Strategic Modeling of
Service Parts Closed-Loop Supply Chain of Philips Healthcare:
A system dynamics approach

by
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I wish you all pleasure with reading this interesting research.

Marjon

Management Summary

Every year Philips Healthcare estimates the expected required budget for next year. This report develops a supporting tool that provides insight into the impact of strategic process improvements on the service parts supply chain and thus indirectly on the required budget. This research is carried out at the Service Parts Supply Chain (SPS) organization of Philips Healthcare. This department is a part of Global Customer Services, and is responsible for the planning, warehousing, distribution, transportation, reverse logistics and repair of service parts for all Philips Healthcare modalities on a global basis.

The goal of this research, as outlined later on, is to identify the key parameters that are critical or essential for effective management of the service parts supply chain as well as the impact on the chain over time. System dynamics modeling is considered as suitable approach to investigate the key parameters impact. This approach focuses on the understanding of interactions of physical processes, information flow and managerial policies.

The concept of system dynamics is applicable to different situations. System dynamics can model operational improvement and business developments. Further, impacts from environmental changes, like financial economical crisis, can be translated into system dynamics. These subjects have an influence on the Annual Operating Plan (AOP). Another application of systems dynamics is the support of strategic decisions. System dynamics can be applied to select the strategic improvement which has the highest impact on the supply chain. System Dynamics gives also insight into the time it takes before the effect is noticeable. This research focuses on this latter application and investigates strategic improvement on the service parts supply chain.

In this report the causal loop diagram contains all possible interrelationships and interactions of the service parts supply chain of Philips Healthcare. Different employees were interviewed to get a complete overview of all processes and their influences. Further, a simulation study is carried out of the business unit Magnetic Resonance (MR) to determine the impact of key parameters on the service parts supply chain. These key parameters are the average and variation of demand, new buy lead time, repair lead time, and return time. Additionally, parameters such as repair yield and target service level are also investigated.

The conclusion is that reduction of average demand and new buy lead time have the greatest decrease in inventory level in relatively a short period of time. Reduction in demand can be established by remote control and training of field service engineer, such that no excess orders are placed. Additional efforts made in modular design of products will also decrease the number of stock-keeping units of spare parts and as such the average demand. However, the average demand is hard to control because the sale of systems grows and it is expected that this results in a higher demand of service parts. Also market penetration rate will increase the number of contracts and agreed service level which results in an increases of demand of service parts.

The average new buy lead time can be reduced by making new agreements with suppliers. However, this might be hard to establish because the average lead time reduction would require new negotiations

with vendors. Therefore, a more practical and valuable advice given in the research is to start with diminishing the variation in production time because a reduction of 50% in variation of production time has a considerable impact on inventory level, namely 40%. Although, it might take one year before the reduction of 40% is achieved. This requires better control. Thus, collaboration with the suppliers to deliver conform contract will have significant impact on the variation in production time and consequently lower overall costs due to reduction of inventory level. The same holds for repair lead time.

Another recommendation based on this research is to focus on the reduction of return cycle time because more repairable parts can be sent to the repair vendors and consequently the number of new buys ordered decreases considerably, namely with 50% if the return cycle time is reduced with 50%. This means a remarkable decrease in production costs. Moreover, a higher service level would be guaranteed due to the higher inventory level because the repair lead time is shorter than new buy lead time on average.

The model in this research provides insight into the impact of strategic improvements of key parameters on the service parts supply chain performance. An extension would be to add operational costs in the model such that also financial aspects are explicitly measured. This results in well considered tradeoffs. It is possible to extend this system dynamics model for other applications as well, like the impact of customer satisfaction on the sale of install base and service contracts.

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1. Introduction

1.1 Company Background

Philips Healthcare is one of the world's top three medical device companies. They develop systems for clinical care, like MR-scan (Magnetic Resonance) and X-ray, but also home healthcare solutions, like implantable device monitoring services which ensure that implanted pacemakers or defibrillators are working correctly and evaluate a variety of clinical data trans-telephonically to hospitals. Moreover, Philips Healthcare created Ambient Experience, which is a purposefully designed environment that makes patients and staff feel more comfortable during medical treatment.

Philips Healthcare is one of the three operating sectors of Royal Philips Electronics:

- Healthcare
- Lighting
- Consumer Lifestyle

The division Healthcare is the second largest sector, closely after Consumer Lifestyle and responsible for more than one third of the total sales of Royal Philips Electronics of 23,189 million euro's in 2009. Philips Healthcare activities date back to 1895, after Royal Philips bought CHF Muller of Hamburg which manufactured the first commercial X-ray tube, and 1918 when it first introduced a medical X-ray tube. Since then, this sector expands enormously and doubled its size and scope of Medical Systems business between 2000 and 2003. At this moment the healthcare division consists of the following businesses:

- Clinical Care Systems
- Customer Services
- Healthcare Informatics-Patient Monitoring
- Home Healthcare Solution
- Imaging Systems

This research is executed at the Service Parts Supply Chain (SPS) organization, which is part of Global Customer Services, and responsible for the planning, warehousing, distribution, transportation, reverse logistics and repair of service parts for all Philips Healthcare modalities on a global basis. Their customers are field service engineers (FSE) and trade customers for their products.

1.2 Service Parts Closed-Loop Supply Chain

Ashayeri, Heuts and Jansen (1994) pointed out the importance of a deliberate supply chain of service parts: 'Although in the design of computers systems, attention is already paid to reliability through careful selection of components, design sophistication, incorporating of various types of redundancy and provision of back-ups, there is no doubt that a good management of service parts inventory is of prime importance to many consumer companies'. For that reason, Philips Healthcare keeps service parts on stock at stocking locations all over the world and has such logistic design in order to serve customers demand in time. This section describes the flow of service parts through this supply chain.

When customers purchase a medical system, in most cases they buy also a service contract which consists of agreements on replacement and repair, such that failure of systems is prevented or solved quickly. Normally, the demand of spare parts is initiated by a FSE who requests the parts to solve the breakdown of equipment. However, it also occurs that a business unit of Philips Healthcare improves a part and wants that all sold systems are upgraded with this new part, which is a field change order. A Business Unit (BU) is the production plant and innovations center belonging to different divisions like MR or X-ray. Further, calls for service come from third parties like distributors, competitors, or engineers of hospitals.

The demand of service parts is fulfilled from stock at distribution centers, which are located on different places all over the world. The forward network of distribution centers is pictured in Figure 1. The world is divided into three main regions, namely North America (NA), Europe, the Middle East and Africa (EMEA), and Asia Pacific (APAC). Each district has its own Time Zone Warehouse (TZW), namely in Louisville, Roermond, or Singapore, which is called a Central Distribution Center (CDC) if it is supplied directly by the vendor or factory from a business unit. When a Time Zone Warehouse is supplied by a CDC instead of a vendor or plant, it is called a Regional Distribution Centers (RDC). These RDC's and CDC's deliver spare parts to Local Distribution Centers (LDC), which supply the Field Stocking Locations (FSL).

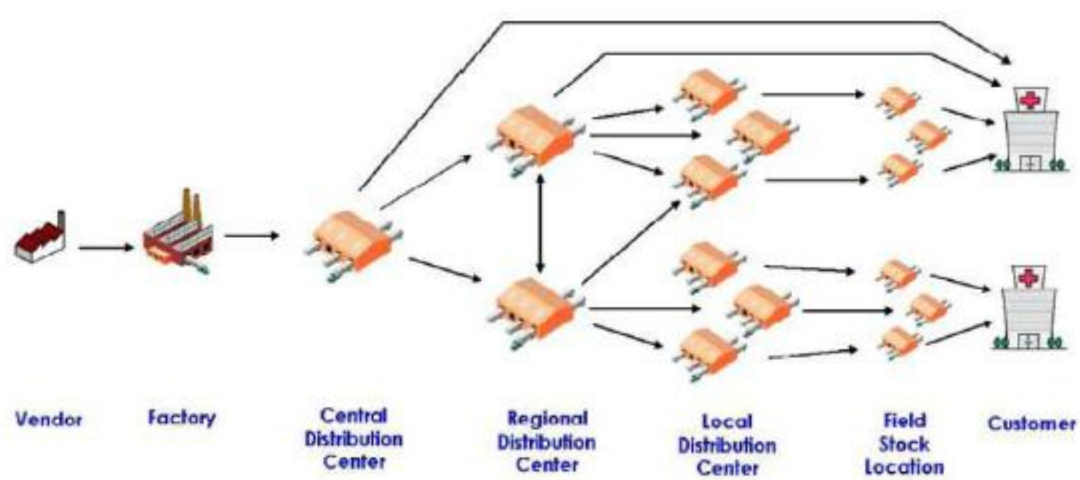


Figure 1: Forward Supply Chain

In general, each demand generates a return because each call for service implies a return of defect or unused spare parts, which flows through the reverse supply chain as pictured in Figure 2. The flow of unused service parts consists of excess orders of FSE, while the stream of defect spare parts contains repairable parts and some consumable. The returns are inspected at bluerooms in Charlotte (NA) and Tatabanya (AMEA) to ensure that correct parts are received after which unused service parts are sent directly to the CDC. Consumable parts are cheap and therefore directly disposed at FSE or at blueroom when special disposal is required, while repairable service parts are expensive and stocked at the blueroom until they are offered for repair to the vendor or business unit factory. So, each period a decision has to be made on how many defect parts are offered for repair and how many new parts are ordered. It is cheaper to repair service parts than to purchase new ones and therefore Philips Healthcare strives to reduce the return and repair time, such that less new buys have to be ordered and a lower stock level is required to serve all customers on time. At this moment the repair lead times vary from three days up to three months or even longer because of the irregularity and unpredictability of repair orders.

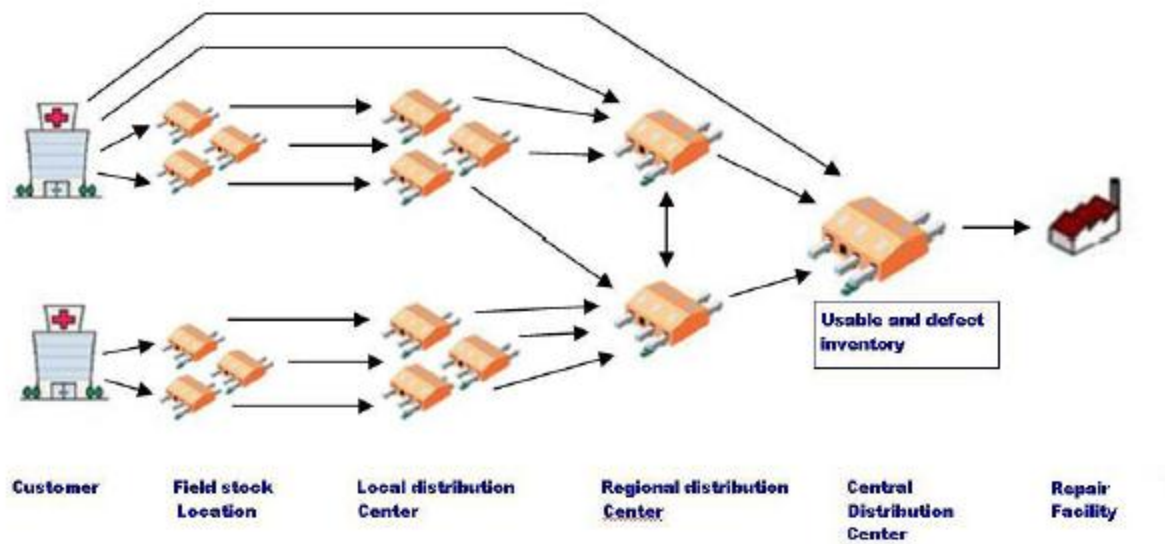


Figure 2: Reverse Supply Chain

The forward and reverse supply chain together is called a close-loop supply chain. This thesis investigates the closed-loop supply chain of spare parts using simulation of a system dynamics model.

1.3 Demand Forecast and Inventory Model

To ensure that there is sufficient stock at each location to fulfill demand, Philips Healthcare forecasts the demand and determines the stock level for each service part at each location. This depends on the target service level of a spare part, which is the fraction of demand that should be delivered before the requested delivery day to the customer. This target service level depends on the classification of the spare parts because customer critical parts have a higher target of 98%, while slow movers require only a service level of 90%. This affects the inventory level and location of stock because high target service level results in inventory located close to the customer. Philips Healthcare has grouped parts into 9 segments, namely the Customer Critical Parts (CCP), High Cost Fast Movers (HCFM), Low Cost Fast Movers (LCFM), Slow Movers (SM), Field Change Orders (FCO), End Of Life (EOL), Last Time Buy (LTB), New Product Introduction (NPI), and Tools. The classification Last Time Buy of parts is the order of one enormous batch to serve all demand of spare parts in the remaining period of service, while parts grouped in the End Of Life segment are the service parts left when the service period is over.

Every month, for every location the parameters of the reorder point, safety stock level, and Economic Order Quantity (EOQ) are determined based on the forecast of the demand. In practice this means when the inventory level of a part drops below its reorder point, the EOQ is ordered. The EOQ depends on the fixed order costs and holding cost related to the value of the service part. Safety stock is the amount of inventory kept on hand to capture uncertainties in demand and supply in the short run and is related to the target service level.

The forecast of demand depends on the classification of the spare part. Parts from the segment CCP, HCFM, and LCFM are forecasted based on a combination of the average demand of the last 6 months and exponential smoothing. The forecast of SM is determined by the average demand of the last 24 months without zero demand, while the forecast of EOL and NPI parts is equal to the average demand of the last 6 months. LTB are determined by a joint forecast made by the business unit and SPS.

When the parameters are determined for each spare part at each location, the values of the parameter for important segments (e.g. CCP/HCFM etc.) are validated and subsequently uploaded in SAP (Systems, Applications, and Products in the informatics) which is the manufacturing planning and control system implemented at Philips Healthcare.

1.4 Forecast to Vendor

To reduce the new buy lead time Philips Healthcare forecasts the new buy orders of consumable service parts to business unit factories and sometimes also to vendors. This is a fully automated process using a simple forecast method like the average demand of last 6 or 12 months, minimum order quantity, safety stock which depends on the service level, and reorder point. The purchase orders of repairable and parts which need extra attention due to quality or technical issues are also forecasted. However, a planner decides manually how many defect parts are forecasted for repair, versus how many new buys. This decision is not based on any quantitative model, just on the intuition and experience of the planner.

At this moment there is a project to classify the repairable into two groups: the PUSH and PULL repair parts. The PUSH-strategy offers returns directly for repair and only a new buy purchase order is placed when the serviceable inventory appears to be too low to satisfy the future expected demands adequately according to Van der Laan, Salomon and Dekker (1998).This has as benefit that fewer new buys are ordered, however the value of the total inventory increases because the value of defect parts on stock is lower than the value of repaired parts on stock. The PULL-strategy offers only parts for repair when there is actual replenishment needed to satisfy demand. The drawback of this strategy is that the parts may not be repaired in time due to uncertainty in repair lead time. To resolve this problem new buy purchase orders have to be placed.

1.5 Research Questions

This thesis investigates the closed-loop supply chain of spare parts using a system dynamics simulation model, which creates the possibility for a more quantitative decision-making process. The objective is to determine the strategic key parameters and their impact is on the supply chain to support the AOP.

Therefore, the main research questions are:

- **Identification of key parameters, those attributes or characteristics of Philips spare parts supply chain system that are considered critical or essential for the effective management of the chain.**
- **Evaluation of the impacts of strategic improvements of these parameters on the spare parts supply chain performance.**

To answer this question, the dynamic relationships of the closed-loop supply chain of Philips Healthcare are translated into a system dynamics model to study the behavior of this closed-loop supply chain over time. Implementing this system dynamics model in a simulation software results in a useful model to scrutinize the behavior of the forward and reverse supply chain of Philips Healthcare. Ashayeri et al. (1994) indicate that 'The models in literature serve as a potential base tool to determine the value of major decision variables and when combined with simulation will allow the management to examine more precisely the effect of factors that have not been fully incorporated in the normative models.' Cohen, Agrawal and Agrawal (2006) also point out that managing service parts supply chain differs significantly from manufacturing supply chain due to complex, and high demand and supply uncertainty. Cohen et al. (2006) explains that a dynamic approach is more appropriated then a static one which is used in manufacturing supply chain.

1.6 Structure of Thesis

Chapter 2 reviews relevant literature on system dynamics and closed-loop supply chain. A system dynamics model is developed in Chapter 3 based on this literature and interviews with employees of Philips Healthcare. Chapter 4 introduces a business case and a system dynamics simulation model of the closed-loop supply chain. The results of the simulation model are described in Chapter 5. The conclusions of this research as well as recommendations on future research are made in Chapter 6.

2. Literature Review

This chapter gives an overview of literature of service parts supply chain based on system dynamics modeling. First, the idea behind system dynamics is explained as well as the value of it. Following by a literature review of closed-loop supply chain with a system dynamics approach. The last section provides more details about influences in a closed-loop supply chain.

2.1 System Dynamics

According to Valchos, Georgiadis and Lakovou (2006) system dynamics focuses on understanding how the physical processes, information flows and managerial policies interact so as to create the dynamics of the variables of interest. System dynamics differs significantly from a traditional simulation method, such as discrete-event simulation where the most important modeling issue is a point-by-point match between the model behavior and the real behavior, i.e. an accurate forecast with as purpose to predict what the total supply chain profit level would be each week for the years to come.

Thus, system dynamics describes dynamic relationships that influence the behavior of systems and is useful to understand the complexity of changes in systems over time, which can be used to make strategic decisions. In practice this means that system dynamics translates business structure into a system with interrelationships between every single variable of the business structure. For example, an increase in production rate causes an increase at stock level. This means that the causal relationship among these variables is in the same direction, which is called positive feedback. There also exist relationships between variables which causes a change in opposite direction, which shows negative feedback.

A causal loop diagram is formed if multiple interrelationships make a loop, which can be a positive or negative feedback loop. A positive feedback loop, or reinforcing loop, exists if the direction at the 'end' of the loop is the same as you start with, otherwise it will be a negative feedback loop, or balancing loop, which influences the system to return to an equilibrium situation after an disturbance. The left circle of Figure 3 shows a positive feedback loop and the right circle a negative feedback loop that together determine how the install base evolves over time. This example is based on Akkermans (2010). The impact of one factor over time, for example the decrease of install base due to end of service or obsoleteness, is calculable. However, it is difficult to estimate the impact of multiple factors that influence each other over time. The main advantage of system dynamics is the possibility to establish the impact of interrelationships over time.

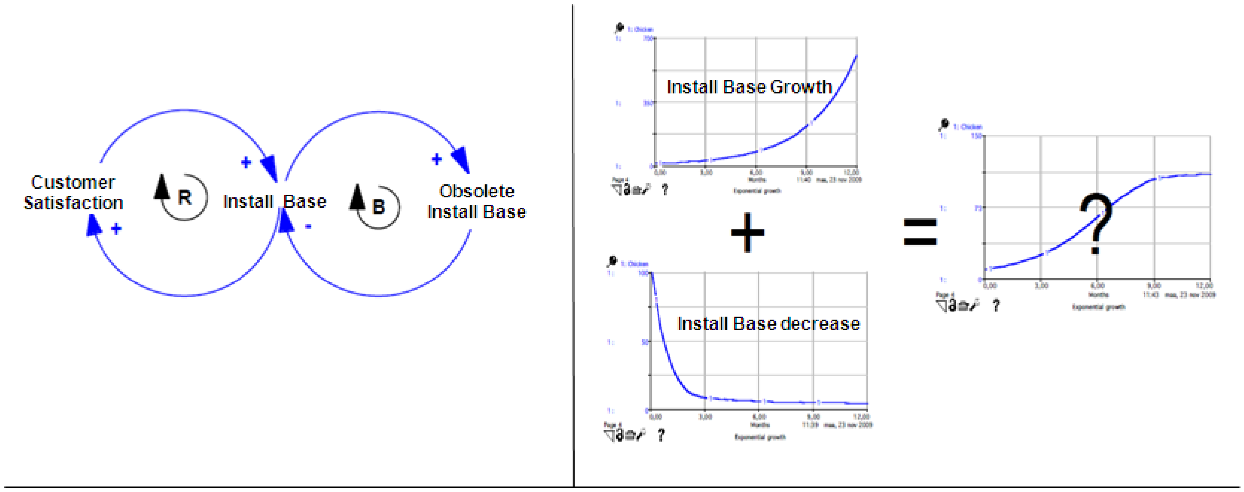


Figure 3: A simple causal loop diagram

To summarize, it is possible to simulate the behavior of a system if it is translated into causal relationships, which is a powerful tool for analyzing how specific variables interact with one another over time, especially when there exist delays in the response to an input or a change in the network. Therefore, system dynamics provides a greater scope for understanding of the overall system.

2.2 Closed-Loop Supply Chains with System Dynamics

Schröter and Spengler (2005) introduced a closed-loop supply chain with a system dynamics approach. They focused on the applicability of parts recovery strategies to obtain spare parts of durable items that are in their final service phase, which begins when the original product is no longer produced, to avoid stock outs in the remaining service time.

The authors developed a strategic management tool based on the theory of system dynamics to design robust policies. They translate the closed-loop supply chain into causal loops and a stock and flow diagram. Simulating different policies showed that a combination of a system wide-inventory policy combined with an early warning system is a robust policy to forecast spare part demands of final phase products. Interesting is that Schröter and Spengler (2005) included an age-dependent recoverability yields for obsolete equipment.

However, they only looked at obsolete equipment and their recoverable spare parts, while the closed-loop supply chain of Philips Healthcare also contains unused spare parts, which can be sent directly back to the CDC without repair. Therefore, the work of Tan and Kumar has complementary value.

Tan and Kumar (2006) developed a decision-making model based on a systematic and dynamic approach that incorporates reuse, remanufacturing, and recycling to determine the demand and profitability of returned spare parts, which are sold to secondary markets or to the consumers themselves.

Tan and Kumar (2006) divided the returns into two types, which are treated differently for reverse logistic:

- Make parts, which can be repackaged, repaired or scrapped by the manufacturer.
- Buy parts, which are purchased by the manufacturer because the suppliers make the parts at a lower cost or the manufacturer does not have the expertise to make them. These parts can be exchanged with suppliers or for credit and scrap.

The authors developed a stock-and-flow diagram of the reverse logistics network for the computer industry, which shows the dynamics and causal relationships of the different flows of reuse, remanufactured, scrapped, and exchanged spare parts. In their simulation, they included different conditions of quality of the spare parts, which influences the costs of treatment and they showed that the quality of the returns has a significant influence on the reverse operations. Tan and Kumar (2006) also concluded that delays have a significant impact on the profitability of reverse logistics operations.

The stock-and-flow diagram in this paper looks very similar to the return supply chain of Philips Healthcare, except for the buy parts flow because Philips Healthcare divides its returns only into unused returns which are repacked, defect returns that are repaired or scrapped it this is not possible, and consumables which are scrapped by definition. Therefore, this model might be a good extension to the model of Schröter and Spengler (2005) to describe the dynamics of the closed-loop supply chain of the spare parts of Philips Healthcare.

However, the paper focuses only on the recovery process and not on the forward supply chain. So, their explicit description of the equation of each variable in a system dynamics software problem does not include this. Therefore the paper of Vlachos, Georgiadis and Lakovou (2006) is a nice addition because they describe also the forward process closed-loop supply chain in detail. Another interesting part of their work is that they look at a two echelon closed-loop supply chain, which enables to extend the model to a multi-echelon closed-loop supply chain.

Hence, a very complete work about closed-loop supply chain with a system dynamics approach is developed by Valchos et al. (2006). However their focus is on the required collection and remanufacturing capacity taking not only economic but also environmental issues into account. Therefore not only the supply chain is closed through remanufactured product, but also as a result of the impact on sales via the environmental issue ‘green’ image effect.

To investigate efficient capacity planning for remanufacturing facilities, they distinguish three capacity strategies to balance the tradeoff between market share maximization and maximization of capacity utilization:

- Leading capacity strategies, where excess capacity is used so that the firm can absorb sudden demand surges.
- Trailing capacity strategies, where capacity lags the demand and therefore capacity is fully utilized.

- Matching capacity strategy, which attempts to match demand capacity and demand closely over time.

They discovered, using numerical experimentation, that leading capacity strategies should be used if there is a reverse supply chain.

Interestingly, Vlachos et al. (2006) describe methods to validate system dynamics models:

- Direct structures tests, which involve comparative evaluation of each model equation against its counterpart in the real system.
- Indirect structures tests that are a more quantitative and structured method, consisting of extreme-condition and behavior sensitivity tests, which determines those parameters to which the model is highly sensitive.

The authors concluded that the model behavior exhibits meaningful sensitivity to parameters raw material, production capacity, remanufacturing capacity, collection capacity, 'green image' effect and sales. This 'green image' effect, a qualitative influence, is described more explicitly by Georgiadis and Vlachos (2004) and is a nice indication how to implement qualitative information in a system dynamics model.

2.3 Impacts in the Closed-Loop Supply Chain.

Ferrer and Ketzenberg (2004) investigated the impact of yield information and supplier lead time on manufacturing costs in a closed-loop supply chain because early information avoids spending costs on unrecoverable parts, and a short supplier lead time avoids unnecessary purchases of new parts because this decision is postponed after the remanufacturing yield is realized.

Their empirical research on a system with two different parts shows that having the ability to identify product yield early in the process is significantly more valuable than having the ability to place purchase orders with a short lead time. Having both capabilities was not a significant improvement compared to the ability of identifying the product yield early. This implies that a more responsive supplier does not provide great help in reducing the cost of the remanufacturing operation.

However, extending the model with additional parts shows that the value of both capabilities becomes more valuable. Therefore, the value of a short lead time may be quite significant for complex products that are composed of a large number of parts.

Their sensitive analysis showed that as the average repair yield increases, the performance improvement of both capabilities is less significant because a higher yield implies that information, which identifies bad parts, is less valuable. Moreover, it becomes more attractive to remanufacture than to purchase new parts. Consequently, any change in lead time will have less impact on total costs. So, therefore it would be beneficial to improve the average repair yield.

Interestingly, there is no monotonic pattern in the effect of repair costs because it has two principle effects. First, the repair cost rate has a direct and significant impact on the attractiveness of remanufacturing. As repair costs increase, the attractiveness of remanufacturing decreases which leads to a reduction in the value of information. Second, it is expected that the value of early information will increase with respect to the repair cost. Yield information eliminates wasting time on unrecoverable parts. Hence, information that identifies unrecoverable parts when the repair cost rate is higher will be more valuable than when the repair cost rate is lower. However, the combination of the two effects results in a pattern that is not monotonic.

Also Guide, Jayaraman, Srivastava and Benton (2000) mentioned the value of early information. They looked at seven major characteristics of recoverable manufacturing systems that complicate the management, planning, and control of supply chain functions and explained how these characteristics are influenced.

One of the characteristics is the uncertainty in timing and quantity of returns, which depends on the life-cycle stage of a product and the rate of technological changes. Early in the life cycle, when few units are in the field, one can expect a very low core-recovery rate. As the product matures more cores should become available since the product has been in use for longer. However, the core availability should follow the product life cycle or market growth curve with a certain time lag.

Another facet of closed-loop supply chains is that it is reasonable to assume perfect correlation between returns and demand, since a demand generates a return. However, there is little control over the quantity, quality and timing of returned products. Therefore, firms must develop strategies, like charging a core deposit, for reducing the uncertainty of return quantities, but this might not reduce timing uncertainty since demand rates would still be stochastic. Moreover, they cannot influence the condition and age of returns.

Purchasing of new parts is also a complicated aspect of reverse logistics because of the uncertain requirements resulting from material-recovery uncertainty and lead times. Therefore, firms should be able to forecast the recovery rates for parts in order to plan for new parts to replace those they cannot recover and thus material recovery must be more predictable. Recovery rates are clearly age, environment, and usage specific. Safety stock does provide limited protection against material-recovery variation.

To conclude, the system dynamics model introduced in Valchos et al. (2006) is of important value because of the detailed causal loop diagram of the forward-reverse supply chain, including general forms of diverse process in the supply chain and the explicit description of the equation of each variable in the closed-loop supply chain. Also their model is complementary to prior models because of the two-level supply chain of producer and distributor. Thus, information provided in this literature research, combined with information from interviews with employees of Philips Healthcare, results in a system dynamics causal loop that is described in the next chapter.

3. System Dynamic Simulation Model

This section translates the closed-loop supply chain and all possible interrelationships of Philips Healthcare into a system dynamics format. Therefore, different employees are interviewed to get a complete overview of all processes and influences in Philips Healthcare. First, the overall causal loop diagram is determined after which the sectors are explained in more detail.

3.1 Causal Loop Diagram of the Closed-Loop Supply Chain of Philips Healthcare

The causal loop diagram in Figure 4 shows the main (strategic) influences of the forward-reverse supply chain with repair of the spare parts of Philips Healthcare. This diagram is divided into five sectors, which will be scrutinized later on. The colors indicate which department of Philips Healthcare is in control of which parameter. Global Customer Services (GCS) is responsible for overall projects related to customer service, while Service Parts Supply Chain (SPS) focus on the flow of spare parts. The Business Units (BU) are the production plants and innovations centers belonging to different businesses like MR or X-ray. Global Sales and Services (GSS) is responsible for the sale of systems and service contract and works together with Key Markets (KM) which have direct contact with customers. This section explains the key parameters and variables of the high level causal loop diagram and their effects, based on interviews with the director of business analytics, senior manager planning and analytics, modality performance manager of MR, performance manager MR and XR, senior manager analytics, business process analysts, project managers on forward and reverse supply chain, and global reverse logistic manager.

The forward supply sector consists of the *Spare Part Demand*, which indicates the demand for spare parts of FSE of Philips Healthcare and third parties like distributors, competitors, or engineers of hospitals. This *Spare Part Demand* is positively influenced by *Service contracts, Warranty,* and *Third Party sales* because a larger number of contracts or third parties result in more requests for spare parts. Service contracts describe the level of service offered during a certain time period to a customer, that is much longer than the warranty period and both are correlated with the *Current Installed Base* which is the number of equipment sold. There is also demand of spare parts from *Obsolete Installed Base*, that are systems which are still in use however they exceeded the 'end of life' period and do not obtain service anymore. A *Field Change order*, meaning that a certain part is replaced with an upgraded version in all sold equipment because of frequently failure for example, is another factor that increases the demand for service parts. This demand is pushed from the business unit that produced the equipment.

The *Spare Part Usage,* which is affected by the *Average Age of Installed Base* and *Utilization Install Base* of the current equipment, influences the *Spare Part Demand* because older and frequently used systems have a higher demand for spare parts. However, improvements in the quality of spare part by *Service Parts Innovations* results in less failures because a part can be used longer and with more intensity before it fails on average and therefore the demand decreases.

Quality Packaging, *Remote Services, Preventive Maintenance* and *Diagnose Field Service Engineers* have an opposite influence on *Spare Part Demand*. This means that an improvement of packaging quality results in fewer spare parts arriving defect at their destination. *Remote Services* reduces the demand for spare parts because it might be the case that a spare part is not required because the problem is caused by something else, which can be discovered with remote control. Also attention is paid to *Preventive Maintenance Policies,* meaning that a failure is avoided through preventive replacements determined by experience of key markets. The advantage is that this demand is controllable, such that it can be planned. Especially the key market Japan uses preventive maintenance. *Training* of the FSE increases theirs accurate knowledge of failures of the installed base, resulting in better *Diagnoses of Field Service Engineers* and consequently a demand for an appropriate spare part instead of a misdiagnose.

The reverse supply sector describes all causal effects in the return part of the supply chain. First of all, the *Spare Part Demand* influences the *Returns at Defect Warehouse,* where all returns are accumulated of a certain time zone because each call for services implies a return of defect or unused spare parts. The location of the installed base determines the return time of spare parts, meaning that a longer *Return Time* has a negative impact on the stock level of *Returns at Defect Warehouse* because the return rate decreases.

The *Returns at Defect Warehouse* increases the *Serviceable Spare Parts Inventory* because good returns are directly send to the time zone warehouse, whereas defect returns are send to vendor for repair according to a *Repair Purchase Order*. The *Serviceable Spare Parts Inventory* is depleted by *Spare Part Demand* and by *Scrap*, which indicates the disposal of serviceable spare parts if they remain unused for some time to prevent an endless accumulation of spare parts. The value of the inventory depends on the *Pricing of Spare Parts*, which is determined once or twice each year.

The procurement sector describes the influences on orders for repairs and new buys. The defect spare parts send to the supplier are influenced by the *Repair Yield*, that indicates the percentage of acceptable parts because a higher yield implies that more parts can be repaired, which indirectly influences the purchase of new buys. This *Repair Yield* can be improved by *Service Parts Innovations.* So, the *Repair Purchase Order* and *New Buy Purchase Order* increase the *Serviceable Spare Parts Inventory* depending on the *Repair Lead Time* and *Production Lead Time* because a longer lead time has a negative effect on the stock level. Interestingly, Philips Healthcare uses external and internal suppliers. The internal suppliers are the business unit factories of Philips Healthcare, if a defect spare part is sent, the business unit can determine independently whether they repair that part or give a new part as long as Service Part Supply Chain (SPS) receives a serviceable spare part back. The replenishment decision for purchase orders is affected by the *Realized Service Level* because a higher level results in fewer *Backorders* and therefore the orders for new buy will decrease, as well as the orders for repair.

