Deman forecasting with real-time status information of equipment utilization and service conditions in after-sales service-networks

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Abstract

Effective spare parts demand planning is essential for provider of after-sales-service networks in the machine and plant engineering industry to achieve high spare parts availability during maintenance and failure orders (call outs). Low spare parts availability is mainly caused by high uncertainty in spare parts management and results in high equipment down time cost and unsatisfied customers. This paper proposes a new forecasting approach by integrating real-time status information of equipment utilization and service conditions in order to reduce uncertainty in spare parts demand planning and inventory management. The method has been developed and validated with provided data of an international elevator company as an industry project partner. Since the elevator business is considered as the pioneer of the increasing service orientation in the mechanical and plant engineering industry, it is representative for provider of after-sales-service networks and can also be transferred to other industries and equipment types.

INTRODUCTION

High availability of spare parts is an important competitive factor in after-sales-service networks. After-sales-service networks are composed of central distributions centers, branches (local offices) and service technicians in order to provide services such as equipment maintenance or repair, after equipment have been sold. For suchlike services, service technicians require spare parts in order to maintain the availability of the equipment to be serviced. Low spare parts availability lead to high equipment down time resulting in down time cost for the operator and possible penalty cost for the after-sales-service provider. High spare parts availability is particularly important for critical spare parts, where the consequences on the process caused by a failure of a part is high in case a replacement is not directly available (Huiskonen, 2001: 129), e. g. for electronic component, which can cause equipment break down. Those parts are frequently required within the mechanical and plant engineering industry. Spare parts demand planning in after-sales-service networks is associated with high complexity due to heterogeneous equipment portfolio, which comprises equipment from several years or decades and multiple manufacturers (Hertz & Finke, 2011: 2). Moreover spare parts demand planning is accompanied by high uncertainty due to increasing fluctuation of the equipment to be serviced. The reasons for the high fluctuation lies in new installations, high cancelation rates of service contracts due to aggressive competition as well as the consolidation of markets due to mergers and acquisition activities (cf. (Blakeley, Argüello, Cao, Hall, & Knolmajer, 2003: 68)). This development can be particularly observed in strongly service oriented manufacturing industries, e. g. in the elevator business. As a consequence operators of after-sales-service networks are faced with high spare parts inventories and misallocation cost, which occur when spare parts are stocked at the wrong location and finally low spare parts availability. In order to cope with these challenges operators of after-sales-service networks need to effectively master two fundamental spare parts planning tasks. Firstly, forecasting spare parts demand in order to anticipate spare parts demand of the equipment to be serviced. Secondly, optimal positioning of inventory units throughout after-sales-service networks (Muhammad Naiman Jalil, 2011: 20). Spare parts demand forecasting methods are particularly important for critical spare parts, since they are frequently required within hours and need to be stocked at the right location within the network. Those kinds of parts cannot be sourced or manufactured when a break down occurs. Hence for operators of after-sales-service networks forecasting spare parts demand for the equipment to be serviced are the fundamental basis for all spare parts management decisions such as the stocking strategies (cf. (Schuh, Stich, & Wienholdt, 2013: 177–178)). Nonetheless existing forecasting approaches are accompanied with high uncertainty due to the focus on historical data (cf. (Hellingrath & Cordes, 2013: 18), (Ihde, Merkel, & Henning, 1999: 79), (Niggeschmidt, 2010: 56)). Hence, there is still a research gap in the development of forecasting method which can cope with strong equipment fluctuation. This paper focusses on spare parts forecasting and contributes to reduce uncertainty in parts demand planning.

The remainder of this paper is structured as follows. In the next section the initial situation and service strategies in after-sales-service networks will be analyzed. Then the developed forecasting methodology will be derived, explained and evaluated in the subsequent section. Finally opportunities to transfer this approach to other industries and equipment types will be discussed and further research work will be revealed.

1 Initial situation and service strategies in after-sales-service networks

Spare parts demand planning is faced with a high number of parts, which are characterized by intermittent demand patterns and high responsiveness requirements (cf. (Bacchetti & Sccanai, 2012), (Cohen, Agrawal, & Agrawal, 2006: 131)). These challenges make spare parts demand planning to a complex planning task. Therefore effective forecasting of spare parts demand is crucial for operators of after-sales-service networks in order to achieve a desired service level and to reduce inventory and transportation cost. By now, forecasting is usually done based on historical data which leads to high uncertainty in spare parts demand planning (cf. above). Since it is neither economical to ship each part to the respective branch or equipment, nor is it time efficient for service technicians to source each part on demand at the responsible local office or branch, respectively, it is essential for operator of after-sales-service networks to anticipate spare parts demand for the daily business of service technicians for the equipment to be serviced. This holds particularly true in large networks since equipment to be serviced are widely dispersed resulting in distinct travel times (Muhammad Naiman Jalil, 2011: 18). Hence only through the effective anticipation of spare parts demand, transportation and stocking pooling effects can be achieved.

