Raw Material Inventory Control Analysis: A Case Study for a Manufacturing Firm in Norway

Thesis submitted in partial fulfilment of the requirements of Master of Philosophy in System Dynamics (Universitetet i Bergen)

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Abstract

Inventory control and finding the correct balance of supply and demand to save storage costs are critical in businesses. Traditional inventory management methods are being phased out in favor of partnering strategies, and system dynamics models are being utilized to explore and test different theories.

This thesis aims to provide an overview of inventory control and goods monitoring to avoid inventory overstocking and understocking. It represents a theoretical model developed and quantified into a simulation model of system dynamics which provides a causal feedback theory of how different sectors in a manufacturing company affect the inventory level over time by considering the flow of goods, services, money, and information.

In general, it is discovered that employing a weighting factor of the raw material orders would reduce the amount of purchased raw material, resulting in lower inventory value. Furthermore, reducing the lead time of receiving raw materials causes higher precision in ordering and stocking raw materials. Increasing the delivery delay, on the other side, could assist in inventory value reduction. It may, however, lead to client dissatisfaction. Also, returning excess stock to the supplier would be beneficial in controlling inventory value. Finally, analyzing multiple policies simultaneously may result in a far more acceptable output.

In the end, the study demonstrated that without a good understanding of the systems within a company, steps intended for addressing those feedback processes might result in less successful policies. This study gives insight into the inventory control challenge and how the system can help reduce inventory value.

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Chapter 1

1-1 Introductions

In today's competitive supply chains, providing items that stimulate customer demand and improve company revenues is an important goal (Taleizadeh et al., 2019). Professionals in companies try to use optimization techniques to establish ideal safety stock levels, order amounts, and order frequency. Restrictions in the companies, including active purchase agreements, accessible storage space, and production capacity, are all taken into consideration to make sure that the company receives the best possible service from the money invested in the available stock and that the inventory plans are always completely viable (Gonçalves et al., 2020).

Ensuring effective inventory management is the critical goal of supply chain management for businesses. Inventory optimization is crucial to supply chain management success since stock surplus numbers raise costs and reduce profit margins. In contrast, inventory bottlenecks limit production and lead to unsatisfactory customer service (Hoppe, 2006). On a part-by-part basis, traditional optimal inventory analysis determines order quantity, stock level guidance (maximum stock), and reorder points (Grange, 1998).

Companies abandon traditional management methods these days in favor of partnering strategies that help them achieve their objectives. The inquiry and analysis are given fresh opportunities by utilizing system dynamics models, and a transition to an operational discussion about results and leverage points is made possible. These models assist in understanding the theories, permit their testing, and support system learning. The simulation results can also inform a multi-criteria analysis or an economic evaluation in the following stages (Herrera de Leon and Kopainsky, 2020). Inventory optimization looks for the best distribution that complies with the given cost and availability objectives (Adams, 2004). From one end of a supply chain to the other, distorted information can cause significant inefficiencies, including excess inventory investment, poor customer service, reduced sales, incorrect capacity planning, inefficient shipping, and missed production schedules (Yang et al., 2021b). The challenge of inventory management is to keep enough of a given item on hand to satisfy a predicted pattern of demand while striking a balance between the cost of keeping the item(s) in stock and the cost (loss of sales and goodwill, for example) of running out (Singh and Kumar, 2011).

Over the years, researchers and practitioners have developed numerous methods for modeling and analyzing varieties of inventory management systems (Saha and Ray, 2019). Determining an acceptable inventory level or replenishment quantity, lowering inventory expenses, and increasing total benefit are the objectives of inventory optimization (Shen et al., 2020).

This thesis aims to address the research question "how to manage and control the inventory and monitor what merchandise comes in to prevent inventory overstocking and understocking by considering cost reduction over time, technical details, and uncertainties". Finding the appropriate criteria for evaluation has been done in this study by researching the literature on the subject, consulting with experts, and conducting interviews. The present work intends to assist the supply chain team in a company in Norway, using a System Dynamics Model (SDM) to optimize the inventory. Poor performance by the supply chain team has significant consequences for the entire business.

In this research, the model has been developed to assist different types of companies with different levels. Customer demand is constantly fluctuating. Keeping too many raw materials may result in obsolete inventory that cannot sell, while keeping too little may result in an inability to fulfill customer orders. Order policies for essential raw materials and methods for creating and executing an inventory plan can assist in adjusting for changes in demand. Some policies under consideration may benefit businesses in the same industry and region. If a company considers a percentage of the orders to minimize inventory value, in the case of a shortage, one of the close companies can provide the raw material. Additionally, lowering lead time would apply to larger businesses with a broad range of goods that require various critical raw materials. It enables lower safety stock levels, resulting in decreased inventory value. It is expected that extending the delivery delay will assist companies in reducing inventory value through decreased purchased raw materials. However, this may cause client dissatisfaction and prompt them to seek another supplier. Companies should also work with their suppliers to determine the return status for core raw materials. It will benefit from more storage space, lower inventory value, and a lower risk of expired raw materials. Finally, it might be advantageous for various businesses to evaluate multiple policies simultaneously in order to attain the goal.

Due to the fact that some of the raw materials like inks and polyester sheets are produced in Korea and the United States in this company, the lead time for sea shipment is long, and air shipment is so costly. Therefore, it is crucial to keep the warehouse well-stocked.

The company has received too much raw materials last summer, which is causing some issues:

1. Insufficient room in the warehouse to stock raw materials (keeping them outside is not an option due to the cold weather in Norway)
2. The raw material's expiration date
3. High inventory value

There are two primary causes for this overstocking. First, the previous supply chain team placed an excessive number of raw material orders without any plan and analysis to prevent a shortage while the company hires the new team members. Second, the company has requested its top customers to complete a document that offers a projection of their forecasted demands. After analysis, it was discovered that the accuracy of the forecast is low and the actual purchases are not matched with the forecast that causes problems. The objective of this study is to improve a perfect balance between demand and supply in order to reduce high storage costs and stock outs.

1-2 Literature Review

Improved inventory management will undoubtedly help resolve any inventory-related issues the business may be experiencing, and also will assist in lowering significant investments or cash holdings in inventory. Sharma and Arya (2016) came to the conclusion that companies can adhere to economic order quantities for the best purchases, retain safety stock for components to prevent stock-out situations and support continuous production flow. As a result, the cost will decrease, and the profit will rise. Even though well-known manufacturers continue to keep high inventory levels nowadays, many material management experts believe that some materials can be handled without advanced inventory management. Regarding this, even if introducing advanced inventory management always seems like a good idea, it is essential to weigh the benefits and costs (Mishra et al., 2021).

In order to improve simple accountability at any given time, inventory control involves determining the quantity, value, and balance of inventory items kept in stock. Knowing the number ordered, how many have been used, how many are left, and when to place the next order helps the company prevent understocking and overstocking (Poi and Ogonu, 2019). The decisions made regarding purchases and distribution have an impact on inventories across the supply chain (Shapiro and Wagner, 2009). Inventory control aims to create a coordinated plan and replenish raw materials from the incomplete market and production resource information (Axsater, 1985).

Several authors have presented prescriptive models and methods that address the strategic and practical supply chain planning problem using the mathematical programming technique in the literature. As an illustration, Villegas and Smith (2006), reduced both order and inventory variance in the supply chain SD model as the defined weighting factor for forecast responsiveness is strengthened. Huchzermeier and Cohen (1996) provided a model that takes exchange rates into account. Canel and Khumawala (1997) investigated multi-period planning problems and Vidal and Goetschalckx (2001) presented a method for calculating transportation costs independent of transfer prices disclosed in multinational supply chains. On the other hand, Sternman (1989) emphasizes using reinforcement loops, while Towill (1996) emphasizes using analytical approaches from control theory.

Chinello et al. (2020) findings imply that the advantages of establishing a product classification outweigh those of decreasing lead times and raising shipping frequency. Furthermore, Lee et al. (2019) illustrate that a supply chain has numerous components of unpredictability. In the semiconductor industry, lead time, demand, and yield uncertainties are very relevant, and higher uncertainty can cause bullwhip effects, undermining the overall performance of the supply chain. In addition, Senapati et al. (2012) performed an extensive Literature Review on lead time reduction and that the two significant competitive elements in business are time and cost. Lead time can be shortened at a cost in many practical situations; in other words, it is adjustable. It was discovered that by reducing the lead time, safety stock might be reduced, reducing the loss caused by stock out, improving customer service, and increasing the competitiveness of businesses.

Ahiska and King (2010) provided reliable, practical descriptions of the best manufacturing/remanufacturing inventory policies identified using Markov decision procedures. A model for an integrated inventory distribution optimization problem for several products in a multi-echelon supply chain context was created by Manatkar et al. (2016).

Making cost-effective decisions on the optimum inventory at the retailers' and distribution centers' locations will be more accessible using the model described in a research (Manatkar et al., 2016). Also, Tom Jose et al. (2013) found that the amount of inventory the company can keep in reserve stock each year can be calculated from the safety stock calculation.

Radhi and Zhang (2019) investigated a dual-channel retailing structure in which customers can return their purchases via the same or a different channel, and items in good condition and returned during the selling season can be resold. Also, Yoo (2014) explored a joint decision problem of the return policy and product quality in a buyer-supplier supply chain in a study. The buyer chooses a return policy for customers and delegates the product quality choice to a supplier. Product quality and return policy affect consumers' product valuation and return behavior. Su (2009) examined the influence of full returns policies and partial returns policies on supply chain performance using a model they offered.

It is discovered that given a specific necessary service level, the average demand level and the ordering cost to holding cost ratio are the two key drivers that might be used as decision variables (Abuhilal et al., 2006). Michalski (2013) proposed two models to demonstrate that value-based alterations will assist managers in making better value-creating decisions in inventory management, even though issues related to optimal economic order quantity and production order quantity still exist. Yan et al. (2020) believe the need for more attention to or simplifying the sub-standard maintenance (IM) activities as continuous improvements in existing studies diminish their applicability in industrial settings. To address this, they examine multi-unit systems' joint maintenance and spare parts inventory optimization, considering IM activities as random improvement variables.

The model's use of the K-means clustering algorithm helped speed up the finding of the ideal inventory solutions. Chen et al. (2022)'s methodology could assist hospitals in reducing medical costs and inventory while improving drug administration's effectiveness. Ahmadini et al. (2021) suggest a multi-objective fractional inventory model to maximize profit with full back ordered quantity simultaneously, optimize cost related to inventory holding cost and various carbon-dioxide emission costs, and minimize potential pollution during the planning of inventory production.

The time required for order picking can be decreased by choosing the best locations for specific products in a warehouse and then figuring out the fastest ways to complete orders. It is the most crucial and advantageous element in lowering warehouse operational costs (Kordos et al., 2020). In addition, a model was constructed and developed by Yang et al. (2021a) for optimizing the storage space in the automated warehouse based on the load-bearing capacity of the shelves and the stacker's operational effectiveness.

Material requirement planning (MRP), vendor-managed inventory (VMI), flexible manufacturing systems (FMS), and just-in-time (JIT) procedures are the techniques used to manage inventory the most frequently (Gaudenzi and Christopher, 2016). Most of the time, a few distinct strategies are used to form the inventory management plan. The inventory controller must be able to recognize which inventory management strategy to employ when dealing with different sorts of material because each strategy is made to fit different types of material (Khalid and Lim, 2018).

Mbah et al. (2019) discovered a significant association between operational performance and inventory cost, just-in-time strategy, materials requirement planning, and strategic supplier partnerships. Thus, the study's main finding is that inventory management significantly improves the operational efficiency of the sampled listed companies in South East Nigeria.

Chapter 2

2-1 Methods

System Dynamics (SD) is the fundamental methodology used in this study. The SD methodology uses mathematical modeling to structure, comprehend, and address complicated problems. The system dynamics model, which incorporates dynamic stocks and flows of numerous feedback loops and time delays, is a continuous time model. When analyzing dynamic and complicated problems and when the system contains feedback loops and delays, the system dynamics approach is appropriate (Sterman, 2000). SD is an effective way to understand systems, identify the causes of complex problems, and propose solutions (Anderson and Garcia-Feijoo, 2006). The basis of system dynamics is the idea that a system's behavior over time is determined by the system's structure, as represented in the model. The feedback loops of cause and effect and the delays between them further define the system structure. In addition to simulating and predicting a system dynamic's behavior, system dynamics models also describe how the behavior is produced (Barlas, 1996).

The SD methodology employs stocks to illustrate accumulation and show the system's state at a specific point in time, providing the system with the memory to calculate the system. Stocks are equivalent to integral formulae, and flows change the stocks by adding or depleting them. Differential equations also represent stocks since their change depends on the net change at any given time. Flows are determined by stocks as well as other state variables. Provided variables and parameters are auxiliary variables in SD models representing stock functions such as constant values or exogenous inputs (Bayer, 2004).

In this thesis, case study research is conducted on the supply chain role in inventory optimization using a system dynamics approach in a manufacturing company. Case study analysis is a widely used research method that is essentially advised for studying phenomena that occur in complex environments where there are frequently more factors to consider than actual observations. Case study analysis has gained significant relevance over time in various research domains, has been improved upon and expanded upon in many significant ways, and has been applied in numerous notable research investigations (Symonds, 1945). The case study method should only be used to define cases and not to analyze cases or model connections between cases. Gerring (2004) explains how this understanding of the topic clarifies some of the ongoing uncertainties in case study work and misunderstandings that are important to the business in some ways.

2-2 Background

Avery Dennison is an international materials science and digital identification solutions business with branches in more than 50 countries and have more than 36,000 staff members globally. Avery Dennison's size, scale, and complexity require utilizing qualified employees, structure, and tools for inventory management. This company is the world leader in heat transfer brands and can therefore offer unique, environmentally friendly products with fantastic quality, color reproduction, and resolution in photo quality. This study aims to address the current problem at Avery Dennison NTP located in Gaupne, Sogn and Fjordane, Norway. Inks, chemicals, and printing films are the primary raw materials used in this company.

The majority of output is destined for the Norwegian market, but they also export an essential amount of the product to prominent businesses like Adidas, Umbro, and Nike. They are the unique provider of player names and numbers for all official FC Barcelona football kits sold globally, among other things. Additionally, this company makes significant sales to European sports and work wear retailers. In addition to the heat transfers, they also provide embroidered and woven brands made by Avery Dennison facilities worldwide.

2-3 Data Collection

Data collection began in November 2022 and concluded in February 2023. The simulation model was created in collaboration with the firm's supply chain manager. Some interviews were used to develop and validate the operating policy modeling. A second validation was performed after an initial model was built and utilized to replicate the company's behavior. Several group meetings with the purchasing analysts, warehouse, and sales employees were held to discuss the model as a whole and determine and evaluate to what extent the model's behavior simulates the behavior of the actual supply chain. The entire conversation was recorded. In addition, Literature is a significant source of information.

Google Scholar has been used to locate books and scientific articles. The data needed for the model's development, calibration, and validation have been gathered from the company's ERP system provided by SQL codes from the IT department and excel file reports.

2-4 Ethics

The rules stated in research ethics regulations have been followed throughout this work to make a significant contribution to the scientific community (Hasan et al., 2021). In fact, there are many ethical requirements for researchers. They must adhere to governmental, institutional, and professional requirements for using human subjects in research (Smith, 2003). Additionally, the researcher admits that plagiarism is unacceptable. All research resources, including the model's equations, assumptions, data sources, and other necessary model documentation, are also made available to other researchers to ensure the transparency of the study in the Appendices section. Data collection involves no human subjects, and the interviews were only for learning about the system. No interview data was used directly for system analysis, and no personal ID information was collected and used.

Chapter 3

3-1 Conceptual Model

The simulation model was built using Stella Architect software. This section provides the model as a Cause and Loop Diagram (CLD). Since it shows a simplified version of the model, structural components are missing from the CLD, which causes certain mismatches with the actual model structure. We will go over each of the model's main loops separately. Later in this chapter, an in-depth description of the model will be provided.

The Market Growth (MG) model of Forrester (1968) is the basis for the central part of the model. It indicates the point at which products, services, money, and information flow. However, these interactions within the company in the market, and between the two lead to these flows across the boundary. Only in the context produced by other company functions can market dynamics be comprehended because these other functions generate the variables that marketing must deal with. Here, the goal is to define and describe a system that can cause stagnation of sales increase even in the presence of an unlimited market.

