MASTER

Designing a multi-echelon inventory control model for the F-35 spare parts supply chain using ADI

Oosterwaal, K.

Award date:
2021

Designing a multi-echelon inventory control model for the F-35 spare parts supply chain using ADI

in partial fulfilment of the requirements for the degree of

Master of Science

in Operations Management and Logistics

TU/e supervisors:	Dr. S. Poormoaied
	Dr. Z. Atan
Company supervisor:	Jürgen Donders
Author:	Kyle Oosterwaal
Student Nr.:	0895882

Eindhoven, February 2021

Abstract

This Master thesis presents the design of a multi-echelon inventory control model for the European F-35 spare parts supply chain, using ADI of component failures. In addition, the use of lateral transshipments between the local warehouses is investigated. The aim of the thesis is to find optimal base-stock levels, for the central warehouse and local warehouses, that minimize the inventory investment costs while satisfying a 95% availability level. To achieve this, multi-echelon inventory models are designed, which are based on the METRIC model. In order to strengthen the findings of the multi-echelon models, simulation models are developed to validate the results. Based on the results of the designed models, it is investigated which model performs best and recommendations for the company are given.

Keywords: Spare parts, Inventory control, Multi-echelon, METRIC model, Advance demand information (ADI), Lateral transshipments, Service logistics.

Executive summary

The Netherlands plays a crucial role in the spare parts logistics for the European F-35 fighter jets in the coming decades. The F-35 Joint Program Office (located at the United States) chose the Netherlands to store and manage spare parts for over 500 F-35s in the EMEA (Europe, Middle East & Africa) region. At the end of 2019, the first F-35s were stationed at various European air bases. A rapid build-up of logistics support for Europe is important for various air forces in the region.

The thesis focuses on designing a multi-echelon inventory control model for the European F-35 spare parts supply chain, using ADI of component failures. The goal of the project is to determine optimal base-stock levels, for the central warehouse and local warehouses, that minimize the inventory investment costs while satisfying a 95% availability level. In addition, it is investigated if using reactive lateral transshipments between the local warehouses yields even better results, i.e., lower inventory investment costs. To achieve this, multi-echelon inventory models are designed. The mathematical models determine at which locations, which parts and in what quantities must be stored in order to achieve the 95% availability requirement while at the same time minimizing inventory investment costs. In order to strengthen the findings of the multi-echelon models, simulation models are developed to validate the results. A continuous one-for-one, $(S-1, S)$, inventory replenishment policy is used and Poisson distributed demand. The problem faced in this paper is known in literature as the repairable inventory problem.

The METRIC (Multi-Echelon Technique for Recoverable Item Control) model is selected from literature based on an extensive literature review, and it is used in this paper as the base model. The base model is the model without ADI of component failures and lateral transshipments. The base model determines optimal base-stock levels, for the central warehouse and local warehouses, that minimize the inventory investment costs while satisfying the 95% availability constraint. This model serves as the baseline.

The model with ADI is the model that makes use of the predictions of component (LRC) failures. The goal of the predictions of component failures (ADI) is to enrich the logistics planning with flight and maintenance data in order to reduce the logistics costs and increase the availability of components. These predictions result in early warnings, which indicate that a component (LRC) is going to fail within a few days at a certain location with a certain probability. The warning time is the time from the moment a warning is received until the moment the component fails. Therefore, by using the early warnings, or ADI, it is known a few days in advance at which location a component (LRC) is needed with a certain probability. The warning time, resulting from the ADI of component failures, is included in the model as a reduction in the supply lead times. The inaccuracy, or imperfectness, of the ADI is included in the model as well. This is done by making a distinction between false negatives and false positives. False negatives are components (LRCs) that fail without receiving a warning in advance, and false positives are components that fail at a later moment than predicted. For the false negatives, the result is no reduction in the supply lead times, whereas for the false

positives a reduction in the supply lead times is applied, but the component is actually not needed yet. False negatives are very problematic because when a component fails unannounced at a local warehouse and there is no stock at that warehouse, it results in a backorder and therefore in downtime for the F-35s.

In addition, the warnings also specify which smaller subcomponent (SRC) is going to fail that will cause the LRC failure. By knowing which SRC causes the LRC failure, inspection time at the repair shop is saved. Furthermore, the repair shop can order the SRCs needed for the repair in advance of the LRC failure, so there will be less waiting time for the subcomponents (SRCs). Zero inspection time and less waiting time on SRCs results in a shorter repair lead time for the LRCs. A shorter repair lead time, in turn, results in lower required base-stock levels. Therefore, the effect of warning time, resulting from the ADI of component failures, on the repair lead time is investigated and included in the model with ADI.

Finally, the model with lateral transshipments (and ADI) is the model that makes use of reactive lateral transshipments. A reactive lateral transshipment is defined as a local warehouse which provides stocked items (LRCs) to another local warehouse which faces a stock out (or the risk of a stock out). Therefore, when using lateral transshipments, a demand of a local warehouse can be satisfied from the central warehouse, as well as from another local warehouse. The model allows for lateral transshipments only when a local warehouse faces demand while it has no inventory on hand, i.e., when it faces a stock out. This is the case when the central warehouse is not able to satisfy the demand of the local warehouse. Two different lateral transshipment rules are used, which are the minimum backorder rule and the maximum inventory on hand rule.

The model results show that the base model requires a network stock of 17 LRCs and achieves an availability level of 95.9%. 9 LRCs are kept in stock at the central warehouse and every local warehouse keeps 1 LRC in stock, i.e., $S_{i,0} = 9$ and $S_{i,j} = 1$. These results are the baseline results. The model results show that including ADI of component failures in the base METRIC model, results in a significant reduction of the network stock and therefore in a significant reduction of the inventory investment costs.

When facing perfect ADI, i.e., 3 days warning time without false negatives, the model with ADI is the best model to use. This model results in a network stock of 10 LRCs, a 96.7% availability level, and an inventory investment reduction of 41.2% compared to the base model. All 10 LRCs should be kept in stock at the central warehouse (centralized allocation), i.e., $S_{i,0} = 10$ and $S_{i,j} = 0$. Including lateral transshipments in this situation yields no further improvements.

When facing imperfect ADI, i.e., 3 days warning time with 10% false negatives, the model with ADI and lateral transshipments is the best model to use. This model results in a network stock of 11 LRCs, a 95.9% availability level, and an inventory investment reduction of 35.3% compared to the base model. 3 LRCs should be kept in stock at the central warehouse and every local warehouse should keep 1 LRC in stock (decentralized allocation), i.e., $S_{i,0} = 3$ and $S_{i,j} = 1$. It can be concluded that using reactive lateral transshipments between the local warehouses almost neutralize the negative effect of the false negatives. Furthermore, no significant performance difference is observed between the two transshipment rules.

Contents

List of figures

List of tables

1. Introduction

In this report, the Master thesis project of Operations Management and Logistics (OML) is described. The Master thesis project is executed at Gordian Logistic Experts B.V. The thesis focusses on designing a multi-echelon inventory control model for the European F-35 spare parts supply chain, using advance demand information (ADI) of component failures. First, a description of the company will be given in this section. Then, the project description will be provided in detail in section 2. The research questions will be described in section 3. Next, the methodology and the METRIC model to be used in the thesis are elaborated in section 4 and section 5, respectively. In section 6, the numerical results of the different models are described and explained. Finally, the conclusions and recommendations for the company are provided in section 7.

1.1 Company description

Gordian Logistic Experts B.V. is an international consultancy firm that is specialized in service logistics and spare parts management. Gordian delivers consultancy services to their customers, which include service and logistic strategy development, service business transformation, inventory optimization, supply chain optimization and supply chain collaboration. Furthermore, Gordian delivers concrete solutions to their customers in addition to the consultancy services. These solutions can be categorized into planning services, customer-specific tool development and business training. Planning services solutions focus on providing the correct forecasting models, inventory models and the parameters within these models. For customer-specific tool development, Gordian has a flexible and modular development platform with which they can make professional, cost-effective, and customer-specific spare parts planning tools in an affordable way. Furthermore, Gordian is actively involved in innovation projects in service logistics and spare parts management in collaboration with the government, industry, universities, and scientific institutions. Gordian has delivered their consultancy services and concrete solutions to a wide range of customers within the service logistics and spare parts management. Examples of the customers of Gordian are BP, Enexis, Gasunie, GVB, KLM, Ministry of Defense, Port of Antwerp, Contiweb, Lely and many more.

2. Project description

In this section, the project will be described. First, the background information is provided in section 2.1, which is followed by a detailed description of the project in section 2.2.

2.1 Background information

The Netherlands plays a crucial role in the spare parts logistics for the European F-35 fighter jets in the coming decades. The F-35 Joint Program Office (located at the United States) chose the Netherlands to store and manage spare parts for over 500 F-35s in the EMEA (Europe, Middle East & Africa) region. At the end of 2019, the first F-35s were stationed at various European air bases. A rapid build-up of logistics support for Europe is important for various air forces in the region and OneLogistics has been commissioned to facilitate this. OneLogistics has hired Gordian Logistic Experts to support them in this task. OneLogistics is a company that extends supply chains by including global transport solutions, warehousing, packaging solutions, customs and value-added tax (VAT) solutions, (ITAR) compliance, (European) transport solutions as well as the management of return shipments. A central warehouse is set up at the Logistics Center Woensdrecht (LCW). In this automated warehouse, spare parts for the F-35s, as well as the F135 engine, are stored and then shipped to the European air bases when they need spare parts. Maintenance activities for the F135 engines are performed at the central repair shop, which is the repair shop at the central warehouse. Furthermore, maintenance and repair of the F-35 spare parts are performed at various repair vendors in Europe, of which the central repair shop can be one of them. OneLogistics has the ambition to function as a regional control tower, which facilitates collaboration between service providers by connecting flows of goods and information. OneLogistics is a fourth-party logistics provider, or 4PL, because it acts as a supply chain director that searches for the best solution for its client's supply chain.

Figure 1 shows a graphical representation of the European F-35 spare parts supply chain. The black box indicates the scope of the project. New spare parts are supplied to the central warehouse in Woensdrecht (LCW) by external suppliers such as Lockheed Martin (LM) and Pratt & Whitney (P&W). However, this process is left out of scope because we deal with repairable items, which are called LRCs (line replaceable components), in a closed loop (it is assumed that no parts are scrapped). Therefore, new spare parts are only supplied to the central warehouse (LCW) in the initial phase. The spare parts are stored in the central warehouse until the parts are demanded by the local warehouses. Part failures constitute the demand of the local warehouses and the demand of the local warehouses constitutes the demand at the central warehouse. Part failures constitute a Poisson process with a constant rate. The central warehouse (LCW) is the supplier of spare parts within the scope of the project and the customers are the local warehouses. Each local warehouse serves a number of F-35s, which is indicated in parentheses in figure 1. Each F-35 consists of a set of repairable parts, which are called LRCs. If a part fails at a local warehouse, a spare part stocked at the local warehouse is used to replace the defective part, if the local warehouse has a spare part on stock. Otherwise, a backorder arises, until a spare part becomes available from the central warehouse and this results in downtime for the F-35s. Upon failure, a replenishment order is immediately placed at the central warehouse. The replenishment order arrives after a deterministic lead time (supply lead time), if LRC stock is available at the central warehouse. Otherwise, the order is backordered until a spare part becomes available from a repair shop at the central warehouse. Replenishment orders from the local warehouses at the central warehouse are fulfilled according to first-come, first-served (FCFS) policy. The defective part at the local warehouse is immediately sent to a repair shop to be repaired there. It takes a certain random lead time (repair lead time) before the defective LRC is repaired and back in stock at the central warehouse. Repaired parts are considered as new parts. The repair lead time, which is the time needed to repair defective parts (LRCs) until they are ready to use again, is indicated with the thick black arrow.

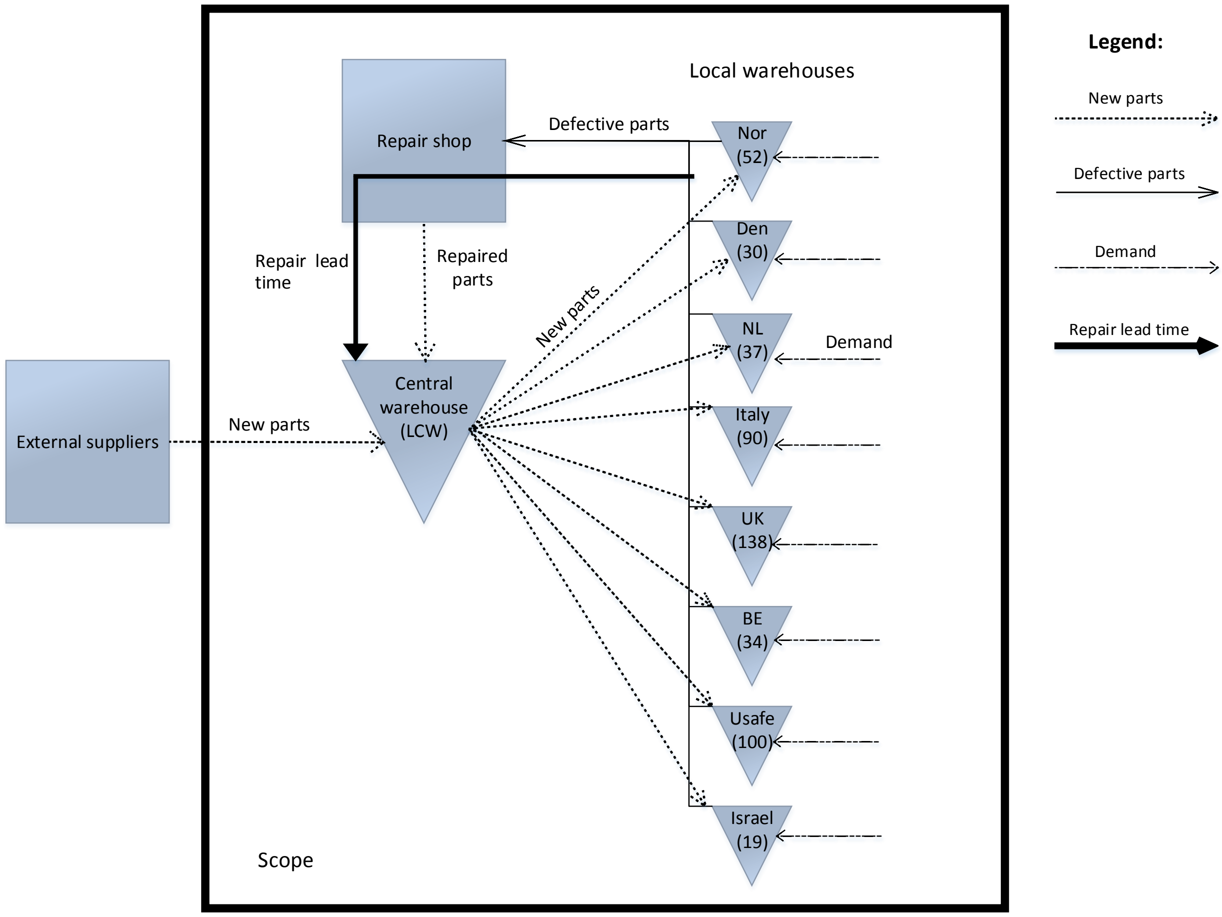

Figure 1. European F-35 supply chain

The service logistics can be innovated and improved by using predictions of component failures (ADI). The Royal Netherlands Aerospace Center (NLR) will provide the predictions of component failures (ADI) in this project. The Royal Netherlands Aerospace Center (NLR) is the central institute for aerospace research in the Netherlands. Since 1937, the NLR has been an independent foundation that provides technological support to the aerospace industry and government. That sector includes industries, users of military and civil aircraft, airport operators, air traffic control organizations, government agencies and international organizations. The goal of the predictions of component failures (ADI) is to enrich the logistics planning with flight and maintenance data in order to reduce the logistics costs and increase the availability of components. NLR uses flight and maintenance data from F-16s to reliably predict the failure time, failure mode and confidence interval for three selected LRCs, which are the 13th stage valve and the main landing gears (features: very expensive and slow movers), that are critical to jet operation. NLR uses machine learning techniques to predict the failure time, failure mode and probability of failure of the LRCs. F-16 data is used because F-35 data is not yet available and because the selected parts of the F-16 are similar to those of the F-35. F-35 data is not yet available because the F-35s are not operational yet in the EMEA region, so there is no flight and maintenance data available. However, the United States has limited F-35 data available, but they are not willing to share this information.

The predictions of component failures (ADI) result in early warnings. These early warnings indicate that a component (LRC) is going to fail within a few days at a certain location with a certain probability. The warning time is the time from the moment a warning is received until the moment the component fails. Therefore, by using the ADI of component failures, or early warnings, it is known a few days in advance at which location a component (LRC) is needed with a certain probability. In other words, the inventory planner will know a few days in advance which parts are possibly needed at which locations. Based on this, the decision is made to ship a part from the central warehouse. Besides, the early warnings also specify the failure mode, so it is also known in advance which SRC (shop replaceable component) will cause the LRC failure. The repair shop can use this information by ordering the SRCs that are needed for the repair earlier.

2.2 The project

The project is about designing a multi-echelon inventory control optimization model for the European F-35 spare parts supply chain, using ADI of component failures. The service logistics can be innovated and improved by using predictions of component failures (ADI), as stated in section 2.1. In order to investigate the effects of advance demand information (ADI) and to uncover the added value on the supply chain, two situations have to be modeled. First, the situation without ADI is needed, which is called the “as-is situation”, and this situation serves as the baseline. Then, the situation with ADI is needed, which is called the “to-be situation”, in order to uncover the effects and added value of ADI compared to the baseline. Both situations will now be described.

2.2.1 As-is situation

Without ADI of component failures, the supply chain sometimes has a relatively short planning horizon. Because it is not known in advance which parts (LRCs) are needed at which locations, extra spare parts are placed in warehouses at strategic locations to meet the needs of the customers. At least one item (LRC) per part number is kept in stock at each air base in order to achieve the availability requirement. However, this results in high local stocks and therefore a high network stock, as shown in figure 2. The network stock is defined as the sum of the stock at the local warehouses and the central warehouse. The stock levels are linked to investment costs in the project, i.e., for every item (LRC) put on stock investment costs have to be paid. Therefore, keeping one item in stock at each air base results in additional inventory investment costs.

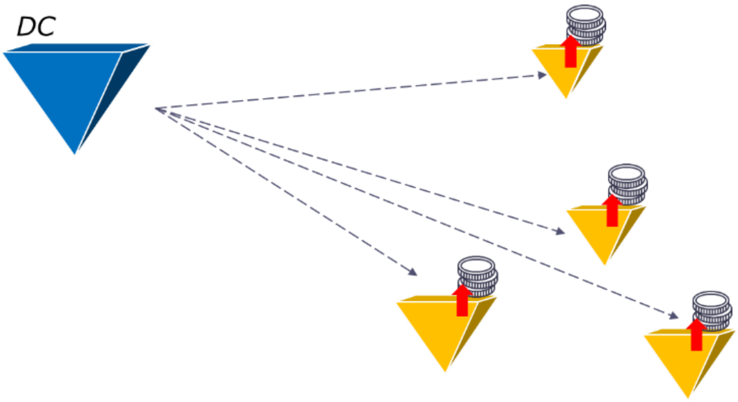

Figure 2. As-is situation

2.2.2 To-be situation

By using the ADI of component failures, it is known a few days in advance which parts (LRCs) are needed at which locations with a certain probability, such that these parts can be shipped earlier. The expected effects of the ADI of component failures are that it leads to the centralization of the stock on LCW (higher central stock), lower local stocks and higher availability due to less waiting time for a component, as shown in figure 3. When the warning time is greater than or equal to the supply lead time, which is the time needed to ship parts from the central warehouse to the local warehouses, even no local stock is needed. In this way, a lower network stock can be realized. Besides, the ADI of component failures also has an effect on the repair lead time, which is the time needed to repair defective parts (LRCs) until they are ready to use again. The early warnings also specify the failure mode, so it is also known in advance which SRC will cause the LRC failure. This shortens the inspection time at the repair shop. Furthermore, the repair shop can order the parts (SRCs) needed for the repair earlier, because it is known which parts will be needed soon. Ordering earlier and a shorter inspection time result in a shorter repair lead time. A shorter repair lead time ensures a shorter resupply time of the components (LRCs) and therefore a lower network stock is required.

