World Academy of Science, Engineering and Technology
International Journal of Economics and Management Engineering
Vol:6, No:8, 2012

An Integrated Logistics Model of Spare Parts Maintenance Planning within the Aviation Industry

Roy Fritzsche, Rainer Lasch

Abstract—Avoidable unscheduled maintenance events and unnecessary spare parts deliveries are mostly caused by an incorrect choice of the underlying maintenance strategy. For a faster and more efficient supply of spare parts for aircrafts of an airline we examine options for improving the underlying logistics network integrated in an existing aviation industry network. This paper presents a dynamic prediction model as decision support for maintenance method selection considering requirements of an entire flight network. The objective is to guarantee a high supply of spare parts by an optimal interaction of various network levels and thus to reduce unscheduled maintenance events and minimize total costs. By using a prognostics-based preventive maintenance strategy unscheduled component failures are avoided for an increase in availability and reliability of the entire system. The model is intended for use in an aviation company that utilizes a structured planning process based on collected failures data of components.

Keywords—Aviation industry, Prognosis, Reliability, Preventive maintenance.

I. Introduction

OPERATORS and designers of complex networks (spare parts warehouses, repair bases, flight plan, aircrafts) in the aviation industry are confronted with complicated challenges. Spare parts must be initially distributed to the stations for high availability and low inventory costs. Furthermore, a high reliability of the entire fleet should be generated. To achieve this, the use of preventive maintenance actions with prognostics is essential. Therefore in this paper a three-level model for a simplified decision support in the aviation industry maintenance planning is presented. The idea behind this concept is the splitting of the whole planning process into three simpler planning sub-areas and with this decrease network planning complexity.

The increasing interest in optimal maintenance strategies is based on rising costs, improved quality of spare parts and an increasing pressure for reduced inventories [1], [45]. Particularly penalty costs for unscheduled maintenance activities and the resulting delay time costs increase more and more in time. To avoid idle times, unscheduled maintenance events and incorrect ordered or missing spare parts the purpose of this paper is to transfer unscheduled maintenance actions to scheduled actions or alternatively fixed service intervals to variable maintenance actions [33] by a simplified logistics planning. It is necessary to utilize the period of use or rather lifetime of the components as long as possible to guarantee a continuous high aircraft availability [10]. The major requirements for each airline operator are aircraft availability [24] and operability [29], as well as reliability levels and product quality [44]. Because of the continuing automation and the high capital tied up in production equipment, maintenance or rather the logistics network is an investment opportunity, which should be optimized as a whole, not a cost to be minimized [43]. With the application of this model, logistics service providers can find a balance between inventory, stock-out and obsolescence costs, while offering competitive service contracts. In the aviation industry there is a continuous growth in demand for planning, customer demand for security and global spare parts support, 24 hours a day, 7 days a week (24/7) recognized [5]. This model is based on preventive maintenance concepts in order to avoid shortages of urgently needed spare parts. A high availability of aircraft is guaranteed. The objectives high reliability of spare parts (high operating time) and availability of spare parts for the entire fleet can be reached by a very good prediction of failure times of components respectively an increase in the probability that the correct spare part is available at the right place and at the right time. Basis of good prognosis values of failures is an excellent data base, which consists of a collection of historical failure data or measured sensor data. The described model here uses the concept of maintenance-free operating periods (MFOP) [21] to calculate the failure rates of installed components, which can be continuously adjusted downwards by the learning effect [13]. A lifetime extension of spare parts is reached with an adjustment of failure rates. The adjustment is based on collected historical failure data and real-time measured sensor data. The main focus of the developed model is upon the avoidance of delays and downtime of aircrafts due to inaccurate maintenance planning and with it increase total costs. As shown in the literature review in section II no logistics network model exists that integrates dynamic, a learning curve and preventive maintenance to reduce planning complexity. For a given flight plan and fixed main bases, there is the exclusive possibility to reduce the idle times by an optimal choice of the maintenance strategy. To illustrate the existing interconnections between a physical area and a coordination area in the aviation industry a three-level model is implemented in section III. The main idea here is the development of a three-level concept to show significant influences of the kind of maintenance to the availability of the whole network and thus to the total cost of an airline. It identifies opportunities for maximum supply of spare parts at minimal costs through the comparison of three maintenance

R. Fritzsche, Department of Business Management and Economics, Dresden University of Technology, Dresden, Germany (e-mail: Roy.Fritzsche@tu-dresden.de)

R. Lasch, Department of Business Management and Economics, Dresden University of Technology, Dresden, Germany (e-mail: Rainer.Lasch@tu-dresden.de)

strategies. Another purpose of this paper is a more efficient use of the components lifetime and ordering of spare parts at the optimal time. The aspired subjective, continuous availability of spare parts at the lowest cost is examined using a simulation tool in section IV.

II. Literature review

Traditionally, maintenance strategies are divided into the following two types: corrective (reactive/unscheduled) maintenance and preventive (scheduled) maintenance [39]. The main difference between the two types is situated in the time of maintenance actions. Corrective maintenance is the replacement or repair of a component after it has failed. While in the preventive maintenance the performance of inspection and/or service activities are pre-planned in order to restore the functions of operating systems or equipment at a specific point in time and for a better scheduling of maintenance activities. Preventive maintenance can be divided into the following two subcategories: time-based and condition-based. While replacing parts after a fixed time interval in the time-based methods, for condition-based methods an optimal replacement time is prognosticated, based on past data and/or measured sensor-state data. With the help of scheduled maintenance with prognostics on, systems will rely in maintenance to be performed only when the system needs maintenance. In order to avoid downtime of the aircrafts in the model presented here, a preventive maintenance strategy with prediction of failure times of installed components by a MFOP approach is used.

In literature prognostics models are classified into the following four main groups: [38]

1) Knowledge-based models: These models determine the similarity between an observed situation and a database of pre-defined failures and relate the life expectancy from previous events.
2) Life expectancy models: These models determine the life expectancy of individual components in relation to the expected risk of deterioration under known operating conditions.
3) Artificial Neural Networks: These models calculate an estimated output for the remaining useful life of a component/machine, directly or indirectly, from a mathematical representation of the component/system.
4) Physical models: These models calculate an estimated output for the remaining useful life of a component/machine from a mathematical representation of the physical behavior of the degradation processes. Types of physical models tend to be application (Failure Mode) specific.