The current model has been developed in this study as it looked aggregate. Focusing on the inventory, raw material, and storage levels is the main difference between the developed version and the main Market Growth model.

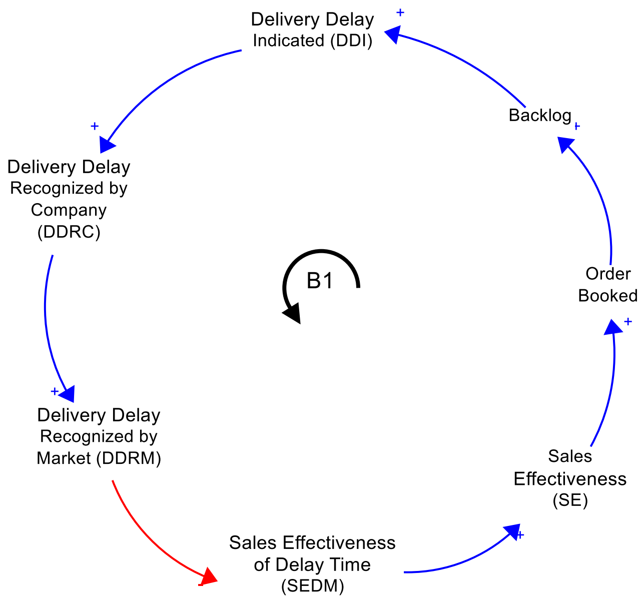

Figure 3. 1) Loop B1.

Figure 3. 1 shows loop B1, a Balancing feedback loop. This loop shows that the Delivery Delay also begins to increase when the backlog grows. As a result, the Delivery Delay Recognized by Company (DDRC) will be higher. Delivery Delay Recognized by Market (DDRM) rises together with the DDRC; however, this results in a reduced Sales Effectiveness of Delay Time (SEDM). When the SEDM falls, the Sales Effectiveness (SE) reduces as well because of the positive effect of the SEDM, which subsequently causes the Order Booked and Backlog to decline. That closes loop B1.

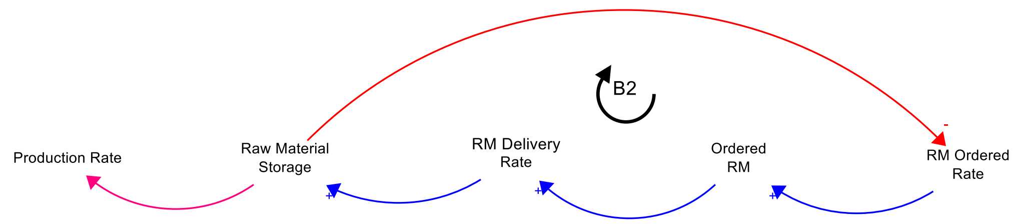

Figure 3. 2) Loop B2.

loop B2 (figure 3. 2) begins at RM Ordered Rate. More raw materials will be ordered as the RM ordered Rate rises, which also increases the RM Delivery Rate. There will be more raw material in the storage if RM delivery grows. But, the raw material order rate will decrease as raw material storage rises, which means a negative effect.

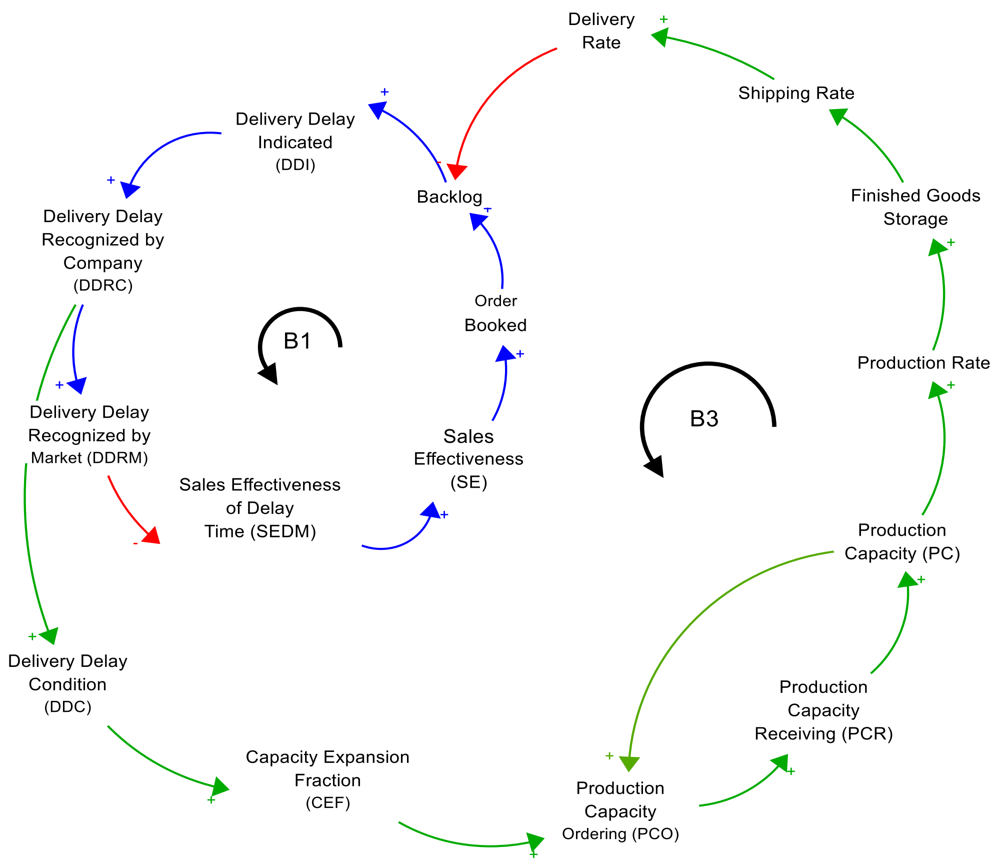

Figure 3. 3) Loops B1 and B3.

Next, another Balancing feedback loop, B3, can be introduced in Figure 3. 3, starting at the Production Capacity (PC). If the Production Capacity increases, there will be more Production rates. If the Production rate increases, there will be more goods in the finished goods storage and shipping rate. If the shipping rate increases, the delivery rate also increases. As it rises, there will be a lower Backlog due to the negative impact. By decreasing the number of Backlog, the Delivery Delay Indicated (DDI) also indicates a decrease. This leads to a lower Delivery Delay Recognized by Company (DDRC). If DDRC diminishes, Capacity Expansion Fraction (CEF) also reduces, leading to a lower Production Capacity Ordering (PCO). PCO decreases the Production Capacity Receiving (PCR), then declines the Production Capacity. So, the less Production Capacity Ordering, the less Production Capacity at the end. This is how B3 balances the loop.

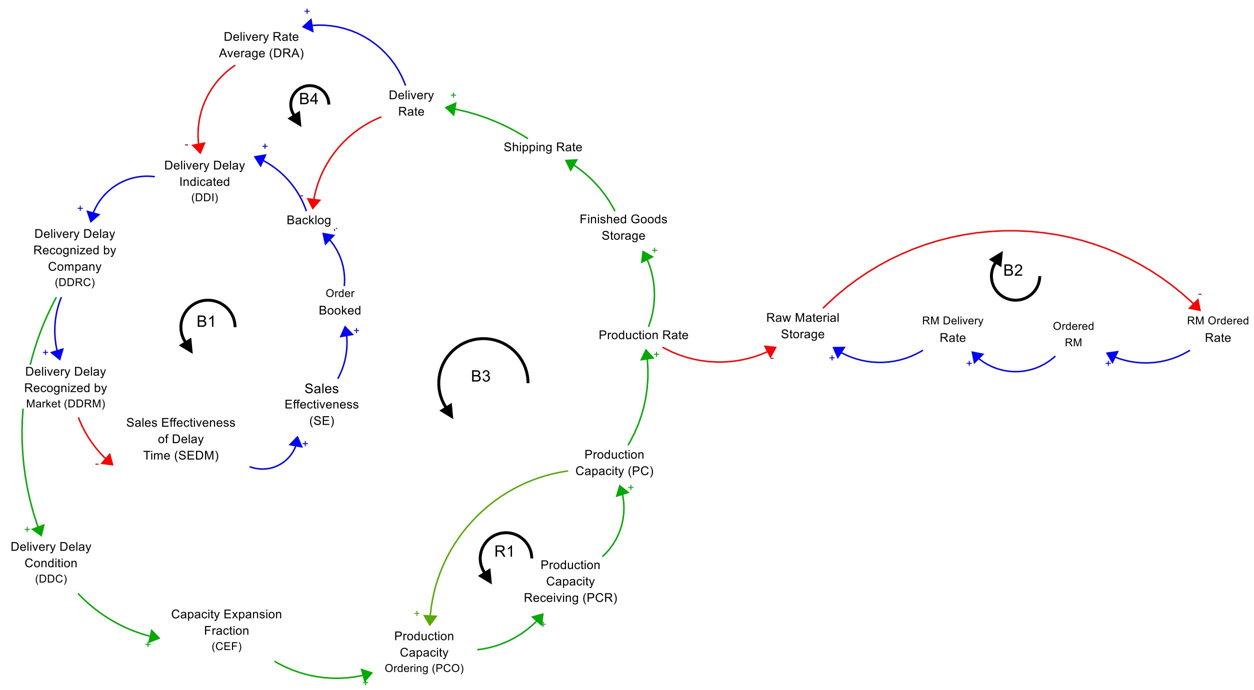

Figure 3. 4) Loops B1, B2, B3, B4 and R1.

R1 and B4, two additional loops, are visible in Figure 3. 4. The Production Capacity Ordering (PCO) is where the reinforcing loop R1 begins. If PCO grows, the Production Capacity Receiving (PCR) would receive more units to increase the Production Capacity (PC). This would then result in increased PCO.

The only distinction between balancing Loop B4 and balancing Loop B3 is that it assumes that as Delivery Rate rises, the Delivery rate average (DRA) increases. However, the Delivery Delay Indicated (DDI) decreases.

After considering the main loops presented in the CLD, the following section will examine the model in more detail.

3-2 Model Description

The model structure is discussed in this section. Equations and graphical functions that require further clarification will be taken into account. As previously stated, while comparing this model to the Market Growth model, the structure of the model has gone through some modifications, as the inventory section is the main focus of this study. Also, some variables have been added/removed, and some equations and data have been revised.

Notably, rather than focusing solely on hiring the salesperson, which assumes a weakness in the MG model, this model considers the entire Effective Sales Budget, including hiring and all costs such as travel, sponsorship, and more. These modifications aid in analyzing the ordered raw material value based on predicted customer orders, raw material storage level, and finished goods storage while considering production and shipping rates. It likewise helps in understanding the impact of various firm parts such as delivery delay, backlog, production capacity, and sales budget on inventory levels.

This section describes the model, including its variables and equations. As mentioned previously, the MG model represents the foundation for the more significant part of the model.

Appendix 1 contains additional information, including model documentation that discusses each variable individually.

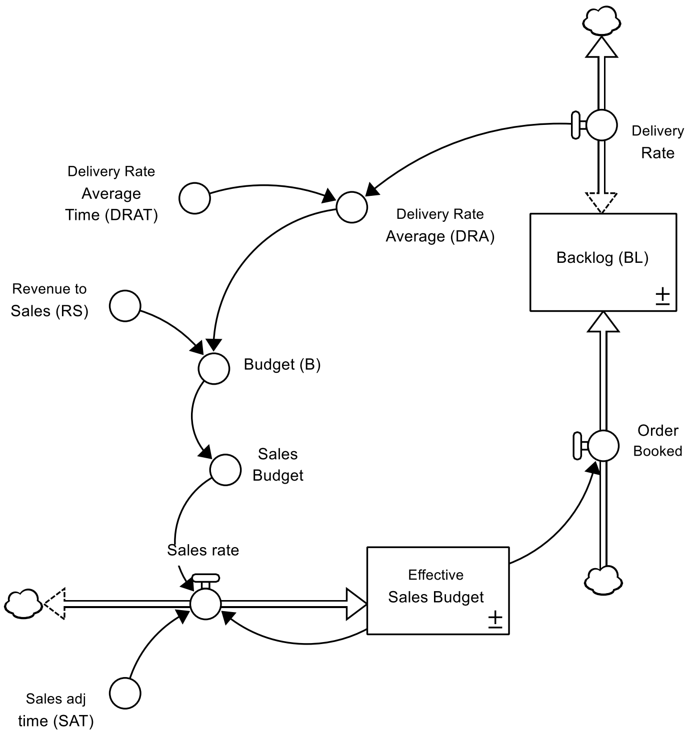

Figure 3. 5) SFD for Sales Budget with Sales Generating Revenue.

The Backlog and the Effective Sales Budget are the two main stocks of the model in Figure 3. 5. The sales rate supplies the Effective sales budget. The Effective sales budget determines the order rate. Order booked at a rate is added to the backlog. The delivery rate reduces the backlog level and is an input to the average delivery rate. The Delivery Rate Average represents the weekly delivery delay for each product unit as shown by the current backlog and the current delivery rate, which reflects the payment and collection delay. Smooth functions are used to simulate information delays, and since we are using smooth 1, the first-order information delay is illustrated here:

$$\text{Delivery Rate Average} = \text{SMTH1 (Delivery Rate, Delivery Rate Average Time)} \tag{1}$$

The level delivery rate average goes into the sales rate. As described above, in the MG model, only Salesman and Salesman hiring was considered as what affected the Order booked. Considering this assumption, there would be a limitation since there are also other items that the budget influences, not only the salesman's salary. Such as advertising, traveling, sponsorship, etc., along with hiring. In this model, we assumed that 1% of the total weekly budget comes to the sales as the sales budget. Moreover, this budget influences the Sales rate and adequate sales budget.

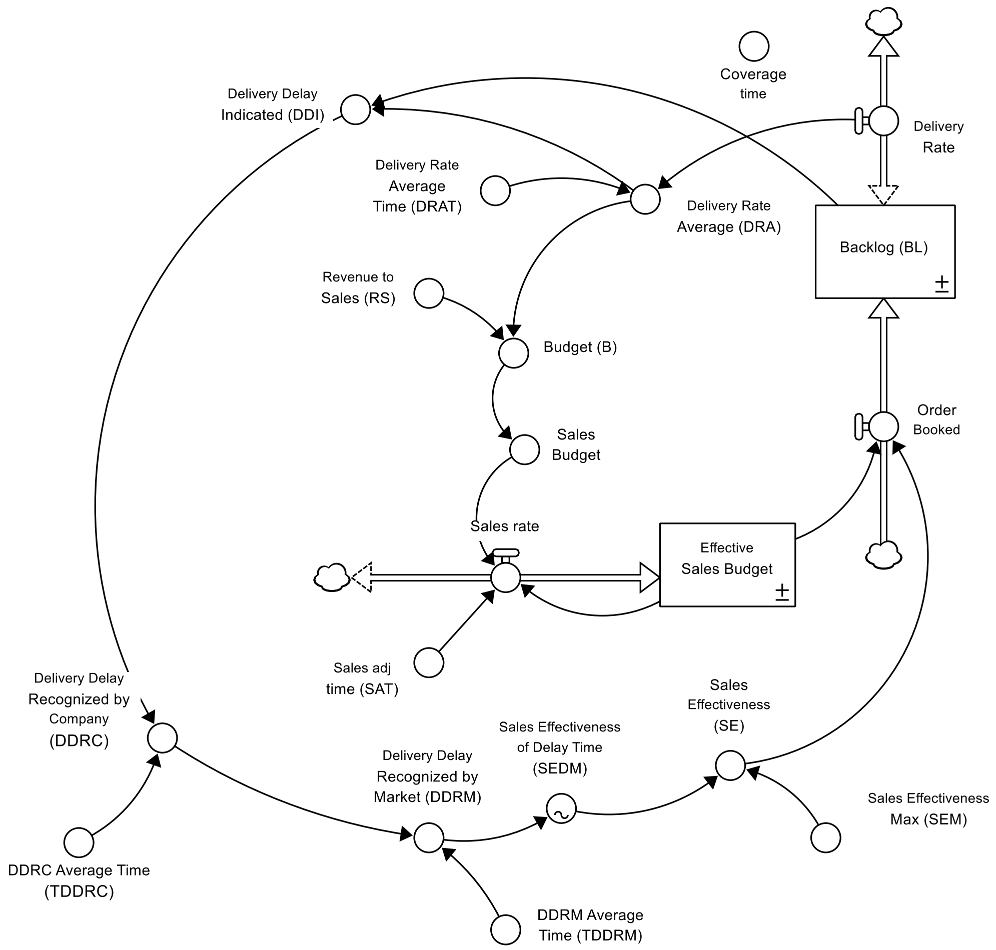

Figure 3. 6) SFD for Market with Delivery Delay.