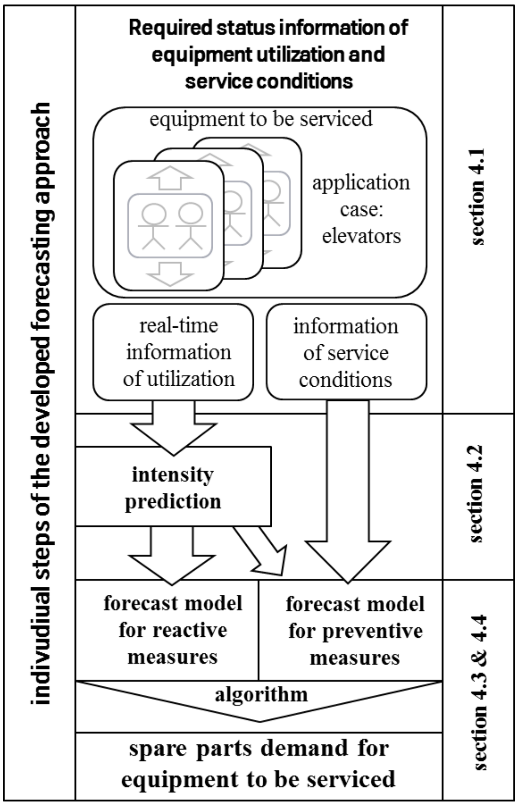
After-sales-service networks are very decentralized and composed of a low number of central distribution centers, which needs to serve a high number of local offices or branches, respectively, and service technicians servicing the equipment under contract. In the elevator business each elevator is assigned to a service technician based on different criteria like distance to residence, skills, workload and customer requirements (Blakeley et al., 2003: 68). The service contract determines the annual number of visits with the respective maintenance duration times for all equipment. Further, for equipment with high availability requirements, response times are defined in the service contract in case a break down occurs. Many types of service contracts exist, but they can generally be classified in two different types of service contracts, basic service contracts and full service contracts. Those types of service contracts are considered in this paper. Basic service contracts (also called oil and grease) are accompanied by a lower annual fee and customers solely pay for maintenance activities, such as adjusting equipment, e. g. elevator-door-operating devices, lubricating parts, e. g. belts and cleaning areas (Blakeley et al., 2003: 68). Full service contracts are associated with a higher annual fee and do also contain the cost of required spare parts. Due to the determined maintenance intervals, the daily business of service technicians mainly consists of maintenance orders, which are scheduled and not time critical. In doing so specific spare parts are replaced preventively after exceeding a fixed interval in order to reduce the probability of equipment break down. Those intervals are frequently driven e. g. by legal requirements due to safety guidelines for public equipment. However when an unscheduled failure of an equipment occurs, which is associated with a component break down, spare parts needs to be replaced reactively. Failure orders (callbacks) are typically urgent and need to be served immediately by assigning the responsible service technician to the equipment to minimize down time.

Generally it can be concluded that spare parts demand in after-sales-service networks is triggered by two kinds of events, maintenance orders and failure orders. They require either preventive measures or reactive measures. Reactive measures are associated with failure orders and required after a component break down. Hence the demand for reactive measures is dependent on the component failure probability and therefore a statistical demand (cf. (Loukmidis & Luczak, 2006: 256–257)). Spare parts demand for preventive measures is mostly predictable and required during maintenance orders, e. g. when a fixed replacement interval is exceeded. In case of full service contracts, demand for preventive measures is deterministic, whereas for basic service contracts, the demand for preventive measures only occurs if a quote has been offered and the customer is placing the order. Thus for the latter it is a statistical demand, which is dependent on the order probability.

