

Information Network Design for Lean Logistics

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ABSTRACT

Manufacturing supply chains are invariably dynamic and complicated in nature. Hence, steady state models are not sufficient for analyzing and designing supply chains. Models of supply chains must accurately capture their dynamic behavior, which is determined by the structure of the organization, and the policies adopted by management. System dynamics modeling provides a powerful framework for this purpose.

The use of system dynamics models in supply chain management has thus far been limited to explaining phenomenon like the bullwhip effect, and for policy development. We provide a structured approach for policy design, which doesn't rely on any simulation experiments. Further, we study the impact that information network design has on the response of supply chains. We use a combinatorial approach to develop guidelines for information network design. Further, we examine the possibility of utilizing a PID information feedback structure to enhance the responsiveness of the supply chain. Lastly, we propose a combined feedback feed-forward information structure to enable a supply chain to rapidly respond to disturbances whose effects are known. The goal of this dissertation is to provide a structured approach for the design of information network structure, and operating policy.

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Chapter 1: Introduction

1.1 Background

Mentzer defines a supply chain as “a set of three or more companies directly linked by one or more of the upstream or downstream flows of products, services, finances, and information from a source to a customer” (1). He argues that in the current paradigm, the fight for market dominance is no longer limited to competing companies. Instead, the fight is now fought by competing supply chains.

The philosophy of supply chain management takes a systems view of the supply channel, rather than looking at it as a set of fragmented entities, each performing its own function. The sharing of information between members of a supply chain is needed for successful operations (2). An important aspect of supply chain management is the ability to make decisions based on accurate data. This requires an accurate and efficient information system. All supply chains require an information stream that parallels the flow of product through the supply chain (3). Without the right information at the right time, the supply chain would shut down (4). Hence, technology forms the backbone of most corporate supply chains and enables the flow of information between various entities of the supply chain. This requires trust and long-term partnerships between different entities of the supply chain.

Taylor mentions that the domain on supply chain management is primarily concerned with the management of three flows along a supply chain, namely (5):

1. Demand (Information Flow)
2. Supply (Inventory Flow)
3. Cash

Forrester mentions in his seminal research that all flows within a system are integrated by information networks (6). He developed the initial framework for system dynamics modeling to capture the impact of these information networks on system behavior. He mentions the system dynamics modeling framework is “one of building models of companies and industries to determine how information and policy create the character of an organization”.

The foundation of system dynamics lies in servomechanism theory. A servomechanism is a system that uses information feedback to control the performance of the system. This concept of an information feedback system provides the underlying structure to integrate the various facets of business activity. Forrester defines an information feedback system as follows:

“An information feedback system exists whenever the environment leads to a decision that results in action which affects the environment and thereby influences future decisions.” (6)

The study of information feedback systems reveals how information is used for control. In order to be profitable, it is necessary to understand how the amount of corrective action and the associated time delays impact the performance of the business system. The behavior of an

information feedback system is governed by its structure, delays within the system, and the amplification of the system. Hence, the design of an information feedback system must consider these three characteristics if it is to be successful.

Lean is a business philosophy that focuses on continuously enhancing the value of a product or service, while eliminating waste from the processes involved in producing those products and services. Womack and Jones mention that the core steps to lean implementation are the identification of value, lining up value adding activities in sequence, carrying out these activities when needed and improving upon these value adding activities over time (7). This value stream oriented approach helps identify wasteful activities and hence identify potential areas for improvement.

Monden mentions that the lean philosophy relies heavily on production smoothing for inventory control (8). This concept is also known as “Heijunka”. The goal of production smoothing is to produce the same amount of finished product in every time period. The Toyota production system relies on forecasts to predict monthly demand for automobiles. The shorter the period of the master production plan, the easier it is to carry out production smoothing and minimize waste. However, if the time span for the master production plan is too short, then smoothing effect on the total production quantity will disappear. Monden suggests that if a production plan were made according to actual orders, which change daily, the function of smoothing of the production quantity would not be possible. This would lead to waste throughout the production system. Hence, this model for production scheduling is sufficient when the demand for products can be forecasted accurately for a significant time period. However, if this is not possible and we

accept demand fluctuations on a daily or weekly basis, then the production smoothing approach may lead to waste and customer dissatisfaction. The strength of the lean approach is that it places an emphasis on value to the customer and helps eliminate the wasteful activities within the production system. However, it does not provide any intuition for how to carry out operations in an environment that has sudden changes in demand.

“Lean Logistics” stems from the fundamentals of the Toyota production system and tries to apply lean principles to all stages along a supply chain, starting from the customer right back to the stage of raw material extraction. It places an emphasis on the concepts of value, value streams, flow, pull and perfection (9). The “pull” concept emphasizes that material should flow downstream only when needed. Hence, for material to be “pulled” downstream, information must flow in the opposite direction to that of material flow. While this is sufficient at a conceptual level, it does not throw much light on how the knowledge of downstream inventory stocks should control upstream production. Further, the aim of lean logistics is operate with small inventory stocks, while maintaining a relatively constant production rate. These are essentially conflicting goals. If the inventory stocks were small, the production rate would have to vary significantly to replenish the inventory loss due to sales. On the other hand, one could maintain a constant production rate if there is a large inventory stock to act as a buffer between the production and sales rates. This is one the challenges of applying lean logistics.

The Law of Industrial Dynamics was defined by Burbidge as follows; “If demand is transmitted along a series of inventories using stock control ordering, then the amplitude of demand variation will increase with each transfer” (10).

This phenomenon results in excessive inventory, production, labor, capacity, and learning curve costs, due to unnecessary fluctuations in perceived demand. One of the key causes for this behavior is the presence of time lags between the initiation of an action and the effect of the action being observed. This is an unavoidable phenomenon in manufacturing as it takes time to produce and subsequently distribute goods.

The empirical work of Sterman further highlights how a lack of understanding of these time delays combined with existing system structure can lead to amplification of demand variation in a supply chain (11). Disney et al show how this situation is often made worse by poorly designed control systems (12). They emphasize the importance of choosing an appropriate information network structure to control the supply chain and then setting the system parameters to their “best” value.

1.2 Problem Statement

The modeling and analysis of supply chains has been approached by many researchers in the past. A majority of the approaches limit their analysis to the steady state response of systems and do not consider the transient behavior of systems. These include most queuing models, operations research models and discrete event simulation models (13). System dynamics modeling is a useful tool for modeling and designing supply chains as one can capture the steady state and transient behavior of the system. Further, this approach provides the framework to capture the impact of information and policy on operations.

Existing efforts to design supply chains using system dynamics tend to assume specific information network structures and are hence limited to “optimizing” the parameters of specific structures (12) (14) (15) (16). In this manner, alternate structures are not considered when designing the system. Further, the processes by which parameters are “optimized” invariably rely on simulation experiments. Thus, one requires a number of experiments to determine the “optimal” set of parameter values. The existing body of research also focuses on explaining phenomenon such as the bullwhip effect, without providing any structural solutions to the problem. Most researchers provide policy solutions, and don’t approach the problem from a design perspective. This research addresses these issues.

1.3 Research Objectives

The objectives of this research are as follows:

1. Within the system dynamics modeling framework, we shall develop a systematic approach for policy design. The goal of this approach shall be to design policies, which ensure that the system responds to changes in demand in a specified amount of time, with minimal inventory overshoot. This solution approach should not be dependent on any particular information network structure and hence should be applicable to the linear model of any supply chain.
2. We shall also use simulation to develop policies for lean logistics.
3. We shall study the impact that different information feedback loop structures have on the performance of a supply chain and use those results to develop guidelines for information network design.
4. We shall develop a system dynamics model that uses the Proportional-Integral-Derivative (PID) information feedback structure, and then study the utility of having such a feedback structure with regards to responsiveness and amplification.
5. We shall develop a system dynamics model that combines information feedback and feed-forward information structures to determine whether such a network configuration is superior to traditional feedback networks with regard to responsiveness and amplification.

Chapter 2: Literature Review

Supply chains are complicated dynamic systems, which respond to customer demand. The choice of equipment, machinery, storage and transportation networks can determine the success of such systems. However, the efficiency of supply chains largely depends on management decisions, which often tend to be based on intuition and experience. Further, the nature of supply chains varies based on changing customer demand, as well as the economics of global sourcing. Due to the increasing complexity of supply chain systems, management decisions are often far from optimum. Another factor that can hinder decision-making is that different stages in supply chains are often supervised by different groups of people with different objectives. For example, a manufacturer may want to produce large batches of the same product to minimize setup costs. However, the retailer may require small batches of a variety of products, so as to cater to a larger pool of customers. This misalignment of objectives along a supply chain can lead to waste and customer dissatisfaction. From the early 1950s, it became evident that a rigorous framework for analyzing the dynamics of supply chains and taking proper decisions could significantly improve the performance of the supply chains. Due to the resemblance of supply chains dynamics to that of mechanical systems seen in the domain of engineering, control theory has provided a solid background for building such a framework. During the last half-century many mathematical tools emerging from the control literature have been applied to the supply chain management problem. These tools vary from classical transfer function analysis to more recent modern control methodologies. We examine the variety of approaches for supply chain modeling and analysis, and identify their strengths and weaknesses.

2.1 Manufacturing Systems

Manufacturing has evolved over time from an age of craft production, through mass production, to lean and agile enterprises. Even though elements of craft production are still found in some manufacturing industries, a large segment of current manufacturing enterprises use some form of mass production. However, in the current paradigm of global supply chains, businesses face greater competition, while customers demand more features or performance at reduced prices. One of the ways in which companies can remain profitable under such conditions is to adopt the principles of lean manufacturing.

Henry Ford introduced the mass production system in 1906. Ford's vision was to produce a simple, but durable car at a low cost (17). The introduction of mass production systems required a focused, scientific approach to manage the resources involved in manufacturing. The leader in this field was Alfred P. Sloan. He introduced management practices with a focus on profits, rather than engineering. Unfortunately, as the industry turned its focus on price and profit versus engineering and quality, automakers introduced fewer innovative technologies into new cars between the late 1920's and the 1950's. Also, since the competitive pressures at the time were not as significant as in present time, companies could make profits based on economies of scale while producing a limited range of models.

Meanwhile in Japan, Toyoda Automatic Loom Works under the leadership of Kiichiro Toyoda entered the automobile manufacturing business. Japan was at the time recovering from World War II. Hence, resources were limited and the demand for cars was small. They realized that the mass production system model would not work under such conditions. Hence, an industrial

engineer named Taiichi Ohno, built on the manufacturing foundations of the mass production system (18). He worked with an American statistician named W. Edwards Deming and developed a production system where the products were “pulled” through the manufacturing operations rather than pushed through (19). Machines and workers would only make parts when the next operation needed them. With this system, Toyota was able to greatly reduce its inventory and its associated costs. This “pull” system, coupled with “just-in-time” deliveries from vendors formed the basis of what would become the Toyota Production System (TPS), arguably the most efficient manufacturing system in the world. Womack et al document the evolution of TPS and the core principles of lean thinking (7). Lean is a business philosophy that focuses on continuously enhancing the value of a product or service, while eliminating waste from the processes involved in producing those products and services (20). Lean relies heavily on production smoothing in accordance with market demand (8). This concept is also known as “Heijunka”. The goal of production smoothing is to produce the same amount of products in every period (usually every day). The TPS relies on forecasts to predict monthly demand for automobiles. This demand is then simply divided by the number of operating days in a month to determine the daily production volume for a product. The shorter the period of the master production plan, the easier it is to carry out production smoothing and minimize waste. However, if the time span for the master production plan is too short, then smoothing of the total production quantity will disappear. Monden suggests that if a production plan were made according to actual orders, which change daily, the function of smoothing of the production quantity would not be possible (8). This would lead to waste throughout the production system. Hence, this model for production planning is sufficient when the demand for products can be forecasted accurately for a significant time period (example: a month). However, if this is not

possible and there are demand fluctuations on a daily or weekly basis, then the production smoothing approach will lead to waste and customer dissatisfaction. TPS performance measures focus on the utilization of the workers and the capacity.

Agile manufacturing is a relatively new concept and was introduced by the Iacocca Institute (21). Nelson and Harvey define agility as, “a capability; it is an organization’s capacity to respond rapidly and effectively to unanticipated opportunities and to proactively develop solutions for potential needs (22). It is the result of an organization and the people who comprise it working together in ways which benefit the individual, the organization, and their customers.” Other definitions for agile manufacturing systems include those provided by Goldman et al (23), Dove (24) and Kidd (25). A common thread in most definitions of agile systems is the need for the system to be responsive. However, the term “responsive” has largely been used in a qualitative manner. There is no consensus in the agile manufacturing literature regarding the quantification of a system’s responsiveness and this is an inherent flaw in the design of agile manufacturing systems.

The design of production systems for agile behavior tends to focus on two areas:

1. Product Design
2. Design of Production Control mechanisms.

He and Kusiak use delayed product differentiation as a means to improve system agility (26). Their approach minimizes the variety of parts and reduces cycle time. Cheng et al propose an approach, which leverages artificial intelligence (AI) and Internet technologies to achieve design

and manufacturing agility (27). Architecture based on AI and java provides design and manufacturing expertise at low cost, which enables the system to tackle problems in real time. Lee discusses the role of re-configurability of manufacturing systems in agile manufacturing (28). The reconfiguration is based on the relationship between component routes, material handling cost and reconfiguration cost. He and Kusiak offer insights into the benefits that can be achieved through the concurrent design of products and assembly systems (29). Further, they offer a design procedure for agile assembly.

A thorough review of further work in the domain of design for agile manufacturing can be found in Sanchez et al (30) and DeVor et al (31). The main problem that is faced in agile manufacturing is to stay responsive and profitable while dealing with fluctuating demand, for a variety of products. The scope of this dissertation is limited to the design of responsive single product manufacturing systems. Further work, which extends the research to multiple product families, could be applied to the design of agile manufacturing systems.

2.2 Modeling of Supply Chain Systems

A supply chain is a network of entities (suppliers, manufacturers, distributors, retailers) that enable the transfer of finished products to the customer. A supply chain typically starts with the procurement of raw material and ends with the transfer of the finished product to the customer. Most supply chains are characterized by a forward flow of materials and a backward flow of information and revenue. However, some supply chains are equipped to enable the customer to send the used product back upstream in the supply chain. This trend of “reverse logistics” further adds to the complexities of supply chain management.

In the current era of global supply chains, competition is no longer limited to rival companies. Instead, competition is between rival supply chains. This has sparked an interest in enterprises for efficient supply chain management. This need for efficiency is fuelled by the rising cost of manufacturing and transportation, the globalization of market economies and the customer demand for diverse products of short life cycles, which are all factors that increase competition among companies. Efficient supply chain management can lead to a lowering of production and distribution costs, while facilitating better customer service throughout all the stages of the supply chain.

Models for production systems are typically classified as either analytical or experimental in nature. Analytical models provide a mathematical abstraction of the real system. A set of equations are used to summarize the aggregate behavior of the system. The limitation of such models is that they cannot capture detailed events that occur in the system. Queuing theory is an example of an analytical modeling approach. Experimental models on the other hand mimic the

events occurring within the system and let the modeler experiment with different parameter values to determine which parameter values yield the desired response. The limitation of this approach is that a lot of experiments are needed to surmise parameter values and hence the approach tends to be time consuming. Most simulation based approaches fall under this category.

Askin and Standridge suggest that the primary use for models include the following (32):

1. Optimization – Finding the best values of decision variables.
2. Performance prediction – Predicting performance under different conditions.
3. Control – Selecting the desired rules to control the system.
4. Insight – Gaining a better understanding of the system.
5. Justification – Using the results as a tool to support decisions.

Queuing network models are a popular approach for modeling manufacturing systems. The focus of queuing network models is on evaluating long-term average (steady-state) behavior of static systems. The term “static” implies that the process parameters do not change over time. This approach also assumes system stability in the sense that capacity is always greater than system demand. For example, the maximum production rate is assumed to be greater than the average demand. Demand is generally assumed to be in terms of the rate at which jobs arrive in the system. Since we assume system stability, it implies that we have finite expected inventory levels and waiting times. The entire manufacturing system is modeled as a network of queues. The workstations and material handling units are looked upon as “servers”, while the parts to be processed are looked upon as “customers” in traditional queuing network terminology. Hence, customers enter the system, visit the relevant servers and then exit the system.

Queuing network models grew in popularity during the 1980s and were applied to a number of problems such as the application of flexible manufacturing systems (FMS) and analysis of computer systems. Snowdon and Ammons survey popular queuing network packages for manufacturing (33). Details about specific packages may be found in Solberg (34), Suri and Diehl (35), and Whit (36). Queuing models usually assume that customer arrival can be captured by a Poisson distribution. Further, the customers are serviced according to an exponentially distributed processing time. First-Come-First-Serve (FCFS) discipline is usually assumed in these models. When these assumptions are reasonable, these models provide a fast way of determining average results for certain networks. The primary limitation of this approach is that it doesn't provide any information about the transient behavior of the system. Further, it does not provide the tools needed to accurately capture the behavior of complicated systems with multiple feedback loops.

Various alternative methods have been proposed for modeling and analyzing supply chains. Beamon proposes that such models can be grouped into four categories: deterministic models where all the parameters are known, stochastic models where at least one parameter is unknown but follows a probabilistic distribution, economic game-theoretic models and models based on simulation, which evaluate the performance of various supply chain strategies (37). The majority of these models are steady-state models based on average performance or steady-state conditions. However, static models are insufficient when dealing with the dynamic characteristics of the supply chain system, which are due to demand fluctuations, lead-time delays, sales forecasting, etc. In particular, they are not able to describe, analyze and find

solutions for a major problem in supply chains, which recently became known as “the bullwhip effect” (38).

From the above discussion, it is clear that consideration of the dynamic characteristics offers a competitive advantage in modeling supply chain systems. Hence, it is not surprising that dynamic analysis and design of supply chain systems as a whole has attracted a lot of attention, both from the academia and the industry. A recent review paper which focused on the alternative approaches that have been proposed for modeling the dynamics of supply chains, categorized the various approaches as follows (13):

- Continuous-time differential equation models
- Discrete-time differential equation models
- Discrete event models
- Classical operations research methods

2.3 Simulation Approaches

There is a widespread use of simulation to design and “optimize” manufacturing systems. Some reasons for this are:

- There has been a substantial increase in competition in the manufacturing sector due to the globalization and hence simulation proves to be a useful tool for companies that are trying to increase competitiveness.
- Manufacturing systems are typically quite complicated and involve a number of stages. Simulation enables companies to gain a better understanding of the interactions that occur within the system.
- Setting up manufacturing systems involves a substantial investment in equipment and hence simulation models can be used to evaluate the utility of investing in different types of equipment.
- Simulation can be used to estimate the effect that changes in process parameter values would have on the performance of the system.

Schmidt and Taylor define a system as “a collection of entities, e.g. people or machines, which act and interact together toward the accomplishment of some logical end” (39). The “states” of the system can be defined as the collection of variables necessary to define the system at given point in time. The choice of state variables generally depends on the objectives of the study. Systems are generally classified as either discrete or continuous in nature depending on the behavior of the state variables of the system with respect to time. A discrete system is one in which the state variables change instantaneously at separated points in time. A continuous system is one where the state variables change continuously with respect to time.

“Discrete-event simulation concerns with the modeling of a system as it evolves over time by a representation in which the state variables change at only at separate points in time. These points in time are the ones at which the event occurs, where an event is defined as an instantaneous occurrence that may change the state of the system”, as per Law and Kelton (40). Discrete event simulation (DES) is the most popular tool for modeling and analyzing dynamic manufacturing systems. DES is typically characterized by queues, servers, and probabilistic distributions of parameters such as arrival and service times. Unfortunately, the DES method generally requires too much time to construct models, perform simulation experiments, and then analyze results. In addition, DES is an event-based simulation and modeling tool. It does not consider the causal relationships between system variables. Hence, there is no analytical solution for the system that can be used for design and analysis. Like most simulation approaches, it often requires the use of design of experiments (DOE) or trial-and-error iterative simulation to determine the process parameters that lead to the desired response. Also, the transient response that is generated by DES is generally considered as the warm-up period behavior and is disregarded, while its output performance measures are statistically evaluated at the steady-state condition. DES does not predict apriori the dynamic characteristics of system models under transient conditions, such as the inventory settling time, inventory overshoot and steady state inventory level. An engineer needs to carry out a large number of replications to collect data, which is then analyzed and used to aid in decision-making.

Complex dynamic systems present many barriers to learning. Forrester first proposed the theory of system dynamics (SD) to address this issue (6). SD is a modeling technique that is used to study complex business and social systems through the understanding of the different feedback

paths in the system. He suggests that designing a system that is stable, robust under extreme conditions and manageable by ordinary people, even in the most unfamiliar of situations is the key to the success of an organization. Sterman suggests that the behavior of dynamic system comprises of some fundamental modes (11). These are:

- a) Exponential growth – Arises from positive feedback
- b) Goal seeking – Arises from negative feedback
- c) Oscillation – Arises from negative feedback with time delays.

Other commonly seen behavior such as S-shaped growth, S-shaped growth with overshoot and oscillation, and overshoot with collapse arise from non-linear interaction of the fundamental feedback structures listed above. The emphasis in SD is to use these modes of behavior to explain the overall behavior of the system qualitatively. This is sufficient if the goal is to gain an understanding of how system parameters affect system behavior. However, this approach is insufficient if the goal is to design a system. To design a system, the effect of each system parameter on the system performance needs to be quantified.

Feedback is one the core concepts on which SD is built. SD uses diagramming tools to build models. The system is defined using a causal loop diagrams (CLD) and a stock and flow diagrams (SFD). The approach for building a model is intuitive and lends itself to capturing the interactions between the various variables in the system. Simulation is then used to test hypotheses and develop policy insights. Several authors, including Towill (14), Lin et al (41) and Edghill et al (42) have applied SD to study and gain insights into the control of supply chains. However, the basic limitation of SD is that it does not provide a one to one correspondence

between the inputs and outputs of the system. Further, the traditional approach for modeling and analysis in SD does not provide any analytical solution to determine key transient system parameters and their corresponding output measures. This is essential from a design perspective.

Zill defines a differential equation as “an equation containing the derivatives or differentials of one or more dependent variables, with respect to one or more independent variables” (43). The order of the highest order derivative in a differential equation is called the order of the equation. Differential equations can be classified as linear or non-linear. A linear equation is one where the dependent variable and all its derivatives are of the first degree. Further, each coefficient depends only on the independent variables. Any differential equation that is not linear is non-linear. For most control engineers, a mathematical model of a dynamic system is usually expressed in terms of differential equations, which are based upon physical laws or idealized relationships among system variables. Chaudhari establishes equivalence between the SD representation and control theoretic representation of some commonly used models of production systems (44).

Supply chain models have traditionally been used to understand the behavior of production systems and optimize the operations of the system. Ortega et al mention that a majority of the supply chain models in the literature are based on steady state conditions or average performance (45). This may have been sufficient in the past when competition was limited and company operations were relatively stable. However, in the current paradigm, companies need to be responsive to uncertainties in market conditions to remain profitable. In such a scenario, models that capture the dynamics of time-varying production systems are needed to assist in the design

of responsive production systems. A responsive production system is one that rapidly responds to changes in demand without any overshoots and oscillatory corrections.

The basic principles of system dynamics (SD) are concisely summarized by Wolstenhome (46) (47). SD is often considered to occupy a position between that of operations research (O.R) and systems thinking. O.R. is a mathematical approach to problem solving and is hence a “hard” science, while systems’ thinking is a philosophical one and is “soft” in nature. Keys concluded that the exact position of SD remains unresolved (48). However, scientists from both domains can relate to it. Forrester examines the methodologies followed by O.R, systems thinking and SD to determine how these approaches overlap and what their unique contributions are to system analysis (49).

Baines presents the merits of using SD and discrete event simulation (DES) to evaluate the effect of proposed changes to a manufacturing system (50). He argues that even though DES appears to give more credible models due to the level of detail that can be included in such models, SD models are advantageous, as they require significantly less building time. Further, he concludes that when considering strategic issues within a manufacturing company, SD is superior to DES. Baines and Harrison present an exhaustive review of SD and DES literature to highlight that manufacturing system modeling represents a missed opportunity for SD modeling and research using DES is far more widespread in the domain of manufacturing systems (51). They suggest that versatility of SD has led to detrimental diversification of research with the result that research in the domain of manufacturing systems has declined.

Reid and Koljonen compare SD and the theory of constraints (TOC) approach for problem solving (52). They conclude that even though TOC provides a systematic approach to understanding organizational structure and its underlying cause and effect relationships, SD modeling provides a supplemental understanding relative to the knowledge gained through the TOC approach. They also argue that TOC is not as effective at capturing the complexities of present day organizations as SD and hence can benefit by the supplemental use of SD with the TOC approach. They suggest that by coupling the tools of SD modeling and TOC, managers can better understand why behavior occurs and design better organizational policies.

Forrester proposes, “The central core of many industrial companies is the process of production and distribution. A recurring problem is to match the production rate to the rate of final customer sales. It is well known that the factory production rate often fluctuates more widely than does the actual customer purchase rate. It has often been observed that a distribution system of cascaded inventories and ordering procedures seems to amplify small disturbances that occur at the retail level (6).” Sterman highlights this issue with a case study in collaboration with McKinsey and Company (11). He discusses how supply chains exhibit amplification, oscillation and phase lags even when all actors in the supply chain are locally rational and manage their piece of the system with decision rules that, in isolation generate smooth and stable responses to unanticipated shocks.

Burbidge defines the Law of Industrial Dynamics as, “If demand is transferred through a series of inventories using stock control ordering, then the amplitude of demand variation will increase with each transfer” (10). This phenomenon is also known as the “Bullwhip Effect” and has been

the primary research area for SD researchers in the domain of manufacturing. Recent examples include Towill et al (53), Geary et al (54), Disney and Towill (55), Disney and Towill (56) and Disney et al (12), and Gaalman and Disney (57). This demand amplification phenomenon is also known as the “Forrester Flywheel Effect” (58), where each “player” orders more than needed to protect themselves against market uncertainties.

Towill [11] states the Cardiff Industrial System Dynamics Group Re-Engineering Methodology, which proposes that the successful implementation of system dynamics to supply chain management requires a number of tools (14). He suggests that industrial engineering is essential if the “true” behavior of the supply chain is to be established. Business re-engineering leads to the development of alternative solutions within the commercial environment, while system simulation can be used to test alternatives. The simulation would help identify the “best” alternative that can be implemented. Further, he adds that knowledge of control engineering provides “lubrication” for the modeling, analysis and simulation phases. Towill identifies the following applications for SD models in supply chain scenarios (14):

- Explaining dynamics behavior of existing systems
- Confirming validity of proposed system modification
- Predicting system behavior under different conditions
- Benchmarking competitive improvement strategies
- Investigating the effectiveness of different control strategies

We conclude that recent literature for SD applications in manufacturing have so far been limited. This is supported by the findings of Baines and Harrison (51), who conduct a thorough review of SD literature to identify which areas are popular with SD practitioners. They conclude “modeling using SD in the manufacturing sector is relatively inactive”. The work currently being conducted by SD researchers in the manufacturing sector is limited to studying the bullwhip effect and how best to minimize it. Further, the emphasis has been on explaining the behavior and exploring the effect of different strategies, rather than looking at the problem from a design perspective. The basic limitation of SD is that it does not provide a one to one correspondence between the inputs and outputs of the system. Hence, a lot of trial and error is needed to determine which parameter combinations lead to an “optimal” response. Further, the traditional approach for modeling and analysis in SD does not provide any analytical solution to determine key transient system parameters and their corresponding output measures, which is essential from a design perspective.

2.4 Control Theoretic Approaches

The 1978 Nobel Laureate for Economics, Simon first explored the idea of using control theory to analyze a manufacturing supply chain (59). He used a simple servomechanism model where the production is driven by the error between the input and the output of the system. He calculated the transfer function for the system and illustrated how the stability of the system could be studied by calculating the roots of the characteristic equation. He concluded that servomechanism theory could be used effectively to analyze and design procedures that would control manufacturing activity.

Vassian replicated the work by Simon in discrete time by using differential equations and the z-transform (60). Axsater documents the use of discrete and continuous time approach to conclude that continuous time modeling is more popular with the academic community (61). Towill proposes an inventory and order based production control system (IOBPCS) model as a means for developing inventory control policy (15). This model is an extension of the model developed by Simon (59). Towill develops a transfer function for the IOBPCS model using block diagram reduction. This transfer function was then used to calculate the natural frequency and damping ratio. Towill et al also use the integral of time multiplied by absolute error (ITAE) criterion to configure the system (53). This approach for modeling a production control system is sufficient for simple models, but becomes very intractable as the complexity of the model increases due to the number of steps needed to reduce the control block diagram into a transfer function. Further, he does not illustrate how to translate a SD model into a control block diagram, which is not an intuitive process. Another limitation of the model is that it uses a causal loop diagram (CLD) as compared to combined stock and flow diagram (SFD) and CLD, which better captures the dynamics of supply chains. The IOBPCS model is essentially a single stage production system and is a very simplistic representation of a production system. Such a model is not useful for the analysis of supply chains, which are multi-stage entities. The transfer function for a single stage production system would ideally be of first order. However, Towill uses a production delay to make the transfer function of second order (15). This is how it differs from the model presented by Simon (59). Edghill and Towill present an extension to the IOBPCS model called the variable inventory and order based production control system (VIOBPCS) (62). They conduct an analysis for the VIOBPCS model similar to that conducted by Towill for the IOBPCS model (15).

Fong et al introduce a similar approach to model manufacturing supply chains (63). They propose using combined SFD and CLD models to capture the production dynamics. They then provide a stepwise approach to translate the SD model into a control block diagram. This control block diagram is then reduced into a transfer function over several iterations, which is the used to plot the root locus of the system. The root locus is then used for design purposes. They utilize a design of experiments (DOE) approach to determine the combination of parameters that yields the best “performance” for the system. Hence, there are a considerable number of experiments that need to be run before an “optimal” combination of parameters can be identified. Most of the limitations highlighted above for the approach proposed by Towill apply to this approach as well (15). The primary limitation of these models is that they rely on block diagram reduction to obtain a transfer function, which is a time consuming process. Further, by limiting the analysis to the frequency domain, they reduce the scope of the analysis to linear models. Additionally, Multi-Input-Multi-Output (MIMO) models are very complicated to analyze in the classical control domain. In the current paradigm of global supply chains, MIMO models are increasingly becoming more and more relevant. This is highlighted by Cachon (64). In spite of all the limitations identified for research involving classical control methods, a majority of the literature dealing with applications of control engineering for the control of supply chains, use transfer functions as a foundation for the analysis.

As seen with SD research in the manufacturing domain, a significant portion of research that applies control engineering to manufacturing focuses on the bullwhip effect and how to minimize it. Examples of this include Dejonckheere et al (65) (66)and Gaalman and Disney (57).

However, the existing work does not examine the problem from a structural perspective and focuses on policy design using optimization methodologies.

Another emerging area of research is that of vendor managed inventory (VMI) supply chains. Traditional supply chains are designed so that the downstream node makes decisions about stock levels and hence places an order to the factory upstream whenever inventory is needed. However, a VMI supply chain is a business model in which the buyer of a product shares certain information with the supplier of that product and the supplier takes full responsibility for maintaining an agreed inventory of the material, usually at the buyer's consumption location. This approach works if there is trust and collaboration between partners across the supply chain. Clark and Hammond studied retailers that implemented VMI at the *Campbell Soup Company* and concluded that retailers who adopted VMI performed significantly better than retailers who used other means to submit orders (67). Disney and Towill introduce a discrete transfer function model to study the dynamic characteristics of a VMI supply chain (55).

Ortega and Lin present a thorough literature review of research that focuses on the application of control theory to supply chain management. They identify two main research areas (45). The first is based on feedback theory and focuses on supply chain management, with an emphasis on extending models in the horizontal direction, considering not one but many factories. The second is based on input-output analysis and tries to extend applications vertically so as to integrate the different hierarchies in the factory. They also conclude that a majority of the tools used for the research efforts are from the classical control domain. Sarimveis et al provide a comprehensive review of recent literature published in the domain of supply chain modeling and analysis (38).

Their review can be considered as a supplement to the review of Ortega and Lin, which reviews older work (45). Disney et al also provide a thorough literature review of the different approaches for modeling supply chains (58). A review of existing literature dealing with application of control theory in manufacturing systems modeling leads us to conclude that a majority of the research being conducted is from the point of view of understanding system behavior and not from a design perspective. Also, classical control methods are far more popular with researchers as compared to modern control methods.

2.5 Summary

The aim of this literature review was to present alternative philosophies that have been applied to the dynamic supply chain management problem. Representative references were provided that could guide the reader to explore in depth the methodologies of their choice. The efforts started in the early 1950s by applying classical control techniques in the frequency domain. More recently, modern control theory methods have been proposed mainly based on the time domain. However, many recent reports state that the majority of companies worldwide still suffer from poor supply chain management. Moreover, undesired phenomena, such as the “bullwhip” effect have not yet been remedied. We find that system dynamics models provide the most accurate representation of supply chain dynamics. Existing research using system dynamics is limited to policy development, mostly through simulation experiments. Hence, models are used primarily to create understanding, and not for design. There is also a lack of work, which addresses the problem from a structural perspective. This dissertation addresses these issues.

Chapter 3: Modeling of Information Networks

3.1 Introduction

Models provide an effective means for understanding complex phenomena, which may not be easily understood by simple observation. A model can provide information at a lower cost quickly, as compared to the actual system. Models can be classified in many ways. Shown below is a classification scheme.

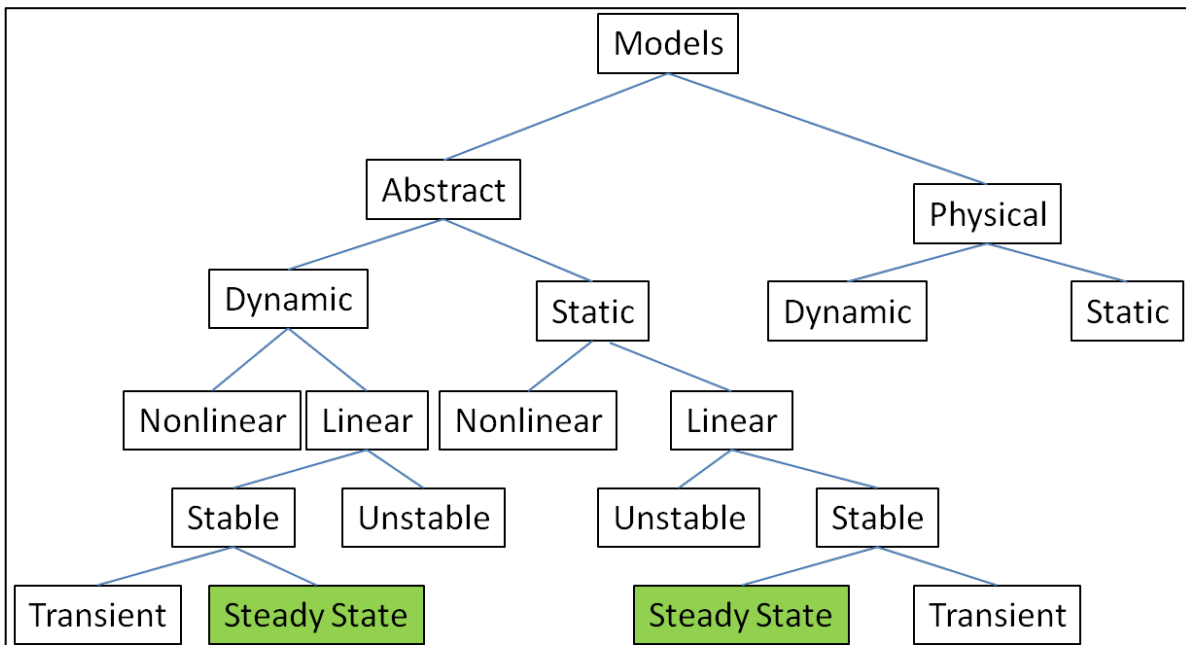


Figure 3.1: Classification scheme for models, Adapted from (6)

Forrester mentions that most of the mathematical models found in management and economics literature fall into the two categories that are highlighted in the above classification scheme. He argues that the practical utility of such models in dealing with economic systems has not been significant. He suggests that to deal with management and economic problems of practical

importance, a model should be able to encompass all the categories shown for abstract mathematical models in Figure 3.1 (6).

In the world of consultancy, a commercial consultant is paid by a client to build models to better understand some problem. Often, the models provide insights, which lead to solutions. A model that is not a “good” abstraction of reality can lead to erroneous conclusions and cause a lot of inconvenience to the client (to say the least). In academic research, the client is the researcher himself and hence it can be argued that the consequences of an erroneous model are less significant. That being said, the issue of “validity” for a model is important in any research effort. Coyle and Exelby (68) present the CATWOE mnemonic to summarize the differences between commercial consultancy and academic research. They provide an alternative in the form of the CATWOVER mnemonic to include validation and risk.

	Commercial Consultancy	Academic Research
Customer (C)	Fee paying client	Research Community
Actor (A)	Modeler and Client	Modeler
Transformation (T)	A client’s problem into a viable solution.	A gap in knowledge into a basis for further work
World View (W)	Competition with other firms - Survival	Contribute to the body of scholarship
Owner (O)	Client	Modeler
Environment (E)	Competitive	Fraternal

Table 3.1: CATWOE mnemonic, Adapted from (68)

	Commercial Consultancy	Academic Research
Customer (C)	Fee paying client	Research Community
Actor (A)	Modeler and Client	Modeler
Transformation (T)	A client's problem into a viable solution.	A gap in knowledge into a basis for further work
World View (W)	Competition with other firms - Survival	Contribute to the body of scholarship
Owner (O)	Client	Modeler
Validation (V)	Validation by consultant and client, Validation by consultant	Validation by researcher, Validation by peer reviewers
Environment (E)	Competitive	Fraternal
Risk (R)	Consultant: Financial litigation Client: Financial loss due to bad decisions based on model	Academic standing and reputation

Table 3.2: CATWOVER mnemonic, Adapted from (68)

3.2 Classification of Error

Before we discuss the different sources of error for the research relevant to this dissertation, it would be beneficial to first study the taxonomy of errors that are common in research. Allchin provides one such classification (69). The types of error relevant to the execution of the research are mentioned below:

Material

- Improper materials (such impure sample)
- Improper procedure
- Perturbation of phenomenon by observer
- Failure to differentiate similar phenomenon through controlled conditions

Observational

- Sampling error
- Observer perceptual error
- Insufficient theory for observation
- Insufficient controls to establish domain of data or observations

Conceptual

- Flaw in reasoning
- Inappropriate statistical model
- Inappropriate specification of model from theory
- Incorrect assumptions or boundary conditions

- Theoretical scope either over/under-generalized
- Incomplete theory
- Theory based cognitive bias

3.3 Sources of error in conducted research

We now discuss these errors as they relate to the research conducted.

a) Material: This research focuses on the design of information networks for lean logistics. For this purpose we use tools from the field of system dynamics, industrial engineering, classical control theory and modern control theory. We use continuous time simulation to test the effectiveness of the policies and information feedback structures, which are proposed. The research does not use samples of any kind and hence is not prone to errors due to contamination of samples.

Errors arising due to improper procedure are unlikely in the research conducted. The primary tool used in the research is differential equations. The theory of differential equations is very well developed, as shown by Zill (43). The use of differential equations is standard and hence the odds of errors arising due to the application of this tool are small.

Errors arising due to perturbation of the phenomenon (by the observer) cannot arise, as the models being used in the research have not been developed by field data collection. They are based on the work of Sterman and Forrester, whose models are widely accepted in the system dynamics community (11).

b) Observational: The research approach doesn't rely on data field data collection to draw conclusions or collect insights. Instead it is grounded in mathematical theory, which is already very well developed. If one were to collect data from industry to validate the model, the elements that would have to be monitored continuously would be inventory. Most companies use software to keep track of inventory, as it is the key to smooth operations and hence it can be observed in real time. Observation of inventory is not biased by the observer and hence is not susceptible to any observer bias. Also, since there is no sampling involved in the measurement of inventory, it is not susceptible to sampling error.

When applying the approach to a particular company, one would have to specify process parameters such as "shipping time", "cycle time" and "inventory adjustment time". There may be errors in the measurement of these parameters. This research treats these parameters as variables and hence the results are independent of the values that these parameters take. In fact, the purpose of the research is to determine the value of these values so that as to obtain an "optimal" response. The problem lies in actually making the process adhere to the values set for the process parameters.

c) Conceptual Error: The models used as a basis for the research represent a high level view of a manufacturing supply chain. The purpose of the models is to illustrate the design approach that is being proposed, as well as studying the impact of different feedback structures on response. The approach is not model specific and is applicable to any linear model of a production system. The model does not make any assumptions regarding the production processes followed by the facility. Further, the model ensures that "flows" such as the production rate and shipment rate are

always positive. This is done because a negative value for a production rate would not have any meaning in reality.

Since the research is based on continuous time models, there is a conceptual difference between the working of the models and reality. Production processes are inherently discrete in nature. For example, parts are often shipped in pallets and hence the assumption of continuous time shipping does not reflect the actual process. Fong compares a discrete event model and continuous time model of a single stage production system to determine that as the time between shipments becomes small, the dynamic characteristics of the discrete event model are similar to those of the continuous time differential equation model (70).

The models that have been used are linear differential equation models. Since no real systems are linear, all linear models carry an inherent error with them. However, the popularity of linear models is due to the fact that they are easier to develop and analyze. There are a number of tools available to analyze linear models and for many situations; the results that one can derive from linear models are sufficient. Most non-linear models are either “linearized” around particular values or are reduced to linear form by making some assumptions. Even though this does introduce some error, the linear model is often sufficient to explain the behavior of several systems.

d) Other sources of error: Sections “a” through “c” discussed sources of error in the proposed research under the framework provided by Allchin (69). There are however some errors that are commonly seen in system dynamics models. Since the proposed research uses system dynamics

modeling as a foundation, it is important to explore these errors in further detail. Some common sources of error are as follows:

- Improper causal relationships
- Inconsistency in units
- Improper time step for simulation that leads to mathematical errors
- Errors in solving simultaneous equations due to dependencies between variables
- Ad hoc approach to understand behavior leads to wrong conclusions
- If variables are not clearly defined, this confusion can lead to errors in understanding

3.4 Validation of Approach

All models are a simplification of reality. Hence, the primary question one would ask is whether the model is “good enough” to serve a particular purpose. It is not always easy to answer this question. The best that can be done is to test the model in a variety of ways and if it passes those tests, the model can be declared as valid. Coyle summarizes validation as “the process by which we establish sufficient confidence in a model to be prepared to use it for some particular purpose” (71). Coyle and Exelby suggest that this process has two aspects, namely validation and verification (68). Validation ensures that the model’s structure and assumptions serve the purpose for which it was intended. Verification implies checking that the equations themselves are technically correct.

Coyle and Exelby (68) summarize the literature on validity of models in system dynamics as follows:

- There is no such thing as absolute validity
- Checking the dimensional consistency of model is key test to determine errors
- The best way to assess the validity of a model is in relation to its purpose, i.e. it should be capable of answering the questions that the client wishes to answer
- The boundary between what is included and what is omitted is crucial
- The boundary of the model should be small enough to be tractable, yet large enough to encompass the solution to the problem
- Examining the details of the model is the best way to test its validity. The behavior of the model should be like the real system and changes in parameters or policies should lead to changes that one would expect in the real system

Some specific guidelines that one could adhere to while building SD models are as follows:

Units Check: Software such as Vensim (72) has the capability to check the units of the different elements of the model to ensure dimensional consistency.

No constants embedded in the model: It can sometimes be convenient to embed constants in the equations for variables. It is better practice to have all constants explicitly modeled as this enables the user to easily vary their values in future simulations. It also helps give the user a more complete picture of all elements in the model.

Avoid mentioning parameter values in documentation: Values of parameters are often changed during the simulation process and it can cause a lot of confusion if the value used for simulation is different from what is mentioned in the documentation.

Choose appropriate time steps: The time step should be significantly smaller than the smallest time constant in the model. By choosing a small time step, the software will increase the frequency at which model equations are solved. This will lead to better approximations in continuous time and avoid mathematical errors.

Stocks can only be changed by flows: The stock equation should only include flows that directly enter it. It should include any other constants or variables.

All flows should be connected to stocks: All flows should be connected to a stock, as a flow in isolation has no practical meaning. The purpose of a flow is to increase or decrease a stock. It should not be used for any other purpose.

Stocks should not directly link with stocks: A stock is an integral of a flow and hence should not directly connect with another stock. If a stock affects another stock, this relationship should be shown in the form of a causal link between the stock and the flow entering the second stock (the one that is affected).

Avoid IF THEN ELSE, MIN/MAX statements: Most processes in reality are gradual in nature and not sudden as these logic arguments suggest. It is generally better practice to use a table function to avoid discontinuities that are introduced by such statements.

Setting initial values: Initial values should be modeled explicitly, rather than mentioning a numerical value in the stock equation. This makes it easier to change the initial values during the simulation process.

3.5 Model of Supply Chain

We model the supply chain as a series of cascaded flows that start from the supplier and end with the consumer. The flows represent the rate at which activities are occurring along a supply chain. Stocks are used to capture the accumulation that occurs between subsequent activities. The outflow of each stock forms the inflow for each subsequent stock. The inflow for the first stock in the series is used to control the flow of material along the supply chain. We assume that suppliers have sufficient capacity to meet the desired production start rates. Each activity/flow along the supply chain has a lead-time associated with it. The outflow of each stock is formulated based on the stock level and the lead-time, as per Little's Law (11). However, the outflow of the terminal stock in the supply chain is determined by the customer demand.

A supply chain can have a number of agents at each stage. Further, each stage may consist of a number of sub-stages. However, we aggregate these within the boundary of a single stock at each stage in the model. Hence, we are aggregating serially and in parallel as well. This is consistent with the guidelines for aggregation within a model, as proposed by Sterman (11).

The information about the stock levels of each stage is used to drive decision-making. Real time measurement of the flows within the Supply Chain is difficult in practice and hence we do not assume that this information is available to aid in decision making. This limitation has been discussed by Forrester (6), as well as Hopp and Spearman (73). It should be noted that with current efforts to implement radio frequency identification (RFID) tracking across a supply chain, this limitation might not be significant in the future. As mentioned earlier, the rate of flow from the terminal stock of the supply chain is determined by customer demand. Real time point-of-sale (POS) data has been leveraged successfully by companies such as Walmart (5). Hence, we assume that the outflow from the terminal stock is measurable in real time and can be used to drive production.

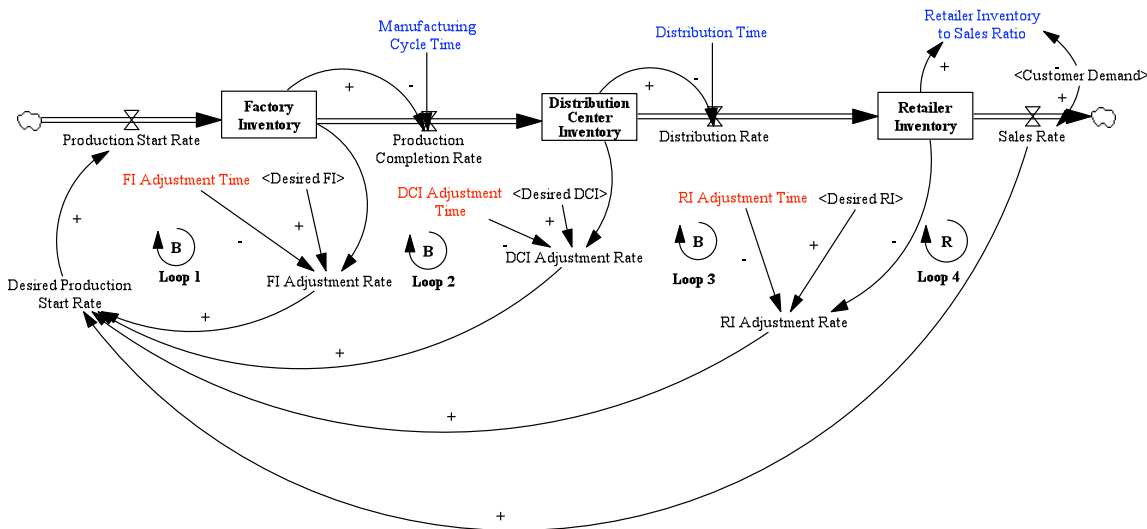


Figure 3.2: System Dynamics Model of 3 Stage Supply Chain

As shown above, the supply chain consists of three stages, namely the factory stage, the distribution center stage, and the retailer stage. The information that is used to control the “Production Start Rate” at the factory is as follows:

- Factory inventory level
- Distribution center inventory level
- Retailer inventory level
- Sales rate

The inventory at each stage is compared with a desired inventory value and this error is used to determine what the production should be at the factory level. The desired inventory level for each stage is calculated dynamically depending on the sales rate and the lead-time associated with each stage. The desired inventory level for a stage is the product of the sales rate and the lead-time associated with that stage. However, the inventory for the terminal stock in the supply chain can not be determined in this manner as the time constant associated with it depends on the sales rate. The time constant for the terminal stock is equivalent to the final inventory to sales ratio. We specify the desired retailer inventory as a product of the sales rate and the sum of the manufacturing cycle time and distribution time. This is a significant amount of inventory. In practice, one might wish to stock a smaller amount of inventory at the retailer stage. The choice depends on management. While a large retailer inventory stock reduces the risk of stock out, it also increases the inventory carrying cost of the retailer. Hence, the desired stock level must be set after careful consideration of these issues.

The error between the desired and actual inventory level is used to control production. However, the rate at which this error controls production is determined by the policy parameters for each stage. These parameters are determined by management and control how quickly inventory adjustment must take place. If the “inventory adjustment time” is set to be small, the production system shall respond rapidly to any discrepancies of inventory. While this may seem to be a desirable attribute, it can make the system unstable. The inverse of the inventory adjustment time determines the proportion of the discrepancy that must be corrected each day. This is not an intuitive choice and can only be made after considering the structure of the system and the lead times associated with it.