Figure 3. 6 illustrates the relationship between market delivery delays, sales effectiveness, and Order booked rates. The backlog-to-delivery rate ratio provides an approximation of a product's delivery delay. It means the amount of time it will take for the current delivery rate to clear the backlog of orders before an order can be filled. The ratio of the current backlog to the current short-term average of the delivery rate, or DRA, is defined as the delivery delay indicated, DDI. Nevertheless, the system's decision-makers are typically unaware of this current delivery delay condition, which is implied by the current backlog and existing delivery rate. Delivery delay indicated, DDI, is a delayed version of delivery delay recognized by the company, DDRC.

Delivery Delay Recognized by Company =

SMTH1(Delivery Delay Indicated (DDI), DDRC Average Time (TDDRC)) (2)

Answering to change delivery delay quotations from the market takes time, and so a further delay intervenes before the delivery delay is identified by the market at DDRM. The DDRM is used to determine how attractive a product is to consumers.

Delivery Delay Recognized by Market (DDRM) =

SMTH1(Delivery Delay Recognized by Company (DDRC), DDRM Average Time (TDDRM)) (3)

The multiplier SEM, a fraction provided in terms of its maximum value, represents the sales effectiveness from the delay in the figure. SEM stands for sales effectiveness when there is no delivery delay, assuming a specific and fixed set of parameters regarding pricing, quality, the competency of the effective sales budget, and other factors that impact the selling process. The delivery delay recognized by the company, DDRC, grows after a delay, and after another delay, DDRM also increases. This results in a fall in the sales effectiveness multiplier, or SEDM, which then lowers sales effectiveness, or SE, and lowers booked orders until the order backlog stops increasing.

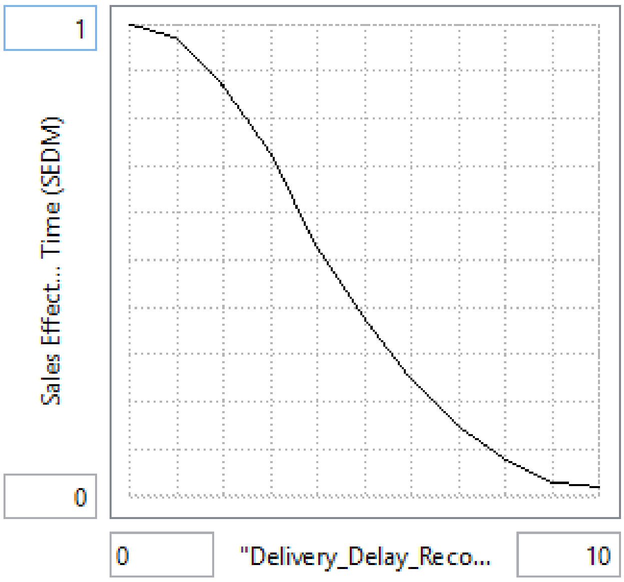

Figure 3. 7) Sales Effectiveness of Delay Time (SEDM).

Sales Effectiveness of Delay Time (SEDM) is expressed in Figure 3. 7 in terms of the maximum value of sales effectiveness and is regarded as a multiplier for sales effectiveness which depends on the delivery delay recognized by the market, DDRM. After a delay, DDRM increases. This causes the sales effectiveness multiplier, SEDM, to decrease, which causes sales effectiveness, SE, to decline. For the slight increase in delivery delay, the sale is somehow unaffected. However, sales effectiveness will drop rapidly when the delivery delay is long enough to concern the customers. A delivery delay of 0 results in a maximum value of the unit. The unit of this converter has no dimensions when used as a fraction.

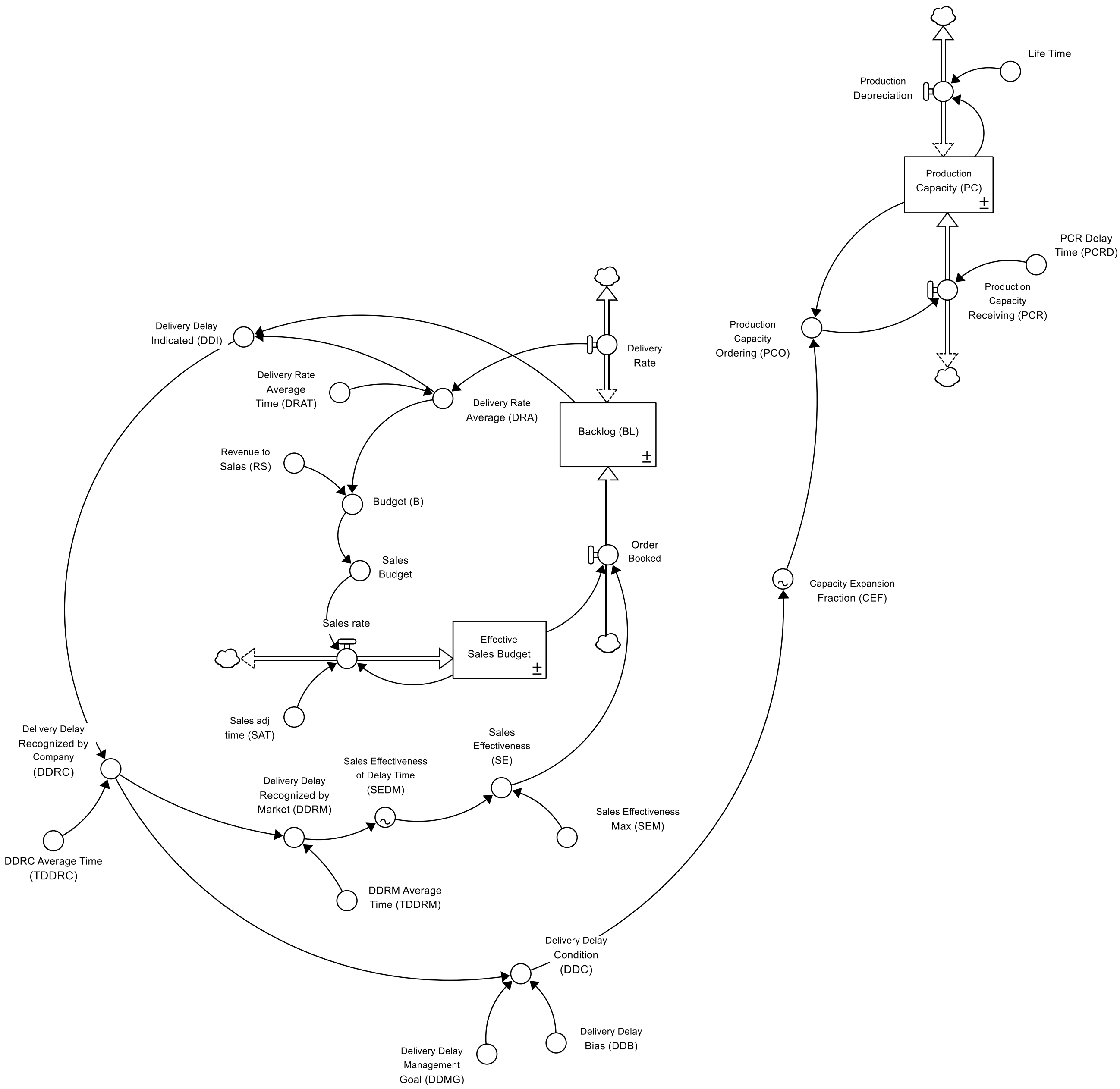

Figure 3. 8) SFD for Market with Delivery Delay.

The ratio of the delivery delay recognized by the company, DDRC, is the delivery delay condition, DDC. The delivery delay bias, DDB, is deducted from this ratio in order to maintain any particular level of resource allocation. DDB represents the competitiveness for resources across the organization:

Delivery Delay Condition (DDC) = Delivery Delay Recognized by Company (DDRC) / (4)

Delivery Delay Management Goal (DDMG) – Delivery Delay Bias (DDB)

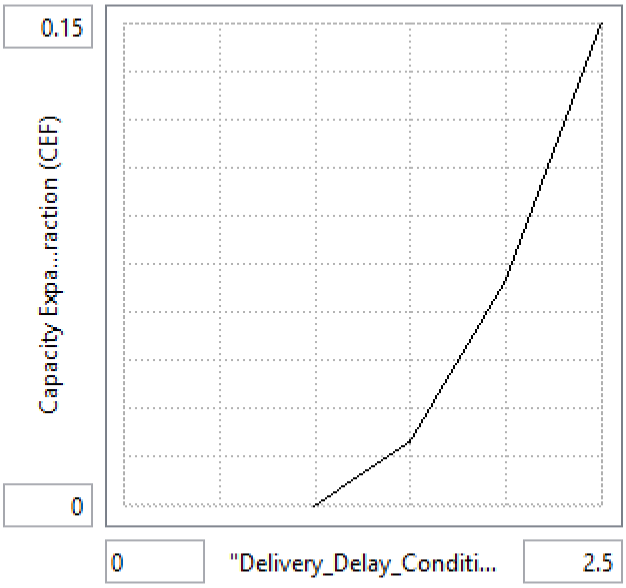

Figure 3. 9) Capacity Expansion Fraction (CEF).

The capacity Expansion Fraction in Figure 3. 9 is a fraction indicated by a graphical function in the model, and it represents the fraction of expanding the production capacity. When the Capacity Expansion Fraction increases, the company invests aggressively in capacity.

It was a problem in the Market Growth model as polarity needed to be clarified. Positive and negative polarities make the polarity of the feedback loop ambiguous and make it impossible to have a definite feedback analysis. Due to the casual links, since the Y axis was between -0.07 and 0.15 due to the particular kind of quantification in the graph and it could be negative or positive. This problem is solved by changing the numerical value of the Y axis (from -0.07 to 0) and adding a new outflow to the Production Capacity stock.

Since the variable coming in from CEF is the fraction each week of the existing capacity, there is a reinforcing loop in the figure. The result is that capacity ordering becomes a function of the system's operational scale.

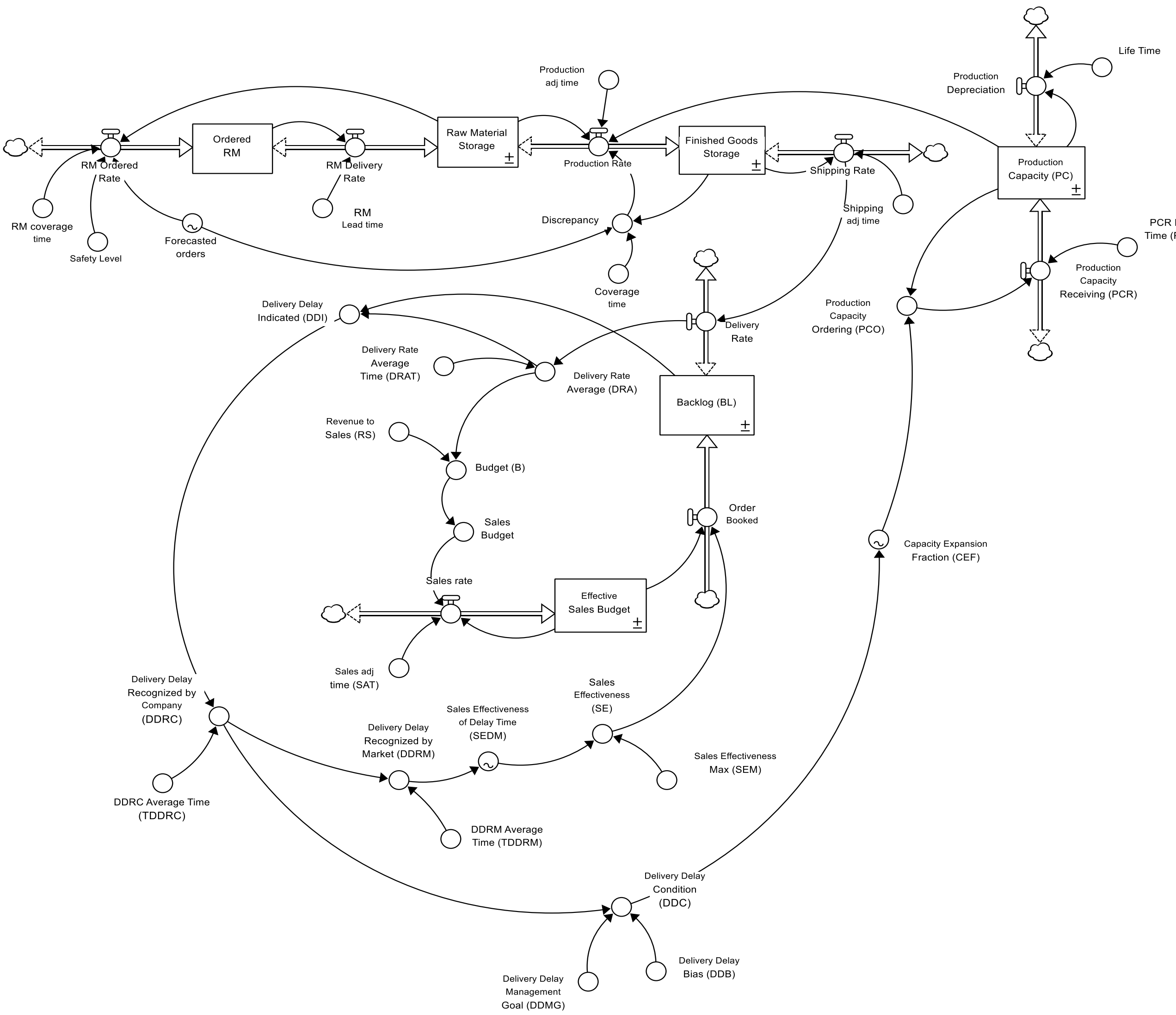

Figure 3. 10) SFD for Raw Material.

As the Raw Material (RM) is essential in this model, it is separated from the main body, as seen in the SFD above. In this sector, the Raw material order rate, which flows to the Ordered Raw Material, is calculated from Safety Level, Forecasted orders, raw material storage, and RM coverage time.

$$\text{Raw Material Order Rate} = \text{Forecasted orders} + (\text{Safety Level}*1.1 - \text{Raw Material Storage}) / \text{RM coverage time} \qquad (5)$$

The Safety Level defines the amount of Raw Material in the warehouse to prevent an out-of-stock situation. Here is multiplied by 1.1 as we considered 10% higher. Safety Level serves as insurance against fluctuations in demand. If the inventory comes below that, it would be a risk of shortage of the RM for the production. Here the deduction of raw material storage from the Safety Level has been considered to cover the gap in Raw Material. In addition, the company asks its main customers to send a weekly forecast of their demand. It helps to calculate how much Raw Material is and when it is needed. Then, the ordered Raw material moves to the raw material storage through the RM delivery rate. The Production rate reduces the raw material storage. The Leontief production function, also known as the fixed proportions production function, is considered here. This is a production function that suggests that the factors of production will be used in fixed (technologically predetermined) proportions because there is no substitutability between factors. For calculating that, Production Capacity (PC), raw material storage, Production adjustment time, and Discrepancy are employed:

$$\begin{gathered}\text{Production Rate} = \\ \text{MIN (MIN (Production Capacity (PC), Raw Material Storage /} \\ \text{Production adjustment time), MAX (0, Discrepancy))}\end{gathered} \tag{6}$$

After production, the goods will be accumulated in the Finished Goods storage. Based on this formula, Discrepancy defines the differences between the amount of the Forecasted orders and the amount of the Finished Goods in storage. Then the Finished Goods will be shipped from the storage to the customers.