2 Concept

Several of forecasting approaches have been developed considering particularly the specific characteristics of spare parts such as intermittent demand patterns. However it is beyond the scope of this paper to review all existing approaches. Detailed spare parts demand forecasting reviews can be found in (do Rego & de Mesquita, 2011) and (Boylan & Syntetos, 2010). However, what many spare parts classes have in common is that they do solely forecast demand based on historical demand data which is associated with high uncertainty in the spare parts planning process. Exemplary forecasting models utilizing historical demand data are time series models. This paper proposes a new forecasting method by integrating real-time status information of the equipment utilization and service conditions and can be classified as a causal model. Causal or explanatory models predict spare parts demand on the basis of one more variables, thus spare parts demand is derived on the development on one or more influencing factors (Loukmidis & Luczak, 2006: 261). Integrating status information can reduce uncertainty in spare parts demand planning and thus enable pooling effects in stocking and transportation. Figure 1 provides an overview of the individual steps of the developed methodology and the respective section in which the considered part of the method will be derived and explained.

Figure 1: Methodology overview



2.1 Required status information of equipment utilization and service conditions

Spare parts demand is a derivative demand (Niggeschmidt, 2010: 8). Thus the type of equipment or equipment model, respectively, to be serviced is an essential information for the spare parts demand planning process. The equipment type determines what kind and quantity of spare parts need to be planned by considering the bill of material (BOM) of the equipment. In order to derive spare parts demand for reactive measures of all equipment, the failure rate of the considered parts needs to be determined. It is an important parameter to characterize life time distribution functions appropriately and is dependent of the equipment utilization time, which is traditionally measured in operating time, e. g. hours (Meyna & Pauli, 2010). In order to determine the appropriate indicator for quantifying equipment utilization of elevators, an extensive field data analysis has been conducted with data provided by the industry project partner as shown in Table 1.

Table 1: scope of the field data analysis

number of elevators	~ 10,000
number of elevator types	9
considered time period	08/2011 – 07/2013
number of order data	~ 290,000
number of material documents	~ 27,500
number of measurement documents	~ 1,550,000

For this purpose the order and spare parts demand data of 10,000 elevators of nine different elevator types over a period of two years have been analyzed. Furthermore real-time retrieval of the number of trips and condition related information of the considered elevator is possible, which resulted into 1,550,000 measurement documents. The field data analysis revealed that the most appropriate indicator for quantifying elevator utilization and thus to derive component reliability is the number of trips per time unit. Moreover the analysis provided a deep insight about the reliability of elevator components, which differs tremendously among different elevator types and elevator components. Since for many equipment types in various industries the utilization is not really measured in a unit of time, we introduce and define the equipment intensity as the most suitable unit of measure in order to quantify the utilization of any equipment type. Thus the equipment intensity is in the following the key parameter for the characterization of the life time distribution and will be integrated as an essential status information of equipment utilization in order to forecast spare parts demand for reactive measures. Service conditions mainly determine the spare parts demand for preventive measures. The service conditions are predominantly specified by the type of service contract, namely a basic or full service contract, which influence spare parts demand a lot. The service contract further specifies the fixed maintenance intervals so that the next maintenance order for the respective equipment is already determined. The derived status information about equipment utilization and service conditions are required for all equipment to be serviced and need to be stored in an appropriate database. The required equipment status information is summarized in Figure 2:

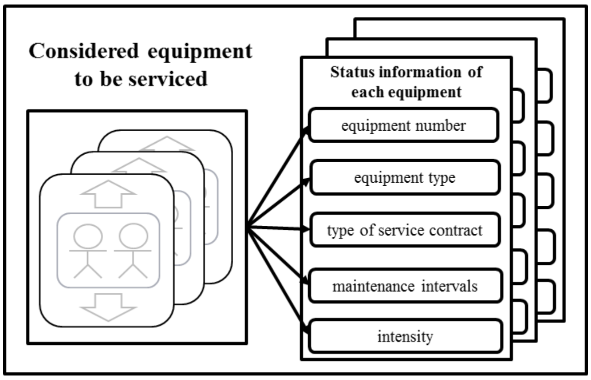


Figure 2: Required equipment status information

2.2 Intensity prediction

As worked out before the number of trips has been revealed as the most appropriate indicator for quantifying equipment intensity appropriately in the case of elevators. The number of trips can be retrieved on a daily basis or at a desired point of time so that the calculation of the equipment intensity can be done with current data and spare parts demand planning can be conducted with real-time status information. This approach allows taking changes of equipment utilization in consideration in the forecasting method. Those changes can result e. g. due to changes of operation conditions. However, in order to find the most appropriate balance between changing operating conditions and temporary utilization peaks, also historical data need to be taken into consideration. An approach which allows the integration of historical as well as current data in the determination of equipment intensity, is the method of moving averages. Let $I_e(t)$ be the intensity of equipment *e* at the point of time *t.* Then the current intensity $\overline{I_e^n}(t)$ over n period of consideration of the equipment can be calculated as follows:

$$\overline{I_e^n}(t) = \frac{1}{n}\sum_{j=0}^{n-1} I_e(t-j) \tag{1}$$

In order to predict the intensity for the planning horizon with the current intensity, the number of planning periods n_{PP} is needed as an additional parameter. The predicted intensity $I_{P,e}[n_{PP}]$ in the planning horizont can then be determined by multiplying the current intensity with the number of planning periods in the planning horizon as shown in the following formula:

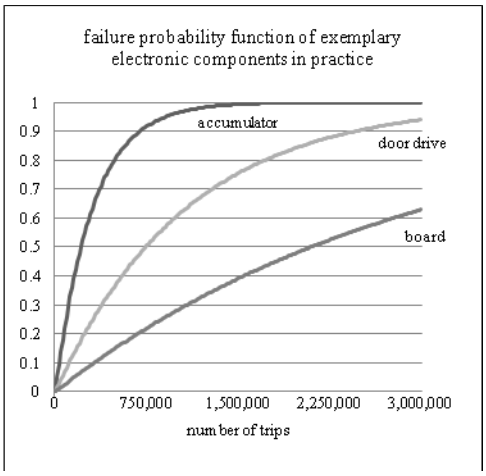
$$I_{P,e}[n_{PP}] = \overline{I_e^n}(t)\, n_{PP} \tag{2}$$

The predicted intensity is fundamental for forecasting model for reactive measures, which will be explained in detail in the next section.

2.3 Forecasting of spare parts demand for reactive measures

As indicated before the demand for reactive measures is mainly dependent on the failure rate and the subsequent life time distribution. The reliability analysis is an approach in order to determine the required parameters and distributions. The main subject of the reliability theory as a scientific discipline is the "assessment, prediction, maintenance and improvement of the reliability of technical systems" (Ryll & Freund, 2010: 43). An essential task of the reliability analysis is the determination of the appropriate life time distribution, which needs to be examined for different components and equipment applications. Since elevators are public equipment and many components fail randomly in practical application and the failure rate often remains constant during the time, the exponential distribution is very well suited for the most elevator components and parts (Sheikh, Callom, & Mustafa, 1991: 51). This has been confirmed by the field data analysis (cf. **Error! Reference source not found.**) and validated by the industry project partner. Exemplary failure probability functions of major equipment components of elevators are shown in Figure 3. The analysis also revealed that electronic components are the most common cause for equipment break down which underlie random failure processes (Niggeschmidt, 2010: 83) (Yang & Niu, 2009: 1020).

Figure 3: failure probability function of different components



The failure rate $\lambda_{i,e}$ of a part or component *i* of the equipment *e* is the main parameter of the exponential distribution, which is a function of a variable *x*. Component failures are mainly dependent on the equipment intensity. Hence the life time distribution will be a function of the equipment intensity. Since the methodology proposes the prediction of the equipment intensity for the considered planning horizon, the variable *x* can be replaced by the predicted intensity $I_{P,e}[n_{PP}]$. Hence the failure probability $P_{i,e}$ of a component or part *i* in equipment *e* for the planning horizon can be estimated as follows:

$$P_{i,e}\left(X<I_{P,e}[n_{PP}]\right)=F_{i,e}\left(I_{P,e}[n_{PP}]\right)=1-e^{-\lambda_{i,e}I_{P,e}} \quad (3)$$

Hence (2) and (3) yield:

$$P_{i,e}\left(X<I_{P,e}[n_{PP}]\right)=F_{i,e}\left(I_{P,e}[n_{PP}]\right)=1-e^{-\lambda_{i,e}\frac{1}{n}\left(\sum_{j=0}^{n-1} I_e(t-j)\right)n_{PP}} \quad (4)$$

It has already been indicated that the equipment specific spare parts demand is dependent on the equipment specific BOM. The BOM is mostly determined by the equipment type, which can vary among identical equipment types due to customized configurations. Therefore further parameters can be considered, e. g. for elevators, the number of serviced levels in a building, which mainly determines spare part demand for door components. The $BOM_{i,e}$ of a part *i* of equipment *e* is an essential parameter for this forecasting method, since spare parts demand is a derivative demand. By the integration of this parameter the demand rate $DR_{i,e}^{RM}$ of a part *i* in equipment *e* for reactive measures for a planning horizon can be determined as follows:

$$DR_{i,e}^{RM}[n_{PP}]=P_{i,e}\left(X<I_{P,e}[n_{PP}]\right)BOM_{i,e}=\left(1-e^{-\lambda_{i,e}\frac{1}{n}\left(\sum_{j=0}^{n-1} I_e(t-j)\right)n_{PP}}\right)BOM_{i,e} \quad (5)$$

