Conceptual approach for integrating condition monitoring information and spare parts forecasting methods

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Precise estimation of part failures, and hence system breakdowns, is required to reduce or avoid the downtimes of machines and stock-outs. If detected sufficiently early, potentially broken parts of a machine may even lead to not necessarily having to store the respective spare part. For estimating the spare parts demand as accurately as possible, this article conceptualizes an approach for integrating condition monitoring information provided by Intelligent Maintenance Systems and forecasting methods. This concept is validated based on an example evaluation. Thus, the research objective is to improve the forecasting quality of estimated machine breakdowns in order to enhance the planning of the spare parts supply chain.

Keywords: condition monitoring; spare parts management; forecasting

Motivation

Efficient and effective spare parts management is crucial for the operation of today’s complex technical systems. Spare parts management in our article is defined as process-oriented design, planning and control of information, and spare parts flows, as well as maintenance service personnel and equipment from suppliers to the end customers in support of repairing and maintaining of technical systems. This definition is based on the definitions of Kutanoglu and Mahajan (2009), Biedermann (2008) and Huiskonen (2001). Furthermore, this definition is extended by core elements relevant for managing the activities of spare parts supply chains deduced from the supply chain management definition of Hellingrath and Kuhn (2002). In industries like mechanical engineering, information systems, automotive, oil industry, ship building, or aircraft manufacturing, spare parts are crucial to repair or manage broken technical systems. Breakdowns of maintained systems result in major negative impacts, i.e. cost effects (downtime costs, emergency shipments, etc.), lost turnover, and a declining customer service perception (Espindola, Frazzon, Hellingrath, & Pereira, 2012, p. 1017). Hence, forecasting of breakdowns and replacement of estimated broken spare parts in advance appears to be beneficial. But the demand for spare parts and maintenance services only arises upon rare system breakdowns. The prediction of similar sporadic demand cannot be forecasted with the same quality as the demand of finished products. The reason for this lies in the fact that the quality of ‘classical’ forecasting models applied for spare parts management is low and cannot achieve appropriate forecasting results (Elwany &
Gebraeel, 2008, pp. 629–631). Utilizing information about the condition of the technical systems – provided by sensors of embedded systems – shows a promising way to enhance forecast quality. Machines incorporating this property are denoted by the term Intelligent Maintenance Systems (IMS). By measuring the components degradation process, IMS provide the probability distribution function and a date of a possible breakdown. The main purpose of integrating output data of IMS into the forecasting methods lies in the possibility to improve the forecast quality of a breakdown before it occurs, so that an early replacement of the part may be carried out. Taking into account this improved forecasting, the planning of all spare parts supply chain activities, like production, inventory, transportation, as well as service personnel management, can be enhanced. As a result, all supply chain operations can be optimized regarding costs as well as service time.

The remainder of this article is structured as follows: the next section explains the chosen research methodology of this article including a description of the research goals of the presented work. In the following section, the state-of-the-art analysis in spare parts forecasting methods and condition monitoring is depicted. Afterwards, an overview of the relevant forecasting methods is presented together with the requirements to be fulfilled for the integration of condition monitoring information into a forecasting method. From the requirements and the theories on forecasting methods, a conceptualization for setting up a suitable integration approach is derived in the next section. The following chapter highlights the procedure of validation and an example validation. The paper finally concludes with summary and final statements, in addition to an outlook into future work.

Research methodology

The overall research goal is the enhancement of forecasting technical system breakdowns in order to improve the results of all different spare parts supply chain planning tasks. Within this article, we follow the approach of integrating condition monitoring information and forecasting methods, and consequently consider the research question: which forecasting methods can be adapted in which method, in order to include condition monitoring information. To answer this research question: the methodology of this work is developed according to the design science approaches of Peffers, Tuunanen, Rothenberger, and Chatterjee (2007) and Hevner, March, Park, and Ram (2004). The foundation for the research method is the identification of the research problem and a detailed literature review in regard to this problem. The literature review follows the described literature search process by Vom Brocke et al. (2009). Therefore, the main keyword is forecasting and the defined keywords which are combined with the main keyword in the search process are method, model, demand, spare part, quantitative, qualitative, condition based maintenance, and condition monitoring. The databases for the search process are the following search engines: EBSCO, Web of Science, ScienceDirect, Base, and Citeseer. In this manner, all relevant proceedings and journals are examined regarding the research problem. A backward and forward search with English and German keywords was carried out.

