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Spare Parts Demand Forecasting in Maintenance, Repair & Overhaul

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Abstract

Despite a high degree of uncertainty about the scope of future orders and the corresponding capacity and material demands, Maintenance, Repair & Overhaul (MRO) service providers face high expectations regarding due date reliability by their customers. To meet these requirements while at the same time keeping delivery times short, the availability of the required spare parts or pool parts is an essential success factor. As these cannot be kept in stock in large quantities due to their high monetary value, reliable spare parts demand forecasts are of vital importance for the profitability of MRO service providers. As a result of a high degree of information uncertainty and the mostly lumpy demand patterns, conventional time-based and statistical methods do not show sufficient forecasting quality for application in the MRO industry. Data-based approaches incorporating machine learning methods offer promising capabilities to achieve improved predictive accuracy but still need to be adequately linked to production planning and control to realize their full potential. This paper first analyses potential approaches to spare parts demand forecasting in the MRO industry, focusing on forecast accuracy and potential for integration into material and production planning. Based on this, a classification of demand forecasting approaches is presented and an approach for order-based material demand forecasting with two-step feature selection is proposed. Finally, the presented approach is applied on a real dataset provided by an MRO service provider.

Keywords

MRO; spare parts demand; forecasting; Machine Learning; Artificial Neural Networks.

1. Introduction

Maintenance, Repair and Overhaul (MRO) of complex capital goods, such as aero engines or wind turbines, is also known as "regeneration" [1]. This process comprises the disassembly, inspection, repair, reassembly, and test (quality control) of mostly high value products [2]. In addition to this, there are up to two pooling stages in the regeneration supply chain (see Figure 1) to provide repairable or serviceable spare parts to their downstream processes and by this improve robustness against disturbances or material shortage along the regeneration process. [3]. These pools are filled either from the respective upstream processes or via the procurement of new or used parts. The availability of the pool parts and the precision of the corresponding demand forecast thus have a significant influence on the punctuality of the material supply for the reassembly and the achievable adherence to delivery dates of the MRO service provider to its customers [4]. In turn, the on-time delivery by MRO service providers is complicated with the high degree of uncertainty about the future work scope at the beginning of the regeneration process. Due to the complexity of goods to be repaired, it is not possible until the end of the inspection to recognize all existing damages and thus to plan repair operations and forecast the material demand. Furthermore, it is uncertain, whether a component can be repaired or has to be replaced (e.g. due to heavy damage) [1].

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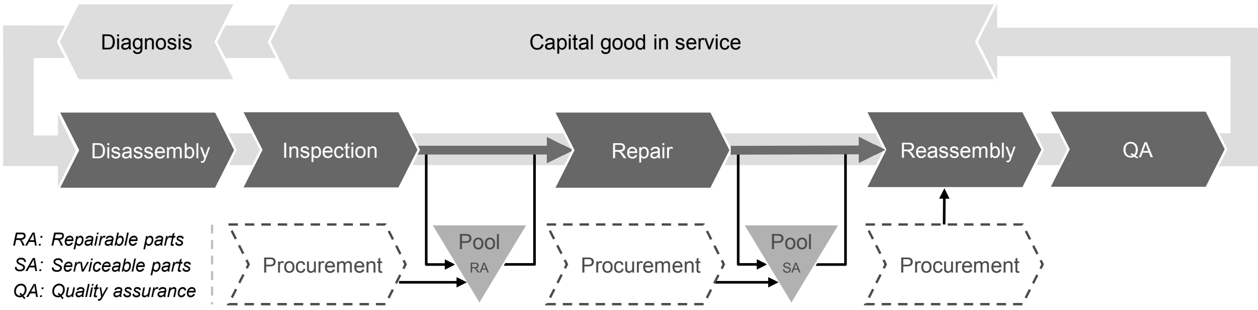

Figure 1 – Universal supply chain structure for the regeneration of aero engines [5]