Formula (5) yields the spare parts demand rate for individual equipment. However, the portfolio of equipment to be serviced, e. g. of a branch, consists of thousands of equipment. Therefore, the total demand rate for reactive measures $TDR_i^{RM}[n_{PP}]$ of a part *i* of a portfolio of equipment to be serviced E_S for a considered planning horizon can be calculated by:

$$TDR_i^{RM}[n_{PP}]=\sum_{e=1}^{E} DR_{i,e}^{RM}[n_{PP}]=\sum_{e=1}^{E}\left(\left(1-e^{-\lambda_{i,e}\frac{1}{n}\left(\sum_{j=0}^{n-1} I_e(t-j)\right)n_{PP}}\right)*BOM_{i,e}\right)$$

$$\forall i \in \text{parts to be planned} \quad (6)$$

2.4 Forecasting of spare parts demand for preventive measures

In order to reduce equipment break down probability many spare parts are replaced preventively after exceeding certain intervals influencing spare parts demand a lot. This demand category has previously been defined as demand for preventive measures and cannot be disregarded when forecasting spare parts demand. Demand for preventive measures only occurs if the next service date (or maintenance order) $t_{SD,e}$ is within the planning horizon, thus (7) needs to hold true for preventive spare parts demand, where t_{pl} is the time of planning:

$$t_{SD,e} \leq t_{PL} + n_{PP} \tag{7}$$

Note that all time units need to be measured in the same unit in order to keep consistency for the calculation.

Since demand for preventive measures is dependent on the type of service contract, it needs to be differentiated between basic service contracts and full service contracts when forecasting equipment specific spare parts demand. Preventive measures for equipment with basic service contracts can only be conducted when the customer places an order. Hence the equipment specific demand is dependent on the order probability, which needs to be determined statistically by analyzing historical data. The analysis of the quote data history of one year of the industry project partner revealed that the order probability is estimated most accurately, when it is determined for each part or component, respectively. The reason of this outcome is obvious, since critical parts which are needed to keep equipment running, will have a higher order probability then non critical parts. Because of these differences the introduction of a part dependent order probability is a suitable way. By integrating this information, the equipment specific demand rate $DR_{i,e}^{PM}$ for preventive measures for a planning horizon n_{PP} can be calculated. For equipment with full service contracts, demand for preventive measures can be calculated deterministically with the following demand heuristics:

$$if\ I_{LT,e} + I_{P,e}[n_{PP}] > I_{RI,i},\ then\ DR_{i,e}^{PM}[n_{PP}] = BOM_{i,e}$$

$$else\ DR_{i,e}^{P}[n_{PP}] = 0 \tag{8}$$

Where $I_{LT,e}$ is the overall life time intensity since equipment installation and $I_{RI,i}$ is the preventive intensity dependent replacement interval for spare part *i*. In the case of elevators, both parameters are measured with the number of trips. Since spare parts demand for equipment with a basis service contract is dependent on the part dependent order probability OP_i, the forecasting approach for basic service contracts is following another demand heuristics:

$$if\ I_{LT,e} + I_{P,e}[n_{PP}] > I_{RI,i},\ then\ DR_{i,e}^{PM}[n_{PP}] = BOM_{i,e} OP_i$$

$$else\ DR_{i,e}^{PM}[n_{PP}] = 0 \tag{9}$$

The total demand rate TDR_i^{PM} for preventive measures of a part or component *i* for a considered planning horizon is also equal to the sum of all equipment specific demands of a portfolio of equipment to be serviced, which yields:

$$TDR_i^{PM}[n_{PP}] = \sum_{e=1}^{E} DR_{i,e}^{PM}[n_{PP}]\ \forall i\ \epsilon\ parts\ to\ be\ planned \tag{10}$$

With those two demand heuristics spare parts demand for preventive measures can be forecasted for all equipment to be serviced.