For enabling the integration of condition monitoring information, the information provided by an IMS has to be analyzed regarding the type of data and the applicability for its inclusion. Furthermore, the existing spare parts forecasting methods have to be investigated with respect to their ability to utilize condition monitoring information. As the forecasting methods need to be adapted for this integration, the requirements for the
adaptation are analyzed and deduced based on the target of improving forecast quality and the provided condition monitoring information. By means of these requirements, an approach will be conceptualized to integrate the condition monitoring information into the forecasting methods for improving the quality of breakdown forecasts. Afterwards, a validation based on a real case is carried out. This example evaluation follows the process of building theory from case study research according to Eisenhardt (1989).

State-of-the-art analysis

Spare parts forecasting methods

Besides the common focus on spare parts inventory management by means of general forecasting methods, the potential of the adapted demand forecasting methods for spare parts management has been identified as a promising new research field (Martin, Syntetos, Parodi, Polychronakis, & Pintelon, 2010, pp. 227–230). Several methods have been developed for demand forecasting; thereof, only a few with the special focus on spare parts demand forecasting. These common demand forecasting methods can be classified concerning their demand pattern of the spare parts. These demand patterns refer to needed volumes and predictability of a particular component and can be divided into the categories of: regular, intermittent, slow moving, and fast moving parts (Huiskonen, 2001, pp. 129–130). The largest amount of spare parts exhibits an intermittent or lumpy demand. These parts characterized by sporadic demand require a detailed investigation as the utilization of ‘classical’ forecasting methods does not lead to adequate estimation results. Referring to Bacchetti and Saccani (2012), Table 1 highlights the existing forecasting methods and draws a line to the sporadic demand of spare parts, which appears to be most relevant for the inclusion of IMS data.

The different forecasting methods can be classified in time series (T), explanatory/ causal (E), hybrid (H), as well as other models (O) (Bacchetti & Saccani, 2012, pp. 725–726). Causal models are used when the demand can be predicted based on one or more explanatory variables, which infers searching for a dependency between the given demand and other variables. Demand forecasting methods based on time series utilize historical demand data to estimate the demand of the next forecasting periods. Three types of time series forecasting methods exist, namely constant demand level, trend, or seasonality. In practice, the time series models used most often are single exponential smoothing (SES), simple moving averages (SMA), or exponentially weighted moving average (EWMA) or its modifications. It has been proven though that these forecasting methods cannot estimate the spare parts demand accurately. If a breakdown occurs, leading to a rise in demand for spare parts, the SMA and the SES overestimate the expected spare parts demand (Bacchetti & Saccani, 2012, p. 725). Two methods commonly used in practice are Croston’s method as well as its modification and Sytentes and Boylan approximation (SBA). These two approaches are the standard and most accurate models to forecast spare parts demand (Croston, 1972, pp. 291–296; Syntetos & Boylan, 2005, p. 303). The hybrid methods combine the time series-based forecasting and the causal forecasting. Other models are those methods which include advanced demand information, where early information is collected from customers as a driver, and are observed for demand forecast (Bacchetti & Saccani, 2012, pp. 725–726). Moreover, the forecasting methods can be categorized if they consider the sporadic characteristic of spare parts demand or not. Several of the investigated methods are applicable to sporadic demand. Aspects that are often pertaining to spare parts demand are autocorrelation, relatively short series, trend, and frequent repeated values (Bacchetti & Saccani, 2012, p. 725).
However, all the above-listed methods are still not utilizing actual condition information of the technical system. They only consider condition-related information or condition monitoring information while forecasting possible breakdowns (see last column of Table 1). Failure rate analysis as a recently developed forecasting method includes a failure function of a part or information about the installed base of the operating machines (Bacchetti & Saccani, 2012, p. 726). As Dekker, Prinçe, Zuidwijk, and Jalil (2013) propose, an installed base forecasting, which is applicable to several forecasting methods, depends on the type of underlying information and the chosen procedure. They use data about the condition of the installed base of technical systems, but they do not integrate the actual condition of the technical system provided by IMS (Dekker et al., 2013, pp. 541–542). However, this installed base information consists, in most cases, of historical data, which are not inclusive of the monitoring data of the current condition of the technical systems. Furthermore, this information is sometimes stemming from old machine types not giving the right basis for estimating the demand of spare parts of a new machine generation. This means that this information is related to the condition of the technical system but it is not the actual condition monitoring information. In literature, only the following three research activities can be found utilizing condition monitoring information for forecasting. They have utilized condition monitoring information as external conditions for forecasting the spare parts demand. This means that they use the condition monitoring information for the inventory decision process while assessing the data in the calculation of the optimal stock levels. However, they