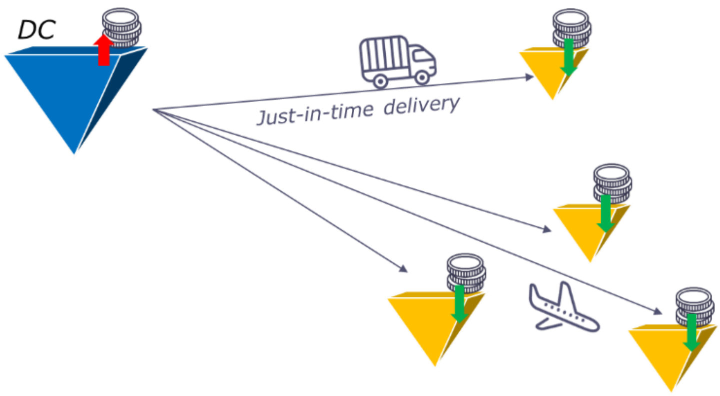

Figure 3. To-be situation

2.2.3 Project goal

The goal of the project is to optimize the inventory control for the European F-35 spare parts supply chain, using ADI of component failures, such that the inventory investment costs are minimized while satisfying a 95% availability level. In specific, the goal of the project is to determine optimal base-stock levels that minimize the inventory investment costs while satisfying a 95% availability level, for the situations with and without early warnings (ADI). The effects of the early warnings on the required stock levels have to be investigated. Besides, the effects of the early warnings on the repair lead time will also be investigated because the repair lead time has impact on the required stock levels. The expected effects of the early warnings (ADI), as described in section 2.2.2, are higher stock at the central warehouse, lower local stocks (zero if warning time ≥ supply lead time), shorter repair lead time, lower required network stock and higher availability, compared to the situation without early warnings. To achieve this, multi-echelon inventory models have to be designed, for the “as-is situation” and the “to-be situation”, that demonstrate and confirm the above-mentioned effects. The mathematical models will determine at which locations, which parts and in what quantities must be stored in order to achieve the 95% availability requirement while at the same time minimizing inventory investment costs. In order to strengthen the findings of the multi-echelon models, simulation models will be developed to validate the results. When the results of the multi-echelon models and simulation models match, it can be stated that the results are valid.

2.2.4 Model assumptions

As stated in 2.2.3, multi-echelon models and simulation models have to be designed, for the “as-is situation” and “to-be situation”, that demonstrate the effects and added value of using ADI of component failures for the European F-35 spare parts supply chain. For designing the multi-echelon models and simulation models the following assumptions are made, which are justified in section 2.1.

- Two-echelon spare parts distribution system for low demand, expensive items
- Poisson distributed demand/failure process with constant rate
- Demand rate is based on the part MTBF (mean time between failures) and the number of aircrafts at the local warehouses (stated between parentheses in figure 1)
- Deterministic supply lead times (all between 0 and 2 days)
- Stochastic repair lead time: normally distributed
- $(S-1, S)$ inventory policy: one-for-one replenishment strategy
- FCFS (first come first served) policy for replenishment orders at the central warehouse
- Advance demand information (ADI) is used by means of predictions of component failures
- No condemnation: all parts are repaired successfully
- No batching: expensive, low demand items
- No multiple demand classes: same service level (95% availability) for all customers
- No criticality: if a LRC fails the system (aircraft) fails
- No emergency shipments: supply lead times are already short
- Lateral transhipments are allowed

3. Research questions

In this section, the main goal and corresponding research questions are described. The main research question follows from the goal of the project. The goal of the project, as mentioned in section 2.2.3, is the following:

- *The goal of the project is to optimize the inventory control for the European F-35 spare parts supply chain, using ADI of component failures, such that the inventory investment costs are minimized while satisfying a 95% availability level.*

Therefore, the main research question is formulated as follows:

- *How to design an inventory control optimization model for the European F-35 spare parts supply chain, using ADI of component failures, such that the inventory investment costs are minimized while satisfying a 95% availability level?*

In order to answer the main research question, it is decomposed into a few sub research questions. The sub research questions are the following:

- *Which models can be used for inventory control optimization in a multi-echelon spare parts distribution system, subject to a service level constraint?*

  This question will give insight into which models exist for optimizing the inventory control without the use of ADI of component failures. The different mathematical models are compared and reviewed, and this analysis forms the basis of the model to be designed.

- *How to design the inventory control optimization model such that ADI of component failures are optimally used?*

  This question will give insight into ways for including the use of ADI of component failures into inventory control optimization models. The designed inventory control model with the use of ADI is applied.

- *What are the results of the designed model?*

  The results of the designed model are analyzed and explained. The results of the model will be compared to the current situation and recommendations for the company can be given.

4. Methodology

In this section, the methodology and solution approach for answering the main research question is described. The first step of the project is to collect all the information and data that is needed to execute the project. The information and data that is needed are for example the demand distribution with corresponding demand rate, what inventory policy is used, who are the suppliers, which warehouses to include, where is the repair shop, what are the (supply and repair) lead times, etc. This information has already been collected.

Furthermore, an extensive literature study is needed before the project can be executed properly. This literature study has already been performed. The goal of the project is to optimize the inventory control for the European F-35 spare parts supply chain, using ADI of component failures, such that the inventory investment costs are minimized while satisfying a 95% availability level. Therefore, the literature study was focused on investigating and evaluating the methods and models that exist in literature for inventory control optimization in a multi-echelon spare parts distribution system, subject to a service level (availability) constraint. Furthermore, the literature study was focused on investigating and evaluating the methods that exist to include advance demand information (predictions of component failures) and lateral transshipments in these inventory control models found in the literature.

According to the reviewed literature repairable inventory systems are common in the military and in a variety of commercial settings. The typical problem is concerned with the optimal stocking of the repairable parts at the bases and at the central depot. The central depot repairs failed units returned from the bases while providing some predetermined level of service. The objective of such a system is typically maximizing the availability of aircrafts, or conversely minimizing the backorders and hence the number of grounded aircrafts, subject to a budget constraint. The METRIC model (Multi-Echelon Technique for Recoverable Item Control) is extensively discussed in literature, since it represents a fundamental development in repairable inventory theory and because so many later models are METRIC based. Many repairable inventory theory models are based on Sherbrooke's METRIC model for setting inventory levels and allocating these units to achieve some desired level of service, measured by the expected backorders at the base level (Sherbrooke, 1968). Later models such as MOD-METRIC (multi-indenture structure) and VARI-METRIC (multi-indenture structure and variance of pipeline inventories) are extensions to the base METRIC model and many modifications, such as lateral transshipments, are based on the METRIC logic. METRIC takes a system view of the repairable inventory problem since it is concerned with setting the initial levels of inventory and the distribution of the inventory among the bases to support a system-wide objective of minimizing backorders. A continuous one-for-one, $(S-1, S)$, inventory replenishment policy is used. Multi-echelon, multi-indenture, METRIC-type models have been implemented in various software tools, in use at various organizations. Historically, military organizations, especially the US military forces, have been the first to adopt such models. Also, outside the military these models have been applied. The repairable inventory problem faced by the METRIC model is identical to the problem faced in the thesis. Also, the assumptions of the METRIC model, stated in section 5, match the assumptions made in the thesis, stated in section 2.2.4. Therefore, the METRIC model is the most suitable and promising model to be used in the thesis and this model will serve as the base model. The METRIC model with the Greedy solution algorithm formulated by Basten & Van Houtum (2014), as described in section 5, will be followed and used in the thesis.

Furthermore, for including advance demand information (ADI) Hariharan & Zipkin (1995) found that demand lead times are, in a precise sense, the opposite of supply lead times. That is, the effect of a demand lead time on overall system performance is precisely the same as a corresponding reduction in the supply lead time. Therefore, the warning time in the thesis, resulting from the ADI of component failures, has to be included in the model as a reduction in the supply lead times. The inaccuracy, or imperfectness, of the ADI has to be included in the model as well. This will be done by making a distinction between false negatives and false positives. False negatives are components that fail without receiving a warning in advance, and false positives are components that fail at a later moment than predicted. For the false negatives, the result will be no reduction in the supply lead times, whereas for the false positives there will be a reduction in the supply lead times, but the component is actually not needed yet. Topan et al. (2018) revealed that using imperfect ADI yields substantial savings, but only when the demand lead time is larger than the supply lead time. In this case, the average PCR (percentage cost reduction) is found to be 30.06%, and the maximum PCR is found to be 89.96%. Furthermore, the amount of savings is sensitive to the levels of the imperfectness aspects. Having fewer false negatives is more desirable than having fewer false positives and returning excess inventory is quite effective in coping with the consequences of false ADI, particularly for slow-moving items. The one-for-one $(S-1, S)$ replenishment strategy, or base-stock policy, can still be used. However, when using real-time condition-based sensor information, which is not the case in the thesis, the best way to incorporate that information is by adapting the base-stock policy to a condition-based inventory policy (Lin et al., 2017; Li & Ryan, 2011).

Finally, for including lateral transshipments the METRIC model can still be used, but it has to be extended with a new variable, i.e., the fraction of demand satisfied by lateral transshipments. Alfredsson and Verrijdt (1999) compared their model with lateral transshipments to the VARI-METRIC model and they found a maximum cost reduction of 43.9% and a minimum cost reduction of 13.2%. The results also show that in many cases the stock levels are lower, especially the central stock level showed a significant decrease. In addition, Kranenburg (2006) discussed a semi-conductor company ASML and showed that using reactive lateral transshipments can save the company up to 50% of annual inventory related costs for spare parts. These results indicate that using lateral transshipments in a distribution network for service parts can be very beneficial. Therefore, the use of lateral transshipments will be investigated for the European F-35 spare parts supply chain. This will be done by including lateral transshipments in the models and by analyzing if this yields better results compared to the models without lateral transshipments.

After having selected the METRIC model from literature that will be used in the thesis, the design phase can be started. The multi-echelon models can now be designed based on the METRIC model that is selected from literature. First, the multi-echelon model without warning time (ADI) is designed. This model will determine the optimal base-stock levels for the

European F-35 spare parts supply chain when ADI of component failures is not used. This model will serve as the baseline, as earlier mentioned. Then, warning time will be included in the multi-echelon model. Based on the methods found in the literature, warning time has to be included in the model as a reduction in the supply lead times (Hariharan & Zipkin, 1995). The new multi-echelon model will determine the optimal base-stock levels for the European F-35 spare parts supply chain when ADI of component failures is used. Therefore, the effects of warning time on the required stock levels can now be determined. The warning time that is included in the multi-echelon model is based on a 100% reliability of the ADI of component failures. However, in practice the reliability will be lower, and this results in prediction errors. Prediction errors can be false negatives or false positives. False negatives are components that fail without receiving a warning in advance, and false positives are components that fail at a later moment than predicted. Therefore, the ADI (in)accuracy has to be included in the multi-echelon model with warning time in order to obtain a model that is as close as possible to reality. The ADI (in)accuracy will be included in the model by applying no reduction in the supply lead times for the false negatives, whereas for the false positives a reduction in the supply lead times will be applied. When this is done, the real effect of warning time on the required stock levels can be determined. The multi-echelon models with and without warning time (ADI) are created by now and the required stock levels are determined in both situations. So far, the designed multi-echelon models did not make use of lateral transshipments. Therefore, new multi-echelon models that make use of lateral transshipments will be designed and this will be done by including a new variable in the model, i.e., the fraction of demand satisfied by lateral transshipments. The results of these models will be compared to the models without lateral transshipments in order to analyse if the use of lateral transshipments is beneficial for the European F-35 spare parts supply chain. All the multi-echelon models are designed by now and the base-stock levels are determined in all situations. In order to strengthen the findings of the multi-echelon models, simulation models will be developed to compare and validate the results. When the results of the multi-echelon models and simulation models match, it can be stated that the results are valid. Finally, the results will be presented in a clear and complete overview.

Until now, only the effect of warning time (ADI) on the required stock levels is investigated. The effect of warning time on the repair lead time will now be investigated. Simulation models will be developed for the situations with and without warning time in which the repair lead time is simulated. From these simulations, the average repair lead time can be determined in both situations. Now, the effect of warning time on the repair lead time is known. The average repair lead time with and without warning time is then used in the designed multi-echelon models as input variable. The multi-echelon models will give the required stock levels as output for both situations. Therefore, the effect of warning time (ADI) on the repair lead time and in turn on the required stock levels is determined. Finally, the results will be presented in a clear and complete overview. After having obtained all the results of the multi-echelon models and simulation models by following the described methodology, the main research question can be answered.

5. Problem analysis

In this section, the METRIC model that will be used in the thesis as the base model will be described in detail. METRIC is a mathematical model, which is capable of determining optimal base and depot stock levels for a group of repairable items; its governing purpose is to optimize system performance for specified levels of system investment. First, the base METRIC model for a two-echelon network is described. The network consists of a number of local warehouses and a central warehouse. Next, the METRIC model assumptions are described. Then, exact analysis of the METRIC model, the optimization problem, and the Greedy solution algorithm are described in detail. Furthermore, some alternative service measures are addressed. At last, the METRIC model extensions that will be used in the thesis, i.e., lateral transshipments and advance demand information (ADI), are described.

5.1 METRIC model

5.1.1 Model description

The Netherlands plays a crucial role in the spare parts logistics for the European F-35 fighter jets in the coming decades. The F-35 Joint Program Office (located at the United States) chose the Netherlands to store and manage spare parts for over 500 F-35s in the EMEA (Europe, Middle East & Africa) region. At the end of 2019, the first F-35s were stationed at various European air bases. A rapid build-up of logistics support for Europe is important for various air forces in the region. A central warehouse is set up at the Logistics Center Woensdrecht (LCW). In this automated warehouse, spare parts for the F-35s, as well as the F135 engine, are stored and then shipped to the European air bases when they need spare parts. Maintenance activities for the F135 engines are performed at the central repair shop, which is the repair shop at the central warehouse. Furthermore, maintenance and repair of the F-35 spare parts are performed at various repair vendors in Europe, of which the central repair shop can be one of them. New spare parts are supplied to the central warehouse in Woensdrecht (LCW) by external suppliers such as Lockheed Martin (LM) and Pratt & Whitney (P&W). However, this process is left out of scope because we deal with repairable items, which are called LRCs, in a closed loop (it is assumed that no parts are scrapped). Therefore, new spare parts are only supplied to the central warehouse in the initial phase. The spare parts are stored in the central warehouse until the parts are demanded by the local warehouses. Part failures constitute the demand of the local warehouses and the demand of the local warehouses constitutes the demand at the central warehouse. Part failures constitute a Poisson process with a constant rate. The central warehouse is the supplier of spare parts within the scope of the project and the customers are the local warehouses. Figure 4 shows a graphical representation of the European F-35 spare parts supply chain. The black box indicates the scope of the project and the repair lead time is indicated with the thick black arrow. The repair lead time is the time from the moment an item has failed until the moment the item is repaired by a repair shop and back in stock at the central warehouse, i.e., the time needed to repair failed parts (LRCs) until they are ready to use again. Therefore, the repair lead time consists of the shipment time from a local warehouse to a repair shop, the repair time at the repair shop, and the shipment time from the repair shop to the central warehouse. Failed or defective parts are parts that cannot perform their functionalities anymore and this results in downtime for the F-35s. At the repair shop, the repair of failed parts (LRCs) consists of the following actions. First, inspecting which subcomponent, which is called a SRC (shop replaceable component), has failed that caused the LRC failure. Then, replacing the failed subcomponent (SRC) with a new one. At last, the repaired part (LRC) is tested for some period of time before it is put back in stock at the central warehouse.

The goal of the project is to optimize the inventory control for the European F-35 spare parts supply chain, using ADI of component failures, such that the inventory investment costs are minimized while satisfying a 95% availability level. In specific, the goal of the project is to determine optimal base-stock levels that minimize the inventory investment costs, while satisfying a 95% availability level. In this section, the focus is on the determination of optimal base-stock levels for the base model, which is the situation without advance demand information (ADI) and lateral transshipments. The type of advance demand information (ADI) that will be used later on are predictions of components failures. These predictions result in early warnings, which indicate that a component (LRC) is going to fail within a few days at a certain location with a certain probability. Therefore, by using the predictions, or early warnings, it is known a few days in advance at which location a component (LRC) is needed with a certain probability. In other words, the inventory planner will know a few days in advance which parts are possibly needed at which locations. Based on this, the decision is made to ship a part from the central warehouse. Besides, the early warnings also specify the failure mode, so it is also known in advance which subcomponent (SRC) will cause the part (LRC) failure. The repair shop can use this information by ordering the subcomponents that are needed for the repair earlier. Furthermore, a lateral transshipment is defined as a local warehouse which provides stocked items (LRCs) to another local warehouse which is out of stock. Therefore, when using lateral transshipments, a demand of a local warehouse can be satisfied from the central warehouse, as well as from another local warehouse. But first the focus is on the model without ADI and lateral transshipments.

There is a non-empty set J^{loc} of local warehouses, numbered $j = 1, \dots, |J^{\text{loc}}|$. Each local warehouse serves a number of F-35s, which is stated in parentheses in figure 4. Each F-35 consists of a non-empty set of repairable items, which are called LRCs, numbered $i = 1, \dots, |I|$. The total stream of failures of item $i \in I$ as observed by local warehouse $j \in J^{\text{loc}}$ constitutes a Poisson process with a constant rate $\lambda_{i,j} \geq 0$, as indicated in figure 4. For at least one item i and local warehouse j, it holds that $\lambda_{i,j} > 0$. Apart from the local warehouses, there exists a central warehouse, denoted by index 0. Define $\lambda_{i,0} = \sum_{j \in J^{\text{loc}}} \lambda_{i,j}$ as the total demand rate for item i at the central warehouse. The demand at the central warehouse is also a Poisson process since it is the superposition of the Poisson demand processes at the local warehouses. Let J denote the set of all stock points, i.e., $J = \{0\} \cup J^{\text{loc}}$. If an item i fails at a local warehouse j, a spare part stocked at the local warehouse j is used to replace the defective item, if local warehouse j has a part on stock. Otherwise, a backorder arises, until a spare part becomes available from the central warehouse and this results in downtime for the F-35s. Upon failure, also immediately a replenishment order is placed at the central warehouse. The replenishment order arrives after a deterministic lead time $L_{i,j}$ (supply lead time), if stock for item i is available at the central warehouse. Otherwise, the order is backordered until a spare part becomes available from a repair shop. It is assumed that, for each item $i \in I$, backordered replenishment orders from the local warehouses at the central warehouse are fulfilled according to first-come, first-served (FCFS) policy. The defective part at the local warehouse is immediately sent to the assigned repair shop to be repaired there. It takes a certain random lead time with mean $L_{i,0}$ (repair lead time) before the defective item is repaired and back in stock at the central warehouse. Repaired parts are considered as new parts. Equivalently, from a modeling point of view, the defective part can be scrapped and after a certain random lead time, a newly purchased part is back in stock at the central warehouse. Notice that each item i at each stock point j is controlled according to a base-stock policy, with base-stock level $S_{i,j}$. The policy in the total network is defined by the $|I| \times |J|$ matrix $\mathbf{S}$, consisting of elements $S_{i,j}$. Each column in this matrix, denoted by a vector $\mathbf{S}_j$, consists of all base-stock levels at stock point $j \in J$.

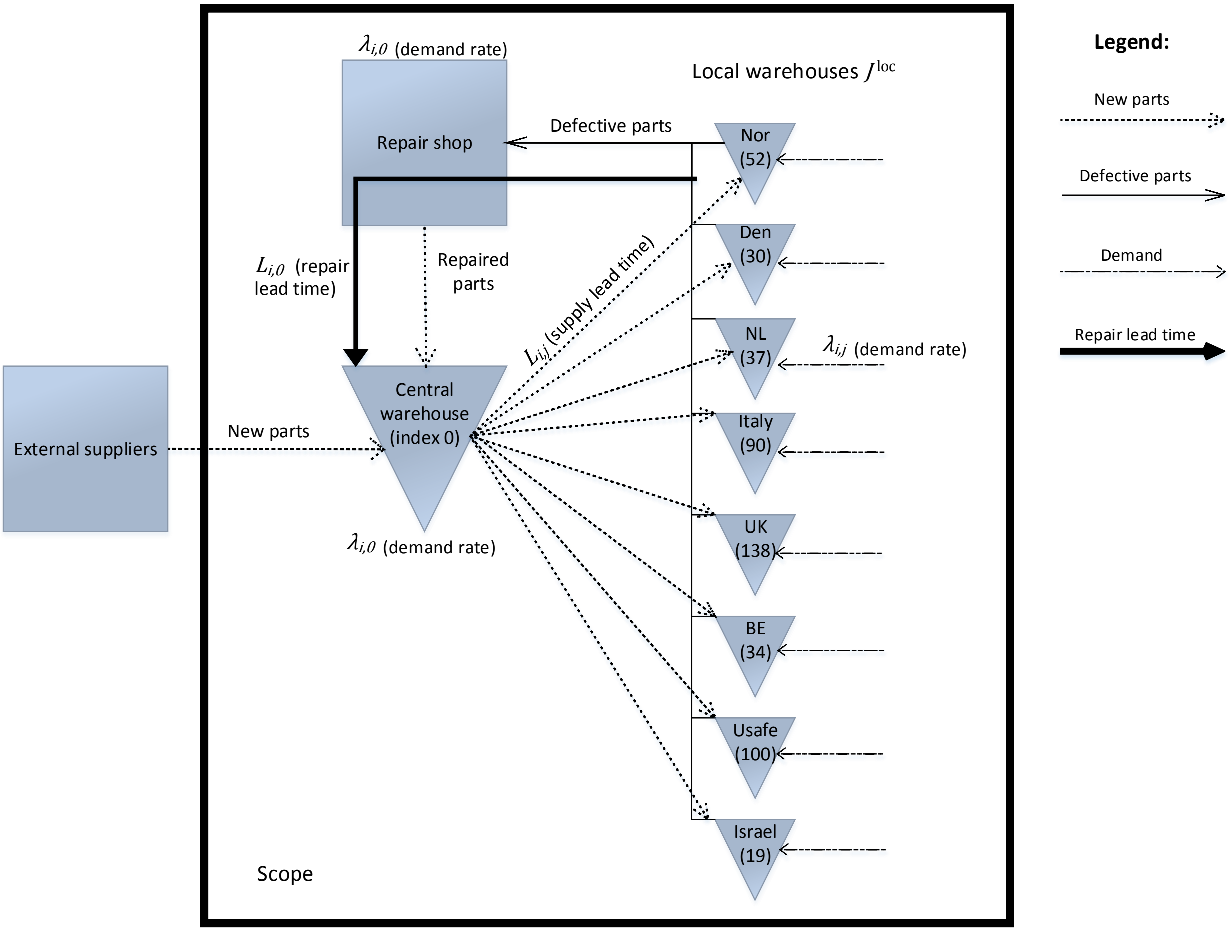

Figure 4. European F-35 supply chain including notations

5.1.2 Assumptions

- Demands for the different items occur according to a stationary Poisson process.
- All items are repaired successfully and there is no scrapping of items.
- There are no lateral transshipments in the distribution network.
- Repair lead times for different items are independent and random.
- For each item, the supply lead times are assumed to be deterministic.
- A one-for-one replenishment policy, $(S-1, S)$, is applied for all items.
- Replenishment orders at the central warehouse are fulfilled in FCFS order.
- There are ample servers at the repair facility, so there is no waiting queue before repair is started.
- The probability of failure of one item is independent of failures occurring for other items.
- Each item failure is caused by a failure of at most one single subcomponent.