The presented model here is classified as a model-based approach (Physics of Failures) as in the model of a statistical/data-driven prognostics and health management (PHM) approach is used. Since the later presented model is not purely based on prognostics, but also integrates the logistics network, the scheme below is given for classification of integrated logistics networks. [19]

- Location selection: **discrete**, continuous
- Objective function: **MiniSum**, MiniMax

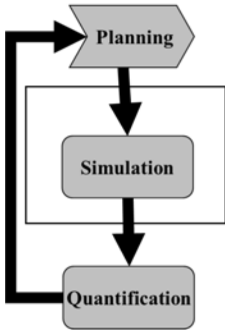

Fig. 1: Simulation supported planning

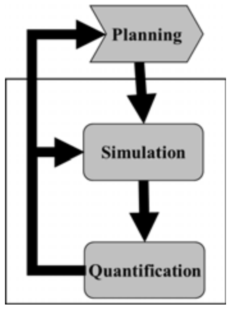

Fig. 2: Simulation-based optimized planning

- Variables: binary, integer (IP), mixed-integer (MIP)
- Cost for spare parts depot: **fixed costs**, no costs, variable costs
- Solution method: accurate methods, metaheuristics, heuristics, simulation

In the following the advanced model will be classified in the given integrated logistics network scheme. The location selection is discrete because of the given flight plan. The objective function is a summation of costs to be minimized. In the model binary and integer variables are possible. Fixed costs are necessary to open a spare parts depot at a location. The enhancement to the existing logistics models is the usage of simulation-based optimizing in the model presented here for a dynamic adjustment of component's failure rates. While at a simulation, supported planning all three areas (planning, simulation and quantification) are closed systems (see Fig. 1), parameters can be evaluated and are immediately integrated during the simulation-based optimization (see Fig. 2) [17]. The integration of the parameters in a simulation-based optimization is implemented in the model by adjusting the MFOP calculated failure rates of the installed components [13]. The adaptation of the failure rate is possible by the use of the learning effect of the dynamical MFOP method. Consequently, the optimization of durability of a working component is necessary and is implemented by the MFOP method [32]. MFOP guarantees a certain number of periods of operation without any interruption for unscheduled maintenance. Each MFOP period is followed by a maintenance recovery period (MRP), where the aircraft is repaired and prepared to complete the next MFOP period. With the help of the model presented here, a designer of an airline is able to prognosticate the point of time and the location of these MRPs. As a result, unscheduled maintenance is changed to scheduled maintenance and allows the production and usage of more reliable aircrafts [6]. The transfer of unplanned maintenance in planned maintenance costs result in higher maintenance costs, because of more maintenance actions, but significantly reduce the total cost of an airline. These savings are generated by avoiding penalty costs of unscheduled maintenance, avoiding transportation costs for urgent deliveries and decreasing inventory costs.

In addition to the identification of logistics models, mainly the application is in the foreground of the discussion. After detailed research it was not possible to identify a comprehensive integrated logistics network model for spare parts logistics in the aviation industry with an underlying preventive maintenance strategy based on prognosis. Indeed there are models of a complex description of a maintenance, repair and overhaul (MRO) network for aircraft components [11], [31]; however, the service requirements are depicted insufficient. Furthermore exists a variety of allocation models for the spare parts logistics in the aviation industry [3], [23], [26]. These models assume the logistics network of depots and supply points as given. In the model presented here a way of shifting spare parts to other depots and a closure of them are possible. In other publications, logistical networks are treated as examples of problems in mathematical optimization methods [16], [37]. Integrated logistic models are divided into three classes of models. In **location and network models** [4], [8], [18], [40] demands are modeled stochastically, multiple products are modeled simultaneously and specific locations are preferred. Whereas in **inventory planning** [12], [27], [36], [47] spare parts demand is modeled constant and Poisson distributed. The insufficient assumption in **integrated network models** [2], [28] is the inventory decision: this decision is limited to a particular part to be stored or not. The introduced existing models are fixed to specific sub-problems, too inflexible and do not consider the overall view of the network, that is no inclusion of flight plan and location allocation, and dynamic failure rate adjustment in the logistic planning. To increase operational reliability of the system, decrease downtime and maintenance costs is a target for every airline and a purpose of the introduced model. The presented model here fits best for aviation industry requirements, to reduce overall costs under a given flight plan for an existing fleet. In this model demand is modeled dynamic, by adjusting the component's failure rate, a single socket is considered, all locations are concerned the same and the designer of the network can store a stock of spare parts at any location. Other models improve model quality especially by the integration of all stages of the supply chain [7]. In this model, however, the focus is entirely on location and capacity decisions. Furthermore, there are models which describe a location inventory approach [9], [34]. Here the costs for safety stocks are mapped nonlinearly. Decision variables in both models include the choice of location and the number of depots and the upper limit of components to be stored per warehouse. Such decisions are not important in the developed model. The models of [4], [18], [41] strongly influenced the model determination.

III. The three-level model

A. Important assumptions and agreements

Below operational requirements of the aviation industry in the form of assumptions are described. In [4], [18], [24] an overview of conditions for logistics networks is given.

1) General logistical requirements:
   - High-value parts: High inventory costs in MRO networks of the aviation industry are ostensibly causes of high-quality, less demanded spare parts.
   - Repairable items: The considered components belong to the serviceable units: they pass a repair cycle in case of a failure.
   - Single item model: The proposed model is a single part model: by repeated application of the algorithms, multi items could be examined.
   - Potential depots: All airports in the network are potential spare parts depots.
   - Multi-sourcing strategy: Depots can be served from other depots by lateral transshipments.
   - Two-echelon model: The model treats a two-level model with depots and demand points.
   - Repair capacity: An infinite repair capacity of the hubs and the manufacturers of new parts is assumed.
   - (S-1, S) Order policy: Because of low demand the replacement is done by a one-for-one policy.
   - Lost-sales case: For non-compliance, an order is considered as lost.
2) Failure rate (Demand rate): The failure rate of installed components is initially assumed to be Poisson distributed with the possibility for adjustment based on excellent underlying prognostics data [13].
3) Fill rate: The fill rate is the percentage of all the demanded spare parts that can be covered by the existing stock. It is therefore dependent on the existing stock of the depot and the associated demand.
4) Warehouse stock and inventory costs: The initial/safety stock will not be allocated deterministically to the depots. It is a decision variable in the model, which can be adjusted during the optimization.
5) Transportation costs: Transportation costs for lateral transshipments of spare parts are assumed to be fixed.
6) Fixed costs for depot opening: The costs for opening a new depot are assumed to be fixed and the same for any location.

