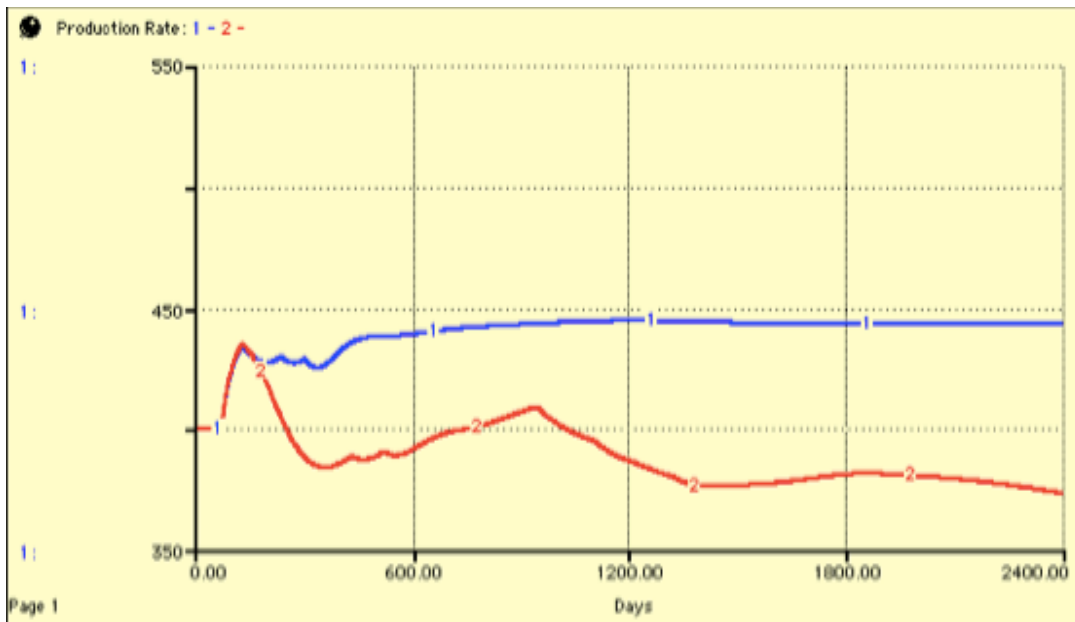


Graph 5.1.3(2)- Behavior of Customer Order Rate when Estimated Arrival Rate is implemented into the real-world model

Firstly, the market demand for company's products dropped dramatically when estimated arrival rate is implemented into the real-world model. The customer order rate started to drop below its normal level after day 60 and maintained a large gap between normal order rate until day 1200. From day 1200, the customer order rate began to decrease even larger and never seems to increase again to a normal level. It suggests that when decision makers misperceive the structure of the system and use estimated arrival rate as the decision input rather than parts arrival rate. The system would underperform as well as lost its customers in the long run.

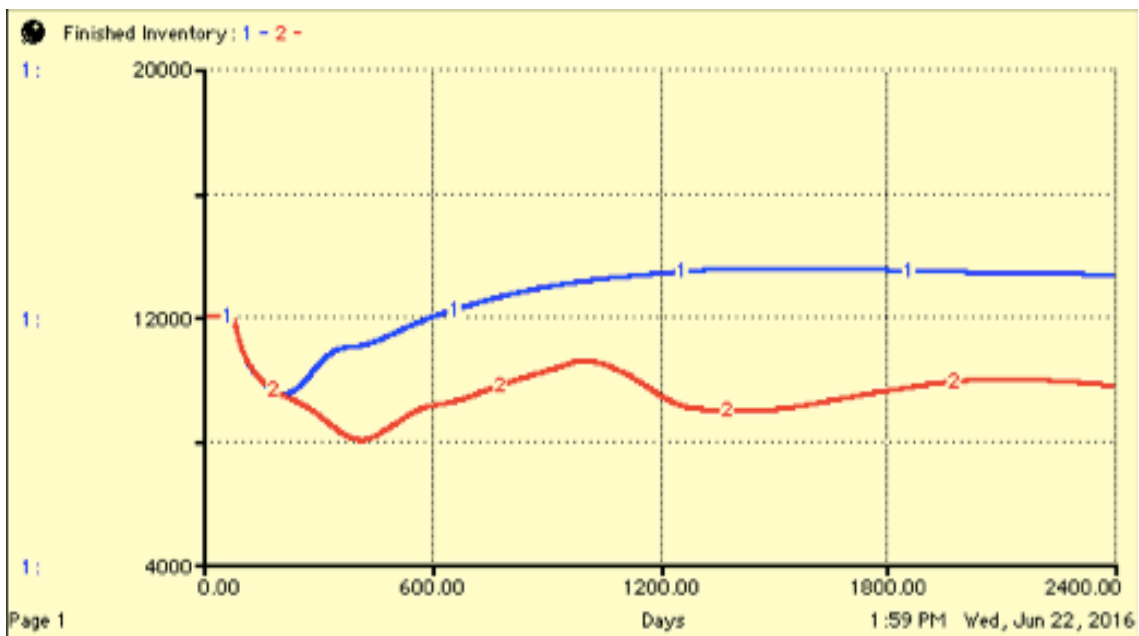


Graph 5.1.3(3)- Behavior of parts inventory with implementation of estimated parts arrival rate



Graph 5.1.3(3)- Behavior of production rate with implementation of estimated parts arrival rate

The parts inventory level and production rate fluctuated a lot and dropped to undesired level when estimated arrival rate is implemented in the real world. Because the decision makers misperceive the actual delivery rate of raw materials, the parts inventory level dropped to an undesirable level and started to fluctuate. Therefore, due to unstable parts inventory level, the production line could not sufficiently function to provide finished products for customers.



Graph 5.1.3(4)- Behavior of finished inventory with implementation of estimated parts arrival rate

When production rate decreased below its normal level, the finished inventory also dropped to a lower level. When there is not enough final products for market demand, the delivery delay from stock and from production would increase, which reduces the market demand even further and thus market share would be affected in the long run.

6.1.4 Decision variables as input to real-world system: Potential Production Rate

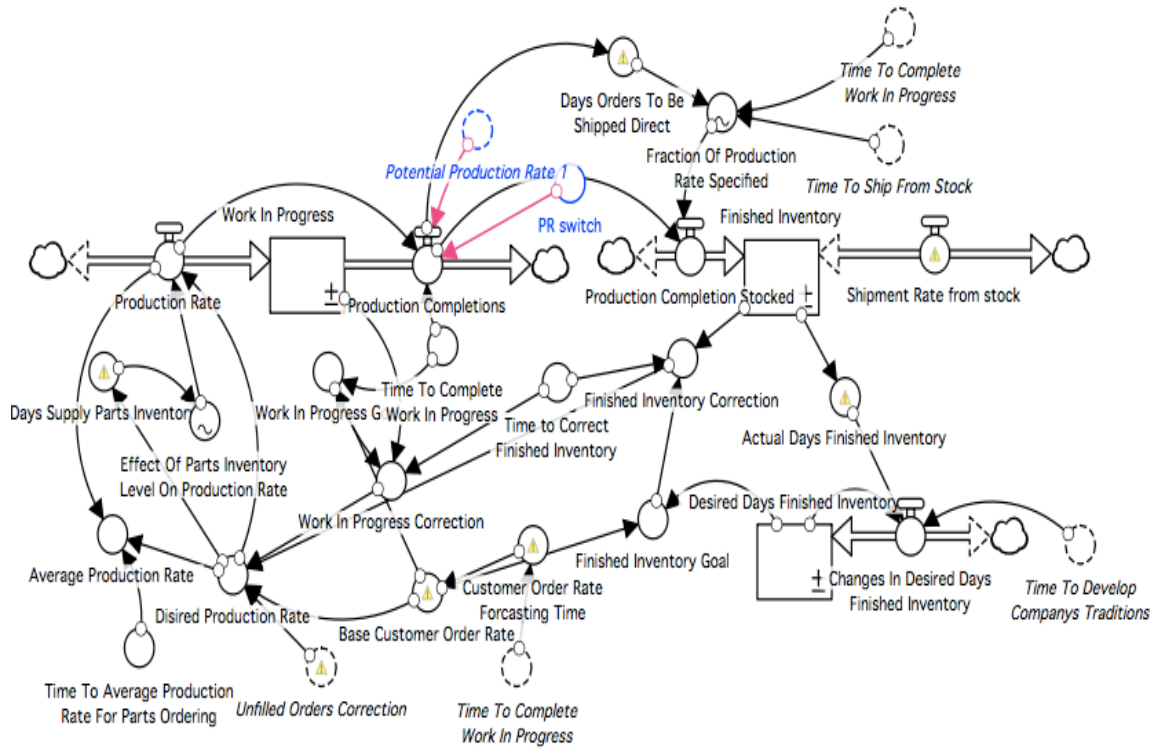
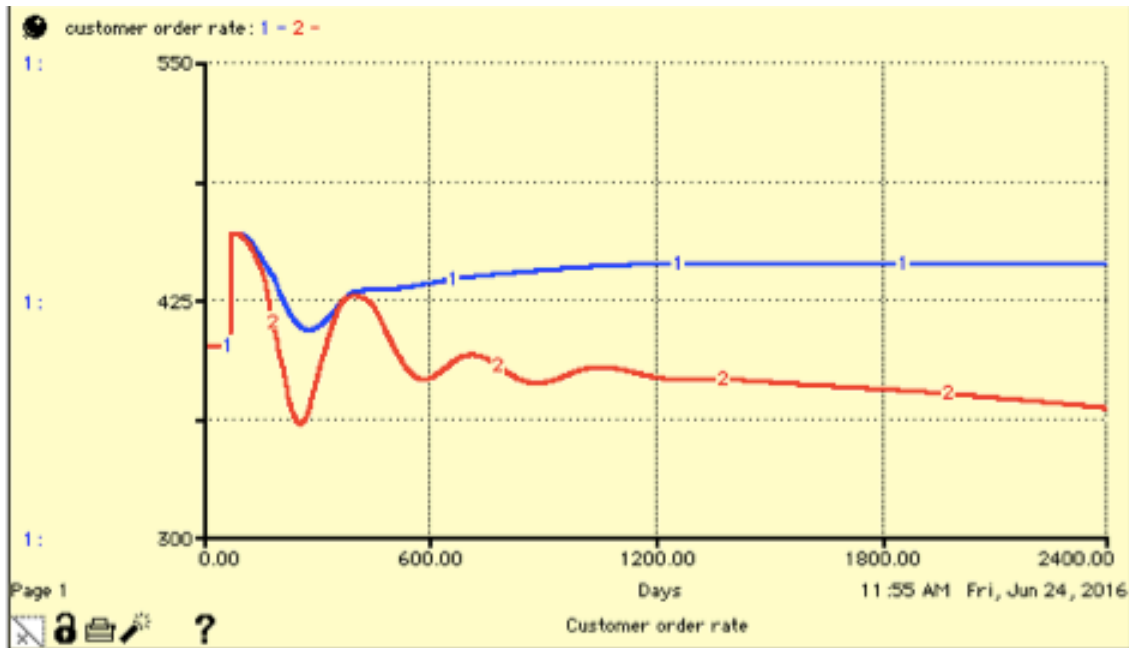