3-3 Model Boundaries

In general, modeling aims to simplify understanding a part of the world by concentrating on a simplified but accurate picture of it. As a result, for all models, it is unavoidable to exclude some specific parts or characteristics that affect the system under consideration (Richardson and Pugh III, 1997). Likewise, this research model contains some constraints.

First, a rough estimate of the Raw Material system was needed to determine its importance to a market. The only solution is simplifying the model while keeping it as close to reality as possible. In addition, the model is limited by the time horizon, which is the period over which a problem develops. The model has a time-based horizon of 52 weeks in 2022. Lastly, due to time constraints, the model excludes some factors and risk regulators that impact inventory, and it aggregates some of the risk regulators and factors for the same reason.

3-4 Model Assumptions

There are some other major assumptions that were made in the process of the creation of the model:

- The company sells different products bedside the finished goods such as raw materials (inks, sheets and chemicals), machines and spare parts. In this research, it is assumed that only Raw materials are sold by this company.
- As there are different kinds of the raw materials, instead of the item unit, the amount of them in NOK is assumed.
- It is difficult to predict the shape of the impact from one variable to the next when using graphical functions. Furthermore, because there are multiple information/knowledge effects on another variable, it was necessary to make assumptions about which variable causes this impact. These uncertainties are addressed through sensitivity analysis

3-5 Model Set Up

The basic model settings that were used in this study are as follows:

- Start time: 0
- Stop time: 52
- Time units: Weeks
- Delta Time (DT): 1/64
- Integration method: Euler.

Chapter 4

This chapter discusses the model's validity and describes the tests employed to determine its validity. Validation tests are classified as structural or behavioral tests in system dynamics. Model structure validation means having a structure that does not go against reality, which includes both the causal effects across the model and the parameters; parameters must also be real and within logical values (Senge and Forrester, 1980). The model validation was carried out using Barlas' guidelines and methods (Barlas, 1996). The three types of validation tests are direct structure tests, structure-orientated behavior tests, and behavior pattern tests.

4-1 Direct Structure Tests

Several tests were run to verify the developed model based on the research conducted by Senge and Forrester (1980). First, direct structure tests were performed: structure and parameter verification, direct extreme conditions, and dimensional consistency tests. These tests will be discussed below:

4-1-1 Structure Verification Test

This test validates the model's structure by comparing equations and equation-based relations to real-world information. The system's knowledge is gathered from the literature, as described in the Literature Review. This was considered during the modeling process as the model structure was developed. As a result, the model passed this test successfully.

4-1-2 Parameter Verification Test

This test verifies and indicates that each parameter in the model has a real-world equivalent. Senge and Forrester (1980) define parameter verification as having two components: conceptual correlation and numerical verification. Conceptual correspondence is correspondence with whether parameters match elements of the structure of a real system. In contrast, numerical verification is tasked with whether or not the parameter value is within a reasonable range.

4-1-3 Direct Extreme Conditions Test

This test determines whether each model equation is consistent with real-world information even when its inputs are replaced with extreme but meaningful values. This test is also carried out without simulating the entire model; each equation is confirmed separately with extreme inputs.

4-1-4 Dimensional Consistency Test

The objective of this test is to ensure that all of the dimensions used in the model are consistent with one another and that all dimensions have a real-world equivalent. Because the model was developed continuously through a literature review, it was evaluated for dimensional consistency at every step of the modeling process. All of the variables in the model have real-world meaning.

4-2 Structure-Oriented Behavior Tests

These tests evaluate the model's structure implicitly by observing the behavior that the model produces. At this stage, the entire model or each module is simulated to run structure-oriented behavior tests, which compare the produced behavior to real-world knowledge and determine whether the model produces any errors.

4-2-1 Extreme-condition Test

This test is carried out by increasing the parameter values of chosen variables to their maximums and running the simulation under these circumstances. Each variable is subjected to these evaluations. The goal of the test is to ensure that the model does not produce any errors and that the generated results are consistent with the model's expected behavior.

4-2-2 Integration Test

This test ensures that the integration technique does not affect the model. The test was carried out by testing each integration method, and it was discovered that the system's behavior remains unchanged with the shift in the integration method. As a result, the system is not affected by the integration method.

4-2-3 Behavior Sensitivity Test

This test determines whether the model's parameters are sensitive and if so, whether they are sensitive in the actual world. Sensitive parameters are anticipated to be sensitive in the real world. Furthermore, sensitivity testing shows sensitive areas of the model that can be used as policy leverage points (Hekimoğlu and Barlas, 2010). There are three types of sensitivity: 1) Numerical sensitivity, significant variations in numerical value but remaining of behavioral pattern, 2) Behavioral sensitivity, significant alters in behavioral modes, and 3) Policy sensitivity, changes in the effects or desirability of a suggested policy (Schwaninger and Grösser, 2020).

The primary variable to examine the effect was Raw Material Storage. For testing the sensitivity in this study, the values of all constant variables have been reduced to half, and increased to double.

The Appendix 2 contains all information on the tested parameters, numbers, and findings. The following explanation is a summary of the test:

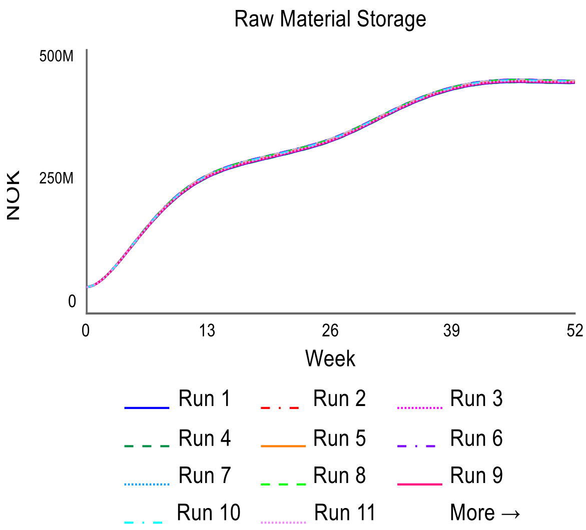

Figure 4. 1) Safety Level effect on RM Storage.

Figure 4. 1 shows that RM storage is not sensitive to the safety level, indicating a gap between expectations and the simulation result. By checking the details in Figure 4. 2, it is realized that the Forecasted orders dominates the RM order rate between the Forecasted orders and the Safety level. So, that is why RM Storage is not sensitive to Safety level.

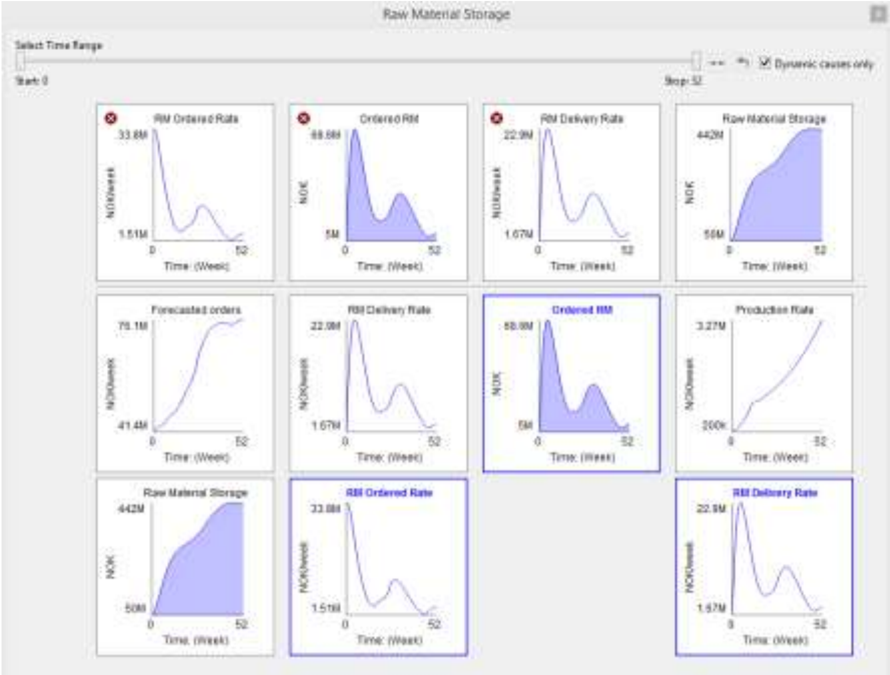

Figure 4. 2) Raw material storage in details.

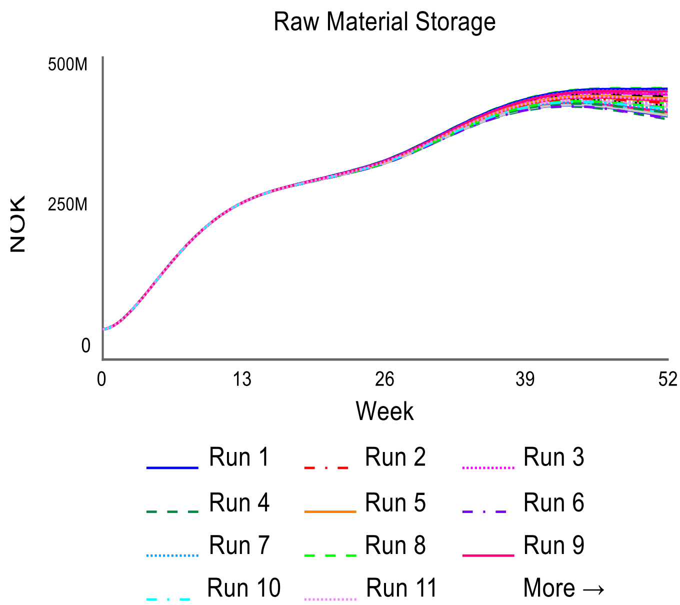

Figure 4. 3) Revenue to Sale effect on RM Storage.

The figure above illustrates that Raw Material Storage is sensitive to the Revenue to Sale. When the revenue to sale decreases, less budget is allocated to the sales department, and this causes fewer received orders from the customers. So, fewer goods are produced, and more Raw Materials will remain in stock. On the other hand, by increasing the revenue to sale, more goods are produced, and fewer Raw Materials will remain in stock.

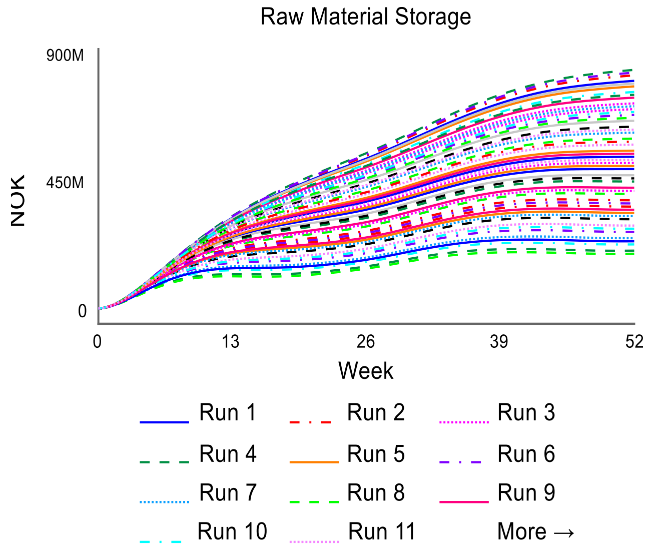

Figure 4. 4) RM coverage time effect on RM Storage.

It can be seen in Figure 4. 4 that Raw Material Storage is significantly sensitive to the RM coverage time. By increasing the RM coverage time, the Ordered Raw Material will be decreased, then there will be less Raw Material in the storage.

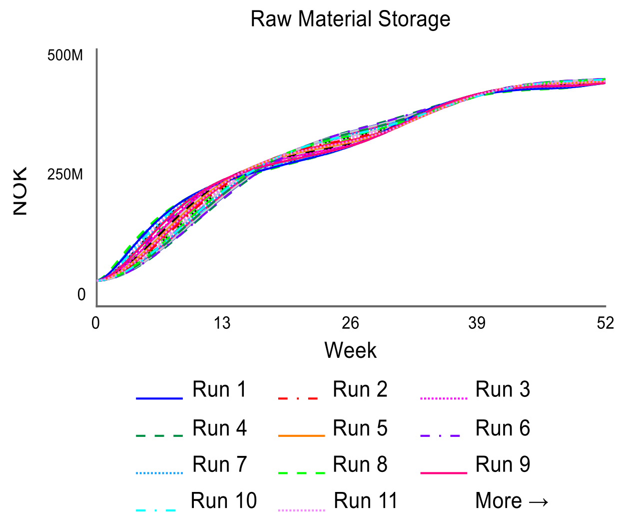

Figure 4. 5) RM Lead Time effect on RM Storage

Figure 4. 5 illustrates that Raw Material Storage is moderately sensitive to RM Lead time. By increasing the RM Lead time, the oscillation of the RM Storage will be decreased, which means less Raw Material will be received and stocked in the warehouse, leading to lower RM Storage value.

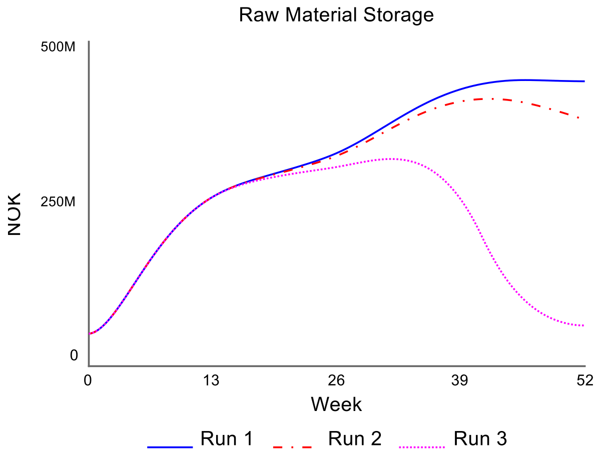

Figure 4. 6) Sales Effectiveness of Delay Time (SEDM) effect on RM Storage.

By focusing on the second graphical function, and after changing the shape of the Sales Effectiveness of Delay Time (SEDM), it can be seen in Figure 4. 6 that RM Storage is sensitive to this graphical function as it directly affects sales.

4-3 Behavior Pattern Tests

After ensuring the model is solid in structure, the next stage is to test the model's behavior pattern. The behavior's pattern, trend, and shape will be the center of the behavior pattern tests. This is useful in determining whether a model and its behavior are comparable to expected behavior and thus whether the model output is reliable.

4-3-1 Model Pattern Test

To examine the model's structure, the entire model was simulated under a business-as-usual situation, and the generated behavior was compared to the data on hand. Figure 4. 7 illustrates the model's behavior concerning the available data.

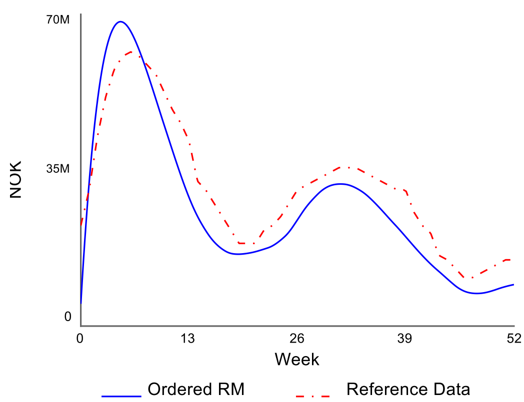

Figure 4. 7) Ordered Raw Material reference data.

Figure 4. 7 shows the company's historical data on Ordered Raw Materials in 2022 (in red) and the Ordered Raw Material model output (in blue). There are minor differences between the two, probably due to the use of different databases and the statistics in each source. The variances are accepted since the model behavior and the reference behavior are comparatively similar; however, additional data and information can improve the model output to achieve improved estimations in new versions of the model.

Theil Statistics for Ordered Raw Materials are shown in the table below. U, U^M, U^S, and U^C represent the inequality coefficient, fraction of the mean square error (MSE) attributed to bias, unequal variance and unequal covariance, respectively in this table.

Table 4. 1) Theil statistics for Ordered Raw Material

Variable	U	U^S	U^M	U^C
Ordered RM	0.228	0.005	0.285	0.694

Table 4. 1 shows that the inequality coefficient is low and the majority of the MSE is focused on unequal covariation (U^C). According to Sternman (1989) explanation, this situation is as follows:

> Though most of the error is concentrated in unequal covariation U^C, while U^M and U^S are small, it suggests that the simulated and actual series point-by-point values do not match, even though the model accurately represents the average value and dominant trends in the actual data. A situation like this could imply a very continuous phase shift or translating in time of a cyclical mode that is otherwise well replicated. A high U^C suggests that one of the variables has a significant random component or has cyclical modes not found in the other series. An extensive U^C may be related to noise or cyclical features in the historical data that the model could not capture.