5.1.3 Exact analysis

For a given base-stock policy with matrix $\mathbf{S}$, consisting of elements $S_{i,j}$, evaluation of the steady-state behaviour can be done exactly, as described for the first time by Graves (1985). Because the different items have no interaction, the steady state behaviour can be evaluated per item i. This leads to a closed-form expression for the expected backorder position for item i at local warehouse j. A top-down approach is followed, which means that the central warehouse is analysed first and then the local warehouses.

The state of the system at time instant t can be described by ($X_{i,0}(t)$, $I_{i,0}(t, S_{i,0})$, $B_{i,0}(t, S_{i,0})$), where $X_{i,0}(t)$ denotes the total number of parts in repair at time t, $I_{i,0}(t, S_{i,0})$ denotes the stock on hand of ready-for-use parts at the central warehouse at time t, and $B_{i,0}(t, S_{i,0})$ denotes the number of backordered demands at the central warehouse at time t. Both $I_{i,0}(t, S_{i,0})$ and $B_{i,0}(t, S_{i,0})$ depend on $S_{i,0}$. Notice that $X_{i,0}(t)$ does not depend on $S_{i,0}$ ($X_{i,0}(t)$ depends only on the Poisson arrival process of defective parts). The amount $X_{i,0}(t)$ represents the number of parts in the repair pipeline and is therefore also called the pipeline stock. The possible values for the tuples ($X_{i,0}(t)$, $I_{i,0}(t, S_{i,0})$, $B_{i,0}(t, S_{i,0})$) are given by:

(0, $S_{i,0}$, 0), (1, $S_{i,0} - 1$, 0), . . . , ($S_{i,0} - 1$, 1, 0), ($S_{i,0}$, 0, 0), ($S_{i,0} + 1$, 0, 1), ($S_{i,0} + 2$, 0, 2), . . .

The first $S_{i,0}$ states in this sequence are with positive stock on hand, the state ($S_{i,0}$, 0, 0) is the unique state in which both the stock on hand and the number of backordered demands is zero, and after that the states with a positive number of backordered demands are obtained. A transition is made from one state to the next state in this sequence when a demand occurs, while a completion of a repair leads to a transition from one state to a previous state in this sequence. For clarification, the following numerical example for the tuple ($X_{i,0}(t)$, $I_{i,0}(t, S_{i,0})$, $B_{i,0}(t, S_{i,0})$) is given:

(0, 10, 0), (1, 9, 0), . . . , (9, 1, 0), (10, 0, 0), (11, 0, 1), (12, 0, 2), . . .

Again, the first states in this sequence are with positive stock on hand, the state (10, 0, 0) is the unique state in which both the stock on hand and the number of backordered demands is zero, and after that the states with a positive number of backordered demands are obtained.

From the sequence with all possible states and the numerical example, it is observed that the values of $I_{i,0}(t, S_{i,0})$ and $B_{i,0}(t, S_{i,0})$ follow directly from the values of $X_{i,0}(t)$ and $S_{i,0}$. It holds that:

$$I_{i,0}(t, S_{i,0}) = (S_{i,0} - X_{i,0}(t))^+, \tag{1}$$

$$B_{i,0}(t, S_{i,0}) = (X_{i,0}(t) - S_{i,0})^+, \tag{2}$$

where $x^+ = \max\{0, x\}$ for any $x \in \mathrm{R}$, where R denotes real numbers. These equations imply that:

$$I_{i,0}(t, S_{i,0}) - B_{i,0}(t, S_{i,0}) = S_{i,0} - X_{i,0}(t), \tag{3}$$

or, equivalently, that:

$$X_{i,0}(t) + I_{i,0}(t, S_{i,0}) - B_{i,0}(t, S_{i,0}) = S_{i,0}. \tag{4}$$

The latter equation is known as the stock balance equation (see, e.g., Sherbrooke, 2004). Let $X_{i,0}$, $I_{i,0}(S_{i,0})$, and $B_{i,0}(S_{i,0})$ be the steady-state variables corresponding to $X_{i,0}(t)$, $I_{i,0}(t, S_{i,0})$, and $B_{i,0}(t, S_{i,0})$, respectively. In other words, they are random variables denoting the number of parts in repair, the number of ready-for-use parts, and the number of backordered demands at the central warehouse in steady state. By (1) and (2):

$$I_{i,0}(S_{i,0}) = (S_{i,0} - X_{i,0})^+, \tag{5}$$

$$B_{i,0}(S_{i,0}) = (X_{i,0} - S_{i,0})^+. \tag{6}$$

In the model, defective parts enter the repair pipeline according to a Poisson process and each defective part stays on average a time $L_{i,0}$ in the repair pipeline. The repair pipeline may be seen as a queueing system with infinitely many servers and service times $L_{i,0}$. In other words, the repair pipeline is an M/G/∞ queueing system, and we may thus apply Palm's Theorem (Palm, 1938):

Palm's Theorem: If jobs arrive according to a Poisson process with rate λ at a service system and if the times that the jobs remain in the service system are independent and identically distributed according to a given general distribution with mean EW, then the steady-state distribution for the total number of jobs in the service system is Poisson distributed with mean λEW.

Application of this theorem to the repair pipeline leads to equation (7) of the following lemma. Equations (8) and (9) of this lemma follow from equation (7) and the equations (5) and (6).

Lemma. Let $i \in I$.

Define $X_{i,0}$ as the total amount on order for item $i \in I$ at the central warehouse in steady state, i.e., the total number of parts that is in repair, also called the pipeline. $X_{i,0}$ is Poisson distributed with mean $\lambda_{i,0}L_{i,0}$, i.e.:

$$\mathrm{P}\{X_{i,0} = x\} = \frac{(\lambda_{i,0}L_{i,0})^x}{x!} e^{-\lambda_{i,0}L_{i,0}}, \quad \forall x \in \mathrm{N}_0, \tag{7}$$

where N_0 denotes all positive integers starting from 0.

Let $I_{i,0}(S_{i,0})$ be the stock on hand for item $i \in I$ at the central warehouse, as a function of the base-stock level $S_{i,0}$. Its distribution is given by:

$$\mathrm{P}\{I_{i,0}(S_{i,0}) = x\} = \begin{cases} \sum_{y=S_{i,0}}^{\infty} \mathrm{P}\{X_{i,0} = y\} & \text{if } x = 0; \\ \mathrm{P}\{X_{i,0} = S_{i,0} - x\} & \text{if } x \in \{1, \ldots, S_{i,0}\}. \end{cases} \tag{8}$$

This equation can be interpreted as follows. $I_{i,0}(S_{i,0}) = 0$, if the total number of parts in repair is greater than or equal to the base-stock level, i.e., $X_{i,0} \geq S_{i,0}$. $I_{i,0}(S_{i,0}) > 0$, if the total number of parts in repair is smaller than the base-stock level, i.e., $X_{i,0} < S_{i,0}$.

Next, define $B_{i,0}(S_{i,0})$ as the number of backordered demands, for item $i \in I$ at the central warehouse, as a function of the base-stock level $S_{i,0}$. It is distributed as follows:

$$\mathrm{P}\{B_{i,0}(S_{i,0}) = x\} = \begin{cases} \sum_{y=0}^{S_{i,0}} \mathrm{P}\{X_{i,0} = y\} & \text{if } x = 0; \\ \mathrm{P}\{X_{i,0} = S_{i,0} + x\} & \text{if } x \in \mathrm{N}, \end{cases} \tag{9}$$

where N denotes all positive integers starting from 1.

This equation can be interpreted as follows. $B_{i,0}(S_{i,0}) = 0$, if the total number of parts in repair is smaller than or equal to the base-stock level, i.e., $X_{i,0} \leq S_{i,0}$. $B_{i,0}(S_{i,0}) > 0$, if the total number of parts in repair is greater than the base-stock level, i.e., $X_{i,0} > S_{i,0}$.

Now define $B_{i,0}^{(j)}(S_{i,0})$ as the number of backorders of item $i \in I$ of local warehouse $j \in J^{loc}$ in the backorder queue at the central warehouse. It is assumed that the backorders at the central warehouse are filled on a first-come, first-serve (FCFS) basis. This implies that the disaggregation of $B_{i,0}(S_{i,0})$ is equivalent to a random disaggregation across the local warehouses. That is, the probability that any backordered demand at the central warehouse stems from local warehouse j is directly proportional to the failure rate of that local warehouse, i.e., $\lambda_{i,j}/\lambda_{i,0}$. To determine the probability distribution of $B_{i,0}^{(j)}(S_{i,0})$, we condition on $B_{i,0}(S_{i,0})$ and use the fact that the conditional distribution of $B_{i,0}^{(j)}(S_{i,0})$ is a Binomial distribution with parameters $B_{i,0}(S_{i,0})$ and $\lambda_{i,j}/\lambda_{i,0}$. Specifically, the probability distribution of $B_{i,0}^{(j)}(S_{i,0})$ is obtained by:

$$\mathrm{P}\left\{B_{i,0}^{(j)}(S_{i,0}) = x\right\} = \sum\nolimits_{y=x}^{\infty} \mathrm{P}\{B_{i,0}(S_{i,0}) = y\}\mathrm{P}\left\{B_{i,0}^{(j)}(S_{i,0}) = x \middle| B_{i,0}(S_{i,0}) = y\right\}$$

$$= \sum\nolimits_{y=x}^{\infty} \binom{y}{x} \left(\frac{\lambda_{i,j}}{\lambda_{i,0}}\right)^{x} \left(1 - \frac{\lambda_{i,j}}{\lambda_{i,0}}\right)^{y-x} \mathrm{P}\{B_{i,0}(S_{i,0}) = y\}. \tag{10}$$

Let, for each item $i \in I$ and local warehouses $j \in J^{\mathrm{loc}}$, $Y_{i,j}$ be defined as the total demand during the supply lead time $L_{i,j}$, and $X_{i,j}(S_{i,0})$ be defined as the total amount on order given base-stock level $S_{i,0}$. It holds that $X_{i,j}(S_{i,0}) = B_{i,0}^{(j)}(S_{i,0}) + Y_{i,j}$. This summation is allowed since the supply lead times are deterministic (see, e.g., Muckstadt, 2005). From the distribution of $X_{i,j}(S_{i,0})$, the distribution of $I_{i,j}(S_{i,0}, S_{i,j})$ can be derived, the physical stock on hand for item i at local warehouse j, and $B_{i,j}(S_{i,0}, S_{i,j})$, the backorder position for item i at local warehouse j, as a function of the base-stock levels $S_{i,0}$ and $S_{i,j}$, analogous to the derivation for the central warehouse. Therefore, the distribution of $I_{i,j}(S_{i,0}, S_{i,j})$, the physical stock on hand for item i at local warehouse j, is given by:

$$\mathrm{P}\{I_{i,j}(S_{i,0}, S_{i,j}) = x\} = \begin{cases} \sum_{y=S_{i,j}}^{\infty} \mathrm{P}\{X_{i,j}(S_{i,0}) = y\} & \text{if } x = 0; \\ \mathrm{P}\{X_{i,j}(S_{i,0}) = S_{i,j} - x\} & \text{if } x \in \{1, \ldots, S_{i,j}\} \end{cases} \tag{11}$$

This equation can be interpreted as follows. $I_{i,j}(S_{i,0}, S_{i,j}) = 0$, if the total amount on order for item i for local warehouse j is greater than or equal to the base-stock level, i.e., $X_{i,j}(S_{i,0}) \geq S_{i,j}$. $I_{i,j}(S_{i,0}, S_{i,j}) > 0$, if the total amount on order for item i for local warehouse j is smaller than the base-stock level, i.e., $X_{i,j}(S_{i,0}) < S_{i,j}$.

Furthermore, the distribution of $B_{i,j}(S_{i,0}, S_{i,j})$, the backorder position for item i at local warehouse j, is given by:

$$\mathrm{P}\{B_{i,j}(S_{i,0}, S_{i,j}) = x\} = \begin{cases} \sum_{y=0}^{S_{i,j}} \mathrm{P}\{X_{i,j}(S_{i,0}) = y\} & \text{if } x = 0; \\ \mathrm{P}\{X_{i,j}(S_{i,0}) = S_{i,j} + x\} & \text{if } x \in \mathrm{N}, \end{cases} \tag{12}$$

where N denotes all positive integers starting from 1. This equation can be interpreted as follows. $B_{i,j}(S_{i,0}, S_{i,j}) = 0$, if the total amount on order for item i for local warehouse j is smaller than or equal to the base-stock level, i.e., $X_{i,j}(S_{i,0}) \leq S_{i,j}$. $B_{i,j}(S_{i,0}, S_{i,j}) > 0$, if the total amount on order for item i for local warehouse j is greater than the base-stock level, i.e., $X_{i,j}(S_{i,0}) > S_{i,j}$.

Finally, it is now easy to obtain the expected backorder position for item i at local warehouse j, which is defined as $EBO_{i,j}(S_{i,0}, S_{i,j})$:

$$EBO_{i,j}(S_{i,0},S_{i,j}) = \mathrm{E}B_{i,j}(S_{i,0},S_{i,j}) = \sum_{x=S_{i,j}+1}^{\infty}(x-S_{i,j})\mathrm{P}\{X_{i,j}(S_{i,0})=x\}$$

$$= \lambda_{i,j}L_{i,j} - S_{i,j} + \sum_{x=0}^{S_{i,j}}(S_{i,j}-x)\mathrm{P}\{X_{i,j}(S_{i,0})=x\}, \quad \forall S_{i,j} \in \mathrm{N}_0, \tag{13}$$

where N_0 denotes all positive integers starting from 0.

Exact evaluation as explained above, leads to a computational issue, since the probabilities $\mathrm{P}\{X_{i,j}=x\}$, $i \in I$, $j \in J$, should be calculated for all values $x \in \mathrm{N}_0$. In practice, however, we limit ourselves to $x \in \{0,\dots,x_{i,j}^{\max}\}$, with $x_{i,j}^{\max} = \min\{x \mid \mathrm{P}\{X_{i,j} \le x\} \ge 1-\epsilon\}$ and $\epsilon = 10^{-6}$, and allocate the remaining probability mass $1-\mathrm{P}\{X_{i,j} \le x_{i,j}^{\max}\}$ to $\mathrm{P}\{X_{i,j} = x_{i,j}^{\max}\}$.

For large systems with many items and local warehouses, the computational effort of the exact evaluations may become too high, and then approximate evaluation methods like METRIC or Graves' approximation can be used. The METRIC approximation assumes that successive replenishment actions at the local warehouses are independent processes, all with the same mean $(L_{i,j}+\frac{\mathrm{E}B_{i,0}(S_{i,0})}{\lambda_{i,0}})\lambda_{i,j}$, which leads to a simple Poisson distribution for the variables $X_{i,j}(S_{i,0})$ (this may be seen as a single-moment fit). Graves (1985) proposes a different approximate evaluation method based on two-moment fits of negative binomial distributions on the variables $X_{i,j}(S_{i,0})$. This two-moment procedure leads to accurate approximations in all cases, while the METRIC approximation is good in many cases, but it does lead to large deviations in several other cases (especially when $\mathrm{E}B_{i,0}(S_{i,0})$ is large). Wong et al. (2007), for instance, present the results of experiments evaluating the accuracy of both approximate evaluation methods when used for executing the greedy procedure.

5.1.4 Optimization problem

Inventory investment cost c_i^{inv} is counted for every item i put on stock, and the aggregate inventory investment costs are given by:

$$C(\mathbf{S}) = \sum_{i\in I}\sum_{j\in J} c_i^{\mathrm{inv}} S_{i,j} \tag{14}$$

The expected number of backorders for an item $i \in I$ at local warehouse $j \in J^{\mathrm{loc}}$ at an arbitrary point in time at the long run is given by $EBO_{i,j}(S_{i,0},S_{i,j})$, which is defined in equation (13) (notice that this number only depends on $S_{i,0}$ and $S_{i,j}$). Therefore, the aggregate expected number of backorders is:

$$EBO_j(\mathbf{S}_0,\mathbf{S}_j) = \sum_{i\in I} EBO_{i,j}(S_{i,0},S_{i,j}) \tag{15}$$

At local warehouse j, there is a maximum level EBO_j^{obj} given for the aggregate expected number of backorders (a target for all warehouses together is also possible). The goal of the METRIC model is to determine optimal base-stock levels that minimize the total inventory investment costs subject to a target for the expected number of backorders per local warehouse. The optimization problem is formulated as follows:

$$\text{Min } C(\mathbf{S})$$

$$\text{Subject to } EBO_j\left(\mathbf{S}_0, \mathbf{S}_j\right) \leq \; EBO_j^{\text{obj}}, \qquad \forall j \; \in J^{loc}$$

$$S_{i,j} \in \; \mathrm{N}_0, \qquad \forall i \; \in I, \qquad \forall j \; \in \; J,$$

where N_0 denotes all positive integers starting from 0.

5.1.5 Greedy algorithm

Feasible solutions can be obtained in an efficient way via a greedy procedure similar to the procedures described in Wong et al. (2007). The basic idea of the Greedy algorithm is the following. For each level of depot stock and each base the expected backorders must be computed as a function of the base stock. For each level of depot stock, the optimal allocation of the units of stock to the several bases must be determined to minimize the sum of expected backorders at all bases. This is accomplished by a marginal allocation. At each step, the next unit of stock is added to the base where it will cause the largest decrease in expected backorders. The expected backorders is a convex function which guarantees that the marginal allocation technique produces optimal solutions. For the multi-item problem, marginal analysis is again employed. This means that at each step the next unit of stock is added to the base where it will cause the largest decrease in expected backorders divided by the unit cost. However, before marginal analysis is used a preliminary convex extension of the functions must be performed because the item backorder functions are not necessarily convex. After each allocation, the system investment and system backorders are computed. Allocation terminates when the investment target is just exceeded or, alternatively, when the expected backorders are just less than a target value. The Greedy algorithm for solving the optimization problem is formulated as follows.

Step 1

$$S_{i,j} := 0 \text{ for all } i \in I, j \in J;$$

$$C(\mathbf{S}) := 0 \text{ and } EBO_j(\mathbf{S}) := \sum_{i \in I} \lambda_{i,j}\left(L_{i,0} + L_{i,j}\right) \text{ for all } j \in J^{\text{loc}}$$

Step 2

$$\tau_{i,j} := \frac{\Delta_{i,j} EBO}{c_i^{\text{inv}}} \text{ for all } i \in I, j \in J;$$

$$(k, l) := \arg\max \tau_{i,j};$$

$$\mathbf{S} := \mathbf{S} + e_{k,l}$$

Step 3

$$C(\mathbf{S}) \coloneqq C(\mathbf{S}) + c_k^{\text{inv}};$$

$$\text{Calculate } EBO_j(\mathbf{S}) \text{ for all } j \in J^{\text{loc}};$$

$$\text{If } EBO_j(\mathbf{S}) \leq EBO_j^{\text{obj}} \text{ for all } j \in J^{\text{loc}}\text{, then stop, else go to step 2.}$$

Where

$$EBO_j(\mathbf{S}) = EBO_j(\mathbf{S}_0, \mathbf{S}_j) = \textstyle\sum_{i \in I} EBO_{i,j}(S_{i,0}, S_{i,j}) \tag{16}$$

And

$$\Delta_{i,j} EBO = \textstyle\sum_{l \in J^{\text{loc}}} \left[\left(EBO_l(\mathbf{S}) - EBO_l^{\text{obj}} \right)^+ - \left(EBO_l(\mathbf{S} + e_{i,j}) - EBO_l^{\text{obj}} \right)^+ \right] \tag{17}$$

And let $e_{i,j}$ be a matrix having the same structure as the base-stock matrix $\mathbf{S}$, with a one at the position corresponding to item $i \in I$ and stock point $j \in J$, and with zeros at all other positions.