Based on these assumptions a logistics network model for maintenance strategy comparison is defined.

B. Concept and measures

The developed model represents a discrete problem as a decision support tool for maintenance cost and ordering cost reduction in the aviation industry. The main idea is a separate consideration for simplification of the logistics network and the optimization of this level to avoid unnecessary, expensive unscheduled maintenance actions. The dynamic nature of the model is reflected in the adjustment of the failure rates of spare parts. For a better estimation of the failure probability of the examined components the MFOP approach is used. It is an adaptation of the failure data for a more current estimation of the parameter for the Weibull distribution, which are used for degradation of components. The aim of the model is an improved logistical planning (determination of failure times, determining the optimal replacement locations with the specific use of man power, distribution of spare parts at the locations in the network, etc.) to reduce unscheduled maintenance actions of the aircrafts, and thus increase overall availability and reduce ordering costs significantly. Furthermore, using this concept, statements about upcoming failures at outstations are possible. Thus, spare parts could be ordered

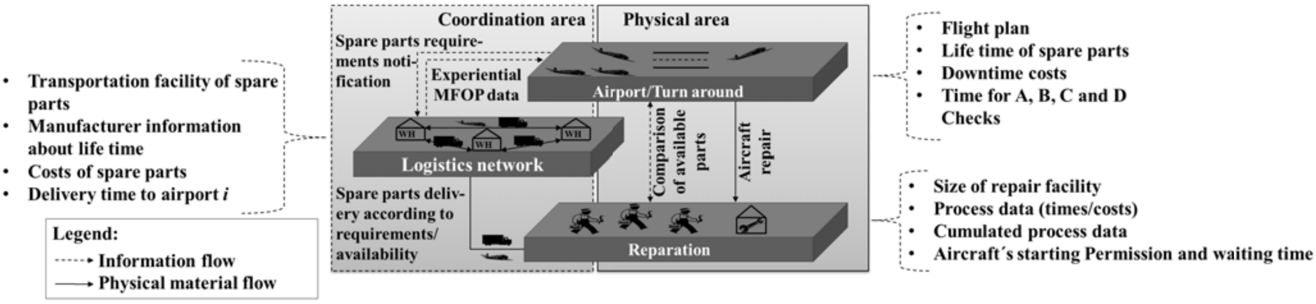

Fig. 3: Illustration of the three-level model

a priori via the logistics network. This has the consequence that upon arrival of an aircraft in the previously calculated destination airport, the serviceable parts are already available and unnecessary waiting time is avoided. Due to a better planning of the spare parts transport a resulting reduction in transport costs is also a positive side effect. A graphical representation of the model is given in Fig. 3. As can be seen in Fig. 3, the model consists of three parallel operating levels, which are connected by flows of goods and information flows. The model presented here is designed to optimize the logistics network for a given flight plan and location network. Conceptually, level 1, airport/turnaround (departure, flight and landing of the aircraft); and level 2, repair (use of man power, replacing defective components), are associated with the physical area. In these two levels the physical movements of aircraft and spare parts take place. The third level of the logistics network is assigned to the coordination area. Here, primarily planning and decision processes are executed (distribution and stock level of spare parts on the locations, failure times and locations of developed components, sourcing non-available parts, cost-efficient lateral transshipments between warehouses), which should be optimized for better reliability and availability. Furthermore, due to efficient maintenance planning, the number of unscheduled failures is minimized.

Upon detection of an impending failure of a component during a turnaround at any airport, the information about this component (type of error, time and location of the next possible exchange) is delivered to the logistics network. If the required spare part is not available at the destination (primarily at less frequented outstations) it is delivered cost-related or urgent from another warehouse based on the pooling idea of spare parts. After landing this machine at the predicted location, the replacement of this component is performed in a hangar. If this happens at an outstation without additional resources man power will be moved there.

The first level in the model is exclusively responsible for the movement of the aircraft according to the flight plan and the degrading of the failure rates. Here, all items are checked in terms of their remaining MFOP time. Once a component has not enough MFOP remaining useful life (RUL) the optimal exchange point and location (comparison of available spare parts at this station) is calculated within the prognostics horizon. For this purpose, a message is forwarded to the logistics network (level 3) and the aircraft is transferred to the repair facility (level 2) at the calculated destination. After multiple application of the model a better estimation of the Weibull distribution parameters and the resulting failure rates of the installed components are achieved by the learning curve. The second level is the physical location of a repair station/hangar at an airport. Components that are declared for exchange by level 1 are removed and replaced by level 3 delivered spare parts. If the required spare part is in stock at the calculated exchange airport, a delivery is not necessary. After the logistics network received a message about the need of spare parts at an airport, an availability check is made whether the spare parts are in stock at this time or should be procured, and whether the transport in the given time to the destination airport is feasible. If this is possible the required spare parts will be transported primarily with their own aircrafts or cargo transport (depending on urgency) to the destination airport. A lateral pooling within the network is assumed. By using this prognostics-based model unscheduled maintenance activities are transfered into scheduled maintenance activities through better planning. The scheduled replacement of spare parts lead to avoid cancellations of aircrafts and thus significant penalty cost savings. If the delivery of spare parts is not possible within the calculated time, the airline should provide a replacement machine or initiate other compensating measures. For a better processing of the collected data and ordering of parts, the logistics network takes over complete control of spare parts supply. This means, there is always a message about needed parts from level 1 to level 3. After the arrival of the aircraft, parts are replaced and the collected information is sent to level 3.