As a result, it is reasonable to state that the model can reasonably reproduce the actual system's behavior. Additionally, not only are all of the Theil statistics' inequality coefficients small, but also the majority of the mistakes are unrelated to bias or unequal variance among the simulated and actual data.

Chapter 5

5-1 Simulation Results

In this chapter, the SD model simulation results for the business-as-usual (BAU) scenario are defined, revealing the baseline performance for the Ordered RM, Raw Material Storage, Production Capacity, and Backlog. Here, the goal is to assess the model's policy sensitivity to its feedback structure based on the previous chapter. For that purpose, the model is examined for the effects of the alternative policies under different scenarios. Then, the evaluation is repeated with different parameter settings (Langarudi et al., 2019). Without further investigation of the evaluation, it is impossible to be certain that behavior sensitivity reflects policy sensitivity. In fact, there are cases of behavior being very sensitive to a parameter while the policy remains uninfluenced by the same parameter (Moxnes, 2005).

5-2 Business as Usual Scenario (BAU)

The graphs in the figures below show the results of the simulation for the RM ordered and the Raw Material Storage in the Business as Usual Scenario. The Ordered RM fluctuates over time, as shown in Figure 5. 1. This is due to fluctuations in the Forecasted Orders received from the customers that affect RM ordered rate. The value of the Raw Material Storage can be observed on the right side of Figure 5. 1. This value begins to grow exponentially from the beginning until week 26. Then, from week 26, there is a modest increase in the value of the Raw Material Storage. This is because of the balancing feedback loop, B2, which includes the raw material order development. As enough raw material accumulates in the Raw Material Storage, the oscillation of the Ordered RM slows down, and finally, the Raw Material Storage grows slightly.

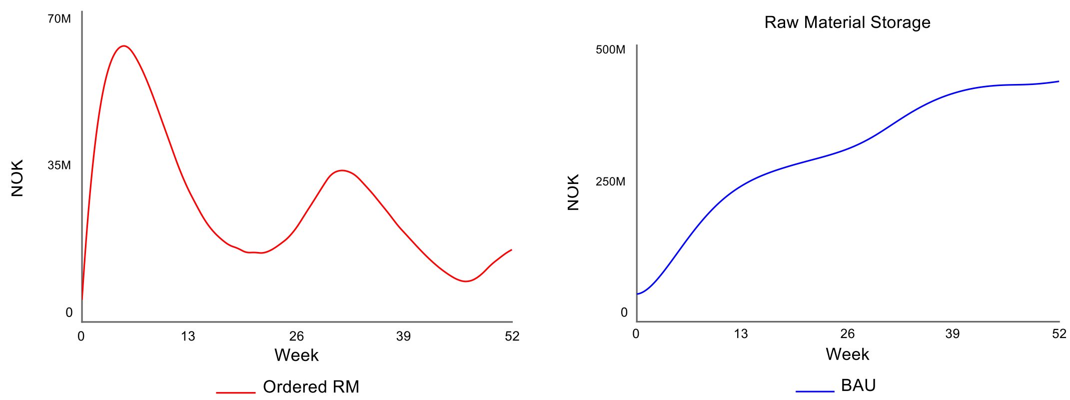

Figure 5. 1) Ordered RM and Raw Material Storage (BAU).

The development of the Production Capacity and Backlog can be observed in Figure 5. 2. It can be seen that from the beginning until week 12, the Production Capacity begins to increase increasingly. Then, the second increase is from week 12 until the end of the period. It is assumed that the growths are because of the R1, the reinforcing loop. As the Production Capacity Ordering increases, the Production Capacity Receiving also increase which results in more Production Capacity. On the other hand, from the beginning until week 12, there is a decline in the Backlog, followed by a significant rise until the end of the period. This is mainly because of B1, the other Balancing feedback loop. In loop B1, the delivery delay recognized by the company will be reduced as the backlog lowers. However, this reduction enhances the Sales Effectiveness of Delay Time, resulting in a rise in the sales and then backlog.

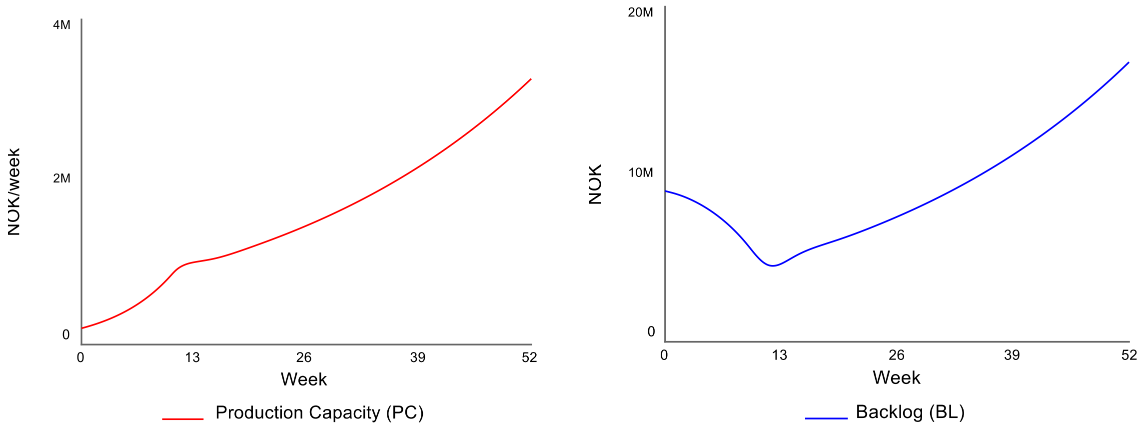

Figure 5. 2) Production Capacity and Backlog (BAU).

5-3 Sales Effectiveness Growth Scenario

In this scenario, an increase in the Sales Effectiveness is tested to reduce the inventory value. In this case, the value of Sales Effectiveness Max is increased from 350 to 700. This relative shift is completely proportional to growth in Sales Effectiveness. The increased Sales Effectiveness results in an improvement in Raw Material Storage.

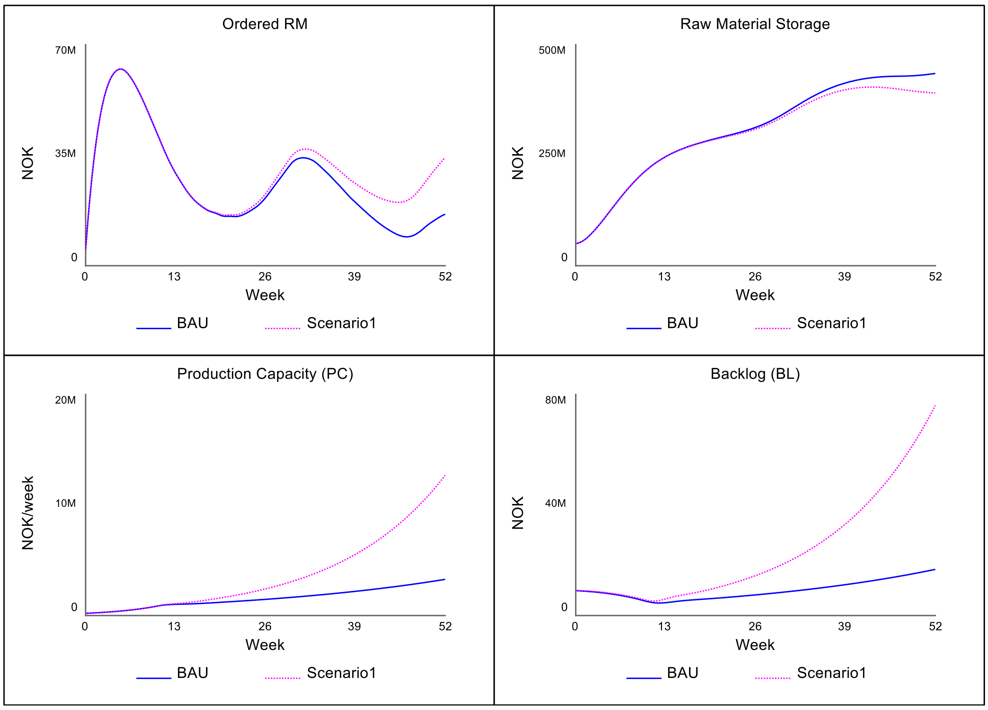

Figure 5. 3) Results of Sales Effectiveness growth scenario.

Based on Figure 5. 3, Sales Effectiveness rises as the Sales Effectiveness Max grows. It leads to a higher Order Booked and also higher Backlog. Loop B3 shows that there is an important influence; as the Backlog grows, so does the Production Capacity. The growth in Production Capacity causes a raise in Production Rate. Raw material storage shrinks because the production rate has a negative influence on raw material storage. a reduction in Raw Material Storage results in an increase in Ordered Raw Material as a result of loop B2. To conclude, Raw Material Storage decreases to 390 million NOK at the end of the period, which is 1.1 times less than the initial value.

5-4 A change in Capacity Expansion Fraction Scenario

The capacity Expansion Fraction denotes the proportion of increasing capacity for production. When the Capacity Expansion Fraction rises, the company raises capacity investments aggressively. There is a reinforcing loop as the variable coming in from CEF is a portion of the existing capacity. As a result, capacity ordering becomes a function of the operational scale of the system. By changing the shape of the Y-axis, a new decision rule will appear. It is understood that increasing the delivery time will result in increased investment.

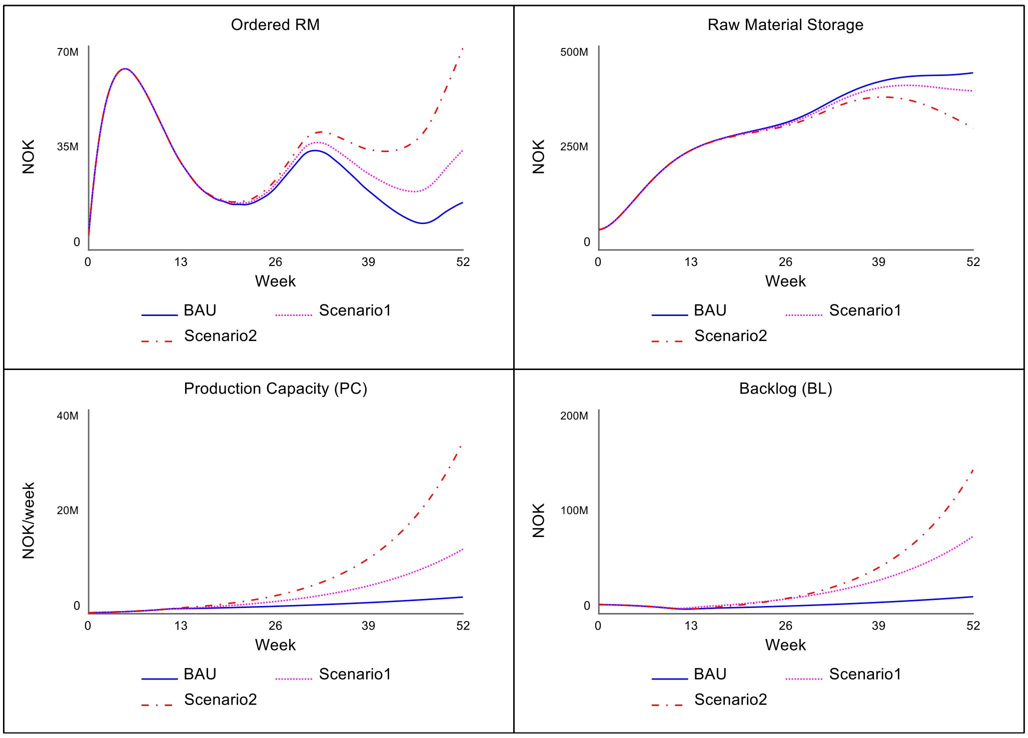

Figure 5. 4) Results of A change in Capacity Expansion Fraction scenario

With regard to the comparison of the results shown in Figure 5. 4, it is clear that changing the shape of the Capacity Expansion Fraction into an S shape improves the inventory outcomes. The Production Capacity Ordering increases much faster to a higher level. Consequently, the Production Capacity grew significantly. As explained before, this increase in Production Capacity leads to a growth in the Production rate. Because the production rate has a negative effect on raw material storage, raw material storage is reduced. As previously stated, the decrease in Raw Material Storage creates an increase in Ordered Raw Material due to loop B2. Furthermore, increased production leads to increased shipment and delivery rates. Because the delivery rate has a negative influence on the Backlog, fewer orders get delivered from the Backlog, resulting in a larger Backlog. As a result, Raw Material Storage drops to 298 million NOK, which is approximately 1.3 times less than the previous scenario and 1.4 times less than the initial value.

5-5 An increase in Revenue to Sales Scenario

The raw material storage is sensitive to the revenue to sale, according to the sensitivity analysis. In this scenario, an increase in the Revenue to Sale is considered in order to minimize the Raw Material Storage value. The Revenue to Sales has been increased from 1 to 3 for this purpose.

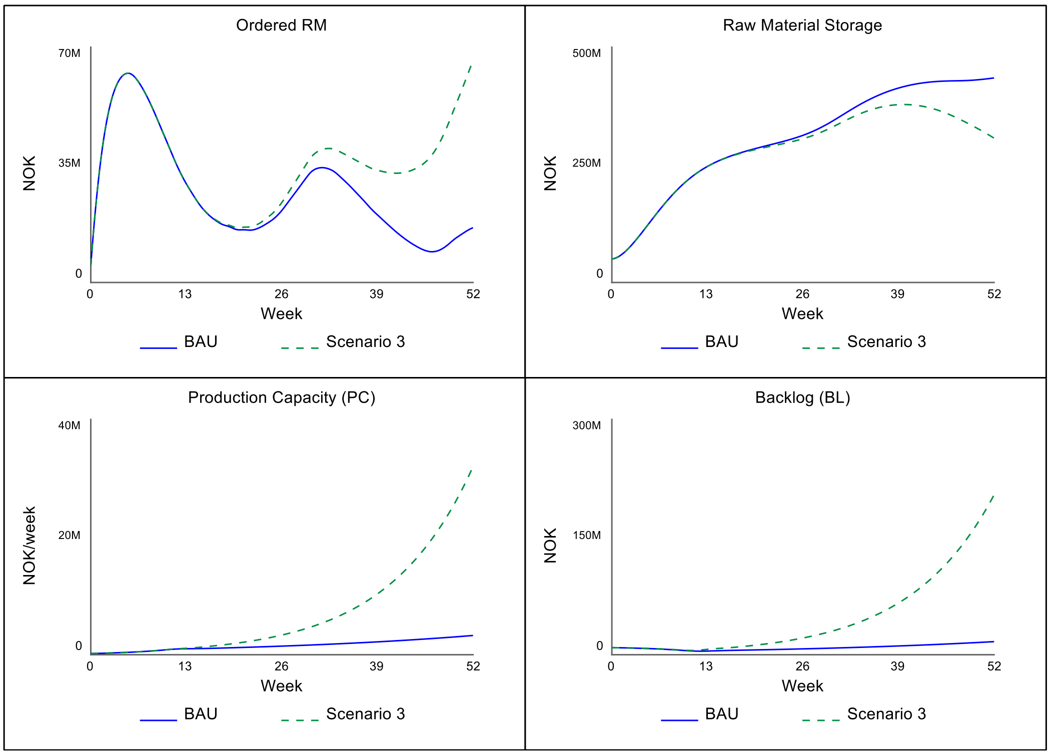

Figure 5. 5) Results of an increase in Revenue to Sales scenario

Figure 5. 5 shows an overview of the results. Apparently, increasing the revenue to sales modifies the inventory results. And, the budget increases as well. Thus, the Effective Sales Budget increased dramatically. As previously stated, a rise in the Effective Sales Budget leads to an increase in Order Booked followed by Backlog. Loop B3 demonstrates that as the Backlog increases, so does the Production Capacity. The increase in Production Capacity leads to an increase in Production Rate. Raw material storage declines as a result of the negative impact of production rate on raw material storage. As an effect of loop B2, a decrease in Raw Material Storage results in an increase in Ordered Raw Material. Finally, Raw Material Storage decreases to 307 million NOK at the end of the period, meaning it is 1.4 times less than the beginning value.