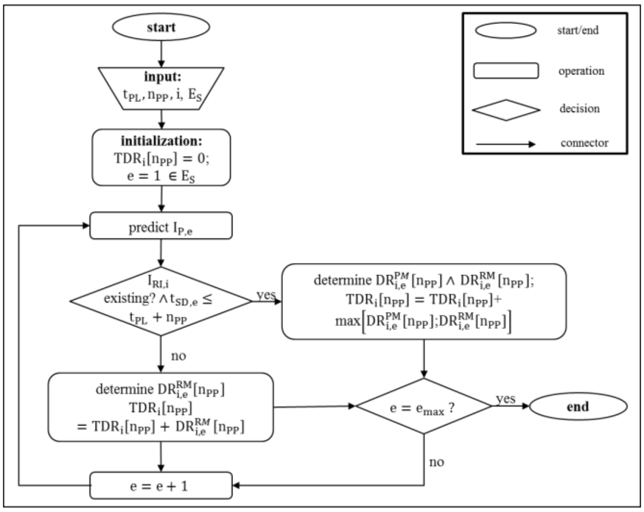
2.5 Algorithm for integrated forecasting of spare parts demand

Since interdependencies between spare parts demand for reactive measures and preventive measures exist, provider of after-sales-service networks cannot conduct isolated planning of those two demand categories. The reason lies in the fact that a component can break down during the planning horizon, thus demand for reactive measures occur. However also a preventive replacement interval for the same component of specific equipment can be exceeded, leading to demand for preventive measures. In order to solve this problem the maximum of the probability of demand for reactive measures as well as for preventive measures for a part or component, respectively, needs to be determined. This logic is valid since the demand category which is associated with a higher probability of occurrence needs to be considered. The formulation for this logic is as follows:

$$DR_i = max\left[DR^{PM}_{i,e}[n_{PP}];DR^{RM}_{i,e}[n_{PP}]\right] \tag{11}$$

For the integrated consideration of both demand categories an algorithm has been developed which facilitates forecasting of a portfolio of equipment to be serviced as shown in Figure 4**Error! Reference source not found.**:

Figure 4: Forecasting algorithm



The result of the algorithm is the total demand rate $TDR_i[n_{PP}]$ of a part *i* of a portfolio of equipment to be serviced for the considered planning horizon. Thus it allows forecasting the demand of a portfolio of equipment to be serviced of e. g. a branch or a service technician for a determined planning horizon.

3 Evaluation

An essential question is the validation and application of the developed forecasting method. It has already been shown with real case data of the industry project partner that the forecasting model is working. Further first validation results based on historical data in order to evaluate the accuracy of the model showed that the model is valid. The model has been validated for a 5000 elevators by integrating intensity data of four consecutive months and forecasting spare parts demand for a considered portfolio of equipment for the subsequent month. For the validation selected critical components such as electronics components (e. g. accumulators or boards) and components which underlie outside influences has been tested, since those types of parts are the most common cause for equipment break down in the elevator business. The first results showed a high forecast accuracy up to two percent deviation of the considered part. Further the results revealed that the higher the number of considered equipment the higher the forecast accuracy. Moreover the analysis shows that the hypothesis of an exponential distributed life time holds true for the considered parts. However, in order to apply this approach in other industries and for other equipment types and parts, first an appropriate life time distribution needs to be determined for the considered parts. Then the most suitable way of measuring the intensity for the considered equipment type needs to investigated and the existing service conditions needs to be analyzed as proposed in this paper.

4 Conclusion

This paper proposed a causal forecasting model for a considered portfolio of equipment to be serviced in after-sales-service networks by integrating equipment real-time status information. This approach facilitates provider of after-sales-service networks to enhance demand planning for decentralized entities, e. g. branches or service technicians, for their equipment to be serviced for a considered planning horizon. It is as a contribution for providing further methods in a field of research, where still a large research gap exists. First of all, status information about equipment utilization and service condition has been analyzed and appropriate status information has been revealed. Further an approach of integrating real-time status information of the utilization condition has been presented in order to reduce uncertainty in spare parts demand planning. Finally, forecasting models for reactive and preventive demand have been proposed and an algorithm has been developed which allows integrated forecasting of spare parts demand for a portfolio of equipment to be serviced. Further research work needs to focus on the validation and possibly benchmarking with comparable forecasting approaches in order to empirically prove the accuracy of the developed forecasting method. This is an essential requirement before the method can be actually applied. After that, there is still a research gap in the development of methodologies for multiple stocks inventory management models based on mathematical optimization or simulation based approaches, which integrates the obtained demand information in order to find optimal inventory levels in large after-sales-service networks. Combining the developed forecasting approach with optimization models can result in a holistic solution for integrated spare parts demand planning and inventory management for operators in large after-sales-service networks.

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