In order to avoid a redesign of the established concept, the planning- or simulation-based optimization is integrated in the current model. The simulation-based optimization is an effective tool to evaluate possible design alternatives. Several alternative solutions can be broadly analyzed and inexpensively evaluated by a simulation. Just the planning effort increases due to creating different simulation alternatives. To antagonize this rising burden, but at the same time to satisfy the high demands on the quality of planning, the concept of planning with simulation-based optimization is integrated in this model. The innovation of this method is the extension of opportunities for evaluation during a simulation. It can intervene directly to different steps of a simulation, immediately after the alternative solutions were evaluated. A complete re-planning is avoided. The model is complemented by a direct connection between simulation and measurement (see Fig. 2). In the present model the failure rates of the used components are adapted continuously, so predicted failure time and real failure time are very close together. Accordingly, no residual life of components is wasted.

$$C_{Tot} := \sum_j (c_I \cdot S_j + c_T \cdot T_j + c_D \cdot U_j) \rightarrow Min \quad (1)$$

C_{Tot}	Total cost
c_I	Inventory cost
c_T	Transportation cost
c_D	Downtime cost
S_j	Inventory level at station j
T_j	Expected transportations to station j
U_j	Downtime at station j

$0 \leq C_{Tot}, c_I, c_T, c_D, S_j, T_j, U_j < \infty$

Using the model presented here the objective function (1) of the total cost of an airline [46] is minimized under the application of a preventive maintenance strategy with dynamic failure rate adjustment. As inventory cost c_I, transportation cost c_T and downtime cost c_D are assumed to be given and constant, the cost-driving parameters are optimized. This means, to reduce S_j inventory level at station j, try to avoid T_j unnecessary spare parts transportations to station j and minimize U_j downtime at station j.

C. Inputs and limitations

For the model described above now the level-specific needed input parameters are defined (see Fig. 3).

- Level 1 (Airport/Flight): To avoid extended downtime for components replacement the flight plan (including departure and arrival time, departure and arrival location) and the times and ranges of the A, B, C, and D checks should be coordinated. Under consideration of the lifetime based on manufacturer's data (later the collected empirical data is used) a degradation of service life of installed components is performed.
- Level 2 (Maintenance): To calculate an aircraft's turnaround time waiting and transfer times for repair of the aircraft, downtime and repair time of spare parts for A, B, C, D checks and installing times for parts are necessary. To generate inexpensive spare parts, exchange repair costs, rental costs for repair facilities, personnel costs and costs of opening location are required.
- Level 3 (Logistics Network): For optimization of the logistics component most input data are required here. This mainly includes inventory holding costs of the depots. For an improved spare parts pooling, transfer times and costs of the components (from a warehouse to the airport/repair facility, or between two main bases) are very important. In order to minimize the total cost of an airline downtime, delay and cancellation costs are required. Furthermore balancing costs to balance the fill rates, distribution costs of repaired components, penalty costs for unscheduled maintenance and incorrect deliveries and maintenance costs are needed. For a redistribution of spare parts in the network their price as well as the location's safety stock (for backfill) are required.

The used MFOP concept requires very high quality information about the component failures in order to make optimal statements on the remaining lifetimes. The Weibull distribution is very versatile. It is suitable to describe all three phases of life (premature failure, random failures and wear failures). The estimation or determination of the Weibull parameters is very difficult. The calculations of the lifetime can vary greatly from the lifetime manufacturer's instructions, the number of test patterns and the duration of the test period. Furthermore, a high quality to the high-value components is provided to prognosticate their failure times. In the known maintenance models, an age-independent Poisson distributed and constant failure rate is assumed [20], [22], [30], [35], [46]. The model presented here uses an adjusted failure rate [13]. For an adjustment the quality of stored historical data or measured sensor data is very important. Higher quality is achieved only at an increasing cost. For a detailed comparison of maintenance strategies (in a simulation) a specific flight network is necessary.

D. Benefits for the company

With the help of this three-level model and its separate considered logistics network, an easier and better failure prognosis for all installed high-value components is achieved. The concept of maintenance free operating period (MFOP) is defined as a measurement for (machine) reliability [21]. In the paper of [15], differences between two maintenance strategies are studied. By using a preventive maintenance policy improved maintenance free success is reachable. Benefits for a company can be quantified into economic and non-economic terms [25]. One of the economic benefits is to reduce cost of maintaining the system [45], which can be extremely high, especially for complex systems. With the help of the presented preventive, scheduled maintenance strategy, maintenance is performed only when the system needs maintenance. This results in longer maintenance free intervals and decrease downtime costs over time. Another effect for the aircraft industry is an improvement of their ability to plan their inventory management, that is, how many spare parts need to be retained and where they should be stored. In a preventive maintenance strategy fewer spare parts at the stations in the network have to be stored, which leads to a significant reduction of inventory holding costs. By using the integrated three-level logistics model presented here, the component lifetime is maximal used and further the failure rate can be adjusted downwards and thus the service lifetime can be significantly extended [13]. Another advantage is the lower spare parts inventory level at the bases. By a preventive prediction of faults an airline do not need to provide as much spare parts as before. This reduces their inventory holding costs. There are also non-economic benefits, which are quantifiable but not necessarily economic. With the help of this model an airline company can improve availability significantly. In the airline industry availability is measured in terms of sorties generated, which cannot easily transfer into a cost benefit. Another non-economic benefit is the prevention of catastrophic and expensive failures such as an engine breakdown during a flight. Through the use of this preventive model, the fixed maintenance intervals are transferred to variable ones and thus avoid unnecessary service. This result in a decreasing of failures, of downtime, of delay time and of cancellation of the machines , and reduces the total costs and increases the airline's image. By a reduction of inventory levels due to using a preventive maintenance strategy the airline's operator deals with fewer spare parts in the network. Due to longer pre-planning of failure times, necessary spare parts are transported using late and cheap flights, an airline's own capacity is used. So lateral transshipment costs are reduced. Preventive maintenance increases the availability of the entire system. More flights under the existing conditions or rather the same flights with fewer aircrafts are feasible and thus results in higher revenues. In general the system performance increases significantly. The model presented here supports tactical and strategic decisions of an airline.