As the spare parts cannot be kept in stock in large quantities due to their high monetary value, reliable forecasting is a crucial factor to ensure the profitability of the MRO service provider. Because of the lumpy patterns of spare parts demand, which will be described in the next section, traditional time-series and statistical forecasting methods do not provide sufficient forecasting quality for application in the MRO industry [6]. However, today more and more condition data, e.g. oil pressure or temperatures are measured during operation, which can be indicators regarding the wear of components [7]. Besides these quantitative parameters, also qualitative parameters, such as region, climate, maintenance politics of aircraft operator or owner have to be considered while forecasting material demand. This is possible e.g. using Machine Learning (ML)-based methods, which thus are the focus of this paper. Based on a brief introduction to spare parts demand classification a brief analysis of characteristics of spare parts demand in the MRO industry and potential methods for spare parts demand forecasting is performed in section 3. Based on this, section 4 presents a hybrid approach to spare parts demand forecasting and outlines the first prediction results obtained. Finally, conclusions are given in section 5.

2. Spare parts demand in the MRO industry

Spare parts demand can be categorized, using periodicity (inter-demand intervals) and quantity variation. Typical demand structures are smooth, erratic, intermittent and lumpy demand (see Table 1) [8,9].

Table 1 – Demand categorization according to [8], [9]

Demand Type	Inter-demand intervals	Quantity variation
Smooth	Low	Low
Erratic		High
Intermittent	High	Low
Lumpy		High

Smooth and erratic demand patterns can be distinguished according to quantity variation, which is relatively low in the case of smooth demand patterns and relatively high in case of erratic demand. Periods between demand occurrence are small in both cases. Intermittent and lumpy demand is characterized by the mostly random appearance of demand and many periods of zero demand. Furthermore, lumpy demand, in comparison to intermittent demand, shows high variance in spare parts quantity [11,10]. Cut-off values regarding the separation of these demand patterns are proposed in [10]. Considering complex capital goods like aircraft about 80% of the demand for repair, and corresponding material demand comes up unplanned [12]. Due to this and corresponding uncertainties regarding damage pattern, work scope and spare parts demand of unplanned MRO-activities can mostly be categorized as intermittent or lumpy (cf. [6] for sources of intermittency and lumpiness for aircraft spare parts). Hence, different forecasting methods and potential fields of application in forecasting of intermittent or lumpy demand are analyzed in the next section.

3. Literature review: Forecasting of material demand

Methods for demand forecasting methods overall can be grouped in deterministic, stochastic demand assessment and subjective estimation methods [13]. [14] categorizes forecasting approaches depending on the influencing variables in causal, lifecycle, time series and consumption analysis. A differentiation between qualitative and quantitative approaches is used in [15], whereby the quantitative methods are subdivided in uni- and multivariate methods. [16] uses a similar structure but subdivides quantitative methods in time-series and causal forecasts. An alternative classification is presented in [17] that distinguishes between past-based and future-based methods, each divided into qualitative and quantitative methods. These are further differentiated in methods for forecasting of time and quantity of material demand by [18]. These approaches to classification of material demand forecasting form the basis for the classification scheme (see Figure 2) that is presented in the following sections.

3.1 Deterministic approaches

Deterministic demand forecasting methods are methods by which material demand is determined solely based on an existing independent primary demand [13]. These methods comprise analytical and synthetic approaches [13]. Analytical methods rely on the bills of material of the finished product. Based on them, the demand on finished product (primary demand) is disassembled in demand for subassemblies and components [13]. Synthetical methods to forecasting make use of parts usage lists as a forecast basis and are suitable especially for long-term planning [13]. Another deterministic approach is e.g. consumption analysis. This method is based on maintenance measures planning [14]. Due to their inability to consider uncertainties and thus unplanned material demand in the regeneration process, deterministic approaches are only suitable for spare parts provision during planned regeneration events (e.g. mandatory replacements of components). For intermittent and lumpy demands, which are in the focus of this paper, stochastic methods are commonly used [19].

3.2 Stochastic approaches

Stochastic demand forecasting can be defined as "mathematical-statistical methods, in which past consumption values are used to infer future demand” [13]. These methods can again be grouped into quantitative and qualitative. Quantitative stochastic methods include univariate and multivariate approaches [15] that are presented separately in the following sections.