5-6 Delivery Delay Management Goal Reduction Scenario

Sensitivity analysis revealed that the raw Material Storage is sensitive to the Delivery Delay Management Goal. The Delivery Delay Management Goal is a fixed delivery target that is constant in this model, and equals to the system's minimal amount of time for order processing and production. This scenario explains how a reduction in the Delivery Delay Management Goal minimize the Raw Material Storage value. For this purpose, the Delivery Delay Management Goal has been declined from 3 to 2 weeks.

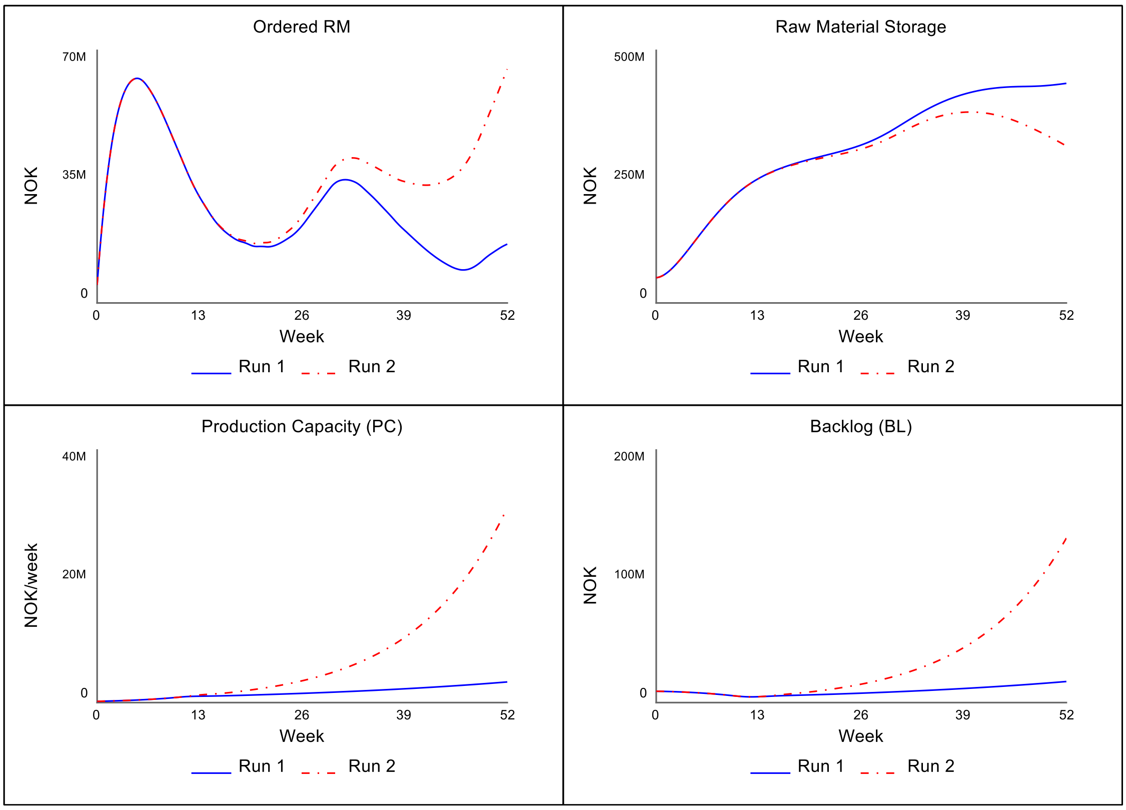

Figure 5. 6) Results of Delivery Delay Management Goal Reduction Scenario

Figure 5-6 provides a summary of the findings. Loop B3 indicates that when the Delivery Delay Management Goal drops, the Delivery Delay Condition increases. This rise leads to an increase in Production Capacity. As mentioned before, increasing Production Capacity causes a rise in the Production Rate. The negative influence of the Production rate on Raw Material storage results in a reduction in the Raw Material storage. A decrease in Raw Material Storage results in a growth in Ordered Raw Material as an outcome of loop B2. Lastly, Raw Material Storage falls to 311 million NOK at the end of the period of time, representing 1.4 times the starting amount.

Chapter 6

6-1 Policy Discussion

The sensitivity test and literature review indicated many areas where policies could be introduced to improve inventory optimization and reduce the oscillation in raw material storage. Although different policies were identified, we studied a limited number in-depth as they are less costly, and the implementation would be faster and easier.

Here are five policy options focused on in this study:

1. Adding a weighting factor
2. Reducing the RM lead time
3. Changing the shape of the graphical function of SEDM
4. Consumer returns policy
5. Combination of Adding a weighting factor and Consumer returns Policies

6-2 Adding a weighting factor

As discussed in the Literature Review chapter, Villegas and Smith (2006) examined how safety stock policies might cause production and delivery quantities to vary throughout the supply chain. The effect was demonstrated using a system dynamics model, and the simulation used real-world demand data. Because of the safety stock policy, they considered "α" as a weight for adjusting production orders. Where $0 < \alpha < 1$ is the weighted average of the proportion of the orders based on the forecast and the proportion based on the safety stock policies.

The weighting factor is a weight given to a data point to assign a lighter or heavier weight. The following equation can be defined in this model if we change equation (5) to include a weight factor for the adjustment of RM orders:

$$\text{Raw Material Order Rate} = \alpha^{*} \text{ Forecasted orders} + \alpha^{*} \text{ (Safety Level*1.1 - Raw Material Storage)/ RM coverage time} \tag{7}$$

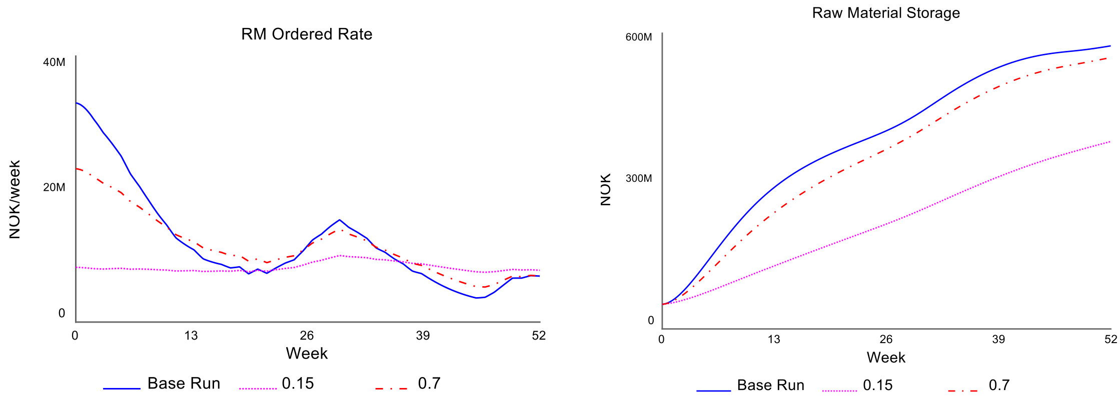

Figure 6. 1) First policy testing.

Villegas and Smith (2006) effectively decreased both order and inventory fluctuations in the supply chain SD model. The same result has been given after testing the current policy in this study. Since employing α provides a lighter RM Ordered Rate, it is realized that the value and also the oscillation of the RM-ordered rate and raw material storage shown in Figure 6. 1 dramatically diminish when the α is 0.15. If α increases to 0.7, the raw material storage will be increased as the RM Ordered Rate grows.

Weighting factors allow us to give more or less preference to one variable over another. As previously stated, clients have been asked to give a forecast of their orders in order to provide a better perspective on buying raw materials for the company. However, the accuracy of their forecast could be higher. Considering this policy, it would be helpful to consider, for example, 50% of the offered forecasting in the beginning for ordering the raw material for the company to reduce the inventory value by using weighting factors. After comparing the actual data and the forecast, this proportion can be modified.

The policy may also be beneficial to businesses operating in the same field in the same region. As an example, consider a manufacturing company in the Netherlands. Suppose the company follows this policy and considers a percentage of the forecasted customer orders to reduce the inventory value in the case of shortage. In that case, it will be possible for the company to purchase or borrow the needed raw material from one of the companies throughout Europe. So, as the lead time will be so short due to the short distance, they will receive the RM quickly.

Using a weighting factor can help soften the effect of a variable like the RM order rate. In this study, α has been considered to reduce the raw material order rate. It means that considering a proportion of the RM order rate, there will be less effect and oscillation of this rate which leads to a lower raw material storage value.

6-3 Reducing the Raw Material Lead time

As mentioned in the literature, Senapati et al. (2012) describes that nowadays, the lead time reduction in the inventory system has attracted more and more attention. It is described that the lead time can be shortened at a cost in many practical situations and is adjustable. It was discovered that minimizing the lead time can reduce the safety stock and stock-out losses, improve customer service, and raise business competitiveness. In business, the two significant competitive elements are time and cost. Under cost issues, a company might use various methods to minimize the lead time to meet its customers' demands.

In this study, the sensitivity tests revealed that the RM Lead time has an impact on raw material storage. So, the possible policy is concerned with decreasing the length of RM Lead time to reduce the RM storage value.

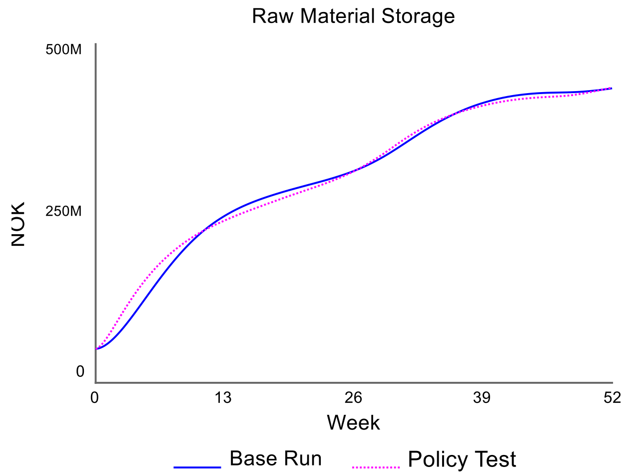

Figure 6. 2) Second policy testing.

As shown in Figure 6. 2, after testing the policy, when the RM lead time is reduced from 3 weeks to 1 week, surprisingly, the raw material storage value does not change significantly. By comparing this with the result from the literature, it is realized that the outputs are not matched. It is assumed that the implementation of the balancing feedback loops has reduced the impact of the RM delivery rate on raw material storage (Figure 6. 3), which is why the RM Storage has a slight change.

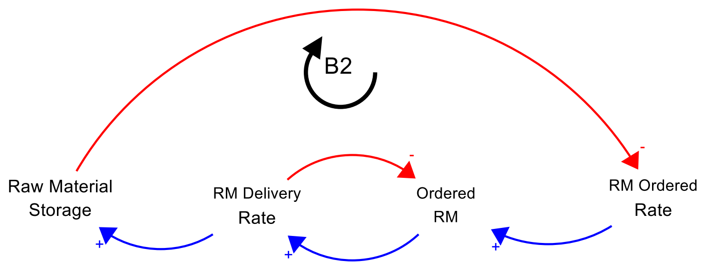

Figure 6. 3) Balancing feedback loops of Inventory.

If the lead time reduces, reordering and receiving the raw material weekly would be possible. As a result, the company would not need to reorder raw materials in large quantities and stock them in the warehouse, which generates issues such as insufficient space and expiry dates. Furthermore, if the reordered quantity reduces, the transportation cost will also be reduced.

This policy would also apply to larger companies with various products that require various raw materials. Reduced lead time allows lower safety stock levels, which results in lower inventory value. Furthermore, the raw material will be fresh, and the possibility of RM expiry will be reduced.

Finally, shortening the lead time might be advantageous in various ways. It allows for early delivery of raw materials and lower transportation expenses. Furthermore, there is no need to have a large number of RM in store, and safety stock can be lowered. The raw material will also have a longer shelf life.

6-4 Changing the shape of the graphical function of SEDM

Forrester (1968) illustrates that for very small increases in delivery delay, the sales are unaffected. As delivery delay becomes long enough to be of concern to the customer, sales effectiveness drops rapidly. Then it levels out as the remaining customers mainly want this specific product and are willing to change to competitive suppliers if the delivery delay becomes too long.

As described in the sensitivity tests, the raw material stored in this model is sensitive to the Sales Effectiveness of Delay Time (SEDM). Therefore, changing the shape of the delay as a graphical function could be a policy for reducing the raw material storage value.

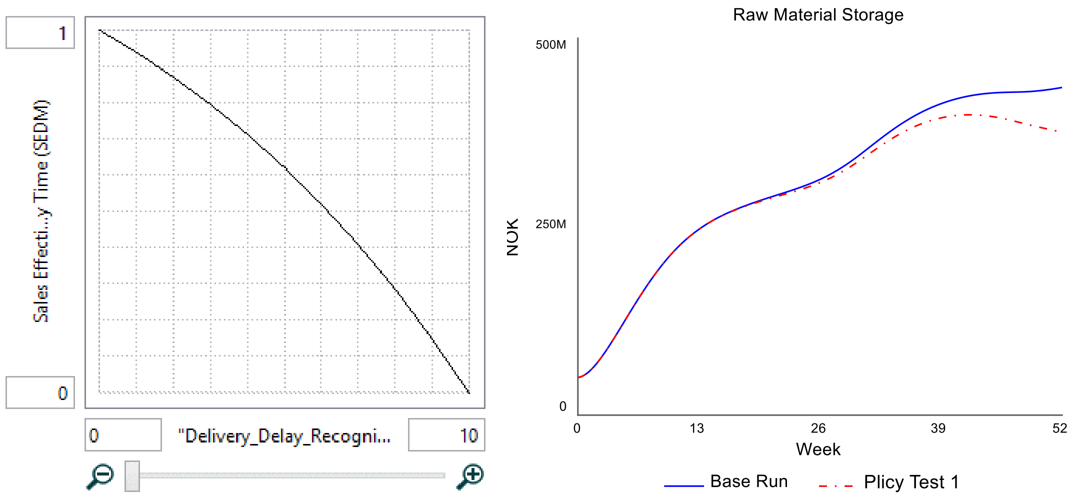

Figure 6. 4) Third policy testing.

Figure 6. 4 demonstrates that the shape of SEDM has changed from an S shape to decreasing increasingly. A reminder, figure 6. 5 demonstrates how a delivery delay affects sales effectiveness. Delivery Delay Recognized by Market (DDRM) has a total impact on SEDM, and this impact is negative. Adjusting the shape of the SEDM will gain more effect from DDRM. As a consequence, when DDRM rises, the delivery delay Sales Effectiveness of Delay Time (SEDM) falls. So, sales effectiveness diminishes, and fewer orders will be booked. Also, production is expected to be reduced. As a result, there will be no requirement to buy a high quantity of raw materials and stock them in the warehouse.

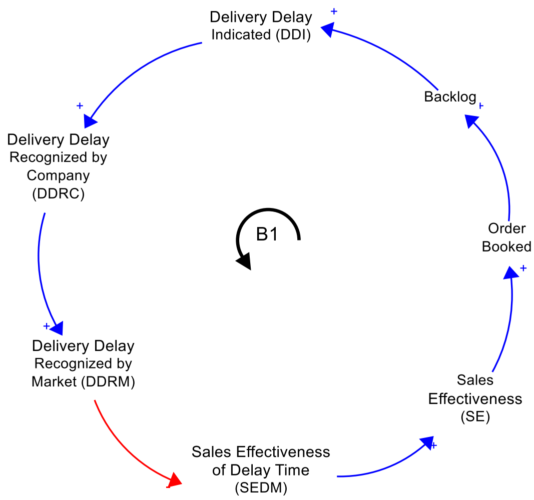

Figure 6. 5) The effect of SEDM.

It is believed that this policy will help big companies reduce inventory value by reducing purchased raw materials. However, there are some limitations. As the raw material in storage falls, the probability of shortage will rise. So, it takes time to receive RM, and the company will deliver the product to the Consumer later. This may lead to customer dissatisfaction and a search for another supplier. Furthermore, fewer customer orders may be received, resulting in less revenue and budget.