5.1.6 Alternative service measures

Instead of using the expected number of backorders as a service level constraint, the expected waiting time can also be used as an alternative service measure. It is straightforward to adapt the service level constraint based on the expected number of backorders to one that is based on the expected waiting time. The expected waiting time for getting a ready-for-use item $i \in I$ at local warehouse $j \in J^{\text{loc}}$ when the base-stock level is $S_{i,0}$ at the central warehouse and $S_{i,j}$ at the local warehouse, $W_{i,j}(S_{i,0}, S_{i,j})$, can be determined by Little's formula (Little, 1961): $W_{i,j}(S_{i,0}, S_{i,j}) = EBO_{i,j}(S_{i,0}, S_{i,j}) / \lambda_{i,j}$. Taking all items together, the aggregate expected waiting time $W_j(\mathbf{S}_0, \mathbf{S}_j)$ at local warehouse $j \in J^{\text{loc}}$ is:

$$W_j(\mathbf{S}_0, \mathbf{S}_j) = \textstyle\sum_{i \in I} \frac{\lambda_{i,j}}{\sum_{k \in I} \lambda_{k,j}} \times \frac{EBO_{i,j}(S_{i,0}, S_{i,j})}{\lambda_{i,j}} = \sum_{i \in I} \frac{EBO_{i,j}(S_{i,0}, S_{i,j})}{\sum_{k \in I} \lambda_{k,j}} \tag{18}$$

Which means that we get a problem that is equivalent to the original problem.

Furthermore, instead of using a service level target per local warehouse, an aggregate service level target over all local warehouses can also be used:

$$\textstyle\sum_{j \in J^{\text{loc}}} EBO_j(\mathbf{S}_0, \mathbf{S}_j) \leq EBO^{\text{obj}} \tag{19}$$

Where EBO^{obj} denotes the aggregate target.

5.2 METRIC model extensions

5.2.1 Lateral transshipments

Paterson et al. (2010) state that reactive lateral transshipments are suitable in an environment where the transshipment costs are relatively low compared to the costs associated with holding large amounts of stock and with failing to meet demand immediately. This is often the case in a spare parts environment. Alfredsson and Verrijdt (1999) compared their model with lateral transshipments to the VARI-METRIC model and they found a maximum cost reduction of 43.9% and a minimum cost reduction of 13.2%. The results also show that in many cases the stock levels are lower, especially the central stock level showed a significant decrease. In addition, Kranenburg (2006) discussed a semi-conductor company ASML and showed that using reactive lateral transshipments can save the company up to 50% of annual inventory related costs for spare parts. These results indicate that using lateral transshipments in a distribution network for spare parts can be very beneficial. Therefore, the use of lateral transshipments will be investigated for the European F-35 spare parts supply chain.

The same two-echelon model is considered as before, but now the following alternative option is considered to satisfy a demand for an item $i \in I$ at local warehouse $j \in J^{\text{loc}}$ if local warehouse j is out of stock; lateral transshipment from a local warehouse. The variables used are $L_{i,j,k}^{\text{lat}}$ for the lateral transshipment lead time, and $c_{i,j,k}^{\text{lat}}$ for the costs of the lateral transshipment. The procedure is as follows. First, the stock is checked at the central warehouse. If the central warehouse has a part on stock then the demand is satisfied by the central warehouse, as described before. If the central warehouse is out of stock, then the stocks are checked at one or more other local warehouses $k \in J^{\text{loc}}$, $k \neq j$, that have a part on stock. If one of these local warehouses has a part on stock, then the demand is immediately coupled to that part and the part is delivered at the required place. If two or more local warehouses have a part on stock, then the location with the lowest demand rate is chosen as the sending source because this location has the lowest backorder probability and the least impact on the aggregate availability level. If none of these local warehouses have a part on stock, then the demand is backordered, and this results in downtime for the F-35s. The demand is satisfied as soon as a part becomes available from a repair shop at the central warehouse.

Axsäter (1990) provided a new approximation technique for modelling such lateral transshipments in a two-echelon system with repairable items. The characteristic feature is that the demand rate at a local warehouse depends on the inventory level. With positive inventory on hand, the normal demand is faced plus demand for lateral transshipments from other local warehouses. With no positive inventory on hand, the only real demand is the demand that has to be backordered. In addition to the fraction of demand satisfied from stock on hand and the fraction of demand that is backordered, a new variable is included in the model. This new variable is the fraction of demand satisfied by lateral transshipments and it is defined as alpha (α). Because exponential lead times are assumed, a birth-death (Markov) queueing model is used to derive the equations of the steady state probabilities of the net inventory.

5.2.2 Advance demand information

For including advance demand information (ADI), Hariharan & Zipkin (1995) found that demand lead times are, in a precise sense, the opposite of supply lead times. That is, the effect of a demand lead time on overall system performance is precisely the same as a corresponding reduction in the supply lead time. Therefore, the warning time in the thesis, resulting from the ADI of component failures, has to be included in the model as a reduction in the supply lead times. The variable that will be used for the warning time is $L_{i,j}^{\mathrm{war}}$. Therefore, the new supply lead times for satisfying a demand are, $\max\{L_{i,j} - L_{i,j}^{\mathrm{war}}, 0\}$ and $\max\{L_{i,j,k}^{\mathrm{lat}} - L_{i,j}^{\mathrm{war}}, 0\}$, for the central warehouse and local warehouses, respectively. The inaccuracy of the ADI has to be included in the model as well. This will be done by making a distinction between false negatives and false positives. False negatives are components (LRCs) that fail without receiving a warning in advance, and false positives are components (LRCs) that fail at a later moment than predicted. False negatives are very problematic because when a component fails unannounced at a local warehouse and there is no stock at that warehouse, it results in a backorder and therefore in downtime for the F-35s. False negatives therefore have a large impact on the availability level. When receiving a warning at the central warehouse that specifies that a component (LRC) will fail in 3 days at a certain local warehouse, an example of a false positive is that the component actually fails in 6 days, instead of 3 days. An example of a false negative is that the component failure is not predicted, and as a result no warning is received at the central warehouse. This means that it is not known in advance that the component will fail in a few days. Therefore, for the false negatives the result will be no reduction in the supply lead times, whereas for the false positives there will be a reduction in the supply lead times, but the component is actually not needed yet. If, for example, the false negative percentage is 10%, the supply lead time for the central warehouse becomes $\left(0.9 \times \max\left\{L_{i,j} - L_{i,j}^{\mathrm{war}}, 0\right\}\right) + \left(0.1 \times L_{i,j}\right)$. Topan et al. (2018) revealed that using imperfect ADI yields substantial savings, but only when the demand lead time is larger than the supply lead time. In this case, the average PCR (percentage cost reduction) is found to be 30.06%, and the maximum PCR is found to be 89.96%. Furthermore, the amount of savings is sensitive to the levels of the imperfectness aspects. Having fewer false negatives is more desirable than having fewer false positives.

In addition, the warnings also specify which smaller subcomponent (SRC) is going to fail that will cause the LRC failure. By knowing which SRC causes the LRC failure, inspection time at the repair shop is saved. Furthermore, the repair shop can order the SRCs needed for the repair in advance of the LRC failure, so there will be less waiting time for the subcomponents (SRCs). Zero inspection time and less waiting time on SRCs results in a shorter repair lead time for the LRCs. A shorter repair lead time, in turn, results in lower required base-stock levels. Therefore, the effect of warning time, resulting from the ADI of component failures, on the repair lead time is investigated and included in the model with ADI. Simulation models will be developed for the situations with and without warning time in which the repair lead time is simulated. From these simulations, the average repair lead time can be determined in both situations. The effect of warning time on the repair lead time is known and can be included in the model with ADI.

6. Numerical results

In this section, the numerical results of the different multi-echelon models will be described and explained. First, the results of the base model, which is the model without ADI and lateral transshipments, will be shown and explained. Next, the results of the model with ADI will be described and explained. Finally, the results of the model with lateral transshipments (and ADI) will be described. The numerical results have been obtained by implementing the optimization problem and corresponding Greedy solution algorithm, as described in section 5.1.4 and 5.1.5, in Excel code. Furthermore, simulations have been developed to validate the results of the different multi-echelon models.

6.1 Base model

The base model is the model without ADI and lateral transshipments. The base model is constructed by implementing the optimization problem and corresponding Greedy solution algorithm from section 5.1.4 and 5.1.5. The model uses Equation (13) from problem analysis section 5.1.3 and Poisson distributed demand to calculate the expected backorders at the local warehouses. Based on these expected backorders at the local warehouses, optimal base-stock levels can be determined for all warehouses. This is accomplished by the Greedy algorithm. At each step of the algorithm, the next unit of stock is allocated to the local warehouse where it will cause the largest decrease in expected backorders. After each allocation, the system investment and system backorders are computed. Allocation terminates when the expected backorders are just less than a target value, i.e., when the 95% availability level is achieved. The base model determines optimal base-stock levels, for the central warehouse and local warehouses, that minimize the inventory investment costs while satisfying the 95% availability constraint. This is done for a local availability constraint, which means that every local warehouse has to satisfy the 95% availability constraint, and for an aggregate availability constraint, which means that over all local warehouses together the 95% availability has to be achieved. The results of the base model have been obtained for four different scenarios. This is done in order to show that the multi-echelon model and simulation provide (almost) the same values using different datasets. The four different scenarios used, are:

- Scenario 1: MTBF=8000 days, $L_{i,0}$=100 days
- Scenario 2: MTBF=6000 days, $L_{i,0}$=100 days
- Scenario 3: MTBF=8000 days, $L_{i,0}$=50 days
- Scenario 4: MTBF=6000 days, $L_{i,0}$=50 days

It can be observed that scenario 1 and 2, and scenario 3 and 4, have the same repair lead time $L_{i,0}$, but a different MTBF. In this way a sensitivity analysis on the MTBF can be performed in order to uncover the effect of the MTBF on the stock levels. Furthermore, it can be observed that scenario 1 and 3, and scenario 2 and 4, have the same MTBF, but a different repair lead time $L_{i,0}$. In this way a sensitivity analysis on the repair lead time $L_{i,0}$ can be performed in order to uncover the effect of the repair lead time on the stock levels. Scenario 1 and scenario 4 have a different MTBF as well as a different repair lead time $L_{i,0}$.

Before the results of the multi-echelon models and simulations will be shown, first a list of notations is given. The list shows the variables and their notations used for obtaining the results, followed by a description of the variables. Table 1 shows the list of notations.

Table 1. List of notations

Notations	Description
J^{loc}	Set of local warehouses, numbered $j = 1, \dots, \lvert J^{\text{loc}} \rvert$
J	Set of all warehouses ($J = \{0\} \cup J^{\text{loc}}$)
$\lambda_{i,j}$	Demand rate for item $i \in I$ as observed by local warehouse $j \in J^{\text{loc}}$
$\lambda_{i,0}$	Total demand rate for item $i \in I$ at the central warehouse ($\lambda_{i,0} = \sum_{j \in J^{\text{loc}}} \lambda_{i,j}$)
$L_{i,j}$	Supply lead time for item $i \in I$ from central warehouse to local warehouse $j \in J^{\text{loc}}$
$L_{i,0}$	Repair lead time for item $i \in I$
$L_{i,j}^{\text{war}}$	Warning time for item $i \in I$ at local warehouse $j \in J^{\text{loc}}$, observed at the central warehouse
$L_{i,j,k}^{\text{lat}}$	Lateral transshipment lead time for item $i \in I$ from local warehouse $k \in J^{\text{loc}}$ to $j \in J^{\text{loc}}$
$S_{i,j}$	Base-stock level for item $i \in I$ at stock point $j \in J$
$\mathbf{S}$	Matrix consisting of elements $S_{i,j}$
$\text{E}B_{i,j}(S_{i,0}, S_{i,j})$	Expected backorder position for item $i \in I$ at local warehouse $j \in J^{\text{loc}}$
$\text{E}B_{i,0}(S_{i,0})$	Expected backorder position for item $i \in I$ at the central warehouse
$\text{E}I_{i,j}(S_{i,0}, S_{i,j})$	Expected inventory position for item $i \in I$ at local warehouse $j \in J^{\text{loc}}$
$\text{E}I_{i,0}(S_{i,0})$	Expected inventory position for item $i \in I$ at the central warehouse
$\text{E}W_{i,j}(S_{i,0}, S_{i,j})$	Expected waiting time for item $i \in I$ at local warehouse $j \in J^{\text{loc}}$
$\text{E}W_{i,0}(S_{i,0})$	Expected waiting time for item $i \in I$ at the central warehouse
$\text{E}A_{i,j}(S_{i,0}, S_{i,j})$	Expected availability for item $i \in I$ at local warehouse $j \in J^{\text{loc}}$
$\text{E}A_{i,s}(S_{i,0}, S_{i,j})$	Expected availability of the system for item $i \in I$ ($\text{E}A_{i,s}(S_{i,0}, S_{i,j}) = \sum_{j \in J^{loc}} (\text{E}A_{i,j}(S_{i,0}, S_{i,j}) \times \frac{\lambda_{i,j}}{\lambda_{i,0}})$)
c_i^{inv}	Inventory investment cost for item $i \in I$
$C(\mathbf{S})$	Aggregate inventory investment cost ($C(\mathbf{S}) = \sum_{i \in I} \sum_{j \in J} c_i^{\text{inv}} S_{i,j}$)

6.1.1 Model results

Table 2 shows the input variables used for the base model and scenario 1, i.e., MTBF=8000 days and $L_{i,0}$=100 days. As can be observed, first the local warehouses are stated and there is ended with the central warehouse. The supply lead times of the local warehouses, $L_{i,j}$, are deterministic and all between 0 to 2 days. The repair lead time of the central warehouse, $L_{i,0}$, is random with an average of 100 days. The expected lead time for a local warehouse is equal to the standard supply lead time plus the expected waiting time for components at the central warehouse, which follows from table 3. Furthermore, the average demand per day at a local warehouse depends on the component MTBF and the number of aircrafts operating from that local warehouse. Therefore, the average demand per day at the local warehouses, $\lambda_{i,j}$, is determined as follows: $\lambda_{i,j} = ((365/\text{MTBF})/365) \times \text{Aircrafts}$. The average demand per day at the central warehouse, $\lambda_{i,0}$, is the sum of the demand rates at the local warehouses, i.e., $\lambda_{i,0} = \sum_{j \in J^{\text{loc}}} \lambda_{i,j}$. The lead time demand then follows from the multiplication of the demand rate with the expected lead time, i.e., $\lambda_{i,j} L_{i,j}$ for the local warehouses and $\lambda_{i,0} L_{i,0}$ for the central warehouse.

Table 2. Base model input variables

Stock point J	Lead time (days)	Expected lead time	Aircrafts	MTBF (days)	Average demand	Lead time demand
Norway	1.0	4.24	52	8000	0.0065	0.0276
Denmark	0.50	3.74	30	8000	0.0038	0.0140
NL	0.10	3.34	37	8000	0.0046	0.0155
Italy	0.80	4.04	90	8000	0.0113	0.0455
UK	0.60	3.84	138	8000	0.0173	0.0663
Belgium	0.10	3.34	34	8000	0.0043	0.0142
Usafe	0.30	3.54	100	8000	0.0125	0.0443
Israel	1.50	4.74	19	8000	0.0024	0.0113
Central warehouse	100.0	100.0			0.0625	6.25

Table 3 shows the output of the base model, using scenario 1 and a 95% aggregate availability constraint. A 95% aggregate availability constraint means that over all local warehouses together the 95% availability level has to be achieved. In other words, the expected availability of the system has to be 95%, however, some local warehouses can have an availability level lower than 95%. The expected availability of the system is determined as follows: $\mathrm{E}A_{i,s}\left(S_{i,0}, S_{i,j}\right) = \sum_{j\in J^{\mathrm{loc}}} (\mathrm{E}A_{i,j}\left(S_{i,0}, S_{i,j}\right) \times \frac{\lambda_{i,j}}{\lambda_{i,0}})$.

Table 3. Base model output for scenario 1 and aggregate availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	97.3%	0.97	0.0004	0.0580
Denmark	1	98.6%	0.99	0.0001	0.0262
NL	1	98.5%	0.98	0.0001	0.0257
Italy	1	95.6%	0.96	0.0010	0.0906
UK	1	93.6%	0.94	0.0022	0.1247
Belgium	1	98.6%	0.99	0.0001	0.0237
Usafe	1	95.7%	0.96	0.0010	0.0774
Israel	1	98.9%	0.99	0.0001	0.0266
Central warehouse	9	95.9%	2.95	0.2028	3.2442

As can be observed, the optimal amount of network stock is 17 LRCs according to the model. The network stock was defined as the sum of the stock at the local warehouses and the central warehouse. At every local warehouse 1 LRC is kept in stock and 9 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 9$. The 95% aggregate availability level is achieved (95.9%), while the inventory investment cost is minimized. Holding 16 LRCs on stock results in an aggregate availability level of 93.0% and holding 18 LRCs on stock results in an aggregate availability level of 97.7%. Thus, 17 LRCs is the minimum amount of stock required to achieve the 95% aggregate availability level and therefore this is the optimal amount. Furthermore, it can be observed from table 3 that despite of the fact that UK has an expected availability level of 93.6%, the aggregate availability level of 95% is still achieved.

Table 4 shows the output of the base model, using scenario 1 and a 95% local availability constraint. A 95% local availability constraint means that every local warehouse has to satisfy the 95% availability constraint. In other words, $\mathrm{E}A_{i,j}(S_{i,0}, S_{i,j}) \geq 0.95$ for all local warehouses. In contrast to the aggregate availability constraint, it is not allowed to have local warehouses with an availability level lower than 95%.

Table 4. Base model output for scenario 1 and local availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	98.3%	0.98	0.0001	0.0220
Denmark	1	99.2%	0.99	0.0000	0.0083
NL	1	99.2%	0.99	0.0000	0.0067
Italy	1	97.3%	0.97	0.0004	0.0323
UK	1	96.3%	0.96	0.0007	0.0416
Belgium	1	99.3%	0.99	0.0000	0.0062
Usafe	1	97.6%	0.98	0.0003	0.0226
Israel	1	99.3%	0.99	0.0000	0.0114
Central warehouse	10	97.7%	3.85	0.1006	1.6089

The optimal amount of network stock is 18 LRCs according to the model. At every local warehouse 1 LRC is kept in stock and 10 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 10$. The 95% local availability level is achieved for all local warehouses, while the inventory investment cost is minimized. Holding 17 LRCs on stock results in a local availability level of 93.6% for the UK, as shown in table 3, and this is not allowed. Thus, 18 LRCs is the minimum amount of stock required to achieve the 95% local availability level and therefore this is the optimal amount.

For scenario 2, a repair lead time, $L_{i,0}$, of 100 days is used, like in scenario 1. However, an MTBF of 6000 days is used instead of an MTBF of 8000 days. This results in different demand rates and lead time demands for all warehouses. Table 5 shows the output of the base model, using scenario 2 and a 95% aggregate availability constraint, i.e., over all local warehouses together the 95% availability level has to be achieved.

Table 5. Base model output for scenario 2 and aggregate availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	97.4%	0.97	0.0003	0.0401
Denmark	1	98.7%	0.99	0.0001	0.0163
NL	1	98.7%	0.99	0.0001	0.0143
Italy	1	95.8%	0.96	0.0009	0.0603
UK	1	94.1%	0.94	0.0018	0.0795
Belgium	1	98.8%	0.99	0.0001	0.0131
Usafe	1	96.2%	0.96	0.0008	0.0456
Israel	1	98.9%	0.99	0.0001	0.0199
Central warehouse	12	96.3%	3.84	0.1713	2.0557

The optimal amount of network stock is 20 LRCs according to the model. At every local warehouse 1 LRC is kept in stock and 12 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 12$. The 95% aggregate availability level is achieved (96.3%), while the inventory investment cost is minimized. Holding 19 LRCs on stock results in an aggregate availability level of 94.0% and holding 21 LRCs on stock results in an aggregate availability level of 97.6%. Thus, 20 LRCs is the minimum amount of stock required to achieve the 95% aggregate availability level and therefore this is the optimal amount. Furthermore, it can be observed from table 5 that despite of the fact that UK has an expected availability level of 94.1%, the aggregate availability level of 95% is still achieved, which was also the case in table 2.

Table 6 shows the output of the base model, using scenario 2 and a 95% local availability constraint, i.e., every local warehouse has to satisfy the 95% availability constraint.

Table 6. Base model output for scenario 2 and local availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	98.2%	0.98	0.0002	0.0187
Denmark	1	99.2%	0.99	0.0000	0.0062
NL	1	99.3%	0.99	0.0000	0.0043
Italy	1	97.2%	0.97	0.0004	0.0263
UK	1	96.2%	0.96	0.0007	0.0321
Belgium	1	99.3%	0.99	0.0000	0.0039
Usafe	1	97.7%	0.98	0.0003	0.0158
Israel	1	99.2%	0.99	0.0000	0.0105
Central warehouse	13	97.6%	4.76	0.0901	1.0814

The optimal amount of network stock is 21 LRCs according to the model. At every local warehouse 1 LRC is kept in stock and 13 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 13$. The 95% local availability level is achieved for all local warehouses, while the inventory investment cost is minimized. Holding 20 LRCs on stock results in a local availability level of 94.1% for the UK, as shown in table 5, and this is not allowed. Thus, 21 LRCs is the minimum amount of stock required to achieve the 95% local availability level and therefore this is the optimal amount.