3.2.1 Quantitative univariate approaches

Univariate approaches are those based on consideration of only one independent variable and include e.g. time-series and life-cycle analysis. Time-series methods are methods by which the forecasting for a future time horizon is made based on a demand history from the past. Among others, the approaches based on well-known statistical methods, such as exponential smoothing or moving average, are to be emphasized. Statistical methods for forecasting intermittent and lumpy demands were first studied by CROSTON [20]. In his work, he found that exponential smoothing does not provide sufficient forecast quality to forecast intermittent demand and proposed his method, based on exponential smoothing, in which demand rate and time intervals between its occurrence are analyzed and forecasted separately [20], [21]. [10] and [22] identified a bias in CROSTON’s method and introduced an additional correction factor to avoid this bias. Further statistical methods for predicting intermittent and lumpy demand are also presented and discussed in [23], [24], [25] and [26].

Life-cycle analytical methods for demand forecasting are based on an "estimation of the time until failure of the corresponding component" [14]. These methods are based on failure rates or, in other words, the probability of a failure as a function of its lifetime [15]. Practical studies on these methods are presented e.g. in [27] and [28].

Time-series and life-cycle analytical methods are easy to use and require a relatively small amount of input data. Nevertheless, the increasing number of influencing factors that MRO service providers are provided with, e.g., from condition monitoring systems, cannot be taken into account completely with the help of these approaches, which leaves potential for improvements of the forecast quality unused.