Figure 5.1.4(1)- Stock-and-flow structure of Potential Production Rate as decision variable implemented to the real-world system

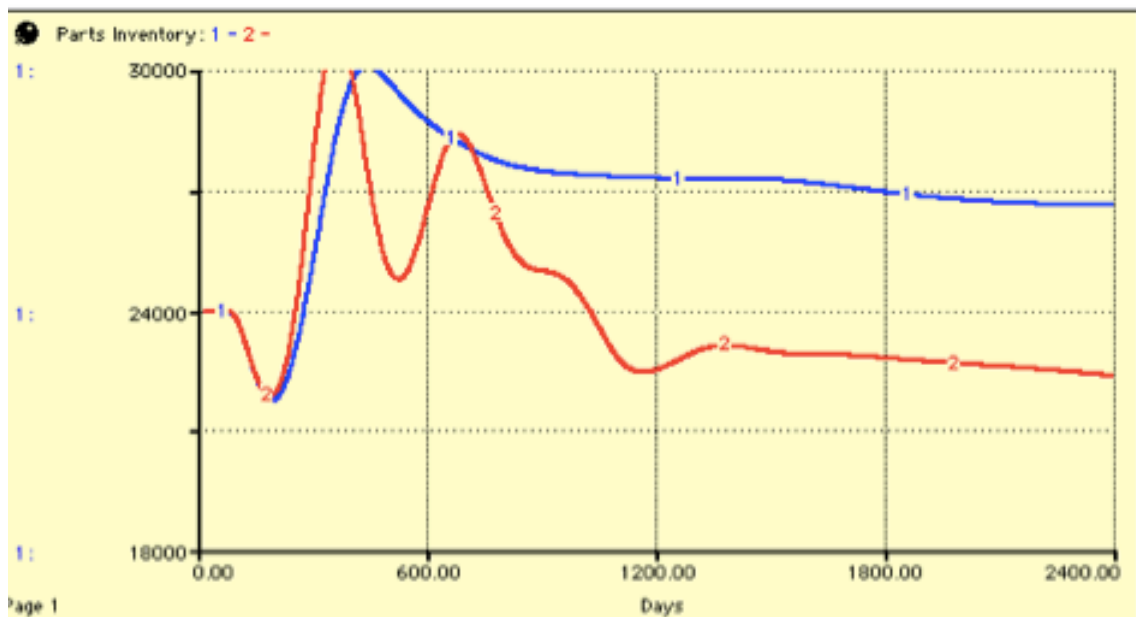
Production Completions=
 IF(PR_Switch)THEN(DELAY3(Potential_Production_Rate_1,
 Time_To_Complete_Work_In_Progress))ELSE (DELAY3(Production_Rate,
 Time_To_Complete_Work_In_Progress))

The potential production rate (colored blue) is an input to production completions, which is formulated based on decision makers' perceived structure of effect of parts inventory level on production rate as well as the desired production rate. Production completions are the outflow of the work in progress stock and inflow to the finished inventory stock.

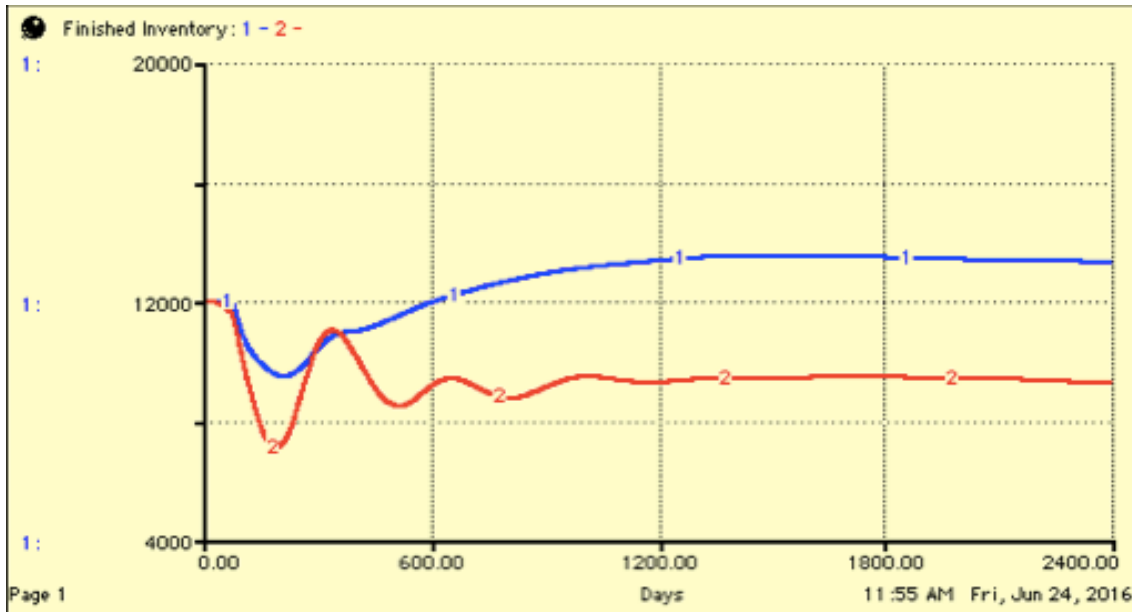


Graph 5.1.4(4)- Behavior of Customer Order Rate when Potential Production Rate is implemented into the real-world model

The customer order rate decreased to around 363 units around day 250 and started to fluctuate a lot thereafter until day 1000. It started to stabilize from day 1226 with a decreasing rate and did not increase until end of the simulation period.



Graph 5.1.4(5)- Behavior of Parts Inventory when Potential Production Rate is implemented into the real-world model



Graph 5.1.4(6)- Behavior of finished inventory when potential production rate is implemented into the real-world model

As we can see from graph 5.1.4(4) to 5.1.4(6) that the overall performance in the inventory system is unsatisfied compared to the normal behavior when managers have perfect mental model (blue line). The unstable parts inventory level cause the unstable production rate, which causes company could not sufficiently produce their incoming orders and thus lengthens the delivery time to their customers. Customers will no longer require their products when delivery time is increased a lot and thus company loss their market share in the long run.