For scenario 3, an MTBF of 8000 days is used, like in scenario 1. However, a repair lead time, $L_{i,0}$, of 50 days is used instead of 100 days. This results in different lead time demands for all warehouses. Table 7 shows the output of the base model, using scenario 3 and a 95% aggregate availability constraint, i.e., over all local warehouses together the 95% availability level has to be achieved.

Table 7. Base model output for scenario 3 and aggregate availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	97.7%	0.98	0.0003	0.0405
Denmark	1	98.9%	0.99	0.0001	0.0173
NL	1	98.8%	0.99	0.0001	0.0161
Italy	1	96.3%	0.96	0.0007	0.0621
UK	1	94.7%	0.95	0.0014	0.0838
Belgium	1	98.9%	0.99	0.0001	0.0148
Usafe	1	96.5%	0.97	0.0006	0.0500
Israel	1	99.0%	0.99	0.0000	0.0194
Central warehouse	5	96.7%	2.03	0.1590	2.5447

The optimal amount of network stock is 13 LRCs according to the model. At every local warehouse 1 LRC is kept in stock and 5 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 5$. The 95% aggregate availability level is achieved (96.7%), while the inventory investment cost is minimized. Holding 12 LRCs on stock results in an aggregate availability level of 93.3% and holding 14 LRCs on stock results in an aggregate availability level of 98.3%. Thus, 13 LRCs is the minimum amount of stock required to achieve the 95% aggregate availability level and therefore this is the optimal amount. Furthermore, it can be observed from table 7 that despite of the fact that UK has an expected availability level of 94.7%, the aggregate availability level of 95% is still achieved, which was also the case in table 3 and 5.

Table 8 shows the output of the base model, using scenario 3 and a 95% local availability constraint, i.e., every local warehouse has to satisfy the 95% availability constraint.

Table 8. Base model output for scenario 3 and local availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	98.7%	0.99	0.0001	0.0128
Denmark	1	99.4%	0.99	0.0000	0.0042
NL	1	99.5%	0.99	0.0000	0.0028
Italy	1	98.0%	0.98	0.0002	0.0179
UK	1	97.3%	0.97	0.0004	0.0217
Belgium	1	99.5%	1.00	0.0000	0.0025
Usafe	1	98.4%	0.98	0.0001	0.0104
Israel	1	99.4%	0.99	0.0000	0.0074
Central warehouse	6	98.3%	2.94	0.0620	0.9920

The optimal amount of network stock is 14 LRCs according to the model. At every local warehouse 1 LRC is kept in stock and 6 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 6$. The 95% local availability level is achieved for all local warehouses, while the inventory investment cost is minimized. Holding 13 LRCs on stock results in a local availability level of 94.7% for the UK, as shown in table 7, and this is not allowed. Thus, 14 LRCs is the minimum amount of stock required to achieve the 95% local availability level and therefore this is the optimal amount.

For scenario 4, an MTBF of 6000 days and a repair lead time, $L_{i,0}$, of 50 days is used. Table 9 shows the output of the base model, using scenario 4 and a 95% aggregate availability constraint, i.e., over all local warehouses together the 95% availability level has to be achieved.

Table 9. Base model output for scenario 4 and aggregate availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	96.8%	0.97	0.0005	0.0619
Denmark	1	98.4%	0.98	0.0001	0.0271
NL	1	98.2%	0.98	0.0002	0.0258
Italy	1	94.7%	0.95	0.0014	0.0955
UK	1	92.5%	0.92	0.0030	0.1296
Belgium	1	98.4%	0.98	0.0001	0.0237
Usafe	1	95.0%	0.95	0.0013	0.0788
Israel	1	98.7%	0.99	0.0001	0.0292
Central warehouse	6	95.2%	2.07	0.2334	2.8013

The optimal amount of network stock is 14 LRCs according to the model. At every local warehouse 1 LRC is kept in stock and 6 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 6$. The 95% aggregate availability level is achieved (95.2%), while the inventory investment cost is minimized. Holding 13 LRCs on stock results in an aggregate availability level of 91.4% and holding 15 LRCs on stock results in an aggregate availability level of 97.4%. Thus, 14 LRCs is the minimum amount of stock required to achieve the 95% aggregate availability level and therefore this is the optimal amount. Furthermore, it can be observed from table 9 that despite of the fact that UK and Italy have an expected availability level of 92.5% and 94.7% respectively, the aggregate availability level of 95% is still achieved.

Table 10 shows the output of the base model, using scenario 4 and a 95% local availability constraint, i.e., every local warehouse has to satisfy the 95% availability constraint.

Table 10. Base model output for scenario 4 and local availability

Stock point J	Stock levels $S_{i,j}, S_{i,0}$	Expected availability	Expected inventory	Expected backorders	Expected waiting time
Norway	1	98.1%	0.98	0.0002	0.0219
Denmark	1	99.1%	0.99	0.0000	0.0077
NL	1	99.2%	0.99	0.0000	0.0057
Italy	1	97.0%	0.97	0.0005	0.0314
UK	1	95.8%	0.96	0.0009	0.0391
Belgium	1	99.2%	0.99	0.0000	0.0052
Usafe	1	97.4%	0.97	0.0003	0.0200
Israel	1	99.1%	0.99	0.0000	0.0120
Central warehouse	7	97.4%	2.94	0.1047	1.2563

The optimal amount of network stock is 15 LRCs according to the model. At every local warehouse 1 LRC is kept in stock and 7 LRCs are kept in stock at the central warehouse, i.e., $S_{i,j} = 1$ and $S_{i,0} = 7$. The 95% local availability level is achieved for all local warehouses, while the inventory investment cost is minimized. Holding 14 LRCs on stock results in a local availability level of 92.5% for the UK and 94.7% for Italy, as shown in table 9, and this is not allowed. Thus, 15 LRCs is the minimum amount of stock required to achieve the 95% local availability level and therefore this is the optimal amount.

The base model output for all four scenarios have been obtained and shown in tables 3 to 10. In addition, figure 5 and 6 show the base model output for the aggregate availability constraint and local availability constraint, respectively. In specific, the figures show the network stock, the expected inventory at the central warehouse, and the sum of the expected waiting times at the local warehouses (downtime), for all four scenarios. As can be observed from figure 5 and 6, and tables 3 to 10, using a local availability constraint results in a slightly higher network stock compared to using an aggregate availability constraint, i.e., in all four scenarios the network stock is 1 LRC higher, because the base-stock level at the central warehouse ($S_{i,0}$) is 1 LRC higher. Therefore, using a local availability constraint also results in a higher expected inventory at the central warehouse and in less waiting time (downtime). Recall that scenario 1 and 2, and scenario 3 and 4, have the same repair lead time $L_{i,0}$, but a different MTBF. When comparing the results of scenario 1 with scenario 2, and when comparing the results of scenario 3 with scenario 4, it can be concluded that a higher MTBF results in a lower network stock. Furthermore, recall that scenario 1 and 3, and scenario 2 and 4, have the same MTBF, but a different repair lead time $L_{i,0}$. When comparing the results of scenario 1 with scenario 3, and when comparing the results of scenario 2 with scenario 4, it can be concluded that a shorter repair lead time ($L_{i,0}$) results in a lower network stock.

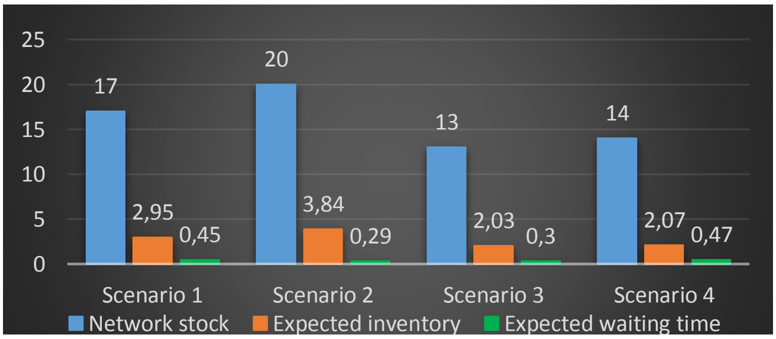

Figure 5. Base model output for aggregate availability constraint

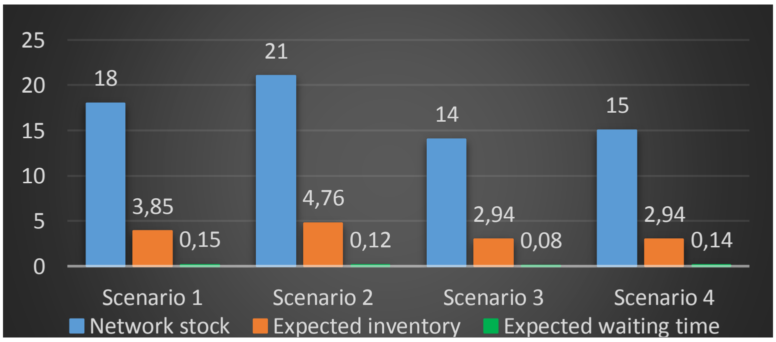

Figure 6. Base model output for local availability constraint

6.1.2 Validation of base model results

The results of the base model, section 6.1.1, have been validated using simulation. This is done for the results using an aggregate availability level. Simulations have been developed for all four scenarios. The optimal network stock, and corresponding availability level, from simulation is compared to the optimal network stock and corresponding availability level of the multi-echelon model. For simulation, a period length of 5000, 10000, 15000, and even longer periods are used with 100 replications. Therefore, the availability level of the simulation is the average availability level over 100 replications. Furthermore, the run time of the simulation is just a few seconds, whereas the run time of the multi-echelon model is approximately a minute. The availability level of the simulation, reported in table 11 to table 14, is the average availability level using 15000 periods and 100 replications. 15000 periods are used because this gives the most accurate results, as will be shown in table 15. Besides the availability level, also the expected inventory level at the central warehouse and the sum of the expected waiting times at the local warehouses (downtime) are reported in table 15. When using even longer periods, such as 20000 or 30000 periods, the operating characteristics remain unchanged.

Table 11 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation, using scenario 1 and a 95% aggregate availability constraint.

Table 11. Validation of results for scenario 1 and aggregate availability

	Network stock = 16	Network stock = 17	Network stock = 18
Availability Level (multi-echelon model)	93.0%	95.9% *	97.7%
Availability Level (simulation)	93.1%	95.9% *	97.6%

** indicates optimal solution*

As can be observed, the optimal amount of network stock, which minimizes the inventory investment costs while satisfying the 95% availability constraint, is 17 LRCs according to both the multi-echelon model and simulation. Furthermore, it can be observed that the availability levels are (almost) the same. This means that the simulation validates the results of the multi-echelon model, i.e., the results of the multi-echelon model are correct (and so are the equations used, like Equation (13) from problem analysis section 5.1.3).

Table 12 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation, using scenario 2 and a 95% aggregate availability constraint.

Table 12. Validation of results for scenario 2 and aggregate availability

	Network stock = 19	Network stock = 20	Network stock = 21
Availability Level (multi-echelon)	94.0%	96.3% *	97.6%
Availability Level (simulation)	94.0%	96.2% *	97.4%

** indicates optimal solution*

As can be observed, the optimal amount of network stock, which minimizes the inventory investment costs while satisfying the 95% availability constraint, is 20 LRCs according to both the multi-echelon model and simulation. Furthermore, it can be observed that the availability levels are (almost) the same. This means that the simulation validates the results of the multi-echelon model, i.e., the results of the multi-echelon model are correct.

Table 13 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation, using scenario 3 and a 95% aggregate availability constraint.

Table 13. Validation of results for scenario 3 and aggregate availability

	Network stock = 12	Network stock = 13	Network stock = 14
Availability Level (multi-echelon)	93.3%	96.7% *	98.3%
Availability Level (simulation)	93.4%	96.8% *	98.2%

** indicates optimal solution*

As can be observed, the optimal amount of network stock, which minimizes the inventory investment costs while satisfying the 95% availability constraint, is 13 LRCs according to both the multi-echelon model and simulation. Furthermore, it can be observed that the availability levels are (almost) the same. This means that the simulation validates the results of the multi-echelon model, i.e., the results of the multi-echelon model are correct.

Table 14 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation, using scenario 4 and a 95% aggregate availability constraint.

Table 14. Validation of results for scenario 4 and aggregate availability

	Network stock = 13	Network stock = 14	Network stock = 15
Availability Level (multi-echelon)	91.4%	95.2% *	97.4%
Availability Level (simulation)	91.6%	95.2% *	97.3%

** indicates optimal solution*

As can be observed, the optimal amount of network stock, which minimizes the inventory investment costs while satisfying the 95% availability constraint, is 14 LRCs according to both the multi-echelon model and simulation. Furthermore, it can be observed that the availability levels are (almost) the same. This means that the simulation validates the results of the multi-echelon model, i.e., the results of the multi-echelon model are correct.

Table 15 shows the comparison of the multi-echelon model results and simulation results for all four scenarios, using different period lengths for simulation. N_s indicates the period length used for simulation. As can be observed, using a period length of 15000 periods gives the most accurate results for all four scenarios. This holds for the expected availability level ($\mathrm{E}A_{i,s}$), as well as for the expected inventory level at the central warehouse ($\mathrm{E}I_{i,0}$) and the sum of the expected waiting times at the local warehouses ($\sum_{j\in J^{loc}} \mathrm{E}W_{i,j}$), or downtime. When using even longer period lengths, such as 20000 or 30000 periods, the operating characteristics remain unchanged. It can be concluded that the simulation validates the results of the multi-echelon model, i.e., the results of the multi-echelon model are correct.

Table 15. Comparison of model and simulation results

Scenarios	Model results	Simulation results		
		$N_s = 5000$	$N_s = 10000$	$N_s = 15000$
	$(\mathrm{E}A_{i,s}, \mathrm{E}I_{i,0}, \sum_{j\in J^{loc}} \mathrm{E}W_{i,j})$	$(\mathrm{E}A_{i,s}, \mathrm{E}I_{i,0}, \sum_{j\in J^{loc}} \mathrm{E}W_{i,j})$	$(\mathrm{E}A_{i,s}, \mathrm{E}I_{i,0}, \sum_{j\in J^{loc}} \mathrm{E}W_{i,j})$	$(\mathrm{E}A_{i,s}, \mathrm{E}I_{i,0}, \sum_{j\in J^{loc}} \mathrm{E}W_{i,j})$
1	(95.9, 2.95, 0.45)	(95.3, 2.96, 0.60)	(95.5, 3.06, 0.52)	(95.9, 2.97, 0.45)
2	(96.3, 3.84, 0.29)	(95.7, 3.95, 0.42)	(96.0, 3.93, 0.33)	(96.2, 3.86, 0.30)
3	(96.7, 2.03, 0.30)	(96.1, 2.15, 0.45)	(96.6, 2.06, 0.26)	(96.8, 2.03, 0.29)
4	(95.2, 2.07, 0.47)	(95.0, 2.27, 0.55)	(95.3, 2.13, 0.50)	(95.2, 2.06, 0.47)

6.2 Model with ADI

The model with advance demand information (ADI) is the model that makes use of the predictions of component (LRC) failures. The predictions of component failures are obtained by the Royal Dutch Aerospace Centre using machine learning techniques to predict the failure time, failure mode, and probability of failure of the LRCs. These predictions result in early warnings, which indicate that a component (LRC) is going to fail within a few days at a certain location with a certain probability. The warning time ($L_{i,j}^{\mathrm{war}}$) is the time from the moment a warning is received until the moment the component fails. Therefore, by using the predictions, or early warnings, it is known a few days in advance at which location a component (LRC) is needed with a certain probability. Besides, the early warnings also specify the failure mode, so it is also known in advance which subcomponent (SRC) will cause the part (LRC) failure. The repair shop can use this information by ordering the subcomponents that are needed for the repair earlier. For including advance demand information (ADI), Hariharan & Zipkin (1995) found that demand lead times are, in a precise sense, the opposite of supply lead times. That is, the effect of a demand lead time on overall system performance is precisely the same as a corresponding reduction in the supply lead time. Therefore, the warning time ($L_{i,j}^{\mathrm{war}}$), resulting from the ADI of component failures, is included in the base model by applying a reduction in the supply lead times of the local warehouses, i.e., $\max\{L_{i,j} - L_{i,j}^{\mathrm{war}}, 0\}$. The model determines optimal base-stock levels using warning time (ADI), for the central warehouse and local warehouses, that minimize the inventory investment costs while satisfying the 95% availability constraint. This is done for a local availability constraint and for an aggregate availability constraint. The results of all four scenarios have been obtained, however, in this section, there is focused on the results of scenario 1, i.e., MTBF=8000 and $L_{i,0}$=100, for both the aggregate and local availability constraint. Scenario 1 is chosen because this scenario best corresponds to reality.

6.2.1 Model results with warning time

Table 16 shows the output of the model with warning time (ADI), using scenario 1 and a 95% aggregate availability constraint.

Table 16. Output model with warning time for scenario 1 and aggregate availability

	Warning time $L_{i,j}^{\mathrm{war}}$ (days)					
	0	1	2	3	4	5
Norway	1	1	0	0	0	0
Denmark	1	0	0	0	0	0
NL	1	0	0	0	0	0
Italy	1	0	0	0	0	0
UK	1	0	0	0	0	0
Belgium	1	0	0	0	0	0
Usafe	1	0	0	0	0	0
Israel	1	0	0	0	0	0
Central warehouse	9	13	11	10	10	9
Network stock	**17**	**14**	**11**	**10**	**10**	**9**

Table 17 shows the output of the model with warning time (ADI), using scenario 1 and a 95% local availability constraint.

Table 17. Output model with warning time for scenario 1 and local availability

	Warning time $L_{i,j}^{\mathrm{war}}$ (days)					
	0	1	2	3	4	5
Norway	1	1	0	0	0	0
Denmark	1	0	0	0	0	0
NL	1	0	0	0	0	0
Italy	1	0	0	0	0	0
UK	1	0	0	0	0	0
Belgium	1	0	0	0	0	0
Usafe	1	0	0	0	0	0
Israel	1	1	1	1	0	0
Central warehouse	10	13	11	10	10	9
Network stock	**18**	**15**	**12**	**11**	**10**	**9**

Without warning time, it is not known in advance which parts (LRCs) are needed at which locations (only at the time of failure). At least 1 LRC is kept in stock at each local warehouse in order to achieve the 95% availability level, as can be observed from tables 16, 17 and 3 to 10. This results in a high local stock and therefore in a high network stock. With warning time, it is known a few days in advance which parts are needed at which locations. Warning time results in centralizing stock and reduced local stock (zero if warning time ≥ supply lead times), as can be observed from tables 16 and 17. This can be explained by the fact that when warning time is greater than or equal to the supply lead times, the central warehouse is always able to satisfy a demand of a local warehouse on time, if there is sufficient stock at the central warehouse, which means there is no need to keep stock locally. Therefore, warning time results in a lower required network stock. Figure 7 shows the results of tables 16 and 17, displayed in a graph. The situation with zero days warning time indicates the result of the base model for scenario 1, i.e., the result of the model without warning time (ADI), which is called the baseline.

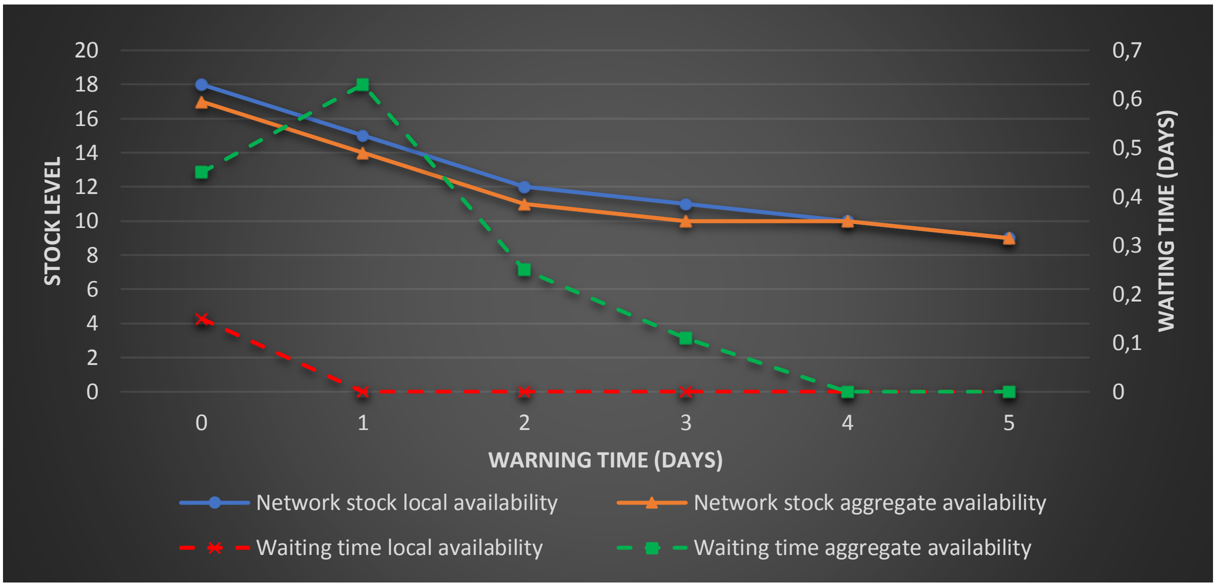

Figure 7. Model results with warning time

It can be concluded, from tables 16 and 17 and figure 7, that increasing warning time results in a lower required network stock, i.e., the network stock decreases when the warning time increases. Furthermore, it can be observed from figure 7 that the waiting time (downtime) also decreases when the warning time increases. However, from the situation without warning time to the situation with 1-day warning time, the waiting time first increases a little for the aggregate availability constraint. For example, the situation without warning time results in a network stock of 17 LRCs and a waiting time of 0.45 days for the aggregate availability constraint, and for the local availability constraint it results in a network stock of 18 LRCs and a waiting time of 0.15 days. The situation with 3 days warning time results in a network stock of 10 LRCs and a waiting time of 0.11 days, and in a network stock of 11 LRCs and a waiting time of 0.00 days, for the aggregate and local availability constraint, respectively. The effect of 3 days warning time compared to no warning time, which is the baseline situation, is an inventory reduction of 41.2% and a waiting time reduction of 75.6% for the aggregate availability constraint, and for the local availability constraint the effect is an inventory reduction of 38.9% and a waiting time reduction of 100.0%. It can be concluded that the effect of warning time (ADI) on the network stock is very positive, i.e., warning time results in a significant reduction of the network stock, for both the aggregate and local availability constraint. Furthermore, it can be concluded that warning time results in less waiting time on components (downtime).