IV. Experimental Validation

To compare three maintenance strategies (PHM Scheduled, PHM Time Based and Unscheduled Maintenance), the model described above is used within an example from practice. For this purpose we created a simulation study in collaboration with an international aviation research company using the simulation framework Plant Simulation by Siemens PLM software for implementation. A long range scenario network

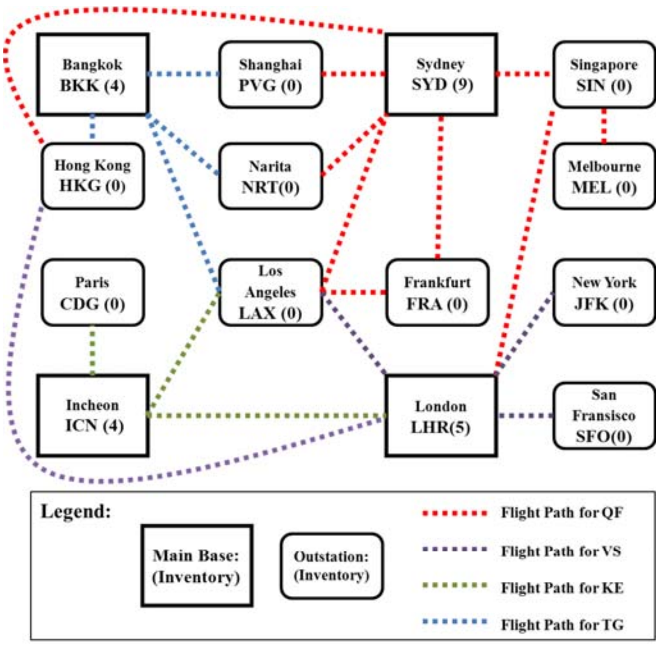

Fig. 4: Airline network information

of 4 airlines (Quantas Airline GF, Virgin Airline VS, Korean Airline KE and Thai Airline TG) with 45 aircrafts (20 for QF, 9 for VS, 7 for KE and 9 for TG) and 4 main bases with 10 outstations (see Fig. 4) based on a real airline flight plan is simulated over two years. On the basis of an externally supplied software and the assumptions of section III-A a starting solution was calculated using a genetic algorithm, which distributes 22 spare parts of one component in varying quantities to the airports (see Fig. 4). In heavily frequented main bases more spare parts are needed than in less frequented outstations. In Table I all required input values are listed. We considered a \$50,000 component per aircraft, with a mean time between unscheduled repairs (MTBUR) of 1500 hours and a replacement time of 20 minutes. As mentioned above, an approximation of the Weibull parameters is difficult. The scale parameter is given with 63.2% of the MTBUR [42]. The shape parameter of 1.7 (bigger than 1 for an increasing failure rate with time) is based on pre-tests. According to manufacturer's data the PHM time based exchange interval was set to 750h. According to [14] the repair time of 25 days indicates how long it takes to restore the state "as good as new". Accordingly, 60 days are required to replace a damaged component. Spare parts can be replaced in 45 minutes turnaround time. Furthermore, annual inventory costs over \$10,000 and \$2,000 for the logistic transportation of spare parts are assumed. The penalty costs for unscheduled downtime of \$90 dominate those of the downtime costs for scheduled maintenance of \$50. The maintenance costs of the aircraft are valued at \$300 per man hour. Delay costs are calculated per seat per hour. Assuming 300 seats per aircraft (Airbus A330-200), the amount of delay costs is \$175. For the cancellation of a scheduled flight due to an aircraft damage, the costs amount to \$60,000. After describing

TABLE I: Required Simulation Values

Price of the installed spare part	\$50,000
MTBUR	1500h
Weibull scale parameter	948h
Weibull shape parameter	1.7
PHM time based exchange interval	750h
Installed spare parts per aircraft	1
Replacement time of the spare part	20min
Repair time of the installed spare part	25 days
Renewal time of the installed spare part	60 days
Turn around time of an aircraft	45min
Annual inventory costs of the spare part	\$10,000
Logistics costs for a spare part transport	\$2,000
Downtime costs per minute	\$50
Penalty downtime costs per minute for unscheduled failures	\$90
Maintenance costs	\$300 per man hour
Delay costs per minute	\$175
Cancellation costs	\$60,000

and determining all input values for the simulation the most important results, comparing the three maintenance strategies, are discussed. The lowest logistical planning work of the three compared strategies results from unscheduled events, a reactive maintenance strategy. In this case no prediction is applied: the installed components are used as long as they fail completely. The advantage is that no remaining lifetime is wasted, adverse, high penalty costs and no ability for planning for these unexpected failures. Accordingly, failed components are replaced when a failure is detected at a turnaround. This results in high downtime, cancellations of the machines and high penalty costs for unscheduled maintenance events. The aviation industry is currently using the time-based maintenance strategy, which prevents much of the unplanned failures by exchanging components after a fixed scheduled interval. It is advantageous to avoid downtime, and a planned replacement of components. Depending on the risk tolerance of the airline, lot of remaining life is given away. The most complex planning maintenance strategy is PHM scheduled maintenance strategy. In this variant a possible failure time is calculated by complex forecasting methods (here MFOP), so that the installed component does not fail, but little remaining lifetime is wasted. It generates higher costs for planning, prognosis and maintenance, but decrease total cost by avoiding unscheduled maintenance events. Another major advantage of this scheduled strategy is the adaption of lifetimes and with this the failure rates of spare parts due to the learning effect from historically collected failure data or sensor data. The simulation was stopped quarterly to get reference values and thereby adjust component's failure rate in PHM scheduled maintenance strategy.

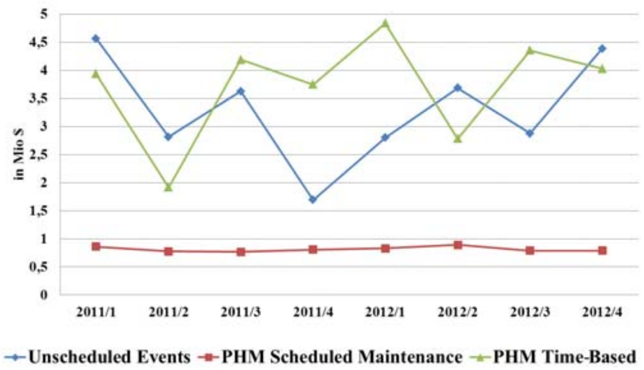

Fig. 5: Quarterly calculated total costs

In Fig. 5 the quarterly calculated total cost of the examined network are presented. These are made up of downtime costs, transportation costs and inventory costs (see Formula 1 in connection with Table I). It can be seen that total costs hardly vary under the PHM scheduled maintenance strategy. Accordingly, the costs of this strategy are predictable and projectable. This is due to the continuous prognosis of possible failure dates and the avoidance of unscheduled failures. Whereas the other two strategies result in significantly higher total costs and behave very volatile. It is justified by randomly occurring failures of components, which result in very high penalty costs and further in delays, or even cancellations of aircrafts. Stationary aircrafts on ground earn no money. The cumulative total costs over the simulated 2 years amount for the unscheduled maintenance strategy $26.4 million, for the PHM scheduled strategy $6.5 million and for the PHM time based strategy $29.8 million. Here, time-based PHM strategy is a little higher than the reactive unscheduled strategy. In the unscheduled case the full lifetime of the components is used and therefore less maintenance must be performed. An additional reason for this is the flight plan. In the present network the four main stations (BKK, ICN, SYD, LHR) are strongly frequented and have spare parts in stock. Thus it can be replaced quickly at an unscheduled failure.