To summarize, increasing the delivery delay time results in fewer received orders, leading to fewer sales. When sales are reduced, there are fewer jobs for production to fulfill, and thus the demand for raw materials is reduced. In this case, fewer RM will be purchased, and the value of Raw Material Storage will be reduced. It may be helpful for a short-term purpose, but it will have a harmful impact on the business in the long run.

6-5 Consumer Returns Policy

As explained in the literature review part, a model of consumer returns policies has been developed by Su (2009). She investigated a situation in which consumers' product valuations are unknown. Consumer returns policies allow the Consumer to choose whether to keep or return the product. In this situation, the seller decides on pricing, quantity, and a suitable return policy. She found that the full refunds are excessively generous and do not improve supply chain performance, and in most cases, the best refund is less than the selling price.

Considering the above state as a policy and after asking the suppliers, it is determined that in case of excess, 30% of the raw materials can be returned to the supplier, and the deadline for returning is two weeks. It means the company has only 14 days to send back the RM to the supplier. In addition, they have noticed that only 70% of the selling price would be refunded .

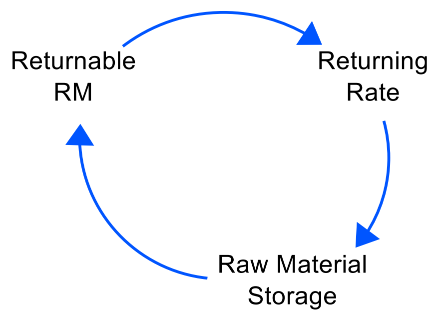

Figure 6. 6) Loop B5.

Figure 6. 6 shows that a new Balancing feedback loop is created by adding this policy to model B5. It can be realized that Raw Material Storage has a positive effect on the Returnable raw material, and it also has a positive effect on the Returning rate. However, the Returning rate

decreases the Raw Material Storage. So, the Raw Material Storage amount drops considerably, yet some slight fluctuations remain.

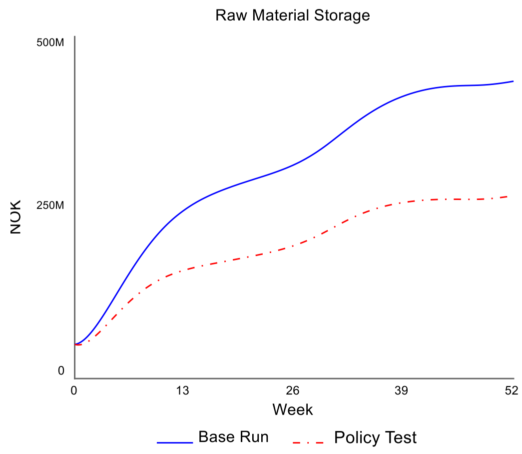

Figure 6. 7) Forth policy testing.

By concentrating on the outcome, it is discovered that it corresponds to the literature result. As previously stated, a company typically requests that its significant customers forecast their upcoming orders. Unfortunately, their forecast accuracy is so low that actual sales do not match their forecast. In this case, the company may have a surplus of stock, which raises the inventory value. This policy would minimize the value of raw material inventories by returning excess stock to the supplier.

The mentioned policy can also help various companies reduce their inventory value. Companies should arrange the return status with their suppliers, at least for the primary raw materials. Then, they can send extra stock to the supplier after analyzing the required raw material based on actual and historical orders. It will help to have more significant storage space, less inventory value, and less chance of having expired raw materials.

In summary, the return policy gives the Consumer the option of keeping or returning the raw material. In this case, the seller determines pricing and quantity. As a result, in the case of excess stock, this policy would assist in reducing the value of raw material inventories by returning excess stock to the supplier.

6-6 Combination of Adding a weighting factor and the Consumer Returns Policies

As previously reported, Villegas and Smith (2006) reduced order and inventory fluctuation by using a weighting factor, α, in a supply chain SD model. In this study, the present policy was tested, and the same outcome was obtained. Since using α makes the RM Ordered Rate lighter, it is apparent that the value and oscillation of the Raw Material Storage decrease as the RM Ordered Rate increases. In addition, Su (2009) discovered that customer return policies give the buyer the option of keeping or returning the product. In this case, the seller determines pricing, quantity, and the appropriate return policy. This policy also has been tested, and as stated, it would assist in reducing the value of the raw material stock by returning excess stock to the supplier.

Combining and employing two policies, the Consumer Returns policy and Adding a weighting factor policy, at the same time is ideal as it helps to gain the goal faster, which is decreasing the Raw Material Storage value. Figure 26 demonstrates the different outcomes of the policies on raw material storage.

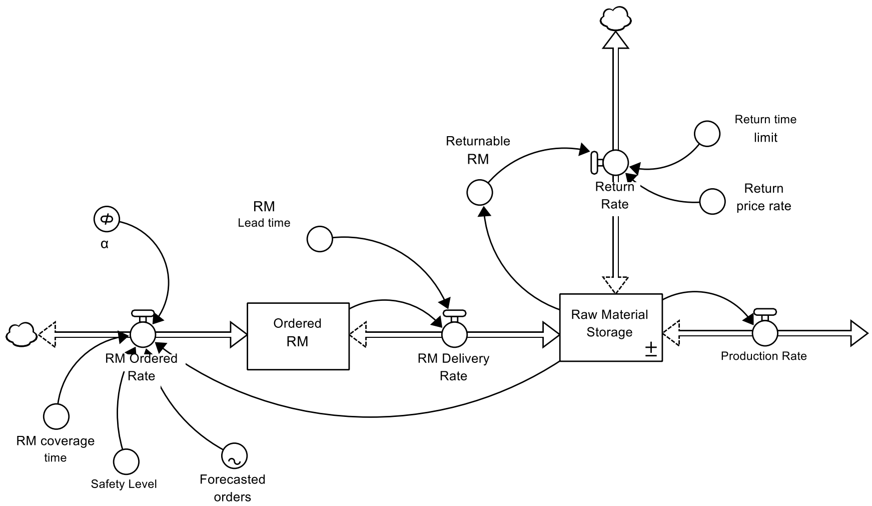

Figure 6. 8) Combination of policy 1 and policy 4.

The Figure above shows the inventory part of the model after employing two policies. The explanation is quite similar to what has already been stated. A new Balancing feedback loop is generated when the returning policy is added to the model. It was clearly defined that Raw Material Storage has a positive effect on the Returnable raw materials as well as the Return Rate. The Return rate, on the other hand, minimizes raw material storage. Also, adding a weighting factor would be beneficial because it reduces the ordered RM rate. By considering a portion of the RM ordered rate, fewer RM will be purchased, and it causes a lowering of the inventory value. So, by choosing both policies simultaneously, the RM storage value decreases dramatically.

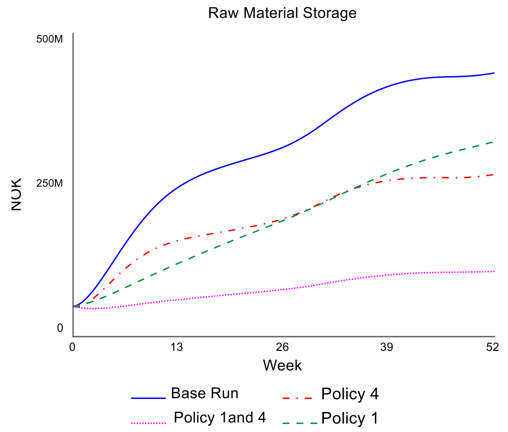

Figure 6. 9) Fifth policy testing.

Figure 6. 9 depicts the Raw Material storage situation after testing each policy. Applying the company's first policy, the RM ordered rate has been lightened. As a result, the amount of purchased raw material is reduced, resulting in lower storage value. The second policy allows the company to refund the excess stock, which helps minimize inventory value and free up storage space. When these two policies are considered together, as shown in Figure 6. 9, the Raw Material Storage value decreases considerably.

It may also be beneficial for different companies to consider multiple policies at the same time in order to achieve the aim. Considering the above explanation, they can minimize the order rate by using a weighting factor to stock less raw material. Simultaneously, by returning the excess raw material stock to the supplier, they will minimize the raw material storage value.

In conclusion, combining and implementing two policies at the same time is ideal as it aids in accomplishing the goal of lowering the Raw Material Storage value. Using a weighting factor can help to mitigate the impact of a variable such as the RM order rate. It means considering a percentage of the RM order rate, which results in a lower raw material storage value. Furthermore, the return policy allows the Consumer to keep or return the raw material. As a result, returning the excess inventory to the supplier help diminish the value of raw material stocks. The RM storage value is drastically reduced by implementing these two policies simultaneously.

Chapter 7

7-1 Conclusion

The main problems of Avery Dennison Company, a case study in Norway, are inventory keeping and management. In addition, monitoring what raw materials and products arrive to avoid inventory overstocking and understocking is challenging for the supply chain team. The company received an excessive number of raw materials, resulting in insufficient storage space in the warehouse, a close expiration date for the raw materials, and a high inventory value.

To begin understanding this, the research presented a theoretical framework for comprehending the underlying structure and interconnections between different parts of the examined company. Second, in addition to the theoretical framework, the study developed a system dynamics simulation model to assess and explain how inventory value is increasing, as well as insights into current policy challenges.

By providing background information on the existing situation at Avery Dennison company, Chapter 1 describes the problem that this study addresses. This chapter also briefly illustrates the frameworks that will be used in this study, the research question, and the definition of the problem and the context. The study's research question was to discover ways to manage and control inventory as well as monitor what product comes in to minimize inventory overstocking and understocking. To analyze the system, this study developed a theoretical model and its mathematical simulation. It also provides a review of relevant literature about the theoretical background of inventory Management and different policies to control inventory value.

Chapter 2 describes the method used in the study, including information regarding the system dynamics approach and its procedure, collecting data, and research ethics. As already stated, the SD methodology is a powerful tool for analyzing complex systems in which humans and the environment interact.

Chapter 3 provides the study's dynamics hypothesis by presenting a theoretical model expressed as a CLD and examining the dynamic interactions within the system based on the recognized feedback loops. It also introduces the theoretical model's quantified structure.

The theoretical model is quantified by discussing each component in depth and demonstrating the fundamental relationships between system parts using equations.

Chapter 4 discusses model validation and all the tests to ensure the model is structurally and behaviorally acceptable. The data regarding the ordered raw materials acquired from the company is then compared to the model's simulated behavior pattern.

The model's behavior is covered in detail in two parts in Chapter 5. The first part simulates the model and displays the resulting behavior to demonstrate the quantified model. This behavior revealed the growing raw material storage. The second section offers a few scenarios based on the sensitivity analysis from chapter 4 for experimenting with the model in order to examine it.

Learning from the model output, chapter 6 discussed five different policies based on the literature and results from the sensitivity analysis to reduce the Raw Material Storage value. As customer demand varies, it would be fair to consider a weighting factor of orders for purchasing raw materials to minimize inventory value. In the case of a shortage, the raw material can be supplied by one of the companies in the same area and region. In addition, the reduced lead time would apply to the more prominent companies with a diverse product line that requires various essential raw materials from far suppliers. It allows reduced safety stock levels, resulting in lower inventory value. Extending the delivery delay will likely help companies reduce inventory value through lower acquired raw materials. However, this may lead to client unhappiness and lead them to search for another supplier. Companies should also collaborate with their suppliers to determine the condition of returned raw materials, at least for critical raw materials. More storage space, a lower inventory value, and a minor threat of expired raw materials will all benefit it. Finally, it may be desirable for several companies to review multiple policies simultaneously to achieve the goal of controlling the stock and inventory value.

Chapter 7 includes the study's conclusion, findings and reflections, a summary for each chapter, limitations, policy implementation and any more work that may be needed to focus on in the future.

The study findings and reflections are undeniably linked to the system dynamics methodology. These facts and insights are summarized as follows:

-For companies, ensuring efficient inventory management is a crucial goal of the supply chain. Inventory control is critical to supply chain management success since stock surpluses raise costs and diminish profit margins, while inventory bottlenecks limit output and result in poor customer service.

-Creating a theoretical simulation model that captures causal feedback loops based on data about system components assists our understanding of the inventory as a whole. Critical feedback loops can be identified, and their influence on the system can be analyzed by measuring this theoretical model.

-The model output demonstrated issues with the Raw Material Storage as there is a fluctuating RM demand. This point of view enables us to see how rising inventory value as an issue evolves over time via causal feedback loops and which aspects of this system we may change. In that sense, the policies tested to optimize the inventory should reduce the fluctuation and Raw Material Storage value.

-Predicting the consequences of actions may only be possible with thinking in feedback loops. Understanding problems inside the framework allows us to consider the effects of our actions. As a result, it is critical to assess the potential unexpected implications. One unexpected consequence could be an increase in the cost of raw materials with the supplier due to requesting longer lead time.

It is typical to face challenges while working on a study, and I was no exception. As some company information and files are confidential, obtaining approval from the appropriate person required time. Furthermore, some of the key managers were either unavailable on-site during the model's development and the present managers lacked relevant information. So, it would be advantageous to start gathering data sooner in order to prevent any time trouble. Also, to discover answers to probable questions, it is also recommended to evaluate historical information in the company or read appropriate literature in the same field.

This study, like any other, has significant limitations. The critical limitation here is the availability of existing data. The previous supply chain team did not record any of the data of the main variables, such as RM storage value and Backlog. And, there is no variable reference data for comparing the simulated behavior with the actual data. Thus, due to a lack of data, some of the model's initial values are based on the author's best assumptions.

Although the policy interventions in the inventory system have been argued based on the identified policy levers, it needs emphasizing that policy implementation comes with uncertainty. All models undoubtedly entail some level of uncertainty because they describe a set of causal assumptions that may not describe "reality accurately enough to build policy"

(Palmer, 2017). As a result, the debate here can only partially inform policy design by generating additional studies on policy implementation, by greater modeling of explicit policy structures, or through other types of policy research. Furthermore, there are costs associated with policy implementation. Because those structures are not clearly described, these costs are not included in the model.

During the preparation of this research, some ideas for future research were generated. Firstly, the impact of reducing the lead time has been analyzed in this study, but finding ways to reduce the lead time needs further research. Furthermore, building new storage in Norway or Europe would be an effective investigate by developing a more specialized model. Finally, focusing on the influences of finding substitutes in Norway or Europe for the main suppliers in America and Asia helps to reduce the inventory value. The supply chain team can then reorder the raw materials using the Just in Time technique, a type of inventory management whereby goods are purchased from suppliers only when needed.

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Appendix 1- Model Documentation

This part contains the model documentation, including each equation for the variables and the values of constant parameters, as well as their explanations.

Total	Count	Including Array Elements
Variables	49	49
Stocks	6	6
Flows	10	10
Converters	33	33
Constants	19	19
Equations	24	24
Graphicals	3	3
Macro Variables	156	

Variable Name	Equation	Properties	Units	Documentation
"Backlog_(BL)"(t)	"Backlog_(BL)"(t - dt) + (Order_Booked - Delivery_Rate) * dt	INIT "Backlog_(BL)" = 9000000	NOK	Backlog is the stock with the inflow of orders booked and the outflow of delivery rate. The products are accumulated in this backlog and wait to be delivered to the customers, then this revenue will be added to the budget. The initial value is 9000000 here.
Effective_Sales_Budget(t)	Effective_Sales_Budget(t - dt) + (Sales_rate) * dt	INIT Effective_Sales_Budget = 15000	NOK	Effective sales budge" is defined as a stock. This variable is indicating the amount of effective budget for sale. The initial number of salesmen is 15000 NOK.
Finished_Goods_Storage(t)	Finished_Goods_Storage(t - dt) + (Production_Rate - Shipping_Rate) * dt	INIT Finished_Goods_Storage = 100000	NOK	Finished goods storage is the stock with the inflow of Production order and the outflow of Shipping rate. The finished goods are accumulated in this stock and wait to be shipped to the customers. The initial value is 100000 NOK.
Ordered_RM(t)	Ordered_RM(t - dt) + (RM_Ordered_Rate - RM_Delivery_Rate) * dt	INIT Ordered_RM = 5000000	NOK	Ordered RM is the stock with the inflow of RM ordered rate and the outflow of RM delivery rate. The values of the products are accumulated in this stock and wait to be delivered to the RM storage. In this model, this value is 5000000 NOK.