These results are based on a 100% reliability of the early warnings, provided by the Royal Dutch Aerospace Centre (NLR). However, in practice the reliability will be lower, and this results in prediction errors. Prediction errors can be false negatives or false positives. False negatives are components that fail without receiving a warning in advance, and false positives are components that fail at a later moment than predicted. False negatives are very problematic because when a component fails unannounced at a local warehouse and there is no stock at that warehouse, it results in a backorder and therefore in downtime for the F-35s. False negatives therefore have a large impact on the availability level. The ADI (in)accuracy is included in the model by applying no reduction in the supply lead times for the false negatives, whereas for the false positives a reduction in the supply lead times is applied. Therefore, the supply lead times of the local warehouses become $\left((1-\mathrm{fn}\%)\times\max\{L_{i,j}-L_{i,j}^{\mathrm{war}},0\}\right)+\left(\mathrm{fn}\%\times L_{i,j}\right)$. Figure 8 shows the results of the model with warning time (ADI), including false negatives, for the 95% local and aggregate availability constraint. The situation with zero days warning time indicates the result of the base model for scenario 1, i.e., the result of the model without warning time (ADI), which is called the baseline.

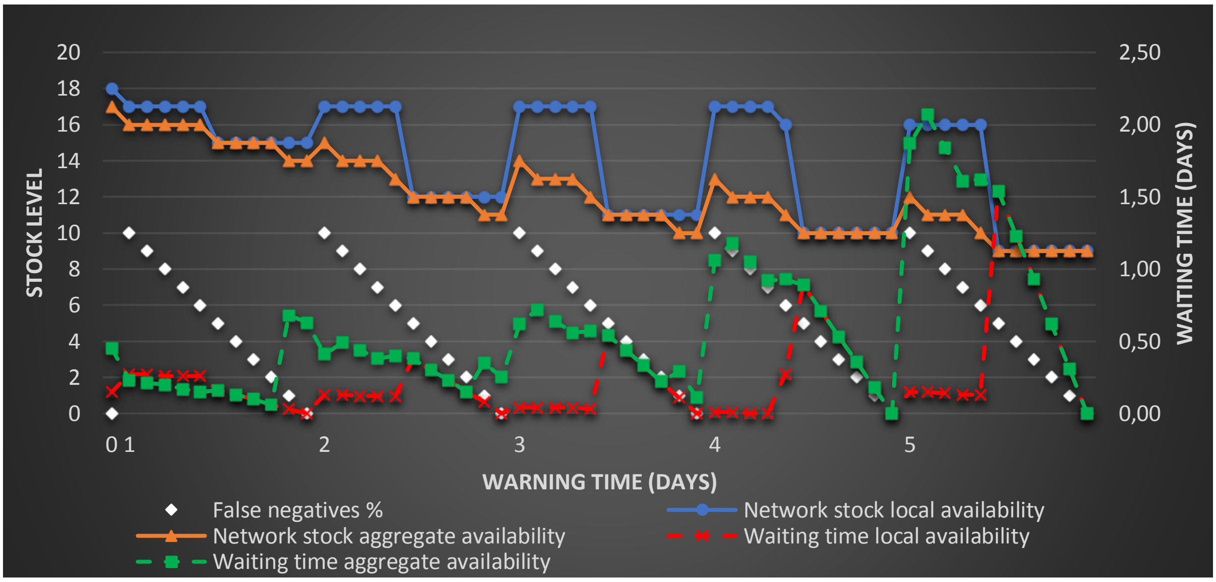

Figure 8. Model results with warning time including false negatives (95%)

As can be observed from figure 8, the positive effect of warning time (ADI) is quickly lost when increasing the false negative percentage, especially for the local availability constraint. For example, the situation with 3 days warning time without false negatives resulted in a network stock of 10 LRCs and a waiting time of 0.11 days, and in a network stock of 11 LRCs and a waiting time of 0.00 days, for the aggregate and local availability constraint, respectively. The situation with 3 days warning time and 10% false negatives results in a network stock of 14 LRCs and a waiting time of 0.62 days, and in a network stock of 17 LRCs and a waiting time of 0.04 days, for the aggregate and local availability constraint, respectively. The effect of 3 days warning time with 10% false negatives compared to no warning time is an inventory reduction of 17.6% for the aggregate availability constraint, but it is accompanied with a waiting time increase of 37.8%, whereas the effect without false negatives was an inventory reduction of 41.2% and a waiting time reduction of 75.6%. For the local availability constraint, the effect of 3 days warning time with 10% false negatives compared to no warning time is an inventory reduction of 5.6% and a waiting time reduction of 73.3%, whereas the effect without false negatives was an inventory reduction of 38.9% and a waiting time reduction of 100.0%. It can be concluded that the false negatives reduce the positive effect of warning time significantly.

Warning time without the false negatives, resulted in centralizing stock and (almost) no stock at the local warehouses. With 5% false negatives and no stock at the local warehouses, 5% of the demand is not satisfied on time and this results in a 95% availability level for all local warehouses. Therefore, until 5% false negatives it is not necessary to keep stock locally, when sufficient stock is kept at the central warehouse, in order to achieve the 95% availability level.

When the false negative percentage exceeds 5%, it is necessary to keep stock at the local warehouses again in order to achieve the 95% availability level. For the local availability constraint, at every local warehouse 1 LRC is kept in stock in order to achieve the 95% availability level at every local warehouse. Therefore, in figure 8, the large increase in network stock is observed when exceeding 5% false negatives. For the aggregate availability constraint, 1 LRC is kept in stock at a few local warehouses in order the achieve the 95% availability level over all warehouses together. Therefore, in figure 8, an increase in the network stock is observed when exceeding 5% false negatives, but this increase is smaller compared to the local availability constraint. It can be concluded from figure 8 that warning time (ADI) results in a significant reduction of the network stock, only if the false negative percentage is low (≤5%). This is especially required when using the local availability constraint. Furthermore, it can be concluded that the aggregate availability constraint results in almost all situations in a lower network stock compared to the local availability constraint.

Figure 9 shows the results of the model with warning time (ADI), including false negatives, for the 90% local and aggregate availability constraint. The situation with zero days warning time indicates the result of the base model for scenario 1, i.e., the result of the model without warning time (ADI), which is called the baseline.

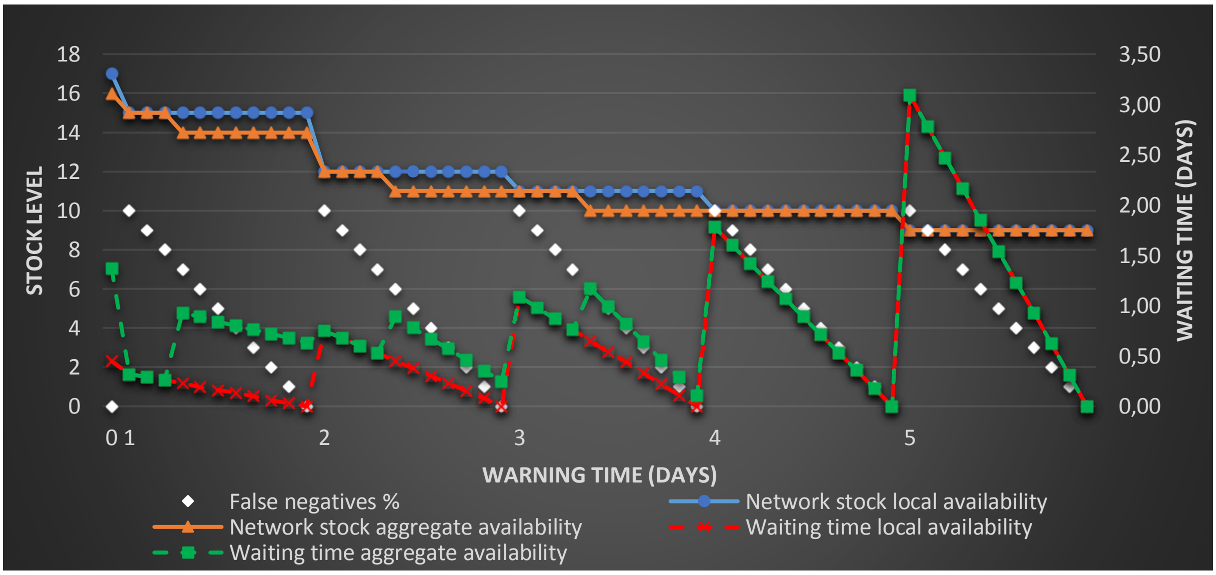

Figure 9. Model results with warning time including false negatives (90%)

With 10% false negatives and no stock at the local warehouses, 10% of the demand is not satisfied on time and this results in a 90% availability level for all local warehouses. Therefore, until 10% false negatives it is not necessary to keep stock locally, when sufficient stock is kept at the central warehouse, in order to achieve the 90% availability level. When the false negative percentage exceeds 10%, it is necessary to keep stock at the local warehouses again in order to achieve the 90% availability level. Therefore, in figure 9, no large increases in the network stock are observed when increasing the false negative percentage until 10%, whereas in figure 8 large increases were observed when exceeding 5% false negatives. It can be concluded from figure 9 that warning time (ADI) results in a significant reduction of the network stock, despite of the false negative percentage (until 10%), when using a 90%

availability level. Furthermore, it can be observed that the aggregate availability constraint results in almost all situations in the same network stock as the local availability constraint. At last, it can be observed from figure 9 that using a 90% availability level results in a lower network stock in almost all situations, compared to using a 95% availability level in figure 8.

Figure 10 shows the results of the model with warning time (ADI), including false negatives, for the 99% local and aggregate availability constraint. The situation with zero days warning time indicates the result of the base model for scenario 1, i.e., the result of the model without warning time (ADI), which is called the baseline.

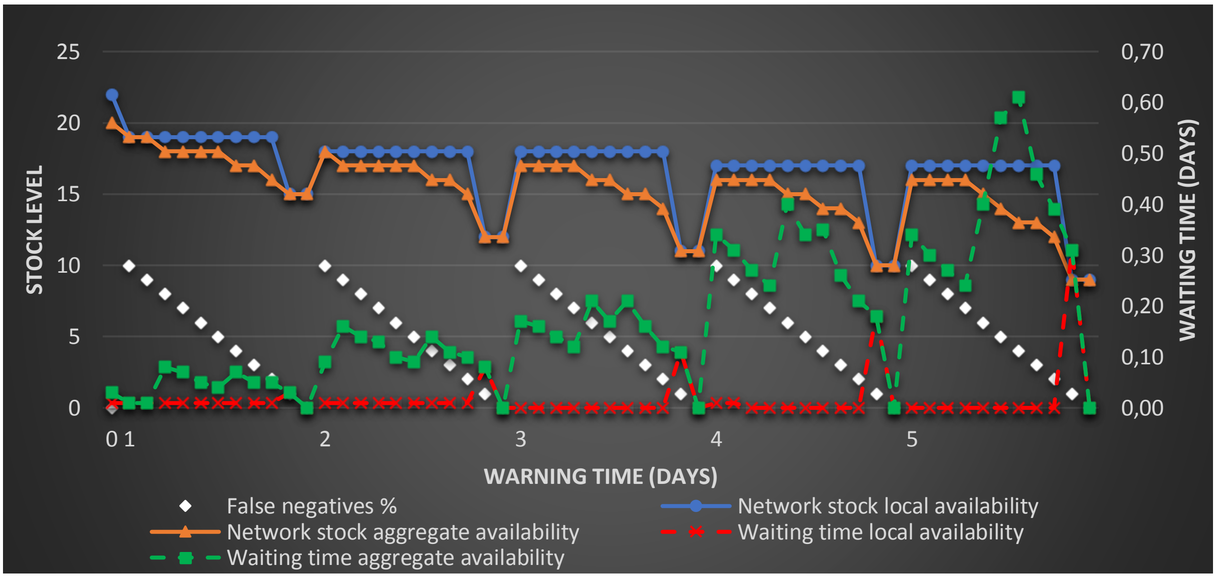

Figure 10. Model results with warning time including false negatives (99%)

With 1% false negatives and no stock at the local warehouses, 1% of the demand is not satisfied on time and this results in a 99% availability level for all local warehouses. Therefore, until 1% false negatives it is not necessary to keep stock locally, when sufficient stock is kept at the central warehouse, in order to achieve the 99% availability level. When the false negative percentage exceeds 1%, it is necessary to keep stock at the local warehouses again in order to achieve the 99% availability level. For the local availability constraint, at every local warehouse 1 LRC is kept in stock in order to achieve the 99% availability level at every local warehouse. Therefore, in figure 10, the large increase in network stock is observed when exceeding 1% false negatives. For the aggregate availability constraint, 1 LRC is kept in stock at a few local warehouses in order the achieve the 99% availability level over all warehouses together. Therefore, in figure 10, an increase in the network stock is observed when exceeding 1% false negatives, but this increase is smaller compared to the local availability constraint. It can be concluded from figure 10 that warning time (ADI) results in a significant reduction of the network stock, only if the false negative percentage is low (≤1%). This is especially required when using the local availability constraint. Furthermore, it can be concluded that the aggregate availability constraint results in almost all situations in a lower network stock compared to the local availability constraint. At last, it can be observed from figure 10 that using a 99% availability level results in a higher network stock in almost all situations, compared to using a 95% availability level in figure 8.

6.2.2 Validation of model results with warning time

The results of the model with warning time (ADI) including false negatives, section 6.2.1, have been validated using simulation. This is done for the results using a 95% aggregate availability constraint. Simulations have been made for all four scenarios, however, as described in section 6.2, there is focused on the results of scenario 1, i.e., MTBF=8000 and $L_{i,0}$=100. The optimal network stock, and corresponding availability level, from simulation is compared to the optimal network stock and corresponding availability level of the multi-echelon model. For simulation, a period length of 15000 periods is used because 15000 periods yield the most accurate results, as was observed in section 6.1.2. Furthermore, 100 replications are used for simulation. Therefore, the availability level of the simulation is the average availability level over 100 replications. The run time of the simulation is just a few seconds, whereas the run time of the multi-echelon model is approximately a minute. Table 18 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation for the situation with 3 days warning time without false negatives, using a 95% aggregate availability constraint. Table 19 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation for the situation with 3 days warning time with 10% false negatives, using a 95% aggregate availability constraint.

Table 18. Validation of results using 3 days warning time without false negatives

	Network stock = 10	Network stock = 11	Network stock = 12
Availability Level (multi-echelon)	96.2% * (0% Israel)	100%	100%
Availability Level (simulation)	93.8%	96.1% *	97.4%

** indicates optimal solution*

Table 19. Validation of results using 3 days warning time with 10% false negatives

	Network stock = 13	Network stock = 14	Network stock = 15
Availability Level (multi-echelon)	94.6%	95.6% *	97.6%
Availability Level (simulation)	92.3%	94.8%	95.9% *

** indicates optimal solution*

As can be observed from tables 18 and 19, there is a difference of 1 LRC between the optimal network stock according to the multi-echelon model and simulation. In both situations, the multi-echelon model recommends 1 LRC less on stock than is actually required. The cause of this is that METRIC models sometimes tend to understate the expected backorders and therefore overstate the expected availability of repairable items (Sherbrooke, 1986). This can be explained by the fact that the multi-echelon model uses the expected lead time, which is an average lead time, for the calculation of the availability level. When the expected lead time is smaller than or equal to the warning time ($L_{i,j} \leq L_{i,j}^{\text{war}}$), the model returns an availability level of 100% for the situation without false negatives (and 90% for the situation with 10% false negatives). This is the case for all locations in table 18 using a network stock of 11 LRCs or more. The model assumes that all LRCs will always be delivered on time to all locations, based on the expected lead time. However, this is an average lead time, so in reality the lead time can in some cases be higher than the warning time and therefore it should result in an availability level less than 100%. Therefore, the multi-echelon model overstates the availability level. Furthermore, when the expected lead time is greater than the warning time ($L_{i,j} > L_{i,j}^{\text{war}}$), the model returns an availability level of 0%. This is the case for Israel in table 18 using a network stock of 10 LRCs. The model assumes that all LRCs will always be delivered late to Israel, based on the expected lead time. Again, this is an average lead time, so in reality the lead time can in some cases be lower than the warning time and therefore it should result in an availability level greater than 0%. In this case, the multi-echelon model understates the availability level. However, it happens far more often that the model overstates the availability level and therefore it can be concluded that the multi-echelon model overstates the expected availability level. The observations made in table 18 and 19 are not unique. The same results hold for all four scenarios, i.e., in all four scenarios the multi-echelon model recommends 1 LRC less on stock than is actually required. As a result, when using 3 days warning time without false negatives the required network stock is thus 11 LRCs. Therefore, the added value is an inventory reduction of 35.3%, instead of 41.2% as stated in section 6.2.1. When using 3 days warning time and 10% false negatives the required network stock is thus 15 LRCs. Therefore, the added value is an inventory reduction of 11.8%, instead of 17.6% as stated in section 6.2.1.

6.2.3 Effect of warning time on the repair lead time

The repairable components (LRCs) consist of smaller subcomponents, which are called SRCs. Recall that the repair lead time, $L_{i,0}$, is the time from the moment a LRC has failed until the moment the LRC is repaired by a repair shop and back in stock at the central warehouse, i.e., the time needed to repair failed LRCs until they are ready to use again. Therefore, the repair lead time ($L_{i,0}$) consists of the shipment time from a local warehouse to a repair shop, the repair time at the repair shop, and the shipment time from the repair shop to the central warehouse. At the repair shop, the repair of failed components (LRCs) consists of the following actions. First, inspecting which SRC has failed that caused the LRC failure. Then, replacing the failed SRC with a new one. At last, the repaired LRC is tested for some period of time before it is put back in stock at the central warehouse. The SRCs are consumables and new subcomponents are ordered from external suppliers according to the $(S-1, S)$ policy. In the situation without early warnings, it is not known in advance which SRC caused the LRC failure, only after inspection by the repair shop it will be known. So, the SRCs are ordered after the inspection and this results in waiting time for the subcomponents (when they are not in stock at the moment they are needed). The early warnings, provided by the Royal Dutch Aerospace Centre, specify which repairable component (LRC) is going to fail in the near future. The warnings also specify which smaller subcomponent (SRC) is going to fail that will cause the LRC failure, so this saves inspection time at the repair shop. By knowing which SRC causes the LRC failure, the repair shop can order the SRCs needed for the repair from the external suppliers in advance of the LRC failure, so there will be less waiting time for the subcomponents (SRCs). Zero inspection time and less waiting time on SRCs results in a shorter repair lead time ($L_{i,0}$). A shorter repair lead time, in turn, results in a lower required network stock. Simulation models are developed to demonstrate the effect of warning time (ADI) on the repair lead time ($L_{i,0}$). Table 20 shows the input variables used for the repair lead time simulation. Furthermore, a MTBF of 8000 days is used to construct the repair demand rate for LRCs at the repair shop. This LRC demand rate is then split up between four different SRCs, and these SRC demand rates are used in the repair lead time simulation.

Table 20. Input variables used for repair lead time simulation

Variables	Without warning time	With y days warning time
Shipment local warehouse → repair shop	10 days	10 days
Inspection time	10 days	0 days
Ordering SRC at day	t=20	t=-y
Replacement time	10 days	10 days
Testing time	30 days	30 days
Supplier lead time	100 days	100 days
Shipment repair shop → central warehouse	3 days	3 days

Table 21 shows the output of the repair lead time simulation, using the input variables from table 20, a base-stock level of 0 for the SRCs, and a 95% aggregate availability constraint. Table 22 shows the output of the repair lead time simulation, using the input variables from table 20, a base-stock level of 1 for the SRCs, and a 95% aggregate availability constraint. For the repair lead time simulation, a period length of 15000 periods is used and 100 replications.

Therefore, the repair lead time ($L_{i,0}$), in both tables, is the average repair lead time over 100 replications of the simulation. Furthermore, the run time of the simulation is just a few seconds.