| Forecasting method                  | Classification | Consideration of the sporadic characteristic of spare parts demand | Usage of condition related information |
|-------------------------------------|----------------|-------------------------------------------------------------------|----------------------------------------|
| SMA, SES                            | x              | No                                                                | No                                     |
| EWMA, adj. EWMA                     | x              | No                                                                | No                                     |
| Adj. Holt and Holt-Winters          | x              | Yes                                                               | No                                     |
| Croston and its modifications       | x              | Yes                                                               | No                                     |
| Bootstrapping                      | x              | Yes                                                               | No                                     |
| Filtering/clustering                | x              | Yes                                                               | No                                     |
| Advance demand information          | x              | Yes                                                               | No                                     |
| Failure rate analysis               | x              | Yes                                                               | Utilizing historical data of the condition of the installed base of technical systems |
| Operating condition analysis        | x              | Yes                                                               | Considering influence of the environment (e.g. temperature) |
| Regression                          | x              | Yes                                                               | No                                     |
| Neural networks                     | x              | No                                                                | No                                     |
| Bayesian approaches                 | x              | Yes                                                               | Condition information is used to adjust the demand value |
| Proportional hazards model          | x              | Yes                                                               | Condition information is used to adjust the demand value |
| Installed base forecasting          | x x x x       | Yes                                                               | Utilizing data about the condition of the installed base of technical systems |
did not consider an adaptation of the forecasting methods (Louit, Pascual, Banjevic, & Jardine, 2011). Elwany and Gebraeel (2008) use a Bayesian approach for a spare part ordering model for a single-unit system, whereas at most, only one part should be stored. Louit et al. (2011) proposed a proportional hazards forecasting model, which is directed to the determination of the ordering decision for a spare part when the related component is monitored by a condition monitoring system (Louit et al., 2011, p. 1837). Wang, Chu, and Mao (2008) are considering external conditions such as parts’ reliability characteristics in their approaches (order replacement policy for a single-unit system using a proportional hazards model). In consequence, research on the improvement of forecasting quality by means of actual condition information is still a research issue to be addressed (Martin et al., 2010, p. 229).

**Condition monitoring**

Condition monitoring is defined as employing external condition like vibration, acoustic, oil analysis, temperature, pressure, moisture, humidity, weather, or environment data for measuring the state of a technical system. This helps to make predictions about when and which systems are going to fail in the future. Condition monitoring is a part of condition-based maintenance (CBM) ‘that recommends maintenance decisions based on the information collected through condition monitoring’ (Jardine, Lin, & Banjevic, 2006, p. 1483). CBM can be divided in the phases of data acquisition, data processing, and maintenance decision-making depicted in Figure 1 (Jardine et al., 2006, pp. 1484–1485).