The *Target Service Level* from the customer service sector has a causal effect at the *Serviceable Spare Parts Inventory* because a higher target level requires a higher inventory level. The *Target Service Level* is the level of service desired and defined in the *Service contracts*, though the *Realized Service Level* might be higher or lower, affecting the *Customer Satisfaction,* which influences the *Sales of Installed Base* and the *Number of Service Contracts* because increased confidence and satisfaction of customers will increase the sale of installed bases and service contracts or the other way around. Also *Service Programs* influence the *Number of Service Contracts* because service programs are a marketing tool with discounts adapted to specific clients, to sell more contracts and this affects also the level of service determined in the *Service Contracts.*

In addition, the *Expected Markets Share* of the Business Unit and Key Markets, which reflects the expectation of experts of the trend in sales of systems, has a causal effect on the *Sales of Installed Base*. Further, *Research and Development* results in the launches of new systems every three years on average, which stimulate the *Sale of Installed Base,* and thus an increase of *Current Installed Base*.

An important loop in this overall diagram is the service contracts loop. The service contract loop is a balancing loop because fewer service contracts decrease the demand which causes an increase in inventory level. This results in a higher service level, which has a positive effect on the number of service contracts sold. Consequently, the demand for service parts increases and this closed the negative feedback loop.

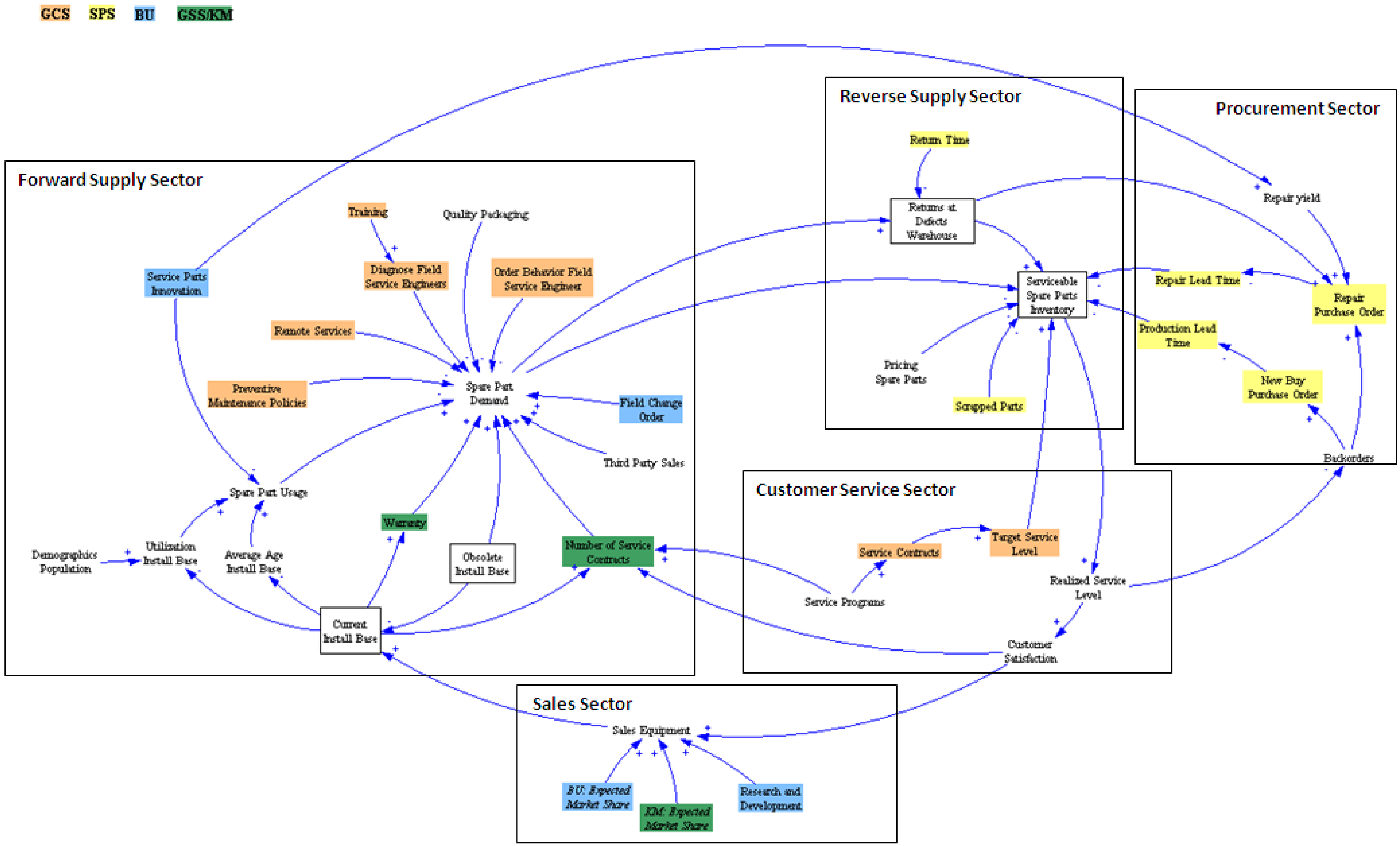


Figure 4: Causal Loop Diagram of the Closed-Loop Supply Chain of Philips Healthcare

SPS has set targets for the year 2010 on several controllable key parameters. The business case investigated some of them. These key parameters are highlighted red in the list below and also integrated in the high level causal loop diagram of the closed-loop supply chain in Figure 5.

SPS Initiatives 2010

1. Customer Demand

1.1 KM issue action plans and install base reviews
1.2 Escalation Tracking with Accenture CRM tool
1.3 SPS-KM Service Level Agreement
1.4 Customer Quality Survey targets

2. Forward Logistics

2.1 Packaging Inspection
2.2 Freight Audit EMEA
2.3 More Ground Returns
2.4 Dangerous Goods Pilot

3. Lifecycle Operations

3.1 Field Change Order material stocking plan
3.2 Forecast model for impact part configuration

4. Strategic Planning

4.1 98% CCP Fill Rate per BU per region
4.2 95% overall Fill Rate performance per BU per region
4.3 New CCP list
4.4 Push Repair Target

5. Supply Management

5.1 New Buy lead time to 35 days
5.2 2.5% materials cost savings external purchases

6. Reverse Logistics

6.1 Goods In Transit reduction to 15 days
6.2 Inbound Backlog time to process of 24 hours
6.3 Aged WIP Reduction 25%
6.4 Overdue Repair Order reduction 25%
6.5 Quality Inspection Reconciliation Process
6.6 Process to quickly identify ZSID scrap parts
6.7 ZREP to ZSID process

7. Repair Base Optimization

7.1 Reduce Repair costs 2.5%
7.2 Improve Reverse velocity
7.3 Reduce number of Repair Vendors
7.4 Implement Sanmina Charlotte/Singapore

8. Service Parts Quality

8.1 Reduce DEFOA Rate
8.2 Pilot Quality Seal
8.3 ZSID DEFOA to scrap

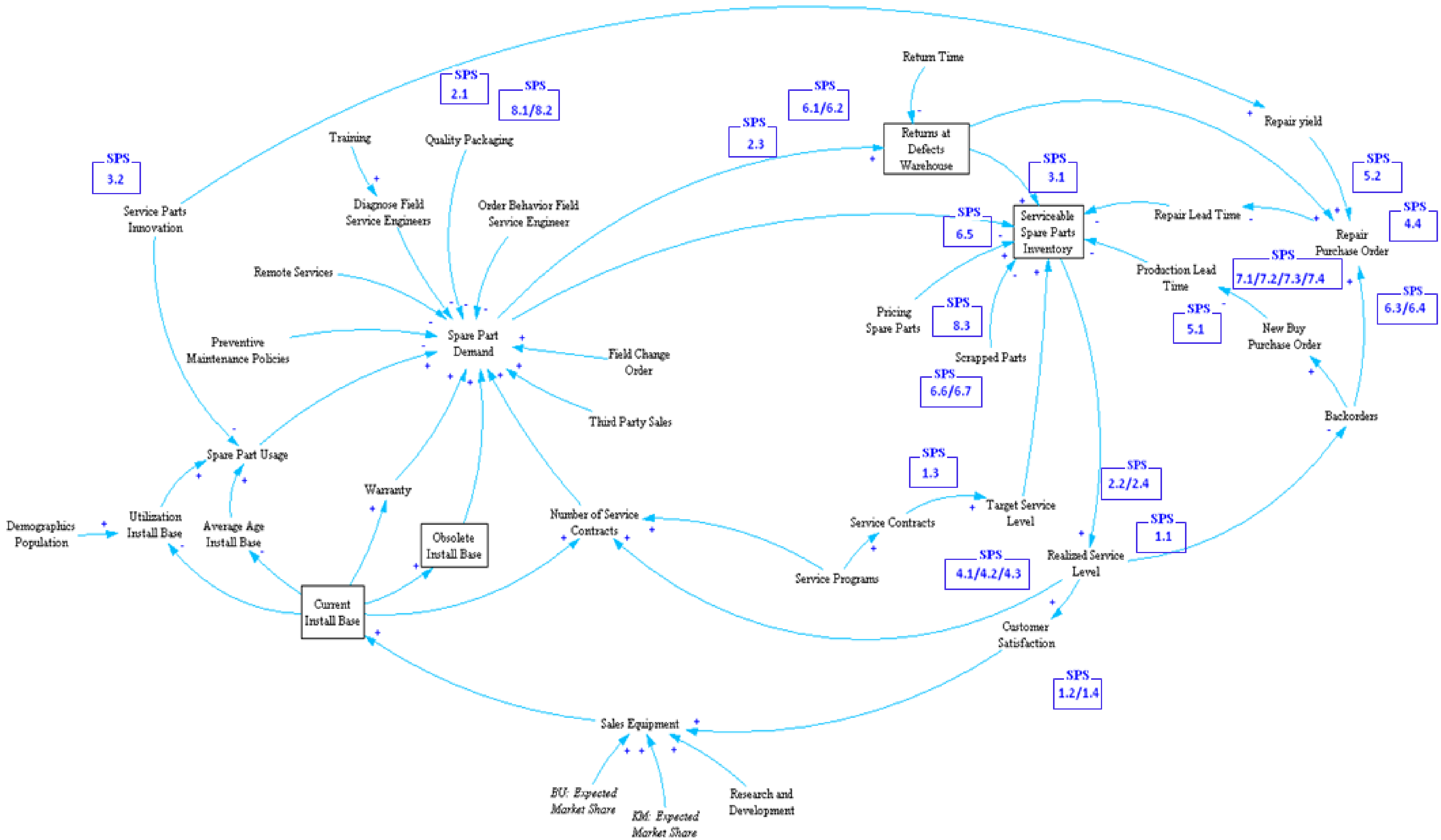


Figure 5: Causal Loop Diagram of the Closed-Loop Supply Chain of Philips Healthcare with SPS targets for 2010

3.2 Causal Loop Diagram of the Sectors of the Closed-Loop Supply Chain

The previous section showed the causal loop diagram of the forward-reverse supply chain, divided into five sectors, on a high level. Looking in more detail to these sectors shows some extra interrelationships, especially in the return and procurement sector, whereas the sale sector is already complete in the overall causal loop diagram.

3.2.1 Forward Supply Sector

Also the forward supply sector is rather detailed in the high level causal loop diagram. One additional key parameter in Figure 6 is the *Forecast Demand*, which is based on the current *Spare Part Demand,* and influences the *Replenishment Decision* in the procurement sector. The link between the forward and reverse supply sector is the generation of a return for each request of services. So, the *Spare Part Demand* affects the *Return Rate* of returns to the defects warehouse.

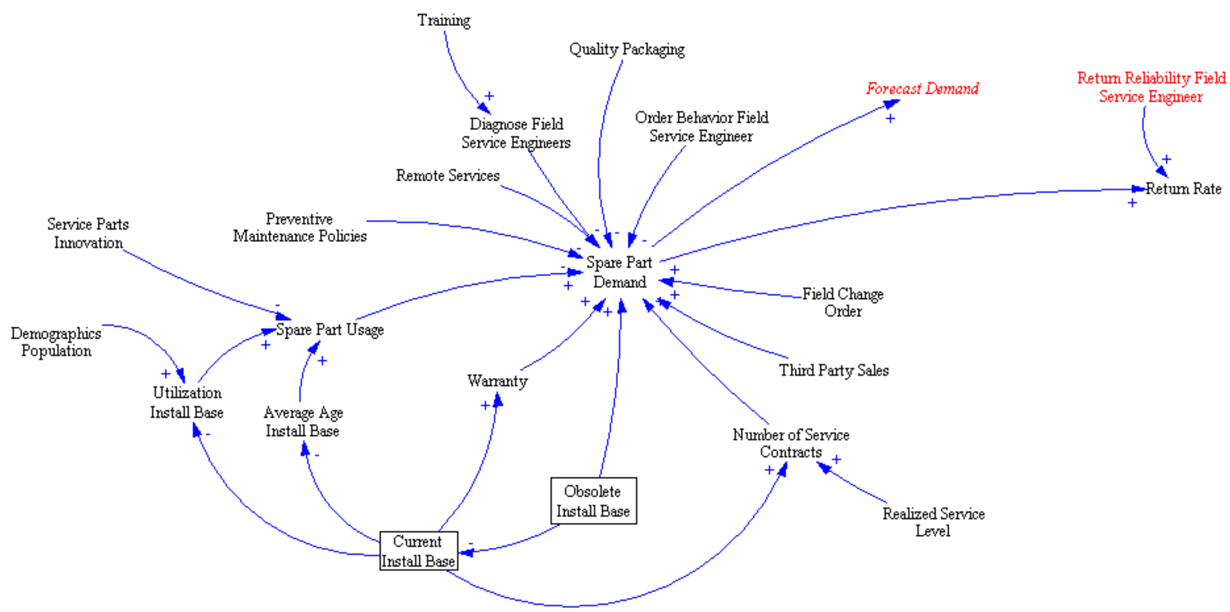


Figure 6: Forward Supply Sector

3.2.2 Reverse Supply Sector

Additional interview with business process analysts of reverse supply chain, (senior) returns managers, senior manager transportation network, project manager reverse logistics, and contact persons from UPS results in the more detailed causal loop diagram in Figure 7 of the reverse supply chain.

The return of defect or unused spare parts arrive within a certain *Return Rate,* which is negatively affected with the *Return Time* that reflects the time it takes to return a spare part from a certain location. Also the *Return Reliability of Field Service Engineers* influence the return rate because sometimes the engineer decides not to send the return back on the same day, but some days later. This delay has an indirect impact on the *Serviceable Spare Part Inventory* because if the return cycle time reduces, which consists of return time plus repair lead time, the stock level of serviceable spare parts can be diminished while the same service level is achieved. The returns are either *Accepted for Reuse* or *Rejected for Reuse* after inspection, which takes *Inspection Time*. This selection depends on the *Percentage Unrecoverable Defects,* which indicates the consumable spare parts that never are repaired because the low cost of new ones and the repairable spare parts with irreparable damages. The stock of *Returns Backlog at Defects Warehouse* is depleted after the inspection because the parts are sent to their selected destination, namely the *Scrapped Parts* for unrecoverable returns, the *Good Returns at Defects Warehouse* for unused spare parts, which are immediately add to the *Serviceable Spare Parts Inventory*, and the *Defects Returns at Defects Warehouse* for defect repairables.

Replenishment Decisions determine when and how much repairables of *Defect Returns at Defects Warehouse* are sent to suppliers for repair, resulting in an increase of *Serviceable Spare Parts Inventory*, which might results in a *Scarp Decision,* if spare parts remain unused for a long time, called the *Shelf Time,* to prevent an endless accumulation of serviceable spare parts.

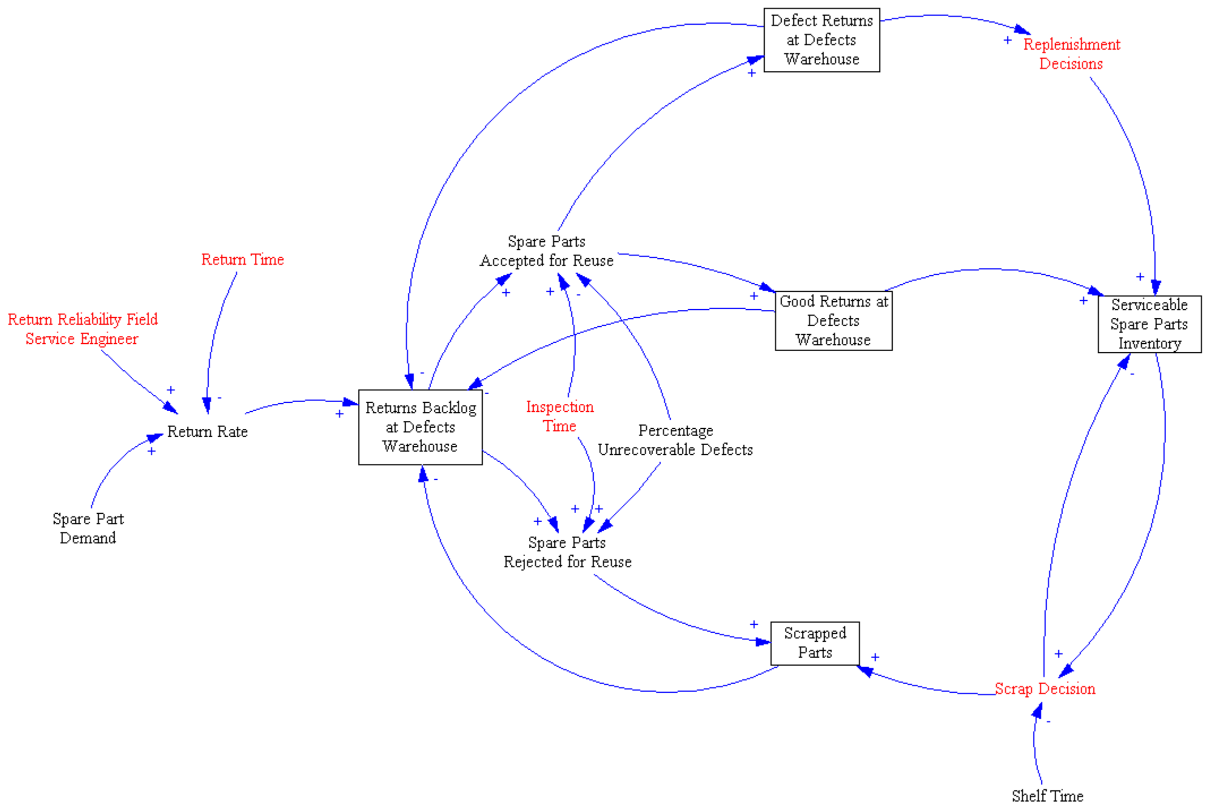


Figure 7: Reverse Supply Sector

3.2.3. Procurement Sector

More insight was gathered by interviewing an inventory controller and business analyst who are specialized in forecasting and repair processes. This results in the causal loop diagram described in this section and pictured in Figure 8.

The central part of the procurement sector is the *Replenishment Decision*, which determines the *New Buy Purchase Orders* and *the Repair Purchase Orders.* This decision is based on the level of *Defect Returns at Defects Warehouse* because it is cheaper to repair a spare part than produce a new one, though the decision also depends on the *Production Lead Time* and *Repair Lead Time*, especially in case of urgency. Of course, the *Backorders* affect the purchase ordering, as well as the *Discrepancy in Service Level* because higher positive discrepancies between the desired service level and the *Realized Service Level*, calls for a higher *Serviceable Spare Parts Inventory* level and thus a higher purchase, and where a negative difference should reduce this inventory because the realized level is higher than the target. The value of the inventory depends on the *Pricing of Spare Parts*, which is determined once or twice each year and affects the *Replenishment Decision* because it is more expensive to hold inventory in case of a higher price, resulting in great necessity of low level inventory.

If a *Repair Purchase Order* is placed, the spare parts are shipped to the *Defect Returns at Supplier* inventory, where they are repaired, which takes *Repair Lead Time.* The *Realized Repairs* are correlated with the *Repair Yield* because this yield indicates the percentage of parts that can be repaired. However, some of the defects spend more than 120 days at the supplier, the *Aged WIP,* and in this case the parts are reserved because it is not expected that they will be repaired anymore and is called *Controllable Scrap at Repair Centre*.

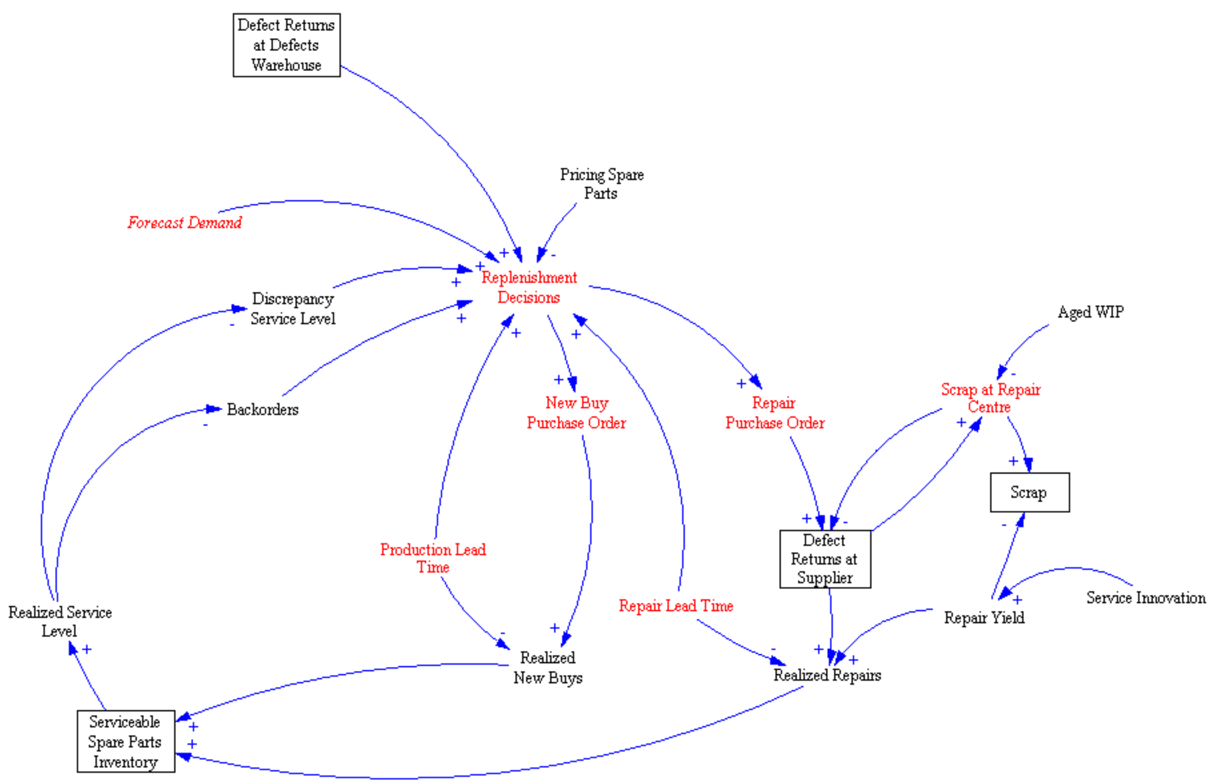


Figure 8: Procurement Sector

3.2.4 Customer Service Sector

The only additional variable in Figure 9 of this sector is the *Discrepancy in Service Level,* which determines the difference in the *Realized Service Level* and the desired level, namely the *Target Service Level.* This difference has an influence on the *Replenishment Decisions* because if the realized level is lower than the target, the *Serviceable Spare Part Inventory* is too low and should be increased. Also the opposite occurs.

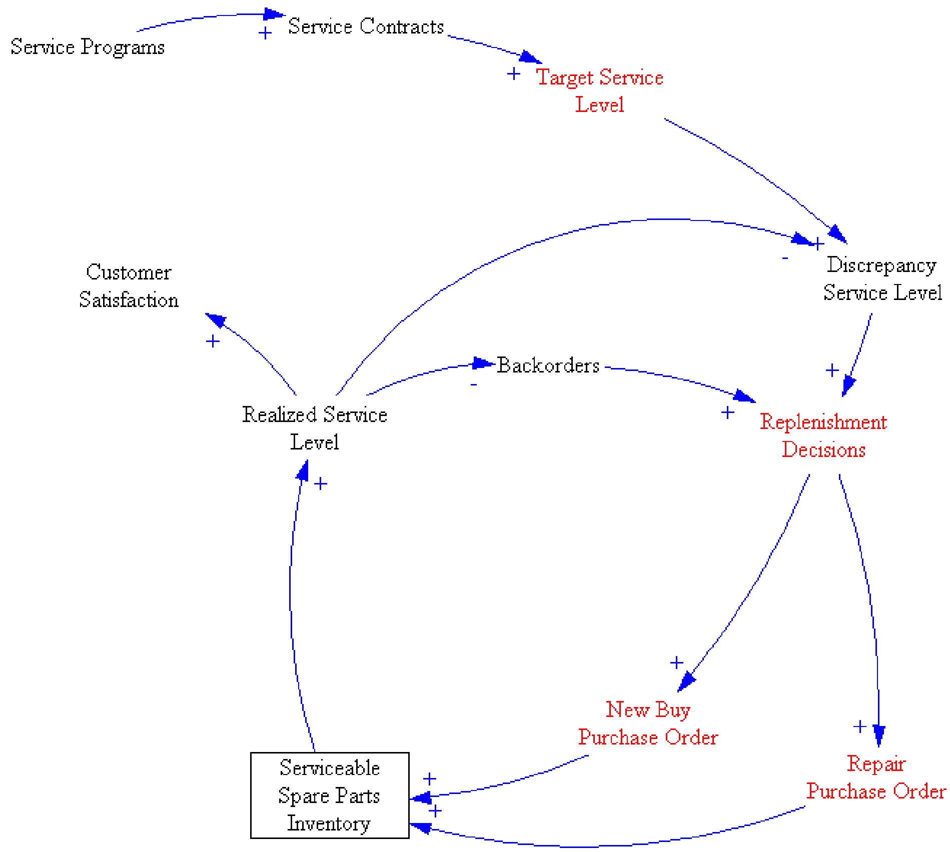


Figure 9: Customer Service Sector

4. Business Case MR

The business case is about all spare parts belonging to the business unit Magnetic Resonance (MR), like coils but also lamps. Service from SPS is required if a system of MR fails. Hence, a call from the hospital triggers the service parts supply chain. There are xxx different spare parts, with a wide price range from xxx up €xxx per part. This chapter first gives some insight in MR followed by the specific data of MR and scenarios for a practical research of the system dynamics closed-loop model.

4.1 Magnetic Resonance

Magnetic resonance imaging (MRI) systems visualize detailed internal structure of the body. MRI was called Nuclear Magnetic Resonance Imaging 15 year ago, but this frightened people because of the association with radioactivity which does not exist. MRI is especially useful in neurological (brain), musculoskeletal, cardiovascular, and oncological (cancer) imaging because MRI provides much greater contrast between the different soft tissues of the body than computed tomography (CT) does. Magnetic resonance imaging is a relatively new technology. The first MR image was published in 1973 and the first cross-sectional image of a living mouse was published in January 1974. The first studies performed on humans were published in 1977. By comparison, the first human X-ray image was taken in 1895.

MRI is diagnostic procedure that uses a powerful magnetic field and radio waves to produce detailed and cross-sectional images of the body's organs and structures being studied, without the use of X-rays or other ionizing radiation. Each picture represents a virtual slice through the part of the body as pictured in Figure 10.

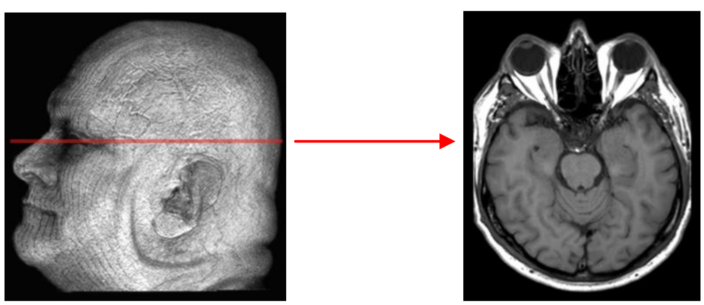


Figure 10: Images produced by MR scan

In our bodies, the nuclei of hydrogen atoms (called protons) normally point randomly in different directions. However, when exposed to the magnetic field in an MRI chamber, the nuclei line up in parallel formation, like rows of tiny magnets. Nearly two-thirds of the body's hydrogen atoms are found in water and fat molecules. When the nuclei are subjected to a strong pulse of radio waves from the MRI machine, they are knocked out of their parallel alignment. As they fall back into alignment, they produce a detectable radio signal. The signal is recorded by the machine and transferred to a computer. The computer uses these signals to reconstruct an image that is based on the strength of signal produced by different types of tissue. This reconstruction also can be made into three-dimensional images, allowing complete and remarkable visualization of the body area scanned from all angles.

The MRI scanning machine is a large donut-shaped magnet with a sliding scanning table (see Figure 11). A person lies on this table, which then slides into the desired position in the MRI magnet. The machine produces loud, repetitive noises, like banging, during the procedure.

Figure 11: MRI scanning machine

To make a comfortable treatment for the patient, Philips Healthcare developed Ambiance Experience as pictured in Figure 12, which includes the whole surrounding of the treatment room. The patient has to possibility to choose an environment style that is relaxing for them and the music, lights and wall pictures fit to that style. There is special attention for children, because they can play before the treatment with a doll and little MRI scan to get familiar with the procedure.

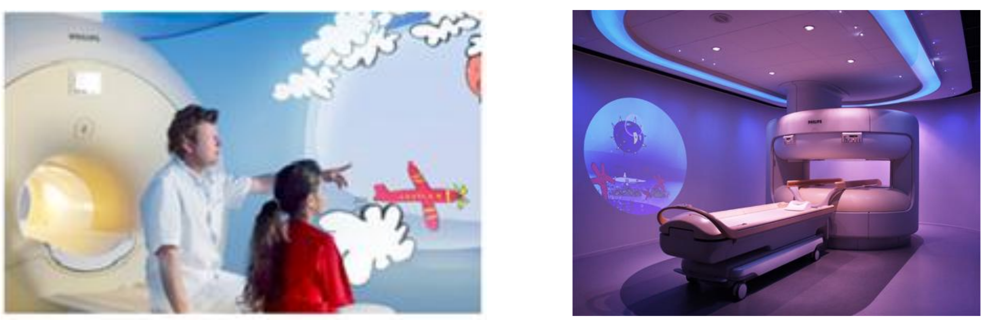


Figure 12: Ambient Experience

4.2 Data Description MR

This section describes the data used in the simulation model in more detail. Attention is paid to how the data is gathered as well as a link to the modification possibilities in the scenario analysis is made.

4.2.1 Demand

The data used as input for the simulation consists of the daily demand of January 2008 until June 2010, meaning that there are 882 input points available. The average demand per day is xxx parts, which amounts to a total value of €xxx. The standard deviation equals xxx parts, meaning that there is a significant variation in service parts each day. The deviation expressed in value is €xxx and shows the same behavior.

There was one extreme outlier in the data, specifically a demand of xxx parts or €xxx on 11th February 2008 that could not be clarified. This outlier is removed from the data set because it has a visible impact on the behavior of the inventory level in the simulation.

4.2.2 Forecast Demand

The demand forecast for the simulation is based on the daily demand. In practice, Philips uses simple moving average as forecast method but on a monthly level. Therefore, the daily demand is transformed into a rolling horizon of 30 days, after which the moving average method is applied to forecast the demand. A moving average of 1 month is selected because it gives the lowest mean squared error (MSE) as well as the lowest mean absolute deviation (MAD) compared to moving average using more months. MSE and MAD are measurements to determine how much the forecast deviates from the actual demand. The former is based on squared errors, while the latter uses absolute differences. The formula for MSE and MAD are:

$$MSE = \frac{1}{n} \cdot \sum_{n} (actual\ demand - forecasted\ demand)^2$$

$$MAD = \frac{1}{n} \cdot \sum_{n} |actual\ demand - forecasted\ demand|$$

The average forecast of 30 days accumulates to xxx parts with a value of €xxx while the standard deviation is xxx parts and €xxx. Figure 13 shows forecast over time for both quantity and value, which indicates that both have the same pattern over time.

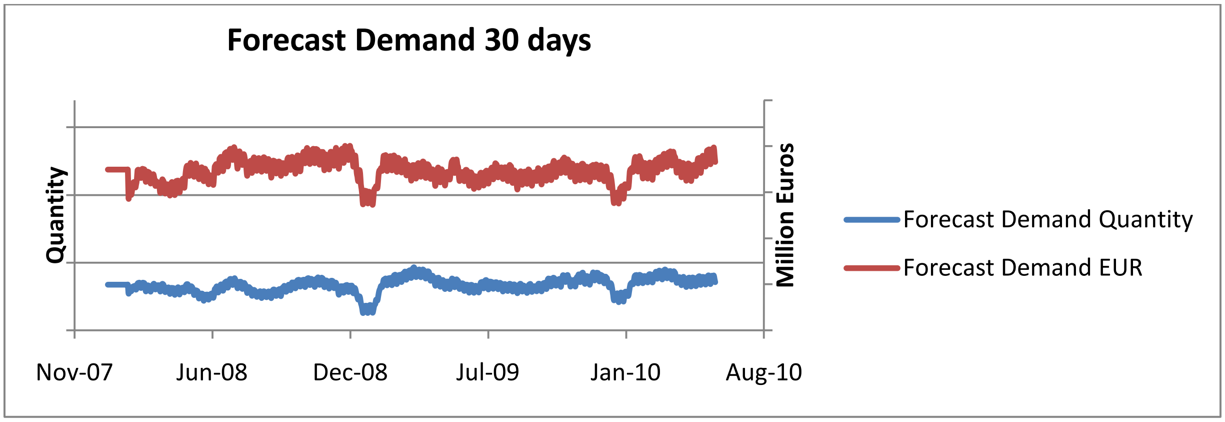


Figure 13: Forecast demand

4.2.3 Repair Lead Time

The repair lead time is the period between creation dates of purchase orders until the orders are received. Lead times are expressed as a distribution in the simulation model, meaning that a probability is assigned to every lead time, for example the probability of a lead time of 12 days is equal to 3%. This distribution is based on a rapport that contains all received repair purchase order in the period from April 2009 until April 2010. One of the extremes is an order created in July 2007 that received in April 2010. This shows the need of good forecast of demand because lead times can be long.