"Production_Capacity_(PC)"(t)	"Production_Capacity_(PC)"(t - dt) + ("Production_Capacity_Receiving_(PCR)" - Production_Depreciation) * dt	INIT "Production_Capacity_(PC)" = 200000	NOK/ week	The units of products we can produce each week are indicated under Production Capacity which is a stock. 200000 units per week are the initial value for this stock with an instantaneous inflow of production capacity receiving.
Raw_Material_Storage(t)	Raw_Material_Storage(t - dt) + (RM_Delivery_Rate - Production_Rate - Return_Rate) * dt	INIT Raw_Material_Storage = 50000000	NOK	"Raw Material Storage" is the stock with the inflow of Raw Material delivery rate and the outflow of Production rate. The products' values are accumulated in this raw material storage and wait to be produced. The initial value is 50000000 here.
Delivery_Rate	Shipping_Rate		NOK/ week	Delivery Rate refers to how many units of the product are available for delivery each week and is an outflow for backlog stock which is equal to the Shipping rate.
Order_Booked	"Sales_Effectiveness_(SE)"*Effective_Sales_Budget		NOK/ week	The Orders Booked flow to the "Backlog" represents the orders that the company receives as a result of the sales team activity. The amount of product units that will be ordered each month is calculated by multiplying the number of sales budget and sales effectiveness each week.
"Production_Capacity_Receiving_(PCR)"	DELAY3("Production_Capacity_Ordering_(PCO)", "PCR_Delay_Time_(PCRD)")		NOK/ Weeks^2	Third-order delay is referred to Production Capacity Delay and viewed as an inflow into the stock of Production Capacity. Since it is represented as a third order delay, each of the three transits inside this variable is understood to be a first order delay with a separate delay duration.
Production_Depreciation	"Production_Capacity_(PC)"/Life_Time		NOK/ Weeks^2	Production depreciation shows the rate of the depreciation of the machines used in the business that end up wearing out over time.

Production_Rate	MIN(MIN("Production_Capacity_(PC)", Raw_Material_Storage/Production_adj_time), MAX(0, Discrepancy))	NOK/ week	"Production rate" is an outflow of the RM storage and the inflow for the Finished Goods stock, which means how much value of the RM is produced and accumulated to the finished goods Storage per week. The equation is based on the Leontief production function that implies the factors of production which will be used in fixed (technologically pre-determined) proportions, as there is no sustainability between factors.
Returning_Rate	Return_price_rate*Returnable_RM/Return_time_limit	NOK/ week	Returning rate is one of the outflows for the Raw Material Storage, means that how much value of the raw material in storage is returned per week.
RM_Delivery_Rate	Ordered_RM/RM_Lead_time	NOK/ week	RM Delivery rate is an outflow for the ordered RM and inflow for the Raw material Storage stock, means that how much value of the RM is delivered to the RM Storage per week.
RM_Ordered_Rate	Forecasted_orders*α + α*(Safety_Level*1.1-Raw_Material_Storage)/ RM_coverage_time	NOK/ week	"RM ordered rate" is an inflow for the Ordered raw material stock, means that how much value of the product is ordered per week.
Sales_rate	(Sales_Budget-Effective_Sales_Budget)/ "Sales_adj_time_(SAT)"	NOK/ week	Salesmen rate is the inflow to the stock of Effective sales budget. As this it is mentioned in the equation, (Sales Budget Effective Sales Budget)/"Sales adj time"), the gap between the goal and the indicated value is being calculated divided by the delay time, representing the delay which is affecting the accumulation in the stock.
Shipping_Rate	Finished_Goods_Storage/ Shipping_adj_time	NOK/ week	Shipping rate is an outflow for the Finished Goods stock, means that how much value of the finished goods storage is shipped per week.

"Budget_(B)"	"Delivery_Rate_Average_(DRA)"*"Revenue_to_Sales_(RS)"	NOK	Budget refers to the total amount of money that is collected each week from sales revenues and the number of products that were ordered before and after the delivery delay and are delivered on a weekly average basis. This implies that the unit must also be NOK per week, hence the equation is "Delivery rate Average * Revenue to Sales"
"Capacity_Expansion_Fraction_(CEF)"	GRAPH("Delivery_Delay_Condition_(DDC)") Points: (0.000, -0.0700), (0.500, -0.0200), (1.000, 0.0000), (1.500, 0.0200), (2.000, 0.0700), (2.500, 0.1500)	1/week	Capacity Expansion Fraction is a fraction which is indicated as a graphical function in the model and is representing the fraction of expanding the production capacity. When the CEF increases, it shows the company can invest more on capacity.
Coverage_time	2	week	Coverage Time is the time indicated in the model to show it takes 2 weeks to clarify the discrepancy of the forecasted orders and the finished goods in the storage.
"DDRC_Average_Time_(TDDRC)"	0.5	week	The Delivery Delay Identified by Company Average Time" is how long it takes the company to update itself with the new delivery delay time. It is 0.5 weeks in this model.
"DDRM_Average_Time_(TDDRM)"	0.1	week	Delivery Delay Recognized by Market Average Time is the average amount of time, which has been determined to be 0.1 week, that it takes for the market to recognize and update the delivery delay.
"Delivery_Delay_Bias_(DDB)"	0.1	dmnl	Delivery Delay Bias, which in this system is taken to be 0.1, illustrates the demand for resources in the company and the variation between goals and performance that is required to maintain any given level of resource allocation.

"Delivery_Delay_Condition_(DDC)"	"Delivery_Delay_Recognized_by_Company_(DDRC)"/"Delivery_Delay_Management_Goal_(DDMG)"-"Delivery_Delay_Bias_(DDB)"	dmnl	Delivery Delay Condition is representing a ratio of delivery delay recognized by the company to the delivery delay goal and from this ratio is subtracted the delivery delay bias. When it is more than 1, capacity expansion happens; however, when it decreases, resources are moved to other parts of the company, and the demand to increase capacity will lessen.
"Delivery_Delay_Indicated_(DDI)"	"Backlog_(BL)"/"Delivery_Rate_Average_(DRA)"	week	"Delivery Delay Indicated" is a ratio of the backlog to the average delivery rate, which indicates that the amount of time needed to fill an order is calculated based on how long it will take the current delivery rate to process the backlog.
"Delivery_Delay_Management_Goal_(DDMG)"	3	week	Delivery Delay Management Goal is a fixed delivery target that is constant, specified in the equation as 3 weeks, and equals to the system's minimal amount of time for order processing and production.
"Delivery_Delay_Recognized_by_Company_(DDRC)"	SMTH1("Delivery_Delay_Indicated_(DDI)", "DDRC_Average_Time_(TDDRC)")	week	It is a factor in the production capacity ordering decision and it is a foundation for market delivery delay quotes. The smooth function is utilized in the model to represent this delay when it is once more shown that this converter is an information delay function.
"Delivery_Delay_Recognized_by_Market_(DDRM)"	SMTH1("Delivery_Delay_Recognized_by_Company_(DDRC)", "DDRM_Average_Time_(TDDRM)")	week	Delivery Delay Recognized by Market illustrates how the market needs some time to adjust to a changing delivery delay; therefore, a further delay occurs before the market recognizes the delivery delay. Based on the market's recognition of delivery delays and the time it takes to update this information, this information delay is also reflected by a smooth function.

"Delivery_Rate_Average_(DRA)"	SMTH1(Delivery_Rate, "Delivery_Rate_Average_Time_(DRAT)")	NOK/ week	The Delivery Rate Average shows the condition of the weekly delivery delay for each product unit indicated by the current backlog and the current delivery rate, which shows the payment and collection delay. For simulating information delays, smooth functions are employed, and since we are using smooth 1, the first-order information delay is presented here.
"Delivery_Rate_Average_Time_(DRAT)"	0.2	week	"Delivery Rate Average Time" is the delay time indicated in the model to show it takes 0.2 weeks to update and estimate the delivery rate average.
Discrepancy	Forecasted_orders-Finished_Goods_Storage/Coverage_time	NOK/ week	The Discrepancy is representing the differences between Forecasted orders and Finished Goods Storage, over the Coverage time which has an effect on the Production rate.
Forecasted_orders	GRAPH(TIME) Points: (0.00, 38800000), (1.01960784314, 38800000), (2.03921568627, 38800000), (3.05882352941, 39200000), (4.07843137255, 40200000), (5.09803921569, 41200000), (6.11764705882, 41500000), (7.13725490196, 42500000), (8.1568627451, 43200000), (9.17647058824, 43800000), (10.1960784314, 44500000), (11.2156862745, 44800000), (12.2352941176, 45800000), (13.2549019608, 46800000), (14.2745098039, 47100000), (15.2941176471,	NOK/ week	Forecasted Orders values are provided by the customers each week for giving the overview to the supply chain team for planning the purchasing of the raw material.

48100000), (16.3137254902, 49100000), (17.3333333333, 49800000), (18.3529411765, 51100000), (19.3725490196, 51100000), (20.3921568627, 52800000), (21.4117647059, 53100000), (22.431372549, 54800000), (23.4509803922, 56400000), (24.4705882353, 57800000), (25.4901960784, 60100000), (26.5098039216, 62700000), (27.5294117647, 64700000), (28.5490196078, 67100000), (29.568627451, 69400000), (30.5882352941, 69700000), (31.6078431373, 70400000), (32.6274509804, 71000000), (33.6470588235, 71000000), (34.6666666667, 71700000), (35.6862745098, 72000000), (36.7058823529, 72400000), (37.7254901961, 72400000), (38.7450980392, 73000000), (39.7647058824, 73000000), (40.7843137255, 73000000), (41.8039215686,

	73000000), (42.8235294118, 73000000), (43.8431372549, 73000000), (44.862745098, 73000000), (45.8823529412, 73400000), (46.9019607843, 74400000), (47.9215686275, 75700000), (48.9411764706, 77000000), (49.9607843137, 77300000), (50.9803921569, 78000000), (52.00, 78300000)		
Life_Time	520	week	Lifetime indicates the average lifespan of the industrial machines which is around 10 years/520 weeks.
"PCR_Delay_Time_(PCRD)"	0.4	week	"Production Capacity Receiving Delay Time" is the higher order delay mentioned in the inflow equation with a delay period of 0,4 weeks.
Production_adj_time	1	week	"Production Adjustment Time" is a constant converter that represents the delays in production. In this model, this value is 1 week.
"Production_Capacity_Ordering_(PCO)"	"Capacity_Expansion_Fraction_(CEF)"*"Production_Capacity_(PC)"	NOK/Weeks^2	Production Capacity Ordering refers to how many units of production capacity can be ordered each week depending on the current production capacity and its growth. The capacity expansion fraction is included in this equation since it is expressed as a percentage of the current capacity each week. This has the result of making the capacity ordering a function of the system's present operational level.
Return_price_rate	0.7	dmnl	This variable defines only 70% of the initial will be paid back after returning.
Return_time_limit	2	week	This variable means the deadline for sending back the RM is only 2 weeks.

Returnable_RM	Raw_Material_Storage*0.3	NOK	This variable means only 3% of the whole RM in the storage can be returned to the supplier.
"Revenue_to_Sales_(RS)"	1	week	"Revenue to Sales" is the money gained from the selling process each week. This converter is essential to the budget equation, which affects the sales budget. The revenue is considered to be 1 per week.
RM_coverage_time	6	week	RM Coverage Time is the time indicated in the model to show it takes 6 weeks to clarify the discrepancy between the forecasted orders and the finished goods in the storage.
RM_Lead_time	3	week	Raw material lead time means it takes 3 weeks for receiving the Raw material from the supplier and accumulating the storage.
Safety_Level	3000000	NOK	Safety stock is a level of extra stock that is maintained to mitigate the risk of stock-outs caused by uncertainties in supply and demand. Adequate safety stock levels permit business operations to proceed according to their plans. In this model, this value is 3000000 NOK.
"Sales_adj_time_(SAT)"	2	week	The constant converter , Sales Adjustment Time, illustrates budgeting delays. This value in the model is 2 weeks.
Sales_Budget	"Budget_(B)"*0.01	NOK	"Sales Budget" is representing the amount of money for sales per week from the total budget. According to this, the equation is 0.01 total budget.

"Sales_Effectivenes s_(SE)"	"Sales_Effectiveness_ Max_(SEM)"*"Sales_E ffectiveness_of_Delay _Time_(SEDM)"	1/wee k	Sales Effectiveness, which is based on the maximum sales effectiveness and its delay time multiplied by each other, represents the amount of products that are sold each week. As a result, when the sales effectiveness of the delay time improves, so does the sales effectiveness and consequently.
"Sales_Effectivenes s_Max_(SEM)"	350	1/wee k	The term Sales Effectiveness Max describes Sales effectiveness. 350 units in this model are sold each week at each price. For instance, if this value is decreased from 400 to 100, it shows that it is four times more difficult to sell these products.
"Sales_Effectivenes s_of_Delay_Time_(SEDM)"	GRAPH("Delivery_Dela y_Recognized_by_Mar ket_(DDRM)") Points: (0.00, 1.000), (1.00, 0.970), (2.00, 0.870), (3.00, 0.730), (4.00, 0.530), (5.00, 0.380), (6.00, 0.250), (7.00, 0.150), (8.00, 0.080), (9.00, 0.030), (10.00, 0.020)	dmnl	Sales Effectiveness of Delay Time is expressed in terms of the maximum value of sales effectiveness and is regarded as a multiplier for sales effectiveness. According to the graphical function, a delivery delay of 0 results in a maximum value of the unit. The unit of this converter has no dimensions when used as a fraction.
Shipping_adj_time	0.4	week	Shipping Adjustment Time is a constant converter that represents the delays in shipment. In this model, this value is 0.4 weeks.
α	0.25	dmnl	α represents a weighting factor in this model.

Appendix 2- Sensitivity Analysis

Variable	Base Value	Range	Expectation	Simulation
RM Lead time	3	1.5-6	Growth in RM Storage by reducing the RM lead time and reduction by increasing that	Sensitive as expected
Revenue to Sales (RS)	1	0.5-2	Growth in RM Storage by reducing the Revenue to Sales (RS) and reduction by increasing that	Sensitive as expected
Backlog (BL)	9,000,000	4,500,000-18,000,000	Growth in RM Storage by reducing the Backlog and reduction in RM storage by decreasing that	Sensitive as expected
RM coverage time	6	3-12	Growth in RM Storage by reducing the RM coverage time and reduction by decreasing that	Sensitive as expected
Delivery Delay Management Goal (DDMG)	3	1.5-6	Reduction in RM Storage by reducing the Delivery Delay Management Goal (DDMG) and growth by increasing that	Sensitive as expected
Delivery Delay Bias (DDB)	0.1	0.05-0.2	No changes	Not Sensitive as expected
Sales Effectiveness Max (SEM)	350	175-700	Growth in RM Storage by reducing Sales Effectiveness Max (SEM) and reduction by increasing that	Sensitive as expected
Production Capacity (PC)	200,000	100,000-400,000	No changes	Not Sensitive as expected
Ordered RM	5,000,000	2,500,000-10,000,000	No changes	Not Sensitive as expected
Finished Goods Storage	100,000	50,000-200,000	No changes	Not Sensitive as expected

Effective Sales Budget	15,000	7,500-30,000	No changes	Not Sensitive as expected
Production adj time	1	0.5-2	No changes	Not Sensitive as expected
Shipping adj time	0.4	0.2-0.8	No changes	Not Sensitive as expected
PCR Delay Time (PCRD)	0.4	0.2-0.8	No changes	Not Sensitive as expected
Coverage time	2	1-4	No changes	Not Sensitive as expected
DDRC Average Time (TDDRC)	0.5	0.2-1	No changes	Not Sensitive as expected
DDRM Average Time (TDDRM)	0.1	0.05-0.2	No changes	Not Sensitive as expected
Sales adj time (SAT)	2	1-4	No changes	Not Sensitive as expected
Delivery Rate Average Time (DRAT)	0.2	0.1-0.4	No changes	Not Sensitive as expected
Safety Level	3,000,000	1,500,000-6,000,000	Reduction in RM Storage by reducing the safety level and growth by increasing that	Not Sensitive