In the first phase – data acquisition – the status of the technical system is measured by gathering and storing condition monitoring information from different sources. Data is not yet analyzed or processed in this phase. Because of the high amount of monitored data, it is necessary to condense the data in order to get information from which the condition of a technical system can be inferred (Höring, 2003, p. 5). This is done in the data-processing phase followed by an automated or manual information analysis. This can be done by models, algorithms, or human knowledge, based on the type of data. Before the monitored data can be condensed and analyzed at all, it has to be cleansed of unfitting data due to sensor malfunctions. The last phase – decision-making – is about using this data to take decisions concerning maintenance measures (Jardine et al., 2006, pp. 1484–1486). In this context, forecasting and diagnostics are carried out, whereas the forecasting is done based on the methods which assess the condition information in the calculation of the optimal stock levels but without integrating the actual condition monitoring information into the forecasting methods, as described earlier. For
a detailed description of the different models and algorithms of the various phases of condition-based maintenance, see Jardine et al. (2006).

To collect condition monitoring information, the research within IMS has provided means for monitoring technical systems’ maintenance condition (Espindola et al., 2012, p. 1017). The intention hereby is that condition monitoring data should provide better information about the status of the technical system to support the precise estimation and detection. Three different types of condition monitoring data exist: value, waveform, and multidimensional. Value data is characterized by a single value and is only measured at a fixed date provided by IMS. Waveform data represents a time series of, for example, vibration or acoustic data, while the multidimensional data includes image data such as infrared thermographs and visual images. Waveform data and multidimensional data are collected during a specific time period (Jardine et al., 2006, p. 1486). Depending on the type of observed condition monitoring data, the parameters which can observed for the forecasting will be able to be derived.

Within our research, the real-world application of monitoring the condition of pumps for oil pipelines serves as a validation case. For this application, the condition of valve actuators in these pumps will be observed which are located at the end customers of a global spare parts supply chain of an international machine manufacturer that develops and produces solutions in automation for the oil industry. Sensors are included in the valve actuators of the pumps, collecting data about the torque, and the opening position of the gear of the pump. The analysis of the data concerning breakdown characteristics is carried out by an IMS supported by a so-called Watchdog Agent Toolbox (Djurdjanovic, Lee, & Ni, 2003). The main analysis functions of this Watchdog Agent toolbox are the health assessment, the condition diagnosis, and the performance prediction of the equipment. Based on the Watchdog Agent analysis, the failure status of the pump gear can be inferred. This condition monitoring data is provided by the IMS in a waveform type giving the basis for generating probability distributions about the system failures. This forms the foundation for the execution of the forecasting and the subsequent validation of the conceptual approach of this work.

**Description of requirements for integration**

Integration of condition monitoring information into forecasting methods depends on three factors. The first factor resembles the category of spare parts. For each category, as described earlier, different forecasting methods are used. Out of this reason, it is necessary to choose the spare parts category and a related forecasting method for the integration analysis. The second factor, being the type of output data from the IMS, affects the modality, how and what parameters have to be adapted for integrating the provided condition monitoring data by the IMS into a forecasting method. The identified requirements of each forecasting method are being used to forecast the spare parts demand by integrating the condition monitoring information to differentiate and resemble the third factor. Thus, for each forecasting method, various parameters and requirements can be identified, which are furthermore interdependent on the type of output data of the IMS. For this reason, it is difficult to provide a general approach or guideline for integrating condition monitoring information in spare parts demand forecasts.

The condition monitoring information or output data provided by the IMS is generated based on the analysis of sensor data. Sensor data might be torque, vibration, temperature values, and so forth. After gathering the sensor data, this data is analyzed by an IMS. The resulting output data are which spare part and related parts need a
replacement, the breakdown probability distribution, and the estimated breakdown date of the respective spare part, which service personnel capability and equipment is required for the replacement and the geographical position of the technical system. This data builds the foundation for the spare parts demand forecasting with the following developed Condition Base Maintenance Forecasting (CBMF) method and the subsequent execution of planning the spare parts supply chain activities. This procedure of how the condition monitoring data is generated and used is depicted in Figure 2.