The average repair lead time is xxx days with a deviation of xxx days based on quantity data. If the same distribution is made but based on value, the mean repair lead time is xxx days and the standard deviation xxx days. Thus, both distributions are quite similar and have a long tail due to some extremely long lead times.

The lead time distribution is changeable in the mean and variance separately because a reduction in variability shows an improvement in supplier's performance on agreed lead times, while a reduction in average reflects new appointments on lead times. This is pictured in Figure 14.

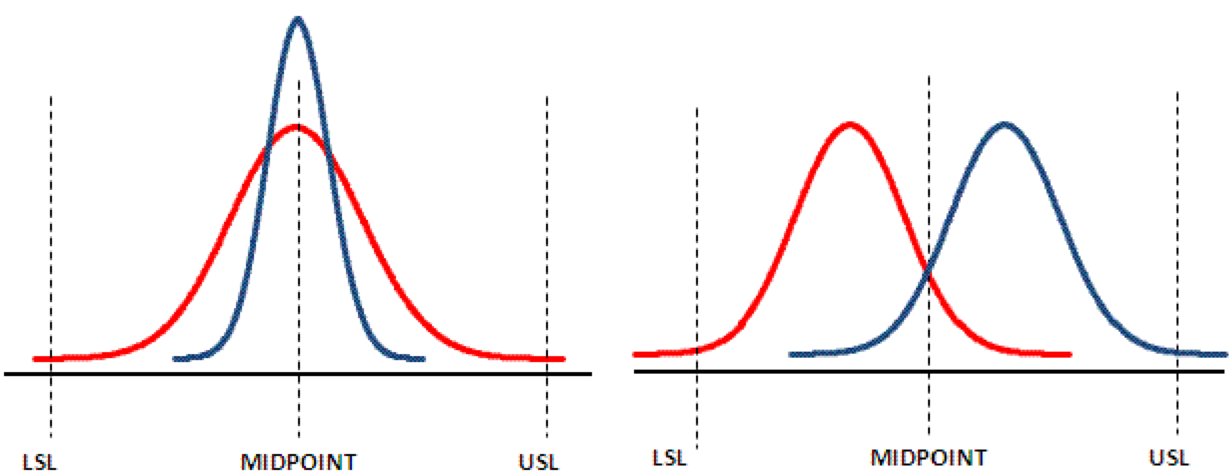


Figure 14: Left - Graph shows a reduction in variation/Right - graph shows a shift in mean

A program in MATLAB, which is numerical computing software, is made in such a way that the variation of a distribution can be manipulated without reducing its mean. This program can be found in Appendix A. The results of a reduction with 25% and 50% are pictured in Figure 15.

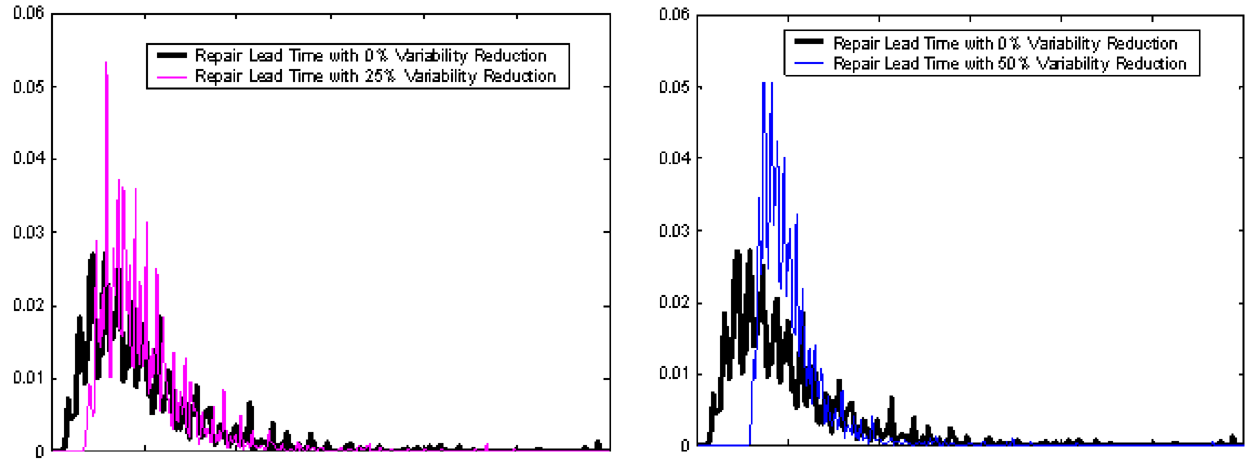


Figure 15: Repair lead time distribution with reduction of 25% (left) and 50% in variability (right)

4.2.4 New Buy Lead Time

The distribution of new buy lead time is generated in the same way as the repair lead time distribution. However, the differences between quantity and value are bigger, specifically an average new buy lead time of xxx days based on value; while average new buy lead time is only xxx days if the distribution is based on quantity. The difference in variation is also significant, explicitly xxx and xxx days for quantity and value respectively. Figure 16 give some examples of the repair lead time with different variation.

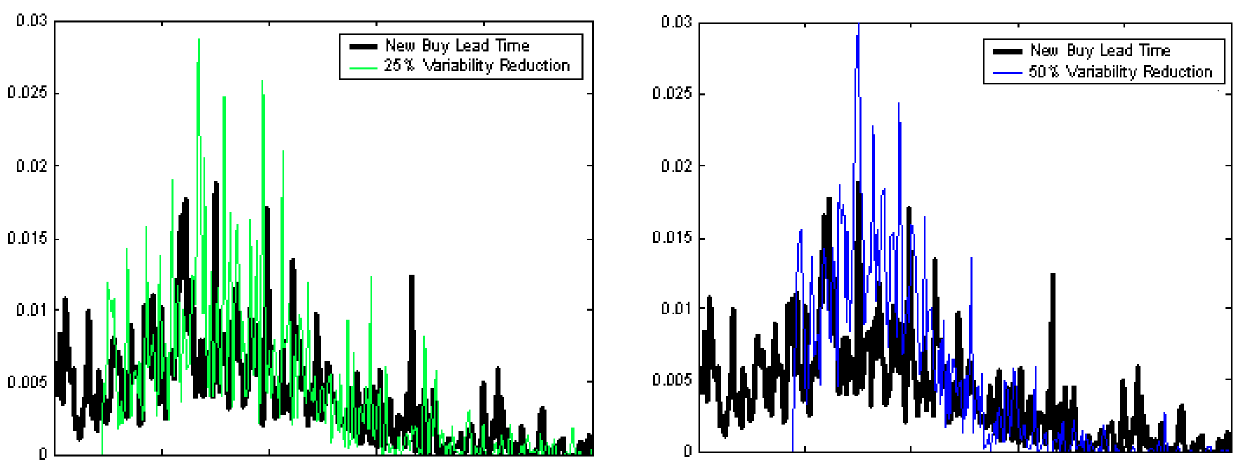


Figure 16: New buy lead time distribution with reduction of 25% (left) and 50% in variability (right)

4.2.5 Return cycle Time

The return cycle time is period from the time a FSE receives a parts until it is disposed or arrived at a blueroom. This return cycle time is defined as a distribution which is based on two independent distributions, to be exact the probability density function of the time a part is in possession of the field service engineer and the distribution of the transit times from PUDO to the bluerooms. Philips Healthcare has no standard report that shows the time a part is at the FSE before he returns a part or disposes a consumable part. From a conversation with a project manager it became clear how this is registered in SAP and what must be combined to get a distribution. This results in a distribution with a mean of xxx days and a standard deviation of xxx days.

Due to outsourcing the transport to UPS there is a lack of information on transit times. Therefore, the global reverser logistic manager combined multiple dataset of UPS and Philips, which was applicable to make a distribution for return transport times. This resulted in an average return time of xxx days, with a standard deviation of xxx days.

Those two distributions are used to make a probability density function for the total return cycle time with an average of xxx and xxx days based on quantity and value respectively. The variability is xxx days based on quantity, while the standard deviation is equal to xxx days of the distribution based on value. Appendix B contains the MATLAB file that makes it possible to combine two independent distributions into a single distribution and is graphically explained in Figure 17. Interestingly, Philips is working on a measurement report that captures the total return cycle time right now.

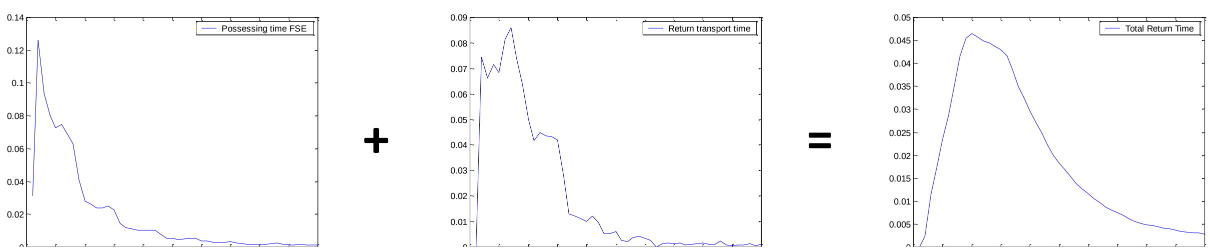


Figure 17: Adding the distribution of possession time FSE and transport time results in total return distribution

The expectation of the global reverse logistic manager of the return improvement in 2010 is investigated because this will be one of the possible modifications in the scenario analysis. His expectations are graphical displayed in Figure 18.

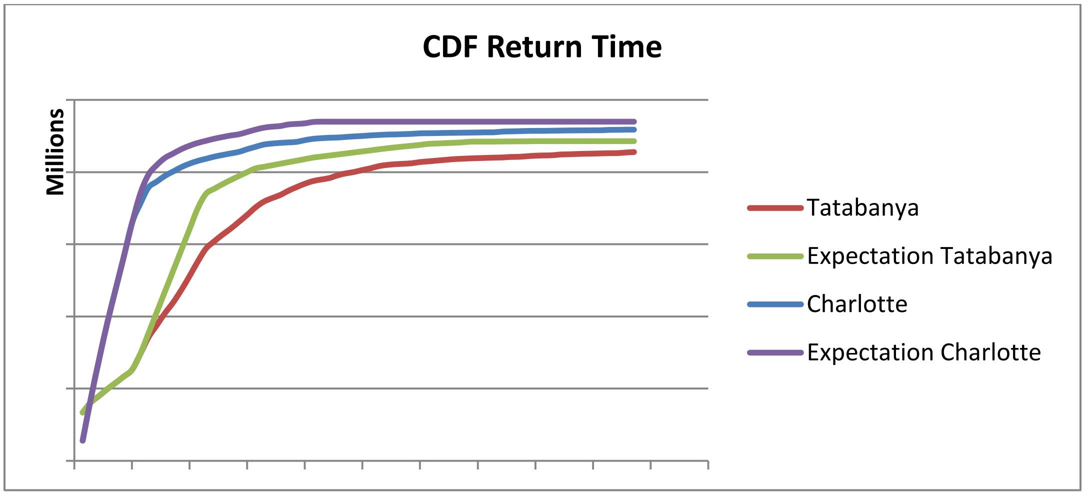


Figure 18: Cumulative density function of the expected improvement of return time in 2010

4.2.6 Repair Yield

The repair yield is not deterministic but a distribution. This distribution determines how much of the parts sent to the supplier are refurbished. Unfortunately, there is not a standard report which shows the repair yield. There are different ways to calculate the repair yield based on data from SAP. Working together with a business process analyst of reverse supply chain a method was selected that provided a distribution for the repair yield. This method diminish the parts sent to repair vendor with the parts scrapped, but also the parts that are going to be scrapped but not yet approved by management. The distribution is pictured in Figure 19 and has an average repair yield of xxx% for quantity as well as for value.

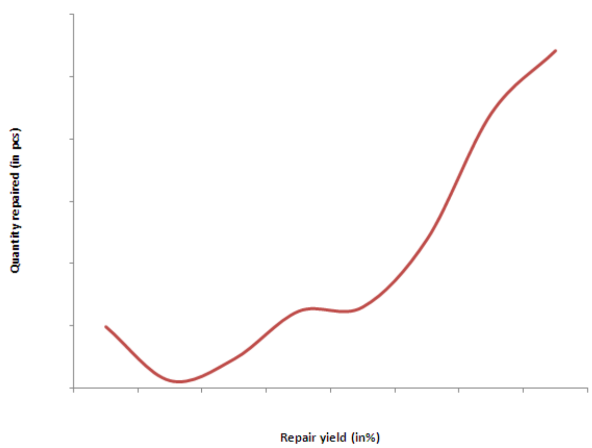


Figure 19: Distribution of repair yield based on quantity

4.2.7 Link between Install Base and Demand

One of the parameters that might affect demand is the total number of systems sold, called install base. The causal loop diagram shows that there is a positive effect between grow of the total systems sold and requests for spare parts. It is expected that this influence has a delay according to Terzi (cited in Van de Poel, 2010), which is pictured in Figure 20.

This section gives a summary of a whole different analysis that is made to find a link between install base and demand. More detailed results can be found in Appendix C.

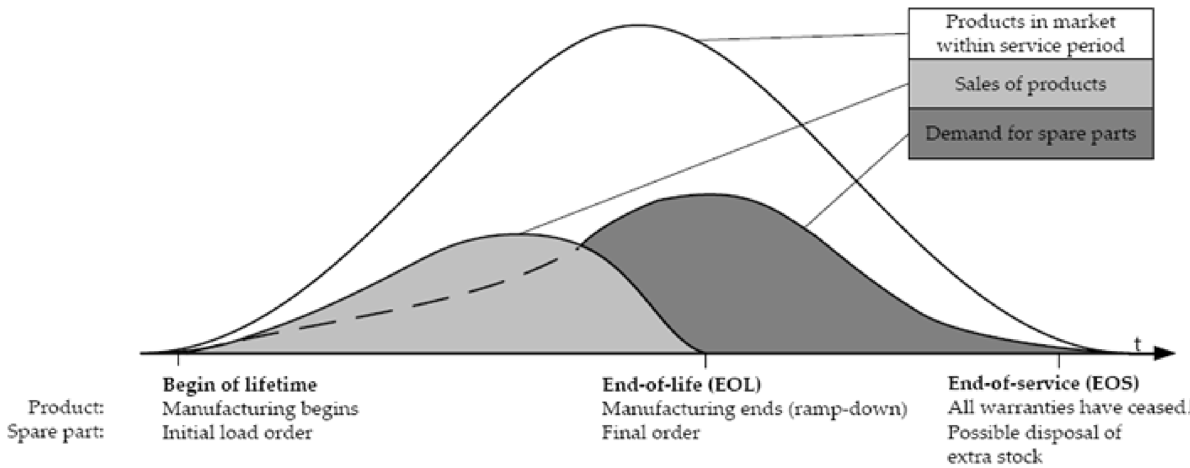


Figure 20: Sales of install base has a delayed effect in demand of spare parts

Different thoughts exist on how a link between install base and demand or consumption might look like. Consumption stands for parts that are actually used to repair equipment, while demand contains also excess ordered parts if for example when the cause of failure in the system is not clear. The next ideas were verified:

- Current and historical installed base might affect current demand.
- Correlation between installed base and consumption instead of demand.
- Classification of installed base might give more insight into the impact on demand.
- Improvements in quality of spare parts or packaging might have a negative impact on current demand.

However, regression analyses showed that on an aggregated level this link does not exist because all regressions show very low explanation of the variation. This might also be caused by the fact that there were only 27 data points available.

However, there was one clear exception: a class of just introduced systems (Figure 21) that has a strong increasing install base, shows that 95% of the variation of the regression could be explained. This might be a direction for future research, although the expectation is that on a disaggregated level a link might be more visible.

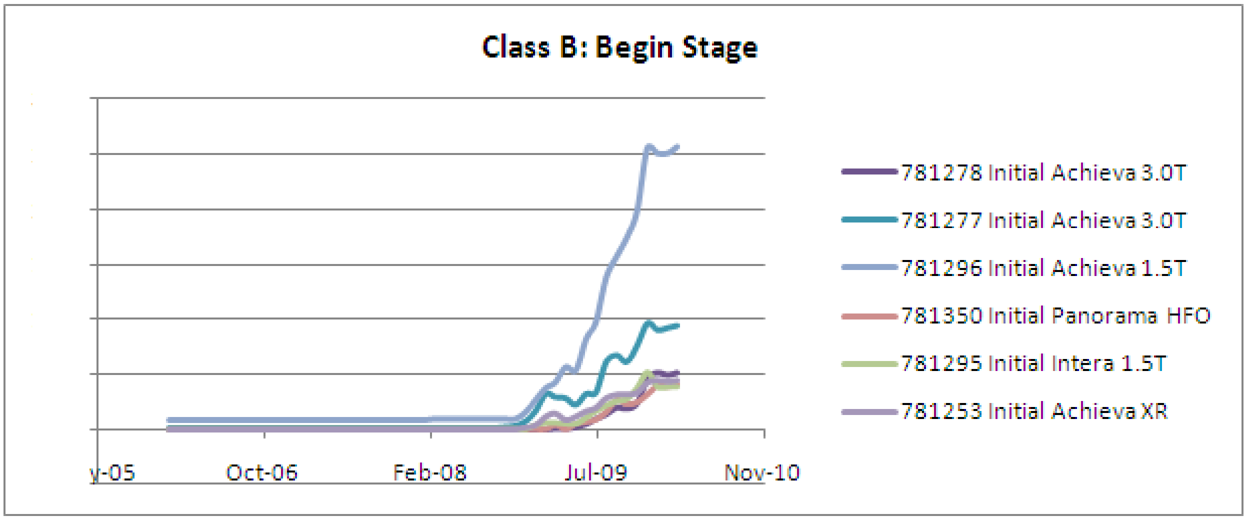


Figure 21: Growing Class of Install Base

4.3 Description Simulation Model in Ithink

The causal loop diagram of Chapter 3 is built in the software program iTthink 9.0.2. The model is adjusted to all available data because not all interrelationships are supported by data or there was not a link visible like the relationship between install base and demand on aggregated level. This section will describe all the remaining sectors and belonging assumptions. The simulation model including the mathematical equations can be found in Appendix F.

In general, iThink translates causal loops into a system of *flows* (double-lined arrows with a lever tap) and *stocks* (rectangles), such that parts or currency can flow through the system. This flow is influenced by *converters* (circles) which contain either numerical values or calculations that can be used for input as well as output. Information between converters, flows, and stocks is shared by *connectors* (single-lined arrows).

4.3.1 Forward Supply Sector

The causal loop diagram of this sector showed interesting interrelationships between variables and demand. However, at this moment it is not yet possible to give a good supported link between different variables because most links are really qualitative and not yet scrutinized. A really important relationship is the link between install base and demand, as described in Section 4.2.7. However, the aggregated level of this thesis makes it not possible to implement this specific interrelationship.

The flow in the forward supply sector in Figure 22 can be described as followed:

- Daily requests for spare parts are received, which are accumulated in the Open Demand stock.
- When there are enough parts on stock, the parts are delivered and the Open Demand diminishes.
- A Forecast of Demand will be used to determine the demand during lead time which is needed for the replenishment decision.

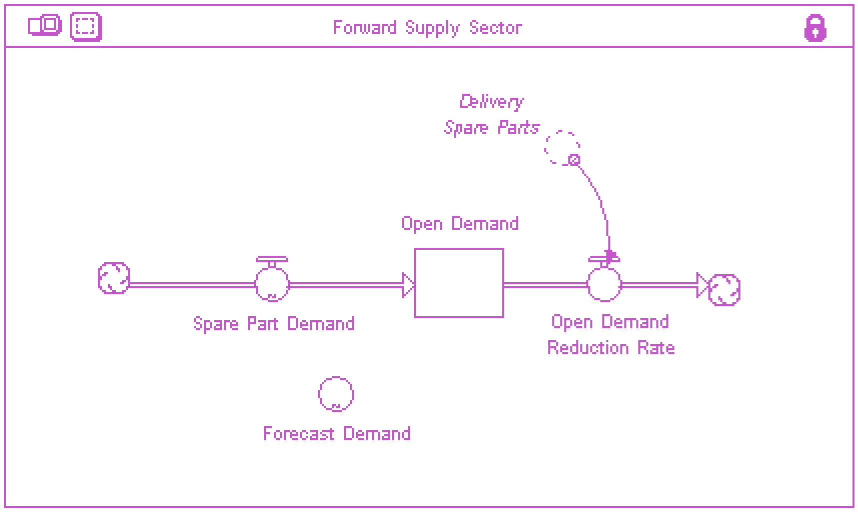


Figure 22: Simulation Model – Forward Supply Sector

4.3.2 Reverse Supply Sector

The reverse supply sector in Figure 23 contains almost all variables from the causal loop diagram mentioned in Chapter 3.

The flow in the reverse supply sector can be described as followed:

- Spare parts that were delivered to FSE are returned to the blueroom with a first order delay if they are unused or classified as repairable parts. Otherwise they are scrapped at FSE within one day. The ratio consumable versus repairable determines if the parts are either scrapped or returned.
- The Return Time is the period between the delivery at FSE until the arrival in blueroom. This return time is expressed as a distribution in which case the simulation accounts for randomness. It is possible to change both the mean and variance separately for this distribution.
- Returns are stored and inspected to split them into good returns and defect returns. The ratio of Good versus Defect Repairables is xxx%, based on the experience of business analyst director, meaning that xxx% of the returns are parts that are not used by the FSE but instead are excess orders.
- The Inspection Time in the blueroom is assumed to be one day because the delay of problem returns is taking into account in the Return Time distribution.
- The good returns are immediately sent to Spare Part Inventory, while defective returns are stored in the Defect stock at the BlueRoom.

4.3.3 Procurement Sector

The procurement sector is split into three parts; purchasing flow, determination of lead times, and determination of the replenishment decision. Otherwise, this sector will be indistinct because there are a lot of variables involved, especially in replenishment decision part.

4.3.3.1 Purchasing Flow

This flow of can be explained as followed (Figure 23):

- Depending on the replenishment decision a certain amount of parts is sent from defect stock to the repair supplier. This stock of defect parts at supplier is a conveyor, which means that an order gets a random assigned lead time after which the order is forwarded to the good stock as one batch instead of bit by bit.
- The repair yield determines how many parts of that batch are refurbished, while the rest is scrapped at supplier. This yield is a distribution that can be modified but takes into account that the maximum repair yield is 100%.
- The repaired parts are forwarded to the Spare Part Inventory. The time the process of repair and transport takes is called Repair Lead Time, which is expressed as a distribution so that the simulation accounts for randomness. It is possible to change the mean and variance separately.
- For the new buy purchase process holds the same: A certain amount, determined based on the replenishment decision, is ordered. The orders are also processed as a conveyor.
- The production time is called New Buy Lead Time, which is also expressed as a distribution with the possibility of modification.
- The Spare Parts Inventory is diminished by the Delivery of Spare Parts, which only takes one day. The size of delivery equals the demand if there are enough parts on stock, otherwise the available parts are delivered and the rest of the Open Demand is delivered in the next period. The simulation model makes no differences in delivery location or kind of part requested, due to strategic purpose of the research. Hence, it is assumed that the right part is stocked on the right location.

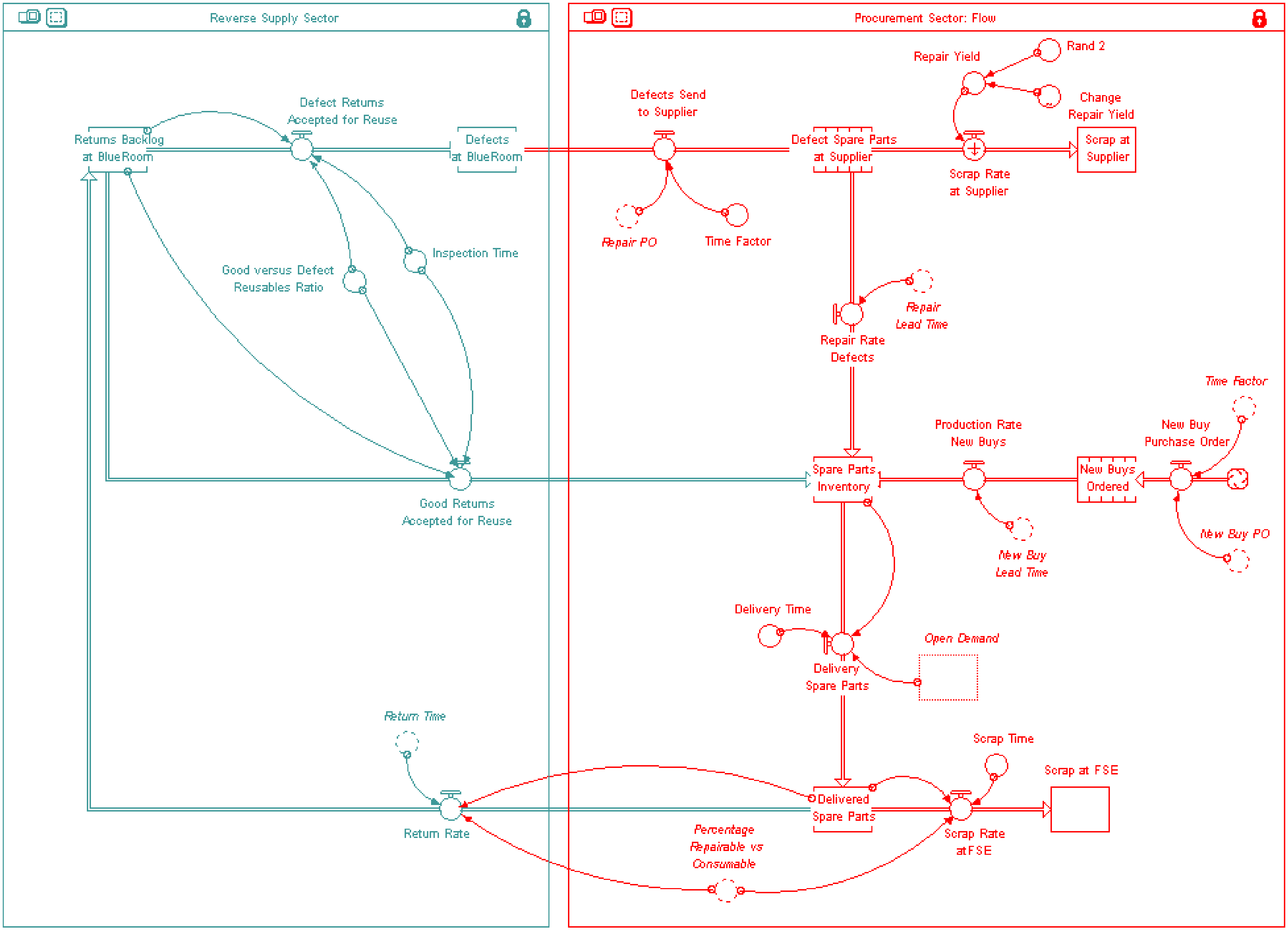


Figure 23: Simulation Model – Reverse and Procurement Sector

4.3.3.2 Lead Times Determination

The second part of the procurement sector in Figure 24 consists of the determination of different lead times and is a supporting sector which provides input values. In general, the 'Rand …' parameters randomly select a lead time from the predetermined distributions which are expressed in the converters '… Lead Time …%'. The average of the distribution can be shifted by the 'Modification Mean …' parameters, while the variation of the distribution can be reduced by converters ' Var …'. An additional converter is used for the determination of return time that ensures that the lead time is not negative, which is not required for repair or new buy lead time because they are used in combination with a conveyor resulting in positive lead times.

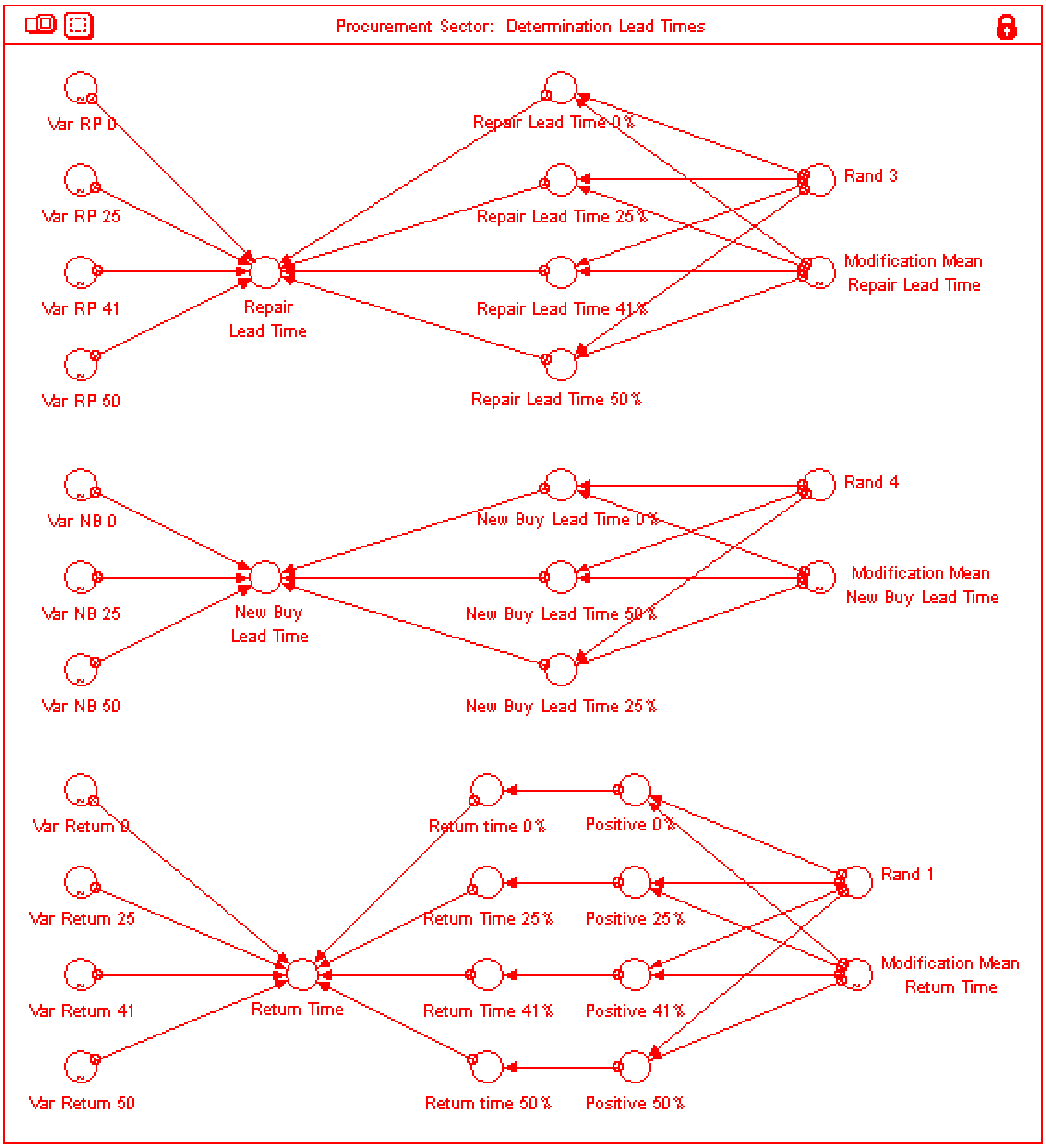


Figure 24: Simulation Model – Determination Lead Times

4.3.3.3 Determination Replenishment Decision

This part of the procurement sector consists of the replenishment decision, where the size of purchase orders is determined every period (Figure 25). This decision depends on different variables, explicitly the purchase orders that have been placed but not yet received, level of inventory, open demand which should still be delivered, forecasted demand during the production time of new parts, and safety stock. The formula of purchase order indicates the number of parts that should be ordered if the total number of parts on stock and already ordered does not capture the total sum of open demand, safety stock, and demand expected during production time.

$$\begin{aligned} \textit{Purchase Order} \\ &= Max\big((\textit{Open Demand} + \textit{Safety Stock} + \textit{Demand during lead time} - \textit{Inventory} \\ &\quad - \textit{Total Open Purchase Orders}), 0\big) \end{aligned}$$

Note that the demand during lead time is based on production time of new buys. This is done to be on the safe side because production time is longer than repair time.

The safety stock depends on a safety factor, average of new buy lead time and demand, and variation in new buy lead time and demand. The next general formula, which is commonly used in supply chain management, calculates the safety stock level:

$$\begin{aligned} &\textit{Safety Stock} \\ &= \textit{safety factor}\sqrt{\textit{avg lead time} \cdot (\textit{st dev demand})^2 + (\textit{avg demand})^2 \cdot (\textit{st dev lead time})^2} \end{aligned}$$

The safety factor is the inverse of the cumulative standard normal distribution depending on the service level, for example a service level of 95% results in a safety factor of 1.64. Again the production lead time of new buys is used instead of repair lead time.