3.6 Simulation of Model

A model is used to capture the structure and policies that best capture the dynamics of the system under study. One can formulate various hypotheses to explain the dynamics of the system. These hypotheses can be tested through simulation. To test a hypothesis, the model is driven from its equilibrium state by some exogenous disturbance. The STEP input is a sudden disturbance which while simple in its application reveals a number of attributes of the system. These include,

- Tendency towards instability: If a system exhibits instability when tested with a STEP input, it is very likely that it shall also exhibit instability when exposed to more realistic inputs.
- Response time: If a system takes a long time to respond to the STEP input, it is likely that such a system will take not respond rapidly when there is growth or decline in business conditions.

Due to the simplicity of analysis when using the STEP input, it is generally the first test input that is used when simulating a system. Simulating the system with more complicated test inputs leads to responses, which are harder to analyze. Other test inputs that can be used for simulation include:

- NOISE: these are random unpredictable variations
- SEASONAL: these are predictable annual variations
- CYCLICAL: these are less regular variations associated with business cycles
- GROWTH/DECLINE: these are variations due to an underlying growth/decline within the business (74)

Random disturbances affect the operations of all organizations. For ease of analysis, it is common practice to use only one NOISE input. It is also noteworthy that most disturbances in organizations are correlated. A disturbance is often statistically related to a past disturbance. Over time, these disturbances tend to vary about some constant value. Hence, the use of correlated noise, called pink noise is common during the testing and simulation of system dynamics models.

Shown below are simulation results for the above model when there is a step increase in the sales rate. The manufacturing cycle time is two days and the distribution time is one day. The inventory adjustment time for all three stages is set to half a day, which is an “aggressive” policy set.

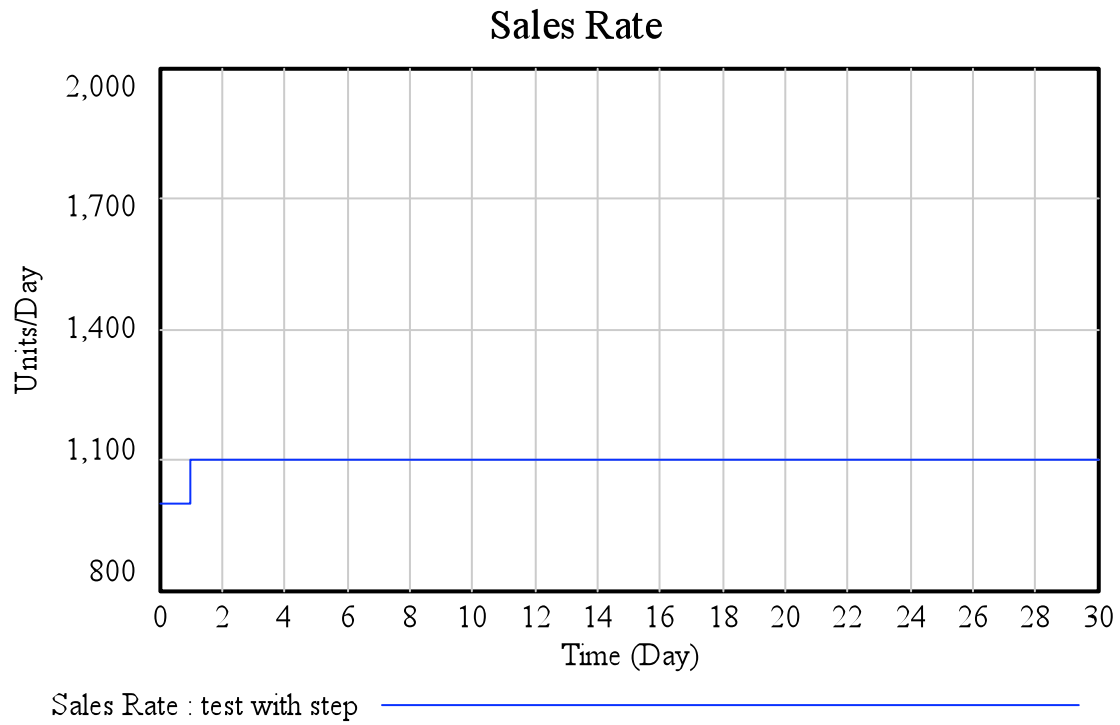


Figure 3.3: Simulation showing a 10% STEP increase in the sales rate

A sudden increase in the sales rate results in a decrease in the retailer inventory. However, the retailer inventory eventually increases and settles at higher level.

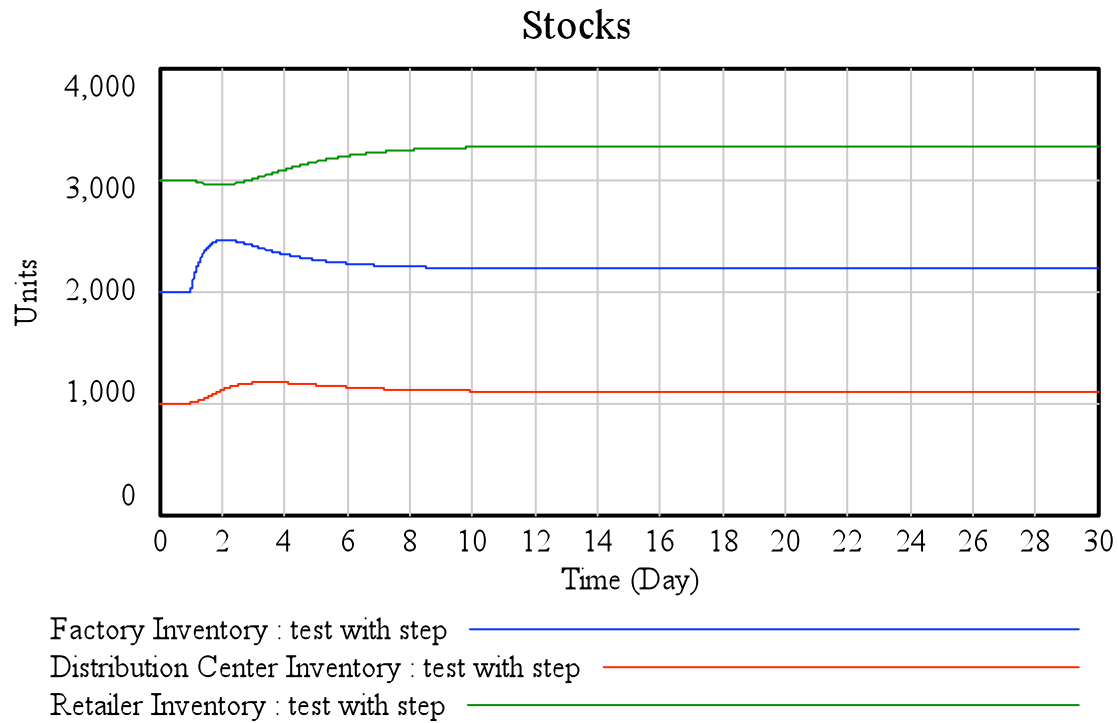


Figure 3.4: Simulation results showing stock levels for all 3 stages

The factory and distribution center inventory level goes up to a higher level before it comes down and settles a lower level. This overshoot in the inventory level is followed by an oscillatory response. It should also be noted that the inventory overshoot at the factory level is higher than at the distribution center level.

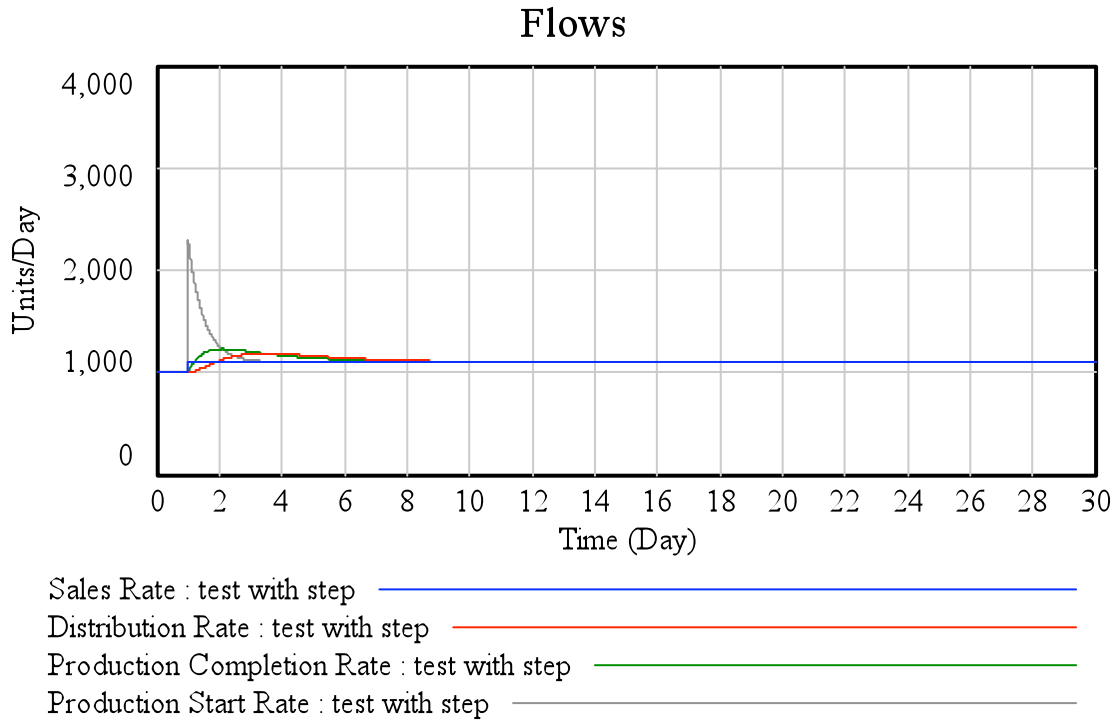


Figure 3.5: Simulation results showing flows for all 3 stages

Figure 3.5 shows the different flow rates of the supply chain. We see that the largest spike is seen at the factory level, where the production start rate increases due to the sudden increase in sales rate. The production completion rate and distribution rate also overshoot their final value, though this is to a lesser extent as compared to the production start rate. The phenomenon where variability increases as one moves upstream in the supply chain is commonly referred to as the bullwhip effect. The amplification of the system is calculated as the ratio of the variance of the production start rate to the variance of the sales rate. It is ideal to have an amplification factor of unity. However, this is rarely the case due to the structure of supply chains.

Eventually, the three flow rates equal the sales rate. It should be noted that for the system to be in a steady state, the input and output rate for each stage must be equal. It is the sales rate that

determines what the steady state flow rate should be for the supply chain. Hence, any change in the sales rate will affect the flow rates seen at the different stages of the supply chain.

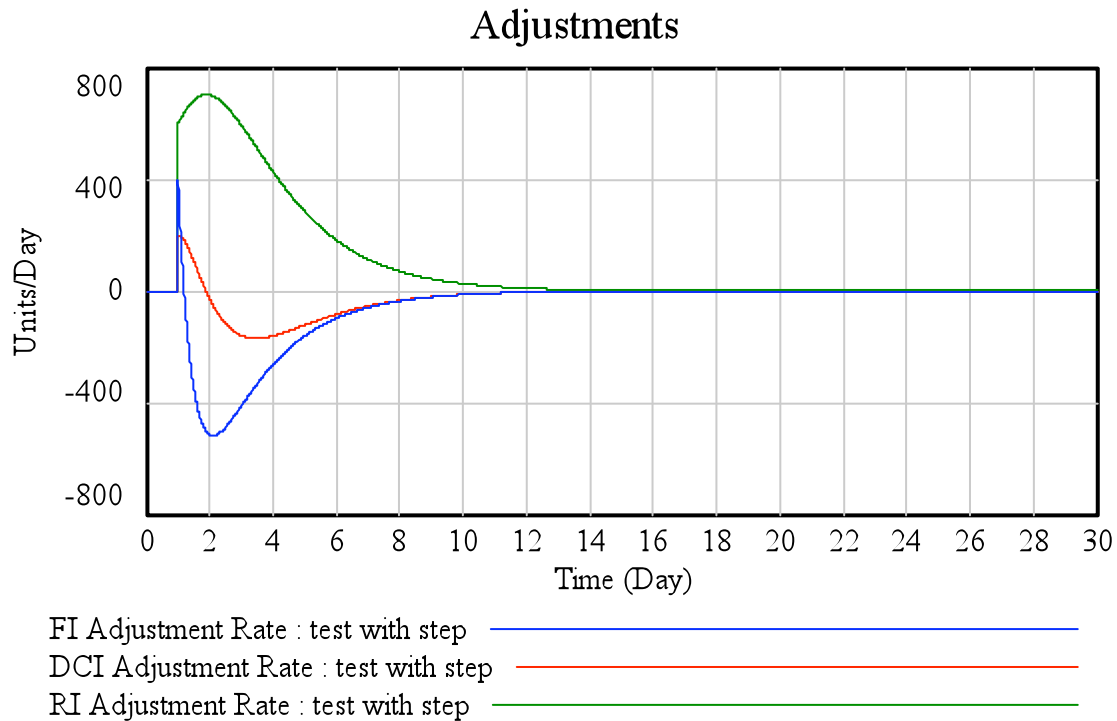


Figure 3.6: Simulation results showing inventory adjustment rates for all 3 stages

Figure 3.6 shows the adjustment rates for each stage of the supply chain. It should be noted that the adjustment rate for the retailer is the only one that doesn't oscillate. It increases in response to the increase in sales rate and then gradually drops to zero as the retailer inventory level approaches the desired inventory level for the retailer. There is an oscillation in the adjustment rate at the factory level and distribution center level. The oscillation is greater at the factory stage as compared to the distribution center stage.

Even though a STEP test input is useful for understanding the dynamics of the system, most real world systems are affected by random disturbances. Hence, we simulate the model with a test input of pink noise to study the impact of random changes in the sales rate on the supply chain operations.

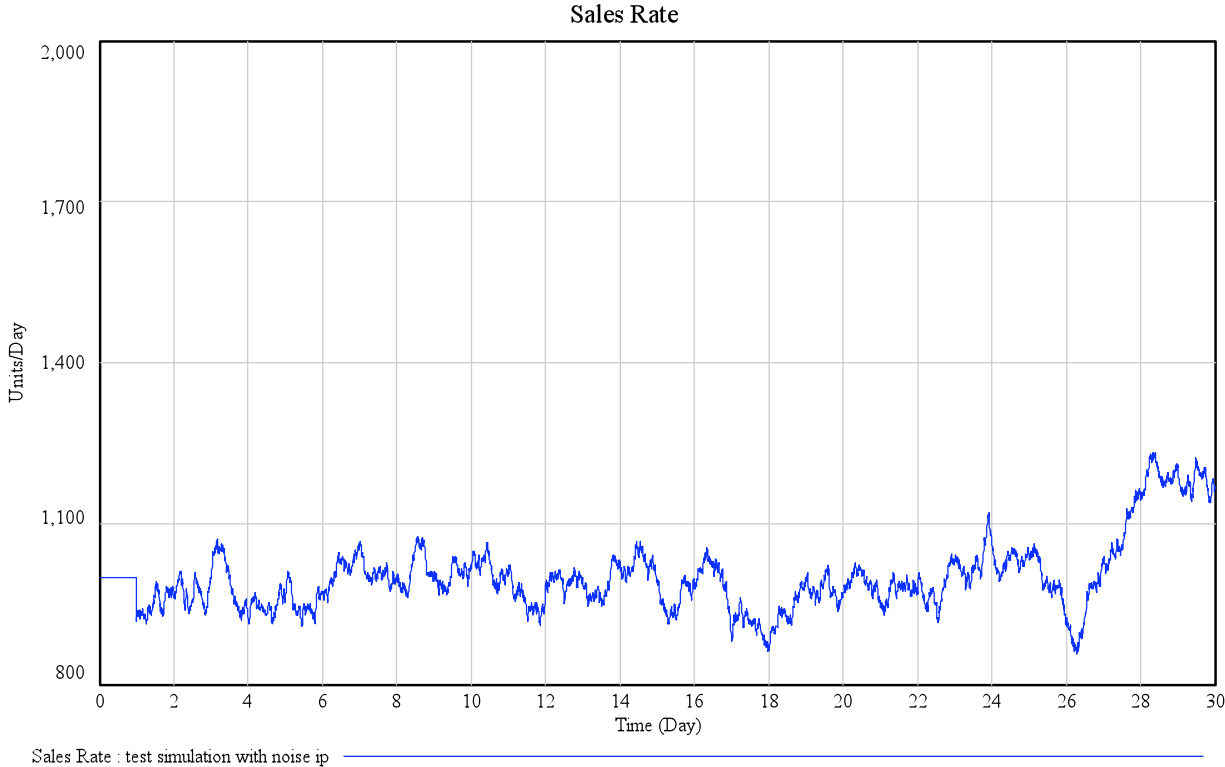


Figure 3.7: Noise input used for Sales Rate

Shown in Figure 3.7 is the pink noise input that is used for the sales rate. The impact of this sales pattern can on the inventory level at the factory, distribution center and retailer stage is shown below in Figure 3.8. The production start rate, production completion rate and distribution rate

are compared to the sales rate in Figure 3.9. The adjustment rates corresponding to the factory, distribution center and retailer are shown in Figure 3.10.

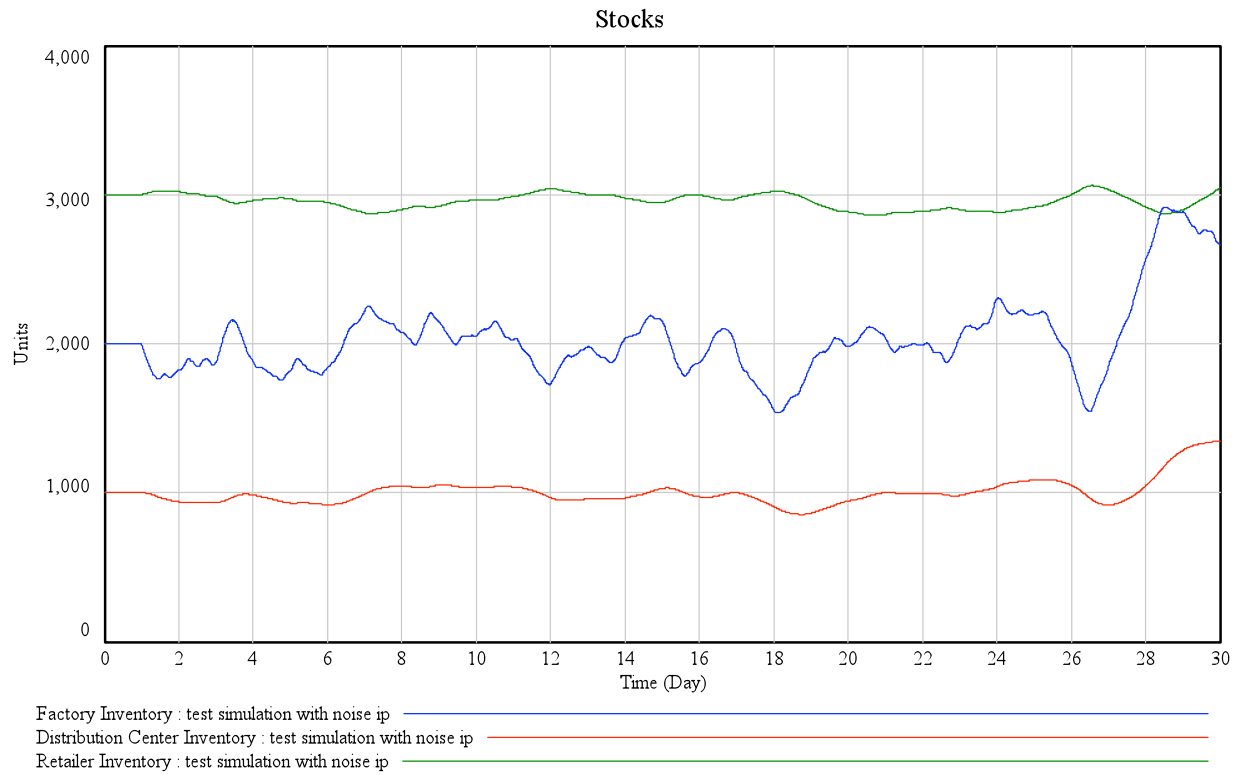


Figure 3.8: Inventory level for factory, distribution center and retailer

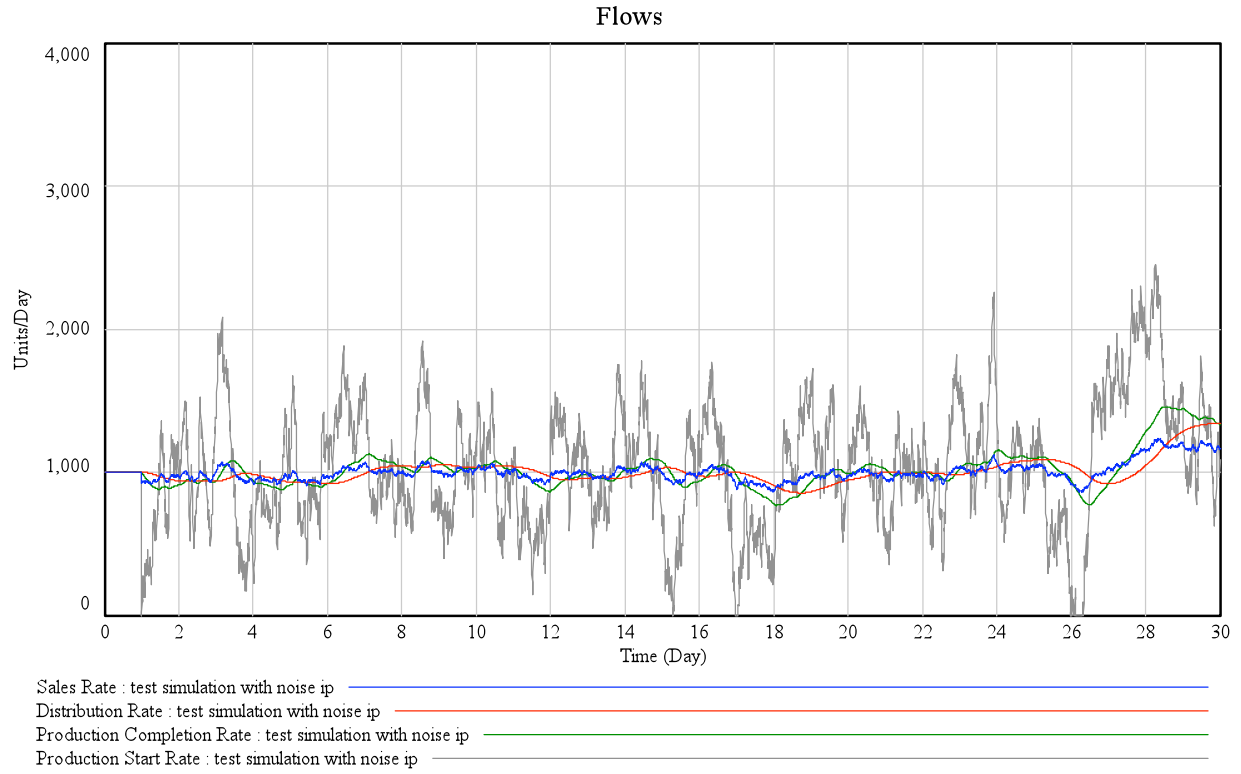


Figure 3.9: Production start rate, production completion rate, distribution rate and sales rate

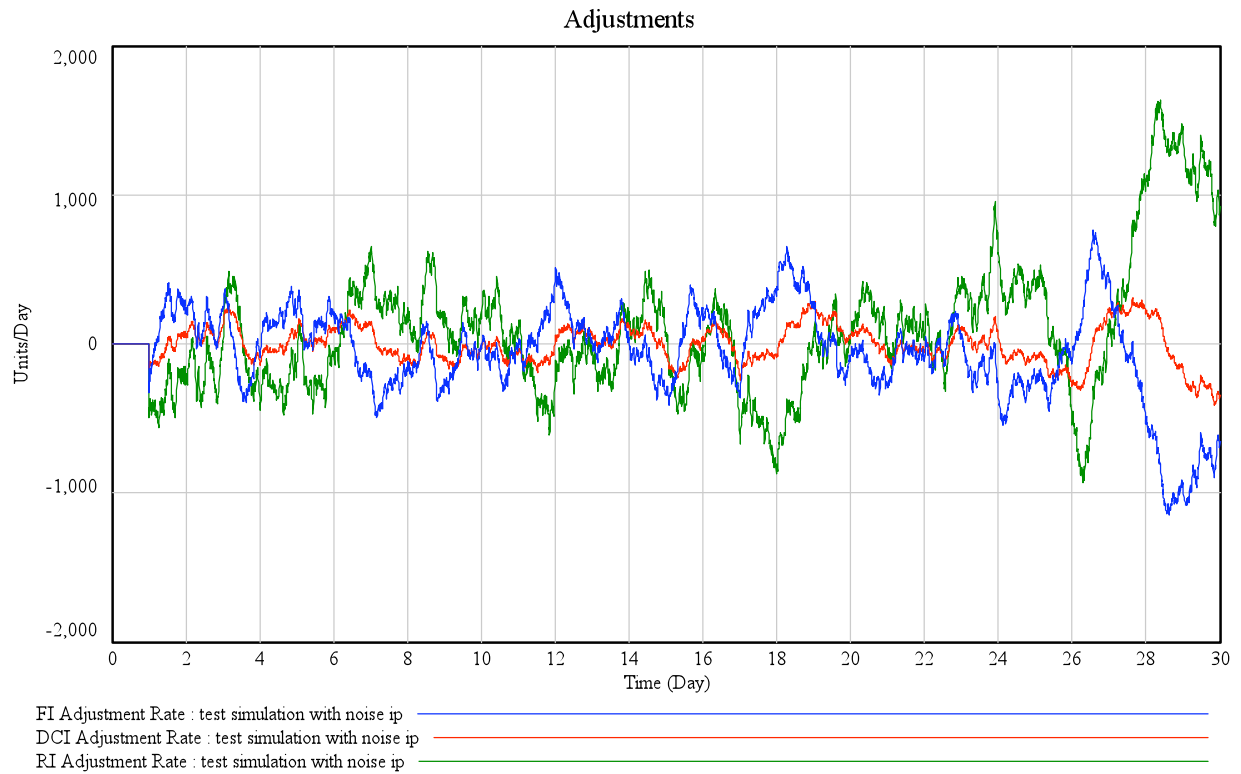


Figure 3.10: Adjustment rates for factory, distribution center and retailer stage

3.7 Summary

From Figures 3.8, 3.9 and 3.10 it becomes apparent that the variability in inventory flow rates increases drastically as one moves upstream from the retailer to the factory. This bullwhip effect that is observed is consistent with the Law of Industrial Dynamics, as proposed by Burbidge (10). One of the goals of this research is to propose solutions for this problem from policy and structural perspective. The next section develops policies to minimize this bullwhip effect that is observed in supply chains.

Chapter 4: Policy Development

4.1 Introduction

Traditionally, the purpose of inventory holdings in manufacturing has been to create a buffer to shield the customer from the delays associated with the production of the finished product. However, there has been a trend over the past decade to operate with smaller inventory holdings, as proposed by lean theory. We develop policy that will enable an organization to operate with smaller holdings of inventory, yet remain responsive to changes in demand. Traditionally, proposed policies are static over time. The efficacy of such static policy in the face of ever changing market conditions is limited. Hence, we propose a dynamic policy for inventory adjustment, which is responsive to changing sales and inventory conditions.

Forrester defines policy as, “a rule that states how day-by-day operating decisions are made” (6). Hence, policies determine how management uses the information available to make decisions. The success of management depends on what information they use and how they process it. The word “policy” in the context of system dynamics is used to describe how information is converted into action. Some organizations may have formal policies that management must adhere to, where as others may only use informal guideline to assist in decision making. Since industrial organizations are dynamic, managers must constantly make decisions based on dynamic information streams. A formal set of policies that are developed after analyzing the structure of the organization can assist management in making effective decisions.

In the context of manufacturing supply chains, policy determines how rapidly management responds to inventory discrepancies. Hence, policy would determine the number of days over which any discrepancies would be corrected. If an organization were to follow an aggressive policy to inventory adjustment, it would hold a small amount of inventory and react quickly to change production to correct inventory discrepancies. This would be an appropriate policy when the cost of holding inventory is relatively high and the cost of changing production is small. On the other hand, an organization might adopt a slow policy if the cost of varying production is very high compared to the cost of holding inventory. An organization that adopts a slow policy would keep production rate relatively stable and permit the fluctuation of inventory levels in response to the sales rate.

The amplification, inventory overshoot and settling time of the supply chain are impacted by the policy adopted by the organization. One would expect a supply chain that adopts an aggressive policy to have a shorter setting time, but a larger amplification and inventory overshoot in comparison with a supply chain that follows a slow policy. Hence, the policies used must be determined by the goals for amplification, inventory overshoot, and setting time metrics that the supply chain aspires to achieve.

We assume that the processing times associated with each operation in the supply chain are constant and deterministic in nature. Further, this research assumes that all the inventory holdings are measurable at all points in time. We use a production control algorithm that continuously compares the inventory level at the factory, distribution center and retailer stage with ideal values. Any discrepancy between the two quantities leads to the generation of

production orders. The inventory adjustment policy determines what fraction of this discrepancy must be corrected in each interval of time. Typically, this policy is constant over time. However, such a static policy, which is not responsive to dynamic market and inventory conditions, may not deliver the desired results. This research aims to test the efficacy of using a dynamic policy for inventory adjustment.

4.2 Policy Development using System Dynamics

The use of system dynamics for development of policies begins with the identification of some behavior that needs to be improved upon. In the case of supply chains, it is of interest to operate with lower levels of inventory, while being responsive to changes in customer demand. Further, it is important to minimize amplification and inventory overshoot, as highlighted previously.

When one has identified the behavior of interest, one must identify the factors and their interrelationships that appear to be contributing to the behavior observed. These may include feedback loops, delays, accumulations and corporate policies. Once this information has been collected, it can be used to construct a computer model of the system. The scope of the model, which is constructed, is of importance. The modeler must ensure that the scope is wide enough to include all-important dynamics, yet concise enough to ensure that analysis is tractable.

The model is then simulated and an effort is made to determine why the structure of the system leads to the behavior being observed. It is important at this stage to compare the simulated response with the actual behavior of the system. If there is a significant difference between the two, then the model must be revised. Since the effectiveness of the policies developed depends

on the accuracy of the model, the model should be refined over several iterations to capture the dynamics of the actual system.

Once there is sufficient confidence in the model, the modeler develops policies identify policies, which alleviate the problem of interest. These policies are generally developed and tested over several simulation runs.

4.3 Proposed Policy and Case Study

We apply the above approach for policy development to the system dynamics model for a manufacturing supply chain, which is discussed in Chapter 3. The model is shown in Figure 3.2.

The supply chain can operate with smaller holdings of inventory by minimizing the lead-time associated with each stage of the supply chain. This is consistent with Little's Law. In this case, there are three stages, where the time constant associated with each stage is as follows:

- i) Manufacturing Cycle Time
- ii) Distribution Time
- iii) Retailer Inventory to Sales Ratio

Thus, the total inventory in the supply chain can be minimized by minimizing these three time constants. This model shown in Figure 3.2 assumes that the “manufacturing cycle time” and “distribution time” is constant. The “Retail Inventory to Sales Ratio” varies depending on the changing sales rate and retailer inventory.

The reduction of the manufacturing cycle time is possible by minimizing the waste involved in the manufacturing process. The seven most common wastes seen in manufacturing activity are as follows (8):

1. Defects
2. Overproduction
3. Transportation
4. Waiting
5. Inventory
6. Motion
7. Processing

To reduce the distribution time, one needs to reduce the transportation time that it takes from the distribution center to the retailer. This can only be done by carefully planning the location of the distribution center network in relation to the retailer network. Further, one could optimize the transportation of goods between the network of distribution centers and the network of retailers so as to minimize the distribution time.

The retailer inventory to sales ratio can only be reduced if retailers operate with smaller holdings of inventory, or if they maintain the same holding of inventory for an increase in sales rate. The retailers can increase sales through promotion activities. However, such an approach is not sustainable over the long term. A more realistic approach is to stock lesser inventory, but have it rapidly replenished as when goods are sold. With reference to the model, this can be done by setting the “desired retailer inventory” parameter to a small value.

We propose the following adjustment policy for the supply chain:

- i) Let the inventory adjustment time for the retailer (RIAT), distribution center (DCIAT), and the factory (FIAT) be set equal to the retailer inventory to sales ratio (RISR). Hence, set a uniform inventory adjustment policy for each stage of the supply chain. The retailer inventory to sales ratio is the number of time units that it would take to deplete the existing retailer inventory stock at the current sales rate. A high ratio implies that the either the “desired retailer inventory” is set to a high value, or the retailers have a high inventory level for the existing sales rate. This dynamic ratio would vary depending on ever changing inventory stock and sales rate. The advantage of using the RISR as the inventory adjustment time is that the system becomes responsive to changing conditions. For instance, if the ratio suddenly drops, the system would correspondingly carry out the inventory adjustment in a shorter period of time to avoid an inventory stock out.

- ii) The ideal inventory level for each stage of the supply chain should be a function of the sales rate and the time constant associated with that stage of the supply chain. Thus, the ideal inventory level for the factory should be a product of the sales rate and the manufacturing cycle time. Likewise, the ideal inventory level for the distribution center should be a product of the sales rate and the distribution time. The time constant for the retailer is the retailer inventory to sales ratio, which is a dynamic quantity. We could set the desired retailer inventory equal to the product of the sales rate and this ratio. However, this would set the desired retailer inventory equal to the existing inventory stock. Alternatively, one could set the desired retailer inventory equal to the product of the sales rate and some time constant. This time constant would reflect how many days worth of inventory one would like to stock.

We test this dynamic policy set by using a STEP and NOISE input. We calculate the desired inventory level for each stage as a product of the sales rate and the time constant for that stage, as discussed above. Due to the specified policy, no corrections are made for the retailer stage. This leads to a decrease in the retailer inventory when there is an increase in the sales rate. However, the overall inventory in the system increases in response to the increase in sales rate, as shown below in Figure 4.2. Hence, the supply chain satisfies a higher sales rate with a smaller quantity of retailer inventory.

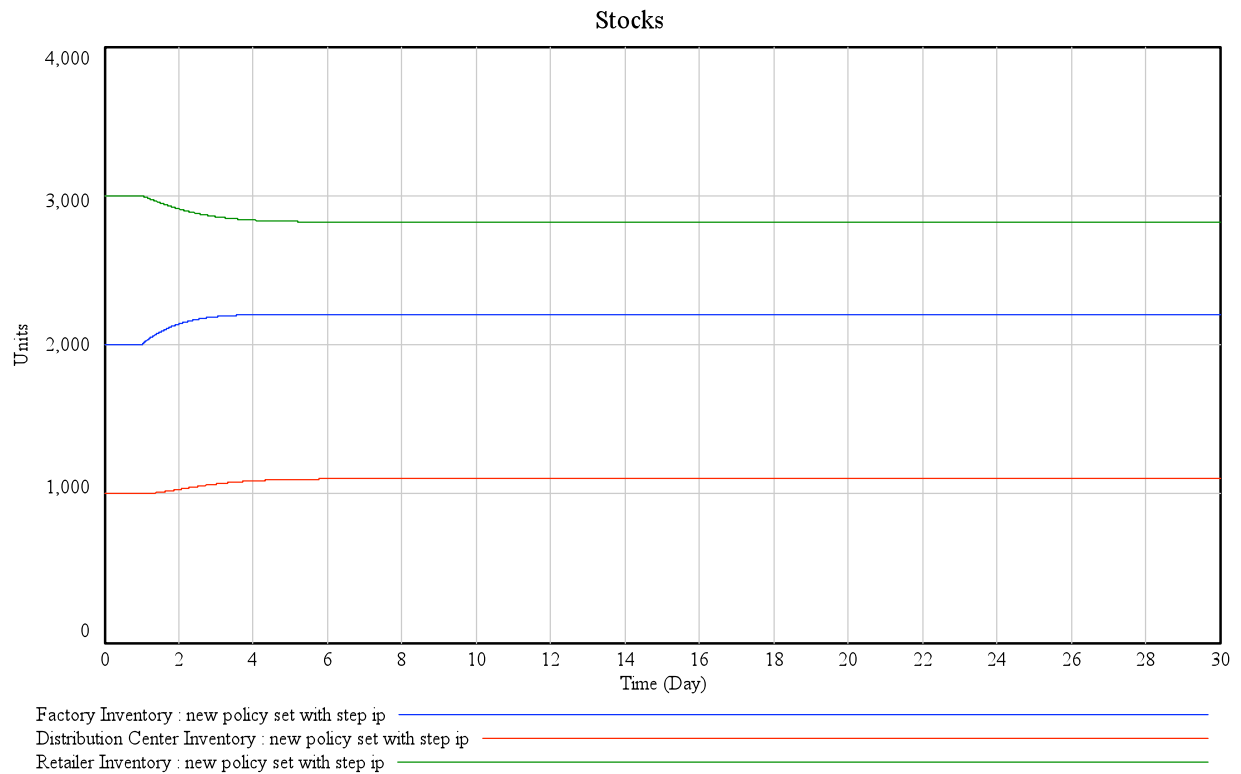


Figure 4.1: Impact of STEP input on system stocks (new policy set)

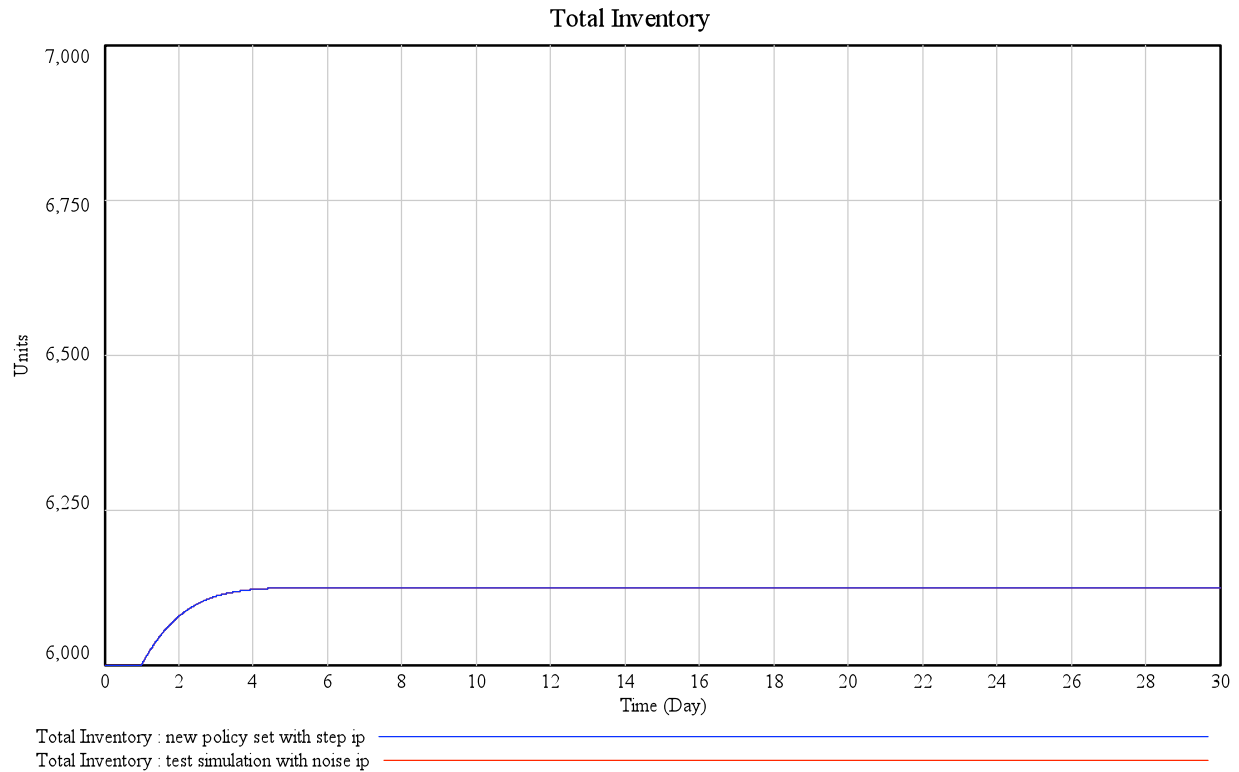


Figure 4.2: Increase in total system inventory due to STEP input

Since the sales rate shall randomly vary around some level, it is expected that the inventory levels at each of the three stages shall also vary around some particular value. When simulating the supply chain with a NOISE input, we see this very phenomenon.

We see below that even the production and distribution rates exponentially converged to the new steady state level without any amplification. This is a vast improvement over the earlier scenario where significant inventory overshoot was seen at the distribution center and factory stage due to the step increase in sales rate at the retailer stage.

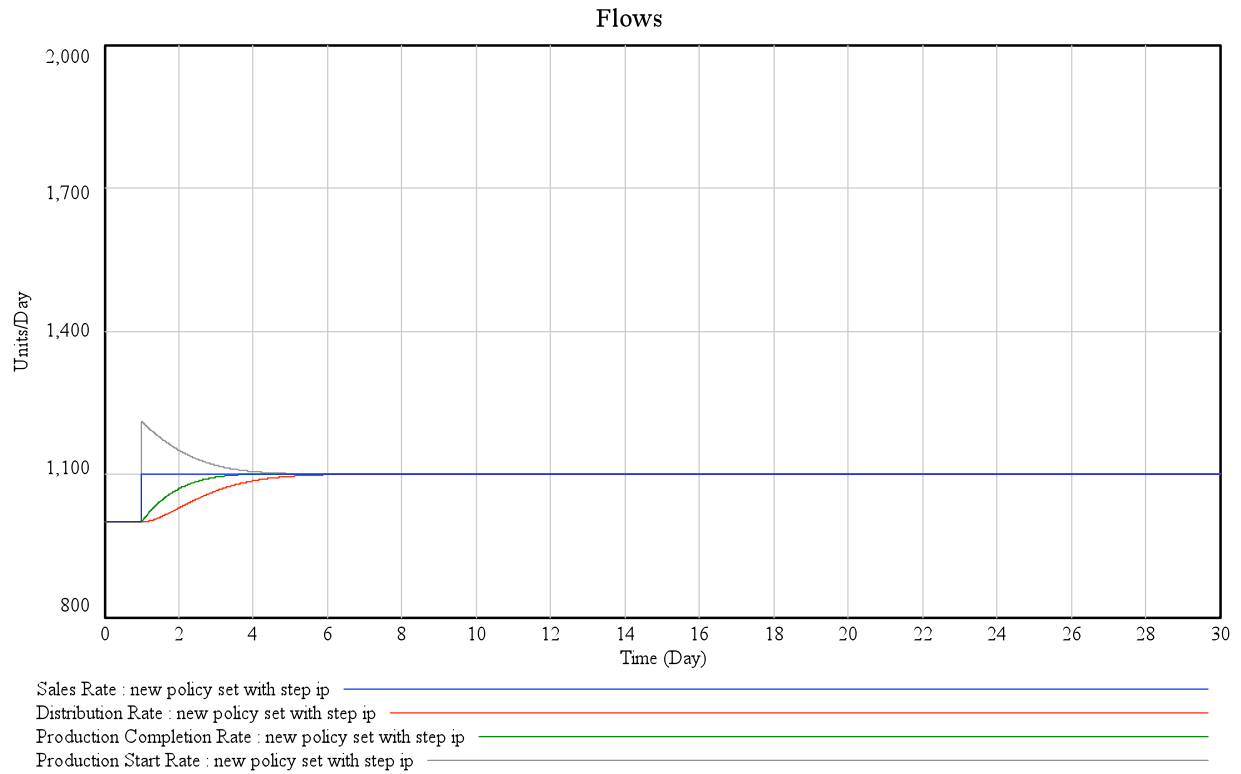


Figure 4.3: Impact of STEP input on system flows (new policy set)

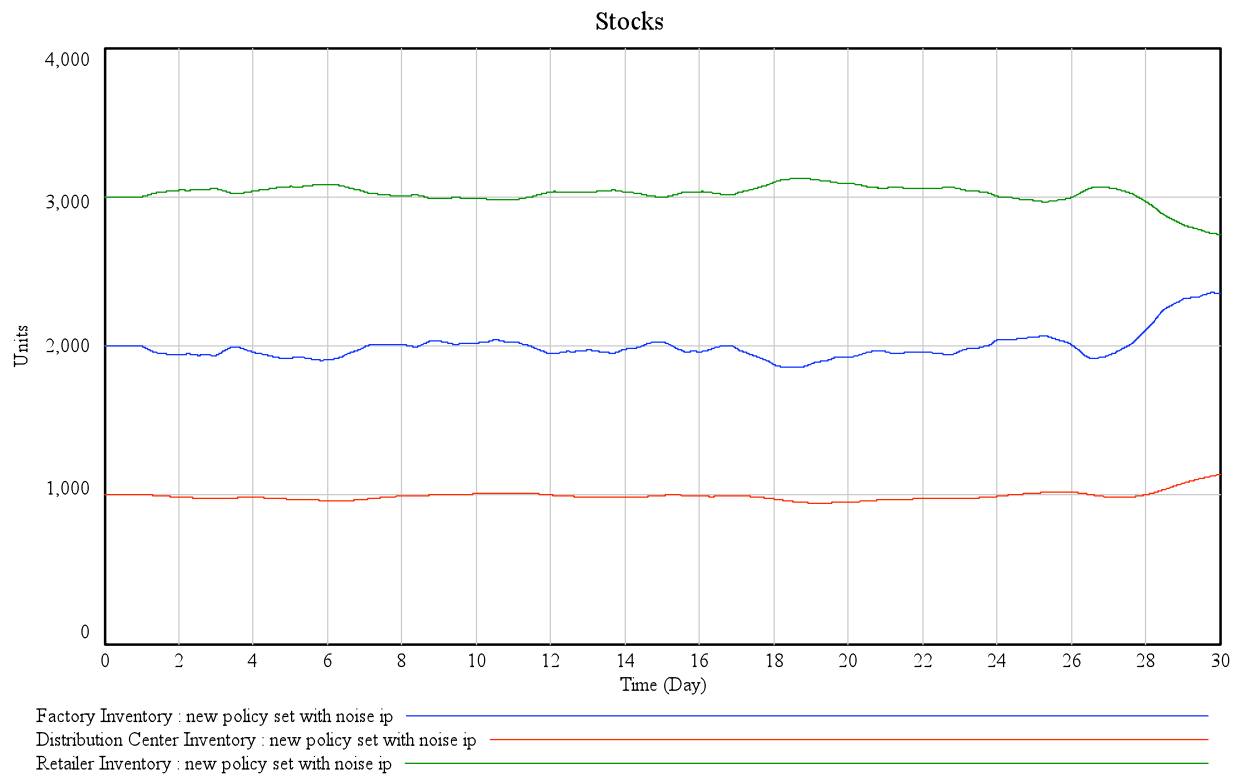


Figure 4.4: Impact of NOISE input on system stocks (new policy set)

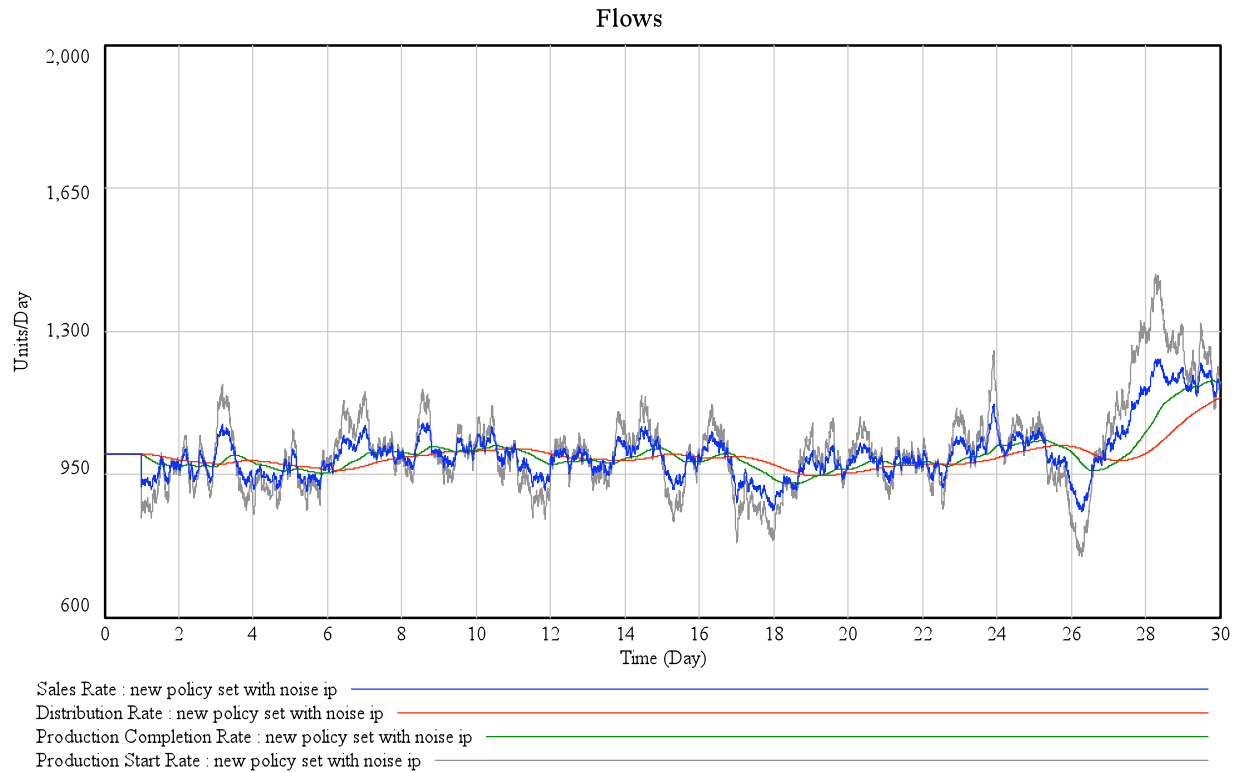


Figure 4.5: Impact of NOISE input on system flows (new policy set)

It can be seen that the proposed policy provide significant reduction in amplification when the model is tested with the NOISE input as well. There is some marginal amplification as the variability in the production start rate is higher than that of the sales rate. However, the amplification is very small compared to that seen when the system was simulated with the original policy set.