6.1.5 Decision variables as input to real-world system: Potential Market Share

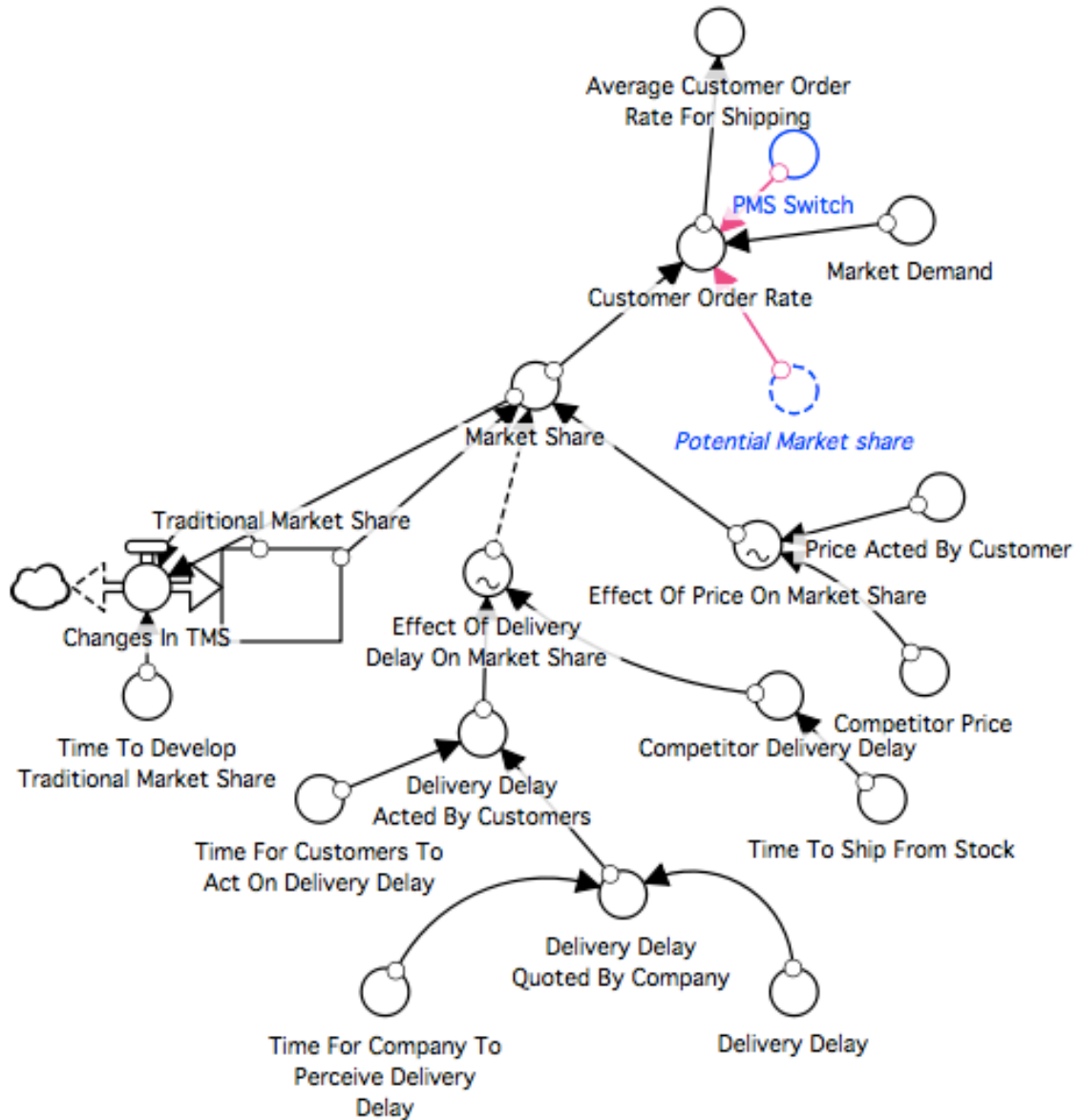
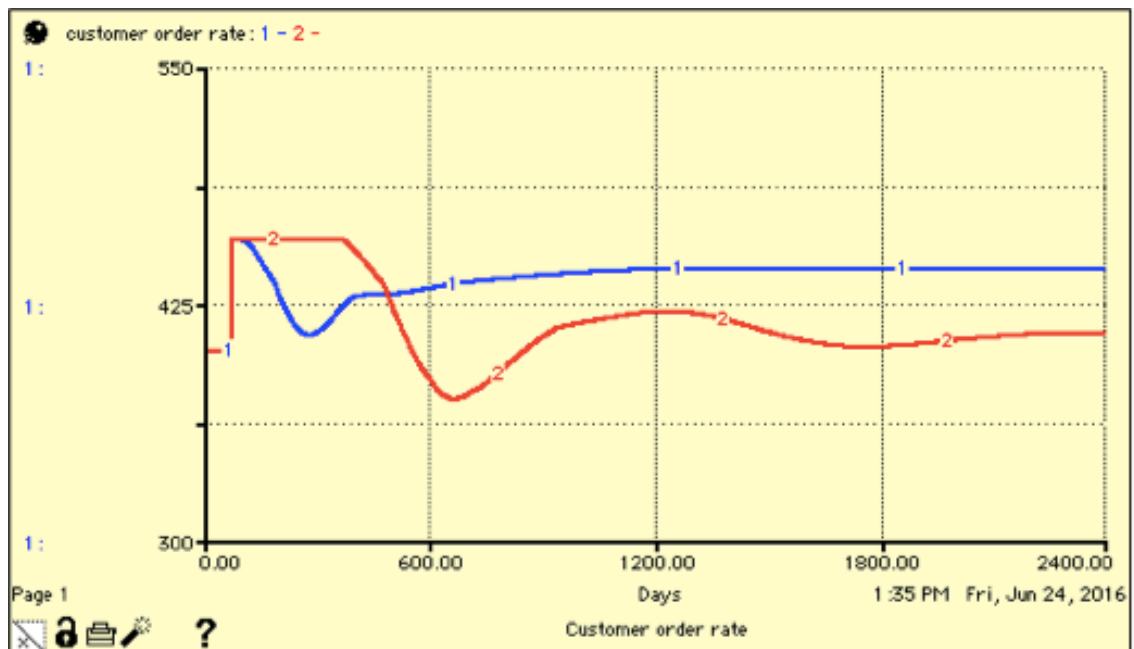


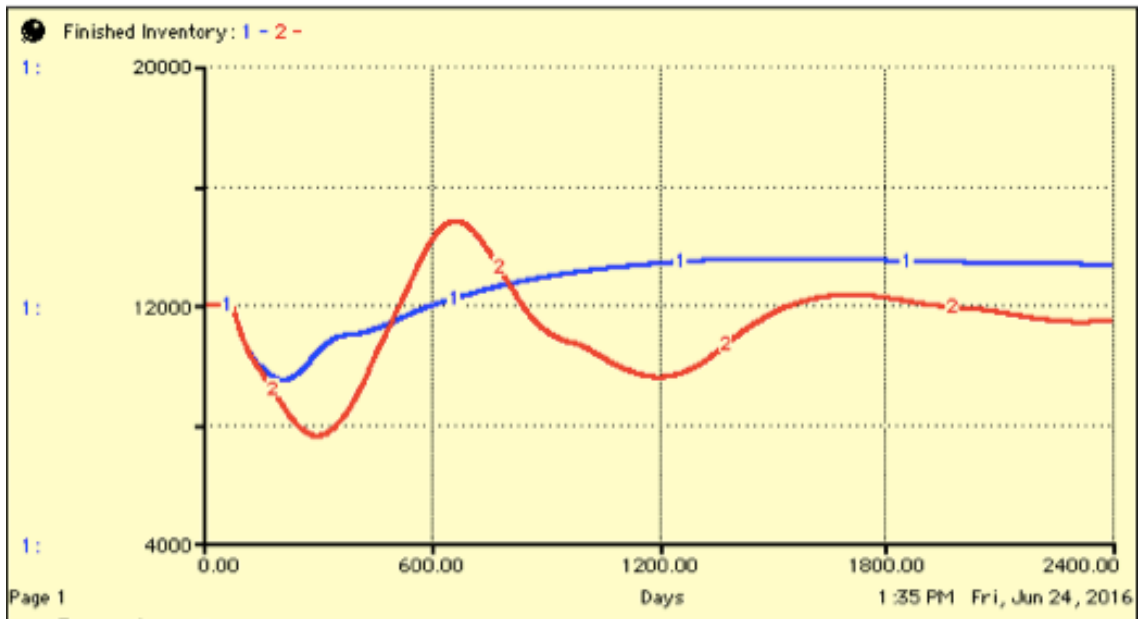
Figure 5.1.5(1)- Stock-and-flow structure of Potential Market Share as decision variable implemented to the real-world system

Customer Order Rate= IF(PMS_Switch) THEN
(Potential_Market_share*Market_Demand) ELSE (Market_Demand*Market_Share)

The customer order rate is consist of market demand and market share. Market demand is starting with 400 units per day and increased to 460 units per day from day 60 and remains the same rate thereafter. Market share is a decision variable that decision makers constructed from their misperceived system. The customer order rate remained at rate of 460 until around day 410, and started to drop dramatically below its normal value (the real-world behavior) and increased again after day 690. It started to fluctuate after day 750 and did not improve again until the end of simulation period.



Graph 5.1.5(2)- Behavior of Customer Order Rate when Potential Market Share is implemented into the real-world model

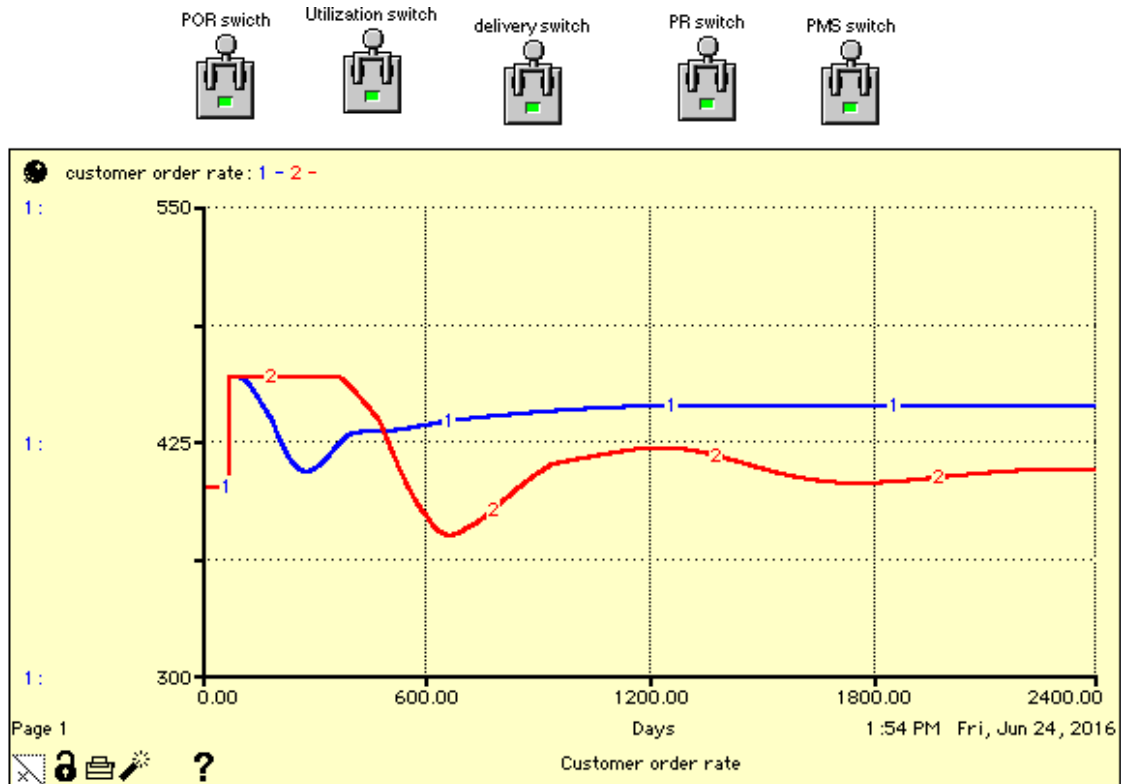


Graph 5.1.5(3)- Behavior of Finished Inventory when Potential Market Share is implemented into the real-world model