The replenishment decision determines how many parts are sent for repair, while the rest of the required parts are ordered at a new buy vendor. This means that a new buy purchase order is placed for all consumable parts, while repairable parts are repaired at the supplier if there are enough defect parts on stock in the blueroom, otherwise new buys are ordered. The repair purchase order takes the mean repair yield into account, meaning that more parts are sent to the supplier, in such way that after repair and scrap due to unrepairable parts enough parts are refurbished and added to the inventory.

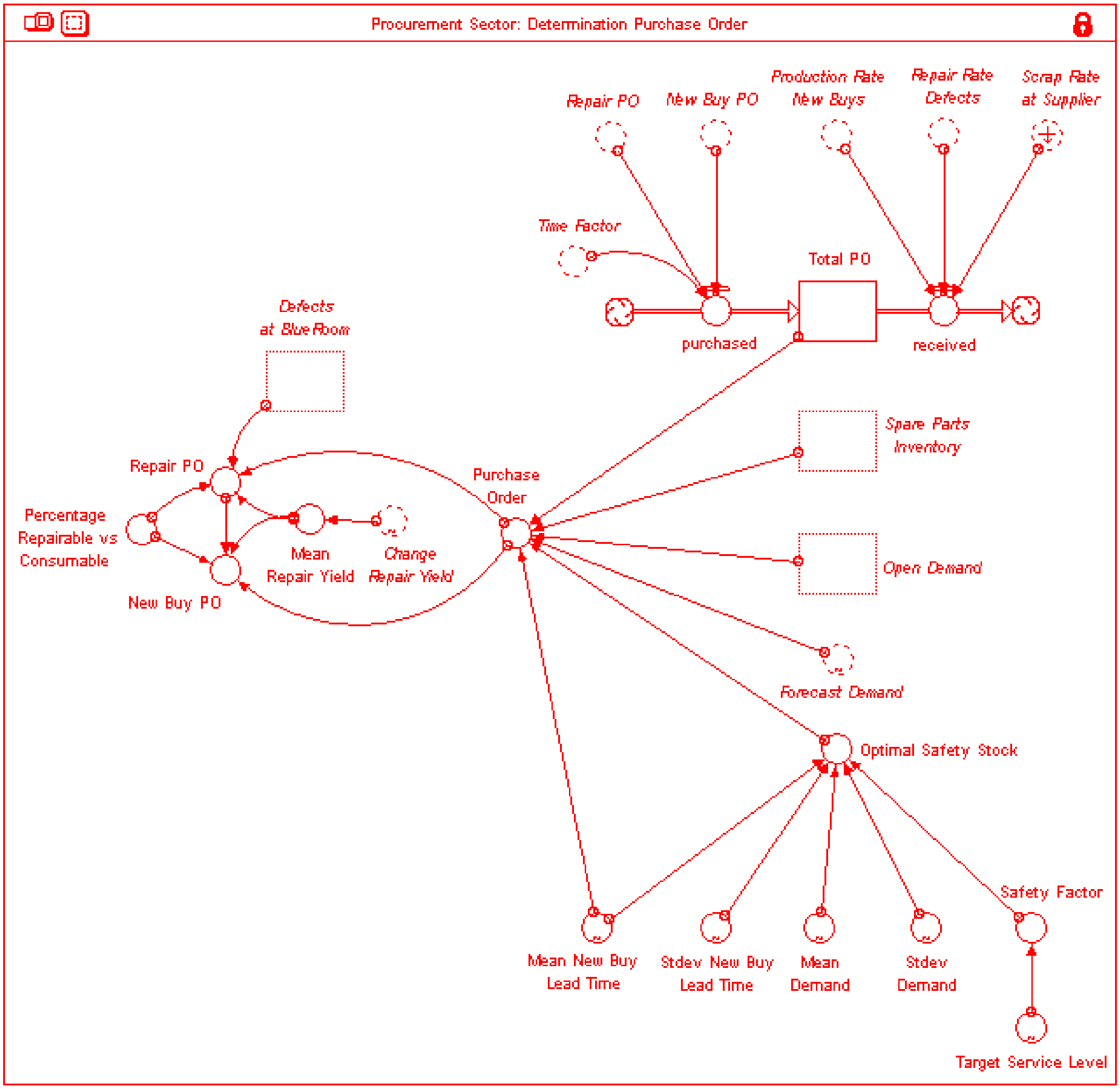


Figure 25: Simulation Model – Determination Replenishment Decision

4.3.3.4 KPI's

There is another sector added to the model to calculate Key Performance Indicators (KPI) as pictured in Figure 26. The indicators used in the model are: average inventory, average defects at blueroom, average repair parts ordered every day, average new buys ordered every day, and average field consignment stock that consists of the parts delivered to the FSE.

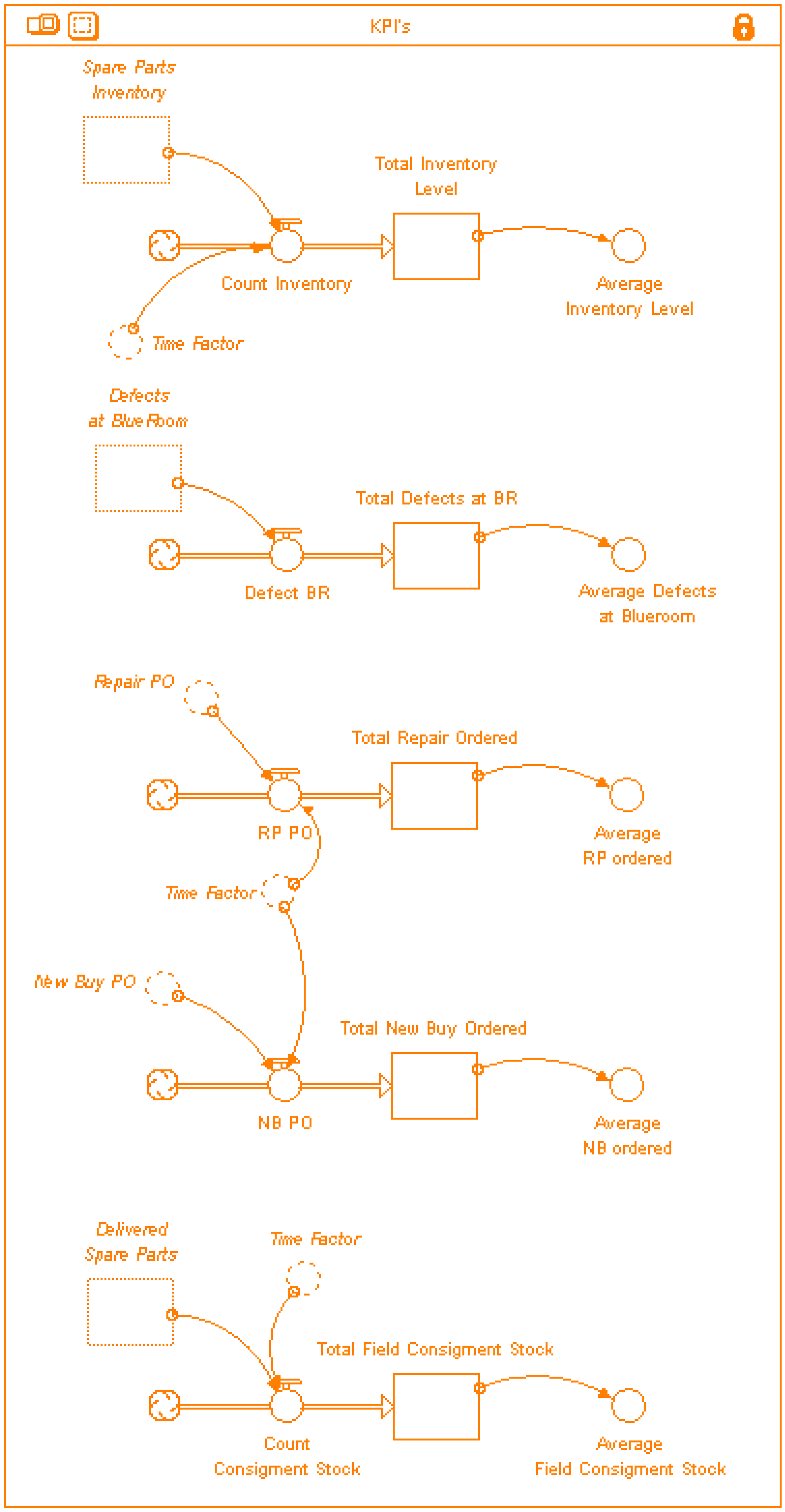


Figure 26: Simulation Model – Key Performance Indicators

4.3.4 Assumptions

This section presents an overview in Table 1 of assumptions made in the simulation model which were among others already mentioned in the previous sections.

Assumptions
Reverse Supply Sector
- The ratio of Good versus Defect Repairables is xxx% - Inspection time in the blueroom is one day
Procurement Sector
- Complete orders are received at once, not bit by bit - The right part is stocked on the right location - The delivery time to the customer is exactly one day - Percentage of repairables is xxx% (quantity) and xxx% (value) - Scrap time at FSE is one day - The average new buy lead time is taken for determination purchase order and safety stock

Table 1: Assumptions of the simulation model

4.4 Validation and Verification Model

The simulation model described in Section 4.3 is validated in different ways. First, the process was scrutinized step by step during the developing process to test whether every added element does exactly what it is supposed to do. Therefore, the model was run after each change and the results of affected variables were compared with the imitated process made by hand in excel. Second, a single demand request was sent through the system. This was used to visualize the flow through the system and to test its validity.

After the validation the expected logical behavior of the model was inspected by looking at the impact that a modification of key parameters revealed. For example, a reduction in lead time increased the rate, while a higher service level increased the safety stock level and consequently more parts were purchased. An explicit description can be found in the section about main effect. The structure and behavior was inspected by MR modality performance manager P. Kampstra and business analyst B. Delnoije (Philips Healthcare) and equals their prospects, with one exception. The output 'material availability' is not identical to the reality due to the high strategic level of the model. Material availability is the KPI that indicates if the requested part is on stock on the right location. However, this is an operational measurement and the model is formulated at strategic level. Therefore, the assumption that every right part is stored at the right location as described in Section 4.3.3 makes it impossible to simulate this KPI because all parts are immediately delivered due to aggregation of enough good stock.

Another way to test the model is to compare the simulated results with real data. Figure 27 showed sufficient similarity in replenishment decision. Also the simulated safety stock of xxx parts is almost equal to the optimal safety stock of xxx parts determined by a business analyst and performance manager of MR. This real safety stock level is based on the forecast of the demand, which takes a different service level and forecast method for different parts into account. They determine also the optimal inventory level, which is €xxx. Interestingly, the initial inventory level determined by the steady state in Section 4.5 is almost equal, namely €xxx.

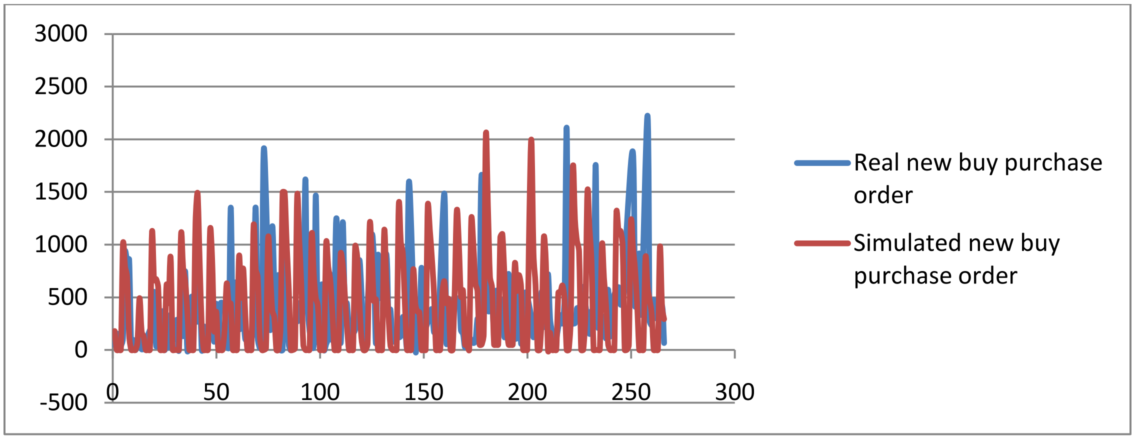


Figure 27: Comparison between simulated new buy purchase order and real data

4.5 Initial Values Determination

The simulation model requires initial values for the inventory level, defect stock at blueroom, open repair and new buy purchase orders, open demand, and the consignment stock before it is possible to run the scenarios. For each of these variables the initial value is based on available data in SAP. However, the established values are not usable for the simulation model due to the discrepancy between operational level and aggregated level. For example, the inventory level in reality is much higher than the simulated inventory level because of the assumption that every part is stocked on the right location. In reality, there are much more stocking locations which all need parts on stock. Therefore, the steady state of the aggregated level has to be established first, after which the initial values of the base case are determined.

For that reason, the model is changed to a model without randomness to find the steady state. So, the next key parameters are put equal to their mean: Demand, Forecast Demand, Repair Lead Time, Repair Yield, New Buy Lead Time, and Return Time. This model is used for different run specifications. To decide what specification would be the best, the sum of simulated stock levels of inventory and open purchase orders are compared to the optimal overall stock level. The overall stock level is equal to the safety stock increased with the demand during lead time. Another factor to keep in mind is that iThink can only deal with 2500 data points for each key parameter, in other words, the demand and forecast should contain less than 2500 periods. It turned out that a simulation time of 2000 days (5.5 years) and a simulation step time of DT=1/16, which improves accuracy of the model, are the best run specifications. Moreover, a warm-up period of 150 days due to some initial noise is required which is visible in Figure 28 that shows the steady state situation; therefore the modification for the scenarios analysis will take place after 150 days to be safe.

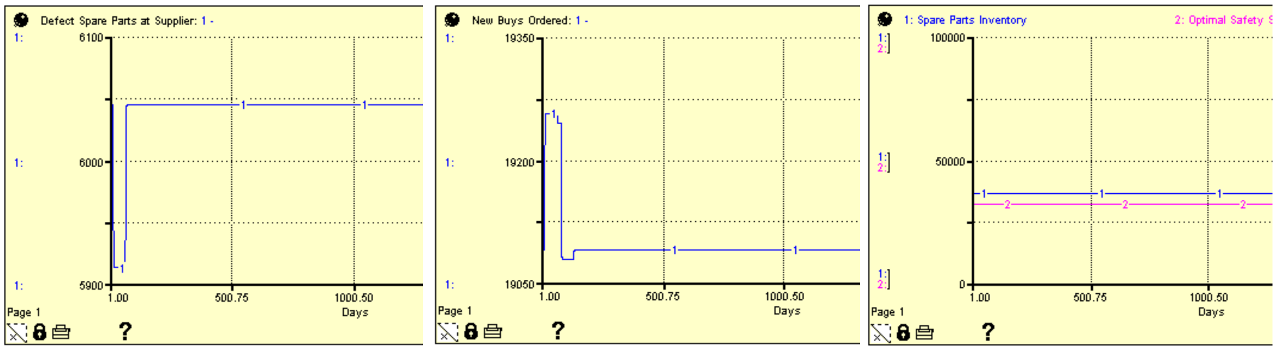


Figure 28: Steady State of Open Repair Purchase Orders, Open New Buy Purchase Order, Spare Part Inventory (blue) and Safety Stock Level (pink) from left to right.

Compared to the real data, the results of the steady state of the model without randomness are as expected. The start inventory level of real data is established based on the optimal inventory level determined by a business analyst and performance manager of MR every month. However, the steady state of the model without randomness reports a lower initial inventory level, which makes sense because the simulation model assumes that the correct parts are on the right location. The consignment stock is lower than the real data because in reality there are problem returns with a long delay of xxx days, while the model without randomness has a constant delay of xxx days. This results in a higher return velocity and consequently lower consignment stock. Furthermore, the assumption that first defect stock is repaired before new repairable parts are ordered is visible in the diminishing of the defect stock at blueroom and the lower level of new buys ordered. Notice, that the level of open new buy ordered is higher than the start level in the value case because there are not enough defects on stock. The open demand is equal to the average demand because all randomness is eliminated.

The values of the steady state of the model without randomness, recapitulated in Table 2, are used as initial values for the base case and scenarios.

Variable	Start Stock Levels (Quantity)	Initial Stock Levels (Quantity)	Start Stock Levels (EUR)	Initial Stock Levels (EUR)
Spare Part Inventory	Xxx	Xxx	Xxx	Xxx
Defect Stock at Blueroom	Xxx	Xxx	Xxx	Xxx
Open Repair PO	Xxx	Xxx	Xxx	Xxx
Open New Buy PO	Xxx	Xxx	Xxx	Xxx
Open Demand	Xxx	Xxx	Xxx	Xxx
Consignment Stock	Xxx	Xxx	Xxx	Xxx

Table 2: Initial values simulation model

5. Simulation Results

This chapter presents the results of the simulation of the selected business case. First the base case that represents the current situation is described, after which the main effects of each key parameter are scrutinized. Finally using a factorial (experimental) design model, some scenarios that combine multiple modifications of key parameters are generated and then simulated.

5.1 Base Case

This section describes in detail the base case and how the interrelationships are visible. The model based on currency is scrutinized because Philips Healthcare is most interested in the dynamic flow of cash. Section 5.3 will show that the behavior of both models is similar in general and that the differences are well explicable. Therefore, the remaining sections capture only results of the value model. However, a complete overview of the main effects of the quantity model is added in Appendix D.

The input data for the base case exist of the values as described in Section 4.5. Table 3 gives a summary of the mean and standard deviation of the different key parameters. The average of five runs of each scenario is used to determine the output, to deal with randomness in lead time and repair yield which affect the results slightly.

	Input Key parameter	Base Case 0
A	Average Demand per day *(EUR)*	€ xxx
B	Variance Demand per day *(EUR)*	€ xxx
C	Average Repair Lead Time *(days)*	Xxx
D	Variance Repair Lead Time *(days)*	Xxx
E	Average New Buy Lead Time *(days)*	Xxx
F	Variance New Buy Lead Time *(days)*	Xxx
G	Average Return Time *(days)*	Xxx
H	Variance Return Time *(days)*	Xxx
I	Target Service Level *(percentage)*	Xxx%
J	Average Repair Yield *(percentage)*	Xxx%

Table 3: Input key parameter of the base case

5.1.1 Inventory and Safety Stock Level

Figure 29 shows that the first 150 days are used to warm up because the open repair and new buy orders at time zero are delivered according a linear function in this period instead of randomly assigned lead times. After this period the model is stabilized and the inventory level is higher than safety stock level of €xxx. This makes sense because the lead time assumed in the replenishment decision is regularly too long to be on the safe site as explained in Section 4.3.3.3. Therefore, sometimes more parts are ordered than required for demand during lead time. Moreover, the pattern of inventory level is exactly as expected because the inventory oscillates around a certain level, namely €xxx. First, the amplitude is large, namely €xxx million, while over time the aberration becomes smoother until €xxx million. This is visible in a Figure 30 that pictures inventory level on a different scale. It is important to keep in mind that this level is based on the assumption that the right parts were on the right stocking location, which does not reflect the reality entirely.

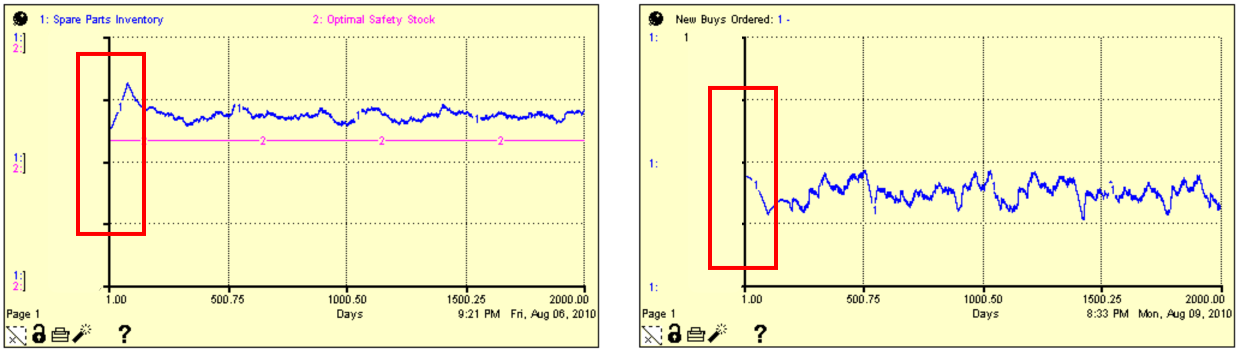


Figure 29: Left - Simulated inventory level (blue) and safety stock level (pink)/Right - open new buy orders

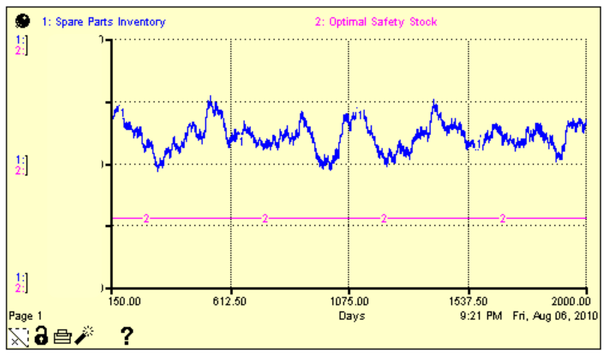


Figure 30: Oscillation in inventory level

5.1.2 Total Repair and New Buy Ordered

Figure 31 illustrates the total number of parts ordered divided into new buys and repairs. The new buys consist of consumable parts but also of newly bought repairable parts if there were not enough defect repairable parts available for refurbishment. There are new buys ordered for almost €xxx million in 5.5 year, while only €xxx million is sent for repair. This means that a new buy purchase order of €xxx and a repair purchase order of €xxx are placed every day on average. Noticeable, the average repair order placed equals almost the average defect stock of €xxx. This means that there are not enough defect parts available for repair as required according to the replenishment decision. This will suggest that if return time improves and consequently a higher defect stock, more parts are repaired and thus a smaller amount of new buys purchase orders are placed.

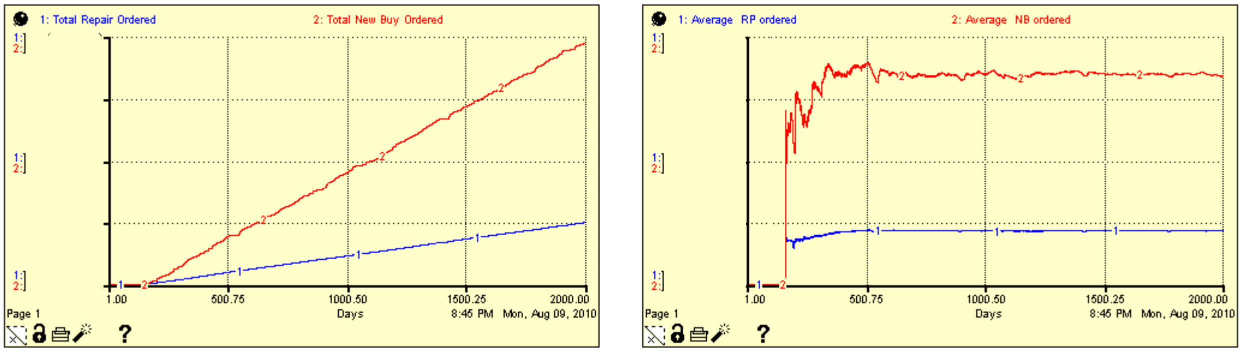


Figure 31: Left – Total repairs ordered (blue) and Total new buys ordered (red)
Right – Average repairs (blue) and average new buys ordered per day (red)

5.1.3 Consignment Stock and Defect Stock at Blueroom

Parts that are delivered to the FSE shift from serviceable spare part inventory to consignment stock. This consignment stock is decreased when parts are returned to the blueroom or consumed. The relationship between those stocks is visible in figure 32. A steep decrease in consignment stock results in a high peak in defects at blueroom. On average there is €xxx in the field and €xxx defect stock at the blueroom, which is significantly lower than the good stock of €xxx million.

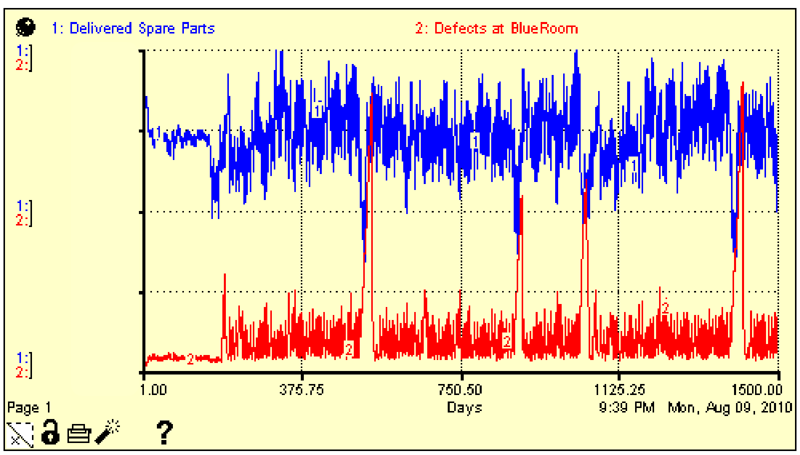


Figure 32: Simulated consignment (blue) and defect stock (red)

5.1.4 Purchase Orders

The model reflects the expected reaction on peaks of demand. If there is a peak in demand then immediately a very high new buy purchase order is placed. Also the demand forecast is affect by the peak in demand, resulting in a reinforced effect in the replenishment decision. Notice that during the warm up period the demand is fixed. Figure 33 shows the base case before the outlier in demand was removed.

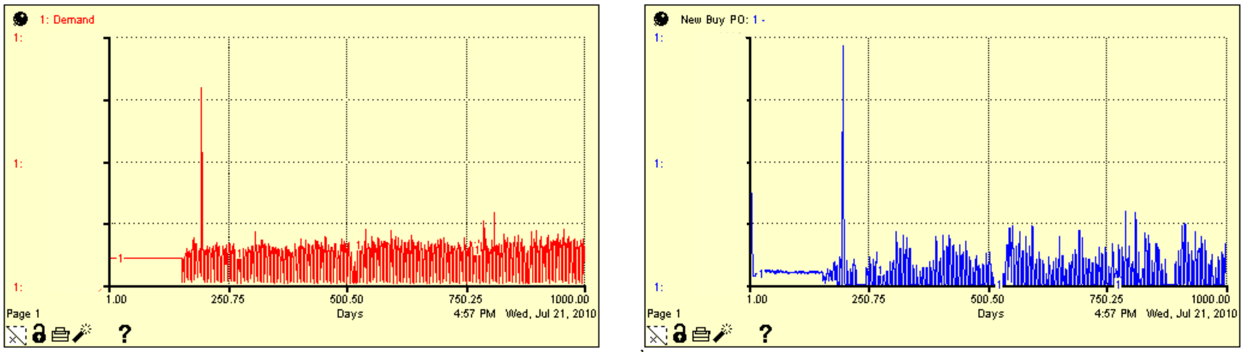


Figure 33: Left – Service part demand/Right – New buy purchase orders

5.1.5 Summary

To compare the different scenarios with the base case, the most important results are put together in Table 4.

Variable (EUR)	Base case 0
Average Spare Part Inventory	Xxx
Average Defect Stock at Blueroom	Xxx
Average Repairs Ordered per day	Xxx
Average New Buys Ordered per day	Xxx
Average Consignment Stock	Xxx
Safety Stock	Xxx

Table 4: Overview results base case

5.2 Main Effects of Key Parameters

Based on a careful analysis of the causal loop, 10 different key parameters are identified and their interactions on the output are described in this section. These parameters are attributes or characteristics of the Philips spare parts supply chain that are considered critical or essential to the development of an effective chain. Hereafter, different scenarios that show the impact of combinations of modification in these key parameters are illustrated.

5.2.1 Modification of Key Parameters

Section 4.3.3.2 described the possibility of adjusting the distribution of lead times. In this section diverse settings are determined for the scenario analysis. Also a different input possibility for demand, target service level, and repair yield are established. Table 5 gives an overview of the different value where setting 0 stands for the base case and setting 1 and 2 both indicate a modification of the input key parameters.

	Input Parameter	Base Case 0	1	2
A	Average Demand per day *(EUR)*	€xxx *(0%)*	€xxx *(-10%)*	€xxx *(-20%)*
B	Reduction Variability Demand per day *(EUR)*	€xxx *(0%)*	€xxx *(-25%)*	€xxx *(-50%)*
C	Average Repair Lead Time *(days)*	xxx *(0%)*	xxx *(-12%)*	xxx *(-31%)*
D	Reduction Variability Repair Lead Time *(days)*	xxx *(0%)*	xxx *(-25%)*	xxx *(-41%)*
E	Average New Buy Lead Time *(days)*	xxx *(0%)*	xxx *(-43%)*	xxx *(-60%)*
F	Reduction Variability New Buy Lead Time *(days)*	xxx *(0%)*	xxx *(-25%)*	xxx *(-50%)*
G	Average Return Time *(days)*	xxx *(0%)*	xxx *(-18%)*	xxx *(-50%)*
H	Reduction Variability Return Time *(days)*	xxx *(0%)*	xxx *(-25%)*	15 *(-41%)*
I	Target Service Level *(percentage)*	xxx % *(0%)*	xxx % *(-2%)*	xxx% *(+3%)*
J	Average Repair Yield *(percentage)*	xxx% *(0%)*	xxx% *(+2%)*	xxx% *(+4%)*

Table 5: Summary of modifications of input key parameter

The reduction in mean demand is based on the difference between actually consumption and demand. In general, consumption requires xxx % fewer parts, thus if it becomes possible to have perfect insight in which parts are required, the demand will be reduced with xxx %. However, this will never be possible in reality because it is difficult to know the exact cause of failure of a system in advance. So, a target reduction of 20% seems reasonable with a middle course of 10%.

The targets of SPS are to diminish the average lead time to xxx days with a variation of xxx days in 2010, which are chosen as input value for the scenario analysis. Also a middle course is investigated. The modification of return time depends on the expectation of global reverse logistic manager and yield up a reduction of 18% on average, while the variation might be reduced with 41%. Also a reduction of 50% of the average lead time is inspected because this will be almost the perfect return cycle time if there were no problem returns.

For CCP part, customer critical parts, a service level of xxx% is required, while for other parts, like slow movers, only a service level of xxx% is demanded. The expectation is that the repair yield can be improved up until xxx%, but it will be much nicer if a repair yield of xxx% can be obtained.

5.2.2 Main Effects of Key parameters

This section describes the impact of every key parameter. To find the main effect of every single key parameter, the key parameters are modified ceteris paribus, meaning that only one parameter is changed while all others remain the same. The different input settings as described in Section 5.2.1 are applied. An overview of all main effects of the value model is added in Appendix D after the main effects of the quantity model.

5.2.2.1 Average demand

The average demand is reduced with 10% and 20% which results in a decrease of 9% and 19% in average inventory level that takes about 6 months. The results are summarized in Table 6.

Input Key Parameter	**Base case 0**	**1**	**2**
Average Demand per day *(EUR)*	€xxx (*0%*)	€xxx *(-10%)*	€xxx *(-20%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	-9.3%	-19.3%
Average Defect Stock at Blueroom	Xxx	-9.6%	-18.2%
Average Repairs Ordered per day	Xxx	-9.6%	-18.1%
Average New Buys Ordered per day	Xxx	-11.1%	-21.0%
Average Consignment Stock	Xxx	-9.6%	-18.0%
Safety Stock	Xxx	-10.1%	-20.1%
Time it takes to stabilize Inventory Level *(days)*		180	200

Table 6: Overview of the impact of reduction mean demand

It might be expected that the inventory level will stay higher because the demand is lower. However, the lower level of average demand also affects the safety stock level and consequently the replenishment decision. Moreover, the forecasted demand during lead time, which is also captured in the replenishment decision, is also diminished. These impacts outweighed the demand reduction, resulting in a decrease of inventory level.

Interestingly, first the inventory level increases after the change after which it diminishes. The increase is caused by the fact that fewer parts have to be delivered, while previously ordered quantities based on a higher demand level are still arriving. However, the demand reduction results also in smaller purchase quantities that become visible over time in the reduction of inventory but this takes a while. Moreover, immediately after the change the purchase order is zero. Figure 34 shows this pattern in inventory level and purchase process.

The consignment stock decreases because fewer parts are delivered due to lower demand request. This again affects the number of defect parts returned to blueroom, which consequently has an impact in the repair orders that can be placed.

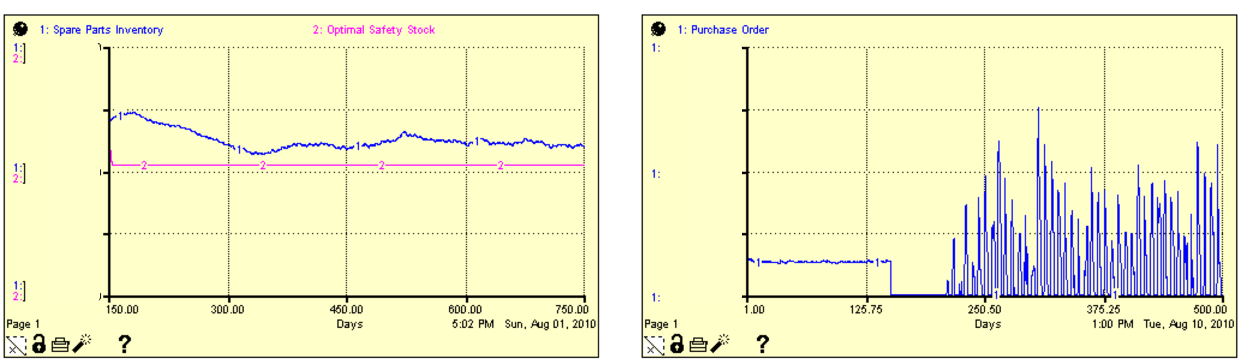


Figure 34: Left – Spare part inventory level (blue) and safety stock (pink)/Right- purchase orders

5.2.2.2 Variability Demand

The variability of daily demand is reduced with 25% and 50%, but this shows not a significant impact on the outputs because the average demand remains the same. The results are summarized in Table 7.