In this work, we focus on spare parts characterized by intermittent demand selecting the modification of Croston’s method – the SBA – as a reference level for the spare parts demand forecasting as this is the model to provide the most valuable results for spare parts demand in practice. Therefore, the SBA is introduced in the following.

For the model, the following assumptions hold true. The spare parts demand ($Y_t$) and the interdemand interval, the interval between two arising spare parts demands, are stationary. The occurrences of spare parts demand are Bernoulli distributed. The demand parameters are normally distributed and the interdemand intervals are assumed to have a geometric distribution. Additionally, the demand size has no limitations (Syntetos & Boylan, 2001, pp. 304–305).

We propose the SBA method, as Syntetos and Boylan (2001) demonstrate that Croston’s estimator is biased. This means that the difference between the expected demand and the true value of the demand is unequal zero (Anderson, 1980, p. 11). Consequently, the estimated value deviates from the true value. For this reason, Syntetos and Boylan (2001) developed an unbiased estimator defined as follows:

$Y_t = \left(1 - \frac{a}{2}\right) \frac{Z_t}{P_t}$  \hspace{1cm} (1)

where $\alpha$ is a smoothing parameter (Syntetos & Boylan, 2005, p. 304). Thereby, the method has two steps: First, the average demand ($Z_t$) is estimated by separate exponential smoothing. Second, after the occurrence of the spare parts’ demand, the average interval between upcoming demands ($P_t$) is determined (Syntetos & Boylan, 2005, p. 459).

Figure 2. Output data of the IMS.
Development of a conceptual approach

The conceptualization of our forecasting approach called CBMF method follows a structured forecasting procedure proposed by Bacchetti and Saccani (2012). The first phase of selecting a forecasting method or developing an approach, akin to the suggested adapted forecasting method, is the pre-processing phase. In this phase, the categorization of the spare part is performed (slow or fast-moving, intermittent, or lumpy). The second phase is the processing phase, in which the respective forecasting method is applied. In the last phase, the post-processing phase, necessary adaptations of the applied method or the sample are implemented.

In the pre-processing phase of the forecasting procedure, the main idea for integrating condition monitoring information and forecasting methods is to generate a hybrid, two-step estimation.

1. The first step of carrying out the demand forecasts is estimating the crucial parameters for forecasting as accurately as possible. Therefore, the provided condition monitoring information is analyzed regarding distribution parameters of potential breakdowns.

2. In the second step, a Bayesian approach according to Dolgui and Pashkevich (2008) is used for providing a probability distribution function of the spare parts demand. The foundation is the determined parameters of step 1.

The execution of the first step of the hybrid estimation is achieved by determining the forecasting parameters. Therefore, the assumption about the demand parameters is adjusted. As normal distribution is not suitable for precise spare parts demand forecasting (Boylan & Syntetos, 2010, p. 230), the current distribution characteristic is supposed to apply to the observed condition monitoring information provided by IMS. Therefore, the procedure of transformation is structured as follows (see Figure 3).

First, the gathered sample of condition monitoring information provided by IMS is analyzed concerning the distribution parameters. This means that the characteristics of the distribution function are determined and the respective parameters are identified. The average value and quantiles for instance are determined. Second, the distribution function has to be determined. The chosen probability function is a beta probability function as this function allows adjusting “the population-average probability distribution using the observation specific to a particular item” (Dolgui & Pashkevich, 2008, p. 888) and this is required to characterize the sporadic spare parts demand. The underlying beta probability distribution has the following density function:

\[ f_{\theta_i}(y|\alpha_i, \beta_i) = \frac{y^{\alpha_i-1}(1-y)^{\beta_i-1}}{B(\alpha_i, \beta_i)} \] 

where \( y \) is the forecast value, \( \rho_i \) is the requested probability for spare part \( i \) (\( i = 1, 2, \ldots, k \)), and an independent beta distributed random variable, \( B \) is the distribution of historical demand data, which is determined based on \( \alpha_i \) and \( \beta_i \), \( \alpha_i \) and \( \beta_i \) are individual