We compare the performance of the proposed policy with an “aggressive” and “slow” policy set, as shown below in Table 4.1. The “slow” policy for inventory adjustment corresponds with an adjustment time of five days for each of the adjustment loops. The “aggressive” policy corresponds with an adjustment time of half a day for each of the adjustment loops. The proposed policy sets the adjustment times equal to the retailer inventory to sales ratio.

Policy Set	Settling Time (Day)	Amplification (Dimensionless)	Inventory Overshoot (Percent)
A. Slow	1.74	2.97	Negligible
B. Aggressive	0.33	99.04	1.36
C. Proposed	1.25	4.59	Negligible

Table 4.1: Comparison of Proposed Policy

We see that the slow adjustment policy leads to the minimum amplification and inventory overshoot, even though it leads to the maximum settling time. On the other hand, the aggressive policy leads to the highest amplification and inventory overshoot, even though it leads to the fastest response. The metrics for the proposed policy lie in between those of the slow and aggressive policy. As with the slow policy, the proposed policy leads to a negligible inventory overshoot and small amplification. However, the proposed policy delivers a much smaller settling time

It should be noted that the performance of a supply chain with a particular policy set depends on the lead times associated with each stage. We assume that these lead times are deterministic and constant. However, this assumption may not hold in practice. In such a scenario, a static policy set may not deliver the desired results. Hence, to use a static policy set which is “aggressive” or “slow” irrespective of market conditions may not lead to lean logistics. We propose a policy, which is responsive to changing inventory and sales conditions. The retailer inventory to sales ratio is a statistic, which is compiled by corporations to measure efficiency. Hence, we assume

that this dynamic policy set can be easily applied. Further, we propose a uniform policy for each stage of the supply chain. This avoids the selection of conflicting policies at different stages. Further, since we are using a dynamic policy set, we are ensuring that the policy at each stage is responsive to changing market conditions.

4.4 Validation of Policies

The model can be represented as a set of linear first order differential equations. The state space notation for the model is as shown below in Equation 4.1.

$$\dot{X} = AX + BU \tag{4.1}$$

Where,

A – Matrix of coefficients for the states “X” (there are 3 states in this model)

B – Matrix of coefficients of the input “U” (there is only one input to this model)

$$A = \begin{bmatrix} -MCT^{-1} - FIAT^{-1} & -DCIAT^{-1} & -RIAT^{-1} \\ MCT^{-1} & -DT^{-1} & 0 \\ 0 & DT^{-1} & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 1 + \frac{MCT}{FIAT} \\ \frac{DT}{DCIAT} \\ -1 + \frac{RISR}{RIAT} \end{bmatrix}$$

A manufacturing process is said to be in a steady state when all the state variables that define the process are constant, in spite of ongoing flow of material through the system. Hence, in a steady state situation, the inflow rate and outflow rate of each stock in the system must be the same.

For the three stocks in the model to be in a steady state, we would have:

$$U = \frac{X_1}{MCT} = \frac{X_2}{DT} = \frac{X_3}{RISR} \quad (4.2)$$

The total inventory in the supply chain

$$= X_1 + X_2 + X_3 \quad (4.3)$$

$$= U * (MCT + DT + RISR) \quad (4.4)$$

Since the steady state inventory of the supply chain only a function of the sales rate and the lead times associated with each level, the total inventory can only be decreased by decreasing each of the variables mentioned in Equation 4.4. Since, a drop in sales would lead to a drop in profit; one would not want the sales rate to decrease. Instead, inventory can be minimized by decrease the total lead-time from the factory to the consumer.

If we apply the proposed adjustment policies, the system can be defined by the following set of differential equations, as shown in Equation 4.5.

$$\dot{X} = AX + BU \quad (4.5)$$

Where,

$$A = \begin{bmatrix} -MCT^{-1} - FIAT^{-1} & -DCIAT^{-1} & RISR^{-1} - RIAT^{-1} \\ MCT^{-1} & -DT^{-1} & 0 \\ 0 & DT^{-1} & -RISR^{-1} \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{MCT}{FIAT} \\ \frac{DT}{DCIAT} \\ \frac{RISR}{RIAT} \end{bmatrix}$$

For a system with Jacobian “A”, the characteristic equation is defined as:

$$|A - \lambda I| = 0 \quad (4.6)$$

Where, λ - Eigenvalue, I – identity matrix

The characteristic equation for the above system with the proposed policies is as follows: (4.7)

$$[(-MCT^{-1} - FIAT^{-1} - \lambda) * (-DT^{-1} - \lambda) * (-RISR^{-1} - \lambda)] + [MCT^{-1} * (-RISR^{-1} - \lambda) * DCIAT^{-1}] = 0$$

Hence, the eigenvalues for the system are as follows:

$$\lambda = (-MCT^{-1} - FIAT^{-1}); (-DT^{-1}); (-RISR^{-1}) \quad (4.8)$$

Since all three of the eigenvalues are negative with no imaginary components, the system shall not exhibit any overshoot and shall remain stable. Further, this property is not dependent on the magnitude of the manufacturing cycle time, distribution time, and retailer inventory to sales ratio. It should also be noted that if these parameters have small magnitudes, the eigenvalue would have a large magnitude as it is determined by the reciprocal of these parameters. A large

negative eigenvalue with no imaginary part ensures that the system responds to changes in the sales rate rapidly, and without any overshoot. Hence, in addition to applying to the proposed adjustment policy, the system can operate with lower inventory and be more responsive to changes in the sales rate if the lead time associated with each stage of the supply chain can be made as small as possible.

4.5 Summary

We discuss the impact of policy on the operations of a supply chain. We demonstrate that to decrease the total inventory in the supply chain, one must decrease the total time that it takes for the product to reach the consumer once a production order is placed. Even though amplification is unavoidable due to the structure of supply chains, it can be minimized by choosing appropriate policy. Traditionally, policies are static over time. We argue that policy, which is independent of market conditions, cannot deliver the “desired” response over the long term. Hence, we propose a dynamic policy set, which is responsive to market conditions. We propose using the inventory to sales ratio as a guide for policy makers to set the “adjustment time” of each stage of the supply chain. By setting the adjustment time equal to the retailer inventory to sales ratio, we ensure that there is no overshoot of inventory in the supply chain. The inventory to sales ratio measures the time period that current inventory levels can sustain the current sales rate, without any new inventory added to the finished goods stock. If any inventory adjustments are to be made for any stage of the supply chain, these adjustments must be made gradually over the time period determined by the inventory to sales ratio, to avoid overproduction. We prove this by examining the state space representation of the mode

Chapter 5: State Space Approach for Policy Design

5.1 Introduction

In control engineering, the state space representation is a mathematical model of a physical system as a set of input, output and state variables related by first order differential equations. The state variables for the system are the smallest subset of variables that are needed to completely describe the behavior of the system. Ogata mentions that, “the dynamic system must involve elements that memorize the values of the input for $t > t_1$. Since integrators in a continuous-time control system serve as memory devices, the outputs of such integrators can be considered as the variables that define the internal state of the system” (75).

The time response of a system consists of two parts, the steady state response and the transient response. A supply chain is said to be in a steady state when the inventory levels are constant in spite of inventory flowing through the system. A supply chain is said to be in a transient state when it is going from some initial steady state inventory level to another steady state inventory level. A system is critically damped when it converges to the steady state in the least amount of time, without any overshoot (75). A supply chain is critically damped when it moves from one steady state inventory level to another steady state inventory level in the shortest amount of time, without any inventory overshoot. If the supply chain operates in such a manner that it overshoots the final steady state level, it is said to be under-damped. This can happen if the organization is following an aggressive policy set where they react rapidly to any inventory discrepancies. On the other hand, if the supply chain reacts very slowly to changes in demand, it said to be over-damped.

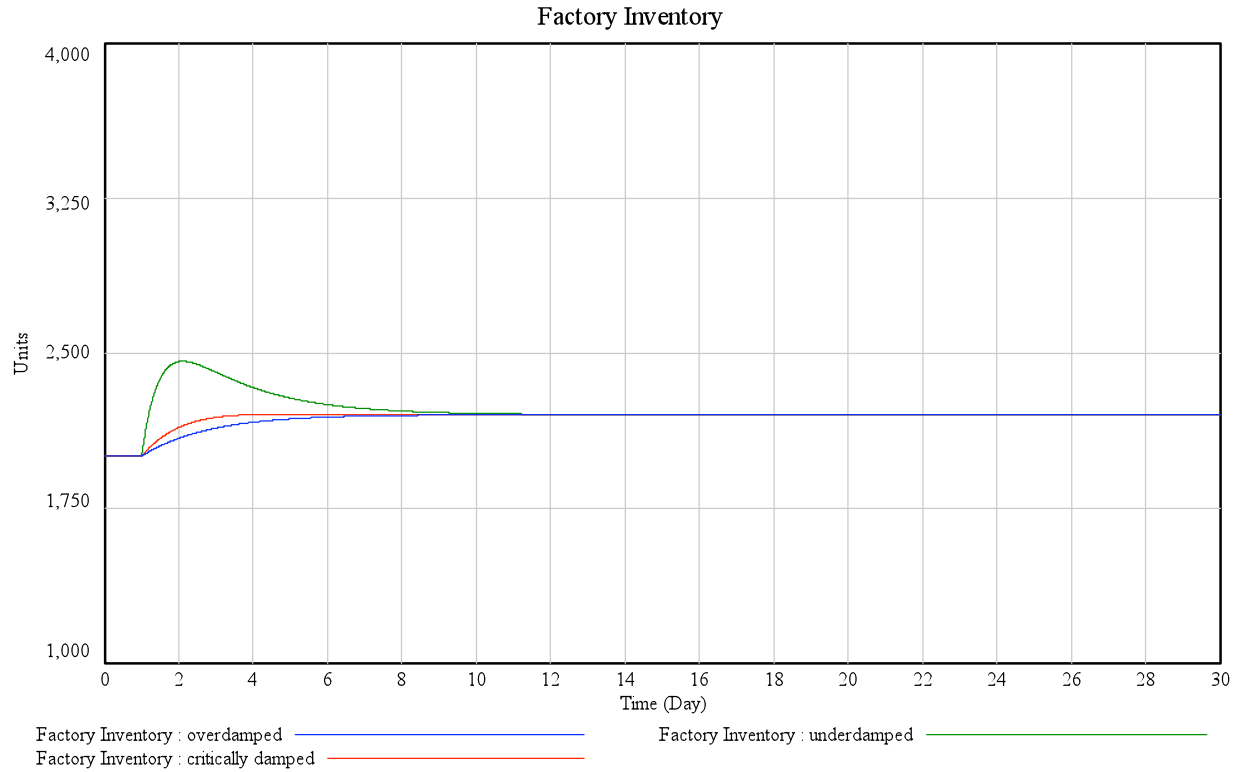


Figure 5.1: Damping of manufacturing supply chains

The above figure shows the response of a supply chain with a STEP increase in sales rate. It clearly shows the impact that policy can have on the response of the supply chain. The policy set that leads to critical damping causes the supply chain to respond in the shortest amount of time, without any inventory overshoot. While it is desirable to have a supply chain, which is critically damped, the current literature does not provide any direct approach to calculate the policy set which leads to critical damping. Existing approaches use a trial and error simulation approach to determine which policy set leads to critical damping. The state space approach for policy design, which is discussed in this chapter, addresses this issue.

Ogata defines the settling time as “the time required for the response curve to reach and stay within a range about the final value of size specified by absolute percentage of the final value”. This range is usually 2% or 5% (75). A small settling time ensures that the supply chain is responsive to a changing sales rate.

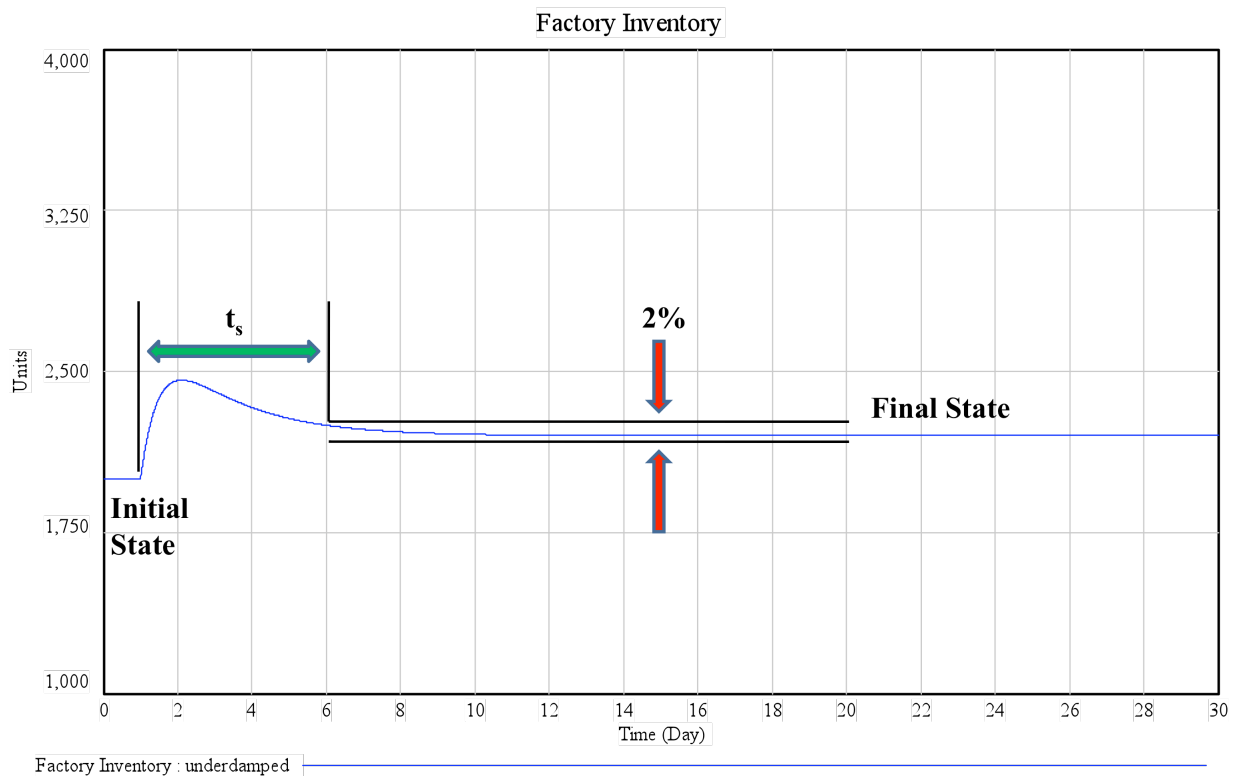


Figure 5.2: Settling time of manufacturing supply chain

The above figure shows how the settling time, t_s , is calculated for the response of any system. It is important for policy designers to know the impact of the policies chosen on the responsiveness of the system. Policy design has traditionally relied on trial and error simulation to determine which policies lead to the desired setting time. The state space approach for policy design, which is discussed in this chapter, addresses this issue.

5.2 Policy Design Methodology

We model the system as a set of linear first order differential equations. The modes of behavior of the system are determined by the eigenvalues of the Jacobian for this set of differential equations. The modes of behavior of a system define how it reacts to changes and hence characterize the transient behavior of the system. Commonly seen modes of behavior include exponential growth, exponential decline, and oscillatory behavior. Negative eigenvalues lead to exponential decline, while positive eigenvalues lead to exponential growth. Further, if an eigenvalue has an imaginary component, the system response exhibits oscillatory behavior. An oscillatory response to changes in demand can lead to periods of surplus and shortages of inventory. Hence, we design the system to have negative eigenvalues with no imaginary components. Also, we design the system so that all the eigenvalues are equal. This is a necessary and sufficient condition for the system to be critically damped.

The settling time, t_s , determines the responsiveness of the supply chain. The settling time is also a function of the eigenvalues of the system. It is the magnitude of the eigenvalue that determines the settling time. A negative eigenvalue of large magnitude will lead to a small settling time. With reference to above discussion, it is preferred to have eigenvalues, which are negative and have no imaginary components. Hence, the magnitude of the eigenvalue is solely determined by the real part of the eigenvalue. The choice of settling time by the policy designer shall determine what value the eigenvalue must take.

Since it is the Jacobian of the system that determines the eigenvalues, they are a function of the parameters of the system dynamics model of the supply chain. The parameters of the model can

be classified as either endogenous or exogenous parameters. Endogenous parameters are calculated dynamically at each time step depending on the relationships specified in the model. Exogenous parameters are those that are specified by the modeler and are generally constant over the course of a simulation. The exogenous parameters include policy parameters that determine how rapidly corrections are made in the system, and flow control parameters that determine how fast material flows through the supply chain. The eigenvalues of the system shall be a function of these exogenous parameters.

The policy design methodology is as follows:

- i. Choose the desired settling time, t_s , for the system
- ii. Calculate the desired eigenvalues that lead to a critically damped system with settling time, t_s
- iii. Calculate the characteristic equation that corresponds to the desired eigenvalues
- iv. Calculate the characteristic equation of the model using the Jacobian “A”
- v. Equate the coefficients of the two characteristic equations from step (iii) and (iv). If the model for the supply chain has “n” inventory levels, the characteristic equation for the model shall be an n^{th} order equation. Hence, by equating the coefficients of the two characteristic equations, we get a set of “n” equations.
- vi. If there are “n” inventory levels in the system, there shall also be “n” policy parameters corresponding to them. Hence, the set of “n” equations from step (v) shall only have “n” unknown parameters. Since the number of unknown parameters equals the number of equations, there must be a unique solution for the policy parameters.

The above methodology is summarized using Figure 5.3, as shown below.

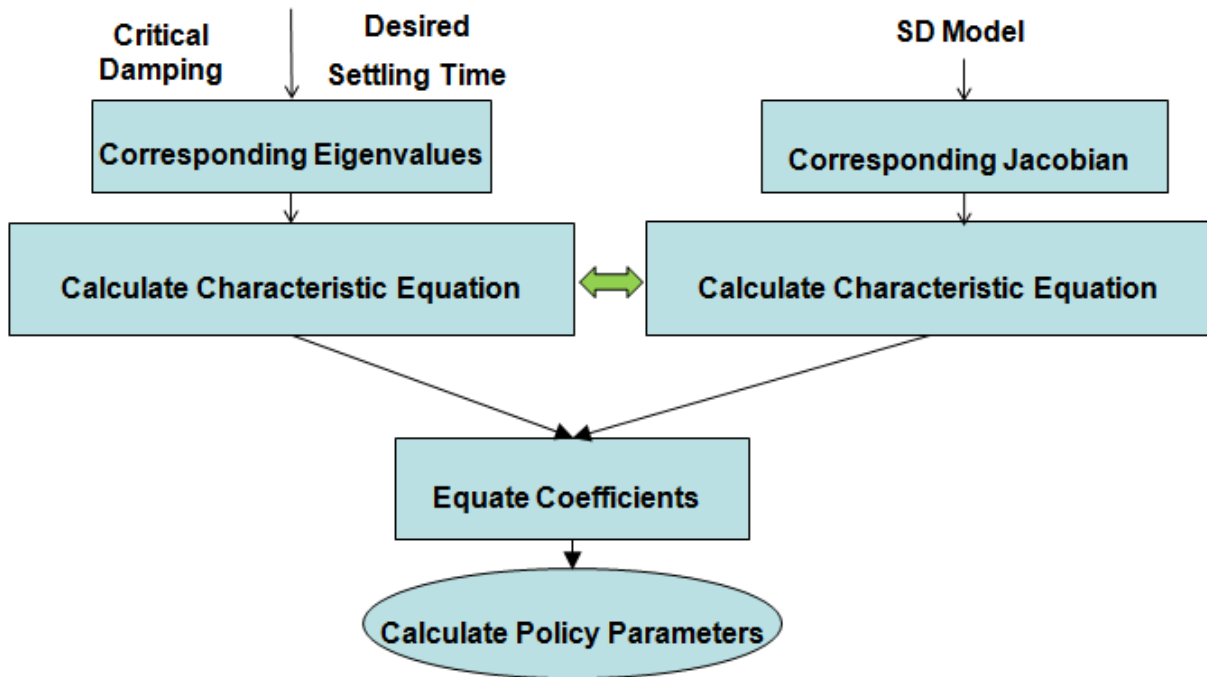


Figure 5.3: Summary of Policy Design Methodology

The policy design methodology shall be elaborated and applied to a case study. The model used in the case study has been discussed thoroughly in Chapter 3. It is a 3-stage supply chain that consists of a factory stage, a distribution center stage and a retailer stage. There are three policy parameters associated with each of these inventory levels. These are the “Factory Inventory Adjustment Time (FIAT)”, “Distribution Center Inventory Adjustment Time (DCIAT)”, and the “Retailer Inventory Adjustment Time (RIAT)”. We apply the above policy design methodology to calculate the values that these policy parameters must take so that the system is critically damped and responds to changes in demand in a specified amount of time.

5.3 Case Study

The model for this case study is shown in Figure 3.2. The Jacobian for that model is shown in Equation 4.1.

If t_s is the desired settling time for the system, then as per the 98% settling time criterion the desired eigenvalues can be calculated as follows:

$$\lambda_s = \ln(0.02) / t_s \quad (5.1)$$

The choice of the settling time determines the eigenvalues that the system must possess. Once, the eigenvalues for the system are determined, we need to determine the corresponding characteristic equation for the system. For this purpose, we suggest using Vieta's formula (76). A system that has three inventory stocks will have a third order characteristic equation.

The standard form of the characteristic equation its corresponding coefficients as determined by Vieta's formula are shown below:

$$\lambda^3 + a_2\lambda^2 + a_1\lambda + a_0 = 0 \quad (5.2)$$

$$a_2 = -(\lambda_1 + \lambda_2 + \lambda_3)$$

$$a_1 = \lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3$$

$$a_0 = -(\lambda_1\lambda_2\lambda_3)$$

Where $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_s$

We can rewrite Equation 4.1 by making the following substitutions:

$$\begin{aligned}
 MCT^{-1} &= g_1 \\
 DT^{-1} &= g_2 \\
 FIAT^{-1} &= g_3 \\
 DCIAT^{-1} &= g_4 \\
 RIAT^{-1} &= g_5
 \end{aligned}$$

The Jacobian can now be re-written as:

$$A = \begin{bmatrix} -g_1 - g_3 & -g_4 & -g_5 \\ g_1 & -g_2 & 0 \\ 0 & g_2 & 0 \end{bmatrix} \quad (5.3)$$

As per equation 4.6, the characteristic equation for the system can be written as:

$$|A - \lambda I| = \begin{vmatrix} -g_1 - g_3 - \lambda & -g_4 & -g_5 \\ g_1 & -g_2 - \lambda & 0 \\ 0 & g_2 & -\lambda \end{vmatrix} = 0 \quad (5.4)$$

Equation 5.4 can be simplified to obtain Equation 5.5:

$$|A - \lambda I| = \lambda^3 + \lambda^2(g_1 + g_2 + g_3) + \lambda(g_1g_2 + g_2g_3 + g_1g_4) + g_1g_2g_5 = 0 \quad (5.5)$$

To obtain a critically damped system with a settling time of t_s , the coefficients of Equation 5.2 and 5.5 must be equal. Since the characteristic equation is of order 3, we obtain a set of 3 equations when we equate the coefficients of the ideal characteristic equation and the system characteristic equation as shown in Equation 5.6.

If we equate the coefficients of the two equations, we get the following set of equations:

$$\begin{aligned}
 g_1 + g_2 + g_3 &= -(\lambda_1 + \lambda_2 + \lambda_3) \\
 g_1g_2 + g_1g_4 + g_2g_3 &= \lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3 \\
 g_1g_2g_5 &= -(\lambda_1\lambda_2\lambda_3)
 \end{aligned} \tag{5.6}$$

Since $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_s$

Equation 5.6 can be re-written as following:

$$\begin{aligned}
 g_1 + g_2 + g_3 &= -3\lambda_s \\
 g_1g_2 + g_1g_4 + g_2g_3 &= 3\lambda_s^2 \\
 g_1g_2g_5 &= -\lambda_s^3
 \end{aligned} \tag{5.7}$$

It should be noted that the policy parameters, g_3 , g_4 , and g_5 are the only unknowns in Equation 5.7. Hence, the equations can be solved to calculate the policy parameters for the model as follows:

$$\begin{aligned}
 g_3 &= -3\lambda_s - g_1 - g_2 \\
 g_4 &= \frac{3\lambda_s^2 - g_1g_2 - g_2g_3}{g_1} \\
 g_5 &= \frac{-\lambda_s^3}{g_1g_2}
 \end{aligned} \tag{5.8}$$

Equation 5.8 shows the solution for the policy parameters that will ensure that the system is critically damped and has a settling time of t_s .

5.4 Validation

We validate the above results by simulating the supply chain with the designed policy set and studying the response.

It should be noted that for the model used, the performance parameters are as shown below in Equation 5.9.

$$\begin{aligned}g_1 &= 0.5 \\g_2 &= 1\end{aligned}\tag{5.9}$$

If we let $t_s = 5$ days, then

$$\lambda_s = -0.782\tag{5.10}$$

Using Equation 5.8, we get:

$$\begin{aligned}g_3 &= 0.847 \\g_4 &= 0.978 \\g_5 &= 0.958\end{aligned}\tag{5.11}$$

Since,

$$\begin{aligned}FIAT^{-1} &= g_3 \\DCIAT^{-1} &= g_4 \\RIAT^{-1} &= g_5\end{aligned}$$

We calculate the policy parameters to get:

$$FIAT = 1.18; DCIAT = 1.02; \text{ and } RIAT = 1.04$$

We now simulate this parameter set. The response is shown below.

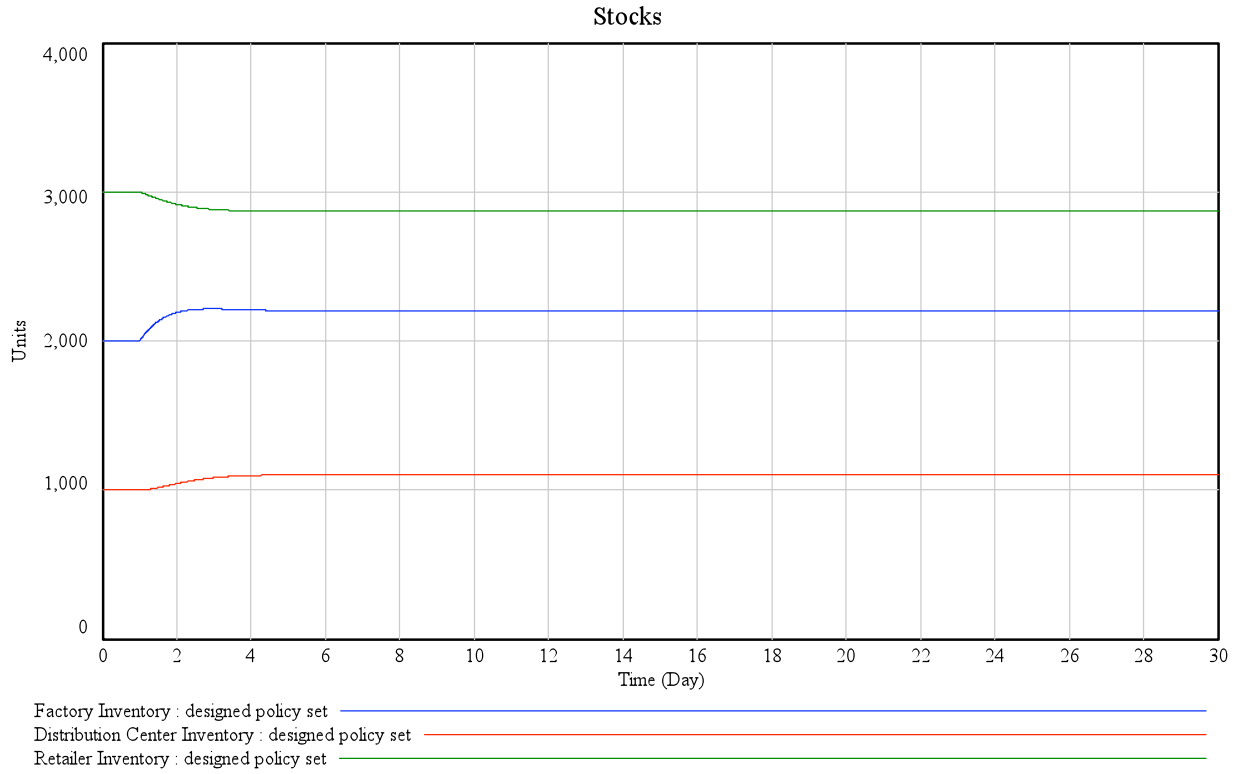


Figure 5.4: Response of Stocks (Designed Policy Set)

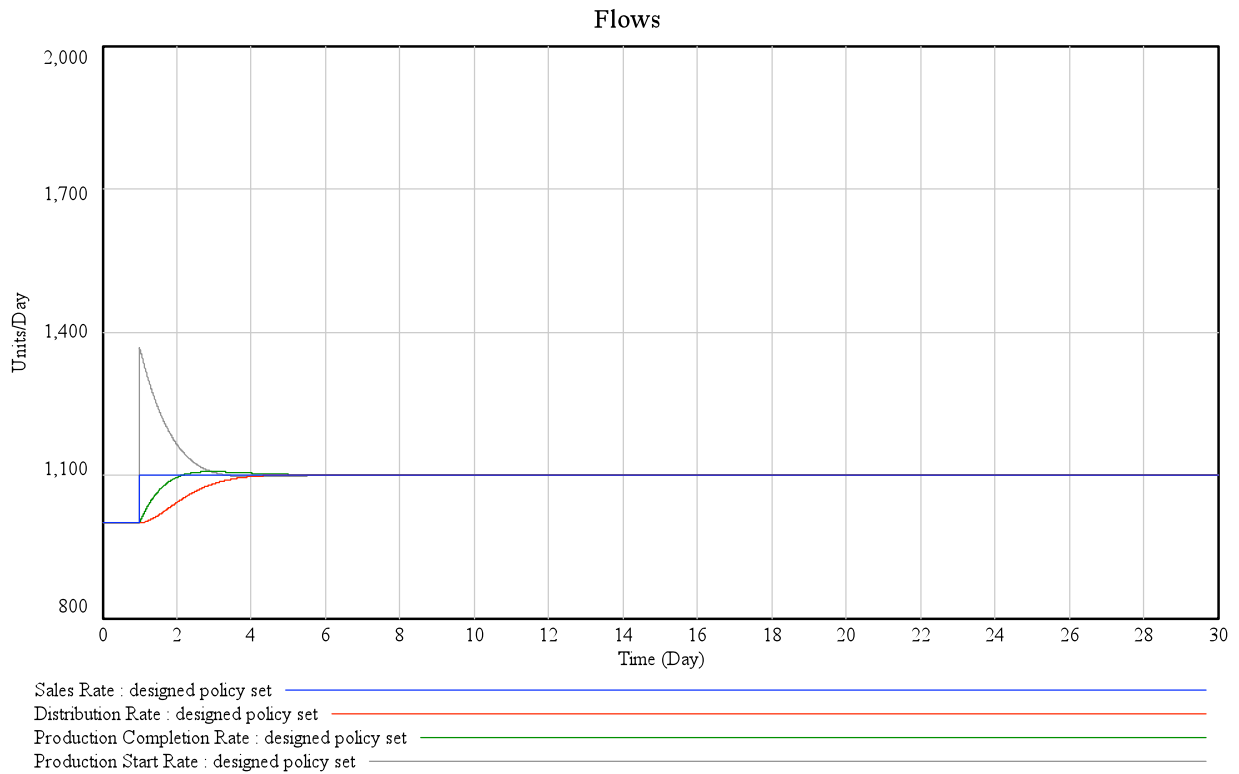


Figure 5.5: Response of Flows (Designed Policy Set)

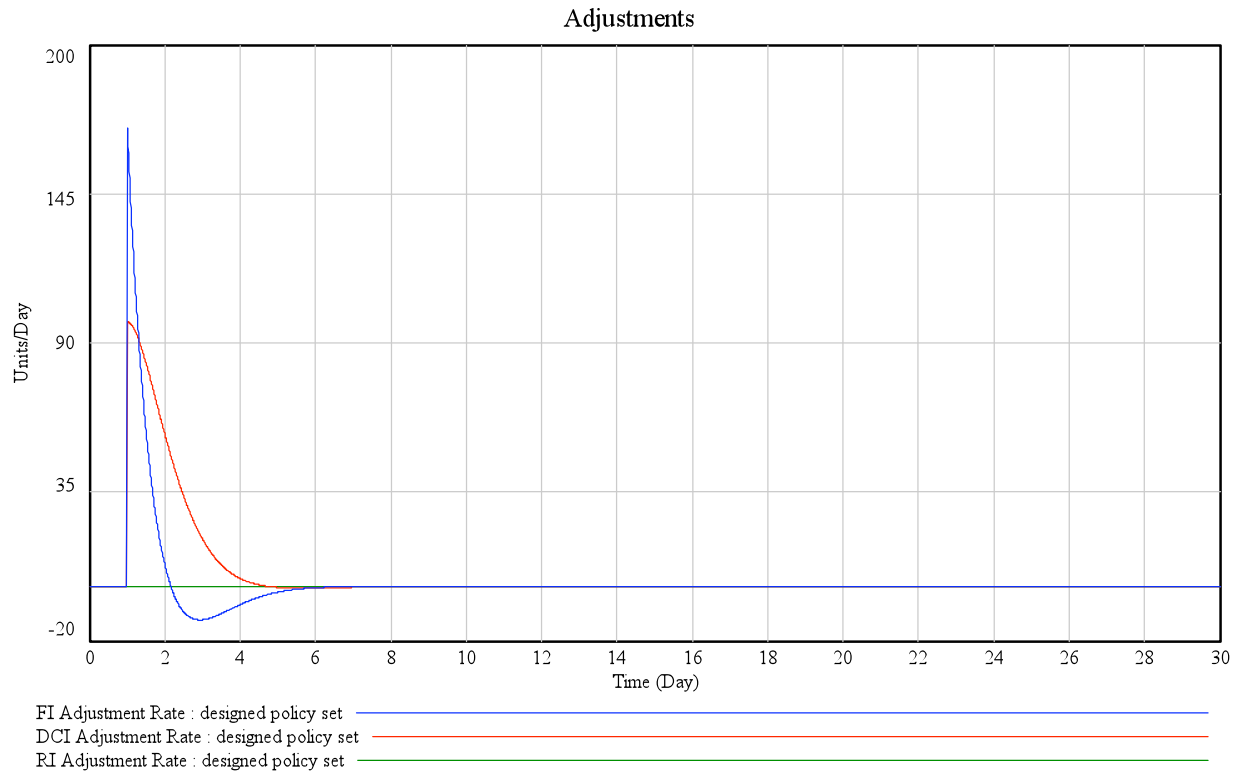


Figure 5.6: Response of Adjustments (Designed Policy Set)

From the above results, we see that the designed policy set does indeed lead to an elimination of inventory overshoot when simulated with a STEP increase in the sales rate. Further, the supply responds to the sudden increase in sales within a specified settling time. We compare this policy set with the “aggressive” and “slow” policies discussed in Chapter 4. The results are summarized in Table 5.1. The comparison of simulated response with a STEP input is shown in Figure 5.7. The comparison of simulated response with a STEP input is shown in Figure 5.8.

Policy Set	Amplification (Dimensionless)	Inventory Overshoot (Percent)
A. Slow	2.36	0.01
B. Aggressive	27.99	1.36
C. Policy Design	10.04	0.66

Table 5.1: Comparison of Policies

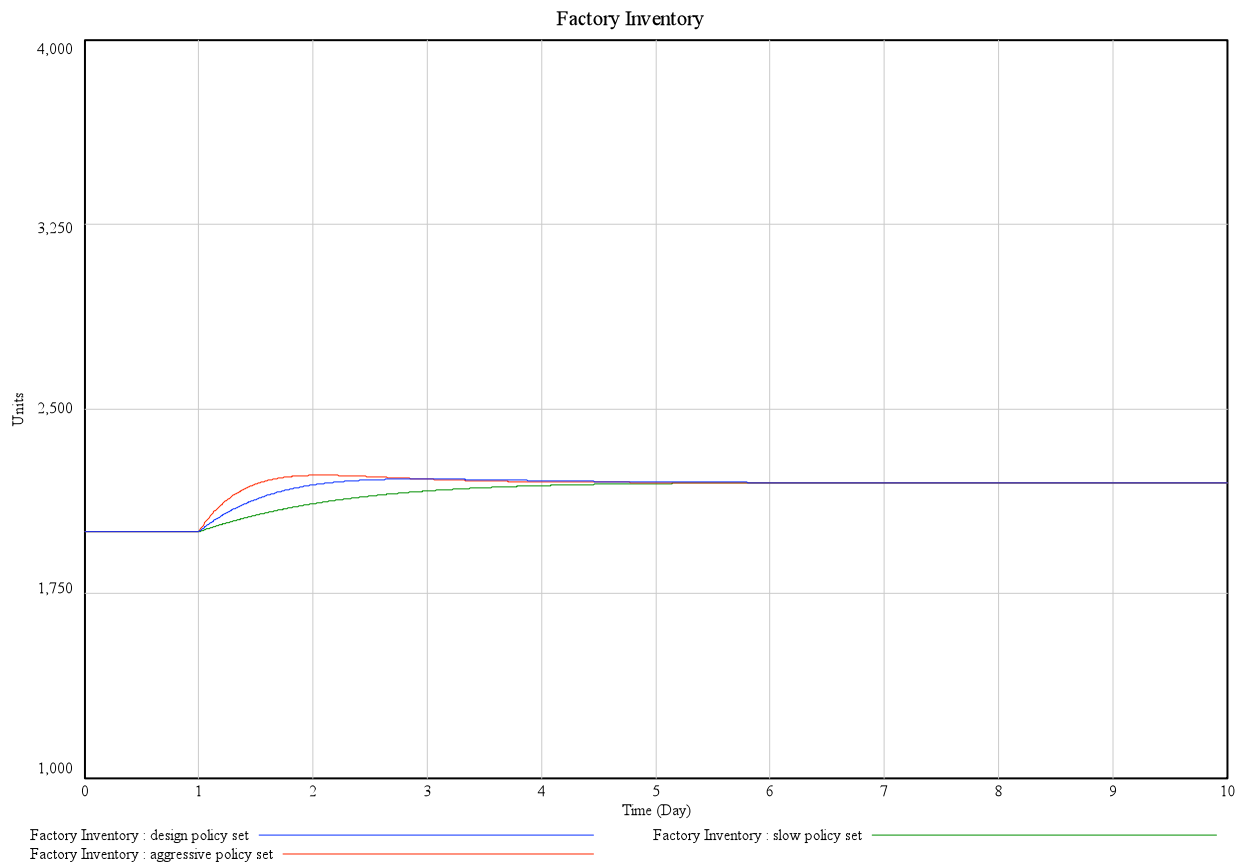


Figure 5.7: Comparison of Policy (Step Input)



Figure 5.8: Comparison of Policy (Noise Input)

From the simulation results, we see that the “slow” policy results in negligible overshoot and small amplification, but a high settling time. On the other hand, the “aggressive” policy leads to a much higher overshoot and a significantly higher amplification, while leading to a small settling time. The “design policy” delivers results, which lie in between the “slow” and “aggressive” policy. It leads to a negligible overshoot and a small amplification. Hence, the policy, which is designed, delivers a good balance in terms of overshoot, amplification and settling time.

5.5 Summary

We present a state space approach for policy design. We design the system to be critically damped and have a specified settling time. The traditional approach for determining policy parameters involved trial and error simulations. We present a systematic approach to calculate the policy parameters, which does not rely on any simulation experiments. We demonstrate the usage of this design methodology using a three-stage supply chain. It can easily be applied to more complicated models of production systems as well. Further, since the approach is well grounded in systems theory, it can easily be used for the design of other systems such as those found in healthcare and construction. The limitation of this work is that it is based on linear systems theory. However, since many non-linear systems can be approximated well by linear models, we expect the proposed approach to give reasonably good results for non-linear systems as well.

The policy itself can be implemented in a static or dynamic form. If the “performance” parameters remain constant, then the policy parameters can also remain constant over time. However, if the lead times associated with the supply chain vary over time, the policy parameters can be specified in terms of these dynamic lead times.

Chapter 6: Combinatorial Design of Information Network Structure

6.1 Introduction

A system dynamics model typically consists of the following elements (6):

- Several levels
- Flows that transport the contents of one level to another
- Decision functions that control the rate of flow between levels
- Information networks that connect the decision functions to the levels

The performance of a supply chain is dependent on the structure of the information network that is being used. The structure of an information network impacts the stability, amplification and settling time of a supply chain. Further, since each link of the information network has a cost associated with it, it of interest to determine what benefit the addition of a link in the information network brings. We use a combinatorial approach to determine which information network structure leads to smallest amplification and smallest settling time. This shall be done by testing each network combination with a STEP input and NOISE input.

6.2 Combinatorial Design

The proposed approach for combinatorial design of the information feedback structure is as follows:

- i. Develop system dynamics model for the supply chain
- ii. Identify the information feedback loops which control the flow of inventory through the supply chain
- iii. Specify policy for information adjustment by setting the adjustment times for the adjustment loops
- iv. Determine the possible loop combinations that can occur within the model, using combinatorial theory
- v. Simulate the supply chain for each of the loop combinations. To enable a loop, simply set the adjustment time to be equal to the value set in step (iii). To disable the loop, set the adjustment time to be an arbitrary large number. If a loop does not have an adjustment time associated with it, introduce a binary switching variable into the model and use to enable/disable the loop
- vi. Measure the amplification and settling time for each loop combination
- vii. Decide the information feedback structure based on the goals for settling time and amplification.

The above steps are elaborated in the context of a case study, as shown below.

6.3 Case Study

The model of the supply chain, which is used for this case study, is shown in Figure 3.2. It has 3 levels, namely the factory, distribution center and the retailer. Material flows from the factory level to the distribution center, from where it flows to the retailer. The material outflow from the retailer level is a function of the sales rate. We have one information feedback loop from each of the three levels that flows to the decision function that controls production. We also have one information feedback loop from the sales rate, which is the outflow of the terminal level in the supply chain. The desired production start rate is a sum of the sales rate and the adjustment rates for each individual inventory level in the supply chain. The adjustment rates are proportional to the amount of error that exists between the ideal inventory level and the actual inventory level. One could also use the derivative and integral of the error to control production. However, the inclusion of those terms would complicate this analysis. Thus, we study the feasibility of those ideas in a subsequent chapter and limit the structures used in this analysis to those that make adjustments in production, which are proportional to the error.

Hence, if we have “ n ” inventory levels in the model, the number of information feedback loops that connect with the decision function shall be “ $n+1$ ”. This model has four information feedback loops. One could implement any combination of these information feedback loops to manage operations. We use a combinatorial approach to determine which information network structure delivers the best response in terms of amplification and setting time.

If there are “n” serially connected levels in the supply chain, the total number of information network structures possible would be:

$$\sum_{j=1}^n C_j^{n+1} = 2^{n+1} - 1 \tag{6.1}$$

For the above model, “n” equals 3. Hence, the total number of information networks that are possible is 15. These are shown in Table 6.1.

Set Number	Enabled Loops
A.	1
B.	2
C.	3
D.	4
E.	1,2
F.	1,3
G.	1,4
H.	2,3
I.	2,4
J.	3,4
K.	1,2,3
L.	1,2,4
M.	1,3,4
N.	2,3,4
O.	1,2,3,4

Table 6.1: Combinations for supply chain with 3 levels

As proposed in the Chapter 4, the adjustment time for each of the three information feedback loops from the factory, distribution center and retailer respectively is set equal to the retailer inventory to sales ratio. It should be noted that loop number 4, which connects the sales rate with the decision function, does not have any adjustment time associated with it.

The ideal inventory level for each stage is determined by the product of the sales rate and the lead-time associated with that stage. Hence, the ideal inventory level for the factory level is a product of the sales rate and the manufacturing cycle time. Similarly the ideal inventory level for the distribution center is a product of the sales rate and the distribution time, and the ideal inventory level for the retailer is a product of the sales rate and the retailer inventory to sales ratio. This ensures that there is no inventory overshoot if the sales rate increases suddenly by a fixed amount.

To test the impact of information feedback structures of supply chain response, we test each of the combinations mentioned in Table 6.1. If any of the information feedback loops connecting the three inventory levels with the decision function is enabled, the adjustment time for that loop shall be set equal to the retailer inventory to sales ratio, as is the proposed policy in Chapter 4. One could conduct this analysis with an alternate policy as well. The purpose of this study is to quantify the impact of the feedback structure for a given policy. Hence, the choice of policy is not critical to this study. If any of these three loops is to be disabled, the adjustment time for that loop shall be set to arbitrarily large number. By making the adjustment time very large, the effect of that information feedback loop is eliminated. Since the information feedback loop connecting the sales rate with the decision function doesn't have any adjustment time associated with it,

switching variable will be inserted into the model to control the impact of this loop. The switching variable shall be a binary variable that either has a value of zero or one at any given time. The impact of the sales rate on the decision function shall be a product of the sales rate and this switching variable. When the switching variable has a value of one, the loop is enabled. On the other hand, if it is set to zero, the loop is disabled.

In such a manner, the 15 information feedback loop combinations shall be simulated with a STEP and NOISE input. In the case of the STEP input, the sales rate shall suddenly be increased by 10% at time equal to one day. In the case of the NOISE input, the sales rate shall have a pink noise input. The noise standard deviation shall equal 0.1, and the noise correlation time shall equal 4 days.

Due to the policy implementation mentioned above, no inventory overshoot is expected when a STEP input is used for the sales rate, as shown in Chapter 4. The metric of interest is the settling time. Ogata defines the settling time as, “the time required for the response curve to reach and stay within a range about the final value of size specified by an absolute percentage of the final value (usually 2% or 5%)” (75).

We use the 98% settling time criterion for the factory inventory to calculate the settling time. Hence, when we calculate the time that it takes the response curve to reach and stay within 2% of the final value for the factory inventory, from when the step increase in sales rate begins. In the case of the NOISE input, it is not easy to discern the settling time due to the random fluctuation of the sales rate.

Even though it is difficult to calculate the setting time when the sales rate is modeled using the NOISE input, it does provide an opportunity to quantify the amplification of the system. The commonly used definition for amplification is as follows Invalid source specified.:

$$\text{Amplification} = \frac{V[\text{Production}]}{V[\text{Demand}]}; V [.] \text{ is the variance operator} \quad (6.2)$$

With reference to the model being used for this dissertation, production is equivalent to the “production start rate”. Further, we use the “sales rate” as a proxy for demand. Hence, we calculate amplification as a ratio of the variance of the production start rate and the variance of the sales rate.

As discussed above, we can calculate the settling time and amplification for each information feedback structure. The settling time is a metric for the responsiveness of the system. A system, which has a small settling time, is one that is responsive to demand. A large amplification factor leads to unnecessary fluctuation in the production rate, which in turn leads to excessive inventory, labor and capacity. Hence, a small amplification factor is needed for lean logistics.

6.4 Simulation Results

The simulation output for both sets of experiments can be found in Appendix B. The summary of both sets of experiments can be found below. Table 6.2 shows the simulation results from the experiments carried out with a STEP input for the sales rate. Further, Table 6.3 shows the simulation results from the experiments carried out with a NOISE input for the sales rate.

Set Number	Enabled Loops	Setting Time	Comments
A.	1	N/A	Exponential decline
B.	2	N/A	Unstable oscillations
C.	3	N/A	Exponential decline
D.	4	3.02 days	Stable
E.	1,2	N/A	Exponential decline
F.	1,3	N/A	Exponential decline
G.	1,4	1.73 days	Stable
H.	2,3	N/A	Unstable oscillations
I.	2,4	1.87 days	Stable
J.	3,4	3.02 days	Stable
K.	1,2,3	N/A	Exponential decline
L.	1,2,4	1.25 days	Stable
M.	1,3,4	1.73 days	Stable
N.	2,3,4	1.87 days	Stable
O.	1,2,3,4	1.25 days	Stable

Table 6.2: Results for STEP Input

Set Number	Enabled Loops	Amplification	Comments
A.	1	N/A	Unstable
B.	2	N/A	Unstable
C.	3	N/A	Unstable
D.	4	1	Stable
E.	1,2	N/A	Unstable
F.	1,3	N/A	Unstable
G.	1,4	3.02	Stable
H.	2,3	N/A	Unstable
I.	2,4	1.84	Stable
J.	3,4	1	Stable
K.	1,2,3	N/A	Unstable
L.	1,2,4	4.51	Stable
M.	1,3,4	3.02	Stable
N.	2,3,4	1.84	Stable
O.	1,2,3,4	4.51	Stable

Table 6.3: Results for NOISE Input

From the above results shown in Tables 6.2 and 6.3, it becomes apparent that loop number 4 is critical to the stability of the supply chain. The production rate at the factory stage is determined by the sum of the sales rate and adjustment rate needed to bring each of the three inventory levels to their ideal value. These adjustment rates are in turn a function of the discrepancy between the ideal and actual inventory level, as well as the management policies that determine how

aggressively the firm shall respond to these discrepancies. Due to the removal of loop 4 from the information feedback structure, the decision function, which calculates the production start rate, does not take into account the inventory depletion due to sales. This makes the system unstable over time as the entire inventory at the retailer level is depleted without replenishment.

From the above results, it appears that loop 3 does not impact either the setting time or the amplification. This is apparent because the metrics for Set G and M are identical. Further, the metrics for Set I and N are identical. This behavior is observed due to the implementation of the policies that were proposed in Chapter 4. Even though the policies were useful to diminish amplification, they eliminated the impact of loop 3 on operations. With the proposed policies, one could eliminate loop 3 without any change in performance. It should be noted that if one were to use a different set of policies, loop 3 would impact the settling time and amplification of the system.

The most important result that comes from this study is that while using information from each inventory stock in the supply chain to control production leads to the smallest settling time, it also leads to the largest amount of amplification. If amplification is of prime importance, one could operate with a subset of the possible information feedback loops. However, this would lead to an increase in setting time, thus making the supply chain less responsive to changes in demand. Likewise, if a small setting time is of prime importance, one should operate with the maximum possible information feedback loops. However, this would lead to an increase in amplification.