Input Key Parameter	**Base case 0**	**1**	**2**
Reduction Variability Demand per day *(EUR)*	€xxx *(0%)*	€xxx *(-25%)*	€xxx *(-50%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	-0.5%	-1.3%
Average Defect Stock at Blueroom	Xxx	0.1%	0.2%
Average Repairs Ordered per day	Xxx	0.2%	0.3%
Average New Buys Ordered per day	Xxx	0.2%	0.4%
Average Consignment Stock	Xxx	0.1%	0.2%
Safety Stock	Xxx	-0.2%	-0.3%
Time it takes to stabilize Inventory Level *(days)*		90	110

Table 7: Overview of the impact of reduction variability demand

The variability of demand has an impact on the determination of safety stock level, but this impact is almost negligible because the inventory level reduces infinitesimal because the reduction in safety stock is less than 0.1%. You might expect that the oscillation of inventory is less, which is indeed visible is the short time interval required before the stock level stabilized.

5.2.2.3 Average Repair Lead Time

The mean repair lead time is diminished until xxx days and xxx days ceteris paribus, which has mainly an impact on inventory level, although it is very small and therefore takes only 3.5 month to be established. Table 8 gives an overview of the results.

Input Key Parameter	**Base case 0**	**1**	**2**
Average Repair Lead Time *(days)*	Xxx *(0%)*	Xxx *(-12%)*	Xxx *(-31%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	1.1%	2.3%
Average Defect Stock at Blueroom	Xxx	-0.2%	-0.2%
Average Repairs Ordered per day	Xxx	-0.2%	-0.2%
Average New Buys Ordered per day	Xxx	0.0%	0.1%
Average Consignment Stock	Xxx	0.0%	0.1%
Safety Stock	Xxx	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		100	110

Table 8: Overview of the impact of reduction mean repair lead time

It makes sense that a reduction in average repair lead time has not a major impact on the system because it does not affect the replenishment decision or safety stock level. Also the smaller number of open repair orders due to a shorter repair time does not affect the replenishment decision because this decision captures both good stock as open purchase orders. So, the shift from open repair orders to inventory level cancels out both in the replenishment decision. However, shorter lead times means a higher inflow rate at good stock, which causes the small increase in inventory level since the outflow of parts remains the same.

Weighted Average Lead Time

In practice, it is a good habit to be on the safe side with the determination of safety stock to capture uncertainties in lead time and demand. However, the assumption that the safety stock and demand during lead time are based on only the longer new buy lead time has a major drawback, namely improvements in repair lead time are not significant. From a statistical point of view, it is interesting to investigate the impact of a weighted average of lead time. Therefore, the results of the main effect of average repair lead time is compared with the model that takes a weighted average of new buy lead time and repair lead time to determine the input lead time for safety stock and replenishment decision.

The weights for the calculation of the weighted average lead time are based on the number of repair purchase orders versus the number of new buy purchase orders placed. The percentage of repair purchase orders place is 33%, while 67% of the replenishments are new buy purchase orders. This affects also the base case; therefore the base case is recalculated after which the main effects of mean repair lead time are compared with the original model.

Table 9 shows the results of the model with weighted average compared to the original model if the mean repair lead time in reduced. There is indeed an impact on the supply chain because the inventory level decreases now which implies that the reduction in required inventory level outweighed the rapidly throughput time for repair. In the original model the inventory level increased because the required inventory level was not significantly affected by the modification of average repair lead time.

Main Effects					
		Mean Repair Lead Time (Original model)		Mean Repair Lead Time (Weighted Average model)	
		Xxx *(-12%)*	Xxx *(-31%)*	Xxx *(-12%)*	Xxx *(-31%)*
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	1.1%	2.3%	-1.2%	-2.5%
Average Defect Stock at Blueroom	Xxx	-0.2%	-0.2%	0.0%	0.2%
Average Repairs Ordered per day	Xxx	-0.2%	-0.2%	0.0%	0.2%
Average New Buys Ordered per day	Xxx	0.0%	0.1%	-0.1%	-0.4%
Average Consignment Stock	Xxx	0.0%	0.1%	0.0%	-0.1%
Safety Stock	Xxx	0.0%	0.0%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		100	110	160	170

Table 9: Comparison original model versus improved model of the impact of reduction in mean repair lead time

5.2.2.4 Variability Repair Lead Time

As expected a reduction in variability of repair lead time has no visible impact on the supply chain because it does not affect the safety stock level or purchase process. Moreover, it will be very improbable if not even a reduction in average repair lead time influences the results. For completeness, the results are summarized in Table 10 where the deviation is caused by randomness.

Input Key Parameter	**Base case 0**	**1**	**2**
Reduction Variability Repair Lead Time *(days)*	Xxx (*0%*)	Xxx *(-25%)*	Xxx *(-41%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	0.1%	0.0%
Average Defect Stock at Blueroom	Xxx	-0.1%	0.0%
Average Repairs Ordered per day	Xxx	-0.1%	0.0%
Average New Buys Ordered per day	Xxx	0.1%	0.0%
Average Consignment Stock	Xxx	0.0%	0.0%
Safety Stock	Xxx	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		0	0

Table 10: Overview of the impact of reduction variability repair lead time

5.2.2.5 Average New Buy Lead Time

The reduction in average new buy lead time gives a very good inside in interrelationship and dynamics of the closed-loop supply chain. A reduction of 43% causes an 11.7% decrease of inventory level, while a lead time improvement until xxx days diminishes the good stock with 17.3%. It takes approximately 5 months to establish the new inventory level. The results are summarized in Table 11.

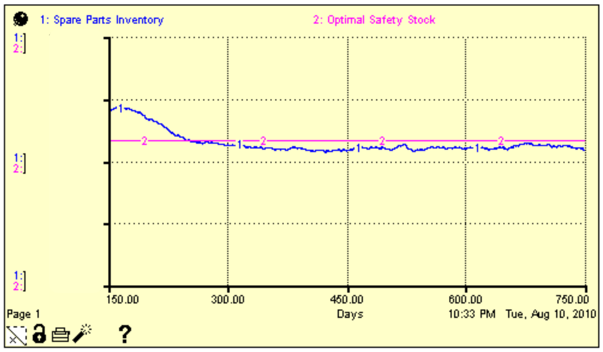
Input Key Parameter	**Base case 0**	**1**	**2**
Average New Buy Lead Time *(days)*	Xxx (*0%)*	Xxx *(-43%)*	Xxx *(-60%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	-11.7%	-17.3%
Average Defect Stock at Blueroom	Xxx	0.0%	0%
Average Repairs Ordered per day	Xxx	0.0%	0%
Average New Buys Ordered per day	Xxx	-2.7%	-3.7%
Average Consignment Stock	Xxx	-0.1%	0%
Safety Stock	Xxx	-0.2%	-0.3%
Time it takes to stabilize Inventory Level *(days)*		140	150

Table 11: Overview of the impact of reduction mean new buy lead time

A decrease in mean new buy lead time causes a decrease in safety stock and forecasted demand during lead time, which impacts the number of new buys ordered and consequently the inventory level. Instantaneously, the stock level increases after the modification due to smaller production time, after which the reduction in required stock outweighed the improvement in production time and causes the reduction in inventory level. This is visible in Figure 35.

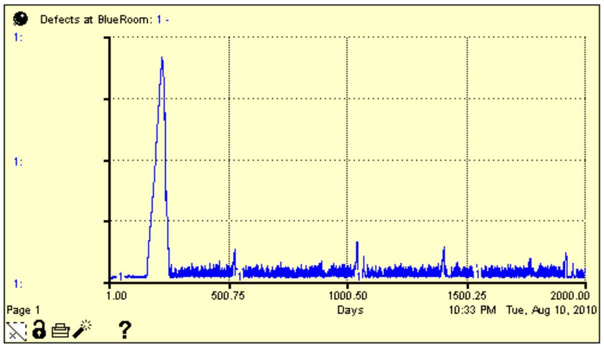
Consequently, the open new buy purchase orders decrease very fast in the beginning because there are no new buy purchase orders placed due to a lower inventory level required to fulfill all demand against a xxx % service level. Moreover, the lower level of open purchase orders is reinforced by the fact that parts are more rapidly produced.

Figure 35 shows also the relationship between defect stock at blueroom and the number of parts refurbished. The number of open repair purchase orders decreases because there are no purchase orders placed due to the lower inventory level needed, while previously placed orders are repaired and transferred to good stock. In the same time the defect stock increases for the similar reason. At the moment, parts are again ordered due to diminished inventory level, the defect stock is totally empty and the parts are sent to repair vendor for refurbishment. According to the replenishment decision even more parts should have been repaired which causes the complete pour out of defect inventory.

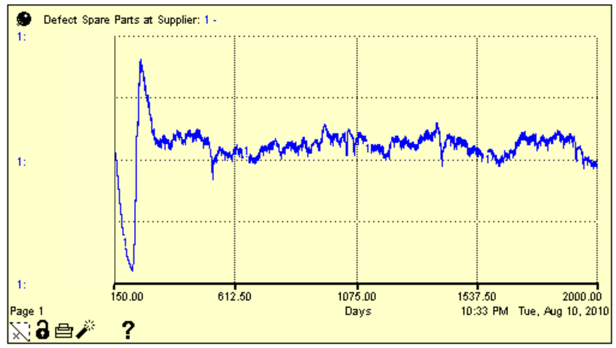


Inventory level (blue) and safety stock (pink)

Open new buy purchase orders



Defect stock at blueroom



Open repair purchase orders

Figure 35: Impacts caused by a reduction in mean new buy lead time

Weighted Average Lead Time

The assumption that the safety stock and demand during lead time are based on only the new buy lead time has also an effect on the main effect of mean new buy lead time. Therefore, the results of the main effect of average new buy lead time is compared with the model that takes a weighted average of new buy lead time and repair lead time to determine the input lead time for safety stock and replenishment decision. Table 12 gives an overview of the results.

As expected the impact of reduction in the average new buy lead time has less impact than in the original model because the importance in safety stock level and replenishment decision is decreased from 100% to 67% due the weighted average lead time.

Main Effects					
		Mean New Buy Lead Time (Original model)		**Mean New Buy Lead Time (Weighted Average model)**	
		Xxx *(-43%)*	Xxx *(-60%)*	Xxx *(-43%)*	Xxx *(-60%)*
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-11.7%	-17.3%	-1.4%	-3.3%
Average Defect Stock at Blueroom	Xxx	0.0%	0%	-0.1%	-0.1%
Average Repairs Ordered per day	Xxx	0.0%	0%	-0.1%	0.0%
Average New Buys Ordered per day	Xxx	-2.7%	-3.7%	-1.7%	-2.4%
Average Consignment Stock	Xxx	-0.1%	0.0%	0.1%	0.1%
Safety Stock	Xxx	-0.2%	-0.3%	-0.1%	-0.2%
Time it takes to stabilize Inventory Level *(days)*		140	150	170	180

Table 12: Comparison original model versus improved model of the impact of reduction in mean new buy time

5.2.2.6 Variability New Buy Lead Time

The impact in reduction of variation in new buy lead time is enormous, namely a reduction up until xxx days reduces the average inventory with more than 40% because less safety stock is required to capture randomness in lead time. It takes more than a year to establish this gigantic impact. The output is recapitulated in Table 13.

Input Key Parameter	**Base case 0**	**1**	**2**
Reduction Variability New Buy Lead Time *(days)*	Xxx (*0%*)	Xxx *(-25%)*	Xxx *(-50%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	-20.3%	-40.2%
Average Defect Stock at Blueroom	Xxx	-0.2%	-0.1%
Average Repairs Ordered per day	Xxx	-0.2%	-0.1%
Average New Buys Ordered per day	Xxx	-1.8%	-3.7%
Average Consignment Stock	Xxx	0.1%	0.0%
Safety Stock	Xxx	-24.8%	-49.4%
Time it takes to stabilize Inventory Level *(days)*		360	370

Table 13: Overview of the impact of reduction variability new buy lead time

The calculation of the safety stock depends on the variation in new buy lead time. The reduction in variation has more impact on safety stock than the mean of new buy lead time has because the standard deviation is taking to the power of two. Therefore, a greater impact is visible on the supply chain.

5.2.2.7 Average Return Time

An improvement in return velocity result mainly in an increased number of parts sent to the repair vendor, which causes the reduction in new buys ordered. Consequently, the inventory level increases to a higher level which take 8.5 month because the lead time of repair orders is smaller than the production time of new items on average. The results are summarized in Table 14.

Input Key Parameter	**Base case 0**	**1**	**2**
Average Return Time *(days)*	Xxx (*0%*)	Xxx *(-18%)*	Xxx *(-50%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	7.2%	15.6%
Average Defect Stock at Blueroom	Xxx	69.3%	138.2%
Average Repairs Ordered per day	Xxx	69.2%	138.1%
Average New Buys Ordered per day	Xxx	-24.1%	-50.1%
Average Consignment Stock	Xxx	-26.1%	-54.2%
Safety Stock	Xxx	0.0%	0.0%
Total Inventory	Xxx	Xxx	Xxx
Total Inventory + Open PO	Xxx	Xxx	Xxx
Time it takes to stabilize Inventory Level *(days)*		250	260

Table 14: Overview of the impact of reduction mean return time

The reduction in mean return time causes a decrease in consignment stock because parts are returned sooner. Therefore, the defect stock in blueroom increases which makes it possible to send more defect parts to the repair vendor, while fewer new parts have to be ordered. The production time of new parts is longer than the repair time, meaning that the inventory level increases because parts arrive sooner at good stock while the same inventory level is required according the replenishment decision. The safety is namely not impacted by the return lead time, thus it has no affect on the inventory level required. This increase in inventory level is reinforced by the fact that also unused parts return quicker to the blueroom and are sent to good stock immediately after inspection.

However, it is still a beneficially modification because the number of new buys is decreased which are more expensive to purchase than parts that are repaired. Thus, probably the total supply chain costs, for example inventory, transport, handling, repair and new buy costs, will decrease if the average return time is decreased. Notice that the total inventory level that consist of good stock, defect stock against xxx% of the good stock price, and consignment stock, does not decrease if the mean return time diminishes. However, if also the open purchase orders are taken into account, the system shows indeed a decrease. Another advantage is that a higher inventory level due to increased return velocity means a higher service level in practice because more good stock is available to serve customers on time.

5.2.2.8 Variability Return Time

The variability of return time is reduced with 25% and 41%. The results are summarized in Table 15.

Input Key Parameter	**Base case 0**	**1**	**2**
Reduction Variability Return Time *(days)*	Xxx (*0%*)	Xxx *(-25%)*	Xxx *(-41%)*
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	-2.5%	-4.1%
Average Defect Stock at Blueroom	Xxx	-25.7%	-32.2%
Average Repairs Ordered per day	Xxx	-25.7%	-32.1%
Average New Buys Ordered per day	Xxx	9.3%	12.1%
Average Consignment Stock	Xxx	10.0%	13.0%
Safety Stock	Xxx	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		250	270

Table 15: Overview of the impact of reduction of variability in return time

The results might look strange but this is caused by the fact that parts are returned against a first order delay. This means that if there are for example 50 parts in consignment stock and the return time is 10 days, the first day 50/10=5 parts are returned, while the second day only (50-5)/10=4.5 parts are returned etcetera. This means that the stock decreases quickly in the beginning, especially if the return time is short. So, the consignment stock never drops quickly if no short return times are generated in the simulation model. This is what happens if the variation in return time is decreased because outliers are less often generated. In other words, there are no extreme short return times generated anymore and consequently the defect stock at blueroom decreases. For the same reason, the consignment stock increases if the variation in return time decreases, while the average return time remains the same.

The higher consignment stock causes a lower defect stock at blueroom and consequently fewer defect parts can be sent to the repair facilities. Therefore, more new buy orders are placed but this means a longer production lead times what causes the reduction in inventory level.

It is expected that if not only a variation in return time but also the average return time is decreased, their impacts on inventory level are cancelled because they have an opposite effect. Scenario 11 of the scenario analysis has more or less this opposite setting in key parameters but it becomes visible that the inventory diminished. This implies that these two key parameters do not cancel each out. However, this might also be caused by the average demand and new buy lead time because these two key parameters are reduced as well.

5.2.2.9 Target Service Level

A small reduction in service level up until xxx% causes a reduction in inventory level, whereas a higher service level of xxx% increases the average stock level with 20%. The output that reflects modifications in service level are recapitulated in Table 16.

Input Key Parameter	Base case 0	1	2
Target Service Level *(percentage)*	Xxx%	Xxx%	Xxx%
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	-8.3%	20.0%
Average Defect Stock at Blueroom	Xxx	-0.2%	0.0%
Average Repairs Ordered per day	Xxx	-0.2%	0.0%
Average New Buys Ordered per day	Xxx	-0.7%	1.9%
Average Consignment Stock	Xxx	0.1%	0.0%
Safety Stock	Xxx	-10.3%	24.9%
Time it takes to stabilize Inventory Level *(days)*		160	260

Table 16: Overview of the impact of modification target service level

A reduction in service level implies a lower safety stock since less stock has to be hold to fulfill the demand because more stock outs are allowed to meet the service level. The opposite is also truth; a higher stock is required to fulfill demand with a higher service level because less stock outs are allowed. This has an impact on the number of parts ordered because a higher service level requires more parts, thus the average new buys ordered will increase.

5.2.2.10 Average Repair Yield

An increase in repair yield does not affect the supply chain significantly, it implies only a small increase in serviceable spare part inventory and a small reduction in new buys ordered. The results are summarized in Table 17.

Input Key Parameter	Base case 0	1	2
Average Repair Yield *(percentage)*	Xxx %	Xxx %	Xxx %
Output Variable (EUR)			
Average Spare Part Inventory	Xxx	0.2%	0.2%
Average Defect Stock at Blueroom	Xxx	0.0%	0.1%
Average Repairs Ordered per day	Xxx	0.0%	0.0%
Average New Buys Ordered per day	Xxx	-0.2%	-0.4%
Average Consignment Stock	Xxx	0.0%	0.0%
Safety Stock	Xxx	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		100	100

Table 17: Overview of the impact of improvement in repair yield

An improvement in repair yield means that fewer parts are scrapped at the repair vendor. Therefore, fewer parts can be sent to the repair vendor to receive the same amount of good parts back. However, the defect stock is not enough to fulfill the required repair purchase order size according to the replenishment decision. Therefore, all defect parts are still sent to the repair facilities such that there is no reduction visible in the average repairs ordered per day. However, the improvement in repair yield also implies that fewer new parts have to be ordered because more parts can be repaired. This causes the reduction in average new buys ordered.

5.2.3 Conclusion

From the main effect analysis, which is summarized in Table 18, it can be concluded that there is a significant difference in the impact of key parameters on the supply chain. Some impacts are in the same direction, meaning that a reduction in input causes also a reduction in output, which is indicated with '+'. Conversely, opposite impacts are indicated with '-'. The next key parameters have a considerable impact on average **inventory level**:

- Average demand (+)
- Average new buy lead time (+)
- Variability new buy lead time (+)
- Average return cycle time (-)
- Variability return cycle time (+)
- Target service level (+)

Remarkably, the average new buy lead time affects the safety stock level which makes sense due to the equation but this impact is negligible. Therefore, actors that have a significant influence on the **safety stock** are:

- Average demand (+)
- Variability new buy lead time (+)
- Target service level (+)

Another interesting results it the **time it takes** before the system is stabilized. The next key parameters cause a relative short period:

- Average demand
- Average new buy lead time
- Target service level

On the other hand, it takes a long time before the impact of the following key parameters is stabilized:

- Variability new buy lead time
- Average return cycle time
- Variability return cycle time

Therefore, based on the main effects, the advice will be to focus on the reduction of average demand and new buy lead time because these two key parameters have a lot of impact in a relative short period of time. In practice, this will mean that there have to come more intelligibility about which parts cause the failure of a system. This can be established by training for FSE and remote control such that the average demand of spare parts reduces because less excess parts are ordered. However, a reduction in demand might be difficult to establish because the sale of systems grows and it is expected that this results in a higher demand of service parts. It is also the question if more training of FSE will results in lower demand requests.

The average new buy lead time can be reduced by making new agreements with suppliers. However, a more practical advice will be to start with reducing the variability in production time, before setting new agreement because this requires new negotiations which take time. It is a valuable investment, since a reduction of 40% in good stock can be established with a reduction of 50% in variation of new buy lead time, although it might take one year before the impact is noticeable. Therefore, collaboration with the suppliers can have significant impact on the performance to customers.

Another advice is to focus on the reduction of return cycle time although it results in an increase of inventory level with 15% when the return cycle time is decreased with 50%. It is an interesting investment because the number of new buys ordered decreases considerable, specifically 50%, because more parts can be sent for repair. This means a tremendous decrease in production costs. Moreover, a higher service level would be guaranteed due to the higher inventory level. Hence, reduction in problem returns due to improved processes or a blueroom and repair facilities in APAC might be of great interest.

Main Effects									
		Mean Demand		Variability Demand		Mean Repair Lead Time		Variability Repair Lead Time	
		€xxx *(-10%)*	€ xxx *(-20%)*	€ xxx *(-25%)*	€ xxx *(-50%)*	Xxx *(-12%)*	Xxx *(-31%)*	Xxx *(-25%)*	Xxx *(-41%)*
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-9.3%	-19.3%	-0.5%	-1.3%	1.1%	2.3%	0.1%	0.0%
Average Defect Stock at Blueroom	Xxx	-9.6%	-18.2%	0.2%	0.3%	-0.2%	-0.2%	-0.1%	0.0%
Average Repairs Ordered per day	Xxx	-9.6%	-18.1%	0.1%	0.2%	-0.2%	-0.2%	-0.1%	0.0%
Average New Buys Ordered per day	Xxx	-11.1%	-21.0%	0.2%	0.4%	0.0%	0.1%	0.1%	0.0%
Average Consignment Stock	Xxx	-9.6%	-18.0%	0.1%	0.2%	0.0%	0.1%	0.0%	0.0%
Safety Stock	Xxx	-10.1%	-20.1%	-0.2%	-0.3%	0.0%	0.0%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		180	200	90	110	100	110	0	0

Main Effects									
		Mean New Buy Lead Time		Variability New Buy Lead Time		Mean Return Cycle Time		Variability Return Cycle Time	
		Xxx *(-43%)*	Xxx *(-60%)*	Xxx *(-25%)*	Xxx *(-50%)*	Xxx *(-18%)*	Xxx *(-50%)*	Xxx *(-25%)*	Xxx *(-41%)*
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-11.7%	-17.3%	-20.3%	-40.2%	7.2%	15.6%	-2.5%	-4.1%
Average Defect Stock at Blueroom	Xxx	0.0%	0%	-0.2%	-0.1%	69.3%	138.2%	-25.7%	-32.2%
Average Repairs Ordered per day	Xxx	0.0%	0%	-0.2%	-0.1%	69.2%	138.1%	-25.7%	-32.1%
Average New Buys Ordered per day	Xxx	-2.7%	-3.7%	-1.8%	-3.7%	-24.1%	-50.1%	9.3%	12.1%
Average Consignment Stock	Xxx	-0.1%	0.0%	0.1%	0.0%	-26.1%	-54.2%	10.0%	13.0%
Safety Stock	Xxx	-0.2%	-0.3%	-24.8%	-49.4%	0.0%	0.0%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		140	150	360	370	250	260	250	270

Main Effects					
		Target Service Level		Repair Yield	
		Xxx%	Xxx%	Xxx%	Xxx%
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-8.3%	20.0%	0.2%	0.2%
Average Defect Stock at Blueroom	Xxx	-0.2%	0.0%	0.0%	0.1%
Average Repairs Ordered per day	Xxx	-0.2%	0.0%	0.0%	0.0%
Average New Buys Ordered per day	Xxx	-0.7%	1.9%	-0.2%	-0.4%
Average Consignment Stock	Xxx	0.1%	0.0%	0.0%	0.0%
Safety Stock	Xxx	-10.3%	24.9%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		160	260	100	100

Table 18: Overview main effects base case

5.3 Differences Quantity Model and Currency Model

The simulation model in iThink can be used to simulate a flow of parts or a flow of cash which are both made and run. Both models show the same behavior, only the impact of two significant differences in input, namely a larger mean new buy lead time and higher repairable percentage in case of value are visible. The impact of those differences for the main effects is explained in this section.

5.3.1 New Buy Lead Time

Main effects refer to modification of one parameter, while all other key parameters remain the same. The target of Philips Healthcare is to reduce new buy lead time to xxx days, which is a proportional reduction of 49% and 60% for quantity model and value model respectively. This difference in percentage causes the smaller impact of reduction in mean lead time for the quantity case, which is visible in inventory level and average new buys ordered, see Table 19. Specifically, mean new buy lead time affects the level of safety stock as well as the forecasted demand during lead time in the purchase order, which results in a lower level of stock required to fulfill the demand. However, this reduction in stock requirement is smaller for the quantity case, which is visible in the smaller decrease of average inventory level and new buys ordered per day compared with the currency model. Consequently, the time it takes before the model is stabilized is shorter.

	Main Effect					
	Mean New Buy Lead Time (Quantity)			**Mean New Buy Lead Time (EUR)**		
	Xxx *(0%)*	Xxx *(-28%)*	Xxx *(-49%)*	Xxx *(0%)*	Xxx *(-43%)*	Xxx *(-60%)*
	0	**1**	**2**	**0**	**1**	**2**
Average Spare Part Inventory	Xxx	-2.4%	-6.8%	Xxx	-11.7%	-17.3%
Average Defect Stock at Blueroom	Xxx	0.0%	0.0%	Xxx	0.0%	0%
Average Repairs Ordered per day	Xxx	0.0%	0.0%	Xxx	0.0%	0%
Average New Buys Ordered per day	Xxx	-1.2%	-2.0%	Xxx	-2.7%	-3.7%
Average Consignment Stock	Xxx	0.0%	0.0%	Xxx	-0.1%	0.0%
Safety Stock	Xxx	-0.2%	-0.3%	Xxx	-0.2%	-0.3%
Time it takes to stabilize Inventory Level *(days)*		80	90		140	150

Table 19: Impact main effect mean new buy lead time for quantity and value model

5.3.2 Repairable Percentage

The difference in repairable percentage between the two models shows up in smaller impacts of reduction in mean and variability of return time for the quantity case, which are most visible at average new buys ordered, and consignment stock. Conversely, this ceteris paribus reduction has greater impact on average defects at blueroom and repairs ordered. This makes sense because the scrap rate at FSE is much higher in the quantity model, namely 63% instead of 19% such that the impact of transporting parts more rapidly to the blueroom has less impact on the field consignment stock . However, the defect stock is relative lower in the quantity case compared to the value case, such that a reduction in return time causes proportionally a higher arrival of parts at blueroom. This results in a higher increase of defect stock which makes it possible to send more defect part to the repair vendor. Consequently, fewer new buy parts are ordered. Table 20 gives an overview of the results.

	Main Effect					
	Mean Return Cycle Time (Quantity)			Mean Return Cycle Time (EUR)		
	Xxx	Xxx *(-13%)*	Xxx *(-50%)*	Xxx	Xxx *(-18%)*	Xxx *(-50%)*
	0	**1**	**2**	**0**	**1**	**2**
Average Spare Part Inventory	Xxx	1.5%	6.7%	Xxx	7.2%	15.6%
Average Defect Stock at Blueroom	Xxx	84.6%	353.8%	Xxx	69.3%	138.2%
Average Repairs Ordered per day	Xxx	84.6%	353.8%	Xxx	69.2%	138.1%
Average New Buys Ordered per day	Xxx	-3.5%	-15.9%	Xxx	-24.1%	-50.1%
Average Consignment Stock	Xxx	-3.8%	-17.0%	Xxx	-26.1%	-54.2%
Safety Stock	Xxx	0.0%	0.0%	Xxx	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		50	50		250	260

	Main Effect					
	Variability Return Cycle Time (Quantity)			Variability Return Cycle Time (EUR)		
	Xxx	Xxx *(-25%)*	Xxx *(-38%)*	Xxx	Xxx *(-25%)*	Xxx *(-41%)*
	0	**1**	**2**	**0**	**1**	**2**
Average Spare Part Inventory	Xxx	-0.1%	-0.2%	Xxx	-2.5%	-4.1%
Average Defect Stock at Blueroom	Xxx	-30.8%	-38.5%	Xxx	-25.7%	-32.2%
Average Repairs Ordered per day	Xxx	-30.8%	-38.5%	Xxx	-25.7%	-32.1%
Average New Buys Ordered per day	Xxx	1.5%	1.7%	Xxx	9.3%	12.1%
Average Consignment Stock	Xxx	1.6%	1.9%	Xxx	10.0%	13.0%
Safety Stock	Xxx	0.0%	0.0%	Xxx	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		150	160		250	270

Table 20: Overview of differences quantity and currency model

5.4 Scenario Analysis

In the previous section it became clear that mainly modification in average demand, average new buy lead time, variability new buy lead time, average return time, and target service level have a significant impact on inventory level. However, it might be possible that a combination of key parameters can reinforce or neutralize the effect. Therefore, it is of interest to investigated combinations of changes in key parameters. In the model there are 10 key parameters that can be modified, thus a lot of combinations are possible. Appendix E gives more details about the selection of the different scenarios. This section describes the most important output visible.

5.4.1 Results

Figure 36 gives a graphical output of some scenarios, while Figure 37 plots the reduction in safety stock against the reduction in inventory level of all scenarios because in general these two variables will be highly correlated. This correlation exists for most scenarios because a linear pattern is visible. However, there are some exceptions that are highlighted in this section. These are indicated in dark grey circles in the plot and are highlighted in italics in the discussion below.

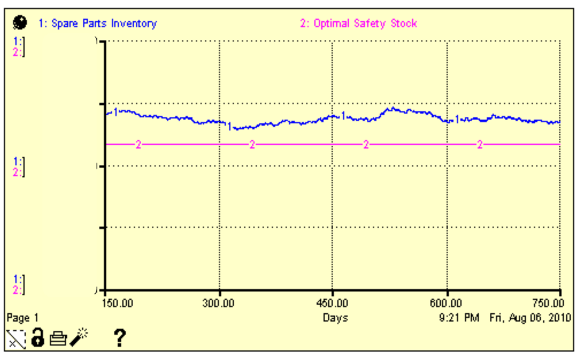
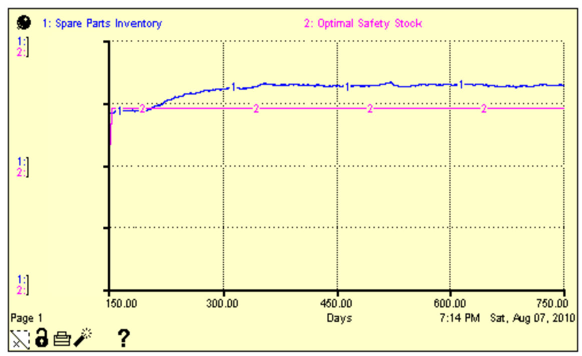
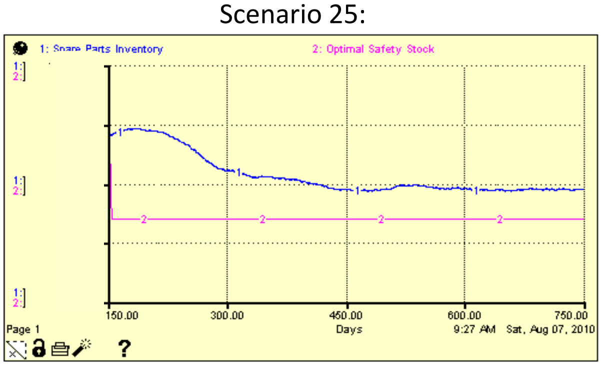
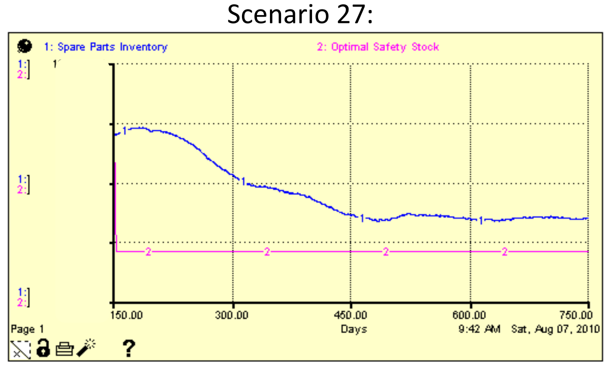
Scenario 1 BASE CASE:	Scenario 9:
	
Average Inventory Reduction: 0% Safety Stock Reduction: 0% Time it takes before stabilized: 0 days	Average Inventory Increase: +20% Safety Stock Increase: +24% Time it takes before stabilized: 190 days
Scenario 25:	Scenario 27:
	
Average Inventory Reduction: 27% Safety Stock Reduction: 40% Time it takes before stabilized: 280 days	Average Inventory Reduction: 44% Safety Stock Reduction: 64% Time it takes before stabilized: 310 days

Figure 36: Overview of the output of all scenarios

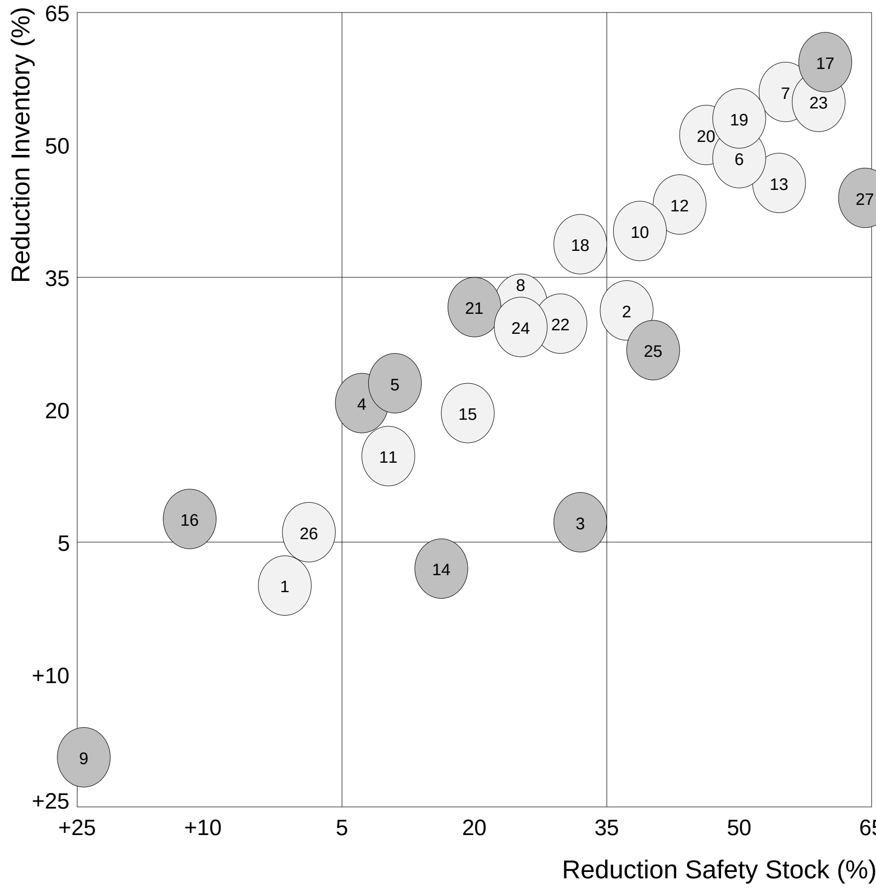


Figure 37: Plot of the different scenarios. The dark grey circles indicate exceptions.