The performance of finished inventory level also suggests that the company experienced undesirable performance during the simulation period. Decision makers misperceive the actual market share would result the whole system to underperform and unable to satisfy its customers. The unstable finish inventory level would cause the company unable ship their products to customers on time. The performance of the system did not improve until the end of simulation period as a whole. The following section will analyze the behavior of the system when decision makers implement all five misperceived decision variables to the real-world system at the same time.

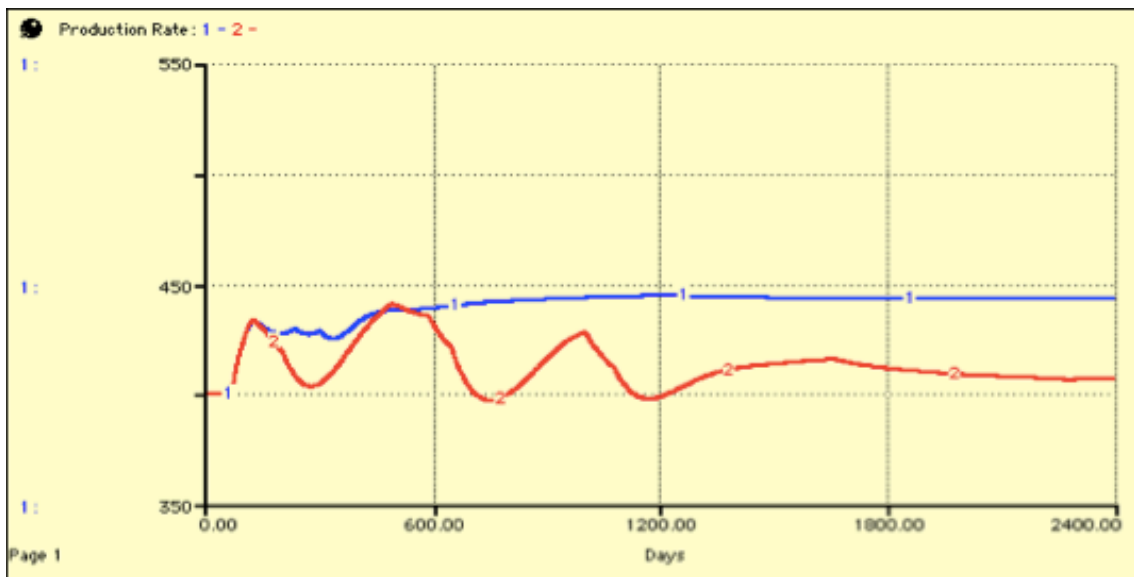
6.1.6 The real-world behavior when all decision variables are operated in the system

It is interesting to test the behavior of the real-world system when managers have operates all their decision variables based on their perceived structure of the system at the same time. The flowing graph illustrated what will happen when potential parts order rate; potential utilization rate; estimated arrival rate; potential production rate and potential market share are operated at the same time as decision variables input to the real-world model.

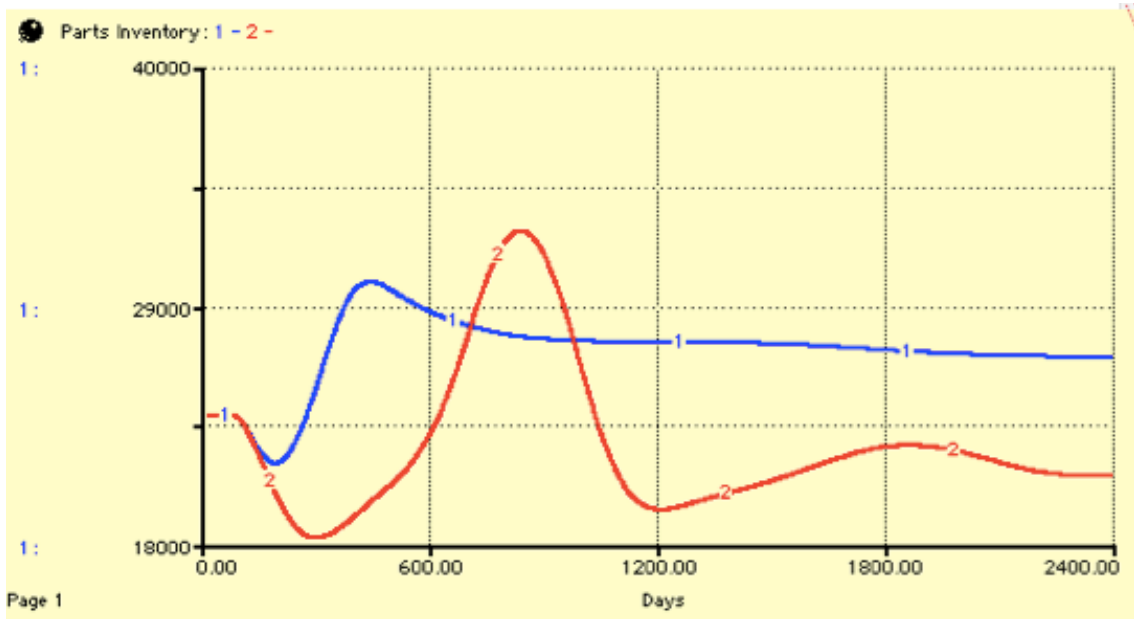


5.1.6(1)- Behavior of Customer Order Rate with five decision variables are implemented

When the five decision variables operating at the same time, the customer order rate has the exact same behavior as “potential market share” is operated. There is no differences between the customer demand for company’s product whether every misperceived decision variable is implemented, or managers is just making decision of potential market share based on their perceived shipment rate from production and from stock. However, the customer order rate is underperformed in both circumstances. It might go down even further after longer period.

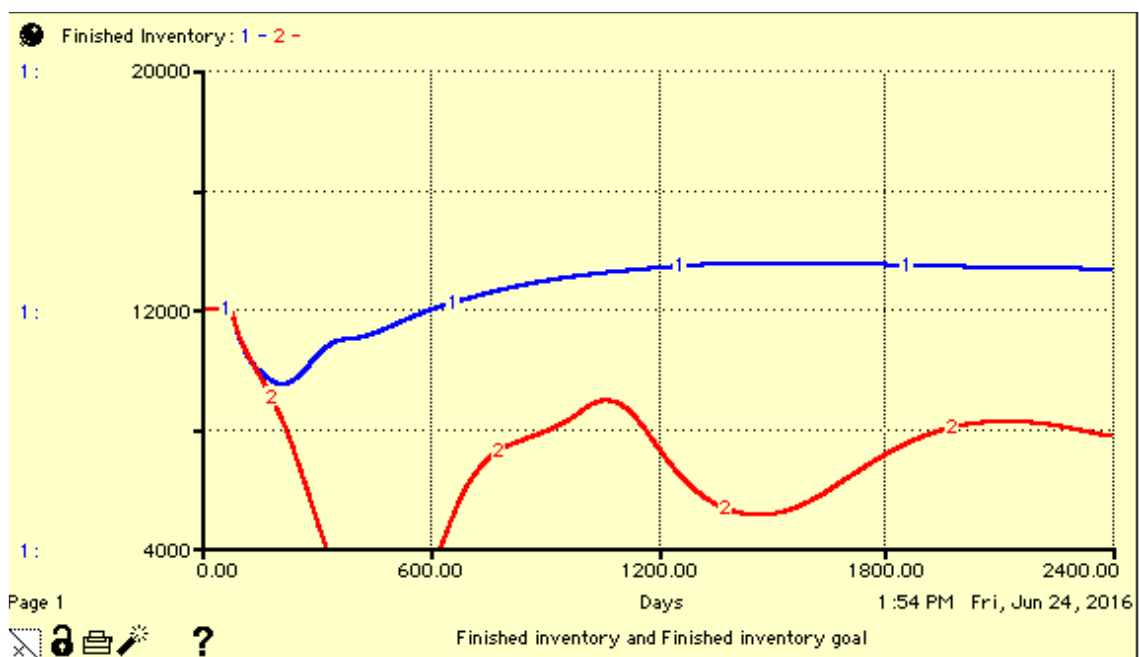


5.1.6(2)- Behavior of Production Rate with five decision variables are implemented



5.1.6(3)- Behavior of Parts Inventory with five decision variables are implemented

The production rate and parts inventory level experienced oscillations during the simulations periods. The level of parts inventory influences production efficiency in the company. After around day 1200, the parts inventory level did not try to increase to the normal level (the real-world behavior), which means the production rate would also decrease below its normal level and causes unstable finished inventory and therefore undesired customer demand for the products.