Table 21. Output repair lead time simulation using base-stock level 0

Situation	Repair lead time ($L_{i,0}$)	Reduction (%)	Network stock
0 days warning time	164.7	0%	17 ($L_{i,0}$=100)
1-day warning time, 0% fn	143.4	12.9%	13 ($L_{i,0}$=87) instead of 14 ($L_{i,0}$=100)
1-day warning time, 10% fn	144.8	12.1%	15 ($L_{i,0}$=88) instead of 16 ($L_{i,0}$=100)
3 days warning time, 0% fn	141.0	14.4%	9 ($L_{i,0}$=86) instead of 10 ($L_{i,0}$=100)
3 days warning time, 10% fn	142.9	13.2%	12 ($L_{i,0}$=87) instead of 14 ($L_{i,0}$=100)
5 days warning time, 0% fn	139.1	15.5%	8 ($L_{i,0}$=84) instead of 9 ($L_{i,0}$=100)
5 days warning time, 10% fn	141.4	14.1%	11 ($L_{i,0}$=86) instead of 12 ($L_{i,0}$=100)

Table 22. Output repair lead time simulation using base-stock level 1

Situation	Repair lead time ($L_{i,0}$)	Reduction (%)	Network stock
0 days warning time	112.6	0%	17 ($L_{i,0}$=100)
1-day warning time, 0% fn	93.2	17.2%	13 ($L_{i,0}$=83) instead of 14 ($L_{i,0}$=100)
1-day warning time, 10% fn	95.4	15.3%	15 ($L_{i,0}$=85) instead of 16 ($L_{i,0}$=100)
3 days warning time, 0% fn	91.7	18.6%	9 ($L_{i,0}$=81) instead of 10 ($L_{i,0}$=100)
3 days warning time, 10% fn	93.8	16.7%	12 ($L_{i,0}$=83) instead of 14 ($L_{i,0}$=100)
5 days warning time, 0% fn	90.4	19.7%	8 ($L_{i,0}$=81) instead of 9 ($L_{i,0}$=100)
5 days warning time, 10% fn	92.0	18.3%	11 ($L_{i,0}$=82) instead of 12 ($L_{i,0}$=100)

The results of the repair lead time simulation, table 21 and 22, show that warning time (ADI) indeed results in a shorter repair lead time ($L_{i,0}$). For example, using 3 days warning time with 10% false negatives and a base-stock level of 0 for the SRCs, results in a 13.2% reduction of the repair lead time. Using a base-stock level of 1 for the SRCs results in a 16.7% reduction of the repair lead time. In section 6.2.1, a repair lead time ($L_{i,0}$) of 100 days was used to calculate the optimal network stocks. In this section, the optimal network stocks from figure 8, i.e., the results of the model with warning time (ADI) including false negatives, are recalculated based on the reduced repair lead times. The recalculated network stocks, for a few situations using the 95% aggregate availability constraint, can be found in the last column of table 21 and 22. As can be observed, the recalculated optimal network stocks in table 21 are equal to table 22. Figure 11 shows the results of the recalculated optimal network stocks using a 95% aggregate availability constraint, i.e., the results of the model with warning time (ADI), including false negatives and reduced repair lead times, using a 95% aggregate availability constraint. Figure 12 shows the results of the model with warning time (ADI), including false negatives and reduced repair lead times, using a 95% local availability constraint. The situation with zero days warning time indicates the result of the base model for scenario 1, i.e., the result of the model without warning time (ADI), which is called the baseline.

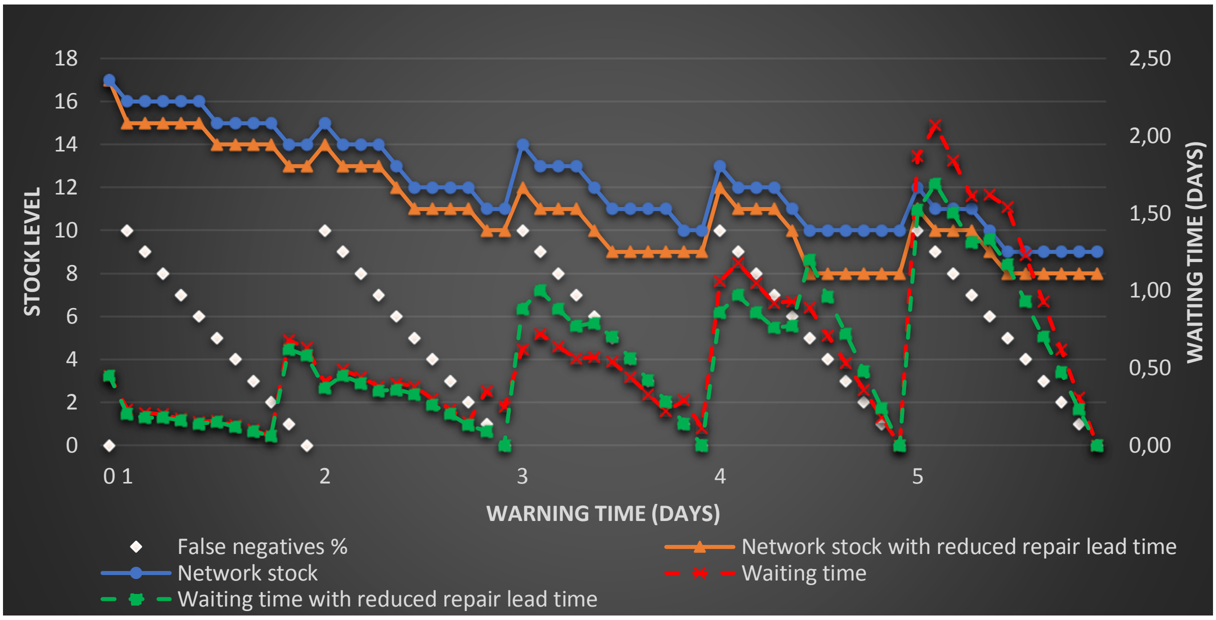

Figure 11. Model results with warning time, including false negatives and reduced repair lead times, using aggregate availability constraint

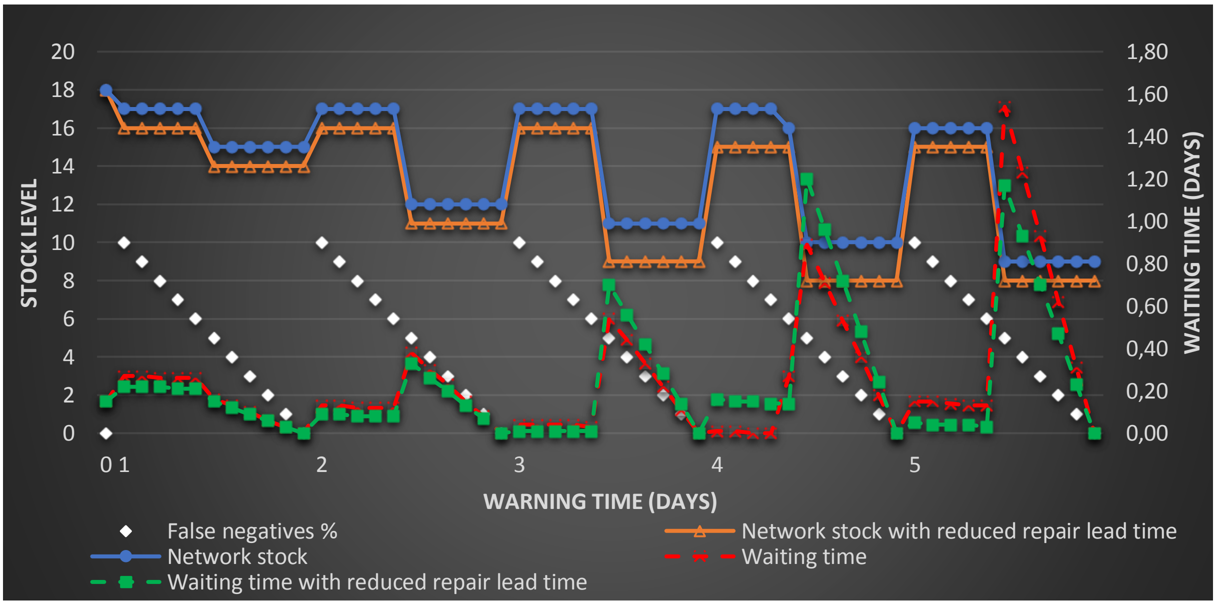

Figure 12. Model results with warning time, including false negatives and reduced repair lead times, using local availability constraint

As can be concluded from figure 11 and 12, incorporating the reduced repair lead time in the multi-echelon model with warning time (ADI) and false negatives, results in an extra network stock reduction of 1 or 2 LRCs for both the 95% local and aggregate availability constraint. For example, the situation with 3 days warning time without false negatives resulted in a network stock of 10 LRCs and a waiting time of 0.11 days for the aggregate availability constraint. Incorporating the reduced repair lead time results in a network stock of 9 LRCs and a waiting time of 0.00 days, as can be observed in figure 11. For the local availability constraint, the situation with 3 days warning time without false negatives resulted in a network stock of 11 LRCs and a waiting time of 0.00 days. Incorporating the reduced repair lead time results in a network stock of 9 LRCs and a waiting time of 0.00 days, as can be observed in figure 12. Furthermore, the situation with 3 days warning time and 10% false negatives resulted in a network stock of 14 LRCs and a waiting time of 0.62 days for the aggregate availability constraint. Incorporating the reduced repair lead time results in a network stock of 12 LRCs and a waiting time of 0.88 days, as can be observed in figure 11. For the local availability constraint, the situation with 3 days warning time and 10% false negatives resulted in a network stock of 17 LRCs and a waiting time of 0.04 days. Incorporating the reduced repair lead time results in a network stock of 16 LRCs and a waiting time of 0.01 days, as can be observed in figure 12. Therefore, it can be concluded from figure 11 and 12, and table 21 and 22, that warning time (ADI) reduces the repair lead time ($L_{i,0}$), which in turn reduces the required network stock.

In figure 11 and 12, the situation with zero days warning time indicates the result of the base model for scenario 1, i.e., the result of the model without warning time (ADI), which is called the baseline. Furthermore, the results of the model with warning time (ADI), including false negatives and reduced repair lead times, are shown in figure 11 and 12. These results are the final results of the model with ADI. By comparing the results of the base model with the final results of the model with ADI, the added value of using early warnings for the failure of components (LRCs) can be uncovered. The situation without warning time (ADI) results in a network stock of 17 LRCs and a waiting time of 0.45 days for the 95% aggregate availability constraint, and for the 95% local availability constraint it results in a network stock of 18 LRCs and a waiting time of 0.15 days. The final result of the model with ADI, for the situation with 3 days warning time without false negatives, is a network stock of 9 LRCs and a waiting time of 0.00 days for both the aggregate and local availability constraint. The final result of the model with ADI, for the situation with 3 days warning time and 10% false negatives, is a network stock of 12 LRCs and a waiting time of 0.88 days for the aggregate availability constraint, and a network stock of 16 LRCs and a waiting time of 0.01 days for the local availability constraint. The added value of using ADI for the failure of components is as follows. When using 3 days warning time without false negatives, the added value is an inventory reduction of 47.1% and a waiting time reduction of 100.0% for the aggregate availability constraint, and for the local availability constraint the added value is an inventory reduction of 50.0% and a waiting time reduction of 100.0%. When using 3 days warning time and 10% false negatives, the added value is an inventory reduction of 29.4% for the aggregate availability constraint, but it is accompanied with a waiting time increase of 95.6%, and for the local availability constraint the added value is an inventory reduction of 11.1% and a waiting time reduction of 93.3%. For the aggregate availability constraint, it seems a high increase in waiting time, however, in absolute terms the waiting time increases by less than half a day. Based on these results, it can be concluded that the model with ADI results in a significant reduction of the network stock, especially when the false negative percentage is low, compared to the base model. In other words, the model with ADI requires (much) less network stock, and therefore inventory investment costs, for achieving the 95% availability level compared to the base model. Therefore, the model with ADI yields better results.

6.2.4 Validation of model results with reduced repair lead time

The results of the model with warning time (ADI) including false negatives and reduced repair lead times, i.e., the final results of the model with ADI, section 6.2.3, have been validated using simulation. This is done for the results using a 95% aggregate availability constraint. Simulations have been developed using a MTBF of 8000 days, as described in section 6.2.3. The optimal network stock, and corresponding availability level, from simulation is compared to the optimal network stock and corresponding availability level of the multi-echelon model. For simulation, a period length of 15000 periods is used and 100 replications. Therefore, the availability level of the simulation is the average availability level over 100 replications. Furthermore, the run time of the simulation is just a few seconds, whereas the run time of the multi-echelon model is approximately a minute. Table 23 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation for the situation with 3 days warning time without false negatives and $L_{i,0}$=83. Table 24 shows the optimal network stock, and corresponding availability level, according to the multi-echelon model and the simulation for the situation with 3 days warning time with 10% false negatives and $L_{i,0}$=85.

Table 23. Validation of results using 3 days warning time without false negatives and $L_{i,0}$=83

	Network stock = 8	Network stock = 9	Network stock = 10
Availability Level (multi-echelon)	67.8% (0% Norway, Italy, Israel)	100% *	100%
Availability Level (simulation)	91.7%	94.5%	96.7% *

** indicates optimal solution*

Table 24. Validation of results using 3 days warning time with 10% false negatives and $L_{i,0}$=85

	Network stock = 11	Network stock = 12	Network stock = 13
Availability Level (multi-echelon)	94.6%	95.6% *	97.6%
Availability Level (simulation)	91.6%	94.5%	95.7% *

** indicates optimal solution*

As can be observed from table 23 and 24, there is a difference of 1 LRC between the optimal network stock according to the multi-echelon model and simulation. In both situations, the multi-echelon model recommends 1 LRC less on stock than is actually required, which was also the case in section 6.2.2. The cause of this is that METRIC models sometimes tend to understate the expected backorders and therefore overstate the expected availability of repairable items (Sherbrooke, 1986). This can be explained by the fact that the multi-echelon model uses the expected lead time, which is an average lead time, for the calculation of the availability level. When the expected lead time is smaller than or equal to the warning time ($L_{i,j} \leq L_{i,j}^{\text{war}}$), the model returns an availability level of 100% for the situation without false negatives (and 90% for the situation with 10% false negatives). This is the case for all locations in table 23 using a network stock of 9 LRCs or more. The model assumes that all LRCs will always be delivered on time to all locations, based on the expected lead time. However, this is an average lead time, so in reality the lead time can in some cases be higher than the warning time and therefore it should result in an availability level less than 100%. Therefore, the multi-echelon model overstates the availability level. Furthermore, when the expected lead time is greater than the warning time ($L_{i,j} > L_{i,j}^{\text{war}}$), the model returns an availability level of 0%. This is the case for Norway, Italy, and Israel in table 23 using a network stock of 8 LRCs. The model assumes that all LRCs will always be delivered late to these locations, based on the expected lead time. Again, this is an average lead time, so in reality the lead time can in some cases be lower than the warning time and therefore it should result in an availability level greater than 0%. In this case, the multi-echelon model understates the availability level. However, it happens far more often that the model overstates the availability level and therefore it can be concluded that the multi-echelon model overstates the expected availability level. The observations made in table 23 and 24 are not unique. The same results hold for all four scenarios, i.e., in all four scenarios the multi-echelon model recommends 1 LRC less on stock than is actually required. As a result, when using 3 days warning time without false negatives the required network stock is thus 10 LRCs. Therefore, the added value is an inventory reduction of 41.2%, instead of 47.1% as stated in section 6.2.3. When using 3 days warning time and 10% false negatives the required network stock is thus 13 LRCs. Therefore, the added value is an inventory reduction of 23.5%, instead of 29.4% as stated in section 6.2.3.

6.3 Model with lateral transshipments

The final results of the model with ADI yield the best results so far. In this section, it is investigated if incorporating reactive lateral transshipments in the lowest echelon of the F-35 spare parts supply chain yields even better results. A reactive lateral transshipment is defined as a local warehouse which provides stocked items (LRCs) to another local warehouse which faces a stock out (or the risk of a stock out). Therefore, when using lateral transshipments, a demand of a local warehouse can be satisfied from the central warehouse, as well as from another local warehouse. Paterson et al. (2010) state that reactive lateral transshipments are suitable in an environment where the transshipment costs are relatively low compared to the costs associated with holding large amounts of stock and with failing to meet demand immediately. This is often the case in a spare parts environment. Alfredsson and Verrijdt (1999) compared their model with lateral transshipments to the VARI-METRIC model and they found a maximum cost reduction of 43.9% and a minimum cost reduction of 13.2%. The results also show that in many cases the stock levels are lower, especially the central stock level showed a significant decrease. Furthermore, Kranenburg (2006) discussed a semi-conductor company ASML and showed that using reactive lateral transshipments can save the company up to 50% of annual inventory related costs for spare parts. These results indicate that using lateral transshipments in a distribution network for spare parts can be very beneficial.

The model with lateral transshipments allows for lateral transshipments only when a local warehouse faces demand while it has no inventory on hand, i.e., when it faces a stock out. This is the case when the central warehouse is not able to satisfy the demand of the local warehouse. Therefore, the procedure is as follows. When the central warehouse receives a warning that a demand will arise at a local warehouse within a few days, the central warehouse satisfies this demand as described before. Only when the central warehouse is not able to satisfy this demand, i.e., when it has no inventory on hand, a lateral transshipment is considered from another local warehouse in order to satisfy the demand. Axsäter (1990) provided a new approximation technique for modelling lateral transshipments in a two-echelon inventory system with repairable items, one-for-one replenishments, and Poisson demand. The characteristic feature is that the demand rate at a local warehouse depends on the inventory level. With positive inventory on hand, the normal demand is faced plus demand for lateral transshipments from other local warehouses. With no positive inventory on hand, the only real demand is the demand that has to be backordered. In addition to the fraction of demand satisfied from stock on hand and the fraction of demand that is backordered, a new variable is included in the model. This new variable is the fraction of demand satisfied by lateral transshipments and it is defined as alpha (α). Axsäter (1990) divided the local warehouses into a number of groups and allowed lateral transshipments within such a group, but not between the groups. Because exponential lead times are assumed, a birth-death (Markov) queueing model is used to derive the equations of the steady state probabilities of the net inventory. Alfredsson and Verrijdt (1999), Kukreja et al. (2001), Grahovac & Chakravarty (2001) also considered lateral transshipments in their inventory models. All articles followed the approach of Axsäter (1990) and used a Markov queueing model as solution methodology. However, Basten & Van Houtum (2014) investigated solving the METRIC model with lateral transshipments using the Greedy heuristic, instead of a Markov model. Basten & Van Houtum (2014) state that the Greedy heuristic should lead to good feasible solutions. In order to obtain a sufficiently fast procedure for problems of real-life size, such a Greedy heuristic should be based on an efficient and still accurate approximate evaluation method. However, so far, such a method is not available. Therefore, it is not possible to solve the METRIC model with lateral transshipments using the Greedy heuristic as solution methodology. As a result, only simulations are developed in this section in order to demonstrate the effect of using reactive lateral transshipments for the F-35 spare parts supply chain.

The simulations are developed as follows. The local warehouses are divided into a number of groups (2 groups) and lateral transshipments are allowed within such a group, but not between the groups. This is also done by Axsäter (1990). Group 1 consist of the local warehouses in the UK, Norway, Denmark, and the Netherlands. Group 2 consist of the local warehouses in Italy, Usafe, Israel, and Belgium. The 2 groups are composed in such a way that each group faces (almost) the same demand rate. Furthermore, two different lateral transshipment rules are used for the choice of the sending source, which are the minimum backorder (min BO) rule and the maximum inventory on hand (max Ioh) rule. These transshipment rules are also used by, for example, Lee (1987) and Seidscher & Minner (2013). With the minimum backorder (min BO) rule, the location with the lowest demand rate is chosen as the sending source, because this location has the lowest backorder probability and the least impact on the aggregate availability level. When the location with the lowest demand rate has no stock available for lateral transshipment, the location with the second lowest demand rate is chosen as the sending source, and so on. With the maximum inventory on hand (max Ioh) rule, the location with the highest inventory on hand is chosen as the sending source. When it occurs that the inventory on hand is equal among possible sending sources, the location is chosen with the lowest demand rate because this location has the lowest backorder probability and the least impact on the aggregate availability level.

The simulation results in section 6.2.4, which are the final results of the model with ADI (without lateral transshipments), are compared to the simulation results while using ADI and reactive lateral transshipments. In this way, it can be uncovered if using reactive lateral transshipments is beneficial for the F-35 spare parts supply chain. Table 25 and table 26 show the optimal network stock and corresponding availability level according to the simulations with and without lateral transshipments (LT), for the situation with 3 days warning time without false negatives and $L_{i,0}$=83. In table 25 the minimum backorder (min BO) transshipment rule is used and in table 26 the maximum inventory on hand (max Ioh) transshipment rule is used.