Scenario 1

None of the key parameters is changed, thus this scenario is exactly the base case.

Scenario 2

The main differences are a substantial decrease in variability of new buy lead time and return time, as well as an increase in service level. Also the variation in return time reduces a little bit.

Scenario 3

This scenario is an outlier because the reduction in safety stock is larger than the reduction in inventory level. This is explained by the fact that the reduced average return time causes a tremendous increase in inventory level that outweighed the diminishing effect of variability in new buy and return lead time, and service level.

Scenario 4

In contrast with scenario 3, this scenario is not influenced by a modification in average return time. Therefore, the inventory level oscillates around the safety stock level. This scenario differs from others because it has relatively a small reduction in safety stock, while the inventory level decreases more proportional. This is caused by the considerable reduction in average new buy lead time that has a *negligible impact on safety stock but does affect the inventory level. The increase in service level neutralizes the impact of the reduction of variation of new buy lead time on the safety stock.*

Scenario 5

Scenario 5 differs not that much in output compared with scenario 4 because also in this case the average new buy lead time has a great impact on inventory level, while its influence on safety stock is nil. However, there is a switch in positive and negative influences on the inventory level between both scenarios, although this gives almost the same overall impact. Scenario 4 has an increase in service level combined with a decrease in variability of new buy lead time, while in scenario 5 the stock increases by a reduction in return time and decrease by lower service level.

Scenario 6

This scenario entails an enormous reduction in mean and variability of new by lead time and return time.

Scenario 7

The mean new buy lead time and service level improves a little bit but the variation in new buy lead time, return time, and demand decrease substantially. Conversely, the repair yield improves significantly.

Scenario 8

This scenario has only small reduction in the most important key parameters, namely for the mean repair, new buy, and return lead time, but also in the variation of new buy and return lead time. Opposite, the repair yield is increased significantly.

Scenario 9

Scenario 9 is not an outlier in the sense that the correlation between safety stock and inventory is different than expected, but scenario 9 is totally separated from the other scenarios due to an increasing stock level. This is caused by the fact that the safety stock and inventory are increased as effect of higher service level and considerable reduction in average return time because the latter has an opposite impact. However the impact of reduction in mean new buy lead time becomes also visible because the inventory level increases less than the safety stock due to the negative influence of a reduction in average new buy lead time on stock level.

Scenario 10

There are no gigantic modifications in the scenarios, only small reductions in average demand, mean new buy and return lead time, and service level. Also the variability in new buy lead time diminishes.

Scenario 11

A significant reduction in mean and variance of the return cycle time, while the average demand and new buy lead time diminishes a little bit.

Scenario 12

Mainly the service level increases and the variation in new buy lead time decreases considerable. Also a small decrease in average demand and new buy lead time distinguishes this scenario from others.

Scenario 13

This scenario has a gigantic decrease in variation of the new buy lead time, while the average and variability of demand and return cycle time decrease a little bit.

Scenario 14

The reduction in safety stock is larger than the reduction in inventory level because the reduced mean return time and increased service level causes a tremendous increase in inventory level that outweighed the diminishing effect of average demand and variability of new buy lead time.

This scenario is an example that key parameter can reinforce each other. The combination of both a reduction in mean demand and variation in new buy lead time, and an increase in service level has a lager decreasing impact on safety stock than the sum of the main effect of those key parameters would suggest.

Scenario 15

This scenario has only small modifications in the most important key parameters, namely in the mean and variability of demand, and service level.

Scenario 16

Interestingly, the inventory level decreases despite a higher safety stock. This is caused by the fact that the impact of increase in service level outweighed other influences on safety stock, while the combination of the reduction in mean demand, new buy and return lead time overshadow the influence of service level on stock level. The average inventory level is even a little bit lower than the safety stock level.

Scenario 17

This scenario is not an outlier like the other discussed scenarios but it has the highest reduction in safety stock and inventory level. This scenario has four main key parameters that decrease inventory level, specifically mean demand and new buy lead time, variation in return time, and service level. These key parameters overshadow the positive influence of average return time on stock level.

Scenario 18

The average new buy lead time has a significant impact, as well as the variation in demand. Conversely, the mean demand and variation in new buy lead time have a minute reduction.

Scenario 19

This scenario has only gigantic medications; the average demand, new buy and return lead time, plus the variability in new buy lead time decrease dramatically. In contrast, the service level has a huge increase.

Scenario 20

The considerable reduction in mean demand and new buy lead time, and variation return time are the most important key parameters. Moreover, there is a small reduction in variability of new buy lead time and service level.

Scenario 21

This scenario is quite similar to scenario 5 because the modification of mean new buy and return time, and the variability in new buy lead time are identical. However, scenario 5 has a reduction in service level, while scenario 21 has lower average demand. It becomes visible that a decrease in demand, in combination with the key parameters that are identically in both scenarios, has more impact on inventory level and safety stock than a reduction in service level. Though, this is not a straight forward conclusion because the reduction in mean demand is 20%, while the service level deteriorates with 2%.

Scenario 22

This scenario has a gigantic decrease in average demand and return time, while the mean new buy lead time, variation demand and service level decrease a little bit.

Scenario 23

This scenario has a small reduction in the mean new buy lead time and variability of demand. Opposite, the mean demand and variability of new buy lead time decreases considerable.

Scenario 24

The service level increases substantially, while the mean demand diminished drastically. Another modification is the small reduction in mean new buy and return lead time, and variability of demand and new buy lead time.

Scenario 25

The decline in safety stock is larger than the reduction in inventory level because the smaller mean return time causes a remarkable increase in inventory level that outweighed the diminishing effect of average demand and variability of new buy lead time. This scenario is similar to scenario 14 for these key parameters. However, the overall impact of these scenarios is completely different. The larger decrease in mean demand and variation return time in scenario 25 and the higher service level in scenario 14 result in a totally different pattern of inventory level. The diminishing of stock level is negligible in scenario 14, while the stock level decreases dramatically in scenario 25. The behavior of reduction in average demand is also visible due to an increase in inventory level after the modification.

Scenario 26

The considerable reduction in mean demand and increase in service level are the most important key parameters. In fact, three other main key parameters are not modified compared to the base case. These key parameters are mean new buy and return lead time, and variation in new buy lead time.

Scenario 27

Scenario 27 has the highest decrease in safety stock compared to all other scenarios due to a combination of a considerable diminution in average demand, variation of new buy lead time, and service level. The reason that the reduction in safety stock is larger than of stock level is similar to some other scenario, namely a higher return velocity does not impact the safety stock level but has a positive influence on the level of inventory.

5.4.2 Conclusion

This section showed different scenarios and explained their differences. In the scenario analysis different modifications in key parameters are combined. However, there are no highly significant reinforced impacts visible due these combinations.

One of the conclusions is that in general, a reduction in average new buy lead time does not impact the safety stock level significantly but has a positive influence on the level of inventory. This causes discrepancy in the expected correlation between safety stock and inventory level, specifically the inventory level decreases relatively more than the safety stock level.

On the other hand, the mean return lead time causes also an inconsistency in correlation but in opposite direction in general. The average return cycle time does not affect the safety stock while it increases the inventory level. Therefore, the inventory diminishes proportional less than the safety stock. As a result, some scenarios show an inventory level that does not reduce until safety stock level.

To conclude, it can be ascertained that the bigger the impact on supply chain the longer it takes before the inventory level is stabilized in general.

6. Conclusion and Recommendations

The previous chapters showed the research process to establish the answer to the research questions to identify key parameters and the impact of strategic improvement of theses parameter on the spare parts supply chain. These questions are answered in this chapter. Further, it is important to indicate the limitations of the research in order to determine the usefulness of this report. Finally, suggestions for further research are provided.

6.1 Conclusion

Philips Healthcare was looking for a tool that could support the yearly determination of required budget for inventory of the next year. This tool should be able to deal with expected changes in the spare parts supply chain and support the AOP. Literature indicates that system dynamics is a modeling method that provides insight in the behavior of service parts supply chain over time.

Therefore, the spare parts supply chain activities are translated into a causal loop diagram that indicates all interrelationships. Accordingly, a simulation model is developed for MR to measure the impact of different key parameters on the supply chain. These key parameters are the average and variation of *demand*, *new buy lead time, repair lead time*, and *return time*. Additional key parameters investigated are the *repair yield* and *target service level*.

From the main effect analysis, in which each key parameter is changed ceteris paribus, it can be concluded that reduction of average demand and new buy lead time diminish the inventory level considerably in relatively a short period of time. However, it remains questionable whether it is possible to reduce the average demand because the sale of systems increases and it is expected that this results in a higher demand of service parts. Also market penetration rate will increase the demand. However, more training of FSE and remote control might reduce demand. Additional efforts made in modular design of products will also decrease the number of stock-keeping units of spare parts and as such the average demand.

Furthermore, the average new buy lead time can be reduced by making new agreements with suppliers. The low volume and unpredictability of service parts results often in suboptimal agreements offered by suppliers. However, this might be hard to establish. Therefore, a more practical and valuable advice will be to start with diminishing the variation in production time. It is a valuable investment, since a reduction of 40% in good stock can be established with a reduction of 50% in variation of new buy lead time. The impact might take one year before the reduction of 40% is obtained, but negotiating about new agreement to reduce the average production time also will be time consuming. Thus, collaboration with suppliers to deliver conform contract can have a significant impact on production time variation and consequently lower overall costs due to reduction of inventory level. The same holds for repair lead time, if this key parameter would be part of the determination of safety stock and replenishment decision.

Another advice is to focus on the decrease of return cycle time since the number of new buys ordered decreases considerably, even up to 50% if the return cycle time is reduced with 50% since more parts can be sent for repair. This means remarkable decrease in production costs. Moreover, a higher service level would be guaranteed due to the higher inventory level because the repair lead time is shorter than new buy lead time on average.

6.2 Limitations

Although this research tries to simulate the reality with the highest quality and greatest care, several limitations of the research can be identified because assumptions had to be made.

The main limitation is the aggregation of the model on inventory level. The consequence of the high strategic level of the model is that it is not feasible to check whether the right part is stocked on the right location. Therefore, the link with the operational KPI ‘realized service level’ or ‘material availability’ is not available because the simulated output indicates that there is enough stock all the time.

Another restriction is that the repair lead time does not affect the safety stock determination and demand forecast during lead time. Therefore, the improvements of repair lead time are almost not visible in the simulation of the service parts supply chain.

A final remark is that simulation of future situations is always rather uncertain because the exact situation cannot be predicted. Hence, the simulated output is an indication of the impact of a specific development in supply chain and do not necessarily represent the exact situation if this improvement is implemented.

6.3 Future Research

One of the limitations can be eliminated by taking a weighted average for the average lead time and standard deviation in the calculation of safety stock and forecasted demand during lead time. This research already gives a short preview of this extension in Section 5.2.2.3 and 5.2.2.5. Another extension of the model will be to update the safety stock level each month because this reflects better the reality of the forecast process. Of course, expansion to an overall model of all business units has more value for Philips Healthcare which is already in progress.

Furthermore, developing a two-level model which reflects both operational level and strategic level will provide insight in material availability. Further research has to indicate how to combine supply chain improvements and operational level because it is expected that a lot of assumption will be required.

The causal loop diagram composed in this research indicates possible direction for future research because there is a lot of (qualitative) information not yet implemented in the current model. The age and utilization of install base in the current simulation model might be an interesting factor. Further, the expected diminishing quality of repairable part after multiple recoveries is a totally new subject, especially if it is possible to find a link between the quality and demand of service parts. Additional, the impact of satisfaction of customers on the install base might give new insight. In fact, Philips Healthcare has a measurement of customer satisfaction. So, it might be possible to translate this relative qualitative information into a link with install base.

Although it was not possible to find a link between install base and demand of spare parts on an aggregated level, it is expected that there exists a link. Therefore, a research on lower level might reveal this interrelationship. In fact, more research in this area is already started.

It will be interesting to combine the output of the model in this research with the overall operational costs. This means that for each scenario the total costs of transportation, good and defect inventory, and production are calculated. This extension gives insight in the financial aspects of different scenarios.

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Appendix A. Reduction variation of a distribution without changing its mean

```
%**********************************************************************************************%
%                                                                                              %
% This file transforms a distribution with mu (mean) and sigma (standard deviation) to a distribution %
% with mu and r*sigma, were r equals the reduction of variability in percentage.              %
%                                                                                              %
%**********************************************************************************************%
%                                                                                              %
% INPUT:   r=(Reduction Lead Time)        (Note: in percentage)                                %
%          x=(Lead Time, Probability).    (Note: Take at least 7 decimals, otherwise the impact of   %
%                                                rounding errors is significant)               %
%                                                                                              %
% OUTPUT:  'pdf' is the new distribution with modified variability, but same mean.            %
%          'LeadTime' and 'Prob' are the colums of 'pdf' and useful to copy to excel.         %
%          'mean'and 'stdev' are the mean and standard deviation of the original distribution. %
%          'meanR'and 'stdevR' are the mean and standard deviation of the modified distribution %
%           without correction for whole days.                                                %
%          'meanRdays' and 'stdevRdays' are the mean and standard deviation of the modified   %
%           distribution with correction for whole days.                                      %
%          'SumProbCheck' is a check to see if the sum of probabilities of the modified distribution %
%           with whole days equals one.                                                       %
%          'stdevCheck' is a check to see if the variance of the modified distribution with whole %
%           days corresponds with the requested variance reduction.                           %
%                                                                                              %
%**********************************************************************************************%

clear all

% INPUT
r=0.50;
x=[  ];

% Determination Mean and Standard Deviation of distribution
m=size(x,1);
maxLT=max(x(:,1));
z=zeros(m,2);
z(:,1)=x(:,1);
z(:,2)=x(:,1).*x(:,2);

mean=sum(z(:,2));

v=zeros(m,2);
v(:,1)=x(:,1);
v(:,2)=(x(:,1)-mean).^2.*x(:,2);

stdev=sqrt(sum(v(:,2)));

% Reduction Variability: Assign lead time closer to the mean for each lead time with belonging probability
xR=zeros(m,2);
xR(:,2)=x(:,2);
xR(:,1)=((x(:,1)+(mean-x(:,1))*r));

% Determination Mean and Standard Deviation of distribution with reduced variability
zR=zeros(m,2);
zR(:,1)=xR(:,1);
zR(:,2)=xR(:,1).*xR(:,2);

meanR=sum(zR(:,2));

vR=zeros(m,2);
vR(:,1)=xR(:,1);
vR(:,2)=(xR(:,1)-meanR).^2.*xR(:,2);

stdevR=sqrt(sum(vR(:,2)));
```

```
% PDF in days
xRdays=zeros(m,2);
xRdays(:,1)=round(xR(:,1))
xRdays(:,2)=xR(:,2)

pdf=zeros(maxLT+1,2);
pdf(:,1)=linspace(0,maxLT,maxLT+1)'

% Reduction Variability: Sum probability of generated lead times that are similar
for i=1:(maxLT+1)
   for j=1:m
      if xRdays(j,1)==i-1
         pdf(i,2)=pdf(i,2)+xRdays(j,2);
      end
   end
end

% Determination Mean and Standard Deviation of distribution with reduced variability in days
zRdays=zeros(maxLT+1,2);
zRdays(:,1)=pdf(:,1);
zRdays(:,2)=pdf(:,1).*pdf(:,2);

meanRdays=sum(zRdays(:,2));

vRdays=zeros(maxLT+1,2);
vRdays(:,1)=pdf(:,1);
vRdays(:,2)=(pdf(:,1)-meanRdays).^2.*pdf(:,2);

stdevRdays=sqrt(sum(vRdays(:,2)));


% OUTPUT
pdf;
LeadTime=pdf(:,1);
Prob=pdf(:,2);
SumProbCheck=sum(pdf(:,2))
stdevCheck=stdev*(1-r)
maxLTR=max(xRdays(:,1))

OUTPUT=[mean       stdev
        meanR      stdevR
        meanRdays  stdevRdays]
```

Appendix B. Adding two sequential independent distribution

```
%*****************************************************************************************%
%                                                                                         %
% This file adds two independent distributions. For example, add the distribution of the time a part  %
% is at the FSE an the distribution of the return time from FSE till blueroom. This are two          %
% independent distribution. The ouput is a distribution of the total return cycle time from          %
% delivering at FSE till arriving at blueroom.                                                        %
%                                                                                         %
%*****************************************************************************************%
%                                                                                         %
% INPUT:   FSE=(Time a part spend at FSE, probabilitity)   (Note: Take at least 7 decimals, otherwise %
%          cycle=(Lead Time, Probability).                  the impact of rounding errors is         %
%                                                           significant)                             %
%                                                                                         %
%                                                          (Note: Both input should start with       %
%                                                           LeadTime = 0                             %
%                                                                                         %
% OUTPUT:  'pdf' is the new distribution with shows the probability of the whole return cycle time   %
%          'LeadTime' and 'Prob' are the colums of 'pdf' and useful to copy to excel.                %
%                                                                                         %
%*****************************************************************************************%

clear all

% INPUT

FSE=[];
cycle=[];

m=size(FSE(:,1));
n=size(cycle(:,1));

maxLT_FSE=max(FSE(:,1));
maxLT_cycle=max(cycle(:,1));

xnew=zeros(maxLT_FSE+1,2);
ynew=zeros(maxLT_cycle+1,2);

xnew(:,1)=linspace(0,maxLT_FSE,maxLT_FSE+1)';
ynew(:,1)=linspace(0,maxLT_cycle,maxLT_cycle+1)';
for i=1:(maxLT_FSE+1)
    for j=1:m
        if FSE(j,1)==i-1
            xnew(i,2)=FSE(j,2);
        end
    end
end

for i=1:(maxLT_cycle+1)
    for j=1:n
        if cycle(j,1)==i-1
            ynew(i,2)=cycle(j,2);
        end
    end
end
```

```
Z=xnew(:,2)*ynew(:,2)';

pdf=zeros(maxLT_FSE+maxLT_cycle+1,2);
pdf(:,1)=linspace(0,maxLT_FSE+maxLT_cycle,maxLT_FSE+maxLT_cycle+1)';

for i=0:maxLT_FSE
    for j=0:maxLT_cycle
        for k=0:maxLT_FSE+maxLT_cycle
            if k==i+j
                pdf(k+1,2)=pdf(k+1,2)+Z(i+1,j+1);
            end
        end
    end
 end

 LeadTime=pdf(:,1);
 Prob=pdf(:,2);
```

Appendix C. Link Installed Base and Demand

Appendix D. Main Effects Base Case

	Input Key Parameter Quantity	0	1	2
A	Average Demand *(parts)*	Xxx *(0%)*	Xxx *(-10%)*	Xxx *(-20%)*
B	Reduction Variability Demand per day *(parts)*	Xxx *(0%)*	Xxx *(-25%)*	Xxx *(-50%)*
C	Average Repair Lead Time *(days)*	Xxx *(0%)*	Xxx *(-13%)*	Xxx *(-33%)*
D	Reduction Variability Repair Lead Time *(days)*	Xxx *(0%)*	Xxx *(-25%)*	Xxx *(-38%)*
E	Average New Buy Lead Time *(days)*	Xxx *(0%)*	Xxx *(-28%)*	Xxx *(-49%)*
F	Reduction Variability New Buy Lead Time *(days)*	Xxx *(0%)*	Xxx *(-25%)*	Xxx *(-34%)*
G	Average Return Time *(days)*	Xxx *(0%)*	Xxx *(-13%)*	Xxx *(-50%)*
H	Reduction Variability Return Time *(days)*	Xxx *(0%)*	Xxx *(-25%)*	Xxx *(-38%)*
I	Target Service Level *(percentage)*	xxx % *(0%)*	xxx % *(-2%)*	xxx% *(+3%)*
J	Average Repair Yield *(percentage)*	xxx% *(0%)*	xxx% *(+2%)*	xxx% *(+4%)*

	Input Key Parameter EUR	0	1	2
A	Average Demand per day *(EUR)*	€xxx *(0%)*	€xxx *(-10%)*	€xxx *(-20%)*
B	Reduction Variability Demand per day *(EUR)*	€xxx *(0%)*	€xxx *(-25%)*	€xxx *(-50%)*
C	Average Repair Lead Time *(days)*	Xxx *(0%)*	Xxx *(-12%)*	Xxx *(-31%)*
D	Reduction Variability Repair Lead Time *(days)*	Xxx *(0%)*	Xxx *(-25%)*	Xxx *(-41%)*
E	Average New Buy Lead Time *(days)*	Xxx *(0%)*	Xxx *(-43%)*	Xxx *(-60%)*
F	Reduction Variability New Buy Lead Time *(days)*	Xxx *(0%)*	Xxx *(-25%)*	Xxx *(-50%)*
G	Average Return Time *(days)*	Xxx *(0%)*	Xxx *(-18%)*	Xxx *(-50%)*
H	Reduction Variability Return Time *(days)*	Xxx *(0%)*	Xxx *(-25%)*	Xxx *(-41%)*
I	Target Service Level *(percentage)*	xxx % *(0%)*	xxx % *(-2%)*	xxx% *(+3%)*
J	Average Repair Yield *(percentage)*	xxx% *(0%)*	xxx% *(+2%)*	xxx% *(+4%)*

Main Effects									
		Mean Demand		Variability Demand		Mean Repair Lead Time		Variability Repair Lead Time	
		xxx *(-10%)*	xxx *(-20%)*	xxx *(-25%)*	xxx *(-50%)*	xxx *(-13%)*	xxx *(-33%)*	xxx *(-25%)*	xxx *(-38%)*
Variable (Quantity)	**Base case 0**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-9.2%	-19.5%	-0.8%	-2.0%	0.7%	0.7%	0.0%	-0.1%
Average Defect Stock at Blueroom	Xxx	-6.1%	-15.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Average Repairs Ordered per day	Xxx	-6.1%	-15.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Average New Buys Ordered per day	Xxx	-10.3%	-19.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Average Consignment Stock	Xxx	-9.5%	-17.8%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%
Safety Stock	Xxx	-9.9%	-19.7	-0.3%	-0.4%	0.0%	0.0%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		180	190	50	50	50	50	0	0

Main Effects									
		Mean New Buy Lead Time		Variability New Buy Lead Time		Mean Return Cycle Time		Variability Return Cycle Time	
		xxx *(-28%)*	xxx *(-49%)*	xxx *(-25%)*	xxx *(-34%)*	xxx *(-13%)*	xxx *(-50%)*	xxx *(-25%)*	xxx *(-38%)*
Variable (Quantity)	**Base case 0**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-2.4%	-6.8%	-22.6%	-30.6%	1.5%	6.7%	-0.1%	-0.2%
Average Defect Stock at Blueroom	Xxx	0.0%	0.0%	0.0%	0.0%	84.6%	353.8%	-30.8%	-38.5%
Average Repairs Ordered per day	Xxx	0.0%	0.0%	0.0%	0.0%	84.6%	353.8%	-30.8%	-38.5%
Average New Buys Ordered per day	Xxx	-1.2%	-2.0%	-1.0%	-1.5%	-3.5%	-15.9%	1.5%	1.7%
Average Consignment Stock	Xxx	0.0%	0.0%	0.0%	0.0%	-3.8%	-17.0%	1.6%	1.9%
Safety Stock	Xxx	-0.2%	-0.3%	-24.7%	-33.5%	0.0%	0.0%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		80	90	120	180	50	50	150	160

Main Effects					
		Target Service Level		Repair Yield	
		xxx%	xxx%	xxx%	xxx%
Variable (Quantity)	**Base case 0**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-9.3%	23.7%	0.3%	0.2%
Average Defect Stock at Blueroom	Xxx	0.0%	0.0%	0.0%	0.0%
Average Repairs Ordered per day	Xxx	0.0%	0.0%	0.0%	0.0%
Average New Buys Ordered per day	Xxx	-0.5%	1.0%	0.0%	-0.2%
Average Consignment Stock	Xxx	0.0%	0.0%	0.0%	0.0%
Safety Stock	Xxx	-10.3%	24.8%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		170	130	0	0

Main Effects									
		Mean Demand		Variability Demand		Mean Repair Lead Time		Variability Repair Lead Time	
		€xxx *(-10%)*	€xxx *(-20%)*	€xxx *(-25%)*	€xxx *(-50%)*	45 *(-12%)*	35 *(-31%)*	38 *(-25%)*	30 *(-41%)*
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-9.3%	-19.3%	-0.5%	-1.3%	1.1%	2.3%	0.1%	0.0%
Average Defect Stock at Blueroom	Xxx	-9.6%	-18.2%	0.2%	0.3%	-0.2%	-0.2%	-0.1%	0.0%
Average Repairs Ordered per day	Xxx	-9.6%	-18.1%	0.1%	0.2%	-0.2%	-0.2%	-0.1%	0.0%
Average New Buys Ordered per day	Xxx	-11.1%	-21.0%	0.2%	0.4%	0.0%	0.1%	0.1%	0.0%
Average Consignment Stock	Xxx	-9.6%	-18.0%	0.1%	0.2%	0.0%	0.1%	0.0%	0.0%
Safety Stock	Xxx	-10.1%	-20.1%	-0.2%	-0.3%	0.0%	0.0%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		180	200	90	110	100	110	0	0

Main Effects									
		Mean New Buy Lead Time		Variability New Buy Lead Time		Mean Return Cycle Time		Variability Return Cycle Time	
		50 *(-43%)*	35 *(-60%)*	46 *(-25%)*	30 *(-50%)*	18 *(-18%)*	*11* *(-50%)*	*20* *(-25%)*	15 *(-41%)*
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-11.7%	-17.3%	-20.3%	-40.2%	7.2%	15.6%	-2.5%	-4.1%
Average Defect Stock at Blueroom	Xxx	0.0%	0%	-0.2%	-0.1%	69.3%	138.2%	-25.7%	-32.2%
Average Repairs Ordered per day	Xxx	0.0%	0%	-0.2%	-0.1%	69.2%	138.1%	-25.7%	-32.1%
Average New Buys Ordered per day	Xxx	-2.7%	-3.7%	-1.8%	-3.7%	-24.1%	-50.1%	9.3%	12.1%
Average Consignment Stock	Xxx	-0.1%	0.0%	0.1%	0.0%	-26.1%	-54.2%	10.0%	13.0%
Safety Stock	Xxx	-0.2%	-0.3%	-24.8%	-49.4%	0.0%	0.0%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		140	150	360	370	250	260	250	270

Main Effects					
		Target Service Level		Repair Yield	
		93%	98%	93%	95%
Variable (EUR)	**Base case 0**	**1**	**2**	**1**	**2**
Average Spare Part Inventory	Xxx	-8.3%	20.0%	0.2%	0.2%
Average Defect Stock at Blueroom	Xxx	-0.2%	0.0%	0.0%	0.1%
Average Repairs Ordered per day	Xxx	-0.2%	0.0%	0.0%	0.0%
Average New Buys Ordered per day	Xxx	-0.7%	1.9%	-0.2%	-0.4%
Average Consignment Stock	Xxx	0.1%	0.0%	0.0%	0.0%
Safety Stock	Xxx	-10.3%	24.9%	0.0%	0.0%
Time it takes to stabilize Inventory Level *(days)*		160	260	100	100

Appendix E. Scenario Selection

This appendix describes the selection of the combination of modifications of key parameters. The problem is that the total number of possible combination for scenario analysis is more than 59000 because each key parameter has three different levels. For that reason fractional factorial design was used, which is a selection method to find those combinations of scenarios that explain the most important interactions between key parameters. Xu (2004) described a selection method based on the minimum aberration design. Table 22 shows the design developed by Xu (2004) for a three level factorial design of 10 key parameters. A complete overview of the different settings of the input key parameters can be found in Appendix D. These 27 scenarios are described and run after which the output is pictured in Figure 46.

Scenario	A	B	C	D	E	F	G	H	I	J
1	0	0	0	0	0	0	0	0	0	0
2	0	0	1	1	0	2	1	2	2	0
3	0	0	2	2	0	1	2	1	1	0
4	0	1	0	1	2	1	0	1	2	1
5	0	1	1	2	2	0	1	0	1	1
6	0	1	2	0	2	2	2	2	0	1
7	0	2	0	2	1	2	0	2	1	2
8	0	2	1	0	1	1	1	1	0	2
9	0	2	2	1	1	0	2	0	2	2
10	1	0	0	1	1	1	1	0	1	1
11	1	0	1	2	1	0	2	2	0	1
12	1	0	2	0	1	2	0	1	2	1
13	1	1	0	2	0	2	1	1	0	2
14	1	1	1	0	0	1	2	0	2	2
15	1	1	2	1	0	0	0	2	1	2
16	1	2	0	0	2	0	1	2	2	0
17	1	2	1	1	2	2	2	1	1	0
18	1	2	2	2	2	1	0	0	0	0
19	2	0	0	2	2	2	2	0	2	2
20	2	0	1	0	2	1	0	2	1	2
21	2	0	2	1	2	0	1	1	0	2
22	2	1	0	0	1	0	2	1	1	0
23	2	1	1	1	1	2	0	0	0	0
24	2	1	2	2	1	1	1	2	2	0
25	2	2	0	1	0	1	2	2	0	1
26	2	2	1	2	0	0	0	1	2	1
27	2	2	2	0	0	2	1	0	1	1

Table 22: Fractional factorial design

Scenario 1

None of the key parameters is changed, thus this scenario is exactly the base case.

Scenario 2

The main differences are a substantial decrease in variability of new buy lead time and return time, as well as an increase in service level. Also the variation in return time reduces a little bit.

Scenario 3

The mean return time is diminished enormously but also the average and variance of repair lead time although their impact may not be that huge. Other modification are a small reduction in variability of new buy lead time and return time, and the service level.

Scenario 4

The service level increases substantially, while the mean new buy is diminished drastically. Another significant modification is the small reduction in variability of new buy lead time.

Scenario 5

A considerable reduction in mean new buy distinguishes this scenario from some others, while the mean return time and service level have a small decrease.

Scenario 6

This scenario entails an enormous reduction in mean and variability of new by lead time and return time.

Scenario 7

The mean new buy lead time and service level improves a little bit but the variation in new buy lead time, return time, and demand decrease substantially. Conversely, the repair yield improves significantly.

Scenario 8

This scenario has only small reduction in the most important key parameters, namely for the mean repair, new buy, and return lead time, but also in the variation of new buy and return lead time. Opposite, the repair yield is increased significantly.

Scenario 9

The main influences in the scenario are the considerable reduction in mean return time and increase in service level. Also the reduction in mean new buy lead time might affect the supply chain.

Scenario 10

There are no gigantic modifications in the scenarios, only small reductions in average demand, mean new buy and return lead time, and service level. Also the variability in new buy lead time diminishes.

Scenario 11
A significant reduction in mean and variance of the return cycle time, while the average demand and new buy lead time diminishes a little bit.

Scenario 12
Mainly the service level increases and the variation in new buy lead time decreases considerable. Also a small decrease in average demand and new buy lead time distinguishes this scenario from others.

Scenario 13
This scenario has a gigantic decrease in variation of the new buy lead time, while the average and variability of demand and return cycle time decrease a little bit.

Scenario 14
The main influences in the scenario are the considerable reduction in mean return time and increase in service level. Further, this scenario has a small reduction in the mean and variation of demand, as well as in variability of new buy lead time.

Scenario 15
This scenario has only small modifications in the most important key parameters, namely in the mean and variability of demand, and service level.