6.5 Summary

Most firms would like to be responsive to demand, while minimizing amplification. However, this study shows that these are conflicting goals for the design of information feedback structures. Structures that lead to fastest response, lead to the highest amplification. To decide which information feedback structure is appropriate for the production control of a supply chain for a given set of policies, it is suggested that each possible structure be ranked on the basis of a composite index. This composite index would be a weighted sum of the amplification and the setting time. If a firm values a small setting time over a small amplification factor, the composite index used by it would have a higher weight for the settling time as compared to the amplification factor. The structure, which has the smallest composite index, would be the one selected for conducting operations.

Chapter 7: Proportional-Integral-Derivative (PID) control structure

7.1 Introduction

The PID control structure is generic feedback control structure that is widely used in industrial control systems. The PID control structure continuously measures a process variable and compares it with a desired set point. The error between the two quantities is used to adjust the process. The algorithm used to control the process involves three separate adjustments:

- Proportional adjustment: This is the adjustment based on the current error
- Integral adjustment: This is the adjustment based on the sum of recent errors
- Derivative adjustment: This is the adjustment based on the rate of change of error

The weighted sum of these three adjustments is used to control the process. The weights chosen are dependent on the requirements of the process. Some applications of this control algorithm may not require all three modes for control. In such cases, the weights for the modes that are not desired shall be set to zero.

The possible combinations that can be used are:

1. Proportional (P) control
2. Integral (I) control
3. Derivative (D) control
4. Proportional-Integral (PI) control

5. Proportional- Derivative (PD) control
6. Integral-Derivative (ID) control
7. Proportional-Integral-Derivative (PID) control

The PID control algorithm continuously monitors a process variable and compares it with a reference point. In the context of supply chains, one can monitor the inventory level of any/all stages of the supply chain. This inventory level can be compared with a desired inventory level to determine the error. This error is then used to control a flow control variable, which determines how much inventory flows through the supply chain. This flow control variable is sometimes referred to as the “manipulated variable” (MV). The sum of the three adjustments determines the value of the manipulated variable, as shown below in Equation 7.1.

$$MV(t) = P_{adj} + I_{adj} + D_{adj} \quad (7.1)$$

The proportional adjustment, P_{adj} makes an adjustment that is proportional to the error, $E(t)$. It is defined as a product of the error and a proportional gain constant, K_p . The proportional adjustment is defined as shown in Equation 7.2

$$P_{adj} = K_p * E(t) \quad (7.2)$$

A high proportional gain shall lead to a large change in the manipulated variable for a given change in error. While this may make the process responsive to change, it can also make the process unstable if the proportional gain is made very high.

The integral adjustment depends on both the magnitude and duration of the error term. The integral adjustment, I_{adj} is defined as a product of integral of the error and an integral gain constant, K_i . Hence, the integral adjustment is defined as shown in Equation 7.3.

$$I_{adj} = K_i * \int_0^t E(\tau) d\tau \quad (7.3)$$

The integral adjustment, when used in addition to the proportional adjustment can enable a system to react in a more responsive manner to disturbances. The impact of the integral adjustment depends on the integral gain constant that is used. However, since the integral adjustment is based on the accumulation of past errors, it can cause the system to overshoot the desired level.

The derivative adjustment, D_{adj} depends on the rate of change of the error term. It is defined as a product of the derivative of the error with respect to time, and a derivative gain constant as shown below in Equation 7.4.

$$D_{adj} = K_d * \frac{dE(t)}{dt} \quad (7.4)$$

The impact of the derivative adjustment depends on the choice of the derivative gain constant. This mode of adjustment is often used in conjunction with integral adjustment as it reduces the overshoot that may be caused by the integral adjustment. This mode of adjustment is sensitive to

noise and may cause the system to become unstable if a large derivative gain is used. The structure of PID control system is summarized in Figure 7.1 below.

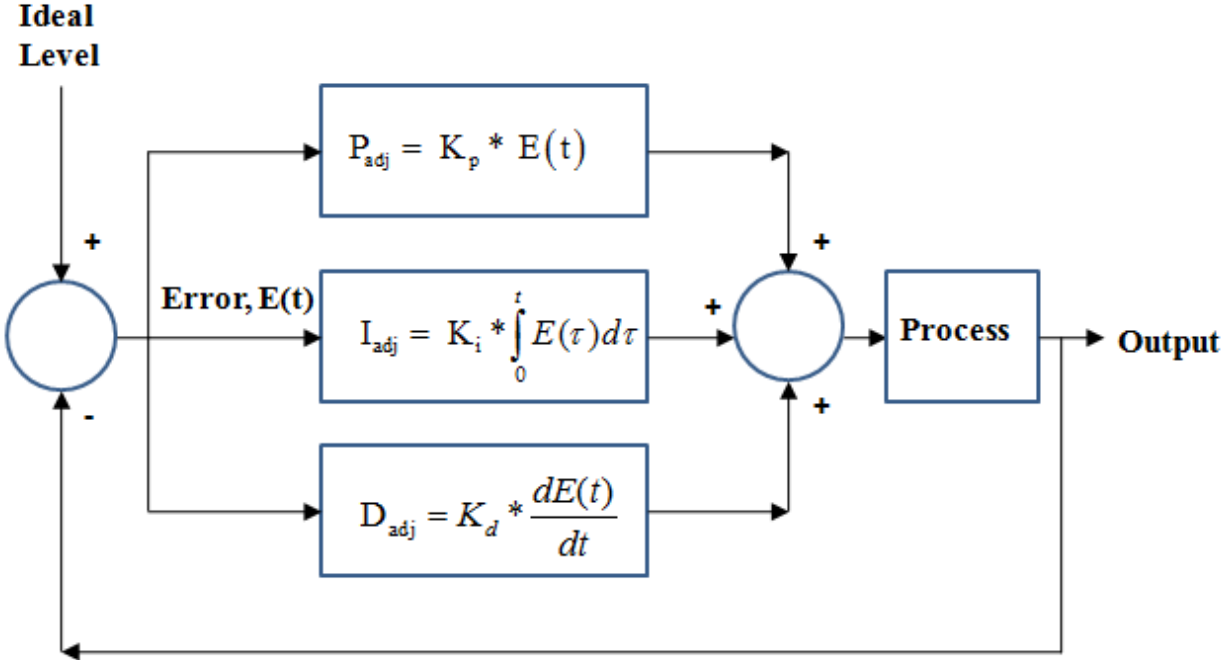


Figure 7.1: PID Control Structure

7.2 Policy Design for PID Control System

The choice of gain constants for the PID control system reflects the policies of the organization. If the organization wishes to aggressively correct inventory discrepancies, it would choose higher gain constants. However, an aggressive policy towards inventory adjustment may lead to inventory overshoot. On the other hand, an organization may follow a slow policy towards inventory adjustment. In such a scenario, the gain constants chosen would be small. While there wouldn't be any overshoot with such a policy set, the settling time may be large. The choice of gain constants thus depends on the objectives of the organization.

It is interesting to note that almost all system dynamics models that are seen in the research literature are special cases of the PID control structure, as they only use proportional control. The correction loops in such proportional models invariably model the adjustment policy by specifying an "adjustment time" for the feedback loop. The discrepancy between the actual level and its ideal value is divided by the adjustment time to determine the adjustment rate for that level. The magnitude of the discrepancy corresponds with the error term, $E(t)$, and the inverse of the adjustment time corresponds with the proportional gain in the PID framework shown above. Hence, the choice of a large proportional gain is equivalent to choosing a small adjustment time. The gain constants in the PID framework are equivalent to the policy parameters of system dynamics models. The choice of the gain constants determines the responsiveness and stability of the system. There are several commonly used approaches to determine these gain constants/policy parameters. They are briefly discussed below. For further details, one can refer to the text by Ogata (75).

Manual approach: The manual approach requires simulation to decide which set of policies leads to the desired response. One could start by setting the integral and derivative gain constants to zero and only vary the proportional gain constant. The proportional gain can be increased till the response begins to oscillate. The proportional gain can be set to half of the value that causes the response to oscillate. One can then increase the integral gain to increase the responsiveness. Increasing the integral gain too much would lead to overshoot. Once the integral gain is at a value where the system is responsive and yet does not overshoot, the differential gain can be increased to see if it can lead to any further improvement in response. The differential gain should be kept at a relatively low value, as it tends to amplify noise. The benefit of the manual approach is that the designer does not need to use any math to determine the gain values. The disadvantage of this approach is that it is a trial and error approach, which requires a lot of experiments.

Ziegler – Nichols Approach: This approach for the determination of gain constants is very effective and is hence very popular with academia and industry (77). Similar to manual approach discussed above, one begins the gain selection process by setting the integral and differential gain value to zero. The proportional gain is increased till the response begins to oscillate. This value of the proportional gain is known as the critical gain, K_c . The oscillation period of the response is known as the oscillation period, P_c . The proportional, integral and derivative gains are then calculated as per the Ziegler-Nichols criteria, as shown in Table 7.1 below.

Type of Control	K_p	K_i	K_d
P	$0.5 * K_c$	-	-
PI	$0.45 * K_c$	$1.2 K_p / P_c$	-
PID	$0.6 * K_c$	$2 K_p / P_c$	$K_p P_c / 8$

Table 7.1: Ziegler-Nichols criteria for gain selection, Adapted from (75)

Other Methods: The research literature is rich in work that deals with the selection of gain parameters in a PID framework. Many of the approaches are online and require considerable experimentation, while others are offline and require mathematical analysis to determine the gain constants. Some of the other popular approaches include:

Feature based methods

- Cohen-Coon (78)
- Astrom Hagglund (79)
- Refined Ziegler Nichols (80)
- Mann (81)

Analytical methods

- Direct pole placement (82)
- Dominant pole design (79)
- Internal model control (83)

The system dynamics model for a 3-stage supply chain shows the flow of inventory from the factory stage to the distribution center stage, and then to the retailer stage. The flow of inventory from the retailer stage is governed by sales rate. To apply the PID structure, one needs to identify an error quantity that can be used to decide what adjustments need to be made. The error variable in this model is defined as the difference between the sales rate and the production completion rate. When the supply chain is in a steady state, one would expect the production completion rate to equal the sales rate. However, when there is an error, it can be used to determine the desired production start rate.

The production start rate is the sum of the proportional adjustment, integral adjustment, derivative adjustment and the sales rate. The formulae used for the calculation of the proportional adjustment, integral adjustment, and derivative adjustment are as shown in Equation 7.2, 7.3 and 7.4.

The model has been developed using the Vensim software for system dynamics modeling and simulation (72). The software does not have the features to directly calculate the integral and derivative of a variable. Hence, we calculate the error integral by modeling it as a stock, and making the inflow of the stock equal the error. To calculate the error derivative, we delay the error by one time unit to get the “error delay” and then subtract it from the actual error value. In absence of any features to calculate the derivative and integral of the error, we suggest that the calculation be made in the manner suggested.

7.4 Validation

Traditional system dynamics models for supply chains only utilize the proportional adjustment to control the flow of the supply chain. We hypothesize that the use of the PID control structure can enable a supply chain to be more responsive to changes in the customer demand as it will use an integral and derivative adjustment, in addition to the proportional adjustment, to control the flow of inventory through the supply chain. We test this hypothesis using the model shown in Figure 7.2. We simulate the model to determine what impact the addition of the integral and derivative adjustment has on the performance of the supply chain.

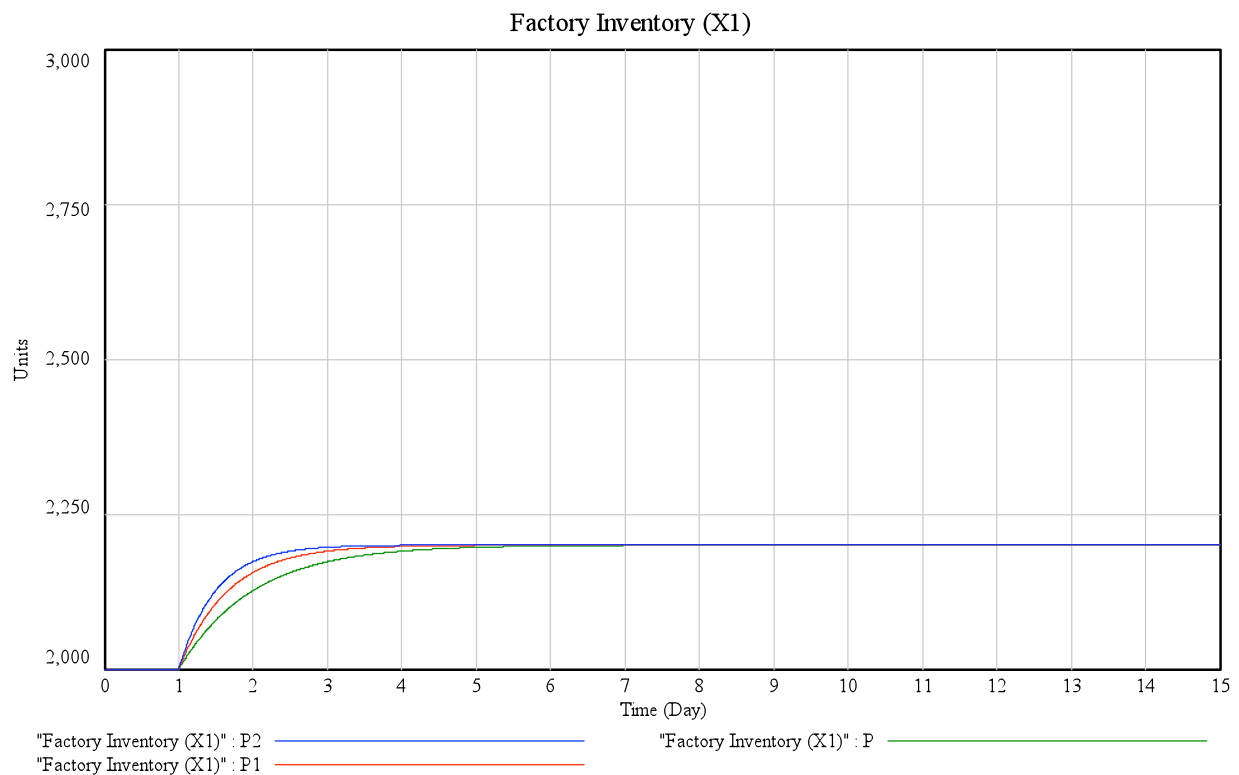


Figure 7.3: Response of system increasing proportional gain

Figure 7.3 shows the response of the system when the proportional gain is increased. The integral and derivative gain is set to zero. The set “P” has a unity proportional gain. When the proportional gain is increased, the responsiveness of the system increases. This is evident because of the response for set “P1” and “P2” have a much shorter settling time as compared to the set P.

To examine the impact of the integral adjustment on supply chain performance, we increase the integral gain, while keeping the proportional gain at unity. We see that the settling time decreases as a result of the addition of the integral adjustment, as shown below in Figure 7.4.

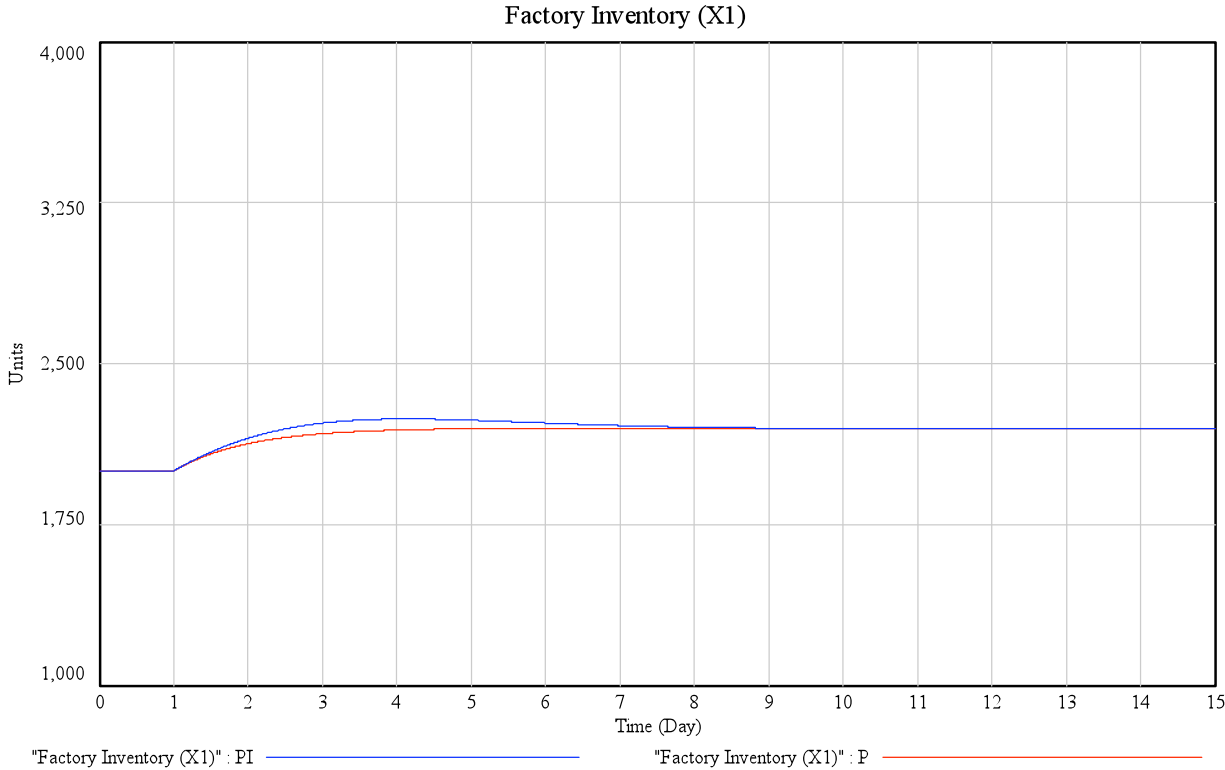


Figure 7.4: Impact of integral adjustment

We increase the integral gain further to see if the settling time can be further reduced. Even though the responsiveness increases as a result of increasing the integral gain further, it eventually causes the inventory level to overshoot the desired level and leads to an oscillatory response. This is shown in Figure 7.5.

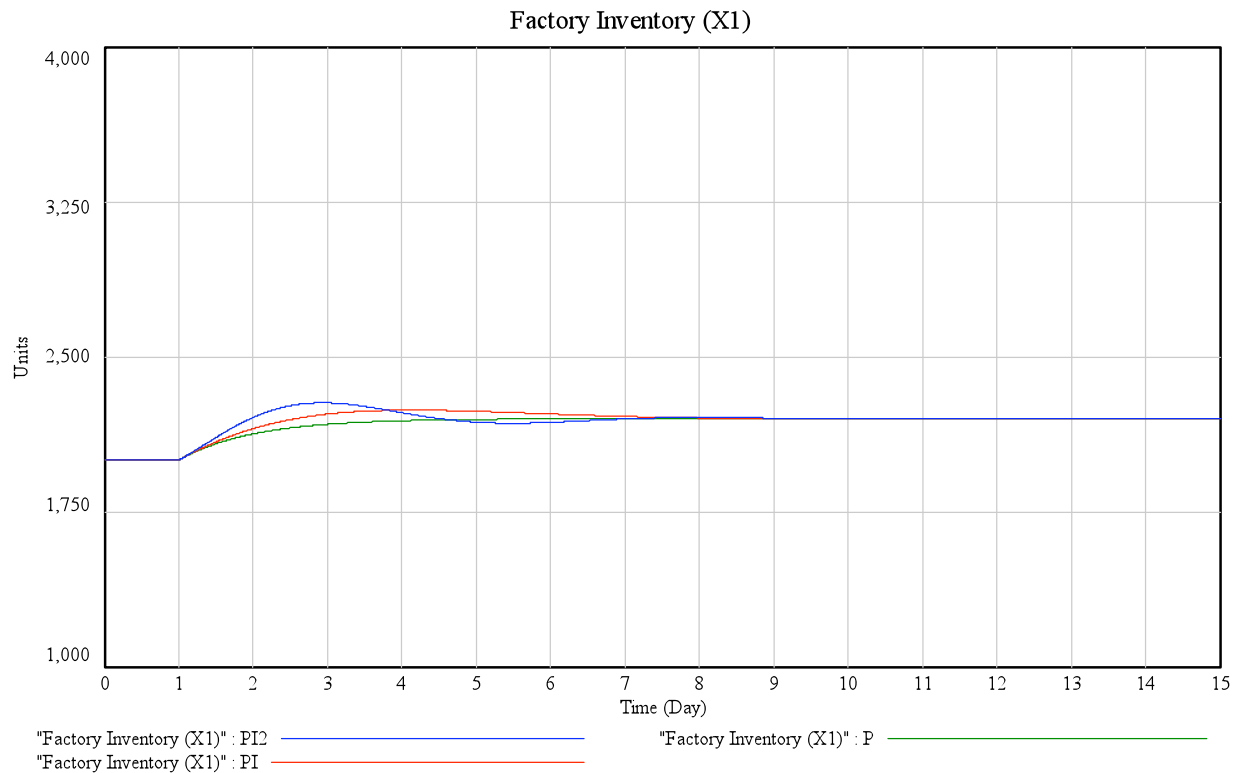


Figure 7.5: Inventory overshoot due to high integral gain

We increase the differential gain to examine the impact that it has on the above response. The increase in the differential gain leads to a dampening of the oscillatory behavior that is seen in Figure 7.6. If the differential gain is increased further, the oscillations are dampened to a larger extent, as seen below in Figure 7.7.

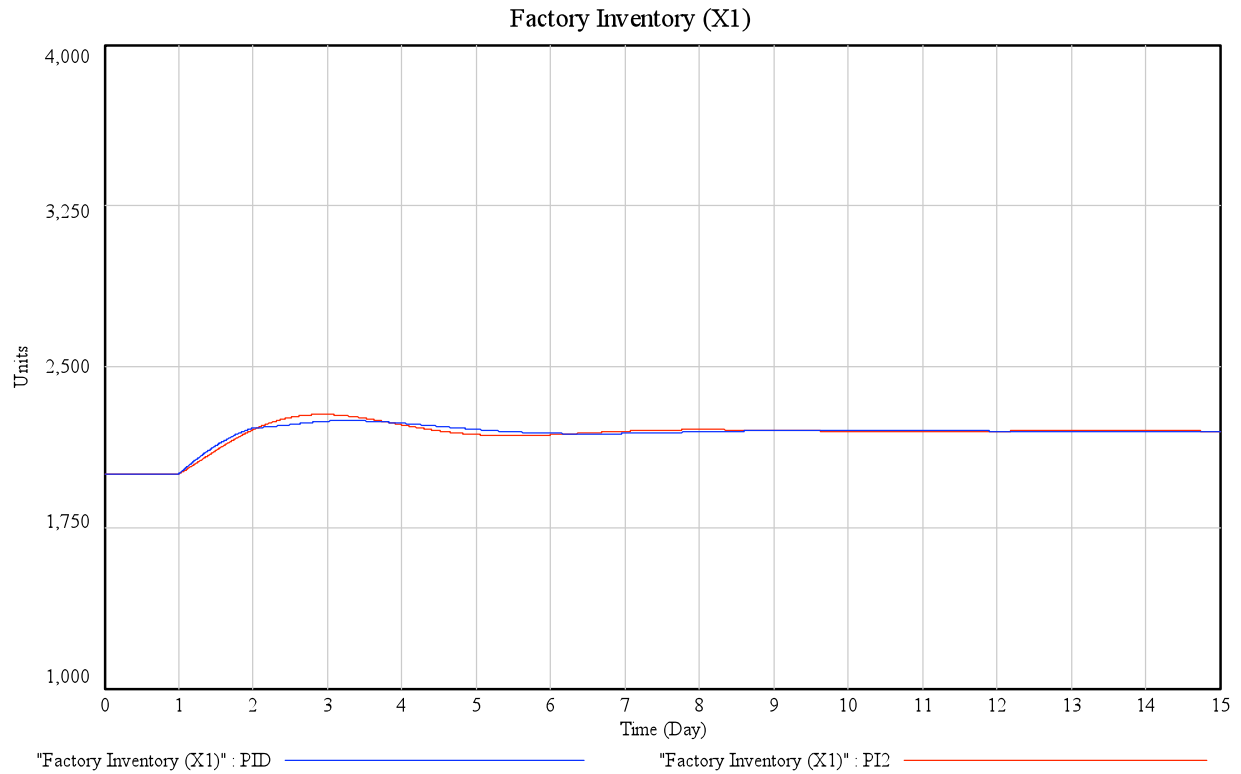


Figure 7.6: Impact of differential adjustment

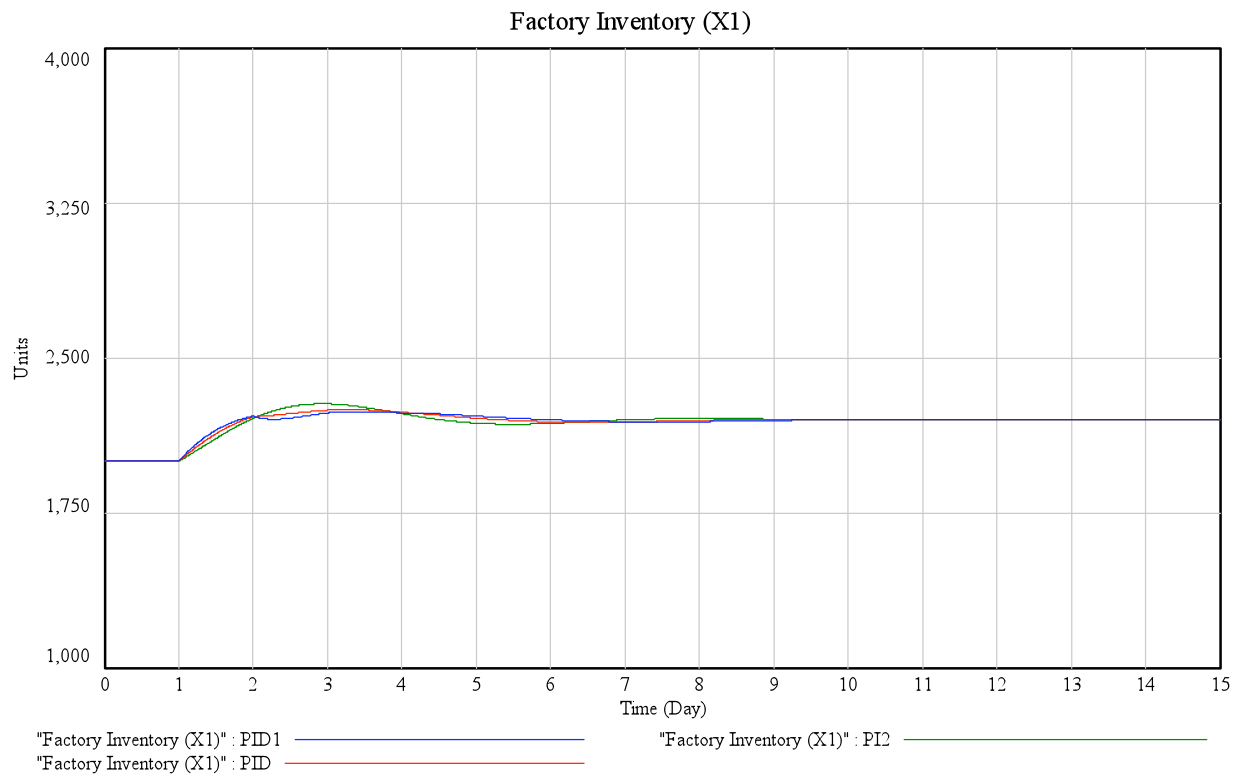


Figure 7.7: Dampening in oscillations due to higher differential gain

We also examine whether the PID framework can help minimize the amplification that is seen in supply chain. We first simulate the supply chain with a unity proportional gain, where the integral and differential gains are set to zero. We see that the variability in the production start rate is significantly higher than the variability of the sales rate. This is due to the amplification of the system.

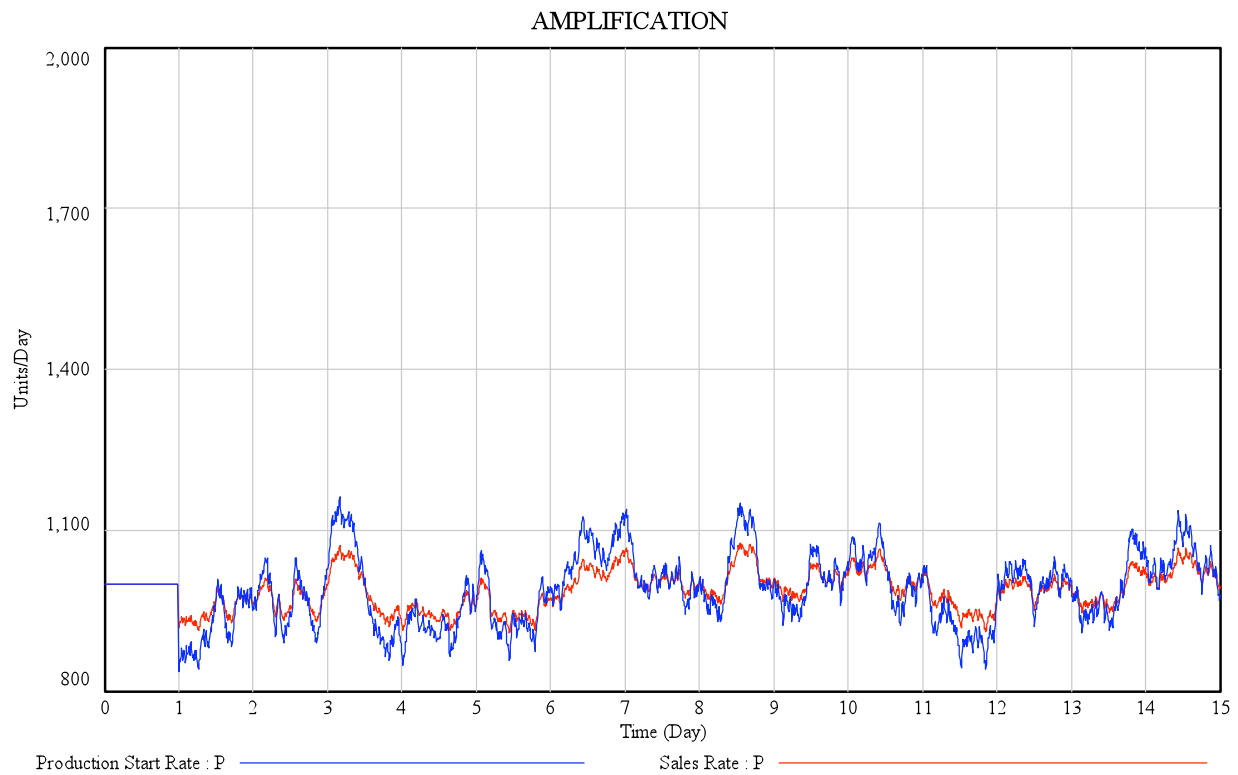


Figure 7.8: Amplification with unity proportional adjustment

We increase the proportional gain to see whether this leads to a reduction in the amplification. With reference to Figure 7.9, we see that as the proportional gain is increased, the amplification observed in the system also increases.

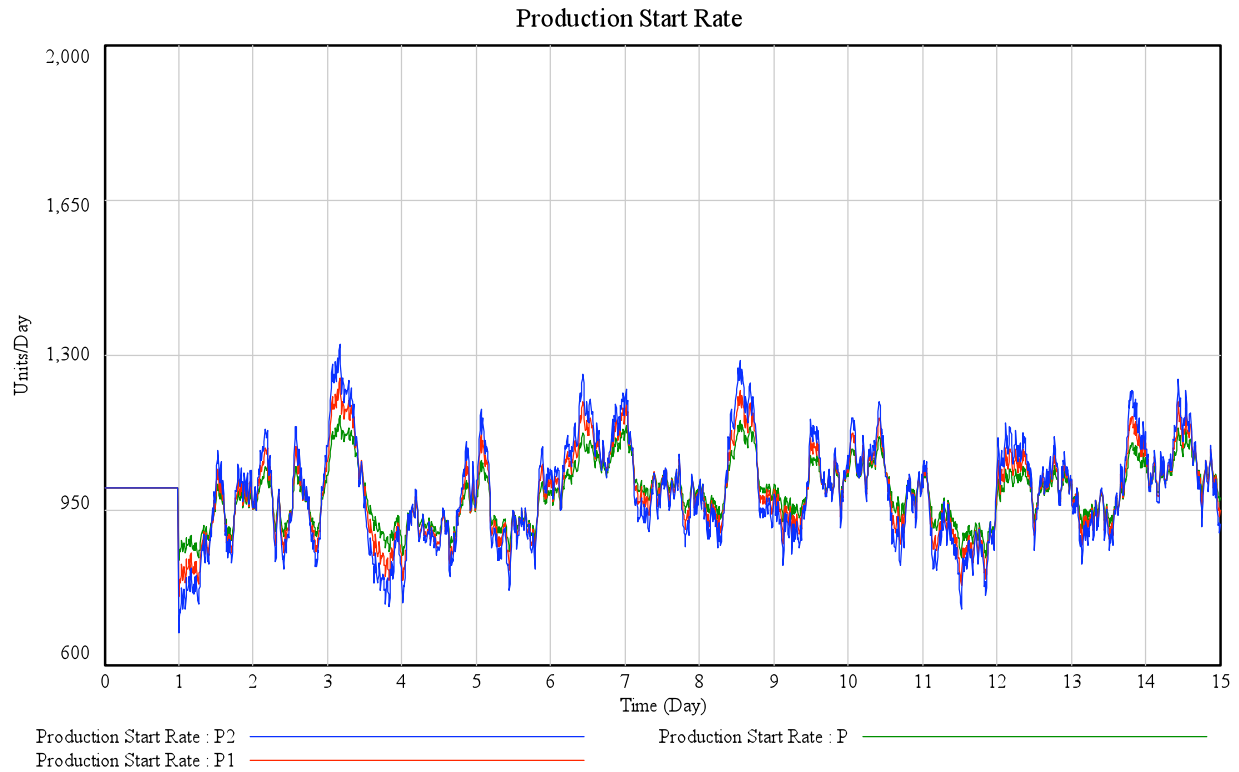


Figure 7.9: Increase in amplification due to increase in proportional gain

We now examine whether an addition of the integral adjustment can help reduce the amplification seen in the system. We see in Figure 7.10 that by adding the integral adjustment to the proportional adjustment, the amplification is increased. Hence, while the addition of the integral adjustment reduces settling time when simulating with a step response, it can increase the amplification when the sales rate is noisy. We then increase the derivative gain to see if it aids in dampening amplification. However, this leads to a further increase in amplification as shown in Figure 7.11.

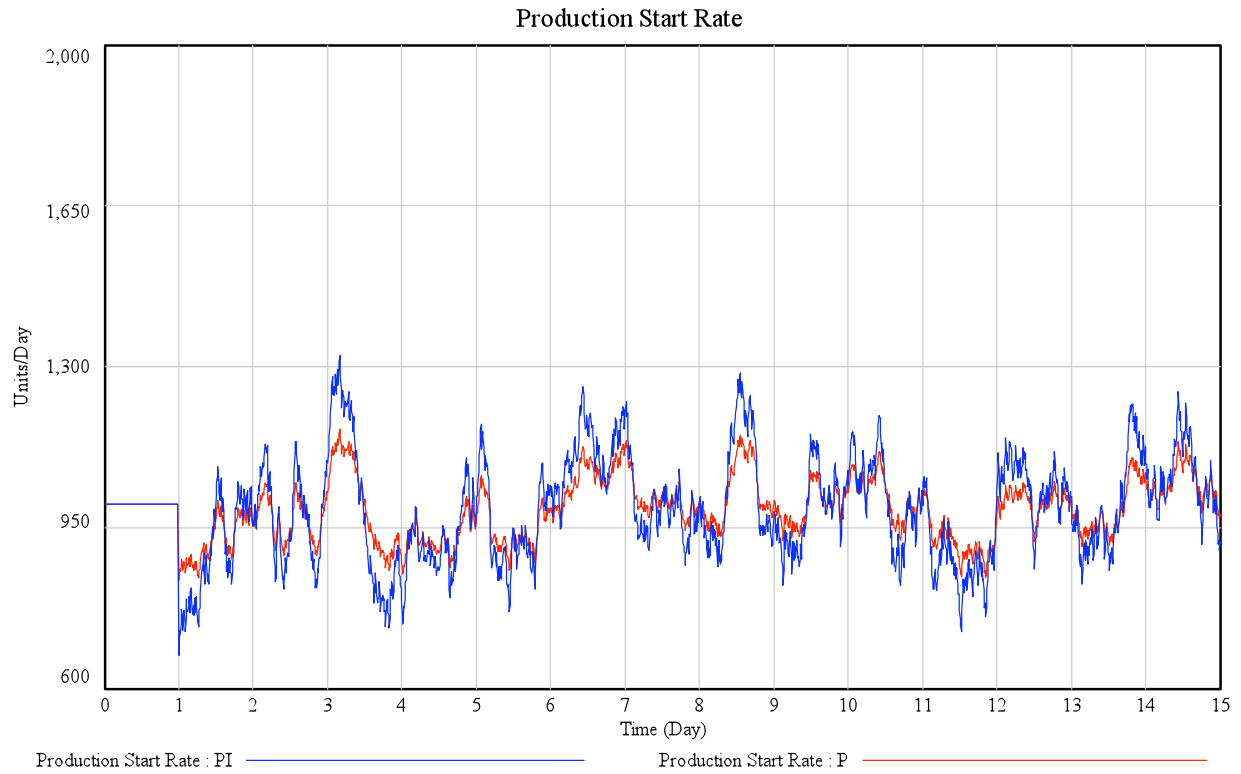


Figure 7.10: Further increase in amplification due to integral adjustment

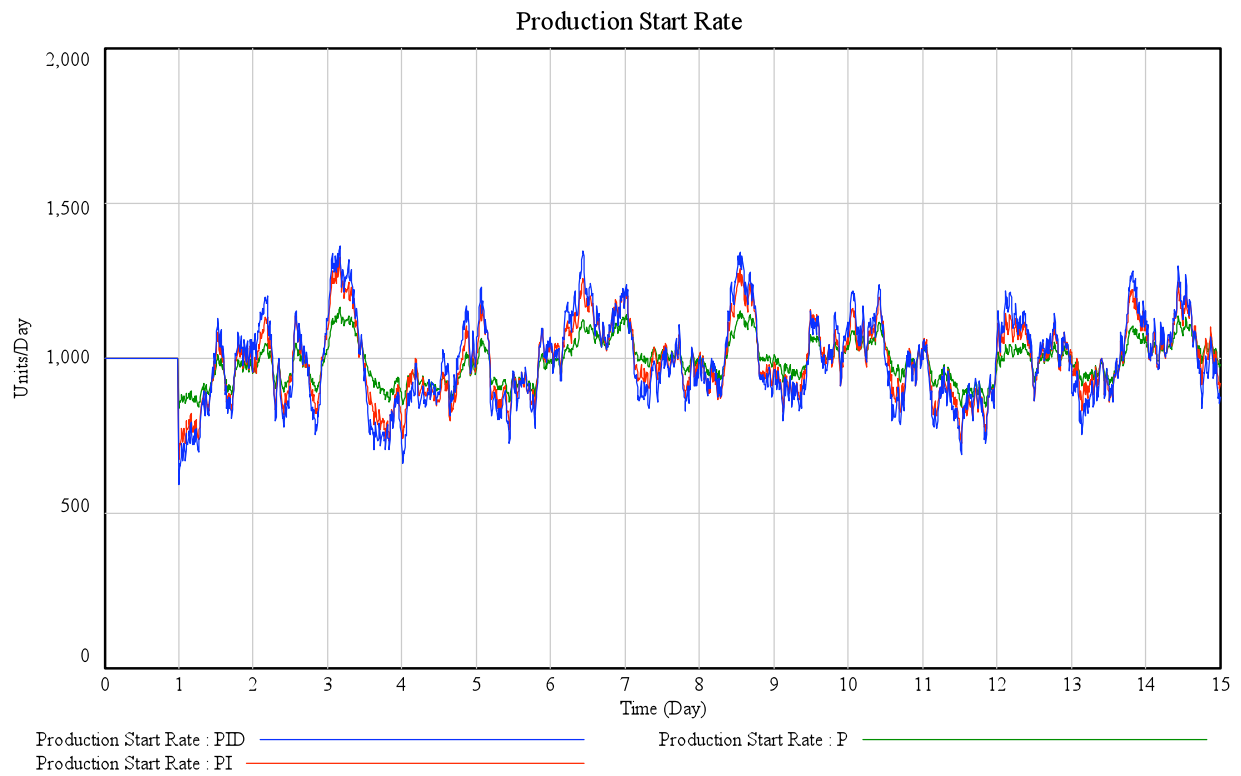


Figure 7.11: PID shows the highest amplification

The preceding discussion tests the hypothesis in a qualitative fashion. We quantify the impact of the PID control structure on supply chain dynamics by conducting a series of simulation experiments. Existing models assume that the control system for a supply chain uses the proportional feedback error to drive production. We wish to determine what impact the inclusion of the integral and differential error feedback would have on supply chain dynamics. Since we wish to quantify the impact of the integral and differential adjustment structures, we treat the integral and differential gain constants as experimental factors. Further, we let each of these factors have three levels, namely low, medium and high. The proportional gain is assumed to have a constant value of unity.

	K_i	K_d
Low	0.2	0.2
Medium	0.5	0.5
High	0.8	0.8

Table 7.2: Experimental Settings

We use a full factorial experimental design with two factors and three levels. Hence, we conduct nine experiments. As in Chapter 6, we measure the settling time and amplification by using STEP and NOISE inputs correspondingly. The results are summarized in Table 7.2. Experiment number zero quantifies the dynamics observed when the integral and differential gains are set to zero. This provides a baseline observation against which the other experimental results can be compared. Experiments one through nine quantifies the impact of the integral and differential gain on supply chain dynamics.

Experiment Number	Integral Gain (K_i)	Differential Gain (K_d)	Settling Time (Day)	Amplification (Dimensionless)
0	Zero	Zero	1.52	3.37
1	Low	Low	1.33	4.2
2	Low	Medium	1.28	5.48
3	Low	High	1.21	6.97
4	Medium	Low	1.16	4.35
5	Medium	Medium	1.05	5.63
6	Medium	High	0.94	7.12
7	High	Low	1.04	4.52
8	High	Medium	0.95	5.79
9	High	High	0.88	7.27

Table 7.3: Experimental Results

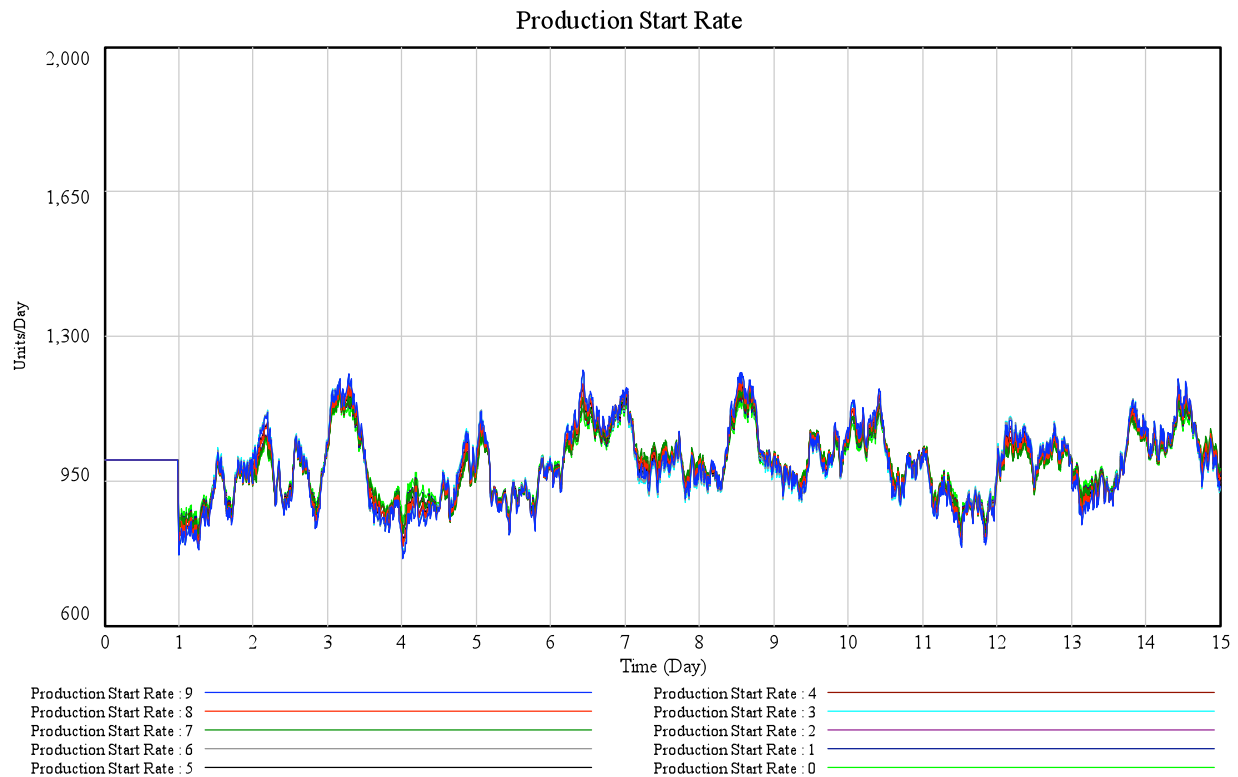


Figure 7.12: Simulation results for NOISE input

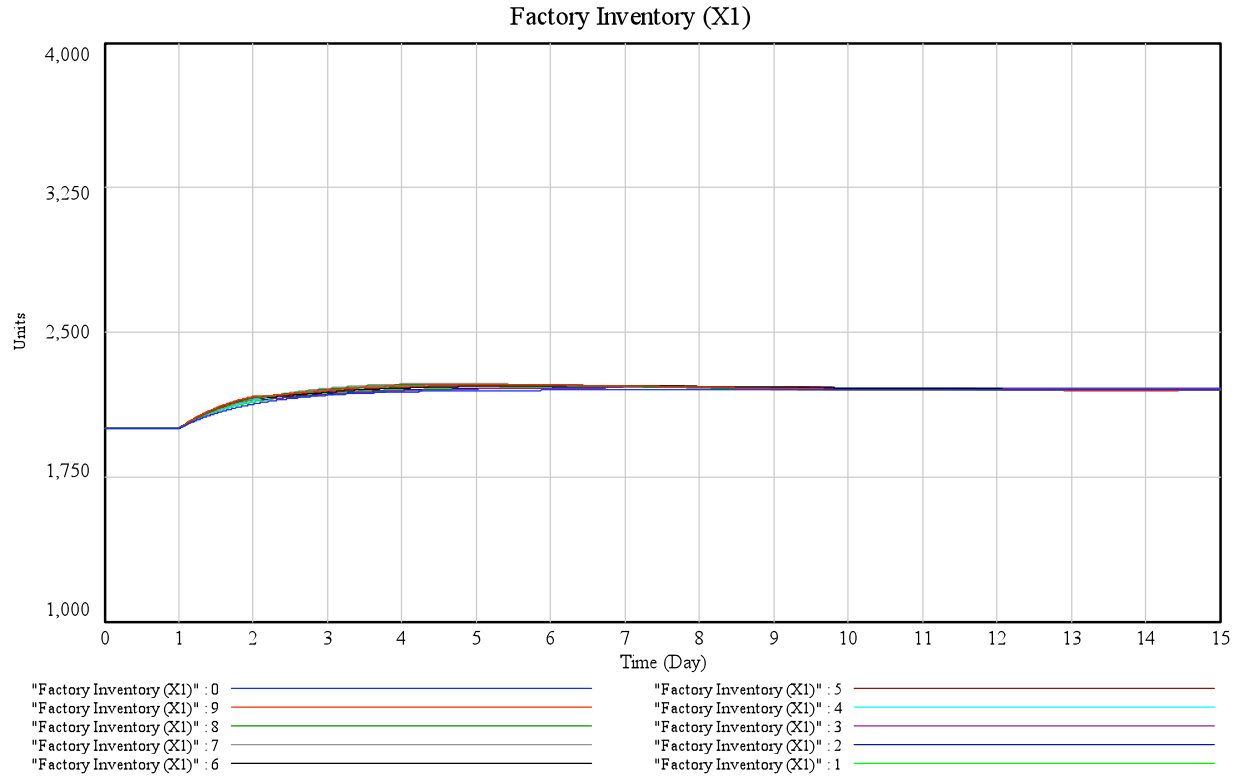


Figure 7.13: Simulation results for STEP input

From the experimental results, we see that the inclusion of the integral and differential error feedback structures leads to a decrease in the settling time, but an increase in amplification. This can be seen by comparing the settling time and amplification metrics for experiments 1-9, with the base case shown as experiment zero.

Further, we see that the PID information network with the highest feedback gains leads to the smallest settling time, but maximum amplification. Similarly, the network with the smallest feedback gains leads to the largest settling time, but minimum amplification.

7.5 Summary

We introduce the PID control structure and discuss how it can be used to control the operations of supply chains. Since, traditional system dynamics models for the control of supply chains only use proportional control; it was of interest to determine whether an advantage can be gained by using the PID structure instead. We find that the inclusion of the integral and differential adjustment to the control algorithm does improve the responsiveness of the supply chain by reducing the settling time. While the addition of the integral adjustment did lead to a reduction in the settling time, it could also lead to an inventory overshoot if the integral gain was set to a high value. The differential adjustment did dampen the oscillations induced by the integral adjustment to some extent, when simulating with a step input. While the PID control structure led to an increase in responsiveness when simulating with the step input, it led to an increase in amplification when simulating with a noisy input. Any increase in the integral and differential gain led to an increase in amplification.

The PID control structure provides a broader structural framework to model the dynamics of business and social systems, which use information feedback control mechanisms, as compared to traditional models, which only use the proportional adjustment structure for control. The PID structure also provides a larger design space for system designers. Further, the research literature is rich with approaches for “tuning” PID control systems. Since the “tuning” of PID control systems is synonymous with the policy development process in the field of system dynamics, we see a great potential for applying these “tuning” methods to system dynamics, since most system dynamics models use a subset of the PID control structure.