Table 25. Simulation results using min BO, 3 days warning time without false negatives, and $L_{i,0}$=83

	Network stock = 8	Network stock = 9	Network stock = 10
Availability Level simulation (without LT)	91.7%	94.5%	96.7% *
Availability Level simulation (with LT)	91.7%	94.5%	96.7% *

** indicates optimal solution*

Table 26. Simulation results using max Ioh, 3 days warning time without false negatives, and $L_{i,0}$=83

	Network stock = 8	Network stock = 9	Network stock = 10
Availability Level simulation (without LT)	91.7%	94.5%	96.7% *
Availability Level simulation (with LT)	91.7%	94.5%	96.7% *

** indicates optimal solution*

In the situation with 3 days warning time without false negatives and without lateral transshipments, all LRCs are kept in stock at the central warehouse. Since no stock is kept at the local warehouses, no improvements are realized when including lateral transshipments, as can be observed in table 25 and table 26. The simulations with and without lateral transshipments show the exact same results. Furthermore, a decentralized allocation of the stock is also considered. In this way, (almost) all the stock is put at the local warehouses and lateral transshipments are made possible. However, a decentralized allocation yields worse results. Therefore, no improvement is realized using lateral transshipments for the situation with 3 days warning time without false negatives. This means that for this situation the final result is a network stock of 10 LRCs, which are all allocated to the central warehouse. Therefore, when facing zero false negatives, the model with ADI in combination with a centralized allocation yields the best results for the F-35 supply chain. The inventory reduction realized compared to the baseline is 41.2%, as already stated in section 6.2.4.

Table 27 and table 28 show the optimal network stock and corresponding availability level according to the simulations with and without lateral transshipments (LT), for the situation with 3 days warning time, 10% false negatives, and $L_{i,0}$=85. In table 27 the minimum backorder (min BO) transshipment rule is used and in table 28 the maximum inventory on hand (max Ioh) transshipment rule is used.

Table 27. Simulation results using min BO, 3 days warning time with 10% false negatives, and $L_{i,0}$=85

	Network stock = 11	Network stock = 12	Network stock = 13
Availability Level simulation (without LT)	91.6%	94.5%	95.7% *
Availability Level simulation (with LT)	93.5%	95.5% *	96.9%

** indicates optimal solution*

Table 28. Simulation results using max Ioh, 3 days warning time with 10% false negatives, and $L_{i,0}$=85

	Network stock = 11	Network stock = 12	Network stock = 13
Availability Level simulation (without LT)	91.6%	94.5%	95.7% *
Availability Level simulation (with LT)	93.6%	95.7% *	96.9%

** indicates optimal solution*

In the situation with 3 days warning time, 10% false negatives, and without lateral transshipments, 9 LRCs are kept in stock at the central warehouse and there are 4 local warehouses that keep 1 LRC on stock in order to satisfy the 95% aggregate availability. So, without lateral transshipments the required network stock is 13 LRCs. Since stock is kept at the local warehouses, lateral transshipments are possible. As can be observed from table 27 and table 28, the optimal network stock is 12 LRCs when lateral transshipments are used. Therefore, using lateral transshipments results in an additional network stock reduction of 1 LRC. Furthermore, no significant performance difference is observed between the two transshipment rules, which was also found by Lee (1987) and Seidscher & Minner (2013).

Next, it is investigated if the allocation of the network stock can be improved in the case of 10% false negatives and lateral transshipments. It is investigated if allocating most of the LRCs locally and some LRCs centrally yields better results than allocating most of the LRCs centrally and some locally, i.e., decentralized versus centralized allocation. Table 29 and table 30 show the optimal network stock and corresponding availability level according to the simulations with and without lateral transshipments (LT), for the situation with 3 days warning time, 10% false negatives, $L_{i,0}$=85, and a decentralized allocation. In table 29 the minimum backorder (min BO) transshipment rule is used and in table 30 the maximum inventory on hand (max Ioh) transshipment rule is used.

Table 29. Simulation results using min BO, 3 days warning time with 10% false negatives, and $L_{i,0}$=85

	Network stock = 11	Network stock = 12	Network stock = 13
Availability Level simulation (without LT)	91.6%	94.5%	95.7% *
Availability Level simulation (with LT)	95.8% *	97.8%	98.5%

** indicates optimal solution*

Table 30. Simulation results using max Ioh, 3 days warning time with 10% false negatives, and $L_{i,0}$=85

	Network stock = 11	Network stock = 12	Network stock = 13
Availability Level simulation (without LT)	91.6%	94.5%	95.7% *
Availability Level simulation (with LT)	95.9% *	98.0%	98.7%

** indicates optimal solution*

As can be observed from table 29 and table 30, the optimal network stock when using lateral transshipments and a decentralized allocation is 11 LRCs. Furthermore, no significant performance difference is observed between the two transshipment rules. The optimal network stock, in table 27 and 28, when using lateral transshipments and a centralized allocation is 12 LRCs. Therefore, a decentralized allocation yields better results than a centralized allocation, but this only holds in the case of false negatives and when lateral transshipments are used. As a result, the required network stock is thus 11 LRCs for the situation with 3 days warning time, 10% false negatives, and lateral transshipments. Without lateral transshipments the required network stock is 13 LRCs, therefore, using lateral transshipments results in an additional network stock reduction of 2 LRCs. The inventory reduction realized of the model with ADI compared to the baseline is 23.5%, as stated in section 6.2.4. However, the inventory reduction realized of the model with ADI and lateral transshipments is 35.3% compared to the baseline. Therefore, when facing false negatives, incorporating reactive lateral transshipments in the model with ADI, in combination with a decentralized allocation, yields the best results for the F-35 spare parts supply chain.

7. Conclusion and recommendations

In this paper a multi-echelon inventory system for the F-35 spare parts supply chain is developed, using ADI of component failures. The goal of the designed inventory system is to determine optimal base-stock levels, for the central warehouse and local warehouses, that minimize the inventory investment costs while satisfying a 95% availability level. In addition, it is investigated if using reactive lateral transshipments between the local warehouses yields even better results, i.e., lower inventory investment costs. A continuous one-for-one, $(S-1, S)$, inventory replenishment policy is used and Poisson distributed demand. The problem faced in this paper is known in literature as the repairable inventory problem.

The METRIC model (Multi-Echelon Technique for Recoverable Item Control) is extensively discussed in literature, since it represents a fundamental development in repairable inventory theory and because so many later models are METRIC based. METRIC-type models have been implemented in various software tools, in use at various organizations. Historically, military organizations, especially the US military forces, have been the first to adopt such models. Also, outside the military these models have been applied. The repairable inventory problem faced by the METRIC model is identical to the problem faced in the thesis. Therefore, the METRIC model with the Greedy solution algorithm formulated by Basten & Van Houtum (2014), as described in section 5, is followed and used in this paper as the base model. The base model is the model without ADI of component failures and lateral transshipments. The base model determines optimal base-stock levels, for the central warehouse and local warehouses, that minimize the inventory investment costs while satisfying the 95% availability constraint. This model serves as the baseline.

The model with ADI is the model that makes use of the predictions of component (LRC) failures. The predictions of component failures are obtained by the Royal Dutch Aerospace Centre using machine learning techniques to predict the failure time, failure mode, and probability of failure. These predictions result in early warnings, which indicate that a component (LRC) is going to fail within a few days at a certain location with a certain probability. The warning time is the time from the moment a warning is received until the moment the component fails. Therefore, by using the early warnings, or ADI, it is known a few days in advance at which location a component (LRC) is needed with a certain probability. For including ADI of component failures in the model, Hariharan & Zipkin (1995) found that demand lead times are, in a precise sense, the opposite of supply lead times. That is, the effect of a demand lead time on overall system performance is precisely the same as a corresponding reduction in the supply lead time. Therefore, the warning time in this paper, resulting from the ADI of component failures, is included in the model as a reduction in the supply lead times. The inaccuracy, or imperfectness, of the ADI is included in the model as well. This is done by making a distinction between false negatives and false positives. False negatives are components (LRCs) that fail without receiving a warning in advance, and false positives are components that fail at a later moment than predicted. For the false negatives, the result is no reduction in the supply lead times, whereas for the false positives a reduction in the supply lead times is applied, but the component is actually not needed yet. False negatives are very problematic because when a component fails unannounced at a local warehouse and there is no stock at that warehouse, it results in a backorder and therefore in downtime for the F-35s.

In addition, the warnings also specify which smaller subcomponent (SRC) is going to fail that will cause the LRC failure, which saves inspection time at the repair shop. By knowing which SRC causes the LRC failure, the repair shop can order the SRCs needed for the repair in advance of the LRC failure, so there will be less waiting time for the subcomponents (SRCs). Zero inspection time and less waiting time on SRCs results in a shorter repair lead time for the LRCs. A shorter repair lead time, in turn, results in lower required stock levels. Therefore, the effect of warning time, resulting from the ADI of component failures, on the repair lead time is investigated and included in the model with ADI.

Finally, the model with lateral transshipments (and ADI) is the model that makes use of reactive lateral transshipments. A reactive lateral transshipment is defined as a local warehouse which provides stocked items (LRCs) to another local warehouse which faces a stock out (or the risk of a stock out). Therefore, when using lateral transshipments, a demand of a local warehouse can be satisfied from the central warehouse, as well as from another local warehouse. Paterson et al. (2010) state that reactive lateral transshipments are suitable in an environment where the transshipment costs are relatively low compared to the costs associated with holding large amounts of stock and with failing to meet demand immediately. This is often the case in a spare parts environment. The model with lateral transshipments allows for lateral transshipments only when a local warehouse faces demand while it has no inventory on hand, i.e., when it faces a stock out. This is the case when the central warehouse is not able to satisfy the demand of the local warehouse. Therefore, the procedure is as follows. When the central warehouse receives a warning that a demand will arise at a local warehouse within a few days, the central warehouse satisfies this demand as described before. Only when the central warehouse is not able to satisfy this demand, i.e., when it has no inventory on hand, a lateral transshipment is considered from another local warehouse in order to satisfy the demand.

Basten & Van Houtum (2014) investigated solving the METRIC model with lateral transshipments using the Greedy heuristic. Basten & Van Houtum (2014) state that the Greedy heuristic should lead to good feasible solutions. In order to obtain a sufficiently fast procedure for problems of real-life size, such a Greedy heuristic should be based on an efficient and still accurate approximate evaluation method. However, so far, such a method is not available. Therefore, it is not possible to solve the METRIC model with lateral transshipments using the Greedy heuristic as solution methodology. As a result, only simulations are developed in order to demonstrate the effect of using reactive lateral transshipments for the F-35 spare parts supply chain. Two different lateral transshipment rules are used for the choice of the sending source, which are the minimum backorder rule and the maximum inventory on hand rule. However, no significant performance difference is observed between the two lateral transshipment rules, which was also found by Lee (1987) and Seidscher & Minner (2013).

Table 31 shows an overview of the different model results obtained in section 6, using a MTBF of 8000 days and a 95% aggregate availability constraint. 3 days warning time is used for the models with ADI. The table shows the required network stock, availability level, percentage inventory reduction, and the allocation of the stock of the different models developed. The percentage inventory reduction is the reduction in inventory investment costs compared to the base model.

Table 31. Overview of the results, using MTBF=8000 days and a 95% aggregate availability level

Model	Network stock (LRCs)	Availability level (%)	Reduction (%)	Allocation
Base model	17	95.9%	0%	9 LRCs central, 8 local
Model with ADI (0% fn)	10	96.7%	41.2%	10 LRCs central, 0 local
Model with ADI and LT (0% fn)	10	96.7%	41.2%	10 LRCs central, 0 local
Model with ADI (10% fn)	13	95.7%	23.5%	9 LRCs central, 4 local
Model with ADI and LT (10% fn)	11	95.9%	35.3%	3 LRCs central, 8 local

As can be observed from table 31, the base model requires a network stock of 17 LRCs and achieves an availability level of 95.9%. 9 LRCs are kept in stock at the central warehouse and every local warehouse keeps 1 LRC in stock. These results are the baseline results. When facing 0% false negatives (fn), the ADI of component failures is always 100% accurate, i.e., perfect ADI. When facing 10% false negatives (fn), 10% of the components fail without receiving a warning in advance, i.e., imperfect ADI.

The model with perfect ADI requires a network stock of 10 LRCs, which are all allocated to the central warehouse (centralized allocation), and achieves an availability level of 96.7%. The model with perfect ADI achieves an inventory investment reduction of 41.2% and a higher availability level, compared to the base model. The model with perfect ADI and lateral transshipments (LT) obtains the same results. Since no stock is kept at the local warehouses, no improvements are realized when including lateral transshipments. Furthermore, a decentralized allocation of the stock is also considered. In this way, (almost) all the stock is put at the local warehouses and lateral transshipments are made possible. However, a decentralized allocation yields worse results. Therefore, no improvement is realized using lateral transshipments for the situation with perfect ADI.

The model with imperfect ADI requires a network stock of 13 LRCs, of which 9 are allocated to the central warehouse and 4 to the local warehouses, and achieves an availability level of 95.7%. The model with imperfect ADI achieves an inventory investment reduction of 23.5% and almost the same availability level, compared to the base model. The model with imperfect ADI and lateral transshipments (LT) requires a network stock of 11 LRCs, of which 3 are allocated to the central warehouse and 8 to the local warehouses (decentralized allocation), and achieves an availability level of 95.9%. A decentralized allocation yields better results than a centralized allocation, but this only holds in the case of imperfect ADI and when lateral transshipments are used. The model with imperfect ADI and lateral transshipments (LT) achieves an inventory investment reduction of 35.3% and the same availability level, compared to the base model.

Based on these results, recommendations for the company can be given. It can be concluded that including (im)perfect ADI of component failures in the base METRIC model, results in a significant reduction of the network stock and therefore in a significant reduction of the inventory investment costs.

When facing perfect ADI, i.e., 3 days warning time without false negatives, the model with ADI is the best model to use. This model results in a network stock of 10 LRCs, a 96.7% availability level, and an inventory investment reduction of 41.2% compared to the base model. All 10 LRCs should be kept in stock at the central warehouse (centralized allocation), i.e., $S_{i,0} = 10$ and $S_{i,j} = 0$. Including lateral transshipments in this situation yields no further improvements.

When facing imperfect ADI, i.e., 3 days warning time with 10% false negatives, the model with ADI and lateral transshipments (LT) is the best model to use. This model results in a network stock of 11 LRCs, a 95.9% availability level, and an inventory investment reduction of 35.3% compared to the base model. 3 LRCs should be kept in stock at the central warehouse and every local warehouse should keep 1 LRC in stock (decentralized allocation), i.e., $S_{i,0} = 3$ and $S_{i,j} = 1$. It can be concluded that using lateral transshipments between the local warehouses almost neutralize the negative effect of the false negatives.

Furthermore, it can be concluded from this paper that increasing warning time results in a lower required network stock, i.e., the network stock decreases when the warning time increases. Also, it can be concluded that increasing the MTBF results in a lower required network stock. At last, it can be concluded that reducing the repair lead time results in a lower required network stock. Therefore, it could be interesting for the company to investigate the options for increasing the reliability of the components, i.e., increasing the MTBF, and to investigate the options for reducing the repair lead time, in order to further reduce the network stock and therefore the inventory investment costs.

For further research it could be interesting to investigate and develop a Greedy heuristic that is able to solve the METRIC model with lateral transshipments. The Greedy heuristic should be based on an efficient and still accurate approximate evaluation method and so far such a method is not available. Furthermore, it could be interesting for further research to include stochastic supply lead times in the models. In this paper it is assumed that the supply lead times are deterministic. At last, for further research it could be interesting to apply the developed models in this paper on an inventory problem with more than two echelons, and to investigate the performance differences subsequently.

References

Alfredsson, P. (1997). Optimization of multi-echelon repairable item inventory systems with simultaneous location of repair facilities. *European Journal of Operational Research, 99*, 584-595.

Alfredsson, P., and Verrijdt, J. (1999). Modeling emergency supply flexibility in a two-echelon inventory system. *Management Science, 45*(10), 1416-1431.

Axsäter, S. (1990). Modelling emergency lateral transshipments in inventory systems. *Management Science, 36*(11), 1329-1338.

Axsäter, S. (2003). A new decision rule for lateral transshipments in inventory systems. *Management Science, 49*(9), 1168-1179.

Axsäter, S. (2006). *Inventory Control.* Springer, New York (NY), second edition.

Basten, R. J. I., and Van Houtum, G. J. (2014). System-oriented inventory models for spare parts. *Surveys in Operations Research and Management Science, 19*(1), 34-55.

Cohen, M. A., Kamesan, P. V., Kleindorfer, P., Lee, H., and Tekerian, A. (1990). Optimizer: IBM's multi-echelon inventory system for managing service logistics. *Interfaces, 20*(1), 65-82.

Deshpande, V., Iyer, A. V., and Cho, R. (2006). Efficient supply chain management at the U.S. Coast Guard using part-age dependent supply replenishment policies. *Operations Research, 54*(6), 1028-1040.

Driessen, M. A., Arts, J. J., Van Houtum, G. J., Rustenburg, W., and Huisman, B. (2010). Maintenance spare parts planning and control: A framework for control and agenda for future research. *BETA working paper 325*.

Elwany, A. H., and Gebraeel, N. Z. (2008). Sensor-driven prognostic models for equipment replacement and spare parts inventory. *IIE Transactions, 40*(7), 629-639.

Gallego, G., Özer, Ö., and Zipkin, P. (2007). Bounds, heuristics, and approximations for distribution systems. *Operations Research, 55*(3), 503-517.

Grahovac, J., and Chakravarty, A. (2001). Sharing and lateral transshipment of inventory in a supply chain with expensive low-demand items. *Management Science, 47*(4), 579-594.

Graves, S. C. (1985). A multi-echelon inventory model for a repairable item with one-for-one replenishment. *Management Science, 31*(10), 1247-1256.

Guide Jr., V. D. R., and Srivastava, R. (1997). Repairable inventory theory: Models and applications. *European Journal of Operational Research, 102*, 1-20.

Hariharan, R., and Zipkin, P. H. (1995). Customer-order information, lead times, and inventories. *Management Science, 41*(10), 1599-1607.

Kennedy, W. J., Patterson, J. D., and Fredendall L. D. (2002). An overview of recent literature on spare parts inventories. *International Journal of Production Economics, 76*, 201-215.

Kranenburg, B. (2006). *Spare Parts Inventory Control under System Availability Constraints.* PhD thesis, BETA research school, Eindhoven (The Netherlands).

Kukreja, A., Schmidt, C. P., and Miller, D. M. (2001). Stocking decisions for low-usage items in a multi-location inventory system. *Management Science, 47*(10), 1371-1383.

Lee, H. L. (1987). A multi-echelon inventory model for repairable items with emergency lateral transshipments. *Management Science, 33*(10), 1302-1316.

Li, R., and Ryan, J. K. (2011). A Bayesian inventory model using real-time condition monitoring information. *Production and Operations Management, 20*(5), 754-771.

Lin, X., Basten, R. J. I., Kranenburg, A. A., and van Houtum, G. J. (2017). Condition based spare parts supply. *Reliability Engineering and System Safety, 168,* 240-248.

Louit, D., Pascual, R., Banjevic, D., and Jardine, A. K. S. (2011). Condition-based spares ordering for critical components. *Mechanical Systems and Signal Processing, 25*, 1837-1848.

Muckstadt, J. A. (1973). A model for a multi-item, multi-echelon, multi-indenture inventory system. *Management Science, 20*(4), 472-481.

Muckstadt, J. A. (2005). *Analysis and algorithms for service part supply chains.* Springer, Berlin.

Ozkan, E., Van Houtum, G. J., and Serin, Y. (2015). A new approximate evaluation method for two-echelon inventory systems with emergency shipments. *Annals of Operations Research, 224,* 147-169.

Paterson, C., Kiesmuller, G., Teunter, R., and Glazebrook, K. (2010). Inventory models with lateral transshipments: A review. *European Journal of Operational Research, 210*, 125-136.

Paterson, C., Teunter, R., and Glazebrook, K. (2012). Enhanced lateral transshipments in a multi-location inventory system. *European Journal of Operational Research, 221*(2), 317-327.

Rong, Y., Atan, Z., and Snyder, L. V. (2017). Heuristics for base-stock levels in multi-echelon distribution networks. *Production and Operations Management, 26*(9), 1760-1777.

Rustenburg, W. D., Van Houtum, G. J., and Zijm, W. H. M. (2001). Spare parts management at complex technology-based organizations: An agenda for research. *International Journal of Production Economics, 71*, 177-193.

Rustenburg, W. D., Van Houtum, G. J., and Zijm, W. H. M. (2003). Exact and approximate analysis of multi-echelon, multi-indenture spare parts systems with commonality. In Shanthikumar, J. G., Yao, D. D., and Zijm, W. H. M., editors, *Stochastic Modelling and Optimization of Manufacturing Systems and Supply Chains,* pages 143-176. Kluwer, Boston (MA).

Seidscher, A., and Minner, S. (2013). A semi-markov decision problem for proactive and reactive transshipments between multiple warehouses. *European Journal of Operational Research, 230*(1), 42-52.

Sherbrooke, C. C. (1968). Metric: A multi-echelon technique for recoverable item control. *Operations Research, 16*(1), 122-141.

Sherbrooke, C. C. (1986). Vari-metric: Improved approximations for multi-indenture, multi-echelon availability models. *Operations Research, 34*(2), 311-319.

Sherbrooke, C. C. (2004). *Optimal inventory modeling of systems: Multi-echelon techniques.* Wiley.

Topan, E., Tan, T., van Houtum, G. J., & Dekker, R. (2018). Using imperfect advance demand information in lost-sales inventory systems with the option of returning inventory. *IISE Transactions, 50*(3), 246-264.

Wong, H., Kranenburg, B., Van Houtum, G. J., and Cattrysse, D. (2007). Efficient heuristics for two-echelon spare parts inventory systems with an aggregate mean waiting time constraint per local warehouse. *OR Spectrum, 29*, 699-722.