Scenario 16
The considerable reduction in mean new buy lead time and increase in service level are the most important key parameters. Also the mean demand and return cycle time have a small impact.

Scenario 17
Three of the main key parameters, mean new buy and return time, and variation in return time, have an enormous reduction. Moreover, the average demand and service level decrease a little bit.

Scenario 18
The average new buy lead time has a significant impact, as well as the variation in demand. Conversely, the mean demand and variation in new buy lead time have a minute reduction.

Scenario 19
This scenario has only gigantic medications; the average demand, new buy and return lead time, plus the variability in new buy lead time decrease dramatically. In contrast, the service level has a huge increase.

Scenario 20
The considerable reduction in mean demand and new buy lead time, and variation return time are the most important key parameters. Moreover, there is a small reduction in variability of new buy lead time and service level.

Scenario 21
The main influences in the scenario are the considerable reduction in mean demand and new buy lead time. Further, this scenario has a small reduction in the mean return time.

Scenario 22
This scenario has a gigantic decrease in average demand and return time, while the mean new buy lead time, variation demand and service level decrease a little bit.

Scenario 23
This scenario has a small reduction in the mean new buy lead time and variability of demand. Opposite, the mean demand and variability of new buy lead time decreases considerable.

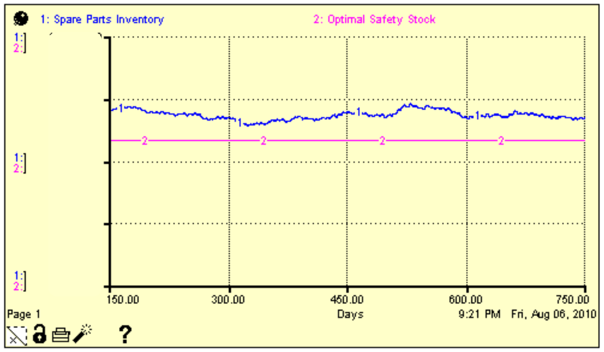
Scenario 24
The service level increases substantially, while the mean demand diminished drastically. Another modification is the small reduction in mean new buy and return lead time, and variability of demand and new buy lead time.

Scenario 25
Mainly the mean demand and return time decrease considerable. Also a small decrease in variation of new buy lead time distinguishes this scenario from others.

Scenario 26
The considerable reduction in mean demand and increase in service level are the most important key parameters. In fact, three other main key parameters are not modified compared to the base case. These key parameters are mean new buy and return lead time, and variation in new buy lead time.

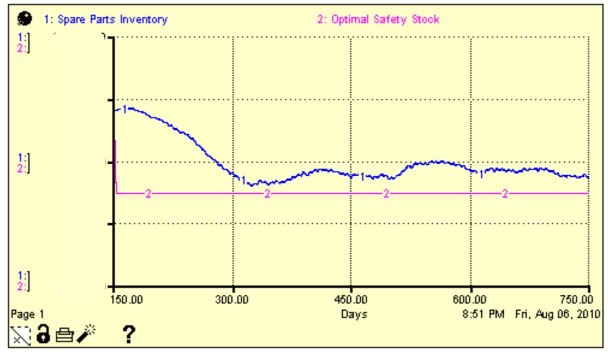
Scenario 27
Two of the main key parameters, mean demand and variability of new buy lead time, have an enormous reduction. Moreover, the average return time and service level decrease a little bit.

Scenario 1 BASE CASE:



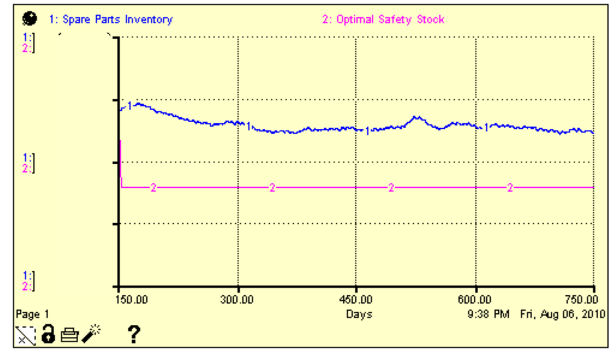
Average Inventory Reduction: 0%
Safety Stock Reduction: 0%
Time it takes before stabilized: 0 days

Scenario 2:



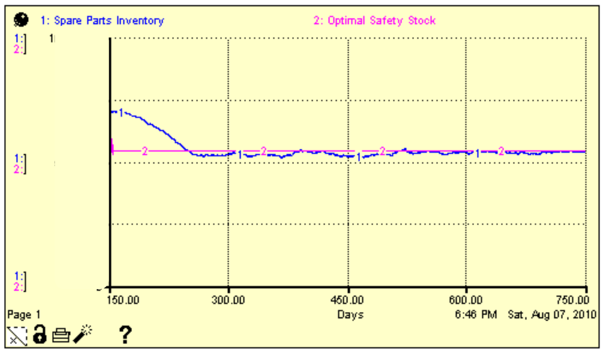
Average Inventory Reduction: 31%
Safety Stock Reduction: 37%
Time it takes before stabilized: 220 days

Scenario 3:



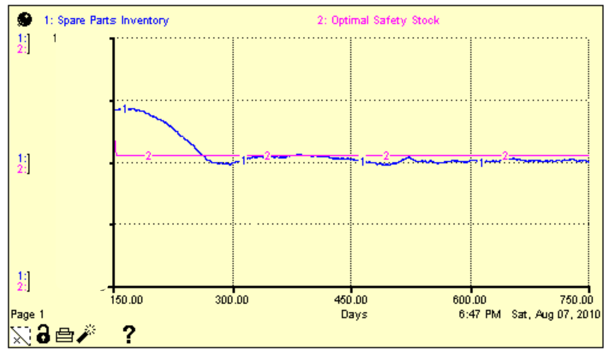
Average Inventory Reduction: 7%
Safety Stock Reduction: 32%
Time it takes before stabilized: 160 days

Scenario 4:



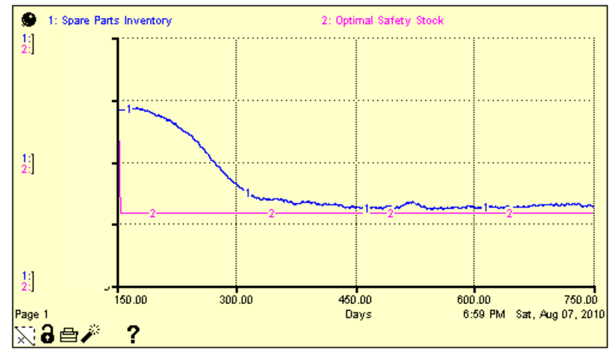
Average Inventory Reduction: 21%
Safety Stock Reduction: 7%
Time it takes before stabilized: 100 days

Scenario 5:



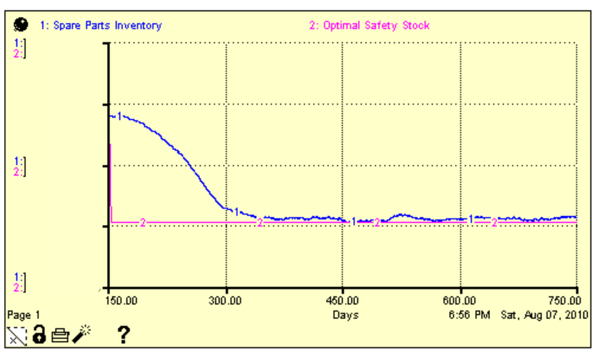
Average Inventory Reduction: 23%
Safety Stock Reduction: 11%
Time it takes before stabilized: 120 days

Scenario 6:



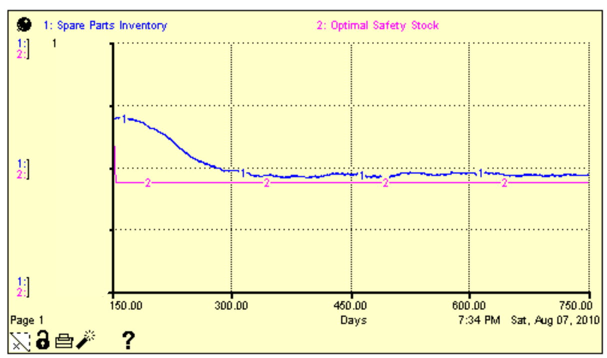
Average Inventory Reduction: 49%
Safety Stock Reduction: 50%
Time it takes before stabilized: 250 days

Scenario 7:



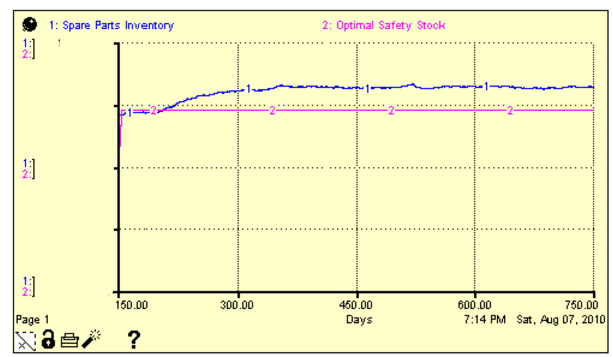
Average Inventory Reduction: 56%
Safety Stock Reduction: 55%
Time it takes before stabilized: 180 days

Scenario 8:



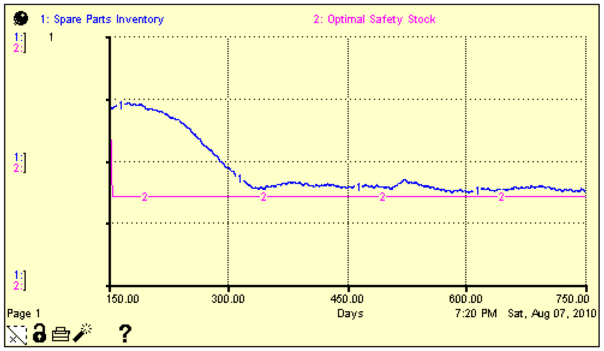
Average Inventory Reduction: 30%
Safety Stock Reduction: 25%
Time it takes before stabilized: 160 days

Scenario 9:



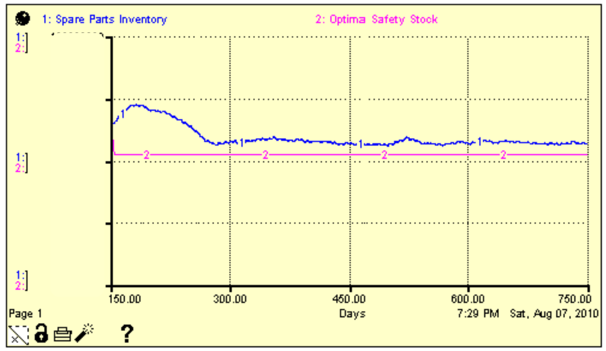
Average Inventory Increase: +20%
Safety Stock Increase: +24%
Time it takes before stabilized: 190 days

Scenario 10:



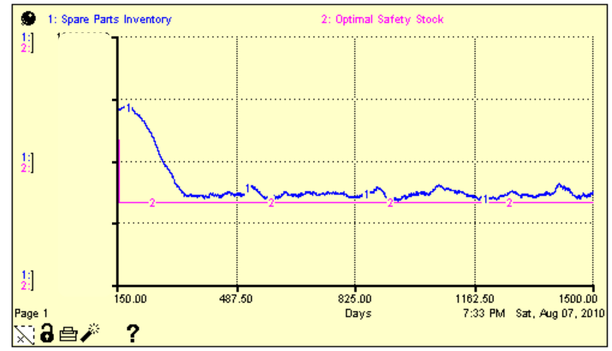
Average Inventory Reduction: 40%
Safety Stock Reduction: 39%
Time it takes before stabilized: 180 days

Scenario 11:



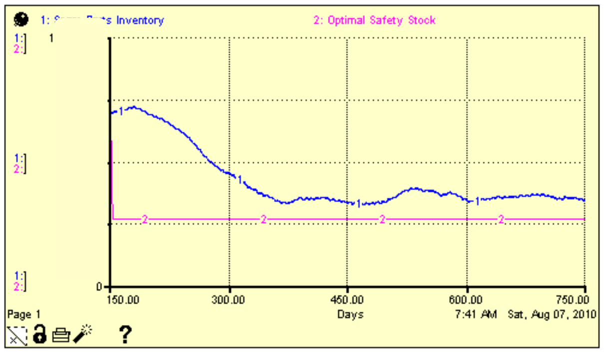
Average Inventory Reduction: 15%
Safety Stock Reduction: 10%
Time it takes before stabilized: 120 days

Scenario 12:



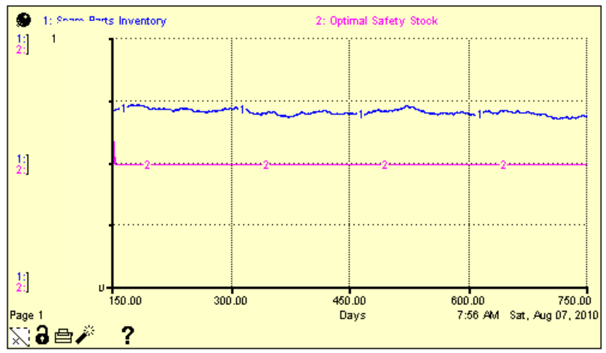
Average Inventory Reduction: 43%
Safety Stock Reduction: 43%
Time it takes before stabilized: 180 days

Scenario 13:



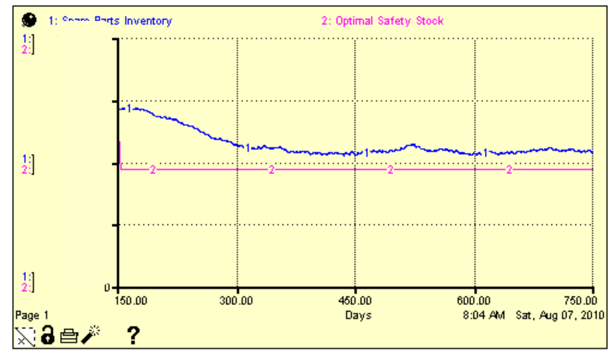
Average Inventory Reduction: 45%
Safety Stock Reduction: 55%
Time it takes before stabilized: 230 days

Scenario :14



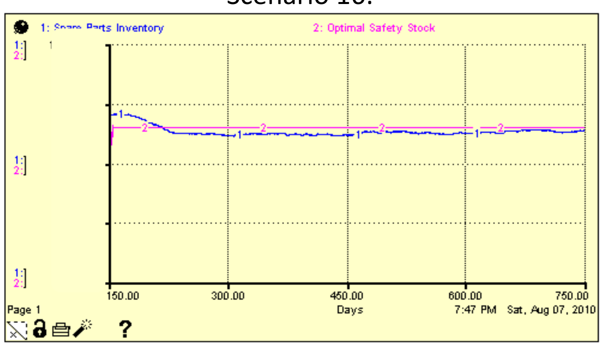
Average Inventory Reduction: 2%
Safety Stock Reduction: 16%
Time it takes before stabilized: 170 days

Scenario 15:



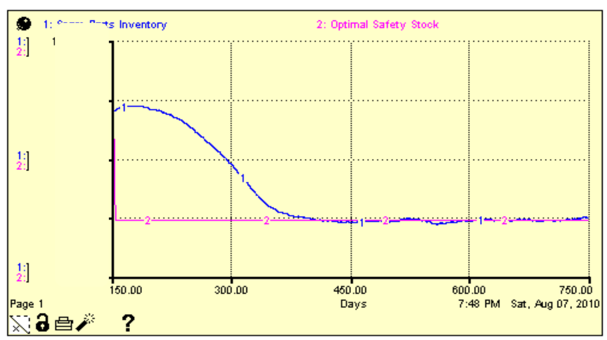
Average Inventory Reduction: 19%
Safety Stock Reduction: 19%
Time it takes before stabilized: 170 days

Scenario 16:



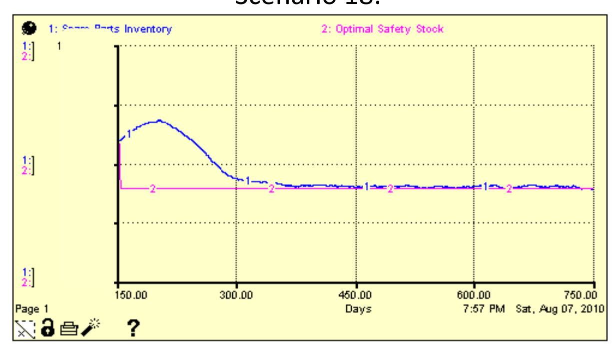
Average Inventory Reduction: 7%
Safety Stock Increase: +12%
Time it takes before stabilized: 80 days

Scenario 17:



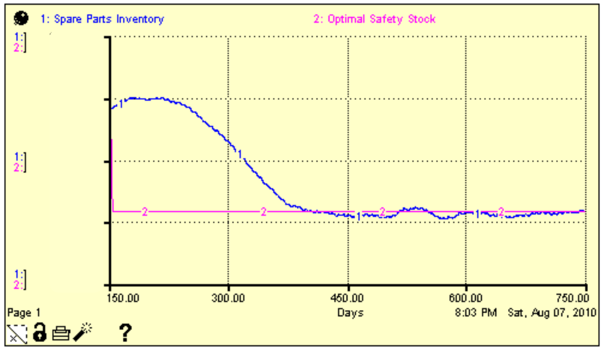
Average Inventory Reduction: 59%
Safety Stock Reduction: 60%
Time it takes before stabilized: 250 days

Scenario 18:



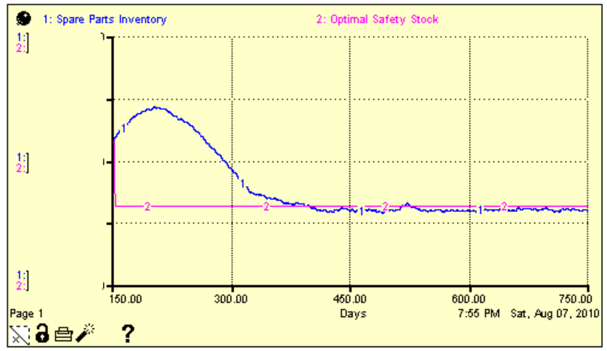
Average Inventory Reduction: 39%
Safety Stock Reduction: 33%
Time it takes before stabilized: 210 days

Scenario 19:



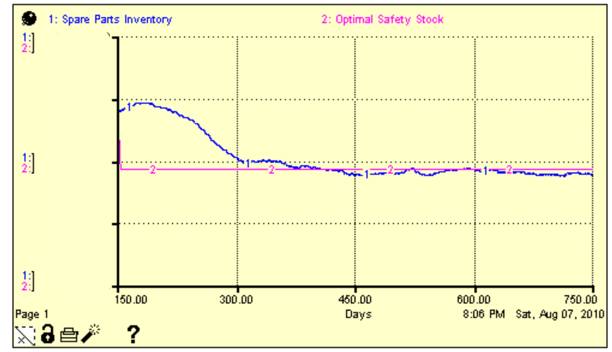
Average Inventory Reduction: 52%
Safety Stock Reduction: 50%
Time it takes before stabilized: 250 days

Scenario 20:



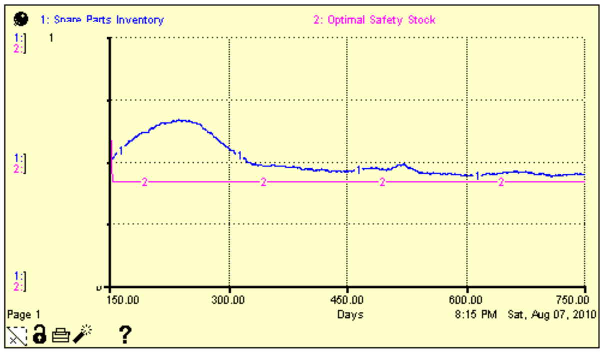
Average Inventory Reduction: 51%
Safety Stock Reduction: 46%
Time it takes before stabilized: 250 days

Scenario 21:



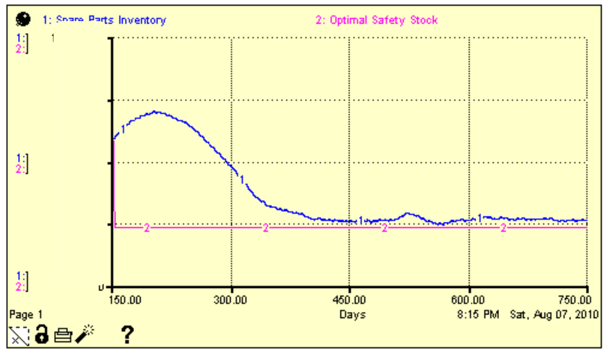
Average Inventory Reduction: 31%
Safety Stock Reduction: 20%
Time it takes before stabilized: 270 days

Scenario 22:



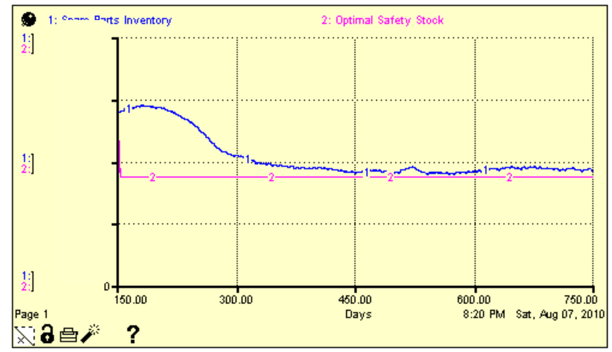
Average Inventory Reduction: 30%
Safety Stock Reduction: 29%
Time it takes before stabilized: 250 days

Scenario 23:



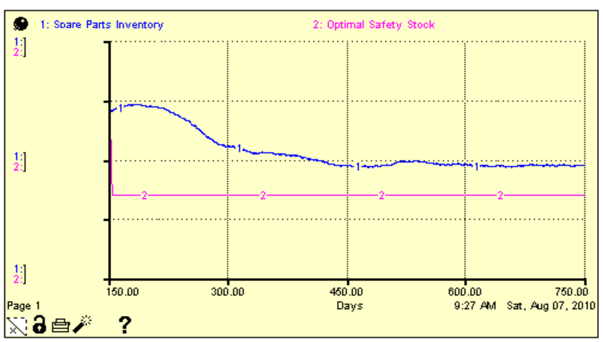
Average Inventory Reduction: 56%
Safety Stock Reduction: 60%
Time it takes before stabilized: 250 days

Scenario 24:



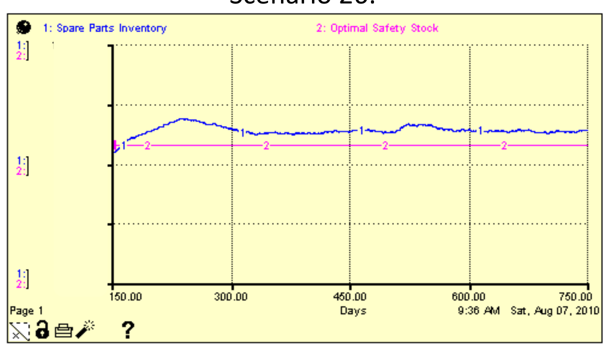
Average Inventory Reduction: 29%
Safety Stock Reduction: 25%
Time it takes before stabilized: 240 days

Scenario 25:



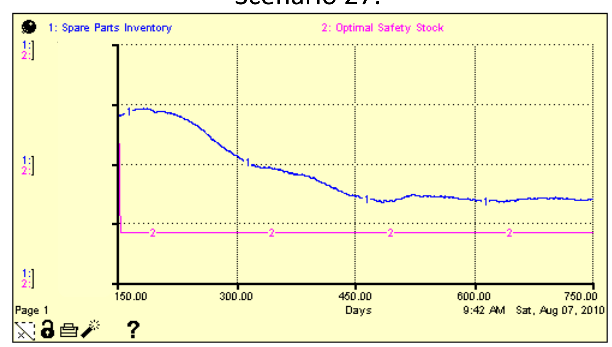
Average Inventory Reduction: 27%
Safety Stock Reduction: 40%
Time it takes before stabilized: 280 days

Scenario 26:



Average Inventory Reduction: 6%
Safety Stock Reduction: 1%
Time it takes before stabilized: 150 days

Scenario 27:

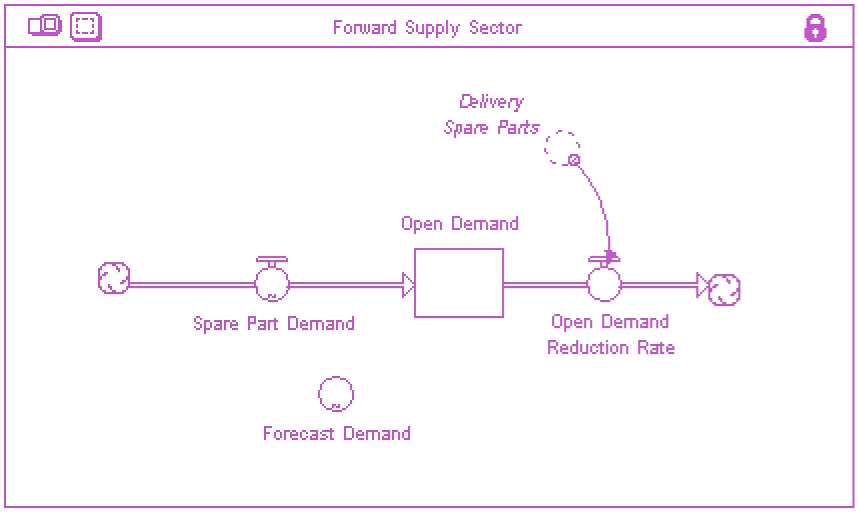


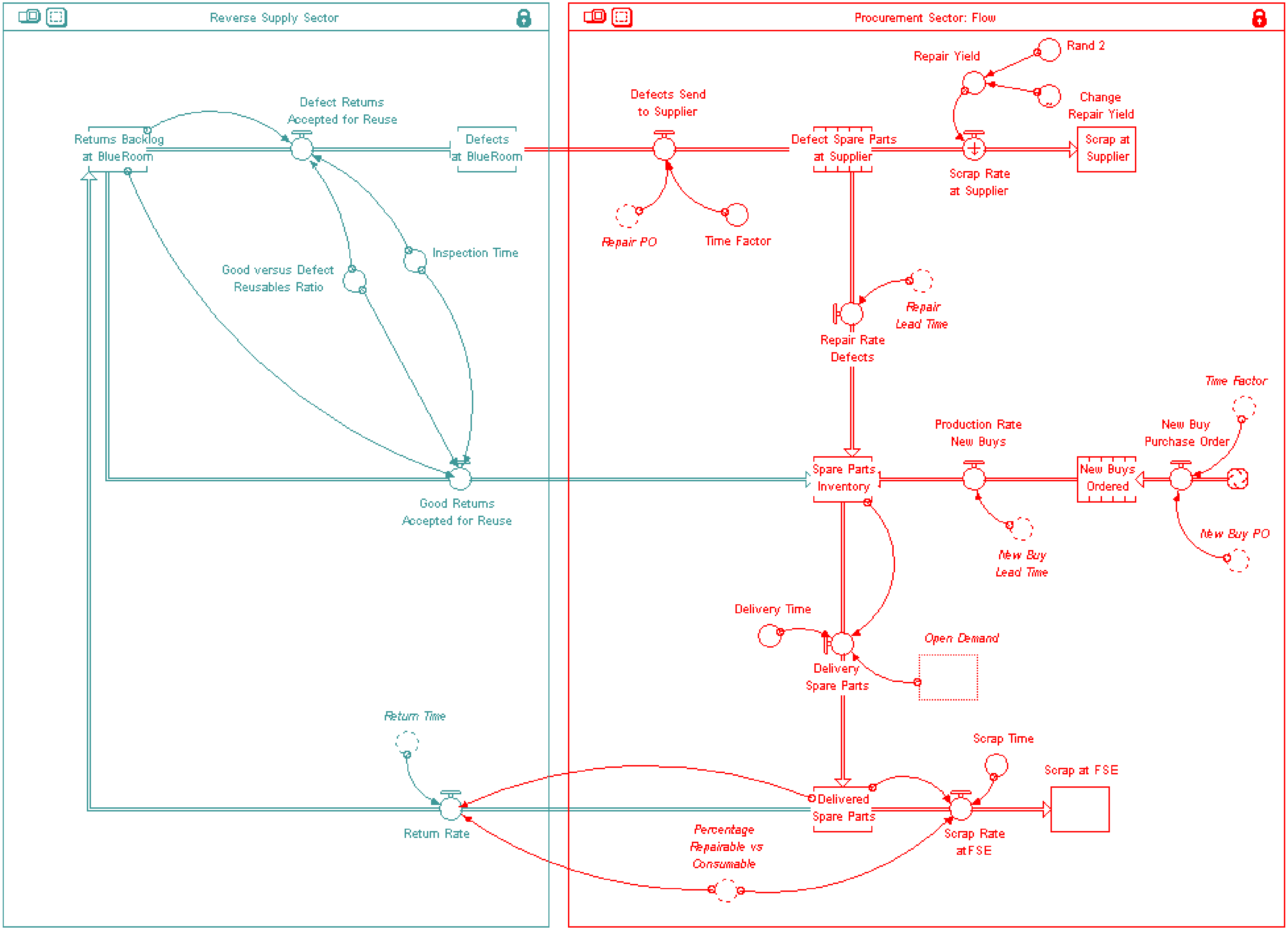
Average Inventory Reduction: 44%
Safety Stock Reduction: 64%
Time it takes before stabilized: 310 days

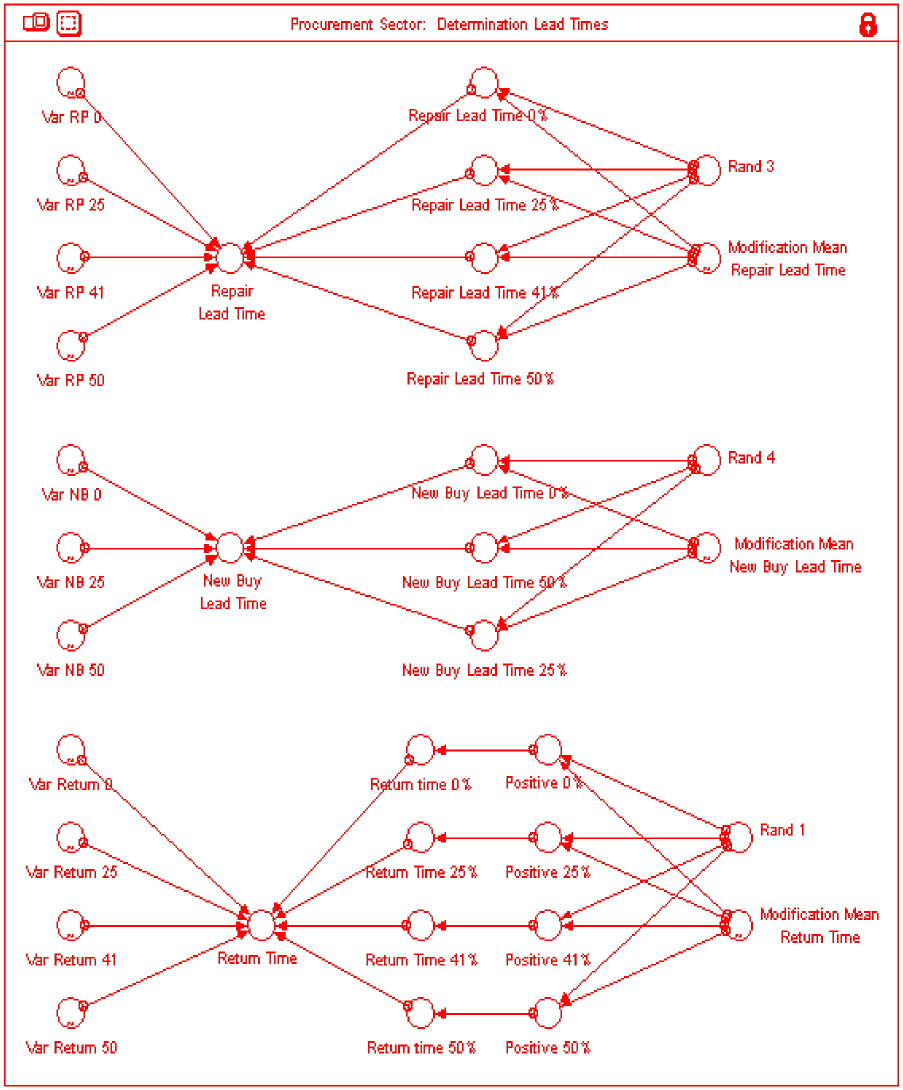
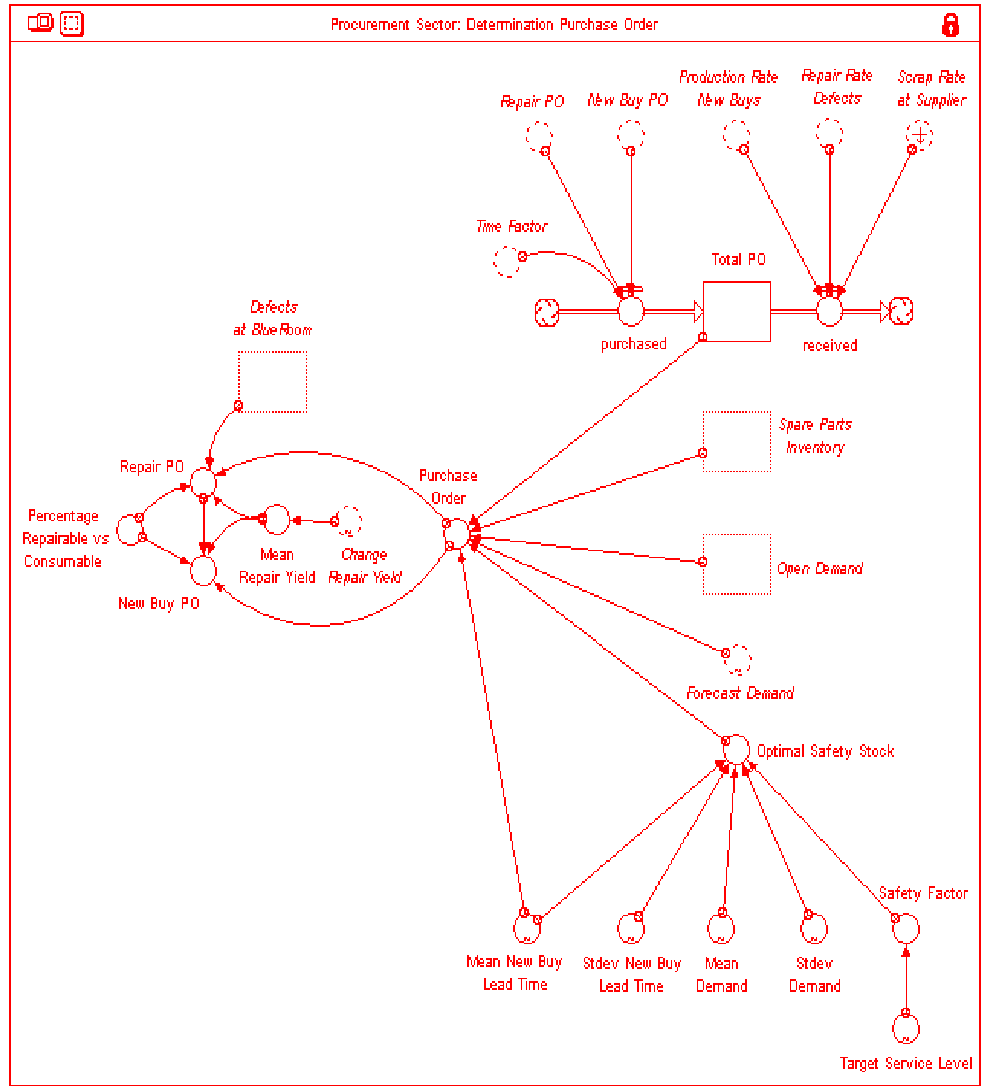
Figure 46: Overview of the output of all scenarios

Appendix F. System Dynamic Model

This appendix represents the iThink system dynamics simulation model as well as the description of the equations.