Figure 3. Procedure of transformation.
parameters of $p_i$ related to $z_i$ ($\alpha_i = a^*z_i$, $\beta_i = b^*z_i$, $a^*, b^* > 0$, $z_i \in (0,1]$) (Dolgui & Pashkevich, 2008, pp. 888–890). Based on $\alpha_i$ and $\beta_i$, the condition monitoring information is integrated into the forecasting method. $z_i$ is the breakdown probability of part $i$ provided by the IMS and the variance of each $p_i$ depends on $z_i$ (Dolgui & Pashkevich, 2008, p. 889):

$$V\{p_i\} = \frac{ab}{(a + b)^2 (a + b)z_i + 1}$$  \hspace{1cm} (3)

Dolgui and Pashkevich (2008) propose to estimate the parameters $a$ and $b$ via the maximum likelihood method. However, we adjust this method at this point to include the condition monitoring information. Therefore, we suggest to estimate the parameters $a$ and $b$ with the SBA estimator. Moreover, in this manner, it is possible to regard the sporadic character of the spare parts demand.

As a last step, the spare parts demand forecasting that is carried out is explained in the following. The occurrence of a demand for spare parts is determined in a more precise way. The advantages of using the distribution function of the observed condition monitoring information lie in the possibility to determine a precisely estimated distribution function of the spare parts expected to fail. In this manner, it is possible to predict a more precise spare parts demand.

In the second step of the proposed procedure to develop a forecasting method, it is suggested to utilize a Bayesian approach. This approach is used as pure time-based forecasting or causal analysis is not suitable to predict the intermittent demand for spare parts. This is the case because these methods are based on historical data which often indicates no constant demand, a trend, or a seasonal pattern (Bacchetti & Saccani, 2012). Moreover, the application of a similar Bayesian approach enables the determination of a probability distribution function for machine breakdowns. Furthermore, the Bayesian approach allows applying different probability distributions for each spare part. That is why the Bayesian approach is ideally suited for integrating condition monitoring information and spare parts forecasting methods (Jones, Jenkinson, Yang, & Wang, 2010, pp. 268–269). The proposed Bayesian approach relies on a Beta-binomial model for the demand (Dolgui & Pashkevich, 2008, p. 888):

$$P(D_i = x) = \binom{m}{x} \frac{B(x_i + x, \beta_i + m - x)}{B(x_i, \beta_i)}$$  \hspace{1cm} (4)

where $x = 0, 1, \ldots, m$ is the period of forecasted demand, and $D_i$ is the spare parts demand.

The presented draft conceptualization of approaches is an excellent foundation for the following validation and the subsequent utilization of the forecasting results for the spare parts planning. The more adequate forecasting results will be used for the planning methods of all spare parts supply chain planning domains. As a result, the spare parts-related logistics processes can be planned in a more precious way.

Validation

Procedure description

According to the suggested forecasting procedure, the pre-processing phase is performed as described earlier. All requirements for integrating condition monitoring information and forecasting methods to enhance spare parts planning are investigated. Additionally, in the previous chapter, we introduced a draft conceptualization approach on how
forecasting can be adapted. The following two steps, the processing and the post-processing phase, will be carried out by applying the extended forecasting approach to the real application case introduced above.

The machine manufacturer of the application case is an MRO (maintenance, repair, and overhaul) service provider for their self-produced machines. This means that either the manufacturer himself repairs the product in use or that he delegates the repair process to a third party service provider. The procurement strategy of the machine manufacturer is a build-to-order strategy. He stores components for the production which can also be used for MRO services. But normally, no special inventory for broken pumps is available. An inventory of components is held only at the place of production. If the broken pump is not in inventory, it is produced by it being added to the normal production schedule with high priority and is delivered to the place of repair upon its completion. From there, further transport is organized by the repair team. The integration into the production schedule is becoming more difficult, as capacity utilization is constantly rising due to original equipment production. That is why it becomes progressively important to estimate breakdowns in an adequate manner. Based on estimated breakdowns, the production schedule and the inventory levels can be adapted at an early stage, so that an interruption of the planned production schedule of original equipment can be avoided. Furthermore, the service personnel may be placed next to the location, where the replacement is needed and replacement delays due to missing service personnel will be consequently prevented.