Chapter 8: Combined Feedback Feed-forward Structure

8.1 Introduction

Forrester mentions, “The first and most important foundation for industrial dynamics is the concept of servomechanisms (or information feedback systems) as evolved during and after World War II.” He also adds “the information feedback system will become a principal basis for an underlying structure to integrate the separate facets of the management process” (6).

Since the field of system dynamics stems from the domain on feedback control theory, a majority of the system dynamics models of supply chains use information feedback for control [(6) (64) (65) (66) (12) (62) (11)].

A feedback system is one that reacts to changes in its environment, usually trying to maintain some desired state. On the other hand, a feed-forward system reacts to a measured disturbance in a pre-defined manner. Hence, the disturbance is measured and action is taken before the disturbance affects the system. The difference between the two schemes for control can be discussed in the context of an example. Consider the cruise control mechanism of an automobile, a well-known feedback system. The purpose of a cruise control mechanism is to maintain the car at a steady speed. When the car encounters an uphill slope, the car would slow down. This difference between the actual and desired speed would generate an error signal, which would cause the throttle to open further, and hence bring the car back to the desired speed. If the cruise control mechanism had been using a feed-forward mechanism for control, it would have used a sensor to detect the uphill slope and open the throttle in anticipation of the decrease in speed.

Hence, the car would not lose any speed before a correction was made. In the context of this example, it should be noted that there are several other factors such as temperature, wind, altitude etc., which can impact the speed of the car. Since the relationship of these variables with the speed of the car cannot be modeled accurately, it would not be possible for a cruise control mechanism to operate solely with feed-forward control. Feedback and feed-forward control structures are not mutually exclusive. One could adopt a combined feedback feed-forward control structure. Feed-forward control would lead to a quick response, while feedback control would correct any error that arose due to the pre-set response.

A feed-forward controller is a good choice if the following conditions can be met:

- Disturbances are known before they impact the system
- Disturbances are measureable
- There are no significant unmeasured disturbances

There are several advantages and disadvantages for both feedback and feed-forward control. These are summarized below in Table 8.1. It can be seen that the two control structures are actually complementary to each other. By using a combined structure, one can increase responsiveness to known disturbances, while being robust to unknown disturbances.

	Feed-forward Control	Feedback Control
Advantages	<ol style="list-style-type: none"> 1. Compensates for disturbance before it affects the system 2. Does not impact the stability of the control system 	<ol style="list-style-type: none"> 1. Zero steady state offset 2. Is appropriate for use with all disturbances. 3. Does not require any additional sensor for each disturbance
Disadvantages	<ol style="list-style-type: none"> 1. Shall require a sensor and model for each disturbance 2. Can't eliminate steady state offset 3. The controlled state variable is not monitored. Hence, no error correction is possible 4. Tends to require more calculation/analysis in design phase 	<ol style="list-style-type: none"> 1. Requires the disturbance to impact the system before any response is made 2. Affects stability of control system.

Table 8.1: Feedback and Feed-forward Control, Adapted from (88)

8.2 Combined Feedback Feed-forward Structure

Figure 8.1 shows the proposed structure for the combined feedback feed-forward control. The feedback control effort focuses on ensuring that one or more states remain at specified set points. The process output is continuously monitored to compare the values of the state variables with their desired set points. If there is a discrepancy, the error is multiplied by an appropriate gain value and fed back to the flow control value for the process. If there is a measurable disturbance, its value is measured and multiplied by an appropriate feed-forward gain. This information is transmitted to the flow control value for the process. The combination of the feedback and feed-forward information flows determines the setting for the flow control value of the process.

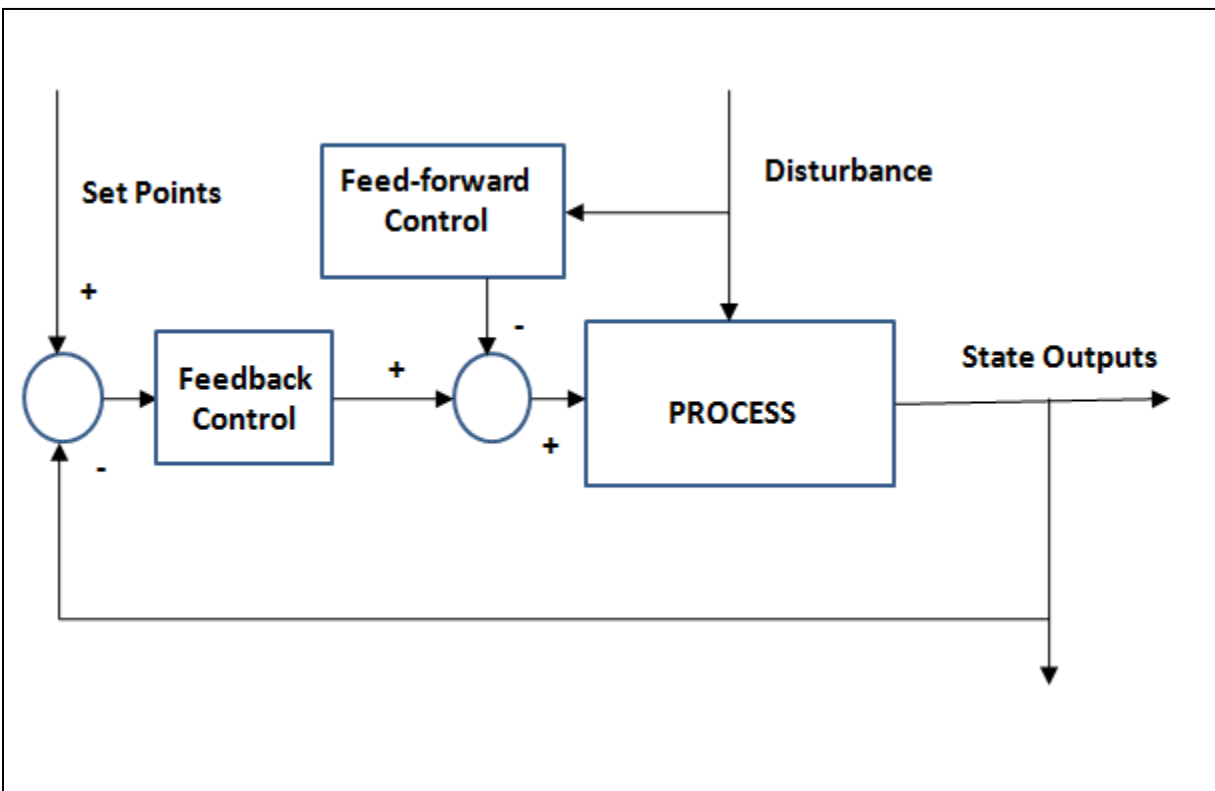


Figure 8.1: Combined feedback feed-forward control structure

It should be noted that in the above framework, the feedback control chosen depends on the nature of the process and the state variables of interest. One could use a PID control structure if appropriate. If not, one could use a P, or PI or PD structure. A combined feedback feed-forward does not restrict this choice in any way.

Feedback control relies on error to control the process. This error may be in terms of one or all of the state variables of the model. We see from Chapter 6 that if we use all the state variables for feedback control, we see the most rapid response. If simplicity is preferred and responsiveness is not of prime importance, one could use just one state for the purpose of feedback control.

The set point chosen for each state variable of interest may be fixed or variable, depending on the policies of the organization. A fixed level is generally simple to use in practice. However, a variable level may help in making the system more responsive to changes in the environment. For example, we may use a fixed reference level for the factory inventory in a supply chain. However, the factory inventory level would not be responsive to the sales rate. If responsiveness is desirable, a variable reference level, which is a function of the sales rate, may be used.

The formulation of the feed-forward control loop also depends on the nature of the disturbance and its impact on the process. Depending on the specifics, the disturbance value can be multiplied by an appropriate gain value to determine its effect on the flow value for the process. The choice of gain depends on the units of the disturbance.

8.3 Case Study

To study the impact of the combined feedback feed-forward control structure, we incorporate it into the 3-stage system dynamics model for a supply, which was introduced in Chapter 3. The feedback structure of the model is identical to the model shown in Figure 3.2. The main difference between the two models is that the model shown in Figure 3.2 doesn't explicitly model capacity. It assumes infinite capacity. The model shown below explicitly models the manufacturing and distribution capacity. The manufacturing capacity is the maximum possible production completion rate that can be achieved with the resources available, while the distribution capacity represents the maximum possible distribution rate that can be achieved with the resources available.

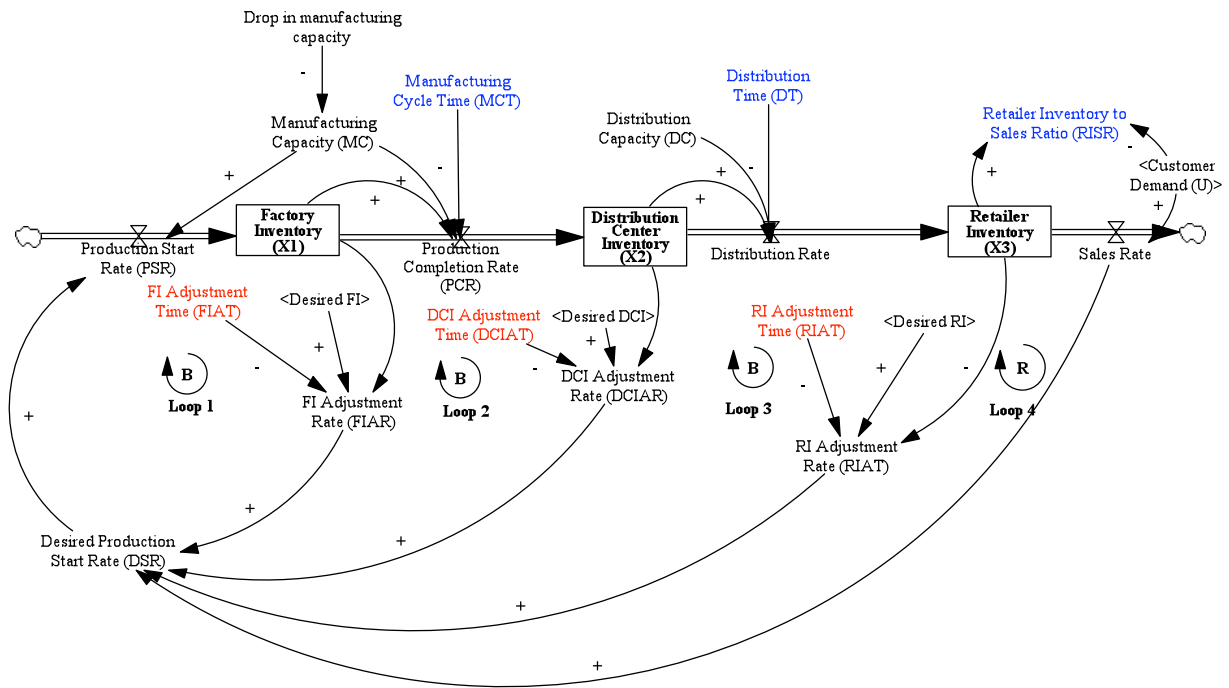


Figure 8.2: Combined Feedback Feed-forward control structure for supply chain

The inflow of this three-stage supply chain is determined by the desired production start rate. This is a sum of the sales rate and the adjustment rates for the three inventory levels in the supply chain. The adjustment rate for an inventory level is formulated as the discrepancy between the level and its ideal value, divided by the adjustment time. The discrepancy is the error term, while the reciprocal of the adjustment time is the gain for that feedback loop. This feedback gain is determined by company policies.

We feed-forward the information about the manufacturing capacity to formulate the production start rate. If there were a disturbance that causes the manufacturing capacity to drop, the production start rate would also decrease. If the information about the manufacturing capacity weren't available, an accumulation of inventory would occur, assuming that the system was operating at full capacity before the disturbance occurred. This accumulation of inventory would lead to the generation of an error, which would be used to make a correction. If the information of the manufacturing capacity is fed to the decision point where the production start rate is decided, then the accumulation of inventory can be avoided. We formulate the production start rate so that it doesn't exceed the manufacturing capacity and is yet a positive quantity. To disable the effect of the feed-forward link, we formulate the production start rate as shown in 8.2

$$\text{Production start rate} = \text{MAX} (\text{MIN} (\text{Desired Start Rate}, \text{Manufacturing Capacity}), 0) \quad \mathbf{(8.1)}$$

$$\text{Production start rate} = \text{MAX} (\text{Desired Start Rate}, 0) \quad \mathbf{(8.2)}$$

We hypothesize that this combined feedback feed-forward control structure shall lead to better responsiveness than would be possible with just the feedback control structure.

8.4 Validation

We simulate the model of the supply chain to validate the hypothesis that a combined feedback feed-forward control structure better responsiveness than a control structure that only uses information feedback.

The manufacturing capacity of the factory drops from 1000 units per day to 900 units per day from the 5th day of the simulation. Consequently, the production completion rate drops to 900 units per day from the 5th day. We wish to study the impact of this drop in capacity has on the factory inventory and the production start rate.

We see from Figures 8.3 and 8.4 that when the drop in capacity occurs, the production start rate drops accordingly in the case of the combined control structure. However, when only feedback is used for control, the production start rate takes some time to adjust to the new steady state level, which is determined by the capacity constraint. There is an excess inventory buildup during this period of adjustment, which is why the steady state inventory level for the system using the combined structure is smaller than that of the system, which uses the feedback structure.

When a system is operating at full capacity, the impact that a drop in capacity will have on the system can be easily predicted. Hence, we were able to effectively leverage a feed-forward control structure. We see that adding this structure leads to smaller settling time as compared to using the standalone feedback structure.

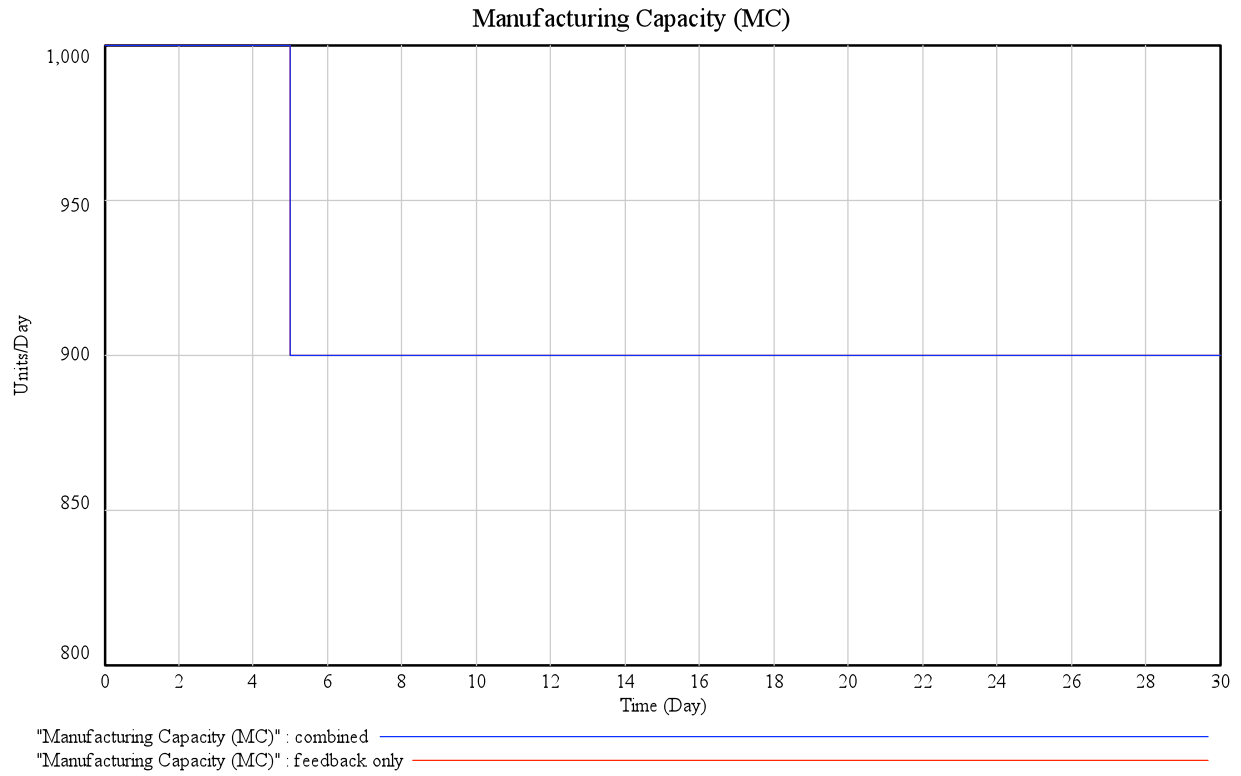


Figure 8.3: Drop in manufacturing capacity

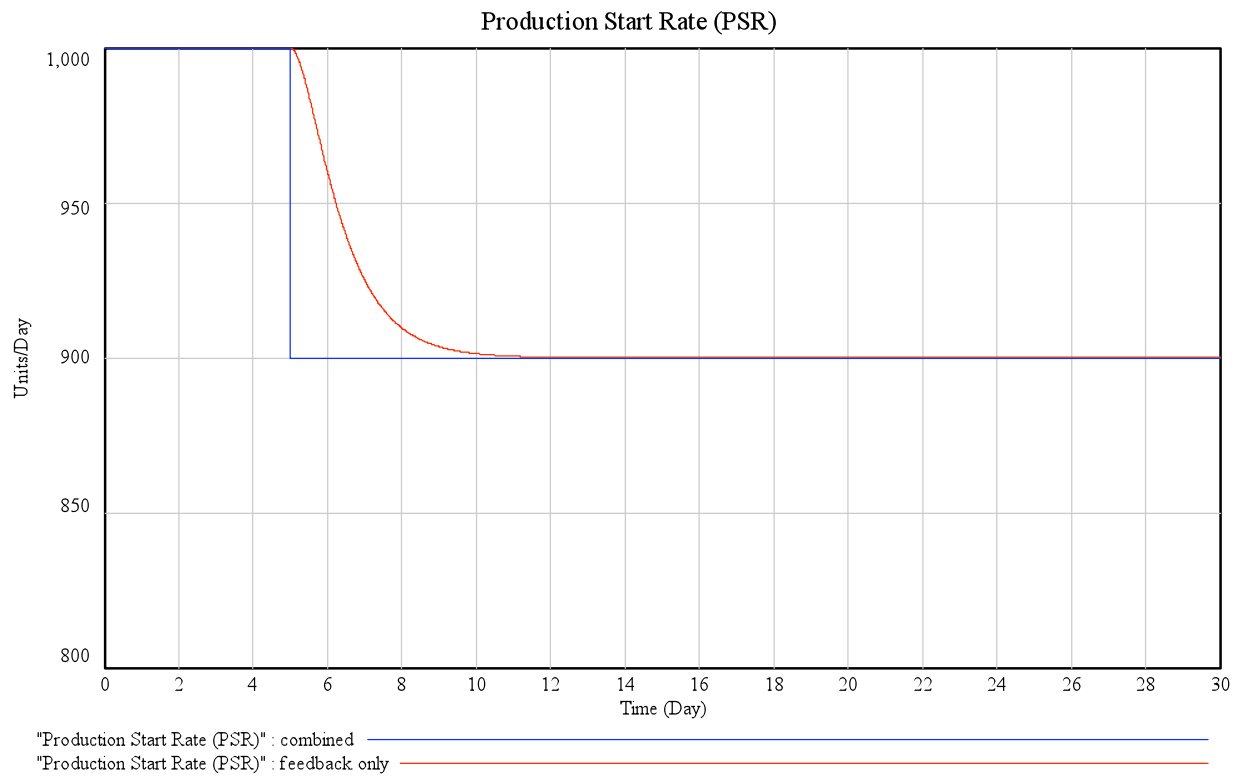


Figure 8.4: Response of Production Start Rate

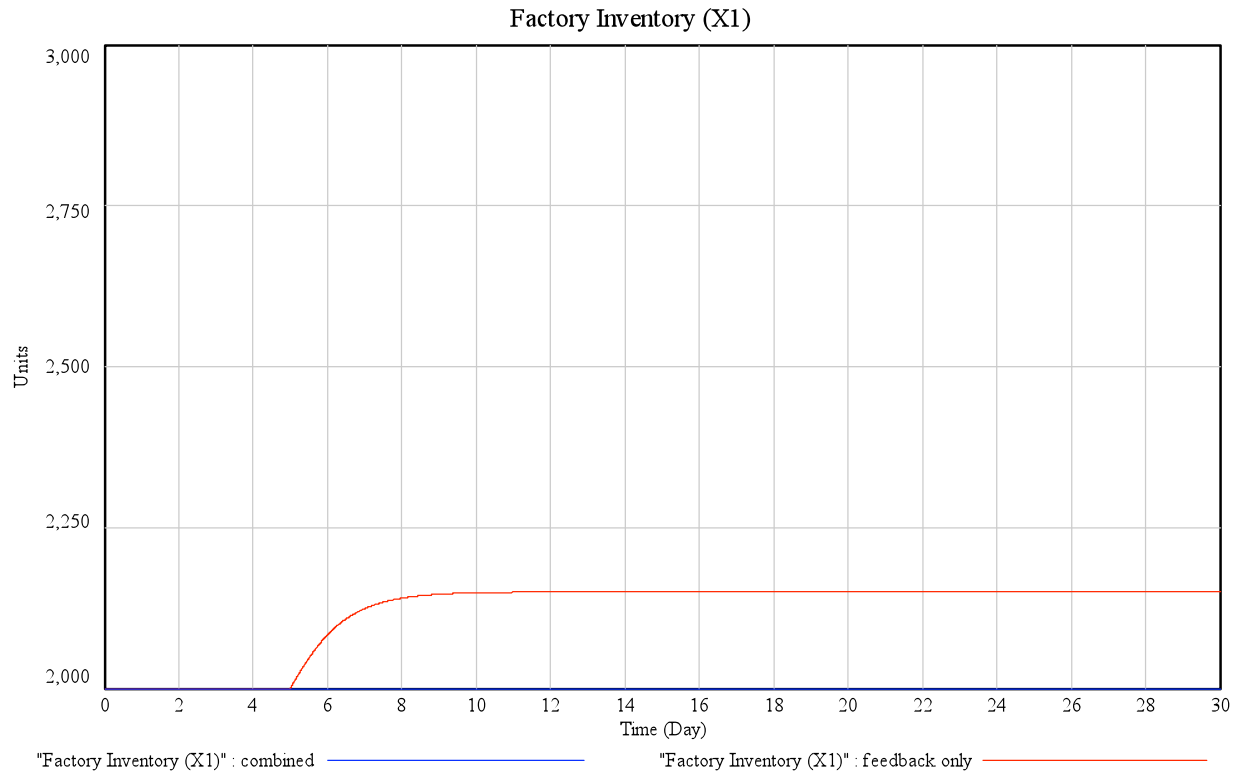


Figure 8.5: Response of Factory Inventory

8.5 Summary

System dynamics modeling uses feedback control theory to provide an underlying structure for models. Hence, systems are modeled as closed loop control systems that can only react to disturbances once the disturbance affects the state variables and causes an error. This may be the case for many systems. However, in the current era of global competition, such a business approach would lead to unnecessary losses. If the impact of a disturbance is not known on a system, the use of feedback control is sufficient. However, often one can anticipate the effect that a disturbance may have on a system and take action before the disturbance affects the system. Such a proactive approach, which uses an open loop control scheme, is commonplace in business systems and everyday life. For example, if there some machinery in a factory breaks down, one

could keep sending new orders to the shop floor and stop only when an accumulation of inventory occurs. Alternatively, one might anticipate this accumulation of inventory and stop all new orders when the information about the machinery breakdown is received. By anticipating the effect, which a disturbance can have on the operations of a business, significant capital savings can be accrued.

Models can be used to capture the dynamics of existing systems or could be used to design new systems. The structure of the model must provide the flexibility for the designer/modeler to accurately capture the dynamics of the system. The current limitation of system dynamics models is that the underlying structure restricts their application to feedback control systems. The application of system dynamics models is even further restricted by the fact that they only consider proportional adjustment for feedback control. The combined feed-forward feedback structure gives a system dynamics practitioner the flexibility to model a system using PID feedback control, as well as feed-forward control. This shall allow the system dynamics practitioner to better capture the dynamics of existing systems and also aid in the design of new systems.

We demonstrate using the case study that the combined structure can leverage the information to increase the responsiveness of the supply chain. While such a combined structure may not be applicable to all systems, it provides us with a framework to better understand the dynamics of systems.

Chapter 9: Industrial Case Study

9.1 Introduction

For the industrial case study, we use a system dynamics model for a hybrid push-pull production system for semiconductor manufacturing. This model was developed by Goncalves et al to represent a particular Intel Corporation plant facility. In their industrial case study, Goncalves, Hines, Sterman, and Lertpattarapong undertook a year-long research project to develop and analyze a manufacturing model of producing semiconductors, using system dynamics. Their case study addressed the causes of oscillatory behavior in capacity utilization at a semiconductor manufacturer and the role of endogenous customer demand in influencing the company's production and service level. For further details on the findings of the original study, one can refer to the paper presented by Goncalves et al at the 22nd International Conference of the System Dynamics Society (89). Fong uses classical control theory to determine the transfer function for this model and subsequently uses a design of experiments framework for policy design (70). He also plots the root locus for the model and uses it to develop a more thorough understanding of the model.

We use the model of the Intel Production facility in the following manner:

1. We apply the dynamic policies developed in Chapter 4 and examine their impact
2. We apply the results from Chapter 6 and approach the problem from a structural perspective

This hybrid push-pull semiconductor production consists of three stages (i.e., Fabrication WIP for wafers, Assembly WIP for dies, and Finished Inventory for chips) as shown in Figure 9.1.

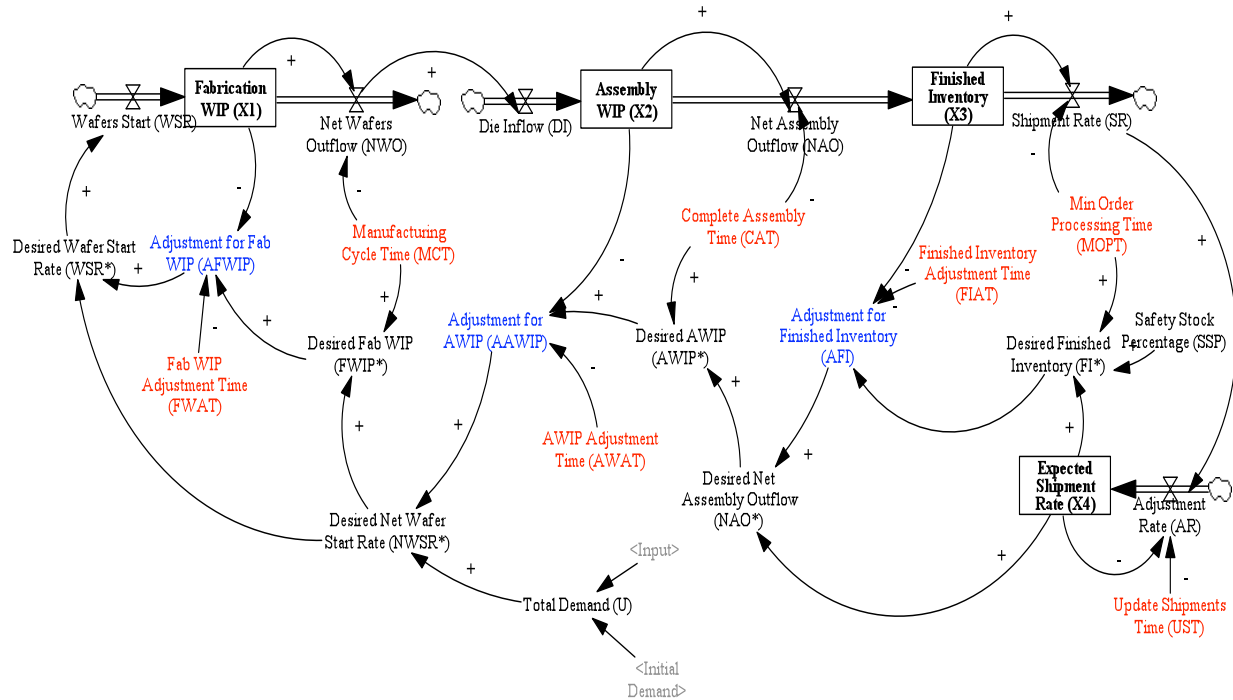


Figure 9.1: Hybrid Push-Pull Production System of Intel Corporation, Adapted from (70)

The push system is utilized in the front-end of the supply chain. Weekly updates from the total demand and an adjustment from the fabrication and assembly WIP stage are used to determine the desired wafer production rate. Since a production rate cannot be negative, the wafer start rate is equal to the desired wafer production rate if it is positive. Else, it is zero.

The back-end of the supply chain operates as a pull system, where assembly, testing, packing, and distribution are based on the current customer demand. The current customer demand drives the shipment and its assembly completion, whereas the demand forecasts influence production

start rate. Intel uses an information system to record all orders from its customers. The orders are tracked until they are shipped to the customer, or are cancelled. If completed chips are available in finished inventory (X3) stock, orders can be filled immediately. Hence, incoming customer orders “pull” the available chips from the finished inventory stock. Any finished inventory that is shipped to the customer is replenished by transferring material from the assembly WIP (X2) stock. The material that leaves in the assembly WIP stock is in turn replenished by the incoming material from the fabrication WIP stock.

The current customer demand drives the flow of good from the assembly WIP and finished inventory stocks, as described above. Since the shipment of goods depends on the existence of customer orders, the shipment can be said to be operating on a “pull” mode. However, if there is not enough finished inventory, the system will ship out only what it is available. The finished inventory (X3, units) is the accumulation of the difference between the net assembly outflow and the shipment rate. The shipment rate (SR, units/month) depends on the stock of finished inventory and the minimum order processing time (MOPT, month) via a simple first-order delay process. Hence, the shipment rate is equivalent to the finished inventory level divided by the minimum order processing time. Since the shipment rate is difficult to measure in real time, we model the expected shipment rate (ESR, units/month) as the current shipment rate with a first-order delay. The time delay to adjust the expected shipment rate is modeled as the Update shipment time (UST, month). The adjustment for finished inventory, AFI (units/month) is the rate at which the finished inventory needs to be adjusted in addition to the shipment rate to bridge the gap between the desired finished inventory FI^* (units) and the actual FI. This adjustment rate is inversely proportional to the finished inventory adjustment time (FIAT,

month). The desired finished inventory is calculated by the product of ESR and MOPT with a safety stock percentage (SSP) factor. The desired net assembly outflow (NAO*, units/month) is the summation of AFI and ESR. At the assembly WIP process stage, the adjustment assembly WIP (AAWIP, units/month) is adjusted between the desired assembly WIP (AWIP*, units) and the current assembly WIP (units). This adjustment rate is inversely proportional to the assembly WIP adjustment time (AWAT, month). The desired assembly WIP is a product of desired net assembly outflow (NAO*, units/month) and the complete assembly time (CAT, month). The desired net wafer start (NWS*, units/month) is the summation of AAWIP (units/month) and the total demand by the customer (TD, units/month). The stock level of assembly WIP (AWIP, units) is the accumulation of difference between Die Inflow (DI, unit/month) and net assembly outflow (NAO, units/month). A first order delay is used to model the NAO, where the delay time associated with the assembly WIP is the complete assembly time.

The wafers produced in the fabrication process stage are pushed into the assembly WIP where they are stored until orders for specific products pull them from AWIP into finished inventory for shipment. While the net wafer outflow (NOW, units/month) depletes fabrication WIP (FWIP, units), wafer start (WS, unit/month) replenishes it. The net wafer outflow is a first-order time delay of manufacturing completion time (MCT, month) from the fabrication WIP (FWIP, units). The decision on actual production rate, WS, is based directly on the desired wafer start (WS*, units/month). The desired wafer start rate is determined based on the desired net wafer start (NWS*, units/month) requested by the assembly stage and an adjustment for fabrication WIP (AFWIP, units/month). The AFWIP is calculated as the difference between the current fabrication WIP and the desired fabrication WIP (FWIP*). This discrepancy is divided by the

FWIP Adjustment Time (FWAT, month) to determine the adjustment rate. The FWIP* is the product of the desired net wafer start (NWS*, units/month) and the manufacturing completion time (MCT).

To simplify the non-linear mathematical expression for the non-negativity constraints to prevent negative production at wafer start, desired net wafer start, and desired net assembly outflow, we assume that there is no backlog in this industrial case study. The system variables, WS, NWS*, and NAO* are hence always positive in value.

9.2 Impact of Policy

The response of a system to changes in its environment is governed by the structure of the system and the policies employed by its management. We study the impact which policy has on the operations of the Intel production system. The Intel production system is simulated with three policy sets. We test the three policy sets mentioned above by using a STEP and NOISE input for the “Total Demand”.

Aggressive Policy: In this case, management responds aggressively to any discrepancy between the ideal inventory level and actual inventory level of stocks in the system. We set a uniform adjustment time of 1 day for the fabrication WIP, assembly WIP and finished Inventory stocks of the system.

Moderate Policy: In this case, management responds less aggressively to any discrepancy between the ideal inventory level and actual inventory level of stocks in the system. We set a

uniform adjustment time of 7 days for the fabrication WIP, assembly WIP and finished inventory stocks of the system.

Slow Policy: In this case, management responds sluggishly to any discrepancy between the ideal inventory level and actual inventory level of stocks in the system. We set a uniform adjustment time of 30 days for the fabrication WIP, assembly WIP and finished inventory stocks of the system.

The simulation results are shown below:

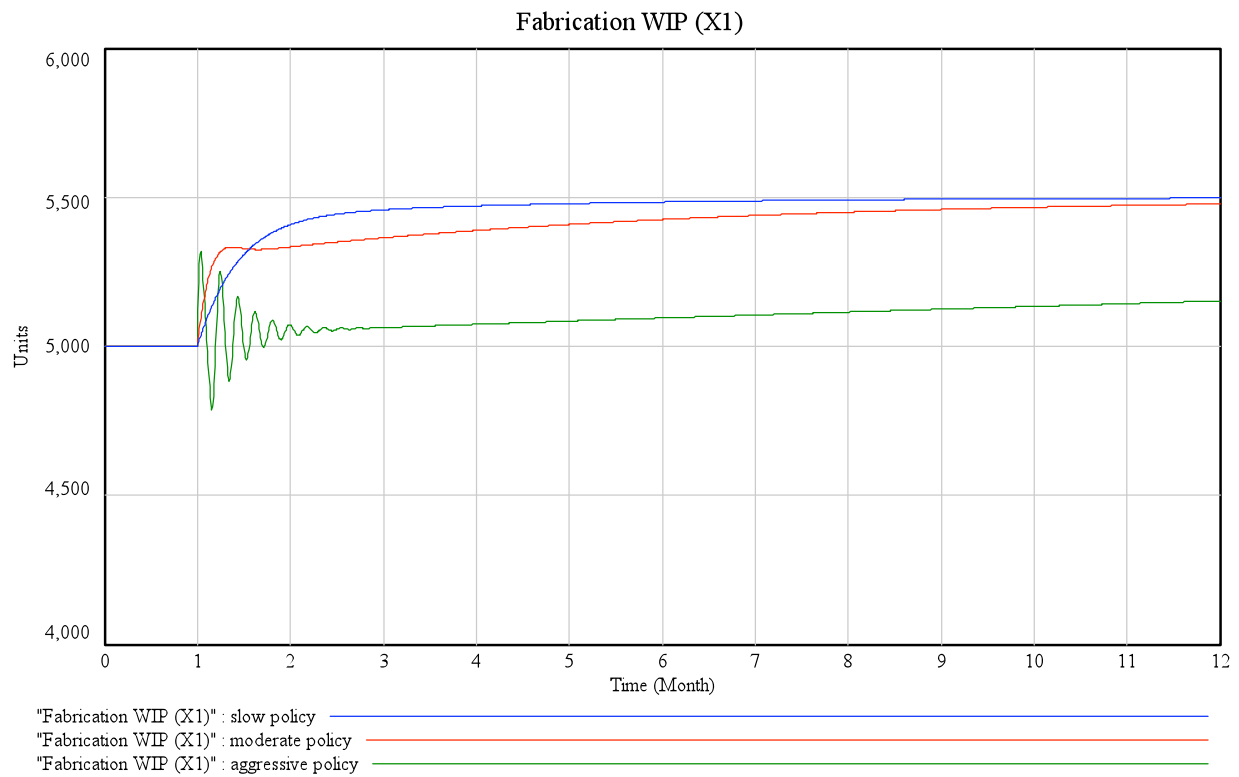


Figure 9.2: Response of Fabrication WIP (STEP Input)

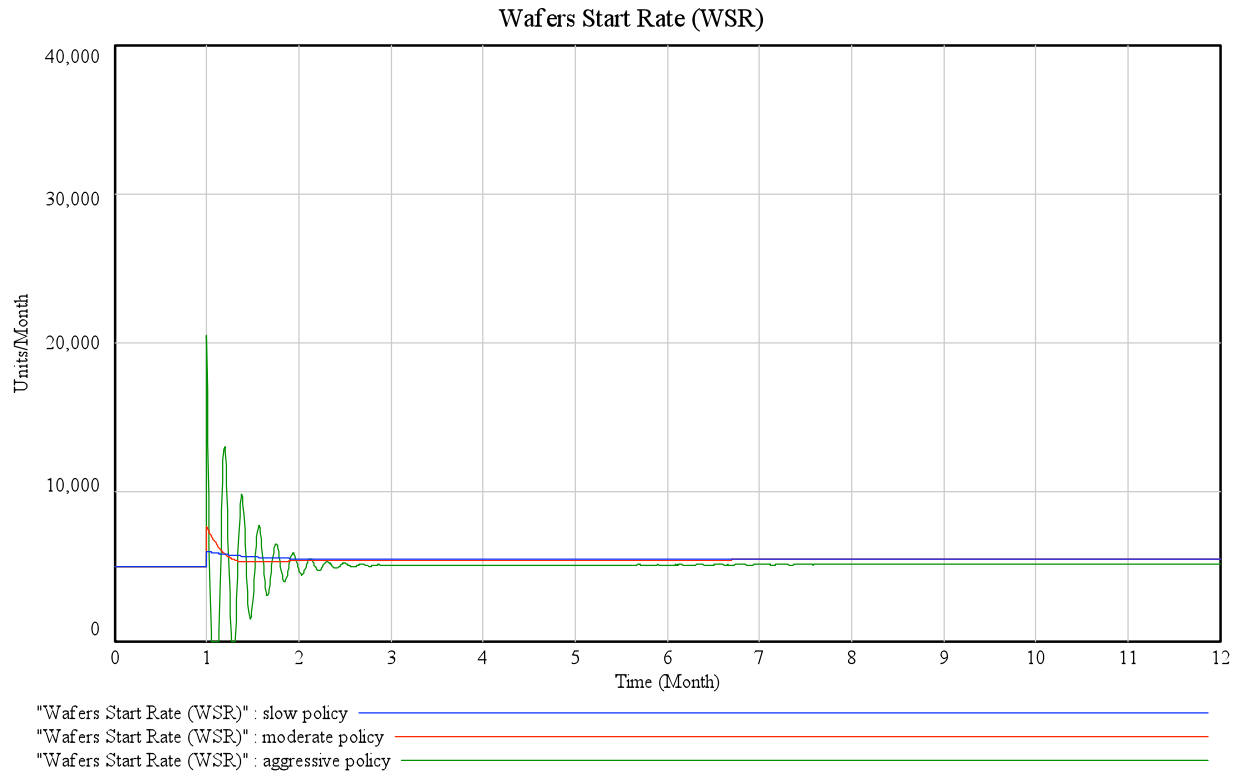


Figure 9.3: Response of Wafer Start Rate (STEP Input)

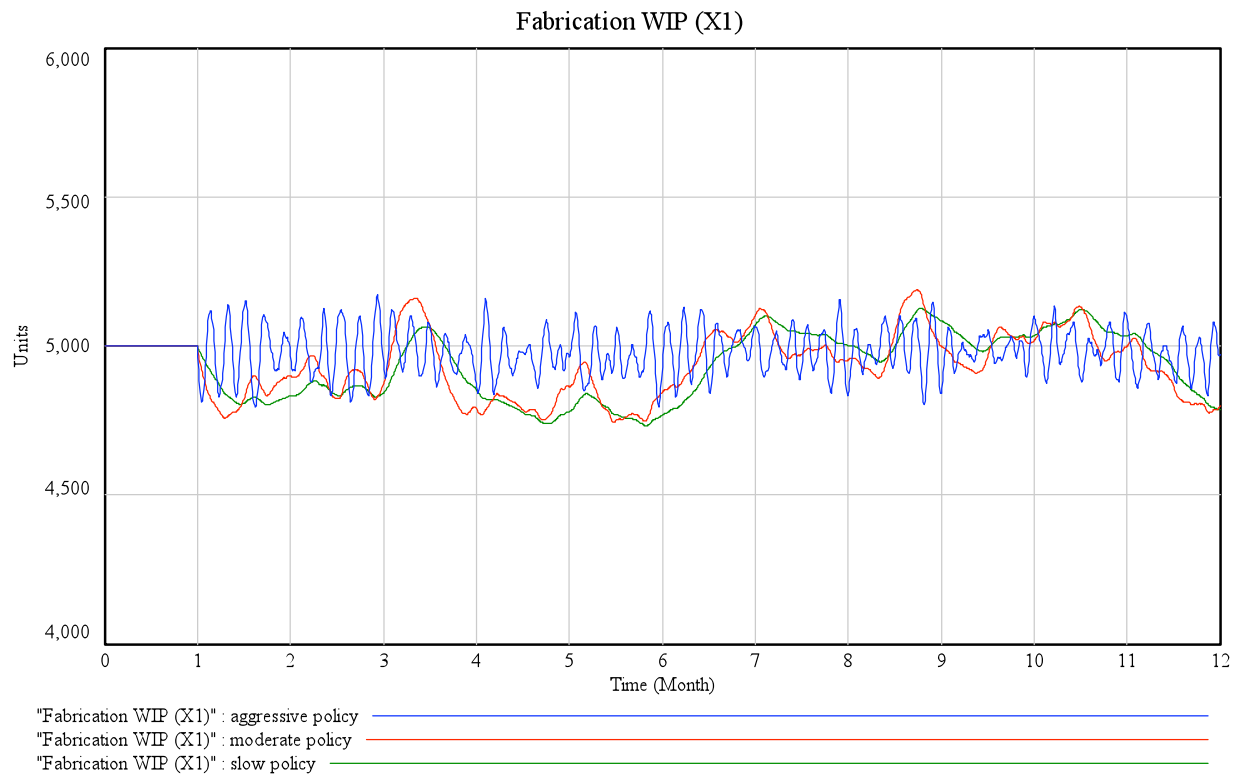


Figure 9.4: Response of Fabrication WIP (NOISE Input)

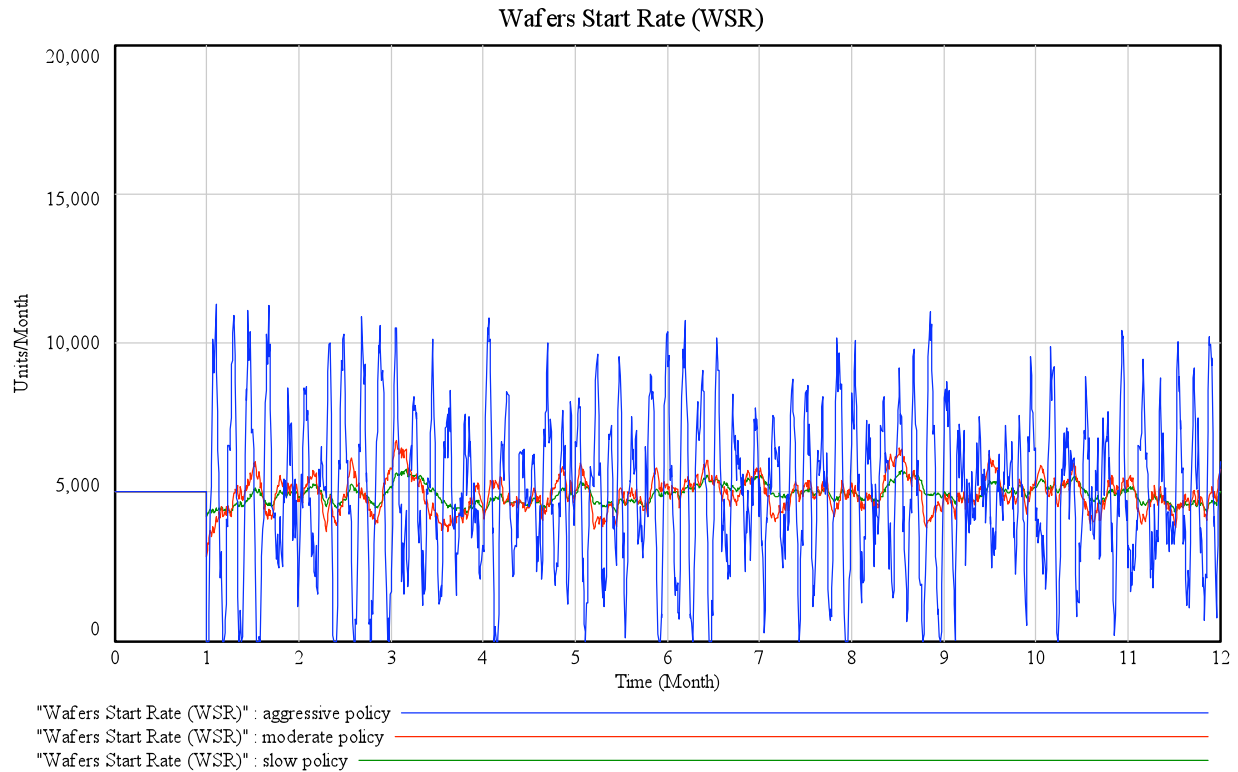


Figure 9.5: Response of Wafer Start Rate (NOISE Input)

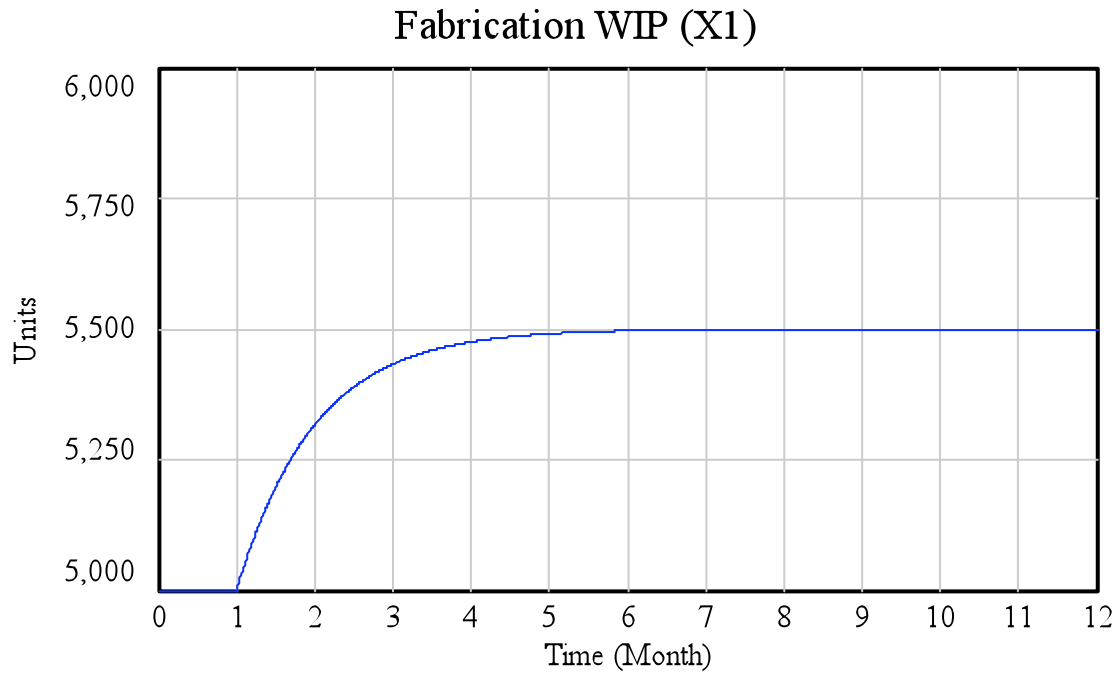
In response to the step increase in demand, we see that the aggressive policy set leads to considerable oscillations in inventory levels. The increase in demand occurs one month after time zero. We see that it takes the oscillations take almost 2 months to settle down after this disturbance occurs. The amplitude of the oscillations gradually decreases over time. It should be noted that even though the oscillations subside after a period of 2 months, the system does not reach the steady state inventory level of 5500 units. The moderate policy set leads to considerably better results. There is only a single overshoot, after which the system approaches the final steady state inventory level. It takes the production system almost 11 months to reach the new steady state inventory level with the moderate policy set. The slow policy delivers the best response in this simulation experiment. We see that by using the slow policy set, the system reaches its final steady state inventory level in 6 months without any overshoot.

When the system is simulated with a noisy input, the aggressive policy set leads to oscillations in inventory, with a time period of approximately one week between the consecutive crests. There is also significant amplification of the noisy demand. We see that the wafer start rate oscillates between a level of zero and 10,000 units per month. The moderate policy set leads to considerably better results as the range of the wafer start rate is much smaller, and there is no significant oscillation in inventory levels. The slow policy set gives a still better response as the response shows much lesser amplification, with no oscillation in inventory levels.