5.1.6(4)- Behavior of finished inventory with five decision variables are implemented

The finished inventory level decreased and it is still fluctuating at the end of the simulations period compared to the system behavior when managers have perfect mental model. The finished inventory might still damping even further until managers improve their understanding of their system, and thus loss its customer base and facing financial problems. It is suggests that the company is underperformed with decision makers' misperceived mental model, managers need to improve their understanding of the system and thus improve the performance of the company.

7. Learning through decision-making

The thesis illustrated and analyzed dynamics of the decision makers' mental model in terms of their operating decision process. We assume that managers' decision-making processes are affected by their short-term perceptions of the real-world information, and their perceptions are affected by their pre-stored understanding of the system in their mind. Moreover, the set of policies that top managers' constructed are based on the comparison between the past performance of the current system and the desired state of the system. In addition, policy designer in the system would be able to detect the diverge between the desired state of the system with past performance through performance evaluation techniques. According to Cyert & March (1963), that decision makers would start scanning their system when there is unsatisfied performance, such scanning activity often improves decision makers' structural understanding of their dynamic system, which would help them with better solution to their problems. Therefore, in the long run, the operating decisions and policies within the system are affected by the development of decision makers' mental model which is based on decision makers' improved understanding of their system (figure 7.1). In this section we will address, through the simulation, the dynamics of decision makers' mental model with regard to how they learn from their system so as to improve their mental model and thus enhance the performance of the system.

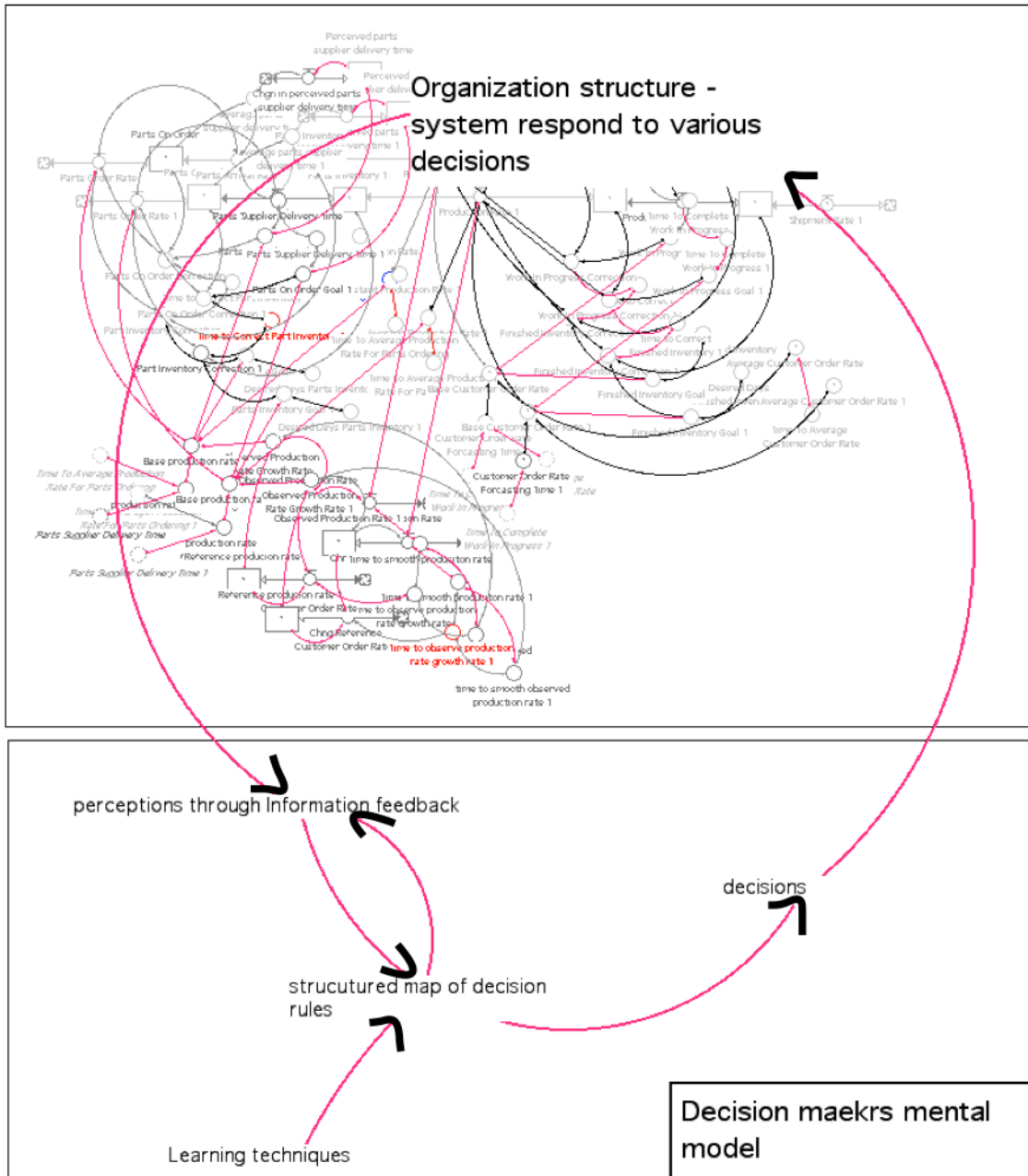


Figure 7.1 the set up of learning techniques implemented from mental model by decision makers.

7.1 Introduction to the dynamic structure of decision makers' mental model development.

Firstly, the learning technique is activated whenever decision makers realized the perceived performance of the system is unsatisfactory (figure 7.2). There are three main stocks in the real-world system that decision maker uses to conduct the performance evaluation of their system. The relative goal achievement for each stock, is to calculate the goal attainment. For example, the discrepancy between desired parts inventory level (goal) and actual parts inventory level (stock level) relative to its desired state (goal). (equation a). In order to evaluate the performance of three stocks together, we have put weight on each stock according to their degree of impacts to the system's performance (equation b). For instance, we have experimented how the entire system's performance is affected by each of these stock's performance alone. In addition, we found out that the parts inventory and finished inventory level would affect the system's performance the most. It is because finished inventory and parts inventory are physical stock level that ensure the company has sufficient products to produce in order to satisfy its customer demand (figure 7.3). Whenever there is not enough finished inventory in the system, the whole system would see as insufficient. Therefore, we have assigned the same weight to the finished inventory and parts inventory and the smallest weight to the parts on order stock.

The decision makers then perceive its system's performance gradually (with delay) as unsatisfactory when their performance evaluation is below 0 and perceive it as satisfactory when the evaluation is equal or above 0 (equation b).

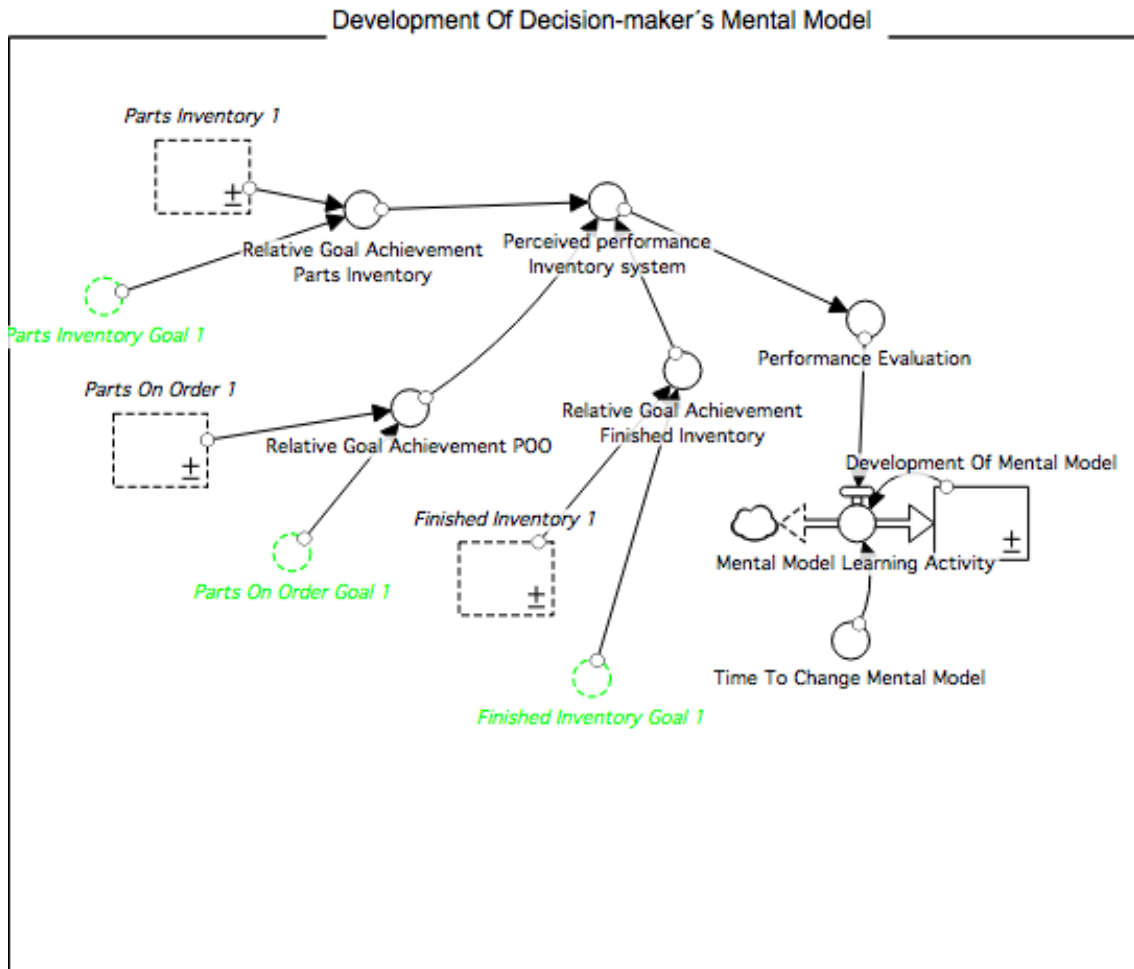


Figure 7.2 Dynamic structure of decision makers' mental model development

Equation a:

$$\text{Relative goal achievement parts inventory} = \frac{(\text{Parts_Inventory_1} - \text{Parts_Inventory_Goal_1})}{\text{Parts_Inventory_Goal_1}}$$

$$\text{Relative goal achievement parts on order} = \frac{(\text{Parts_On_Order_1} - \text{Parts_On_Order_Goal_1})}{\text{Parts_On_Order_Goal_1}}$$

$$\text{Relative goal achievement finished inventory} = \frac{(\text{Finished_Inventory_1} - \text{Finished_Inventory_Goal_1})}{\text{Finished_Inventory_Goal_1}}$$

Equation b:

Perceived Performance Inventory System=

$$(0.4 * \text{Relative_Goal_Achievement_Parts_Inventory}) + (0.2 * \text{Relative_Goal_Achievement_POO}) + (0.4 * \text{Relative_Goal_Achievement_Finished_Inventory})$$

System would be seen as underperformed when performance of the inventory system is 1, and system would be seen as satisfied when perceived performance is 0:

Performance Evaluation=

IF(Perceived_performance_Inventory_system >= 0) THEN 0 ELSE 1

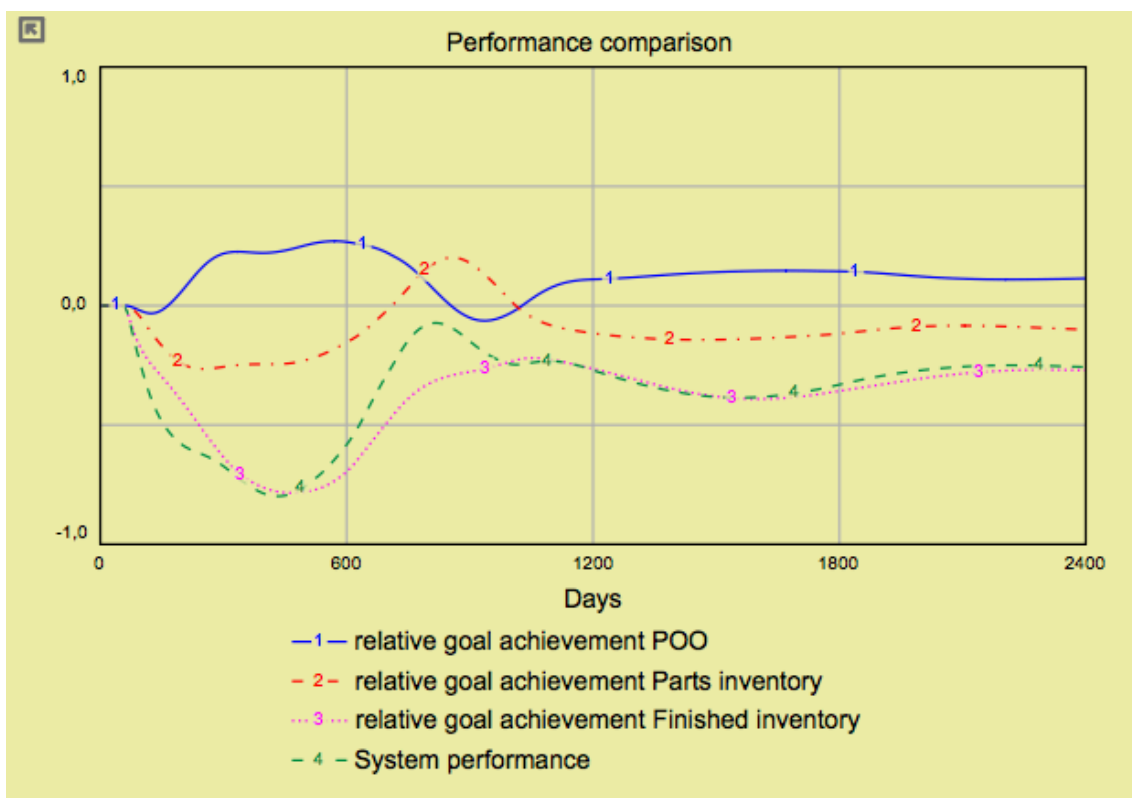


Figure 7.3 Comparison each stock's performance with the performance of entire system

Secondly, when modeling the decision makers' mental model, we have assumed that the level of decision makers mental model is 100% when they have perfect understanding of dynamics of their system. However, they will have 0% level of the mental model when they totally misperceive the structure of their system. Decision makers are learning based on their perceived performance of the system. They are improving their understanding of dynamics of their system gradually whenever they perceive a unsatisfactory performance from the system (figure 7.3). Therefore, their level of mental model can be improved when they are learning from experience (equation c). The initial value of decision makers mental model has been set to 80%.

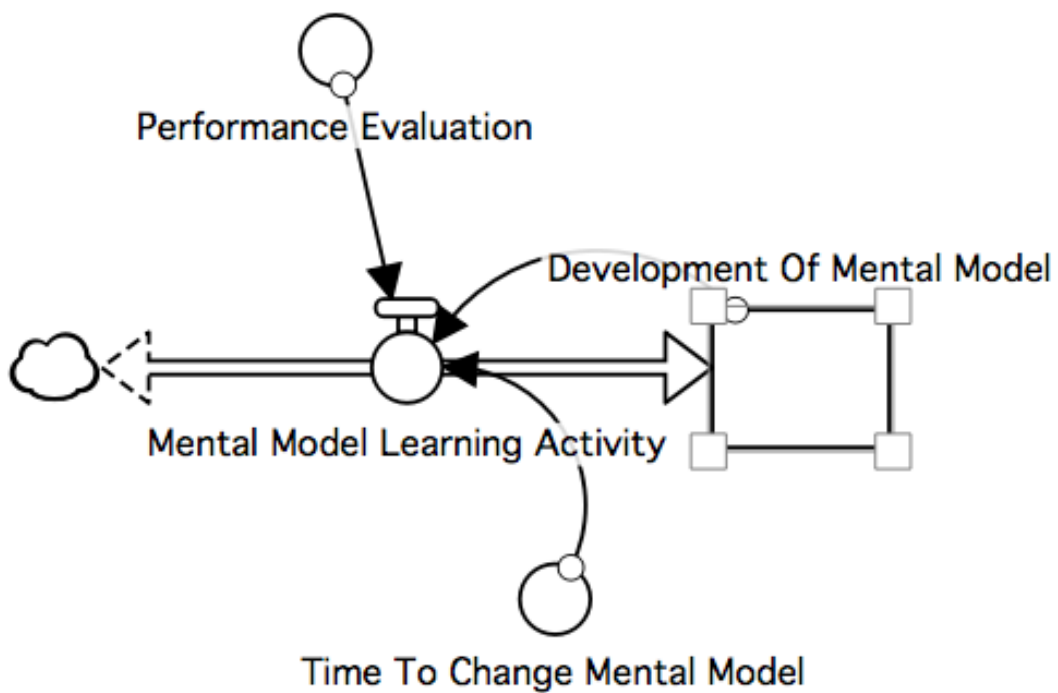


Figure 7.3 Stock and flow structure of development of decision makers' mental model

Equation c:

$$\text{Mental Model Learning Activity} = \frac{(\text{Performance_Evaluation} - \text{Development_Of_Mental_Model})}{\text{Time_To_Change_Mental_Model}}$$

$$\text{Development Of Mental Model} = 0.8$$

$$\text{Time To Change Mental Model} = 450 \text{ days}$$

7.2 Implementation of level of mental model development decision makers' mental model

Finally, the learning activity is implemented into the mental model to represent decision makers' mental model development and try to improve their understanding of their dynamics system to make better decision in order to reach their desired performance in the future. The learning activity is implemented into the five decision variables that decision makers made based on their perceived structure of the real-world system. The decision variables from decision makers' mental model are now depending on the decision makers' mental model. The weighting factor is depends on their level of understanding of their system. If decision makers have perfect understanding of their structural system, the mental model will equal to one (equation d).

Equation d:

$$D^{\text{perceived}} = \text{mental model development} * D^{\text{real-world}} + (1 - \text{mental model development}) * D^{\text{perceived}}$$

The first variable that decision makers made based on their perceived structure of the system is parts order rate. The parts order rate is the variable that suppliers use to adjust their production capacity in order to provide sufficient amount of raw materials. After implemented the learning activity of mental model, the parts order rate perceived will move towards the actual parts order rate when there is crisis in the system and decision makers started scanning their whole system try to improve their mental model (figure 7.3 and equation e). The other four decision variables are also followed the same process to move toward the actual decision variables used in the real world.