Based on the provided data of the application case and the results of the IMS, the conceptualization approach will be evaluated. Thereby, the quality and the potential of improvement of the adapted forecasting method can be depicted and verified. Moreover, the real case will be used in the first step in order to identify further adaptation requirements. Secondly, the integration of condition monitoring information and forecasting methods to improve spare parts planning is going to be finalized by implementing the identified further adaptation requirements.

**Example evaluation**

The input variables for carrying out the spare parts demand forecasting based on the CBMF method are derived from the output variables of the IMS and the gathered data of the application case. Based on these variables, the forecasting is determined.

In order to generate the values of the input variables, the data of the used case has to be analyzed and the data-set has to be cleaned and condensed to make the data applicable for the forecasting. The data-set is mainly divided in four groups: demand, product, customer information and the output data of the IMS. The demand data includes the information about the amount of spare parts demand and the interval between breakdowns for the respective part. The product information characterizes the size, weight, and specific characteristics of the spare part related to the demand of the respective demanded spare part. The customer information provides the requirements of the customer and the location of the technical system, in which the part is broken. This data is historical data and provides information about the past spare parts demand, whereas the output data of the IMS contains actual information about the condition and the future degradation of the parts fitted in the technical systems. Unfortunately, the data-set provided by the manufacturer does not include IMS information. That is why we generated the output data about the breakdown probability distribution based on a data-set generated in a laboratory environment for a similar technical system.
To forecast the spare parts demand based on the CBMF method by incorporating the condition monitoring information in a first step, the density function of the underlying beta probability distribution has to be calculated. As a second step, the parameters $a$ and $b$ have to be determined through the SBA estimator. Afterwards, the variance of each $p_i$ has to be defined. These results build the foundation for forecasting the spare parts demand.

By carrying out these steps exemplarily for five different critical spare parts, the results depicted in Table 2 are yielded. These results show commendably that by incorporating condition monitoring data in the CBMF method, the estimated spare parts demand is more precise than without regarding the condition monitoring data. This is only an example evaluation and of course such an evaluation has to be proven based on more than one case study and the results of the CBMF method have to be compared with the results of other forecasting methods to investigate if this technique is more suitable to forecast the spare parts demand than other methods.

### Conclusion

With this article, a first conceptualization of an approach to integrate condition monitoring information and forecasting methods has been developed with the intention to enhance spare parts demand forecasting and hence improve the foundation for spare parts supply chain planning. The state-of-the-art analysis regarding spare parts forecasting has exposed a research gap in the integration of spare parts forecasting methods and condition monitoring information. Focusing on this gap, the requirements for such integration have been highlighted and in the first phase, the forecasting procedure has been carried out by conceptualizing a forecasting approach. To evaluate the results of the pre-processing phase, data of a real case from the oil industry is going to be used. By applying the conceptualized approach to further cases, the expected benefits and further adaptation requirements will be identified for carrying out the final adjustment. Future work has to focus on the detailed validation of the forecasting approach. Therefore, as a first step, data of further case studies has to be collected. Followed by a detailed assessment, the data can be used for identifying the potential of utilizing similar adapted forecasting methods for planning the inventories. Moreover, it has to be investigated in how far further data sources like service reports and information about the installed base might be integrated in the proposed forecasting method.

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| Spare part | Estimated demand without IMS data (rounded off) | Estimated demand with IMS data (rounded off) | Real demand |
|------------|-----------------------------------------------|---------------------------------------------|-------------|
| Sp1        | 21                                            | 17                                          | 18          |
| Sp2        | 5                                             | 3                                           | 2           |
| Sp3        | 9                                             | 6                                           | 6           |
| Sp4        | 9                                             | 7                                           | 8           |
| Sp5        | 7                                             | 4                                           | 3           |
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