9.3 Validation

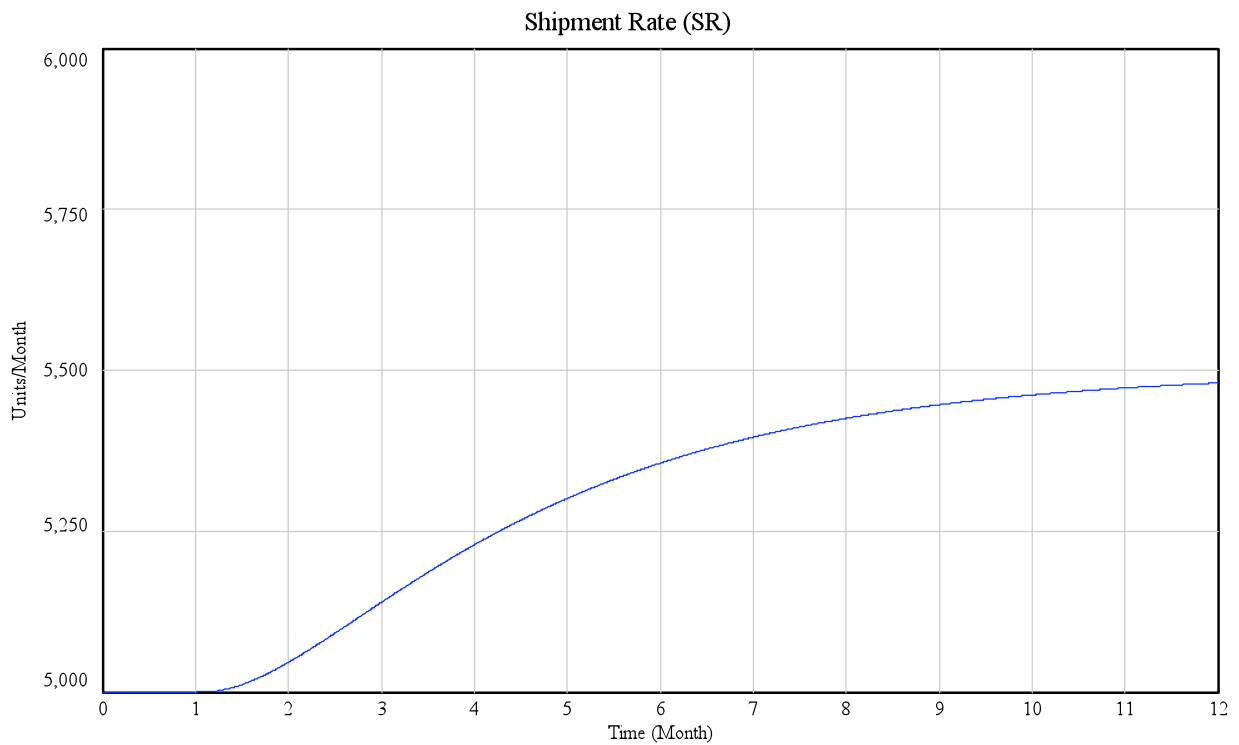
We validate this research effort by applying using some of the results from this research to solve the above problem of oscillatory behavior. The problem can be addressed in two ways, namely by redesigning the structure of information network, or by redesigning the policies controlling the adjustment rates of the system.

We first address the problem from a structural perspective. It was seen in Chapter 6, a structure consisting of the least number of information feedback loops led to the least overshoot in response to a step increase in demand. Further, such a structure also led to least amplification. The downside of such a structure was that it led to an increase in the settling time. Since the central problem, which led to this industrial case study, was that of oscillation, we recommend using an information feedback structure with a minimal set of loops. Hence we set the adjustment time of each of the three feedback loops from the stocks to be an arbitrary large value, so as to disable them. The effect of this is seen in Figure 9.6.



"Fabrication WIP (X1)" : solution approach 1 —————

Figure 9.6: Response of FWIP with solution approach 1



"Shipment Rate (SR)" : solution approach 1 —————

Figure 9.7: Response of Sales Rate with solution approach 1

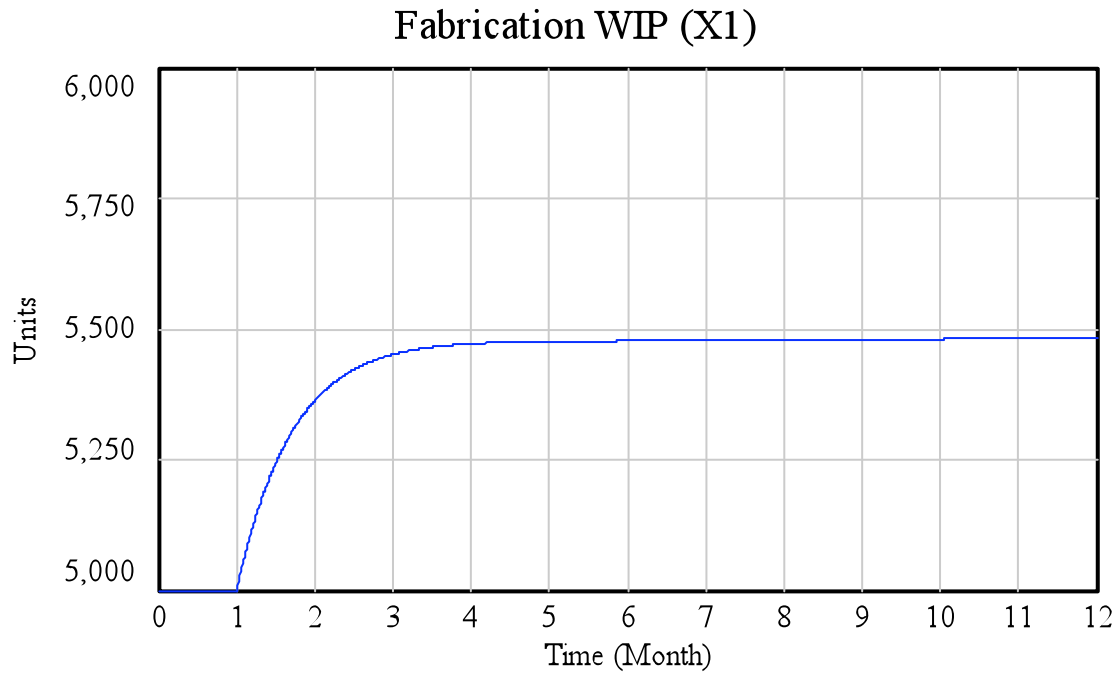
As expected, there is no oscillation when an information structure comprising of the minimal number of feedback loops is used to drive production. The downside of such an approach is evident when the sales rate is observed. We see that the sales rate requires a very long period to adjust to this change in demand.

We now approach the problem from a policy perspective. In this case, we enable all the feedback information feedback loops of the system and design the adjustment policy in such a manner that the oscillatory behavior is avoided.

The two primary policies proposed in Chapter 4 are as follows:

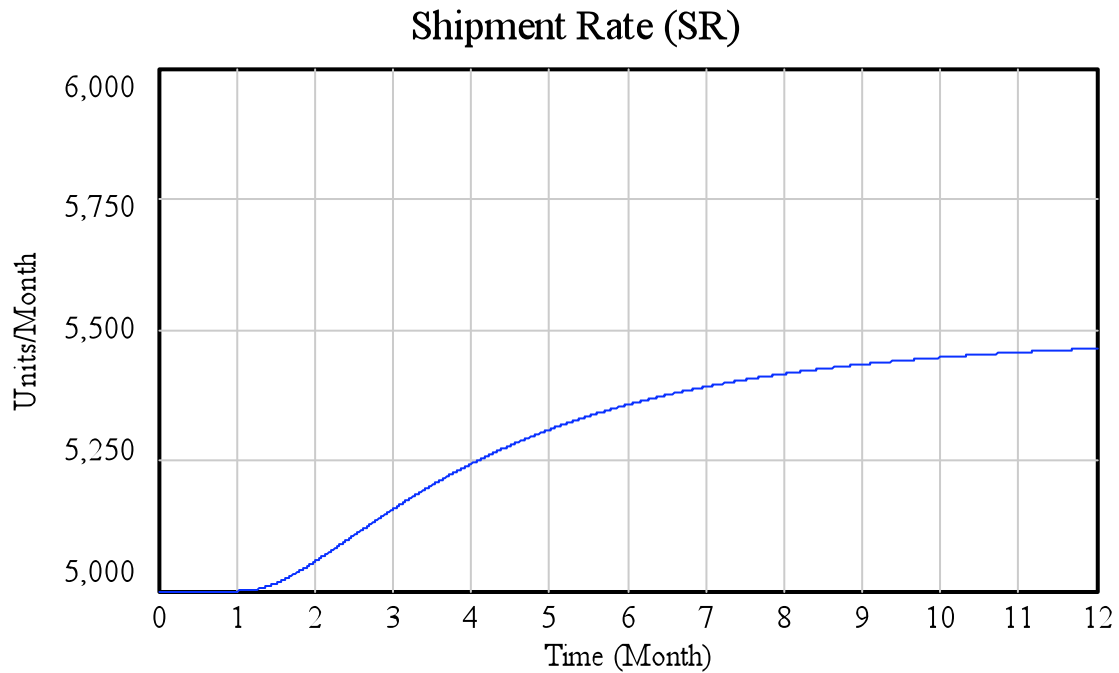
- i) Adopt a uniform adjustment policy for the entire supply chain, where the adjustment time is equal to the time constant associated with the terminal stock of the supply chain. In the context of this case study, the time constant associated with the terminal stock is the minimum order processing time. Hence, we set the adjustment time of each of the three stocks equal to the minimum order processing time.

Figure 9.8 and Figure 9.9 show the response when we set the adjustment times for each of the three adjustment loops equal to the lead time for the terminal stock in the supply chain, i.e. the minimum order processing time. We see that there is no overshoot or oscillation in the inventory level.



"Fabrication WIP (X1)" : solution approach 2 —————

Figure 9.8: Response of FWIP with proposed adjustment policy



"Shipment Rate (SR)" : solution approach 2 —————

Figure 9.9: Response of Sales Rate with proposed adjustment policy

ii) Let the ideal inventory level for a stock be a function of the lead-time associated with the stock and the sales rate. In this case study, we see that the ideal inventory for the finished inventory stock is calculated on the basis of the lead-time for that stock, and the expected sales rate. We propose calculating the ideal inventory level for the finished inventory stock as a product of the lead-time associated with the stock (minimum order processing time), and the actual sales rate. This proposed reorder policy causes the information feedback structure of the model to change, as shown in Figure 9.10.

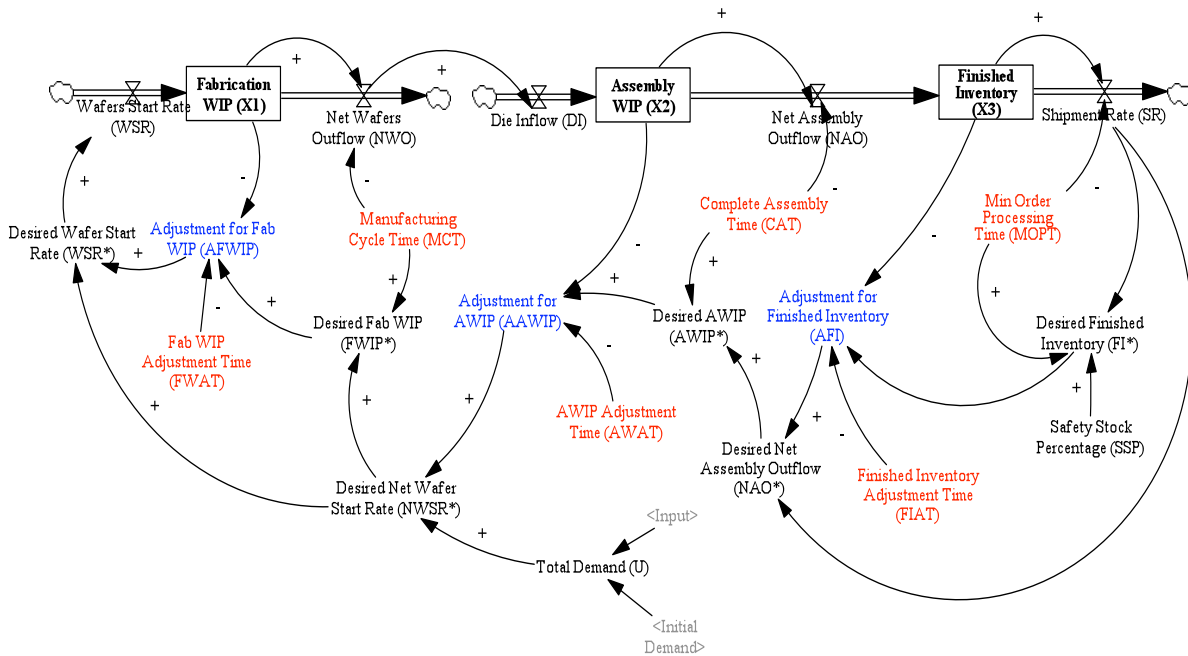


Figure 9.10: Ideal inventories determined by actual sales rate

We then simulate the system using the aggressive policy set, where the adjustment time for each of the inventory adjustment feedback loops is set equal to 0.5 of a month. We see below that this approach leads to no overshoot and amplification, as was seen in originally in Figure 9.2.

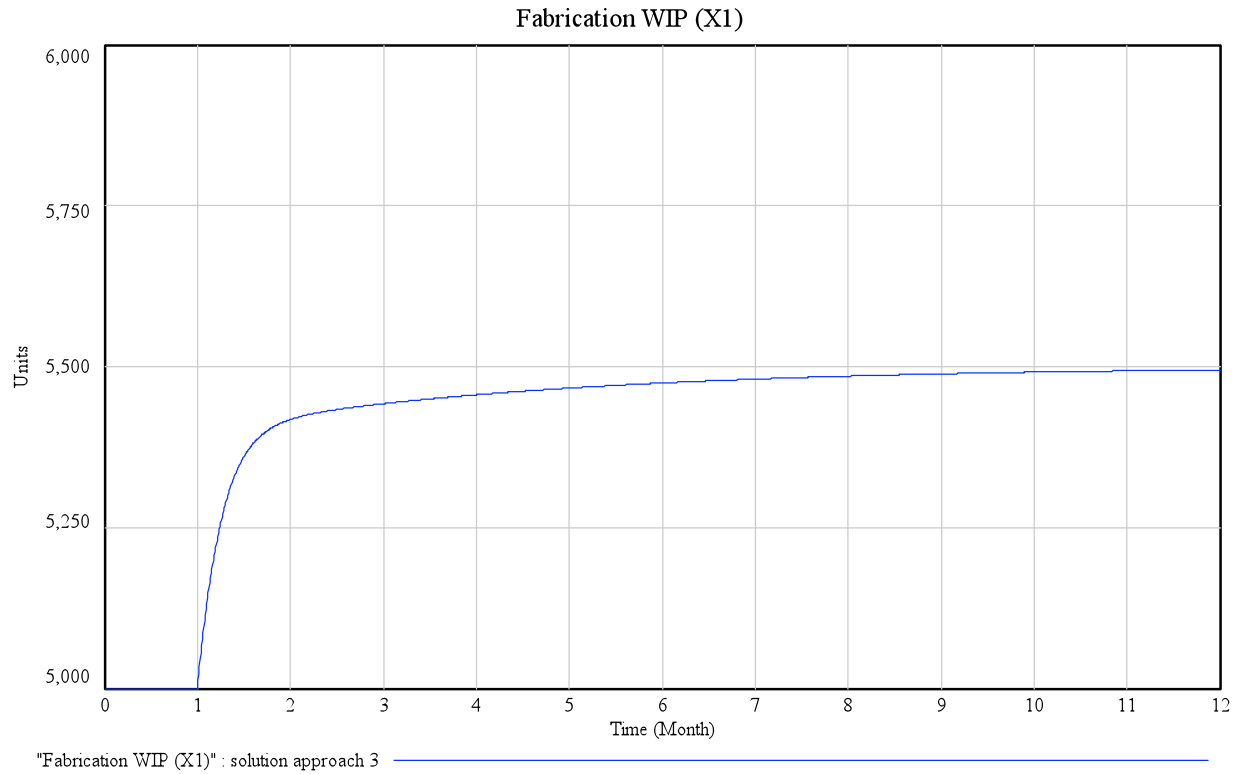


Figure 9.11: Response of FWIP with proposed reorder policy

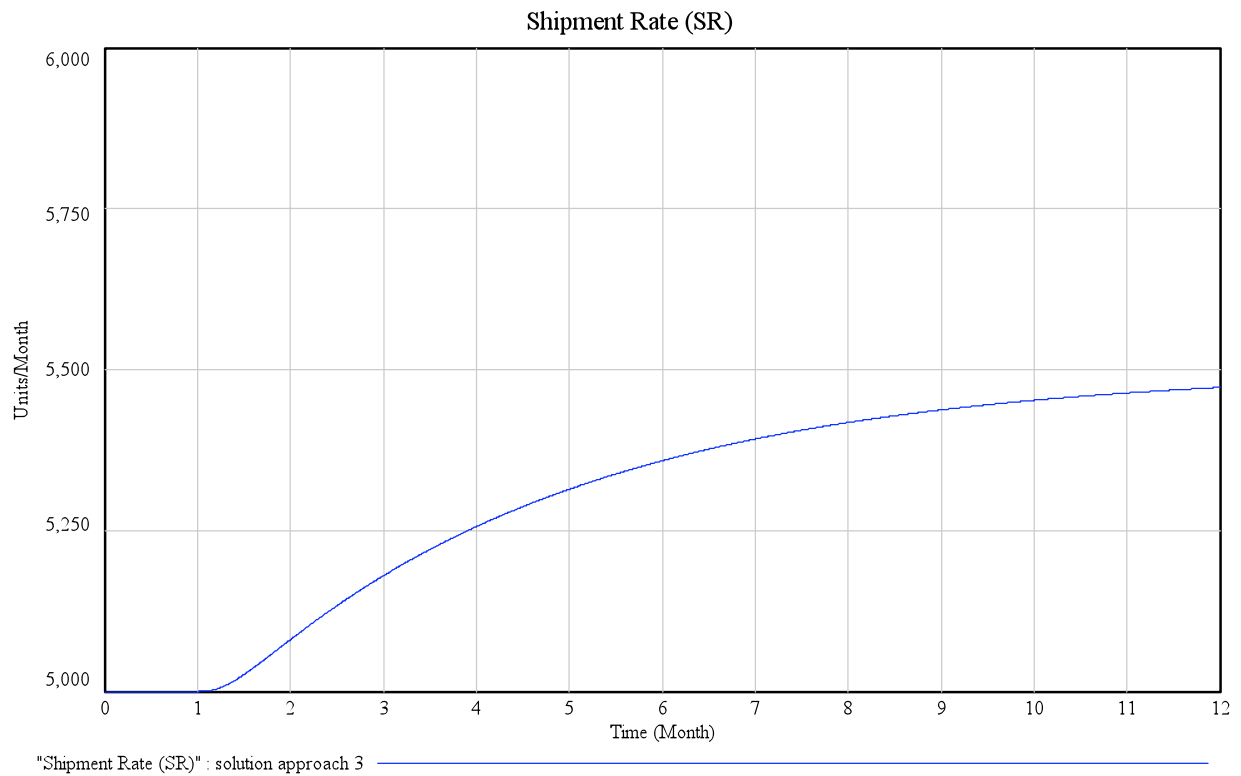


Figure 9.12: Response of Sales Rate with proposed reorder policy

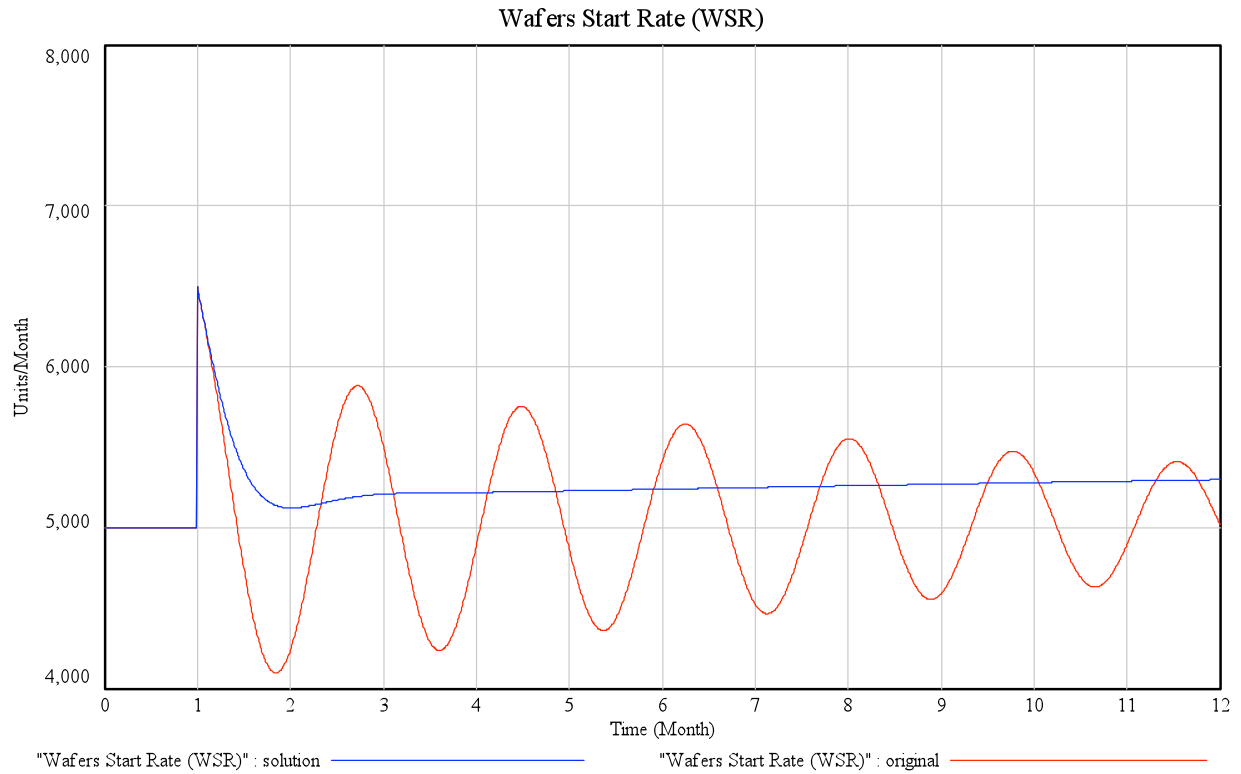


Figure 9.13: Comparison between original and solution response – Wafer Start Rate

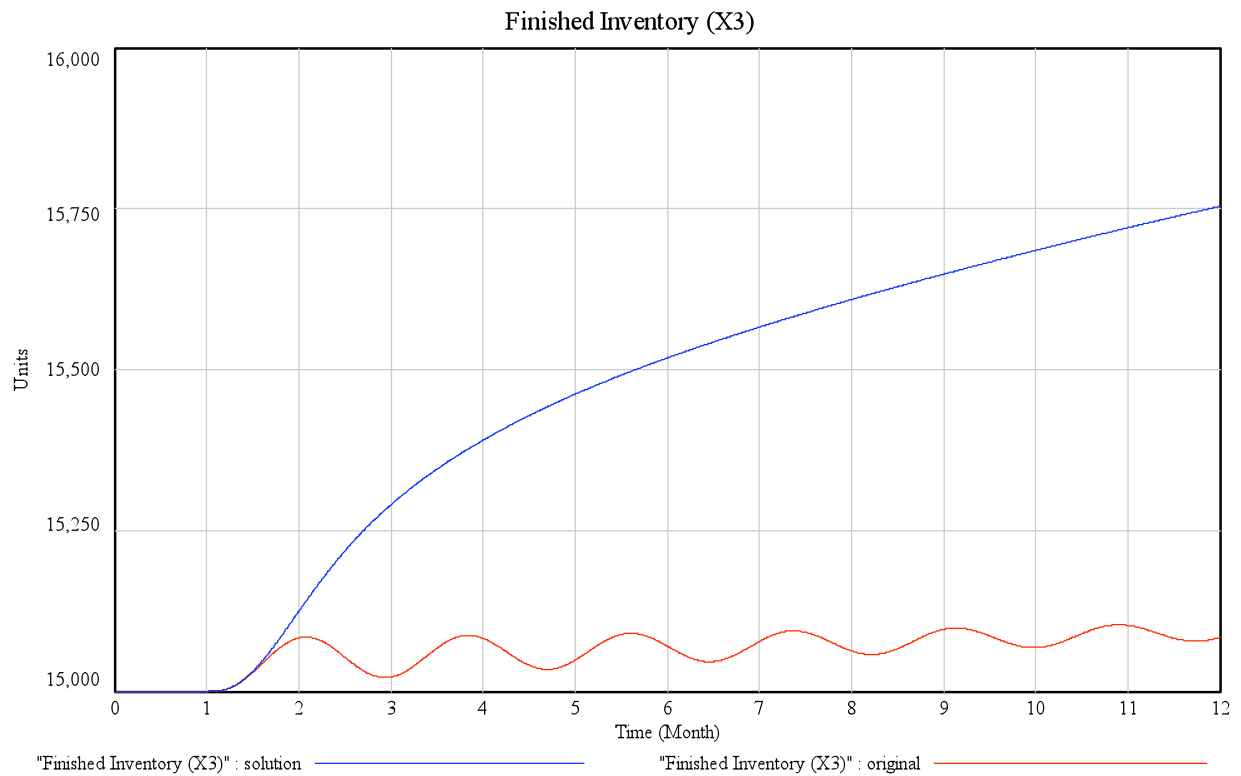


Figure 9.14: Comparison between original and solution response – Finished Inventory

9.4 Summary

The model used for this industrial case study is of a 3-stage hybrid production system, which is used by the Intel Corporation. The primary issue of concern for management was the oscillatory response of the production system. We apply the guidelines proposed in Chapter 4 and 6 to resolve this problem. We specifically propose three solution approaches for this problem:

- Information feedback structure: We show that by using a large set of information feedback loops for controlling production, we cause greater overshoot and oscillations in inventory levels. Hence, we propose using a smaller set of information feedback loops, in order to minimize the undesired oscillations in inventory.
- Adjustment policy: The choice of adjustment policy can cause a system to overshoot and oscillate. This is especially significant when management adopts an aggressive policy towards inventory adjustment. We propose setting a uniform adjustment policy along a supply chain, where the adjustment time equals the lead-time associated with the terminal stock of the supply chain. We see that by the adoption of this adjustment policy, the problem of overshoot and oscillations in inventory is resolved.
- Desired inventory level: The Intel Production system calculated the ideal inventory levels for stocks based on the expected sales rate. We show how the problem of oscillation is resolved by simply using the actual sales rate for calculation of ideal inventory levels, rather than basing the calculation on an expected value.

Chapter 10: Conclusions and Future Work

In this research, we study various issues related to the use of information networks in supply chains. System dynamics modeling forms a basis for this work as it provides a powerful framework to model the material and information flows in a supply chain, while also capturing the impact of policy on a supply chain's performance. Further, system dynamics provides the means to capture the dynamics of supply chains, which enabled this research to focus on the dynamic behavior of supply chains, as compared to the steady state behavior, which has been the primary focus of researchers in the domain of supply chain management.

Previous research efforts, which use system dynamics to analyze supply chains, have largely focused on the modeling of supply chain dynamics. These models form the basis for policy development, which is carried out through simulation. These policies are often specific to the model and not easy to apply in the context of other models for supply chains. We find that there is a lack of research literature addressing the design of systems, using system dynamics models. One of the motivations for this research was to provide a set of guidelines to aid supply chain professionals in designing information networks for the purpose of control.

We address the information network design problem from two perspectives. Firstly, we examine the problem from a policy perspective. We use the traditional simulation based approach to propose and validate adjustment and reorder policies for supply chains. We also provide a structured approach for policy design, which enables the user to design policies without any trial and error simulation. Secondly, we approach the problem from a structural perspective. We study

how the information feedback structure impacts the settling time and amplification of the supply chain. We also examine whether the use of the PID and feed-forward information structures can be leveraged to improve the response of supply chains.

The specific contributions of this research are as follows:

1. Traditionally the policy for inventory adjustment is static in nature. We propose a dynamic policy, which is responsive to sales and inventory conditions. Such a dynamic policy minimizes the possibility of a stock out in the case of a sudden increase in sales, or drop in finished inventory stock.
2. We propose a structured approach for policy design, which can be applied to any linear system dynamics model. The proposed approach can be used by a policy designer to determine what parameters values are needed to enable a supply chain to achieve a specified settling time without any inventory overshoot.
3. We propose a combinatorial approach to design the information feedback structure of a supply chain. We show that the structure, which uses the minimum set of information feedback, loops leads to the minimum amplification, but maximum settling time. On the other hand, the structure with the maximum set of feedback loops leads to the minimum settling time, but maximum amplification. Since it is preferable to have a supply chain with a small settling time and small amplification, we find that these are conflicting goals from standpoint of information feedback structure design. It is proposed that a composite index

comprising of a weighted sum of the amplification and settling time be used when using this combinatorial design approach.

4. We examine the possibility of using a PID information feedback for the control of supply chains and conclude that such a feedback structure can in fact increase the responsiveness of a supply chain. However, the “tuning” of these information networks is critical as they can increase amplification and in some cases, make the system unstable.

The other contribution of this work is to highlight the limitation of the existing structure of system dynamics models. Existing stock and flow control models only use proportional feedback of error to control the process. Hence, existing models only use a subset of the PID structure. By using integral and derivative feedback of error in addition to the proportional feedback of error, one can better model the dynamics of systems. Such a structure also provides a larger design space when designing the system.

5. Traditionally, system dynamics models use a feedback control structure to explain the dynamics of systems. We examine the possibility of using a combined feedback feed-forward structure for controlling supply chains. We conclude that such an information structure can enhance the response of supply chains in cases where there are disturbances whose impact on the supply chain is known. Such a combined structure can enable the supply chain to respond without the disturbance having any effect on the supply chain. Since feedback and feed-forward structures are complementary to each other, a business advantage can be gained by using a combined structure for controlling the system.

Forrester, in his seminal work on system dynamics mentions that the objective of a model is to, “aid in the understanding of an enterprise”, and “help establish desirable policies” (6). This philosophy of using models as tools to facilitate understanding and using experimentation to develop policies permeates the work of most researchers in the system dynamics community. The policies developed are functions of the underlying model structure, which is an abstraction of the system. Even though this approach is sufficient for organizations whose structure is static over time, it is unsatisfactory for systems whose structure itself is dynamic in nature. In present era, the collaboration of firms is dependent on the ever-changing economic climate. This leads to industrial structures, which evolve over time. Further, companies constantly re-structure their operations to increase efficiencies. Hence, the present approach of developing policies for static structures needs to be re-evaluated to increase the utility of such business models. Further, methodologies need to be developed, which enable management to evaluate different business structures. This would assist management in restructuring business processes to the increase the overall efficiency of the business system.

One of the founding principles of system dynamics is the notion that all systems use information feedback for control. More specifically, systems are modeled as entities that employ proportional feedback control. While, this assumption may be satisfactory for many systems, it may fail for others. Further, the assumption that systems only use proportional information feedback for control, limits the design space for a system. The incorporation of the PID feedback control structure, and feed-forward control structure can enable a modeler to better capture the dynamics of existing systems, as well as provide designers with greater options when designing the information control structure of a system. One of the possibilities for the future includes the

development of a canonical structure for system dynamics models. Such a structure would encompass all information structures and provide a firm basis for the modeling and design of systems. It would also assist management in systematically re-structuring the organization to increase the efficiency of the system.

We also find that there are very few researchers in the domain of system dynamics domain, who are developing new analysis tools, which can be applied to any system dynamics model. A large proportion of the current work focuses on extracting “knowledge” from models, rather than on the development of approaches, which enable the extraction of knowledge. This is an avenue for future work.

We mention before that the primary concern of researchers who use system dynamics to model and analyze supply chains is that of policy development. The policy development problem in system dynamics is analogous to the “tuning” problem in control engineering. While, an “online” approach, which uses experimentation, is used for the tuning of many controllers, the literature is rich with methodologies for the “offline” tuning of controllers. The Ziegler – Nichols approach for tuning PID controllers is one such example, as discussed in Chapter 7. We propose an approach for tuning the gain parameters of a system dynamics model in Chapter 5 as well. One of the impediments in the development of such approaches using system dynamics is lack of a canonical structure, which facilitates the application of such approaches to any model.

To conclude, we feel that system dynamics provides a powerful framework for the modeling, analysis and design of systems. However, presently, the underlying structure of system dynamics

models is limited due to the assumptions of Forrester's seminal work (6). Further, the lack of a canonical structure, which encompasses all possibilities, limits the use of effectiveness of modeling and analysis using system dynamics. We also find that the use of such models is presently restricted to policy development. The process of policy development can be refined into more structured approaches. Further, the system dynamics provides a tool, which can be used to design, and subsequently re-design systems in a structured manner.

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Appendix A – Formulae for Supply Chain model

(01) "Retailer Inventory to Sales Ratio (RISR)"= "Retailer Inventory (X3)"/"Customer Demand (U)"

Units: Day

Average time that a finished inventory item spends on a retailer's shelf

(02) Change in Pink Noise = (White Noise - Pink Noise)/Noise Correlation Time

Units: 1/Day

Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input.

(03) "Customer Demand (U)"= Initial Demand*Input

Units: Units/Day

Customer demand in the market

(04) "DCI Adjustment Rate (DCIAR)"= (Desired DCI-"Distribution Center Inventory (X2)"/"DCI Adjustment Time (DCIAT)"

Units: Units/Day

Adjustment rate for distribution center inventory

(05) "DCI Adjustment Time (DCIAT)"= 0.5

Units: Day

Time to correct discrepancy in distribution center inventory

(06) $\text{Desired DCI} = \text{Customer Demand (U)} * \text{Distribution Time (DT)}$

Units: Units

Desired distribution center inventory level

(07) $\text{Desired FI} = \text{Customer Demand (U)} * \text{Manufacturing Cycle Time (MCT)}$

Units: Units

Desired factory inventory level

(08) $\text{"Desired Production Start Rate (DPSR)} = \text{Sales Rate (SR)} + \text{FI Adjustment Rate (FIAR)} + \text{RI Adjustment Rate (RIAR)} + \text{DCI Adjustment Rate (DCIAR)}$

Units: Units/Day

Desired rate at which production should begin

(09) $\text{Desired RI} = \text{Customer Demand (U)} * (\text{Distribution Time (DT)} + \text{Manufacturing Cycle Time (MCT)})$

Units: Units

Desired retailer inventory level

(10) $\text{"Distribution Center Inventory (X2)} = \text{INTEG (Production Completion Rate - Distribution Rate, Desired DCI)}$

Units: Units

Number of units in distribution center inventory

(11) $\text{Distribution Rate} = \frac{\text{Distribution Center Inventory (X2)}}{\text{Distribution Time (DT)}}$

Units: Units/Day

Rate at which the goods leave from the distribution center for the retailer.

(12) $\text{"Distribution Time (DT)" = 1}$

Units: Day

Time to distribute one unit

(13) $\text{"Factory Inventory (X1)" = INTEG ("Production Start Rate (PSR)" - Production Completion Rate, Desired FI)}$

Units: Units

Number of units in factory inventory

(14) $\text{"FI Adjustment Rate (FIAR)" = (Desired FI - "Factory Inventory (X1)") / "FI Adjustment Time (FIAT)"}$

Units: Units/Day

Adjustment rate for factory inventory

(15) $\text{"FI Adjustment Time (FIAT)" = 0.5}$

Units: Day

Time to correct discrepancy in factory inventory

(16) FINAL TIME = 30

Units: Day

The final time for the simulation.

(17) Initial Demand= 1000

Units: Units/Day

Initial value of the desired stock.

(18) INITIAL TIME = 0

Units: Day

The initial time for the simulation.

(19) Input= 1+STEP(Step Height, Step Time)+ (Pulse Quantity/TIME STEP)*PULSE(Pulse Time, TIME STEP)+ RAMP(Ramp Slope, Ramp Start Time, Ramp End Time)+ Sine Amplitude*SIN(2*3.14159*Time/Sine Period)+ STEP(1,Noise Start Time)*Pink Noise

Units: Dimensionless

Input is a dimensionless variable, which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise.

(20) "Manufacturing Cycle Time (MCT)"= 2

Units: Day

Time to complete manufacturing one unit

(21) Noise Correlation Time = 4

Units: Day

The correlation time constant for Pink Noise.

(22) Noise Standard Deviation= 0

Units: Dimensionless

The standard deviation of the pink noise process.

(23) Noise Start Time= 1

Units: Day

Start time for the random input.

(24) Pink Noise = INTEG (Change in Pink Noise, 0)

Units: Dimensionless

Pink Noise is first-order auto-correlated noise. Pink noise provides a realistic noise input to models in which the next random shock depends in part on the previous shocks. The user can specify the correlation time. The mean is 0 and the standard deviation is specified by the user.

(25) Production Completion Rate= "Factory Inventory (X1)"/"Manufacturing Cycle Time (MCT)"

Units: Units/Day

Rate at which production is completed in the factory

(26) "Production Start Rate (PSR)"= MAX ("Desired Production Start Rate (DPSR)", 0)

Units: Units/Day

Rate at which production is started in the factory.

(27) Pulse Quantity=0

Units: Dimensionless*Day

The quantity to be injected to customer orders, as a fraction of the base value of Input.

For example, to pulse in a quantity equal to 50% of the current value of input, set to .50.

(28) Pulse Time= 1

Units: Day

Time at which the pulse in Input occurs.

(29) Ramp End Time=1e+009

Units: Day

End time for the ramp input.

(30) Ramp Slope=0

Units: 1/Day

Slope of the ramp input, as a fraction of the base value (per week).

(31) Ramp Start Time= 1

Units: Day

Start time for the ramp input.

(32) "Retailer Inventory (X3)"= INTEG (Distribution Rate-"Sales Rate (SR)", Desired RI)

Units: Units

Number of units that are stored by the retailers.

(33) "RI Adjustment Rate (RIAR)"= (Desired RI-"Retailer Inventory (X3)"/"RI Adjustment Time (RIAT)"

Units: Units/Day

Adjustment rate for retailer inventory

(34) "RI Adjustment Time (RIAT)"= 0.5

Units: Day

Time to correct discrepancy in retailer inventory

(35) "Sales Rate (SR)"= "Customer Demand (U)"

Units: Units/Day

Rate at which goods are sold

(36) SAVEPER = TIME STEP

Units: Day

The frequency with which output is stored.

(37) Sine Amplitude=0

Units: Dimensionless

Amplitude of sine wave in customer orders (fraction of mean).

(38) Sine Period=50

Units: Day

Period of sine wave in customer demand. Set initially to 50 weeks (1 year).

(39) Step Height = 0.1

Units: Dimensionless

Height of step input to customer orders, as fraction of initial value.

(40) Step Time= 1

Units: Day

Time for the step input.

(41) TIME STEP = 0.0078125

Units: Day

The time step for the simulation.

(42) White Noise = Noise Standard Deviation*((24*Noise Correlation Time/TIME STEP)
^0.5*(RANDOM 0 1() - 0.5))

Units: Dimensionless

White noise input to the pink noise process.