Equation e:

$$((\text{Potential_parts_Order_Rate_Perceived} - \text{Parts_Supplier_Average_Parts_Order_Rate}) / \text{Parts_Supplier_Time_To_Average_Parts_Orders}) * (1 - \text{Development_Of_Mental_Model}) + ((\text{Parts_Order_Rate} - \text{Parts_Supplier_Average_Parts_Order_Rate}) / \text{Parts_Supplier_Time_To_Average_Parts_Orders}) * \text{Development_Of_Mental_Model}$$

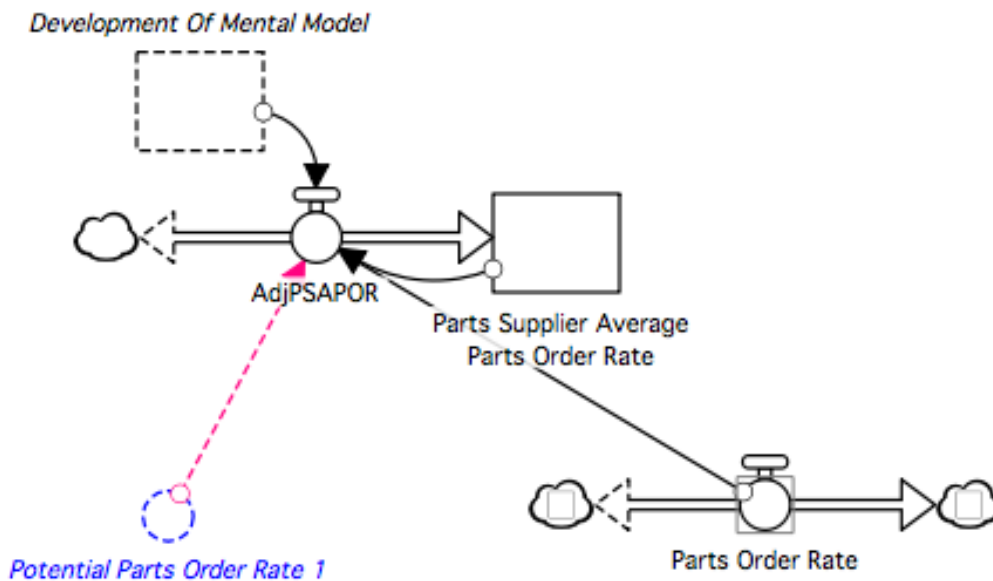


Figure 7.4 Implementation of mental model development to the system

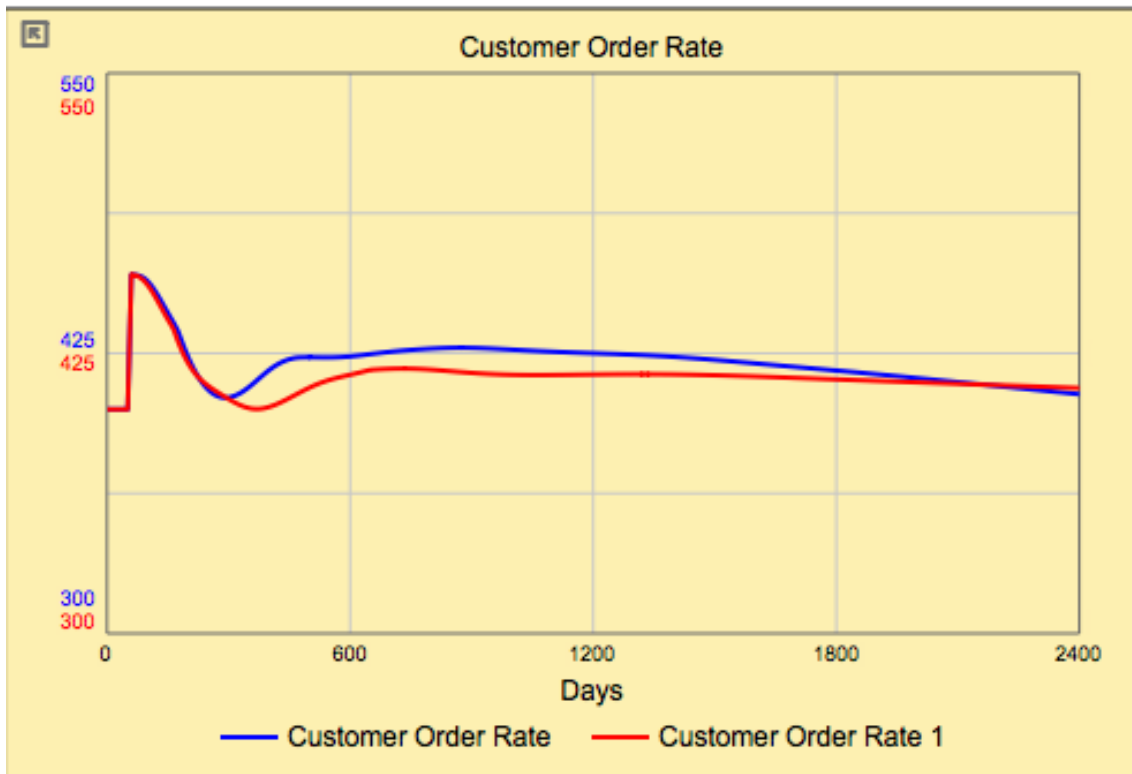


Figure 7.6 Behavior of customer order rate when decision makers have improved their mental model through learning activity

As we can see that the behavior of customer order rate (red line) that simulated from misperceived mental model compared with customer order rate (blue line) from the real-world model. The behavior of customer order rate in decision makers' mental model decreased below the real-world behavior but try to follow the movement of real customer order rate from day 320 and they became totally equal in day 2170. The behavior of perceived customer order rate indicates that decision makers have gradually improved their mental model towards the real-world system. The customer order rate starts to decrease below the perceived customer order rate, which implies that decision makers also improved their performance of the system in the long run.

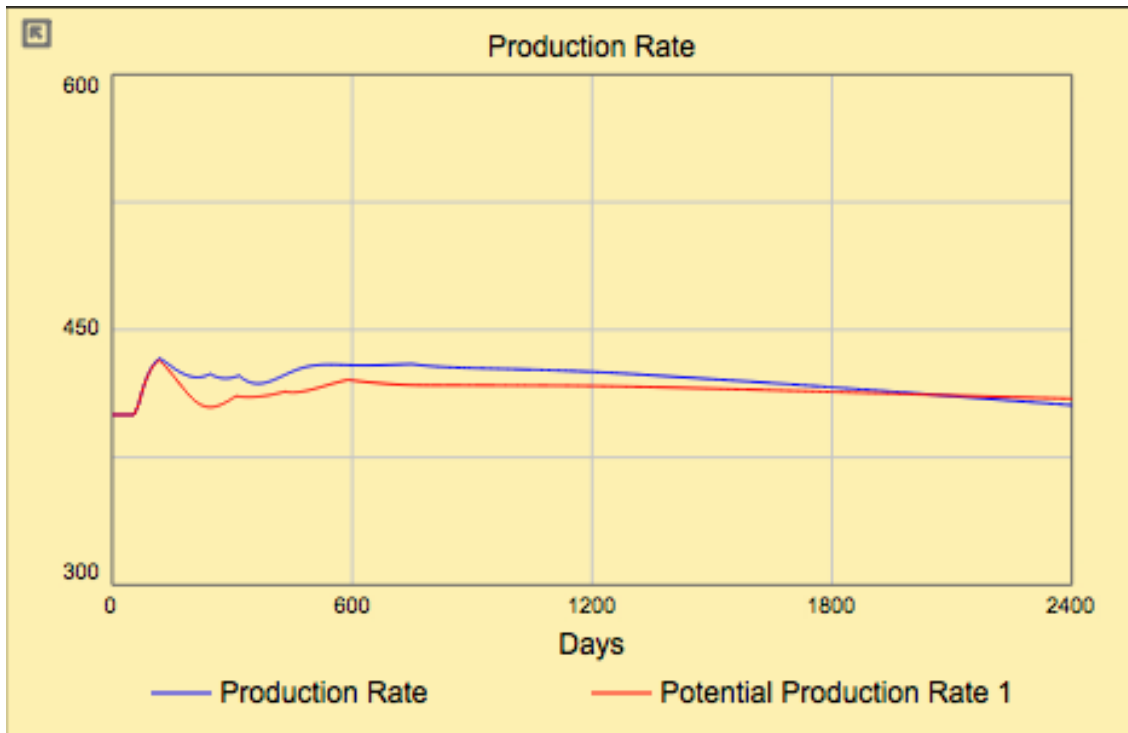


Figure 7.7 Behavior of production rate when decision makers have improved their mental model through learning activity

The result of production rate also indicates that decision maker has improved their mental model and following the behavior of actual production rate. The production rate in decision makers' mental model start to increase above the actual production rate after day 2244 and which implies that performance of the system is improved when decision makers increase their learning activity.