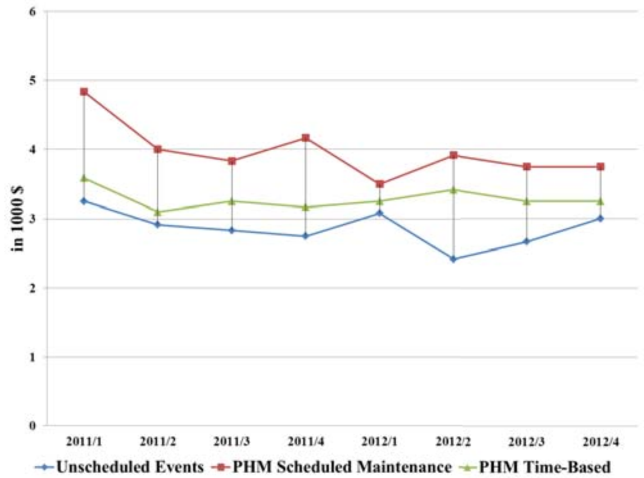

Fig. 6: Quarterly calculated maintenance costs

In Fig. 6 the applicable maintenance costs are shown. The maintenance costs of unscheduled maintenance strategy are always less than the costs of the two other predictive strategies. In the reactive case maintenance actions will only be carried out when components have no remaining service life and break down. The penalty costs for unscheduled maintenance activities are not integrated in the maintenance costs of Fig. 6. The maintenance costs of the scheduled maintenance strategy are clearly highest. Components are replaced shortly before their failure. There is a lost in remaining lifetime, but the scheduled actions do not lead to penalty costs, no unnecessary downtime on ground and no loss of image of the airline.

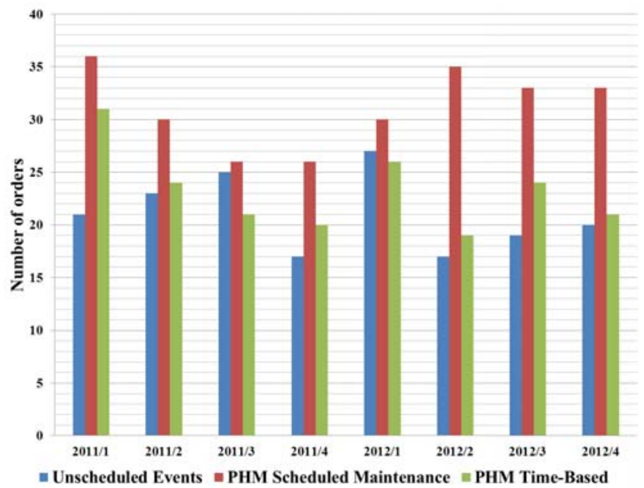

Fig. 7: Number of ordered spare parts

Fig. 7 shows the number of orders for spare parts. Similar to the maintenance costs is the number of orders in the reactive strategy the lowest, in this strategy a component will only be replaced if it is broken. If this happens at an airport (outstation) which has not a spare parts stock, the flight is canceled and the spare part is supplied to the location. The number of orders and hence the number of deliveries of spare parts is in the scheduled case at the highest. In this strategy are more frequently preventive maintenance actions performed, which need spare parts for replacement.

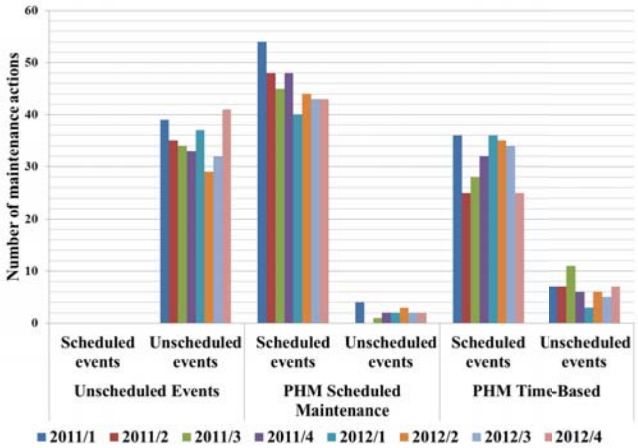

Fig. 8: Kind of maintenance actions

Fig. 8 clearly illustrates the advantages of using a preventive maintenance strategy. The PHM scheduled strategy and the PHM time-based strategy generate more overall maintenance actions, but almost avoid unscheduled maintenance activities. There are no scheduled maintenance events in the reactive case, because preventive maintenance actions in this strategy are not planned. Because of many unscheduled maintenance events and associated penalty costs, the overall cost of an airline increase significantly. Most scheduled maintenance events occur in the preventive strategy with forecast (PHM Scheduled Maintenance). These proposed activities, however, cause no additional running costs. Since the required spare parts are already available at the predicted location, this evolves no downtime, no delays and no damage to airline's image.

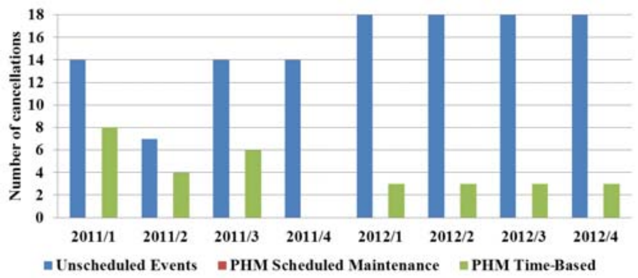

Fig. 9: Constituted aircrafts cancellations

Fig. 9 shows clearly that a reactive maintenance strategy without prognosis results in significantly more unscheduled failures. In this strategy installed components are used until they fail at any airport. Thus, no planning regarding impending failures is possible. If the replacement of the component within a specified time is possible (in this study 2 hours), the flight will not be canceled. Without a stock or repair station this is almost impossible at outstations. In the time-based strategy, it is also possible that the fixed interval of the lifetime is exhausted at an outstation and unscheduled failures are generated. Fig. 9 also shows that the prognostics model used is well chosen. The PHM scheduled maintenance strategy causes no unscheduled failures.