Appendix B – Simulation results for Chapter 6

SIMULATION WITH STEP INPUT

1) Loop 1

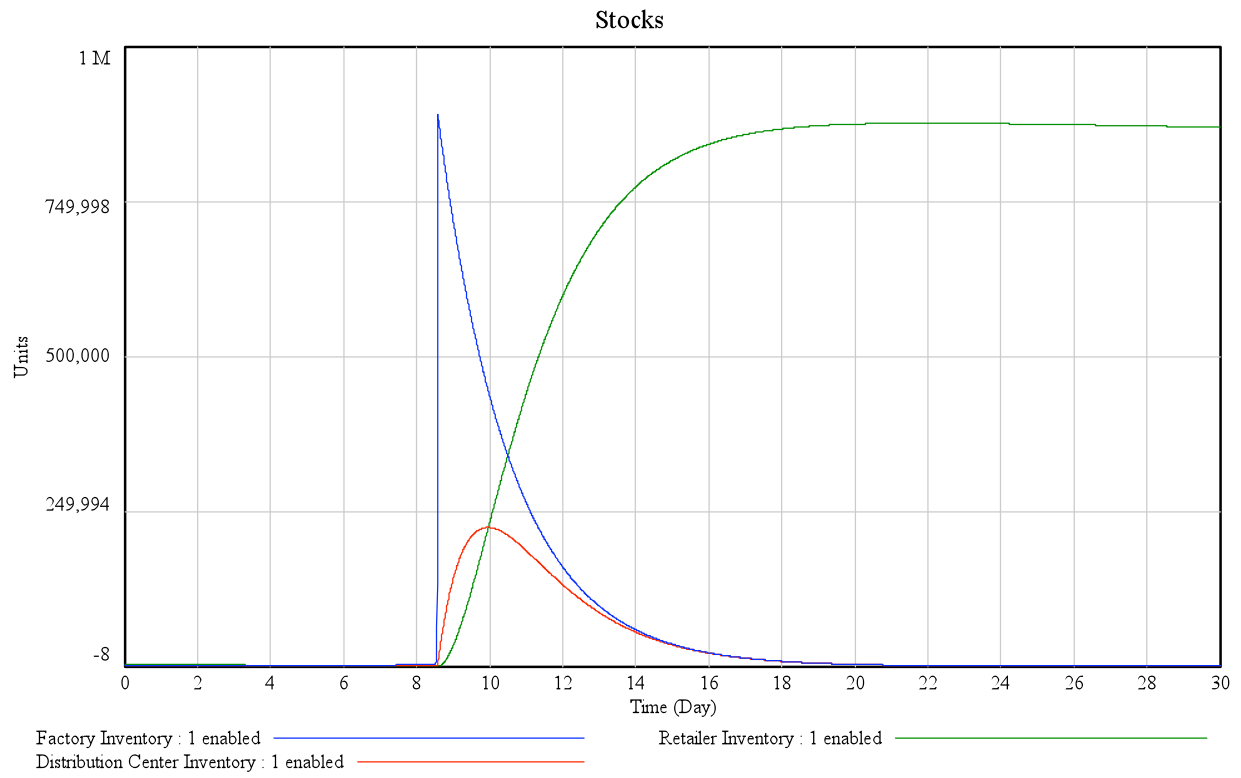


Figure B-1: Step Response for Loop 1

2) Loop 2

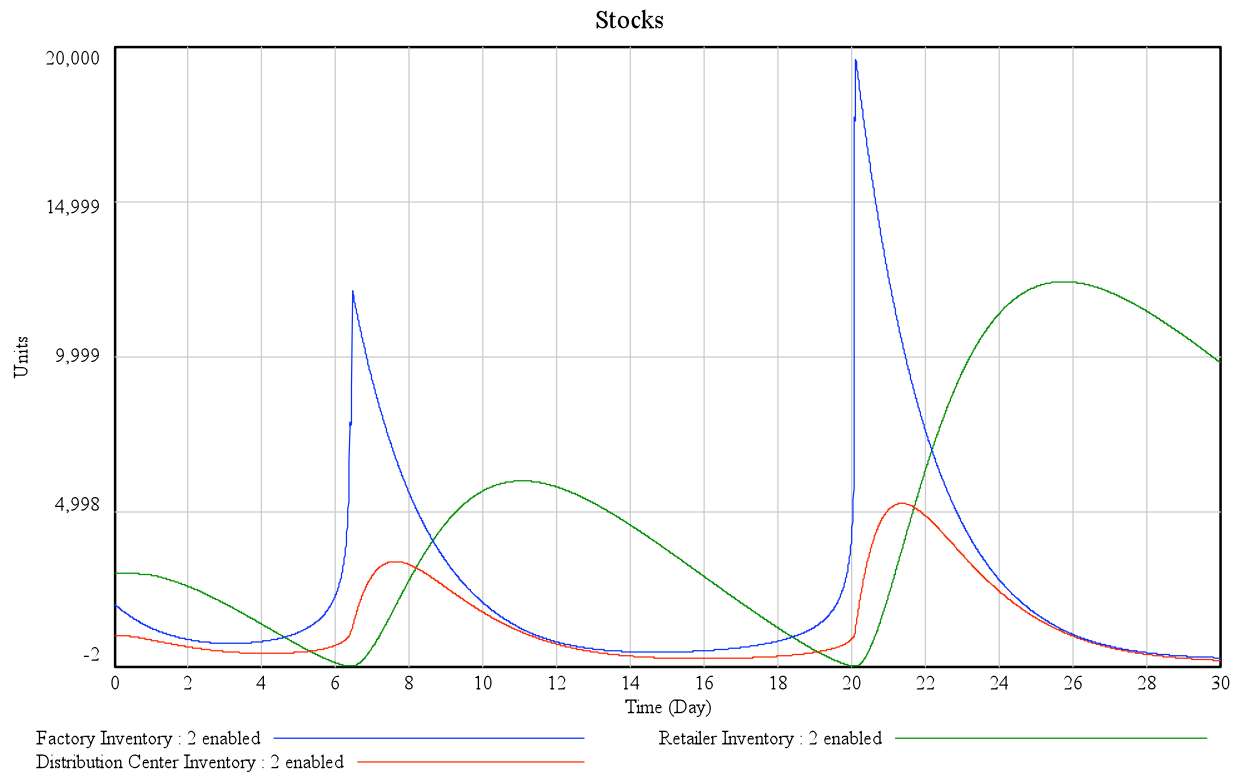


Figure B-2: Step Response for Loop 2

3) Loop 3

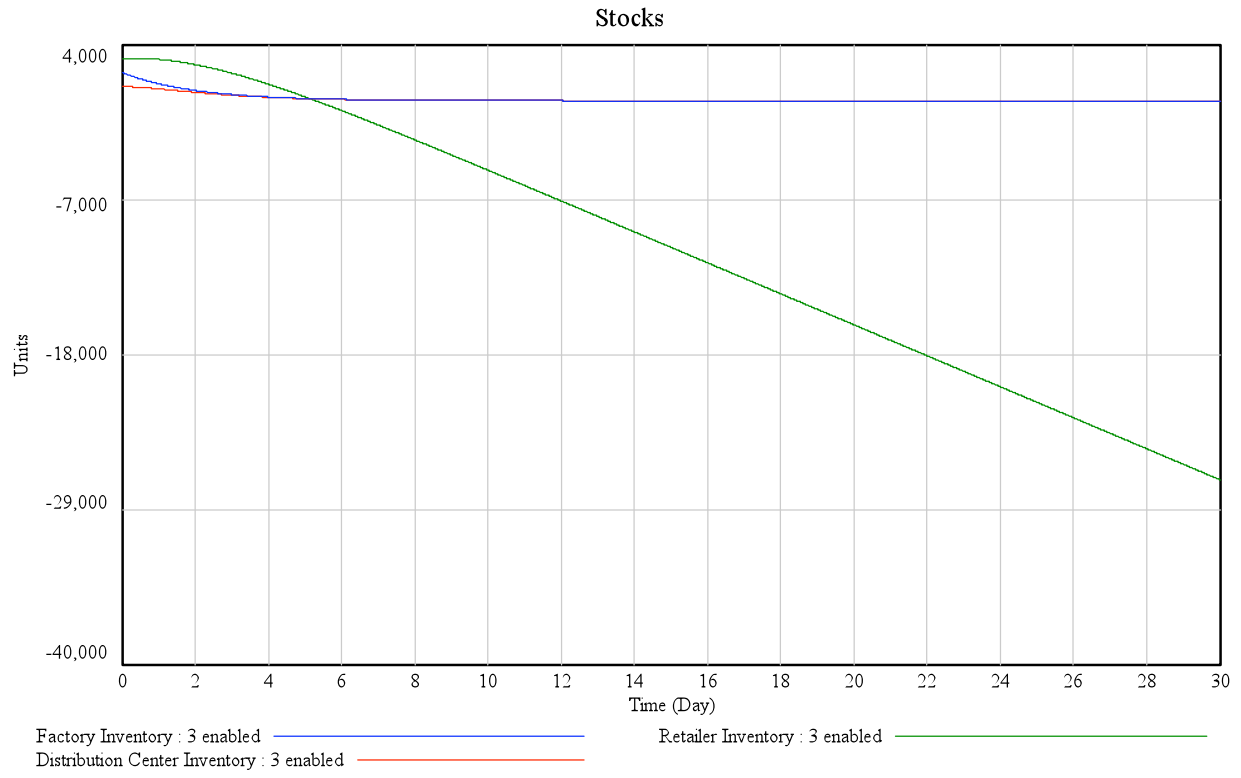


Figure B-3: Step Response for Loop 3

4) Loop 4

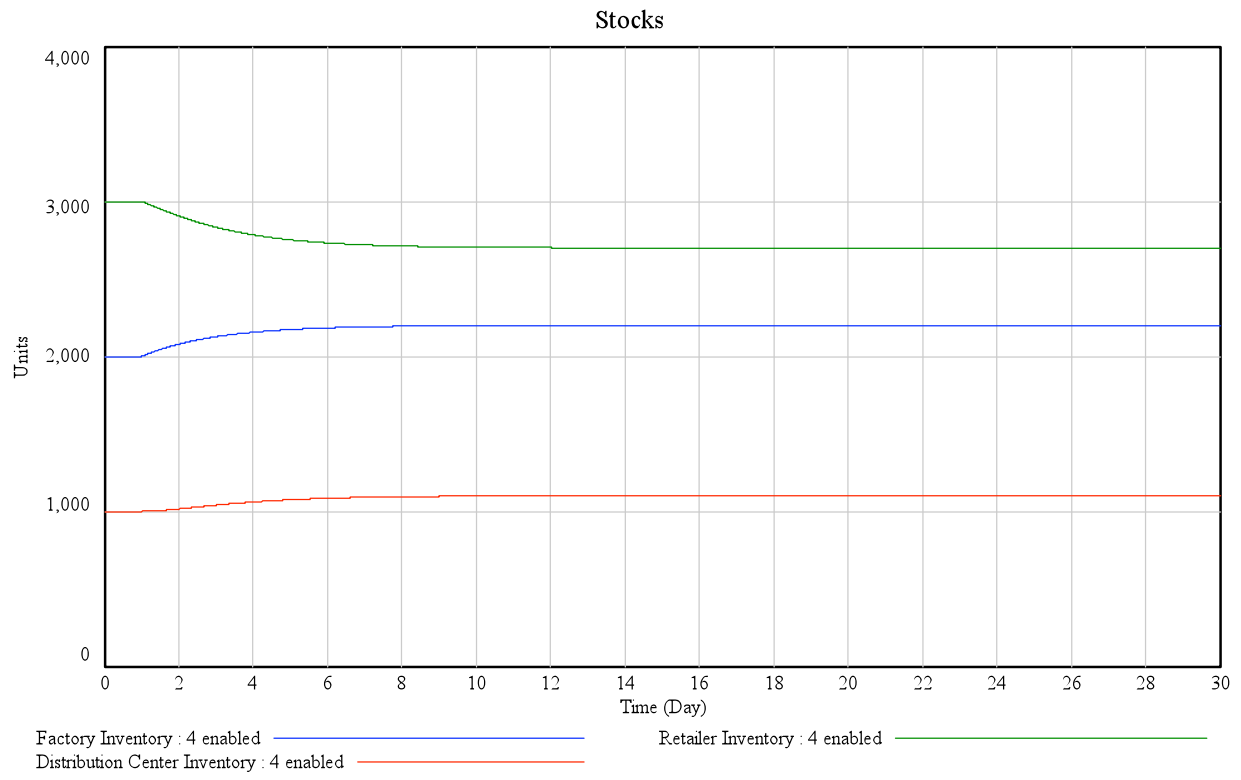


Figure B-4: Step Response for Loop 4

5) Loop 1 and 2

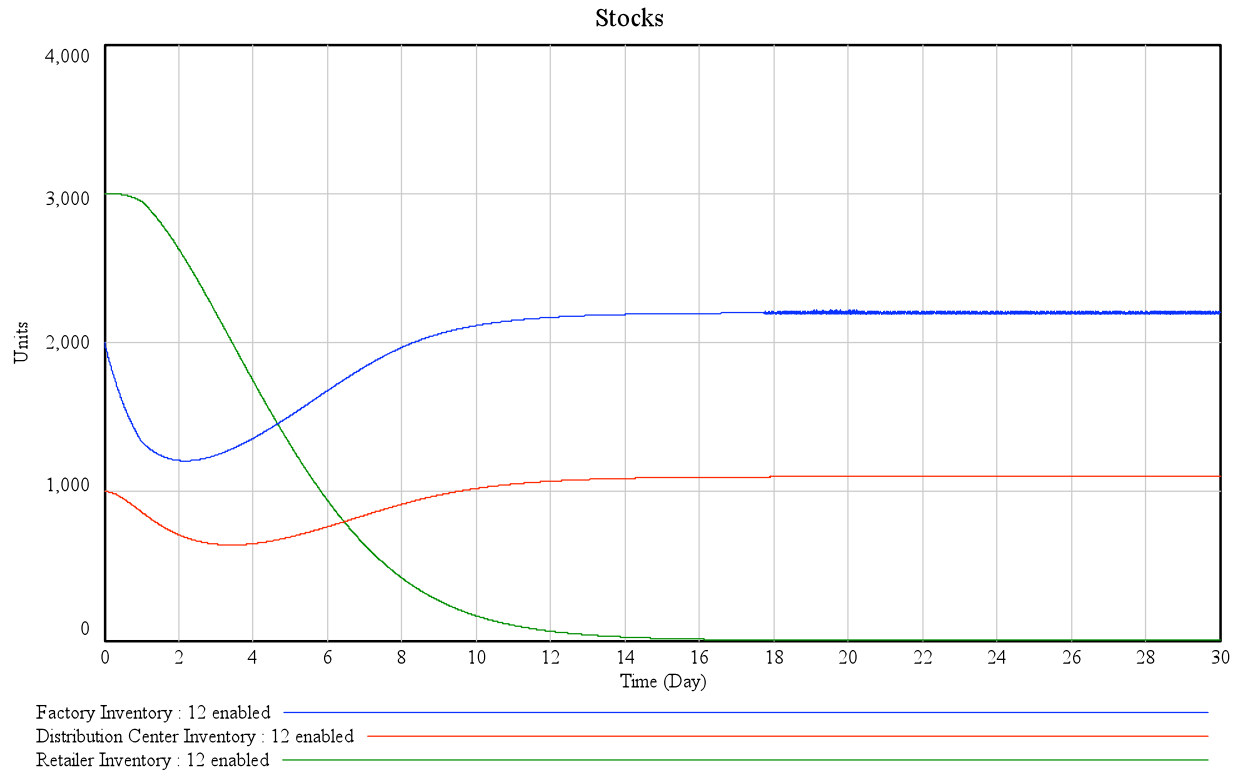


Figure B-5: Step Response for Loop 1 and 2

6) Loop 1 and 3

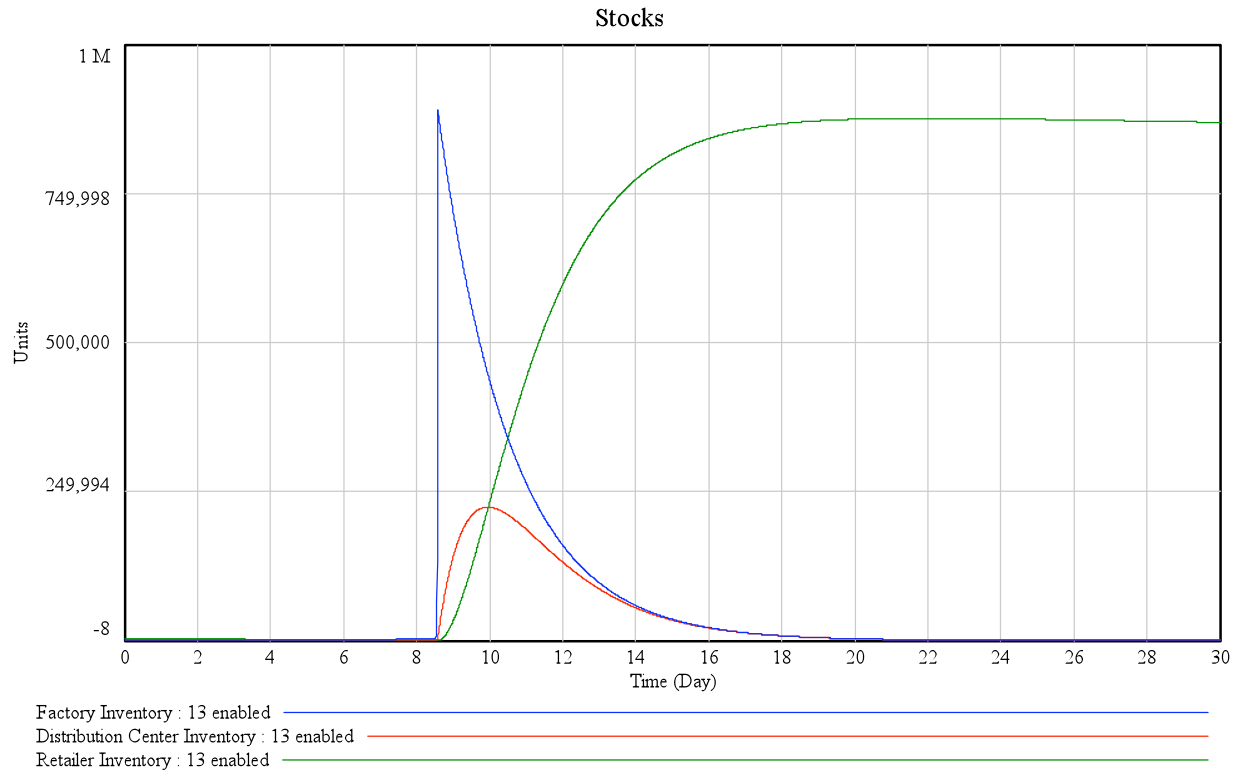


Figure B-6: Step Response for Loop 1 and 3

7) Loop 1 and 4

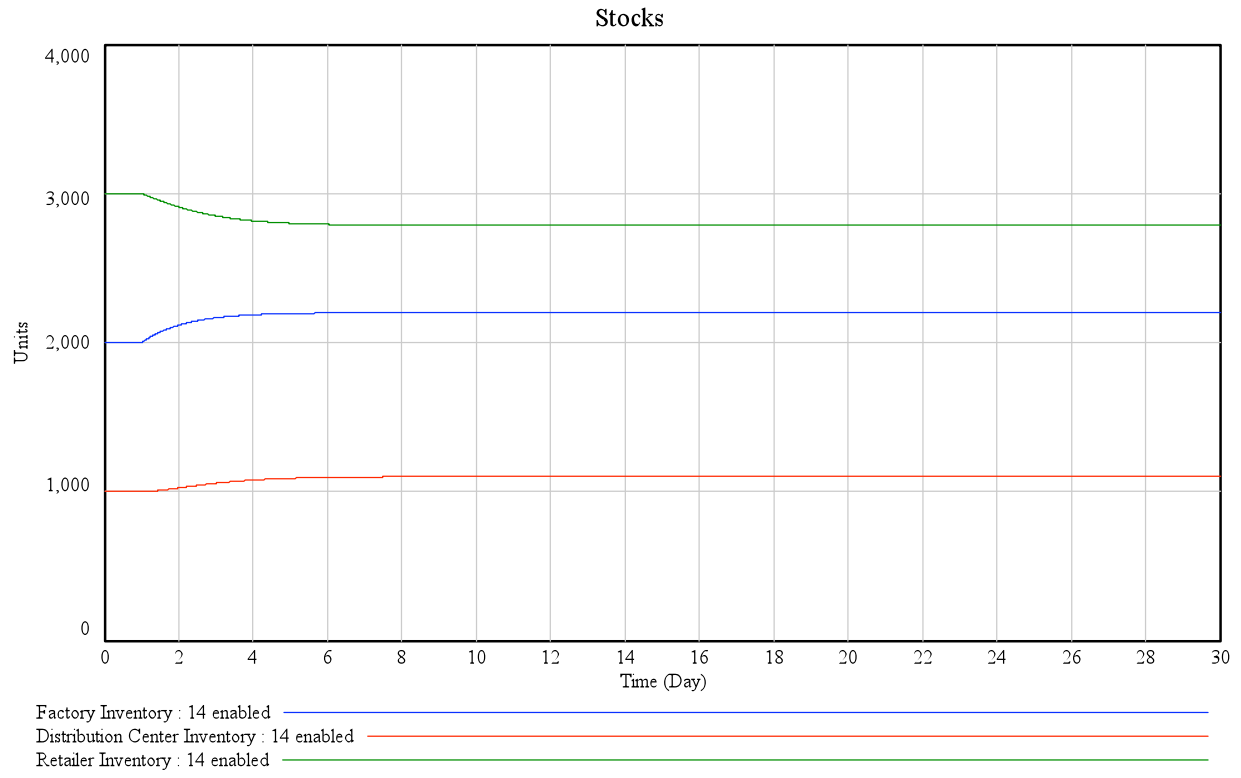


Figure B-7: Step Response for Loop 1 and 4

8) Loop 2 and 3

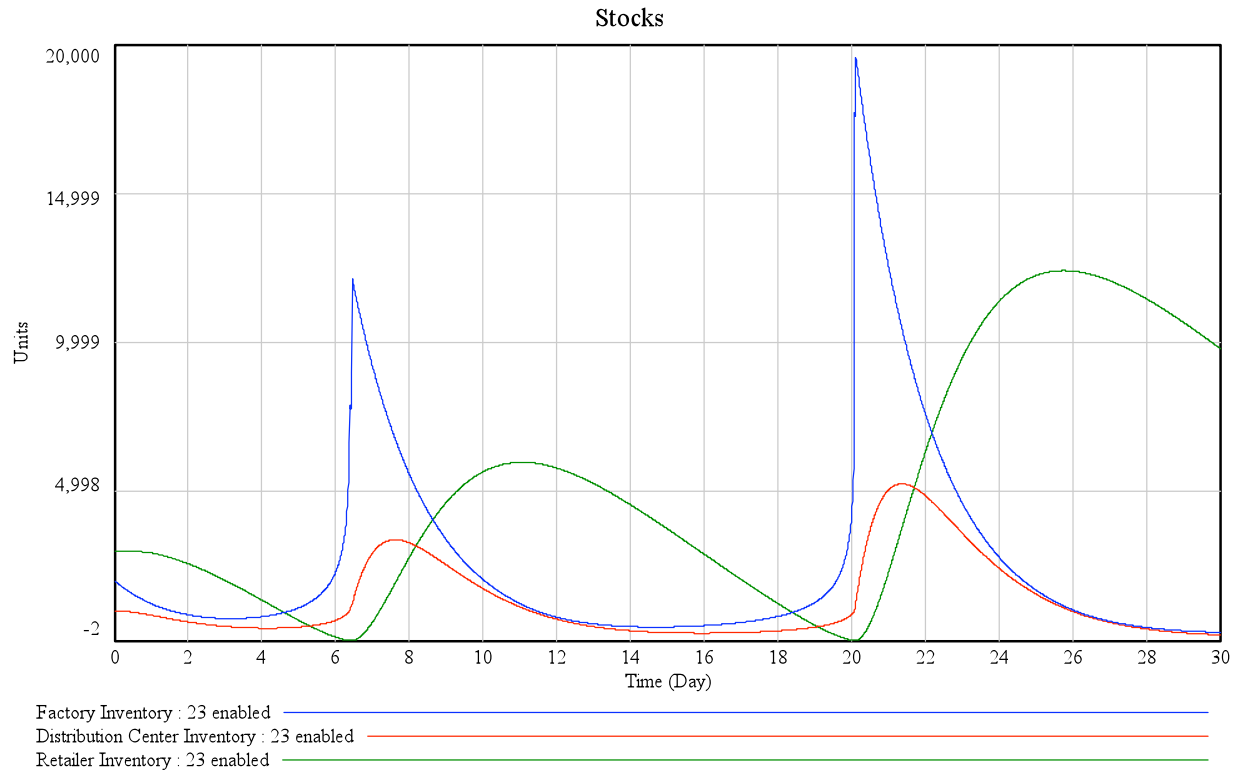


Figure B-8: Step Response for Loop 2 and 3

9) Loop 2 and 4

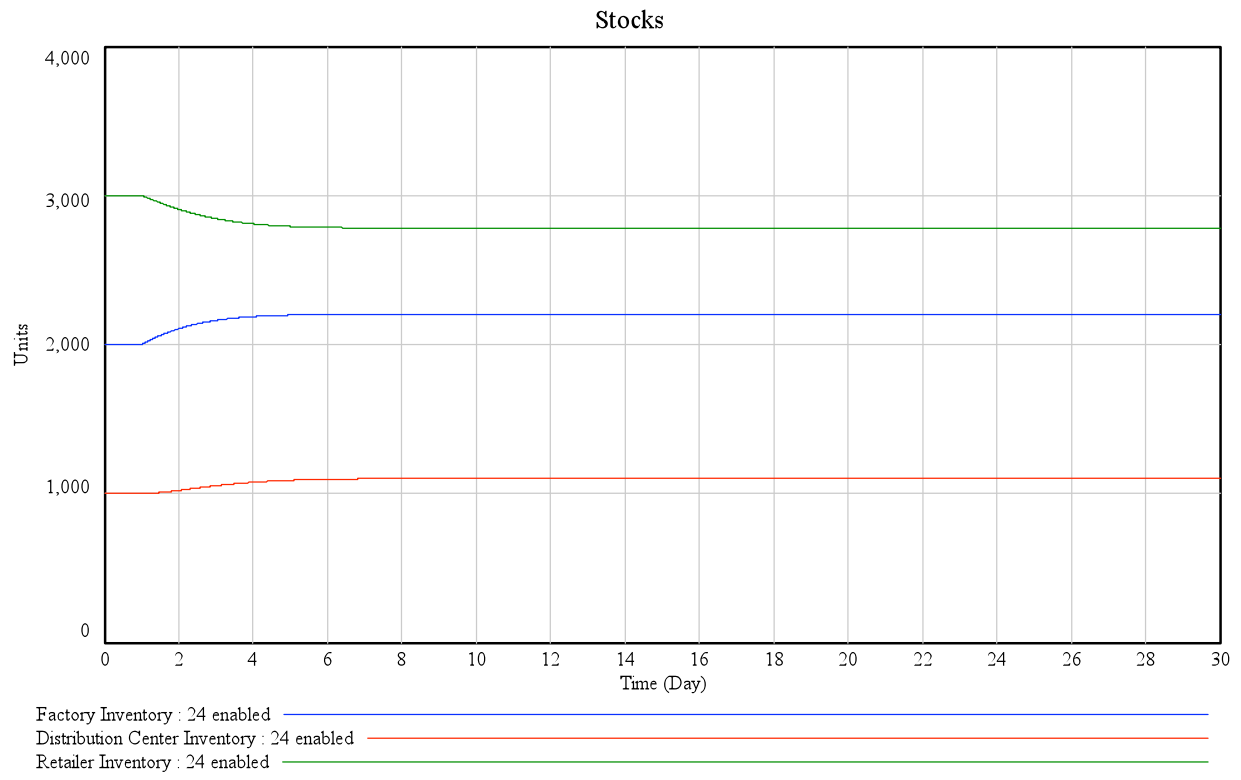


Figure B-9: Step Response for Loop 2 and 4

10) Loop 3 and 4

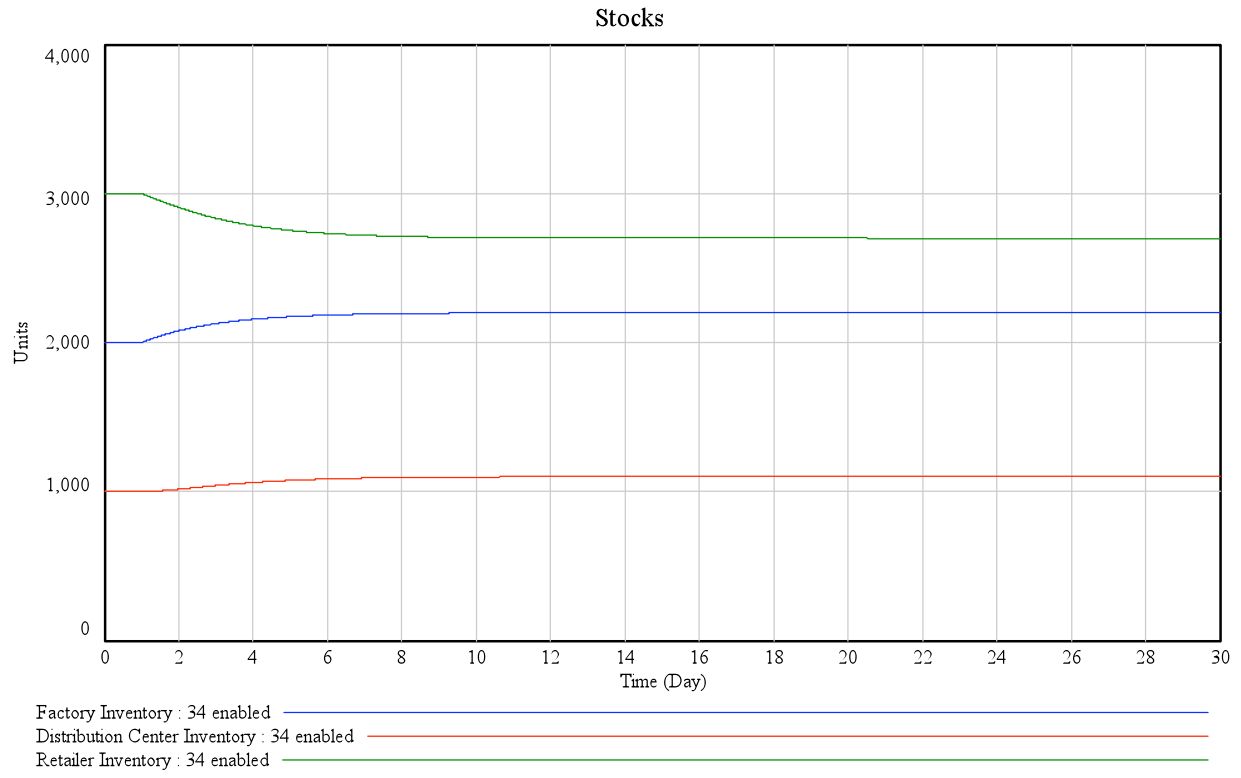


Figure B-10: Step Response for Loop 3 and 4

11) Loop 1, 2 and 3

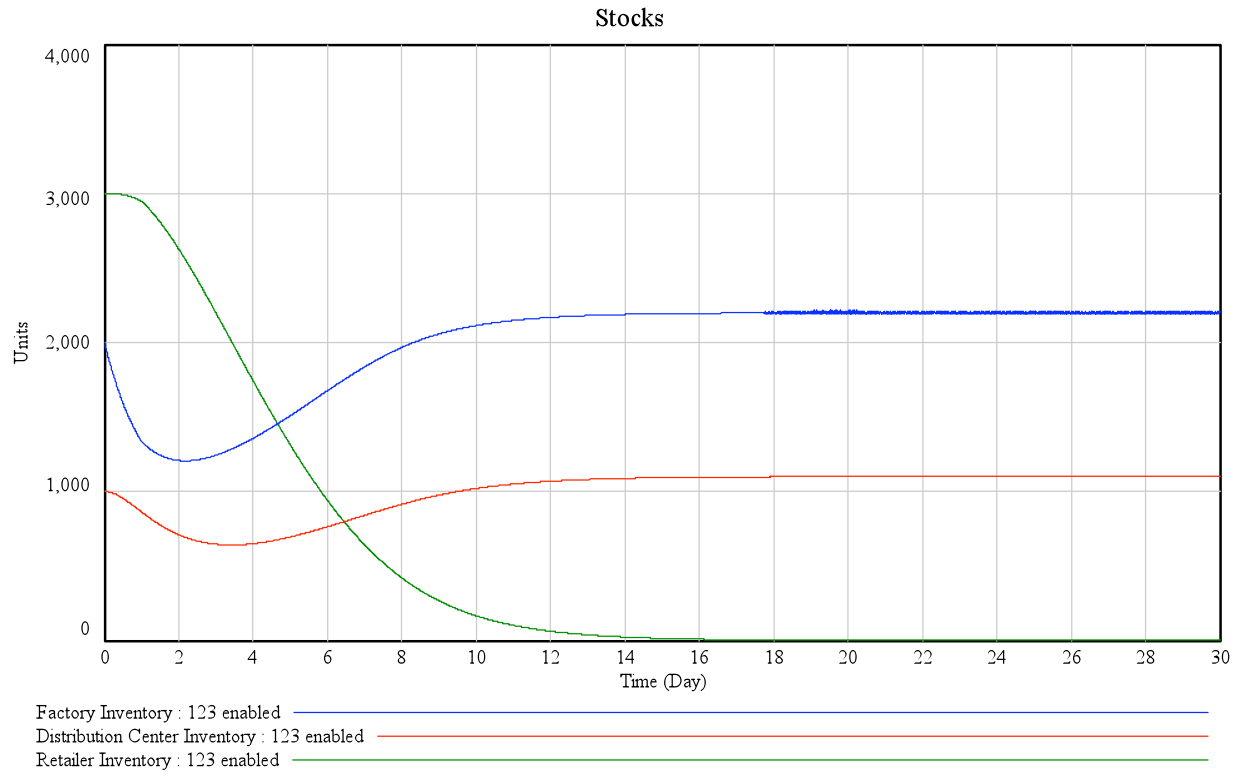


Figure B-11: Step Response for Loop 1,2 and 3

12) Loop 1, 2 and 4

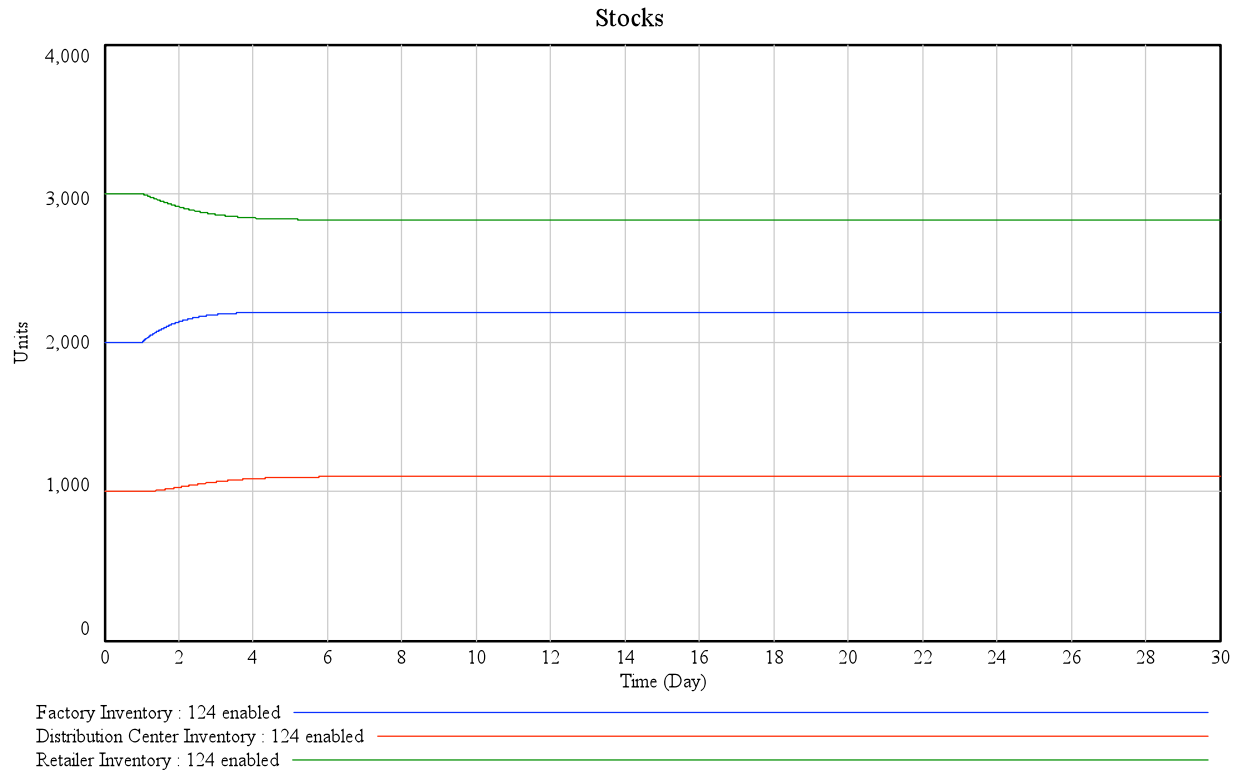


Figure B-12: Step Response for Loop 1,2 and 4

13) Loop 1, 3 and 4

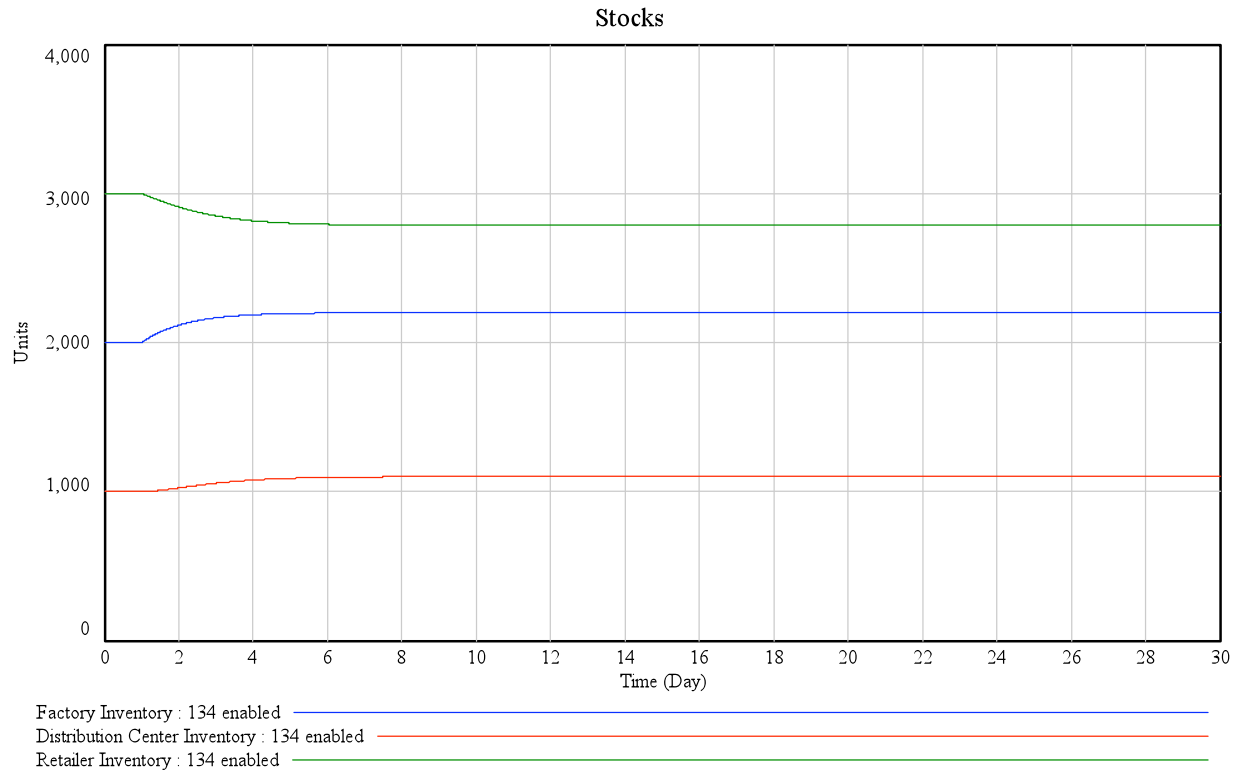


Figure B-13: Step Response for Loop 1,3 and 4

14) Loop 2, 3 and 4

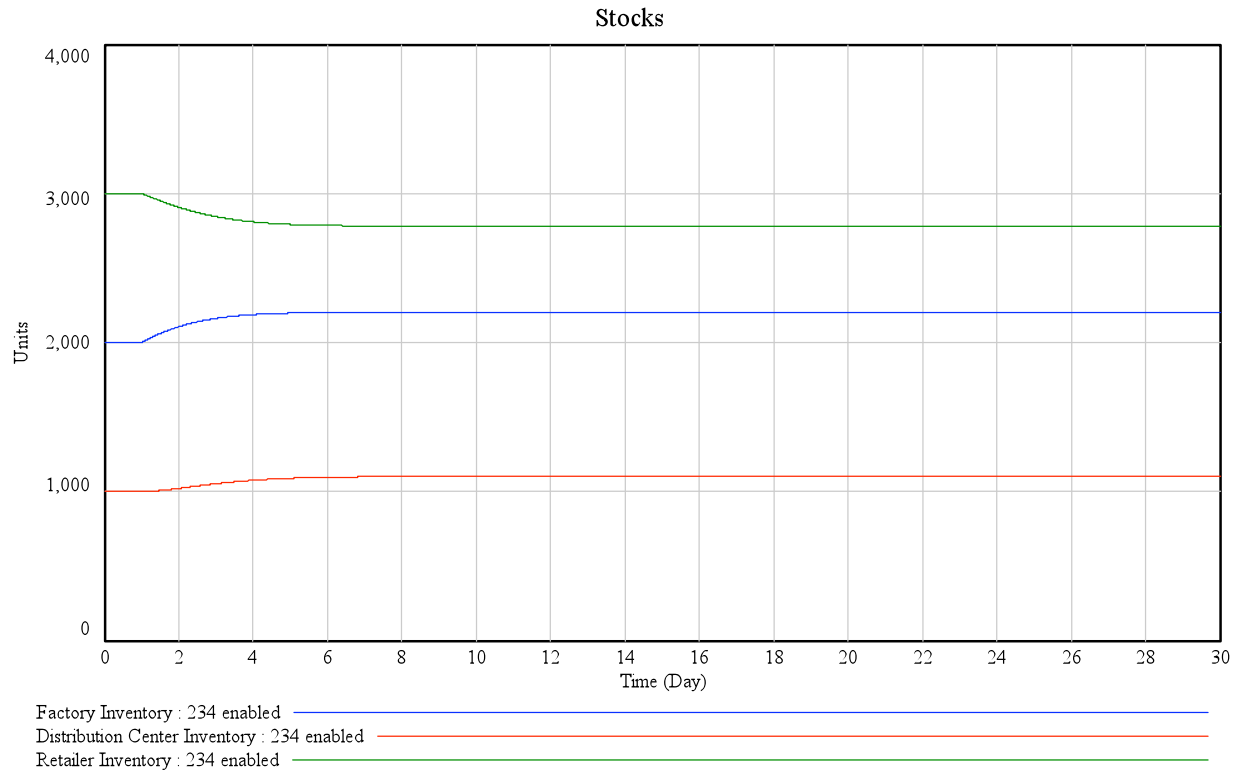


Figure B-14: Step Response for Loop 2,3 and 4

15) Loop 1, 2, 3 and 4

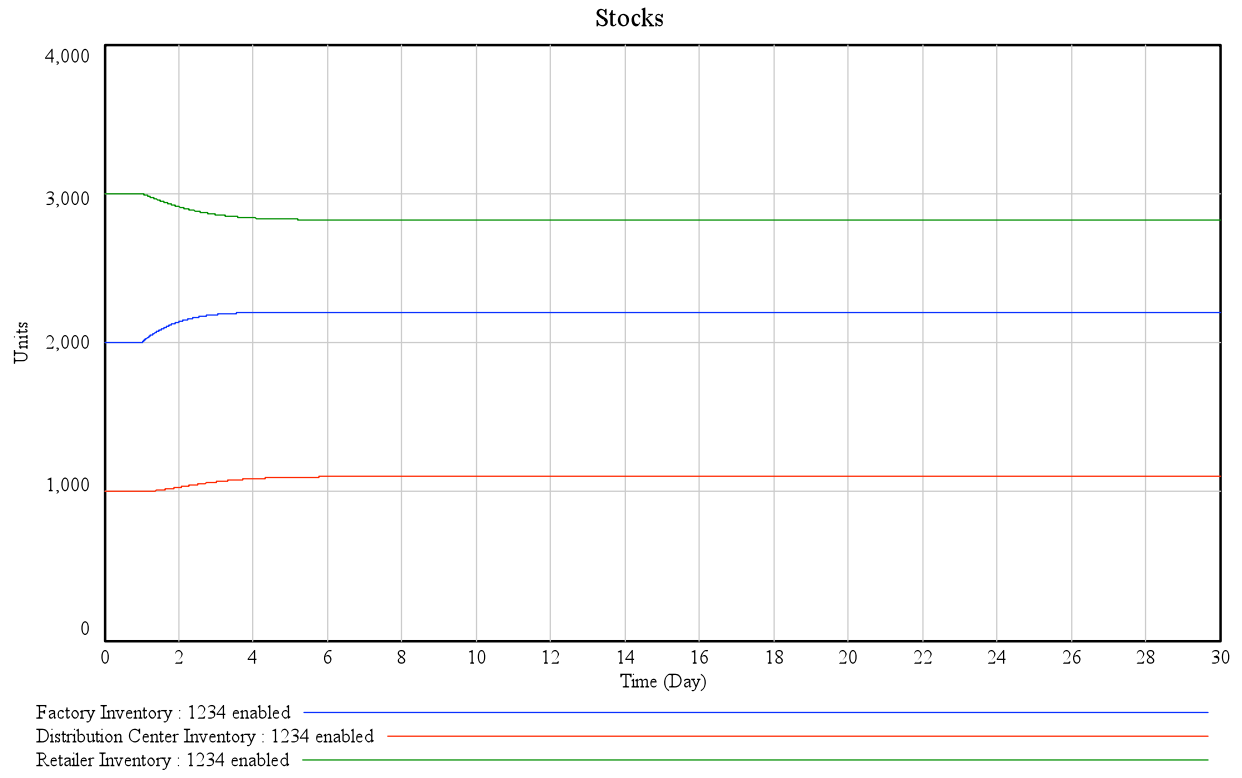


Figure B-15: Step Response for Loop 1,2,3 and 4

SIMULATION WITH NOISE INPUT

1) Loop 1

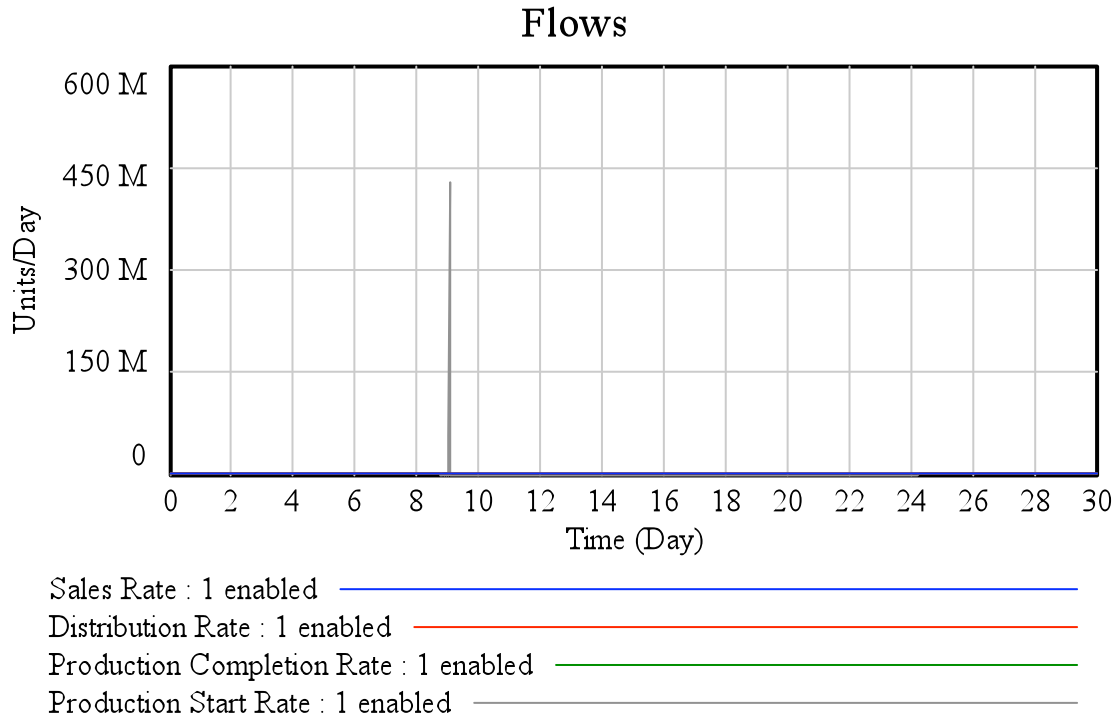
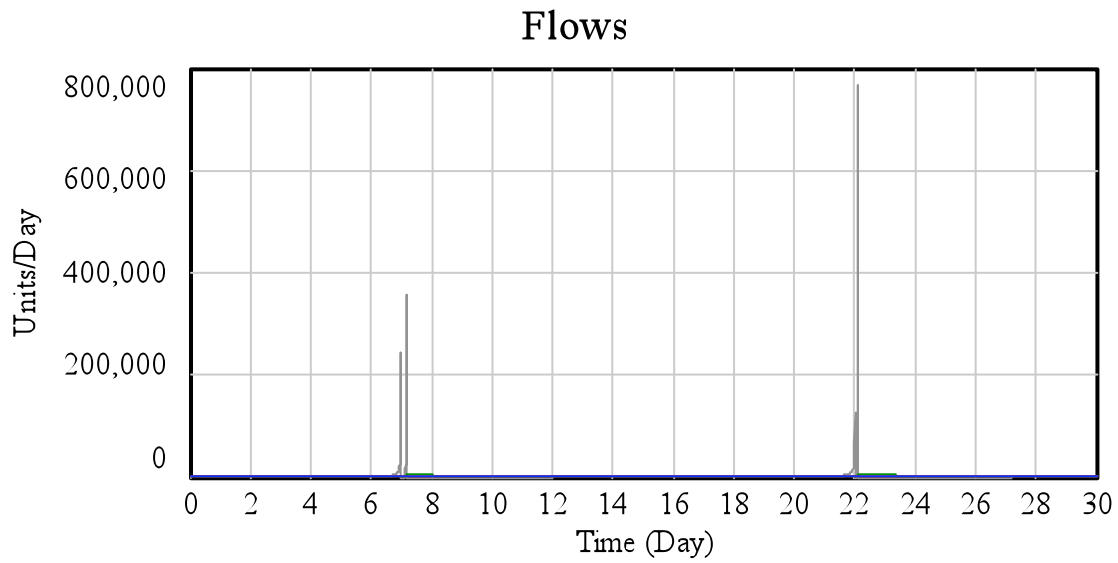