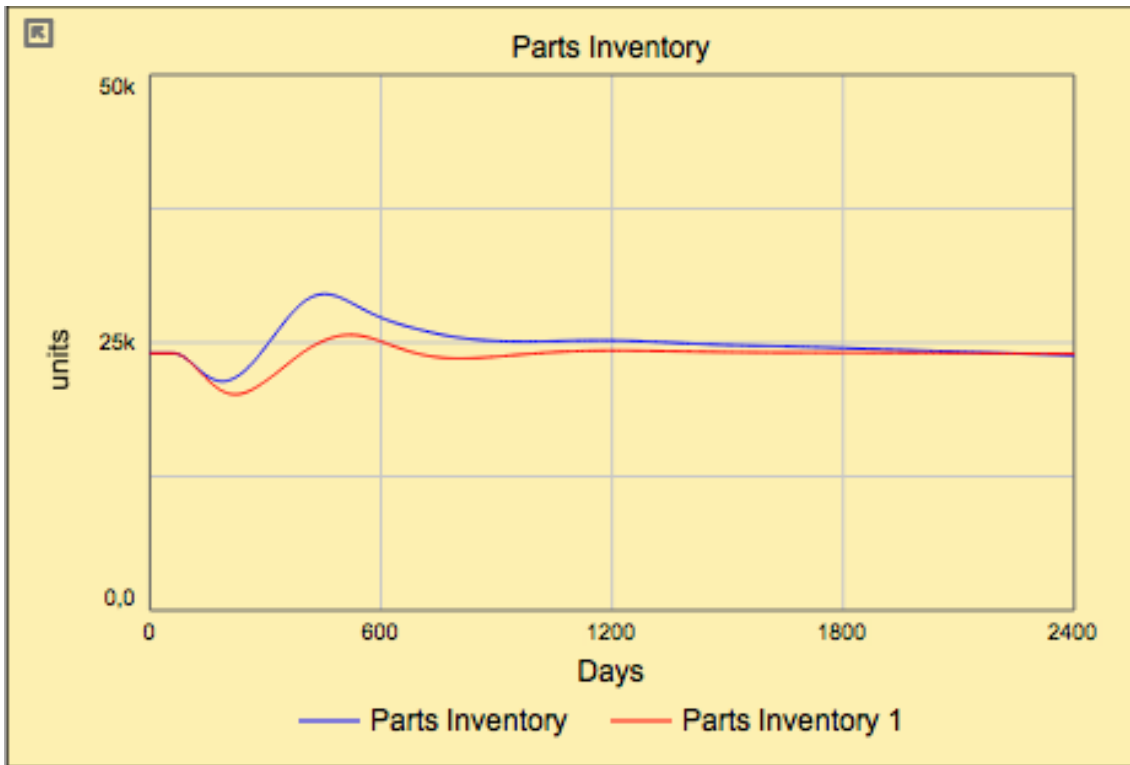


Figure 7.8 Behavior of parts inventory when decision makers have improved their mental model through learning activity

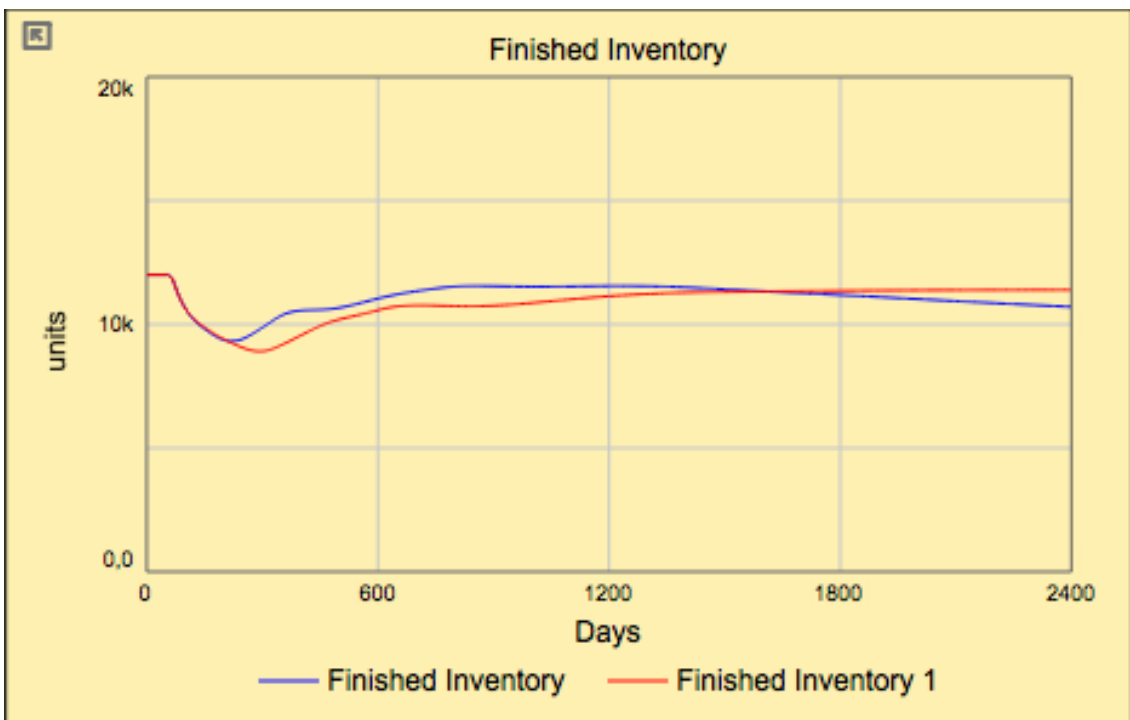


Figure 7.9 Behavior of finished inventory when decision makers have improved their mental model through learning activity

The behavior of parts inventory in decision makers' mental model also showed improvement in terms of perceiving actual parts inventory level. From day 1794, the perceived parts inventory level and actual parts inventory level became the same, which indicates that manager has accurate perception of the real-parts inventory level. At the same time, the finished inventory level in the mental model increased beyond the real finished inventory level after day 1818. Decision makers improved their understanding of their inventory system and improved the behavior of their system as well.

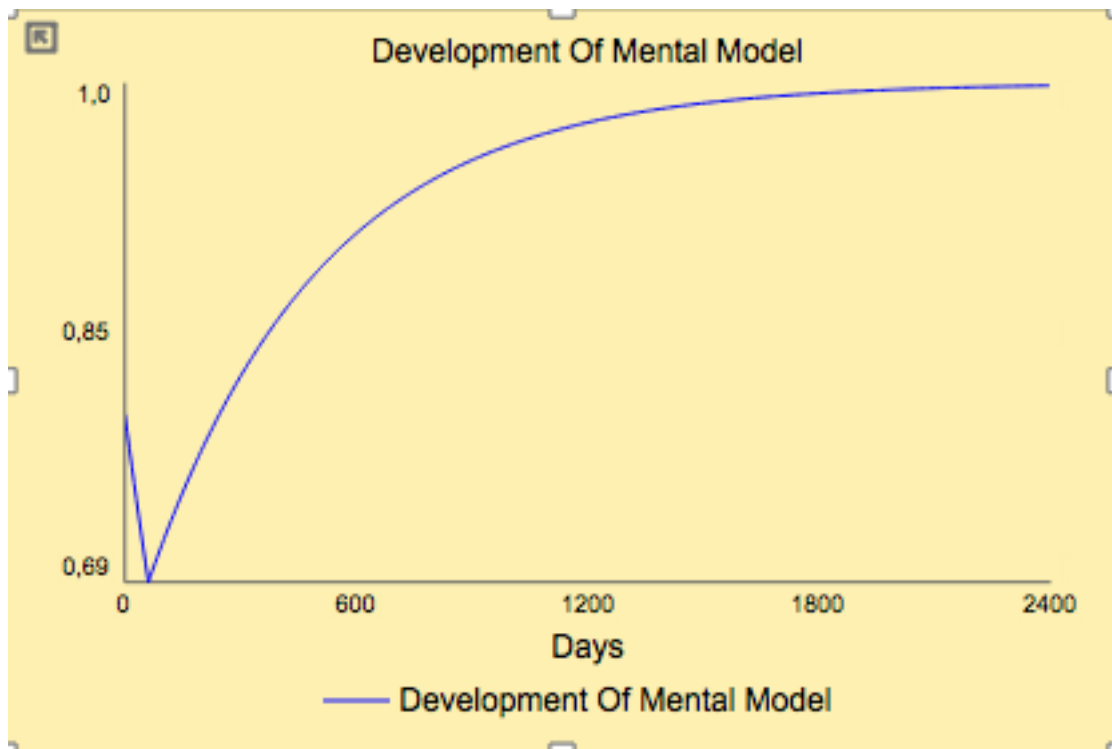


Figure 8 Behavior of mental model development

The development of mental model starts from 80%, then it decreased to 69%, it started to increase from day 61 after the system experienced a sudden increase in customer demand. The mental model gradually increases to 100% from day 1900 to represent that manager has perfect mental model.

8. Conclusion.

In conclusion, the thesis developed and analyzed a method to study and illustrate the impact of decision making process in a social system, which are affected by decision makers' perceived dynamic structural of their social system. The thesis firstly introduced a typical real-world inventory system to present how an organization balances their production supply with the changing market demand. There were several essential decision variables that need to be seriously considered within the firm by decision makers. Decision makers should be able to develop appropriate policies when organization's performance is unsatisfied in the market. However, it is been argued that decision makers often have limited mental model to capture the dynamics of their system thus making ineffective decisions based on their limited mental model.

The thesis then developed a mental model based on decision makers' perceived structural of the real-world model. Those decision variables that are developed in decision makers' perceived structural of their dynamic system then implemented into the real-world model each at a time to analyze the performance of organization. The result showed that when decision makers developing policies based on their immature mental model, the inventory level became unstable and thus caused firm unable to satisfy their customer, which lead to decreased market demand for company's production in the long run.

Finally, the thesis analyzed how decision makers start scanning their dynamic system when they detect unsatisfied performance. Decision makers could be able to improve their understanding of dynamic system that they are managing through scanning for

solutions within the system. Decision makers' improved mental model then could gradually improve their decision-making processes to solve problems. The inventory system in the thesis however did not include financial and market section in real-world system for illustration. Financial and market sectors could be another important areas in an organization to evaluate their policy development for further studies in the future.

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