V. Results

It can be seen from the simulation study that total costs of an airline can be significantly reduced under a well-chosen maintenance strategy, the constant interchange of information between the three levels and an elaborated forecast method. The defined requirements in section III-A for a maintenance model should be given high attention. With the help of excellent underlying prognostics data (collected historical data or sensor data) significant improvements in the performance of an airline's PHM are possible. The prognostics costs have been ignored in the present study, but they should not exceed the calculated difference of scheduled maintenance strategy to time-based or unscheduled maintenance strategy. About $20 million can be spent for prognostics care in the two simulated years. Even in this case the image would be higher because of very few failures. With the help of this underlying airline network the dependence of the kind of maintenance of the maintenance strategy is shown. From Fig. 6, it is clear that a preventive maintenance strategy needs more maintenance actions and with it higher maintenance costs. In Fig. 7 it is shown that under a preventive maintenance strategy with prognosis more spare parts are ordered to locations where they are needed. But Fig. 8 shows an intense impact to the kind of maintenance actions. A scheduled maintenance strategy almost avoids unscheduled maintenance events and with this lots of emerging consequential costs, e.g. penalty costs, negative image costs. Furthermore, Fig. 9 shows obviously that the reactive case leads to significantly higher unscheduled failures, thus results in loss of profits and penalties by non-fulfillment of flights and services. In the prognostics case, 22 spare parts distributed to the 4 airports are completely sufficient to avoid unscheduled maintenance and can be moved to the location of use by a few lateral transshipments. As can be clearly seen from Fig. 9 it is not possible to avoid unscheduled failures with this distribution of spare parts. Therefore, a higher stock of spare parts across the entire network is necessary and with it higher inventory costs.

VI. Conclusion

In the presented paper, a new preventive three-level model for an improved aviation industry logistics network planning is shown. The introduced model is divided into three simplified planning levels. The airport level and reparation level dedicated to the physical area and the logistics level dedicated to the coordination area. Especially, the separation of the logistics level reduces the planning complexity for network designers in the aviation industry. A reduced network complexity associated with a scheduled maintenance strategy achieves enormous total cost savings for an airline by prognosticating failure times and an enhanced maintenance planning. The integration of the

MFOP concept and the simulation-based optimization in the planning process and the interaction of these two methods, result in a total cost saving and a preventive maintenance strategy. In order to achieve such significant cost savings, an excellent prognosis under dynamical adjustment of the failure rate is necessary. The incurred costs of the forecast limit the application of the model a bit. For storing historical data, the collection of sensor data or the installation of redundant systems are necessary resulting in high investments. The combination of separated consideration of the logistics network and a dynamical adjustment of failure rates by simulation-based optimization is the main contribution of the model presented here. The effects for the aviation industry are the improved ability to plan their inventory management. Through the improved maintenance planning a shift is attained from unwanted and unplanned downtimes to planned and better-to-handle failures. Fewer spare parts at the respective stations in the network are stored, which leads to a significant reduction in holding costs. The increased predictability of repair reduces the risk of lateral incorrect deliveries of spare parts. Thus, the model presented here supports tactical and strategic decisions of an airline. Through a more detailed forecast the manager or operator of an airline improves his chances of making effective maintenance decisions. To summarize, a total cost minimization, by reducing or even avoiding unscheduled maintenance actions on the basis of a well chosen maintenance strategy, is achieved. Future research could be done in the sector of avoiding aircraft on ground situations and detecting an optimal prognostics horizon for predicting times of failures.

VII. References

References

[1] P. Ayeni, T. Baines, H. Lightfoot and P. Ball, “State-of-the-art of “Lean” in the aviation maintenance, repair, and overhaul industry”, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 225 (11), SAGE Publications, 2011, pp. 2108-2123.

[2] F. Barahona and D. Jensen, “Plant location with minimum inventory”, Mathematical Programming 83 (1-3), 1998, pp. 101-111.

[3] P. Batchoun, A. Ferland Jacques and R. Clroux, “Allotment of aircraft spare parts using genetic algorithms”, Pesquisa Operacional 23 (1), 2003, pp. 141-159.

[4] M. F. Candas and E. Kutanoglu, “Benefits of considering inventory in service parts logistics network design problems with time-based service constraints”, IIE Transactions 39 (2), 2007, pp. 159-176.

[5] O. Candell, R. Karim and P. Söderholm, “eMaintenance-information logistics for maintenance support”, Robotics and Computer-Integrated Manufactoring 25 (6), 18th International Conference on Flexible Automation and Intelligent Manufactoring, 2009, pp. 937-944.

[6] P. F. Cini and P. Griffith, “Designing for MFOP: towards the autonomous aircraft”, Journal of Quality in Maintenance Engineering 5 (4), 1999, pp. 296-308.

[7] J. F. Cordeau, F. Pasin and M. M. Solomon, “An integrated model for logistics network design”, Annals of Operations Research 144 (1), 2006, pp. 59-82.

[8] M. S. Daskin, “Network and discrete location: Models, Algorithms, and Applications”, Wiley, New York, USA, 1995.

[9] M. S. Daskin, C. R. Coullard and Z. J. M Shen, “An inventory-location model: Formulation, solution algorithm and computational results.”, Annals of Operations Research 110 (1-4), 2002, pp. 83-106.

[10] R. Dekker, C. Plinge, R. Zuldwijk and M. Jalil, “On the use of installed base information for spare parts logistics: A review of ideas and industry practice”, International Journal of Production Economics, 2012.

[11] H. Ewe, M. T. Melo and P. Savant, “A milp model to optimise the logistics network configuration for the maintenance of turboshaft engines”, 2007.

[12] G. J. Feeney and C. C. Sherbrooke, “The (S-1,S) inventory policy under compound poisson demand”, Management Science 12 (5), 1966, pp. 391-411.

[13] R. Fritzsche, “Cost adjustment for single item pooling models using a dynamic failure rate: A calculation for the aircraft industry”, Transport. Res. Part E., 2012.

[14] H. Fromm, “Bewertung innovativer Instandhaltungsszenarien in den frühen Phasen des Innovationsprozesses in der Luftfahrt”, Shaker Verlag, Aachen, Germany, 2009.