Figure B-16: Noise Response for Loop 1

2) Loop 2



Sales Rate : 2 enabled —————

Distribution Rate : 2 enabled —————

Production Completion Rate : 2 enabled —————

Production Start Rate : 2 enabled —————

Figure B-17: Noise Response for Loop 2

3) Loop 3

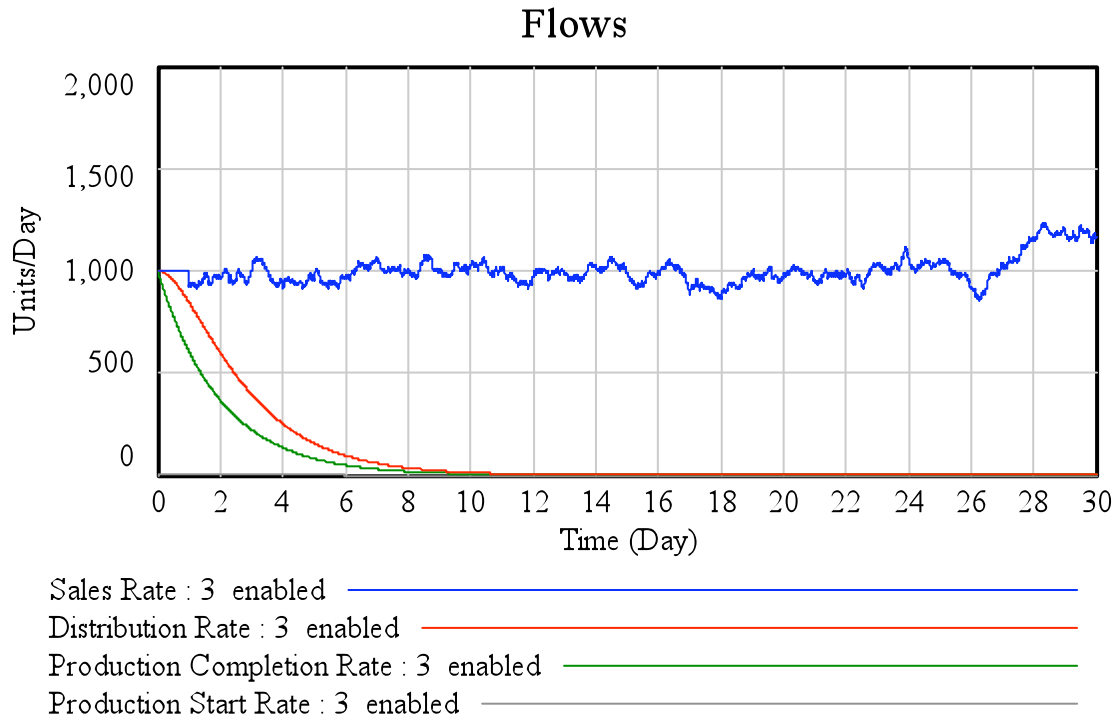


Figure B-18: Noise Response for Loop 3

4) Loop 4

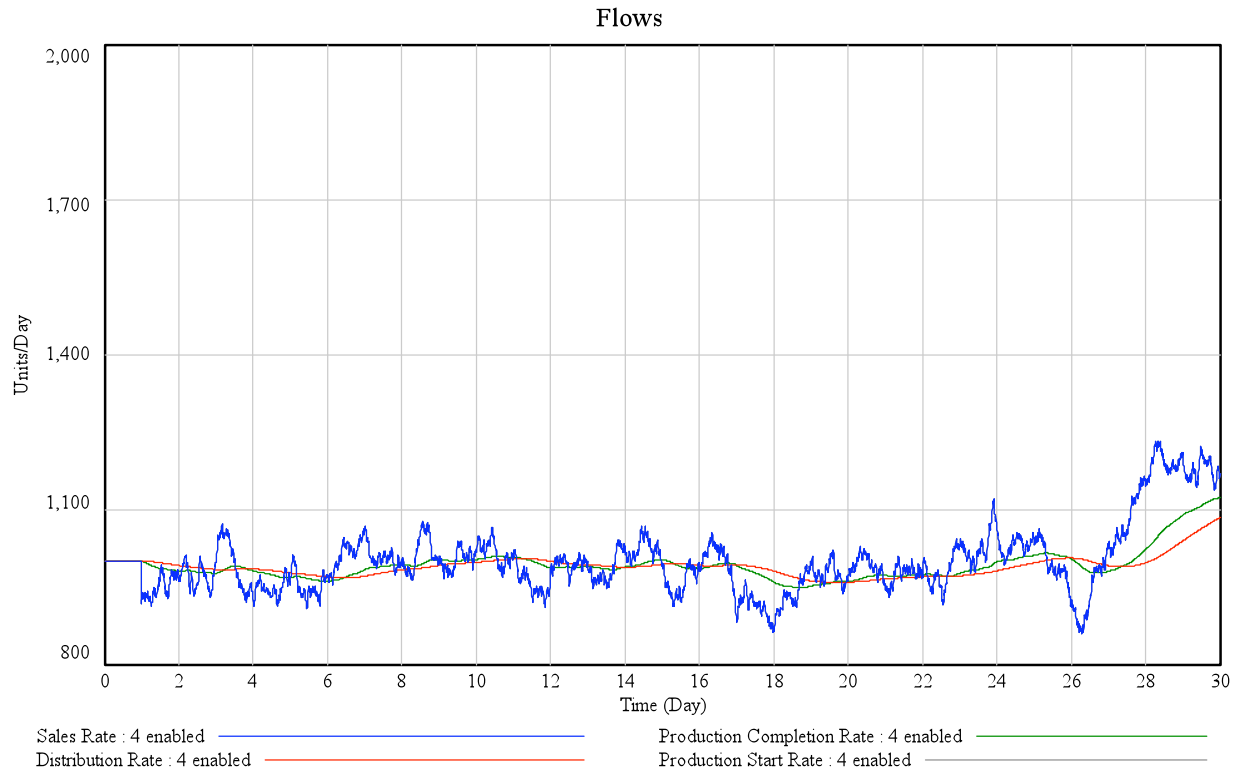


Figure B-19: Noise Response for Loop 4

5) Loop 1 and 2

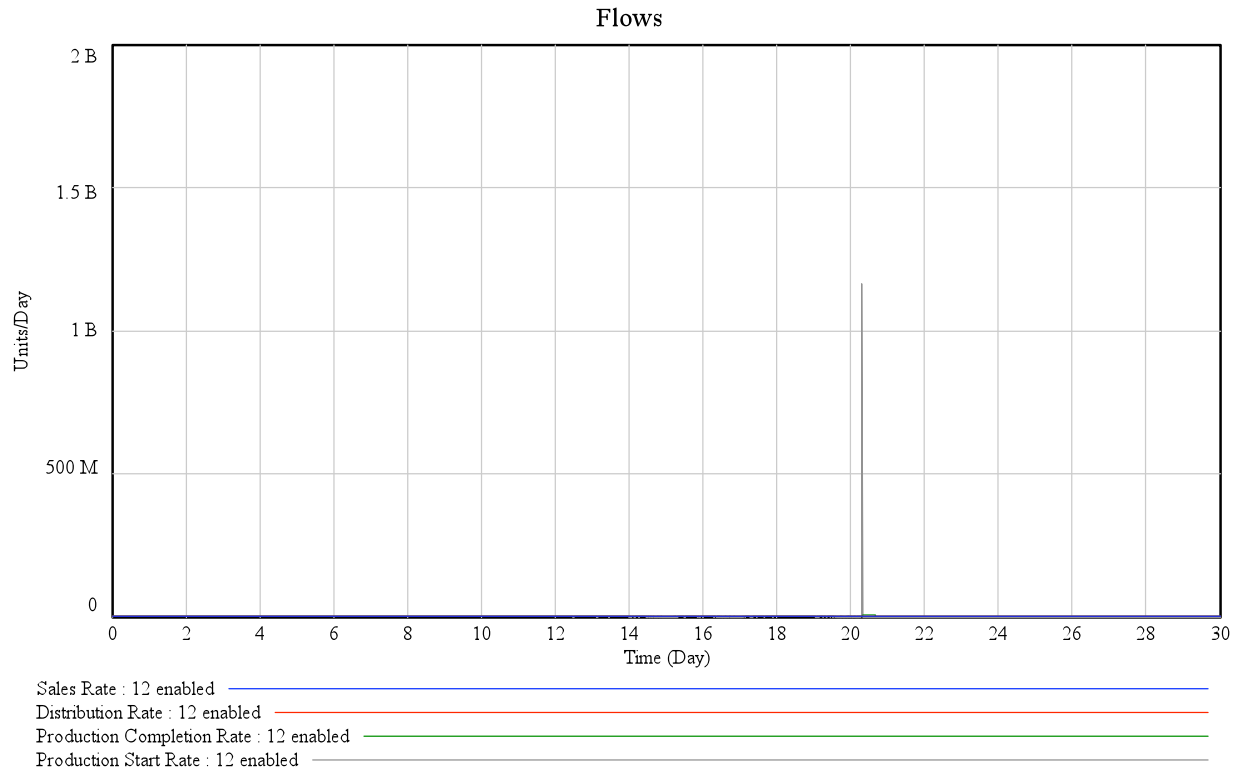


Figure B-20: Noise Response for Loop 1 and 2

6) Loop 1 and 3

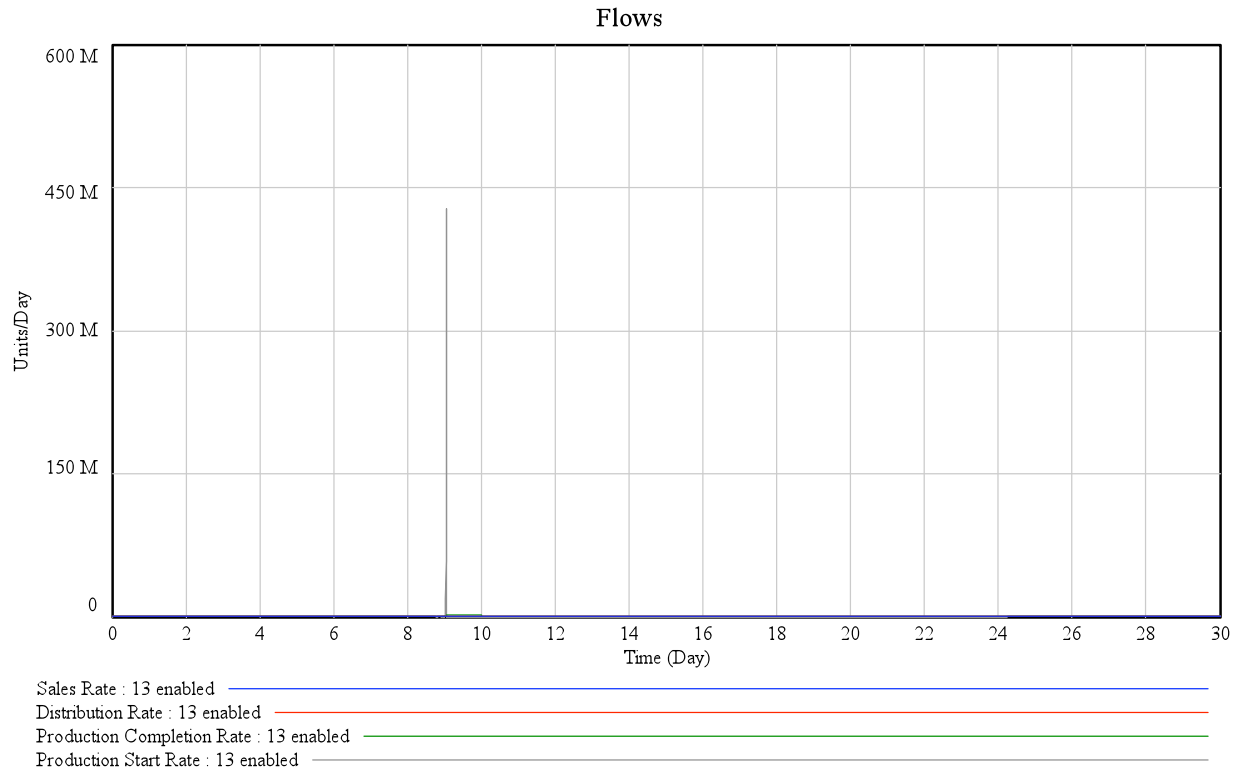


Figure B-21: Noise Response for Loop 1 and 3

7) Loop 1 and 4

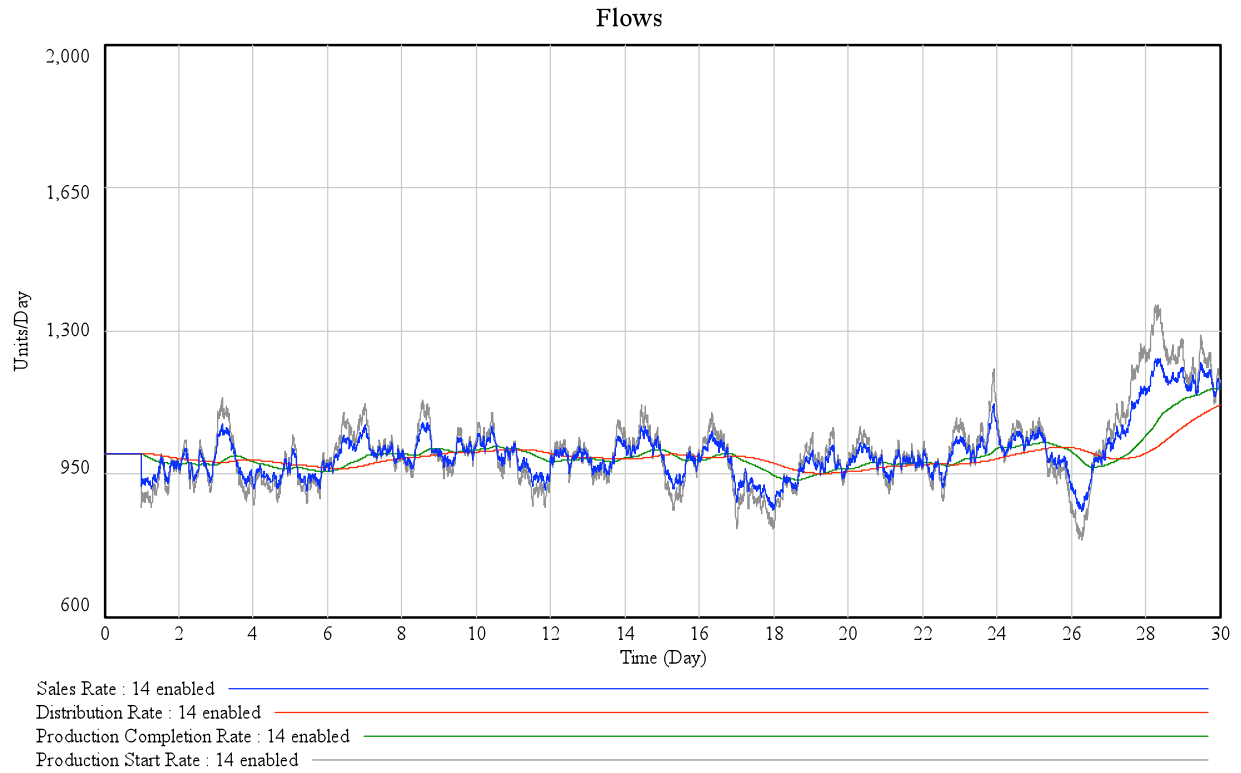


Figure B-22: Noise Response for Loop 1 and 4

8) Loop 2 and 3

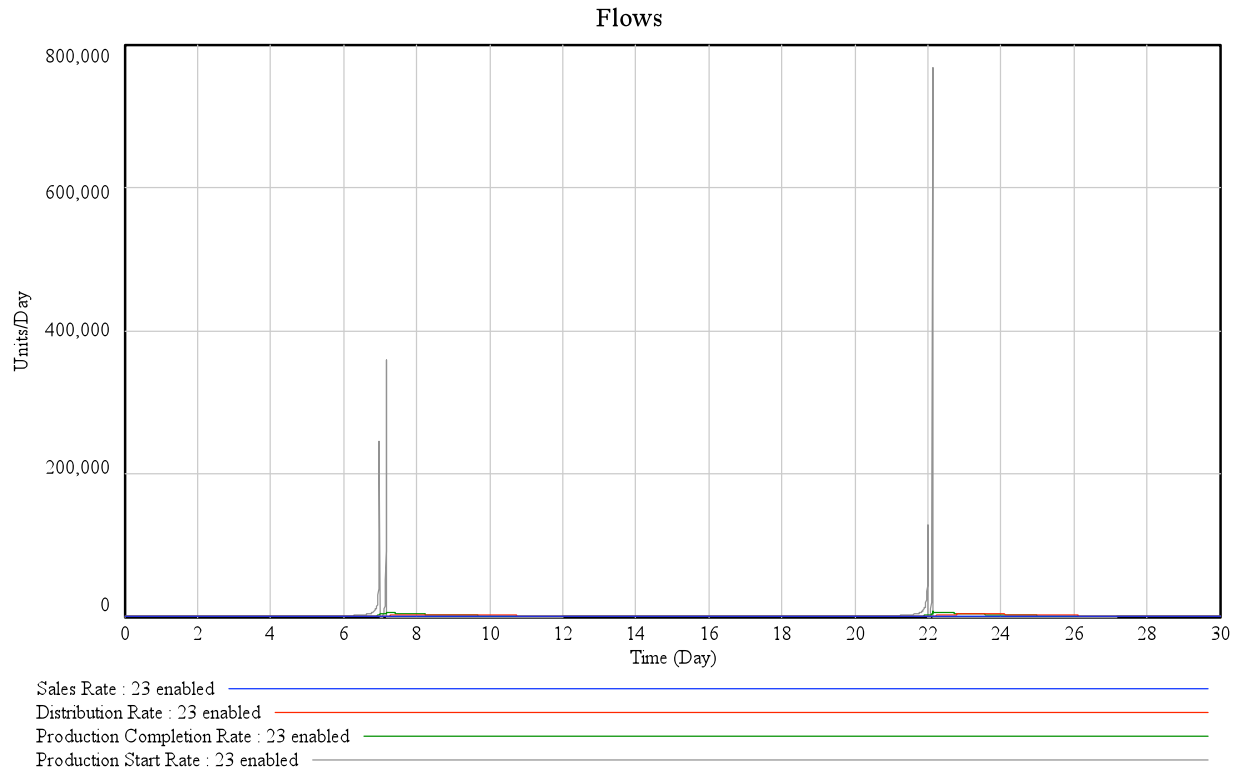


Figure B-23: Noise Response for Loop 2 and 3

9) Loop 2 and 4

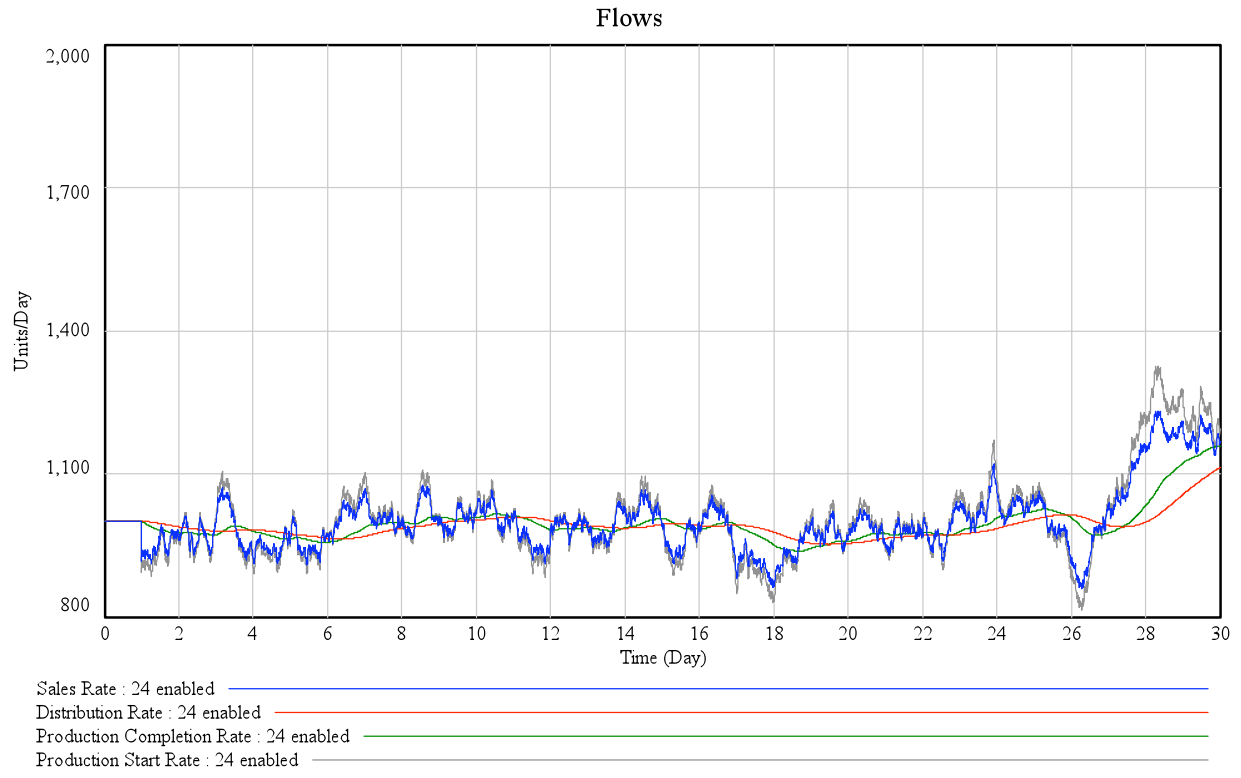


Figure B-24: Noise Response for Loop 2 and 4

10) Loop 3 and 4

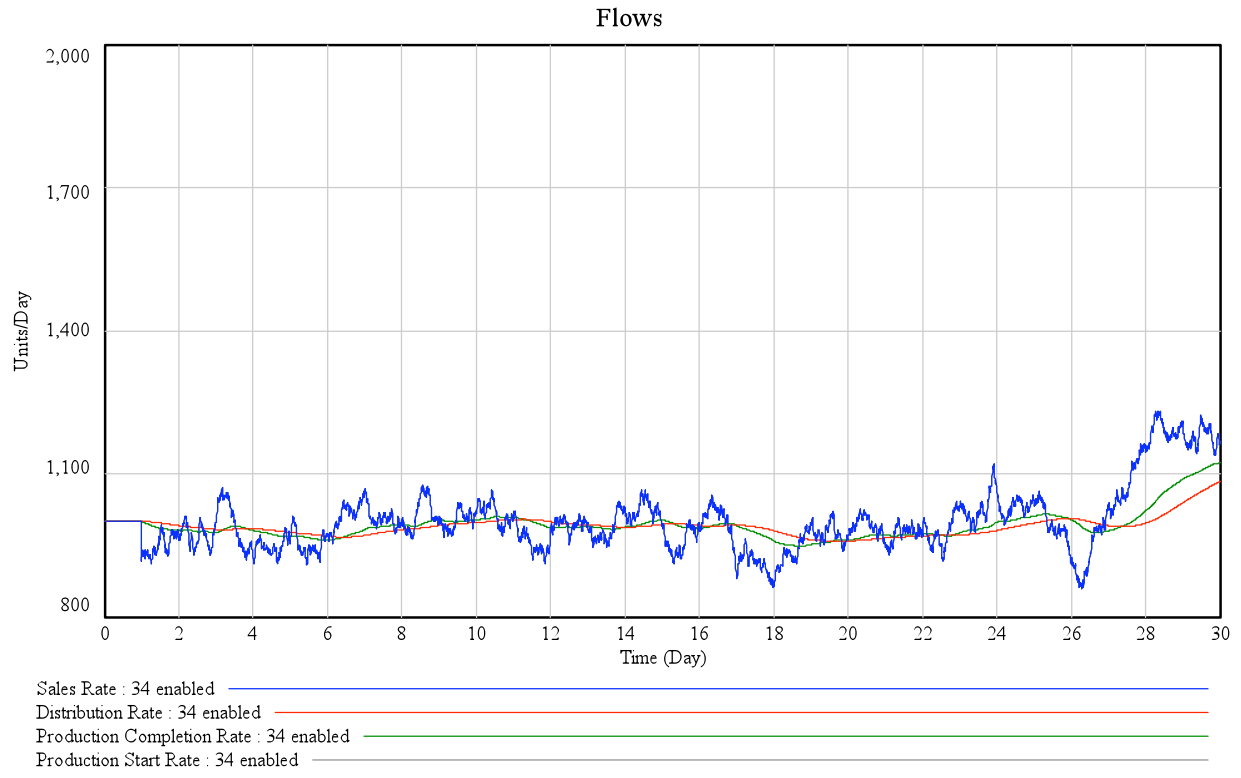


Figure B-25: Noise Response for Loop 3 and 4

11) Loop 1, 2 and 3

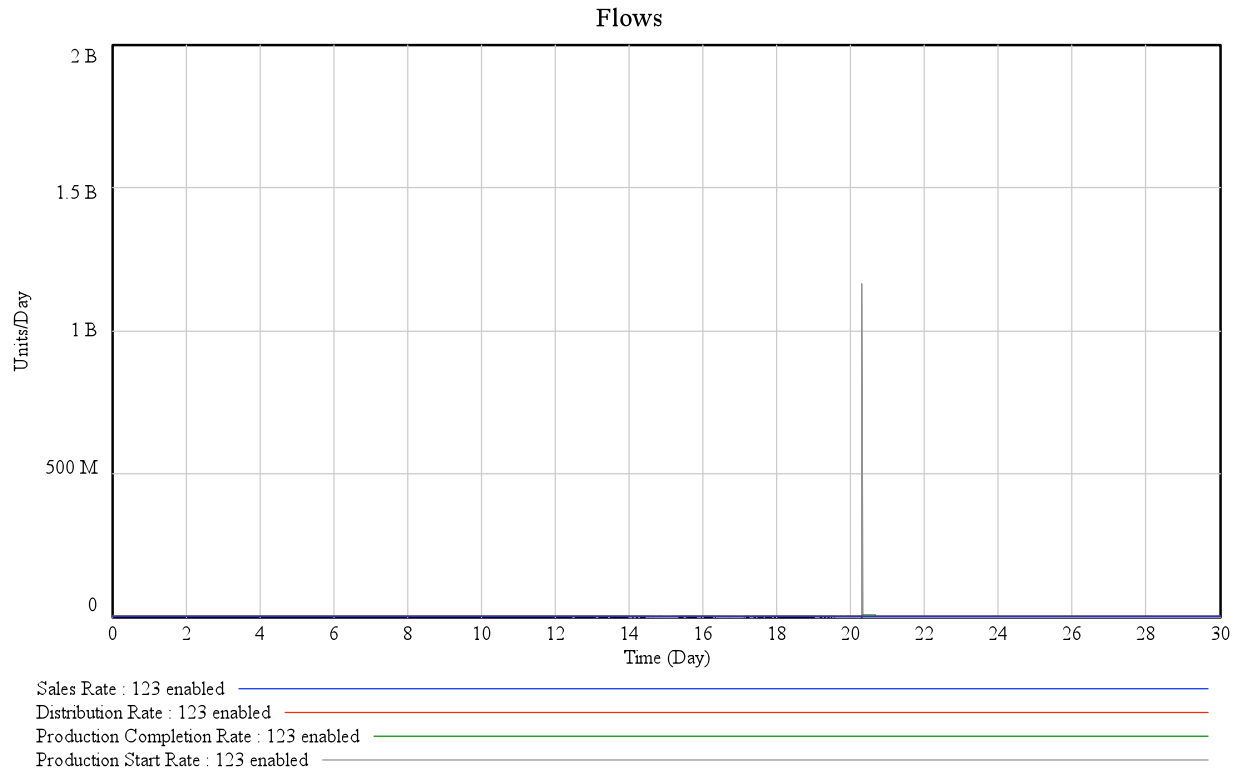


Figure B-26: Noise Response for Loop 1,2 and 3

12) Loop 1, 2, and 4

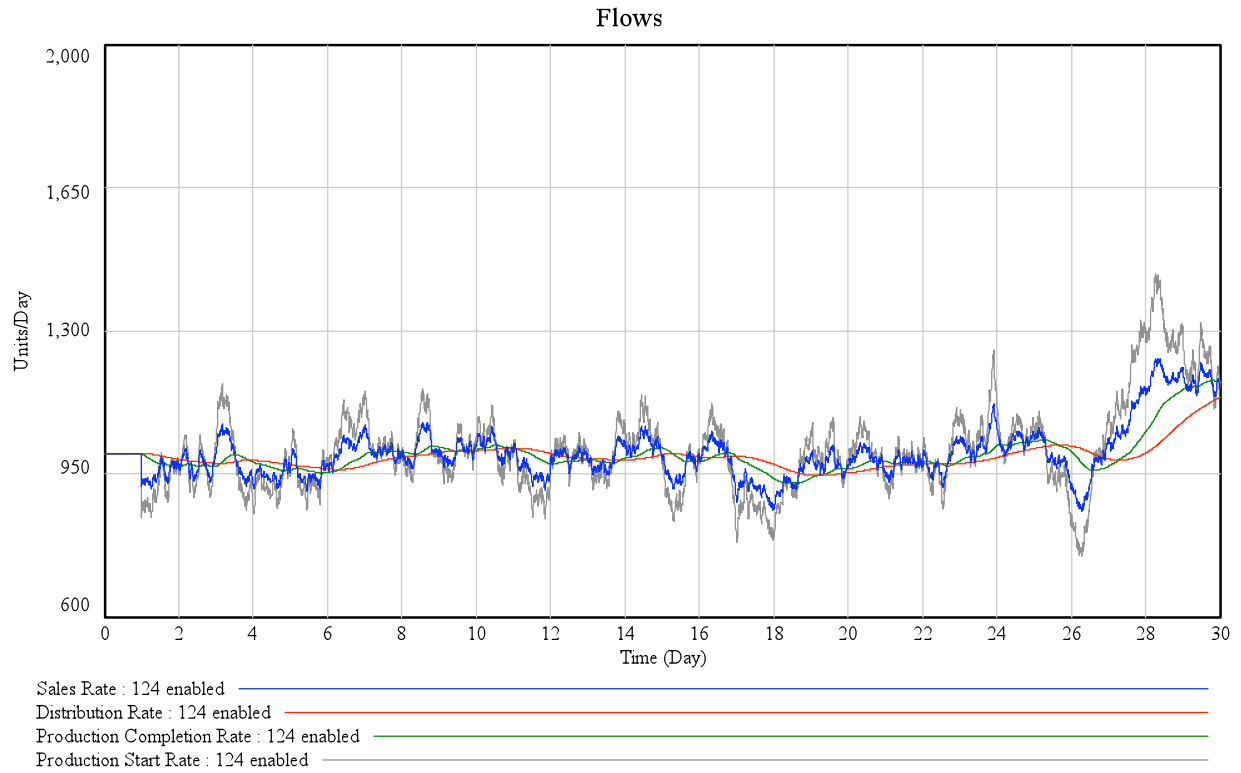


Figure B-27: Noise Response for Loop 1,2 and 4

13) Loop 1, 3 and 4

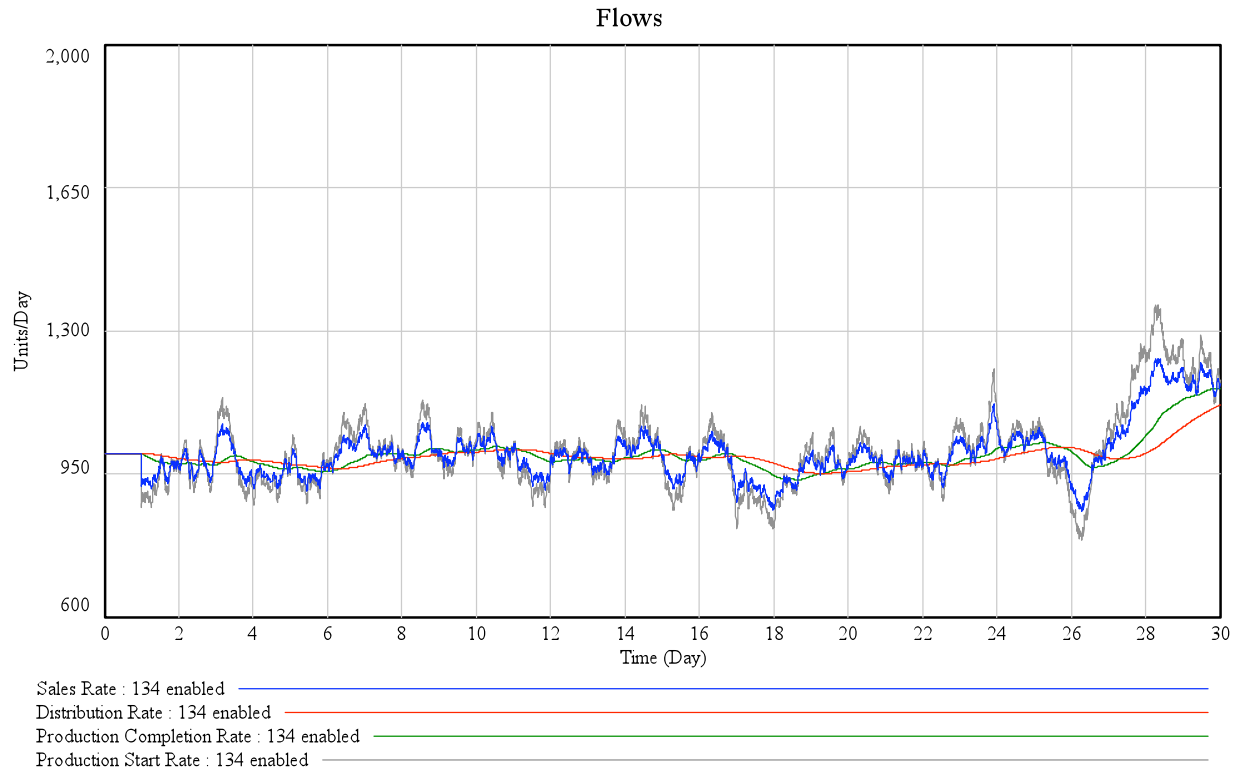


Figure B-28: Noise Response for Loop 1,3 and 4

14) Loop 2, 3 and 4

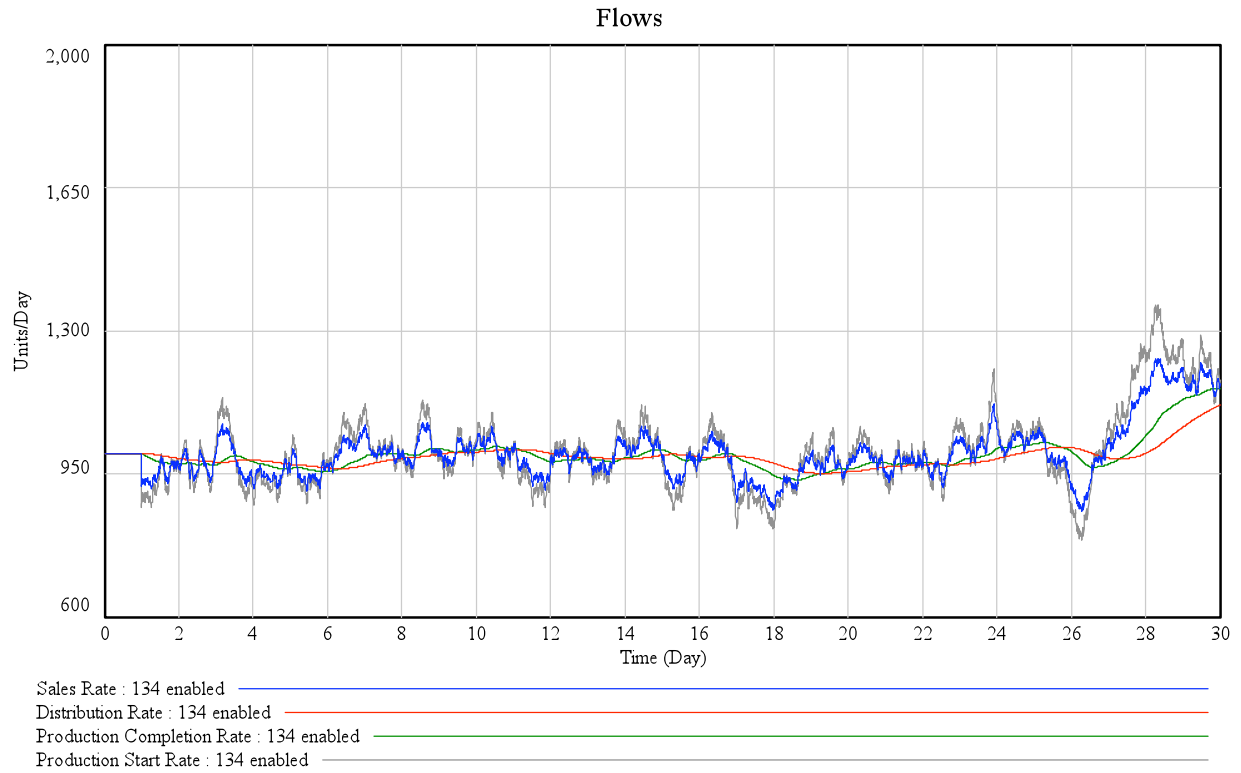


Figure B-29: Noise Response for Loop 2,3 and 4

15) Loop 1, 2, 3 and 4

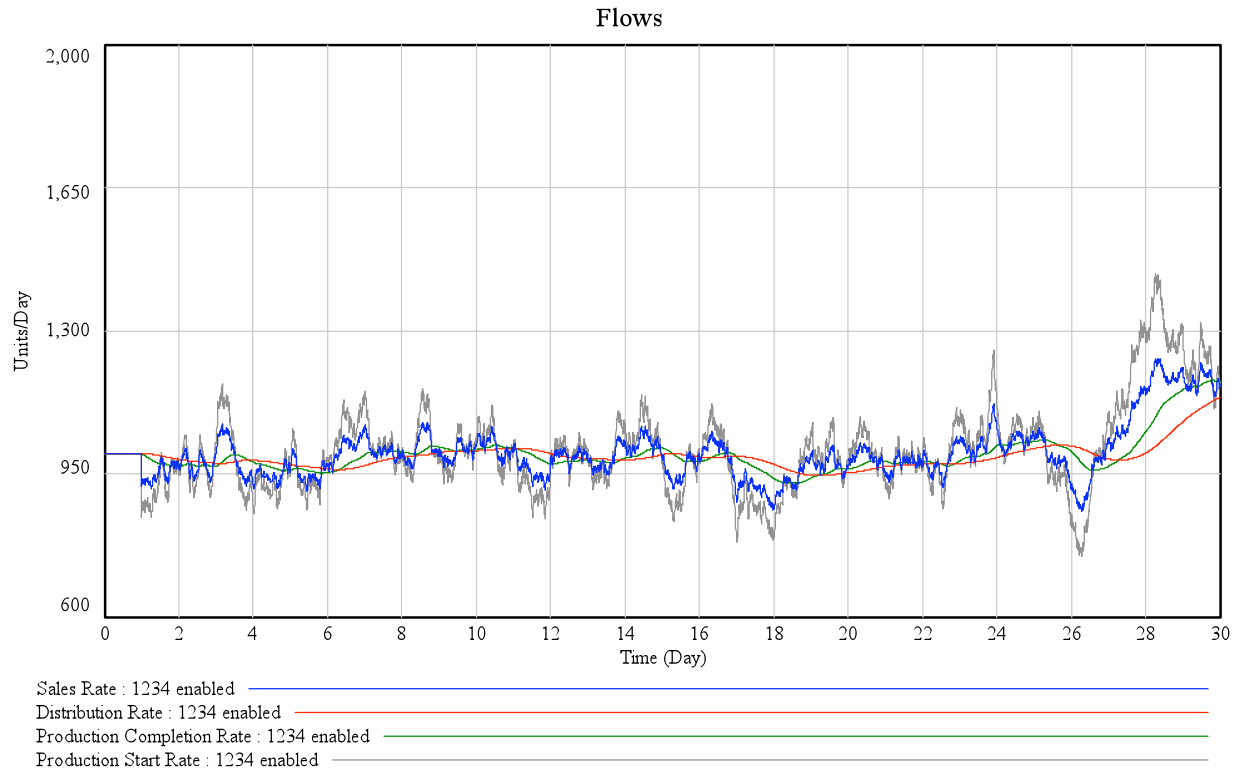


Figure B-30: Noise Response for Loop 1,2,3 and 4

Appendix C – Formulae for PID Model

(01) "Retailer Inventory to Sales Ratio (RISR)"= "Retailer Inventory (X3)"/"Customer Demand (U)"

Units: Day

Average time that a piece of finished inventory stays with the retailer

(02) Change in Pink Noise = (White Noise - Pink Noise)/Noise Correlation Time

Units: 1/Day

Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input.

(03) "Customer Demand (U)"= Initial Demand*Input

Units: Units/Day

The aggregate demand for the finished product in the market

(04) Derivative Adjustment= K_d *Error Derivative

Units: Units/Day

Derivative adjustment for error

(05) Desired Distribution Center Inventory= "Customer Demand (U)"*"Distribution Time (DT)"

Units: Units

(06) Desired Finished Inventory= "Customer Demand (U)"* "Manufacturing Cycle Time (MCT)"

Units: Units

(07) Desired Production Start Rate= Sales Rate +Proportional Adjustment +Integral Adjustment + Derivative Adjustment

Units: Units/Day

Rate at which production is desired

(08) Desired Retailer Inventory= "Customer Demand (U)"* "Average Retail Time (ART)"

Units: Units

(09) "Distribution Center Inventory (X2)"= INTEG (Production Completion Rate-Distribution Rate, Desired Distribution Center Inventory)

Units: Units

Inventory level in distribution center

(10) Distribution Rate= "Distribution Center Inventory (X2)"/"Distribution Time (DT)"

Units: Units/Day

Rate at which distribution is carried out

- (11) "Distribution Time (DT)"=1
Units: Day
Time to distribute one unit
- (12) Error= Sales Rate-Production Completion Rate
Units: Units/Day
Error between sales rate and production completion rate
- (13) Error Delay= DELAY FIXED (Error, 1, 0)
Units: Units/Day
Error delayed by one time unit
- (14) Error Derivative= Error-Error Delay
Units: Units/Day/Day
Derivative of error
- (15) Error Integral= INTEG (Error Rate, 0)
Units: Units
Integral of error
- (16) Error Rate= Error
Units: Units/Day

Rate at which error occurs

- (17) "Factory Inventory (X1)"= INTEG (Production Start Rate-Production Completion Rate,
Desired Finished Inventory)

Units: Units

Inventory level in factory

- (18) FINAL TIME = 15

Units: Day

The final time for the simulation.

- (19) Initial Demand=1000

Units: Units/Day

Initial value of the desired stock.

- (20) INITIAL TIME = 0

Units: Day

The initial time for the simulation.

- (21) Input= 1+STEP (Step Height, Step Time) + (Pulse Quantity/TIME STEP)*PULSE (Pulse
Time, TIME STEP) + RAMP (Ramp Slope, Ramp Start Time, Ramp End Time) + Sine
Amplitude*SIN (2*3.14159*Time/Sine Period) + STEP (1, Noise Start Time)*Pink

Noise

Units: Dimensionless

Input is a dimensionless variable, which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise.

(22) Integral Adjustment= K_i *Error Integral

Units: Units/Day

Integral adjustment for error

(23) $K_d = 1$

Units: Day

Derivative gain

(24) $K_i = 0.5$

Units: 1/Day

Integral gain

(25) $K_p = 3$

Units: Dimensionless

Proportional gain

(26) "Manufacturing Cycle Time (MCT)"=2

Units: Day

Time to manufacture one unit

(27) Noise Correlation Time = 4

Units: Day

The correlation time constant for Pink Noise.

(28) Noise Standard Deviation= 0.1

Units: Dimensionless

The standard deviation of the pink noise process.

(29) Noise Start Time=1

Units: Day

Start time for the random input.

(30) Pink Noise = INTEG (Change in Pink Noise, 0)

Units: Dimensionless

Pink Noise is first-order auto-correlated noise. Pink noise provides a realistic noise input to models in which the next random shock depends in part on the previous shocks. The user can specify the correlation time. The mean is 0 and the standard deviation is specified by the user.

(31) Production Completion Rate= "Factory Inventory (X1)"/"Manufacturing Cycle Time (MCT)"

Units: Units/Day

Rate at which production is completed

(32) $\text{Production Start Rate} = \text{MAX}(\text{Desired Production Start Rate}, 0)$

Units: Units/Day

Rate at which production begins

(33) $\text{Proportional Adjustment} = \text{Error} * K_p$

Units: Units/Day

Proportional adjustment to error

(34) $\text{Pulse Quantity} = 0$

Units: Dimensionless*Day

The quantity to be injected to customer orders, as a fraction of the base value of Input.

For example, to pulse in a quantity equal to 50% of the current value of input, set to .50.

(35) $\text{Pulse Time} = 1$

Units: Day

Time at which the pulse in Input occurs.

(36) $\text{Ramp End Time} = 1e+009$

Units: Day

End time for the ramp input.

(37) Ramp Slope=0

Units: 1/Day

Slope of the ramp input, as a fraction of the base value (per week).

(38) Ramp Start Time= 1

Units: Day

Start time for the ramp input.

(39) "Retailer Inventory (X3)"= INTEG (Distribution Rate-Sales Rate, Sales Rate*3)

Units: Units

Inventory level of retailer

(40) Sales Rate= "Customer Demand (U)"

Units: Units/Day

Rate at which goods are sold

(41) SAVEPER = TIME STEP

Units: Day

The frequency with which output is stored.

(42) Sine Amplitude=0

Units: Dimensionless

Amplitude of sine wave in customer orders (fraction of mean).

(43) Sine Period=50

Units: Day

Period of sine wave in customer demand. Set initially to 50 weeks (1 year).

(44) Step Height= 0

Units: Dimensionless

Height of step input to customer orders, as fraction of initial value.

(45) Step Time=1

Units: Day

Time for the step input.

(46) TIME STEP = 0.0078125

Units: Day

The time step for the simulation.

(47) White Noise = Noise Standard Deviation*((24*Noise Correlation Time/TIME STEP)

$\wedge 0.5 * (\text{RANDOM } 0 \ 1() - 0.5)$)

Units: Dimensionless

White noise input to the pink noise process.

Appendix D – Formulae for Combined Structure Model

(01) "Retailer Inventory to Sales Ratio (RISR)"= "Retailer Inventory (X3)"/"Customer Demand (U)"

Units: Day

The average time that a unit of inventory sits on the retailer's shelf

(02) Change in Pink Noise = (White Noise - Pink Noise)/Noise Correlation Time

Units: 1/Day

Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input.

(03) "Customer Demand (U)"= Initial Demand*Input

Units: Units/Day

Aggregate demand for product

(04) "DCI Adjustment Rate (DCIAR)"= (Desired DCI-"Distribution Center Inventory (X2)"/"DCI Adjustment Time (DCIAT)"

Units: Units/Day

(05) "DCI Adjustment Time (DCIAT)"= 0.5

Units: Day

Time to adjust distribution center inventory

(06) Desired DCI= "Customer Demand (U)"*"Distribution Time (DT)"

Units: Units

Desired distribution center inventory

(07) Desired FI= "Customer Demand (U)"*"Manufacturing Cycle Time (MCT)"

Units: Units

Desired factory inventory

(08) "Desired Production Start Rate (DSR)"= Sales Rate+"FI Adjustment Rate (FIAR)"+"RI
Adjustment Rate (RIAT)"+"DCI Adjustment Rate (DCIAR)"

Units: Units/Day

Desired rate at which production should start

(09) Desired RI= "Customer Demand (U)"*"Average Retail Time (ART)"

Units: Units

Desired retailer inventory

(10) "Distribution Capacity (DC)"= 2000

Units: Units/Day

Maximum distribution rate

- (11) "Distribution Center Inventory (X2)"= INTEG ("Production Completion Rate (PCR)"-
Distribution Rate, Desired DCI)
Units: Units
Inventory level of distribution center
- (12) Distribution Rate= MIN ("Distribution Capacity (DC)", "Distribution Center Inventory
(X2)"/"Distribution Time (DT)")
Units: Units/Day
Rate at which distribution occurs
- (13) "Distribution Time (DT)"=1
Units: Day
Time to distribute one unit
- (14) Drop in manufacturing capacity= 100*STEP (1, 5)
Units: Units/Day
Sudden decrease in manufacturing capacity
- (15) "Factory Inventory (X1)"= INTEG ("Production Start Rate (PSR)"-"Production
Completion Rate (PCR)", Desired FI)
Units: Units
Inventory level of factory

(16) "FI Adjustment Rate (FIAR)"= (Desired FI-"Factory Inventory (X1)"/"FI Adjustment Time (FIAT)"

Units: Units/Day

(17) "FI Adjustment Time (FIAT)"=0.5

Units: Day

Time to adjust factory inventory

(18) FINAL TIME = 30

Units: Day

The final time for the simulation.

(19) Initial Demand= 1000

Units: Units/Day

Initial value of the sales rate

(20) INITIAL TIME = 0

Units: Day

The initial time for the simulation.

(21) $\text{Input} = 1 + \text{STEP}(\text{Step Height}, \text{Step Time}) + (\text{Pulse Quantity}/\text{TIME STEP}) * \text{PULSE}(\text{Pulse Time}, \text{TIME STEP}) + \text{RAMP}(\text{Ramp Slope}, \text{Ramp Start Time}, \text{Ramp End Time}) + \text{Sine Amplitude} * \text{SIN}(2 * 3.14159 * \text{Time}/\text{Sine Period}) + \text{STEP}(1, \text{Noise Start Time}) * \text{Pink Noise}$

Units: Dimensionless

Input is a dimensionless variable, which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise.

(22) "Manufacturing Capacity (MC)"= 1000-Drop in manufacturing capacity

Units: Units/Day

Maximum production completion rate

(23) "Manufacturing Cycle Time (MCT)"=2

Units: Day

Time to make one unit

(24) Noise Correlation Time = 4

Units: Day

The correlation time constant for Pink Noise.

(25) Noise Standard Deviation=0

Units: Dimensionless

The standard deviation of the pink noise process.

(26) Noise Start Time=1

Units: Day

Start time for the random input.

(27) Pink Noise = INTEG (Change in Pink Noise, 0)

Units: Dimensionless

Pink Noise is first-order auto-correlated noise. Pink noise provides a realistic noise input to models in which the next random shock depends in part on the previous shocks. The user can specify the correlation time. The mean is 0 and the standard deviation is specified by the user.

(28) "Production Completion Rate (PCR)"= MIN ("Manufacturing Capacity (MC)", "Factory Inventory (X1)"/"Manufacturing Cycle Time (MCT)")

Units: Units/Day

Rate at which production is completed

(29) "Production Start Rate (PSR)"= MAX (MIN ("Desired Production Start Rate (DSR)", "Manufacturing Capacity (MC)"), 0)

Units: Units/Day

Rate at which production is started

(30) Pulse Quantity=0

Units: Dimensionless*Day

The quantity to be injected to customer orders, as a fraction of the base value of Input.

For example, to pulse in a quantity equal to 50% of the current value of input, set to .50.

(31) Pulse Time=1

Units: Day

Time at which the pulse in Input occurs.

(32) Ramp End Time=1e+009

Units: Day

End time for the ramp input.

(33) Ramp Slope=0

Units: 1/Day

Slope of the ramp input, as a fraction of the base value (per week).

(34) Ramp Start Time=1

Units: Day

Start time for the ramp input.

- (35) "Retailer Inventory (X3)"= INTEG (Distribution Rate-Sales Rate, 3*Sales Rate)
 Units: Units
 Inventory level of retailer
- (36) "RI Adjustment Rate (RIAT)"= (Desired RI-"Retailer Inventory (X3)")/"RI Adjustment Time (RIAT)"
 Units: Units/Day
- (37) "RI Adjustment Time (RIAT)"= 0.5*1e+008
 Units: Day
 Time to adjust retailer inventory
- (38) Sales Rate= "Customer Demand (U)"
 Units: Units/Day
 Rate at which goods are sold
- (39) SAVEPER = TIME STEP
 Units: Day
 The frequency with which output is stored.
- (40) Sine Amplitude=0
 Units: Dimensionless
 Amplitude of sine wave in customer orders (fraction of mean).

(41) Sine Period=50

Units: Day

Period of sine wave in customer demand. Set initially to 50 weeks (1 year).

(42) Step Height=0

Units: Dimensionless

Height of step input to customer orders, as fraction of initial value.

(43) Step Time= 1

Units: Day

Time for the step input.

(44) TIME STEP = 0.0078125

Units: Day

The time step for the simulation.

(45) White Noise = Noise Standard Deviation*((24*Noise Correlation Time/TIME STEP)

$\wedge 0.5 * (\text{RANDOM } 0 \ 1() - 0.5))$

Units: Dimensionless

White noise input to the pink noise process.

Appendix E – Formulae for Industrial Case Study

(01) "Adjustment for AWIP (AAWIP)"= ("Desired AWIP (AWIP*)" - "Assembly WIP (X2)")/"AWIP Adjustment Time (AWAT)"

Units: Units/Month

The order rate is adjusted to close any gap between the desired and actual supply line.

(02) "Adjustment for Fab WIP (AFWIP)"= ("Desired Fab WIP (FWIP*)"-"Fabrication WIP (X1)")/"Fab WIP Adjustment Time (FWAT)"

Units: Units/Month

(03) "Adjustment for Finished Inventory (AFI)"= ("Desired Finished Inventory (FI*)"-"Finished Inventory (X3)")/"Finished Inventory Adjustment Time (FIAT)"

Units: Units/Month

The adjustment for the stock is proportional to the gap between the desired and actual stock.

(04) "Adjustment Rate (AR)"= ("Shipment Rate (SR)"-"Expected Shipment Rate (X4)")/"Update Shipments Time (UST)"

Units: Units/Month/Month

(05) "Assembly WIP (X2)"= INTEG ("Die Inflow (DI)"-"Net Assembly Outflow (NAO)", "Desired AWIP (AWIP*)")

Units: Units

The quantity on order; what has been ordered but not yet received.

(06) "AWIP Adjustment Time (AWAT)"=0.5

Units: Month

The time period over which the gap between the desired and actual supply line is closed.

(07) Change in Pink Noise = (White Noise - Pink Noise)/Noise Correlation Time

Units: 1/Month

Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input.

(08) "Complete Assembly Time (CAT)"= 0.1

Units: Month

The average delay between order and acquisition of new units.

(09) "Desired AWIP (AWIP*)"= "Desired Net Assembly Outflow (NAO*)"*"Complete Assembly Time (CAT)"

Units: Units

The desired supply line maintains sufficient units on order to yield the desired acquisition rate.

- (10) "Desired Fab WIP (FWIP*)"=
 "Desired Net Wafer Start Rate (NWSR*)"*"Manufacturing Cycle Time (MCT)"
 Units: Units
- (11) "Desired Finished Inventory (FI*)"= (1+"Safety Stock Percentage (SSP)")*"Expected
 Shipment Rate (X4)"*"Min Order Processing Time (MOPT)"
 Units: Units
- (12) "Desired Net Assembly Outflow (NAO*)"= "Adjustment for Finished Inventory
 (AFI)"+"Expected Shipment Rate (X4)"
 Units: Units/Month
 The desired acquisition rate is expected losses adjusted to bring the stock in line with the
 desired level.
- (13) "Desired Net Wafer Start Rate (NWSR*)"= "Adjustment for AWIP (AAWIP)"+"Total
 Demand (U)"
 Units: Units/Month
- (14) "Desired Wafer Start Rate (WSR*)"=
 "Adjustment for Fab WIP (AFWIP)"+"Desired Net Wafer Start Rate (NWSR*)"
 Units: Units/Month

(15) "Die Inflow (DI)"= "Net Wafers Outflow (NWO)"

Units: Units/Month

The order rate is constrained to be nonnegative. Cancellations should be modeled explicitly as a separate outflow from the supply line.

(16) "Expected Shipment Rate (X4)"= INTEG ("Adjustment Rate (AR)", "Shipment Rate (SR)")

Units: Units/Month

(17) "Fab WIP Adjustment Time (FWAT)"= 0.5

Units: Month

(18) "Fabrication WIP (X1)"= INTEG ("Wafers Start Rate (WSR)"-"Net Wafers Outflow (NWO)", "Net Assembly Outflow (NAO)"*"Manufacturing Cycle Time (MCT)")

Units: Units

(19) FINAL TIME = 12

Units: Month

The final time for the simulation.

(20) "Finished Inventory (X3)"= INTEG ("Net Assembly Outflow (NAO)"-"Shipment Rate (SR)", "Total Demand (U)"*"Min Order Processing Time (MOPT)")

Units: Units

The stock accumulates acquisitions less discards.

(21) "Finished Inventory Adjustment Time (FIAT)"= 0.5

Units: Month

The time period over which the gap between the desired and actual stock is closed.

(22) Initial Demand= 5000

Units: Units/Month

Initial value of the desired stock.

(23) INITIAL TIME = 0

Units: Month

The initial time for the simulation.

(24) Input= 1+STEP (Step Height, Step Time) + (Pulse Quantity/TIME STEP)*PULSE (Pulse Time, TIME STEP) + RAMP (Ramp Slope, Ramp Start Time, Ramp End Time) + Sine Amplitude*SIN (2*3.14159*Time/Sine Period) +STEP (1, Noise Start Time)*Pink Noise

Units: Dimensionless

Input is a dimensionless variable, which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise.

(25) "Manufacturing Cycle Time (MCT)"=1

Units: Month

(26) "Min Order Processing Time (MOPT)"=3

Units: Month

The average life of units in the stock is assumed to be 8 years.

(27) "Net Assembly Outflow (NAO)"= "Assembly WIP (X2)"/"Complete Assembly Time (CAT)"

Units: Units/Month

The acquisition rate is determined by the quantity on order and the average acquisition delay. In this simple model, the acquisition delay is first-order, but in general can be any high-order process.

(28) "Net Wafers Outflow (NWO)"= "Fabrication WIP (X1)"/"Manufacturing Cycle Time (MCT)"

Units: Units/Month

(29) Noise Correlation Time = 4

Units: Month

The correlation time constant for Pink Noise.

(30) Noise Standard Deviation= 0

Units: Dimensionless

The standard deviation of the pink noise process.

(31) Noise Start Time =1

Units: Month

Start time for the random input.

(32) Pink Noise = INTEG (Change in Pink Noise, 0)

Units: Dimensionless

Pink Noise is first-order auto-correlated noise. Pink noise provides a realistic noise input to models in which the next random shock depends in part on the previous shocks. The user can specify the correlation time. The mean is 0 and the standard deviation is specified by the user.

(33) Pulse Quantity=0

Units: Dimensionless*Month

The quantity to be injected to customer orders, as a fraction of the base value of Input.

For example, to pulse in a quantity equal to 50% of the current value of input, set to .50.

(34) Pulse Time=1

Units: Month

Time at which the pulse in Input occurs.

(35) Ramp End Time=1e+009

Units: Month

End time for the ramp input.

(36) Ramp Slope=0

Units: 1/Month

Slope of the ramp input, as a fraction of the base value (per week).

(37) Ramp Start Time=1

Units: Month

Start time for the ramp input.

(38) "Safety Stock Percentage (SSP)"= 0

Units: Dimensionless

(39) SAVEPER = TIME STEP

Units: Month

The frequency with which output is stored.

(40) "Shipment Rate (SR)"="Finished Inventory (X3)"/"Min Order Processing Time (MOPT)"

Units: Units/Month

First order discards with a constant average life are assumed.

(41) Sine Amplitude=0

Units: Dimensionless

Amplitude of sine wave in customer orders (fraction of mean).

(42) Sine Period=50

Units: Month

Period of sine wave in customer demand. Set initially to 50 weeks (1 year).

(43) Step Height= 0.1

Units: Dimensionless

Height of step input to customer orders, as fraction of initial value.

(44) Step Time=1

Units: Month

Time for the step input.

(45) TIME STEP = 0.0078125

Units: Month

The time step for the simulation.

(46) "Total Demand (U)"= Input*Initial Demand

Units: Units/Month

(47) "Update Shipments Time (UST)"=10

Units: Month

(48) "Wafers Start Rate (WSR)"= MAX ("Desired Wafer Start Rate (WSR*)", 0)

Units: Units/Month

(49) White Noise = Noise Standard Deviation*((24*Noise Correlation Time/TIME STEP)
)^0.5*(RANDOM 0 1() - 0.5))

Units: Dimensionless

White noise input to the pink noise process.