Reverse Supply Sector
Defect Returns Accepted for Reuse
Returns Backlog at BlueRoom
Defects at BlueRoom
Inspection Time
Good versus Defect Reusables Ratio
Good Returns Accepted for Reuse
Return Time
Return Rate
Procurement Sector: Flow
Rand 2
Repair Yield
Change Repair Yield
Defects Send to Supplier
Defect Spare Parts at Supplier
Scrap at Supplier
Scrap Rate at Supplier
Repair PO
Time Factor
Repair Lead Time
Repair Rate Defects
Time Factor
Production Rate New Buys
New Buy Purchase Order
Spare Parts Inventory
New Buys Ordered
New Buy PO
New Buy Lead Time
Delivery Time
Open Demand
Delivery Spare Parts
Scrap Time
Scrap at FSE
Delivered Spare Parts
Percentage Repairable vs Consumable
Scrap Rate at FSE


Procurement Sector: Determination Lead Times
Var RP 0
Var RP 25
Var RP 41
Var RP 50
Repair Lead Time
Repair Lead Time 0%
Repair Lead Time 25%
Repair Lead Time 41%
Repair Lead Time 50%
Rand 3
Modification Mean Repair Lead Time
Var NB 0
Var NB 25
Var NB 50
New Buy Lead Time
New Buy Lead Time 0%
New Buy Lead Time 50%
New Buy Lead Time 25%
Rand 4
Modification Mean New Buy Lead Time
Var Return 0
Var Return 25
Var Return 41
Var Return 50
Return Time
Return time 0%
Return Time 25%
Return Time 41%
Return time 50%
Positive 0%
Positive 25%
Positive 41%
Positive 50%
Rand 1
Modification Mean Return Time

Procurement Sector: Determination Purchase Order
Repair PO
New Buy PO
Production Rate New Buys
Repair Rate Defects
Scrap Rate at Supplier
Time Factor
Total PO
purchased
received
Defects at Blue Room
Repair PO
Percentage Repairable vs Consumable
New Buy PO
Mean Repair Yield
Change Repair Yield
Purchase Order
Spare Parts Inventory
Open Demand
Forecast Demand
Optimal Safety Stock
Safety Factor
Mean New Buy Lead Time
Stdev New Buy Lead Time
Mean Demand
Stdev Demand
Target Service Level

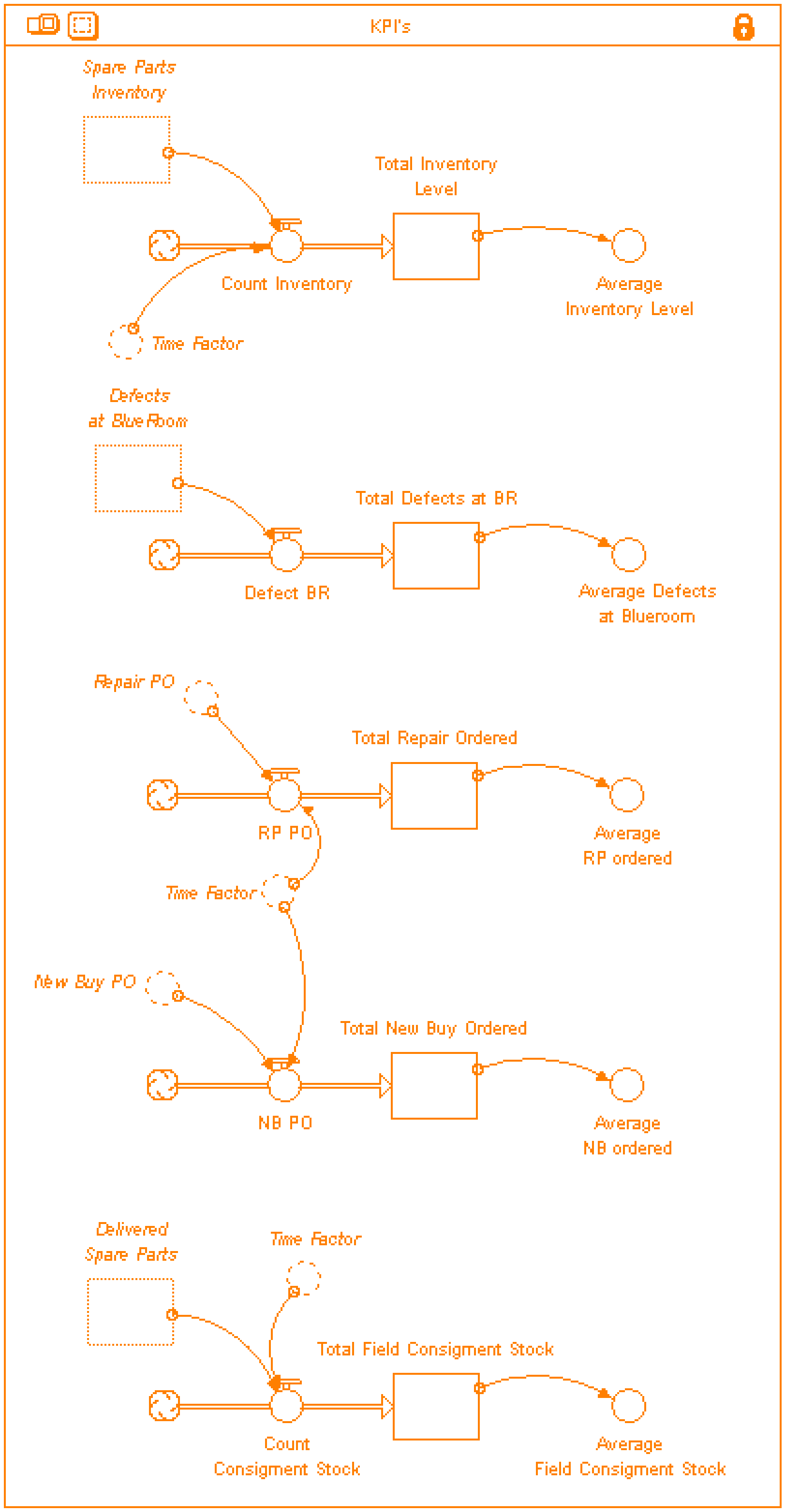


Figure 47: iThink Simulation Model

Forward Supply Sector

The demand that have to be delivered increases with the demand of this period and diminishes with the delivery in this period

Open_Demand(t) = Open_Demand(t - dt) + (Spare_Part_Demand - Open_Demand_Reduction_Rate) * dt

INIT Open_Demand = xxx

INFLOWS:

Spare_Part_Demand = GRAPH(TIME)

OUTFLOWS:

Open_Demand_Reduction_Rate = Delivery_Spare_Parts

Forecast_Demand = GRAPH(TIME)

KPI's

Supporting equation to measure the average defects at blueroom starting after the modification in the key parameters on time period 150

Total_Defects_at_BR(t) = Total_Defects_at_BR(t - dt) + (Defect_BR) * dt

INIT Total_Defects_at_BR = 0

INFLOWS:

Defect_BR = IF TIME > 150 THEN Defects_at_BlueRoom ELSE 0

Supporting equation to measure the average delivered parts starting after the modification in the key parameters on time period 150

Total_Field_Consigment_Stock(t) = Total_Field_Consigment_Stock(t - dt) + (Count__Consigment_Stock) * dt

INIT Total_Field_Consigment_Stock = 0

INFLOWS:

Count__Consigment_Stock = IF TIME > 150 THEN Delivered_Spare_Parts/Time_Factor ELSE 0

Supporting equation to measure the average stock level starting after the modification in the key parameters on time period 150

Total_Inventory_Level(t) = Total_Inventory_Level(t - dt) + (Count_Inventory) * dt

INIT Total_Inventory_Level = 0

INFLOWS:

Count_Inventory = IF TIME > 150 THEN Spare_Parts_Inventory/Time_Factor ELSE 0

Supporting equation to measure the average new buys ordered every day starting after the modification in the key parameters on time period 150

Total_New_Buy_Ordered(t) = Total_New_Buy_Ordered(t - dt) + (NB_PO) * dt

INIT Total_New_Buy_Ordered = 0

INFLOWS:

NB_PO = IF TIME > 150 THEN New_Buy_PO/Time_Factor ELSE 0

Supporting equation to measure the average repairs ordered every day starting after the modification in the key parameters on time period 150

Total_Repair_Ordered(t) = Total_Repair_Ordered(t - dt) + (RP_PO) * dt

INIT Total_Repair_Ordered = 0

INFLOWS:

RP_PO = IF TIME > 150 THEN Repair_PO/Time_Factor ELSE 0

Average_Defects_at_Blueroom = if TIME > 151 THEN Total_Defects_at_BR/(TIME-151) ELSE 0
Average_Field_Consigment_Stock = if TIME > 151 THEN Total_Field_Consigment_Stock/(TIME-151) ELSE 0
Average_Inventory_Level = if TIME > 151 THEN Total_Inventory_Level/(TIME-151) ELSE 0
Average__NB_ordered = if TIME > 151 THEN Total_New_Buy_Ordered/(TIME-150) ELSE 0
Average__RP_ordered = if TIME > 151 THEN Total_Repair_Ordered/(TIME-150) ELSE 0

Procurement Sector: Flow

Defect_Spare_Parts_at_Supplier(t) = Defect_Spare_Parts_at_Supplier(t - dt) + (Defects_Send_to_Supplier - Repair_Rate_Defects - Scrap_Rate_at_Supplier) * dt
INIT Defect_Spare_Parts_at_Supplier = xxx

TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:
Defects_Send_to_Supplier = Repair_PO/Time_Factor

Purchased parts are received as a complete order after a certain new buy lead time

OUTFLOWS:
Repair_Rate_Defects = CONVEYOR OUTFLOW
TRANSIT TIME = Repair_Lead_Time
Scrap_Rate_at_Supplier = LEAKAGE OUTFLOW
LEAKAGE FRACTION = 1-Repair_Yield
NO-LEAK ZONE = 100%

Delivered_Spare_Parts(t) = Delivered_Spare_Parts(t - dt) + (Delivery_Spare_Parts - Return_Rate - Scrap_Rate_at_FSE) * dt
INIT Delivered_Spare_Parts = *xxx*

The amount of parts delivered is equal to the demand that have to be delivered if there is enough good stock. Otherwise the available parts are delivered

INFLOWS:
Delivery_Spare_Parts = MIN(Open_Demand,Spare_Parts_Inventory)/Delivery_Time
OUTFLOWS:
Return_Rate (IN SECTOR: Reverse Supply Sector)

Consumable parts are scrapped at FSE, while repairable and excess orders are returned

Scrap_Rate_at_FSE =
(1-Percentage_Repairable_vs_Consumable)*Delivered_Spare_Parts/Scrap_Time

New_Buys_Ordered(t) = New_Buys_Ordered(t - dt) + (New_Buy_Purchase_Order - Production_Rate_New_Buys) * dt

INIT New_Buys_Ordered = *xxx*

TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:
New_Buy_Purchase_Order = New_Buy_PO/Time_Factor
OUTFLOWS:
Production_Rate_New_Buys = CONVEYOR OUTFLOW
TRANSIT TIME = New_Buy_Lead_Time

Scrap_at_FSE(t) = Scrap_at_FSE(t - dt) + (Scrap_Rate_at_FSE) * dt
INIT Scrap_at_FSE = 0
INFLOWS:
Scrap_Rate_at_FSE =
(1-Percentage_Repairable_vs_Consumable)*Delivered_Spare_Parts/Scrap_Time

Scrap_at_Supplier(t) = Scrap_at_Supplier(t - dt) + (Scrap_Rate_at_Supplier) * dt
INIT Scrap_at_Supplier = 0

Parts that cannot be refurbished at repair vendor are scrapped, which depends on the repair yield

INFLOWS:
Scrap_Rate_at_Supplier = LEAKAGE OUTFLOW
LEAKAGE FRACTION = 1-Repair_Yield
NO-LEAK ZONE = 100%

Spare_Parts_Inventory(t) = Spare_Parts_Inventory(t - dt) + (Production_Rate_New_Buys + Repair_Rate_Defects + Good_Returns_Accepted_for_Reuse - Delivery_Spare_Parts) * dt
INIT Spare_Parts_Inventory = *xxx*

Purchased parts are received as a complete order after a certain new buy lead time

INFLOWS:
Production_Rate_New_Buys = CONVEYOR OUTFLOW
TRANSIT TIME = New_Buy_Lead_Time
Repair_Rate_Defects = CONVEYOR OUTFLOW
TRANSIT TIME = Repair_Lead_Time
Good_Returns_Accepted_for_Reuse (IN SECTOR: Reverse Supply Sector)
OUTFLOWS:
Delivery_Spare_Parts = MIN(Open_Demand,Spare_Parts_Inventory)/Delivery_Time

Delivery_Time = 1

The repair yield is randomly assigned each period and will never be larger than 100%

Rand_2 = Random(0,1)

Repair_Yield = if
(IF Rand_2 <0.0386 THEN 0.00 ELSE
IF Rand_2 <0.0416 THEN 0.07 ELSE
IF Rand_2 <0.0417 THEN 0.13 ELSE
IF Rand_2 <0.0426 THEN 0.14 ELSE

...

IF Rand_2 <0.5559 THEN 0.99 ELSE
IF Rand_2 <=1 THEN 1.00 ELSE 0)*Change_Repair_Yield < 1.00

THEN

(IF Rand_2 <0.0386 THEN 0.00 ELSE
IF Rand_2 <0.0416 THEN 0.07 ELSE
IF Rand_2 <0.0417 THEN 0.13 ELSE

...

IF Rand_2 <0.5559 THEN 0.99 ELSE
IF Rand_2 <=1 THEN 1.00 ELSE 0)*Change_Repair_Yield

ELSE 1.00

Scrap_Time = 1

Time_Factor = 1

Change_Repair_Yield = GRAPH(TIME)

(1.00, 1.00), (2.00, 1.00), (3.00, 1.00), (4.00, 1.00), (5.00, 1.00), (6.00, 1.00), (7.00, 1.00), (8.00, 1.00), (9.00, 1.00), (10.0, 1.00), (11.0, 1.00), (12.0, 1.00), (13.0, 1.00), (14.0, 1.00), (15.0, 1.00), (16.0, 1.00), (17.0, 1.00), (18.0, 1.00), (19.0, 1.00), (20.0, 1.00), (21.0, 1.00), (22.0, 1.00), (23.0, 1.00), (24.0, 1.00), (25.0, 1.00), (26.0, 1.00), (27.0, 1.00), (28.0, 1.00), (29.0, 1.00), (30.0, 1.00), (31.0, 1.00), (32.0, 1.00), (33.0, 1.00), (34.0, 1.00), (35.0, 1.00), (36.0, 1.00), (37.0, 1.00), (38.0, 1.00), (39.0, 1.00), (40.0, 1.00), (41.0, 1.00), (42.0, 1.00), (43.0, 1.00), (44.0, 1.00), (45.0, 1.00), (46.0, 1.00), (47.0, 1.00), (48.0, 1.00), (49.0, 1.00), (50.0, 1.00), (51.0, 1.00), (52.0, 1.00), (53.0, 1.00)...

Procurement Sector: Determination Purchase Order

Total_PO(t) = Total_PO(t - dt) + (purchase - received) * dt
INIT Total_PO = init(Defect_Spare_Parts_at_Supplier)+init(New_Buys_Ordered)
INFLOWS:
purchase = (Repair_PO+New_Buy_PO)/Time_Factor
OUTFLOWS:
received = Production_Rate_New_Buys+Repair_Rate_Defects+Scrap_Rate_at_Supplier

Mean_Repair_Yield = *Change_Repair_Yield

The number of new buys ordered depends on the number of parts already sent to the repair vendor and average repair yield

New_Buy_PO = IF Repair_PO = Percentage_Repairable_vs_Consumable*Purchase_Order/Mean_Repair_Yield
THEN (1-Percentage_Repairable_vs_Consumable)*Purchase_Order
ELSE (Purchase_Order-Repair_PO*Mean_Repair_Yield)

The safety stock is determined based on a general formula, which is commonly used in supply chain management

Optimal_Safety_Stock = Safety_Factor*SQRT((Mean_New_Buy_Lead_Time)*Stdev_Demand^2+Mean_Demand^2*Stdev_New_Buy_Lead_Time^2)

Percentage_Repairable_vs_Consumable =

The purchase order depends on the parts needed and already on stock or ordered

- Purchase_Order =
  max((Open_Demand+Optimal_Safety_Stock+Forecast_Demand*((Mean_New_Buy_Lead_Time)
  /30)-Spare_Parts_Inventory-Total_PO),0)

The number of parts sent to the supplier depends on the defect stock and the repair yield

- Repair_PO = IF Purchase_Order > 0 THEN
    IF Defects_at_BlueRoom >
  Percentage_Repairable_vs_Consumable*Purchase_Order/Mean_Repair_Yield
      THEN Percentage_Repairable_vs_Consumable*Purchase_Order/Mean_Repair_Yield
    ELSE Defects_at_BlueRoom
  ELSE 0

The safety factor is the inverse of the cumulative standard normal distribution depending on the service level

```
Safety_Factor = If Target_Service_Level <  0.805  THEN  0.842  ELSE
If Target_Service_Level <  0.815  THEN  0.878  ELSE
If Target_Service_Level <  0.825  THEN  0.915  ELSE
If Target_Service_Level <  0.835  THEN  0.954  ELSE
If Target_Service_Level <  0.845  THEN  0.994  ELSE
If Target_Service_Level <  0.855  THEN  1.036  ELSE
If Target_Service_Level <  0.865  THEN  1.080  ELSE
If Target_Service_Level <  0.875  THEN  1.126  ELSE
If Target_Service_Level <  0.885  THEN  1.175  ELSE
If Target_Service_Level <  0.895  THEN  1.227  ELSE
If Target_Service_Level <  0.905  THEN  1.282  ELSE
If Target_Service_Level <  0.915  THEN  1.341  ELSE
If Target_Service_Level <  0.925  THEN  1.405  ELSE
If Target_Service_Level <  0.935  THEN  1.476  ELSE
If Target_Service_Level <  0.945  THEN  1.555  ELSE
If Target_Service_Level <  0.955  THEN  1.645  ELSE
If Target_Service_Level <  0.965  THEN  1.751  ELSE
If Target_Service_Level <  0.975  THEN  1.881  ELSE
If Target_Service_Level <  0.985  THEN  2.054  ELSE
If Target_Service_Level <  0.995  THEN  2.326  ELSE
If Target_Service_Level <=  1 THEN  7.852 ELSE 0
Mean_Demand = GRAPH(TIME)

Mean_New_Buy_Lead_Time = GRAPH(TIME)
```

Stdev_Demand = GRAPH(TIME)

Stdev_New_Buy_Lead_Time = GRAPH(TIME)

Target_Service_Level = GRAPH(TIME)

Procurement Sector: Determination: Lead Times

Supporting equation to change the lead times on time period 150

New_Buy_Lead_Time = If SWITCH(NB_0,NB_50)=1 THEN New_Buy_Lead_Time_0% ELSE
If SWITCH(NB_25,NB_0)=1 THEN New_Buy_Lead_Time_25% ELSE
New_Buy_Lead_Time_50%

Different distributions for lead times that are randomly assigned

New_Buy_Lead_Time_0% = (IF Rand_4 < 0.0090 THEN ELSE
IF Rand_4 < 0.0174 THEN
IF Rand_4 < 0.0210 THEN

…

IF Rand_4 < 0.9989 THEN
IF Rand_4 < 0.9997 THEN
IF Rand_4 <=1 THEN 500 ELSE 0)+Modification_Mean_New_Buy_Lead_Time

New_Buy_Lead_Time_25% = (IF Rand_4 < 0.0049 THEN
IF Rand_4 < 0.0090 THEN
IF Rand_4 < 0.0210 THEN

…

IF Rand_4 < 0.9996 THEN ELSE
IF Rand_4 <=1 THEN ELSE 0)+Modification_Mean_New_Buy_Lead_Time
New_Buy_Lead_Time_50% = (IF Rand_4 < 0.0049 THEN
IF Rand_4 < 0.0174 THEN
IF Rand_4 < 0.0317 THEN

...

IF Rand_4 < 0.9994 THEN
IF Rand_4 <=1 THEN ELSE 0)+Modification_Mean_New_Buy_Lead_Time

Supporting converter such that the return lead time remains positive

Positive_0% = (IF Rand_1 < 0.0031 THEN ELSE
IF Rand_1 < 0.0180 THEN
IF Rand_1 < 0.0397 THEN

...

IF Rand_1 < 0.9999 THEN ELSE
IF Rand_1 <=1 THEN ELSE 0)+Modification_Mean_Return_Time
Positive_25% = (IF Rand_1 < 0.0031 THEN ELSE
IF Rand_1 < 0.0180 THEN
IF Rand_1 < 0.0685 THEN

...

IF Rand_1 < 0.9995 THEN ELSE
IF Rand_1 <=1 THEN ELSE 0)+Modification_Mean_Return_Time
Positive_41% = (IF Rand_1 < 0.0180 THEN ELSE
IF Rand_1 < 0.0685 THEN
IF Rand_1 < 0.1024 THEN

...

IF Rand_1 < 0.9999 THEN
IF Rand_1 <=1 THEN ELSE 0)+Modification_Mean_Return_Time
Positive_50% = (IF Rand_1 < 0.0031 THEN ELSE
IF Rand_1 < 0.0397 THEN
IF Rand_1 < 0.1024 THEN

...

IF Rand_1 < 0.9997 THEN ELSE
IF Rand_1 <=1 THEN ELSE 0)+Modification_Mean_Return_Time
Rand_1 = Random(0,1)
Rand_3 = Random(0,1)
Rand_4 = Random(0,1)
Repair_Lead_Time = If SWITCH(RP_0,RP_50)=1 THEN Repair_Lead_Time_0% ELSE
If SWITCH(RP_25,RP_0)=1 THEN Repair_Lead_Time_25% ELSE
If SWITCH(RP_41,RP_0)=1 THEN Repair_Lead_Time_41% ELSE
Repair_Lead_Time_50%
Repair_Lead_Time_0% = (IF Rand_3 < 0.0002 THEN ELSE
IF Rand_3 < 0.0004 THEN
IF Rand_3 < 0.0005 THEN

...

IF Rand_3 < 0.9992 THEN ELSE
IF Rand_3 <=1 THEN ELSE 0)+Modification_Mean_Repair_Lead_Time
Repair_Lead_Time_25% = (IF Rand_3 < 0.0002 THEN ELSE
IF Rand_3 < 0.0005 THEN
IF Rand_3 < 0.0012 THEN

...

IF Rand_3 < 0.9995 THEN ELSE
IF Rand_3 <=1 THEN ELSE 0)+Modification_Mean_Repair_Lead_Time

Repair_Lead_Time_41% = (IF Rand_3 < 0.0005 THEN ELSE
IF Rand_3 < 0.0012 THEN ELSE
IF Rand_3 < 0.0128 THEN ELSE

...

IF Rand_3 < 0.9998 THEN ELSE
IF Rand_3 <=1 THEN ELSE 0)+Modification_Mean_Repair_Lead_Time

Repair_Lead_Time_50% = (IF Rand_3 < 0.0005 THEN ELSE
IF Rand_3 < 0.0012 THEN ELSE
IF Rand_3 < 0.0128 THEN ELSE

...

IF Rand_3 < 0.9999 THEN ELSE
IF Rand_3 <=1 THEN ELSE 0)+Modification_Mean_Repair_Lead_Time

Return_Time = If SWITCH(Return_0,Return_41)=1 THEN Return_time_0% ELSE
If SWITCH(Return_25,Return_0)=1 THEN Return_Time_25% ELSE
If SWITCH(Return_50,Return_0)=1 THEN Return_time_50% ELSE
Return_Time_41%

Return_time_0% = If Positive_0% > 0 THEN Positive_0% ELSE 1

Return_Time_25% = If Positive_25% > 0 THEN Positive_25% ELSE 1

Return_Time_41% = If Positive_41% > 0 THEN Positive_41% ELSE 1

Return_time_50% = If Positive_50% > 0 THEN Positive_50% ELSE 1

Modification_Mean_New_Buy_Lead_Time = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

Modification_Mean_Repair_Lead_Time = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

Modification_Mean_Return_Time = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

NB_0 = GRAPH(TIME)

(1.00, 1.00), (2.00, 1.00), (3.00, 1.00), (4.00, 1.00), (5.00, 1.00), (6.00, 1.00), (7.00, 1.00), (8.00, 1.00), (9.00, 1.00), (10.0, 1.00), (11.0, 1.00), (12.0, 1.00), (13.0, 1.00), (14.0, 1.00), (15.0, 1.00), (16.0, 1.00), (17.0, 1.00), (18.0, 1.00), (19.0, 1.00), (20.0, 1.00), (21.0, 1.00), (22.0, 1.00), (23.0, 1.00), (24.0, 1.00), (25.0, 1.00), (26.0, 1.00), (27.0, 1.00), (28.0, 1.00), (29.0, 1.00), (30.0, 1.00), (31.0, 1.00), (32.0, 1.00), (33.0, 1.00), (34.0, 1.00), (35.0, 1.00), (36.0, 1.00), (37.0, 1.00), (38.0, 1.00), (39.0, 1.00), (40.0, 1.00), (41.0, 1.00), (42.0, 1.00), (43.0, 1.00), (44.0, 1.00), (45.0, 1.00), (46.0, 1.00), (47.0, 1.00), (48.0, 1.00), (49.0, 1.00), (50.0, 1.00), (51.0, 1.00), (52.0, 1.00), (53.0, 1.00)...

NB_25 = GRAPH(TIME)

(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

NB_50 = GRAPH(TIME)

(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

Return_0 = GRAPH(TIME)

(1.00, 1.00), (2.00, 1.00), (3.00, 1.00), (4.00, 1.00), (5.00, 1.00), (6.00, 1.00), (7.00, 1.00), (8.00, 1.00), (9.00, 1.00), (10.0, 1.00), (11.0, 1.00), (12.0, 1.00), (13.0, 1.00), (14.0, 1.00), (15.0, 1.00), (16.0, 1.00), (17.0, 1.00), (18.0, 1.00), (19.0, 1.00), (20.0, 1.00), (21.0, 1.00), (22.0, 1.00), (23.0, 1.00), (24.0, 1.00), (25.0, 1.00), (26.0, 1.00), (27.0, 1.00), (28.0, 1.00), (29.0, 1.00), (30.0, 1.00), (31.0, 1.00), (32.0, 1.00), (33.0, 1.00), (34.0, 1.00), (35.0, 1.00), (36.0, 1.00), (37.0, 1.00), (38.0, 1.00), (39.0, 1.00), (40.0, 1.00), (41.0, 1.00), (42.0, 1.00), (43.0, 1.00), (44.0, 1.00), (45.0, 1.00), (46.0, 1.00), (47.0, 1.00), (48.0, 1.00), (49.0, 1.00), (50.0, 1.00), (51.0, 1.00), (52.0, 1.00), (53.0, 1.00)...

Return_25 = GRAPH(TIME)

(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

Return_41 = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

Return_50 = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

RP_0 = GRAPH(TIME)
(1.00, 1.00), (2.00, 1.00), (3.00, 1.00), (4.00, 1.00), (5.00, 1.00), (6.00, 1.00), (7.00, 1.00), (8.00, 1.00), (9.00, 1.00), (10.0, 1.00), (11.0, 1.00), (12.0, 1.00), (13.0, 1.00), (14.0, 1.00), (15.0, 1.00), (16.0, 1.00), (17.0, 1.00), (18.0, 1.00), (19.0, 1.00), (20.0, 1.00), (21.0, 1.00), (22.0, 1.00), (23.0, 1.00), (24.0, 1.00), (25.0, 1.00), (26.0, 1.00), (27.0, 1.00), (28.0, 1.00), (29.0, 1.00), (30.0, 1.00), (31.0, 1.00), (32.0, 1.00), (33.0, 1.00), (34.0, 1.00), (35.0, 1.00), (36.0, 1.00), (37.0, 1.00), (38.0, 1.00), (39.0, 1.00), (40.0, 1.00), (41.0, 1.00), (42.0, 1.00), (43.0, 1.00), (44.0, 1.00), (45.0, 1.00), (46.0, 1.00), (47.0, 1.00), (48.0, 1.00), (49.0, 1.00), (50.0, 1.00), (51.0, 1.00), (52.0, 1.00), (53.0, 1.00)...

RP_25 = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

RP_41 = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

RP_50 = GRAPH(TIME)
(1.00, 0.00), (2.00, 0.00), (3.00, 0.00), (4.00, 0.00), (5.00, 0.00), (6.00, 0.00), (7.00, 0.00), (8.00, 0.00), (9.00, 0.00), (10.0, 0.00), (11.0, 0.00), (12.0, 0.00), (13.0, 0.00), (14.0, 0.00), (15.0, 0.00), (16.0, 0.00), (17.0, 0.00), (18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.00), (26.0, 0.00), (27.0, 0.00), (28.0, 0.00), (29.0, 0.00), (30.0, 0.00), (31.0, 0.00), (32.0, 0.00), (33.0, 0.00), (34.0, 0.00), (35.0, 0.00), (36.0, 0.00), (37.0, 0.00), (38.0, 0.00), (39.0, 0.00), (40.0, 0.00), (41.0, 0.00), (42.0, 0.00), (43.0, 0.00), (44.0, 0.00), (45.0, 0.00), (46.0, 0.00), (47.0, 0.00), (48.0, 0.00), (49.0, 0.00), (50.0, 0.00), (51.0, 0.00), (52.0, 0.00), (53.0, 0.00)...

Reverse Supply Sector

Defects_at_BlueRoom(t) = Defects_at_BlueRoom(t - dt) + (Defect_Returns_Accepted_for_Reuse - Defects_Send_to_Supplier) * dt
INIT Defects_at_BlueRoom =

This equations selects the defect parts from the return flow and stores these parts on defect stock blueroom

INFLOWS:
Defect_Returns_Accepted_for_Reuse = (Returns_Backlog_at_BlueRoom*(1-Good_versus_Defect__Reusables_Ratio))/Time_Factor
OUTFLOWS:
Defects_Send_to_Supplier (IN SECTOR: Procurement Sector)

Returns_Backlog_at_BlueRoom(t) = Returns_Backlog_at_BlueRoom(t - dt) + (Return_Rate - Good_Returns_Accepted_for_Reuse - Defect_Returns_Accepted_for_Reuse) * dt
INIT Returns_Backlog_at_BlueRoom = 0
INFLOWS:
Return_Rate = Percentage_Repairable_vs_Consumable*Delivered_Spare_Parts/Return_Time

This equations selects the good returns and sent these parts to good stock

OUTFLOWS:
Good_Returns_Accepted_for_Reuse = (Returns_Backlog_at_BlueRoom*Good_versus_Defect__Reusables_Ratio)/Time_Factor
Defect_Returns_Accepted_for_Reuse = (Returns_Backlog_at_BlueRoom*(1-Good_versus_Defect__Reusables_Ratio))/Time_Factor

Good_versus_Defect__Reusables_Ratio =