[15] S. Garg, A. Puliafito, M. Telek and K. Trivedi, “Analysis of preventive maintenance in transactions based software systems”, IEEE Transactions on Computers 47 (1), 1998, pp. 96-107.

[16] M. Gen, R. Cheng and L. Lin, “Network Models and Optimization”, Springer Verlag, London, England, 2008.

[17] A. Gosavi, “Simulation-Based Optimization: Parametric Optimization Techniques and Reinforcement Learning”, Kluwer Academic publisher, Norwell, USA, 2003.

[18] V. Jeet, E. Kutanoglu and A. Partani, “Logistics network design with inventory stocking for low-demand parts: Modeling and optimization”, IIE Transactions 41 (5), 2009, pp. 389-407.

[19] M. Kaviani, “Location-Inventory Problem”, Physica Verlag, Berlin/Heidelberg, Germany 2009.

[20] W. J. Kennedy, J. Wayne Patterson and L. D. Fredendall, “An overview of recent literature on spare parts inventories”, International Journal of production economics 76 (2), 2002, pp. 201-215.

[21] U. D. Kumar, “New trends in aircraft reliability and maintenance measures”, Journal of Quality in Maintenance Engineering 5 (4), 1999, pp. 287-295.

[22] E. Kutanoglu and D. Lohiya, “Integrated inventory and transportation mode selection: A service parts logistics system”, Transportation Research Part E: Logistics and Transportation Review 44 (5), 2008, pp. 665-683.

[23] L. H. Lee, E. P. Chew, S. Teng and Y. Chen, “Multi-objective simulation-based evolutionary algorithm for an aircraft spare parts allocation problem”, European Journal of Operational Research 189 (2), 2008, pp. 476-491.

[24] S. Lee, Y.S. Ma, G.L. Thimm and J. Verstraeten, “Product life cycle management in aviation mainenance, repair and overhaul”, Computers in Industry 59 (2-3), 2008, pp. 296-303.

[25] J. Luna, P. Kolodziejski, N. Frankle, D. C. Conroy and R. Shroder, “Strategies For Optimizing The Application Of Prognostic Health Management To Complex Systems”, Computers in Industry 59 (2-3), 2008, pp. 296-303.

[26] M. Marseguerra, E. Zio and L. Podofillini, “Multiobjective spare part allocation by means of genetic algorithms and Monte Carlo simulation”, Reliability Engineering & System Safety 87 (3), 2005, pp. 325-335.

[27] J. A. Muckstadt, “Analysis and algorithms for service parts supply chains”, New York, USA, 2005.

[28] L. K. Nozick and M. A. Turnquist, “Inventory, transportation, service quality and the location of distribution centers”, European Journal of Operational Research 129 (2), 2001, pp. 362-371.

[29] N. Papakostas, P. Papachatzakis, V. Xanthakis and D. Mourtzis, “An approach to operational aircraft maintenance planning”, European Journal of Operational Research 199 (3), 2009, pp. 781-792.

[30] C. Paterson, G. Kiesmüller, R. Teunter and K. Glazebrook, “Inventory models with lateral transshipments: A review”, European Journal of Operational Research 210, 2011, pp. 125-136.

[31] J. A. Rappold and B. D. Van Roo, “Designing multi-echelon service parts networks with finite repair capacity”, Microelectronics Reliability 47 (12), 2007, pp. 1899-1901.

[32] M. M. Relf, “Maintenance-free operating periods - the designer‘s challenge”, Quality and Reliability Engineering International 15 (2), 1999, pp. 111-116.

[33] P. A. Sandborn and C. Wilkinson, “A maintenance planning and business case development model for the application of prognostics and health management (PHM) to electronic systems”, Microelectronics Reliability 47 (12), 2007, pp. 1899-1901.

[34] Z. J. M Shen, C. Coullard and M. S. Daskin, “A joint location-inventory model”, Transportation Science 37(1), 2003, pp. 40-55.

[35] C. C. Sherbrooke, “Vari-metric:Improved approximations for multi-indenture, multi-echelon availability models”, Operations Research 34 (2), 1986, pp. 311-319.

[36] C. C. Sherbrooke, “Optimal inventory modeling of systems multi-echelon techniques”, Kluwer Academic Publisher, Boston, 2004.

[37] P. Siarry, "Advances in metaheuristics for hard optimization", Springer Verlag, Berlin/Heidelberg, Germany 2008.
[38] J. Z. Sikorska, M. Hodkiewicz and L. Ma, "Prognostic modelling options for remaining useful life estimation by industry", Mechanical Systems and Signal Processing 25 (5), 2011, pp. 1803-1836.
[39] A. Smith and G. Hinchcliffe, "RCM: gateway to world class maintenance", Butterworth-Heinemann, 2007.
[40] L. V. Snyder, M. S. Daskin and C. P. Teo, "The stochastic location model with risk pooling", European Journal of Operational Research 179 (3), 2007, pp. 1221-1238.
[41] K. Sourirajan, L. Ozsen and R. Uzsoy, "A genetic algorithm for a single product network design model with lead time and safety stock considerations", European Journal of Operational Research 197 (2), 2009, pp. 599-608.
[42] G. C. Stone and R. G. Van Heeswijk, "Parameter estimation for the Weibull distribution", IEEE Transactions on Electrical Insulation 12 (4), 1977, pp. 253-261.
[43] A. Van Horenbeek, L. Pintelon and P. Muchiri, "Maintenance optimization models and criteria", International Journal of Systems Assurance Engineering and Management 1 (3), 2010, pp. 189-200.
[44] L. Wang, J. Chu and J. Wu, "Selection of optimum maintenance strategies based on a fuzzy analytic hierarchy process", International Journal of Production Economics 107 (1), 2007, pp. 151-163.
[45] K. Wheeler, T. Kurtoglu and S. Poll, "A survey of health managment in aviation industry", Prognostics and System Health Management Conference (PHM Shenzhen), 2010.
[46] H. Wong, G. J. Van Houtum, D. Cattrysse and D. Van Oudheusden, "Stocking decisions for repairable spare parts pooling in a multi-hub system", International Journal of Production Economics 93-94 (1), 2005, pp. 309-317.
[47] P. H. Zipkin, "Foundations of inventory management", McGraw Hill, Boston, USA, 2000.