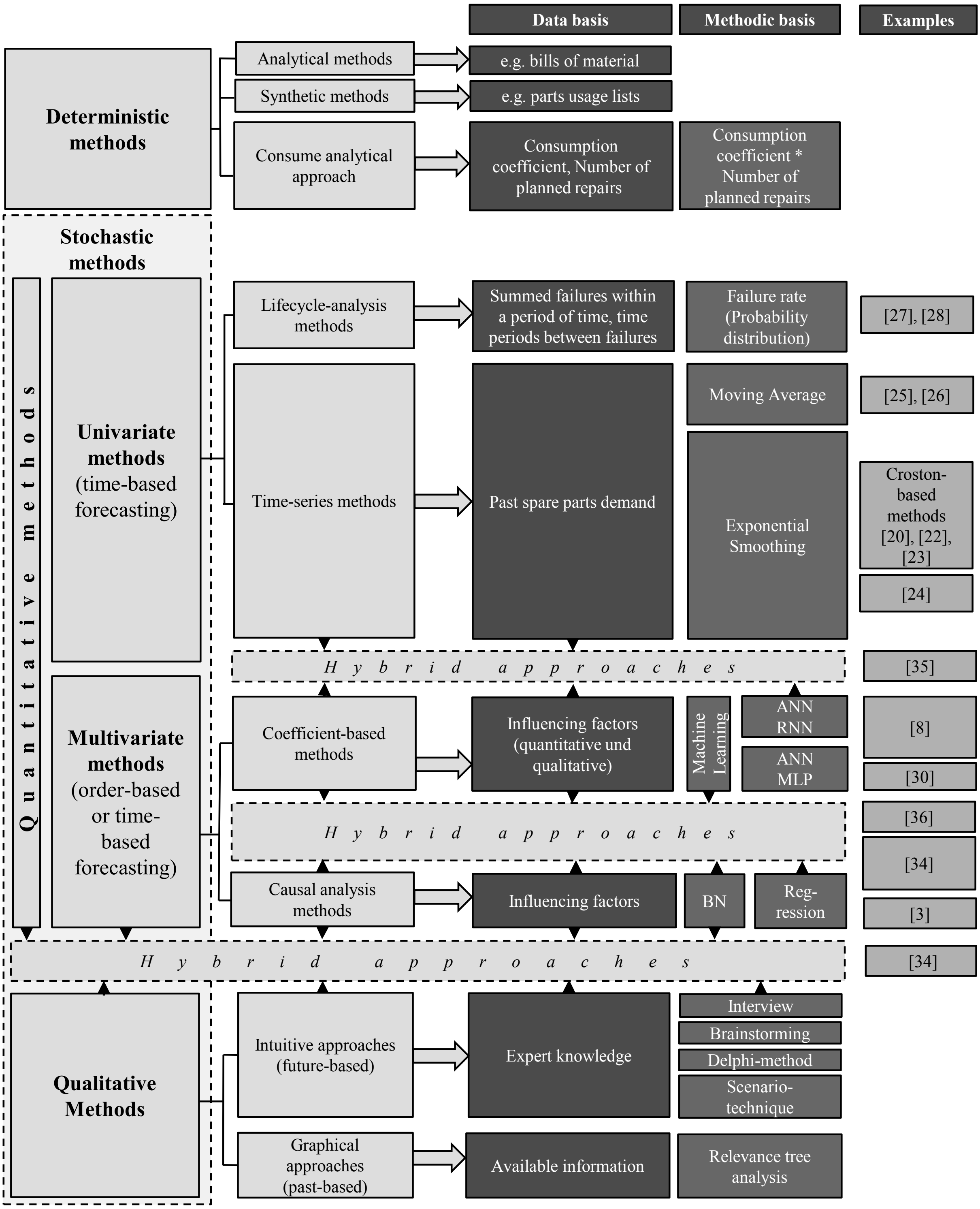

Figure 2 – Classification of demand forecasting methods (based on [13], [14], [15], [16], [17], [18])

3.2.2 Quantitative multivariate approaches

As forecasting material demand is usually dependent on more than one variable, multivariate forecasting methods are gaining more and more importance over the recent years. These methods include coefficient-based and causal analysis methods [15]. These approaches typically apply data from the use phase, for example using condition monitoring systems, or the maintenance phase of the goods (cf. [7]). Coefficient-based methods consider several influencing factors (quantitative and qualitative) to determine a wear coefficient (cf. [15] for definition). These methods include, for example, ML-based methods, such as Artificial Neural Networks (ANN) that represent simplified representations of the biological neural network (cf. [29] for the definition of ANN). They consist of several information processing units ("neurons") that contain mathematical functions and are interconnected. The signals entering a neuron are weighted and converted into the output signals using an activation function. To do so, the ANN is trained based on a training data set, e.g. to achieve desired prediction results. Lumpy demand forecasting using a multilayer perceptron (MLP) type of ANN is explored and analyzed in [8], [30], and [31]. The analysis of 60 contributions related to ANN-based intermittent demand forecasting in [8] reveals, that MLP-based methods provide the best forecasting performance compared to other types of ANN. Above mentioned research also proves that the forecasting accuracy of MLP outperforms that of time series analytical methods. Other ANN-based methods for forecasting material demand are investigated in [32] (e.g. Recurrent Neural Networks (RNN)), that also show good results in the forecasting of non-stationary demand in the field of aircraft spare parts management. Through good forecasting performance, big input-data requirements as well as poor traceability auf causal relationships can be highlighted as disadvantages of ANN-based methods. These can be identified using causal analysis forecasting methods [15]. One of the most common causal forecasting methods are Bayesian networks (BN). BN are a set of variables (nodes) and directed edges between them, that form a directed acyclic graph (DAG). Edges of this graph represent potentially causal dependencies between the nodes [3], [33]. First applications of different types of BN (expert-initiated BN, data-based BN, and hybrid ML-based BN, which combines the first two approaches) for forecasting lumpy spare parts demand are performed in [34]. Here, the hybrid BN outperforms the expert-initiated BN and the data-based BN as well as logistic regression in terms of prediction accuracy [34]. First applications of BN in regeneration logistics can be found in [3]. In this context, they are used to determine the probability with which regeneration orders are required for a component or an assembly. For this purpose, the product structure of the regeneration good is represented in form of a BN, in which the assemblies and components are mapped as its nodes. The edges are derived from the product structure and existing influencing factors. For the determination of the initializing probability distribution, existing service data from the past is provided as the basis for the BN. In both [3] and [34] good causality determination performance of BN is reported. In contrast to time-series based methods, quantitative multivariate forecasting can be used for order-specific forecasting to predict the demand for a certain regeneration order, e.g. based on conditional or operating data of a certain regeneration good. However, this only allows the total demand per order to be predicted and does not include information about the specific time this demand occurs. This is illustrated graphically in Figure 3 using a fictitious demand time-series.

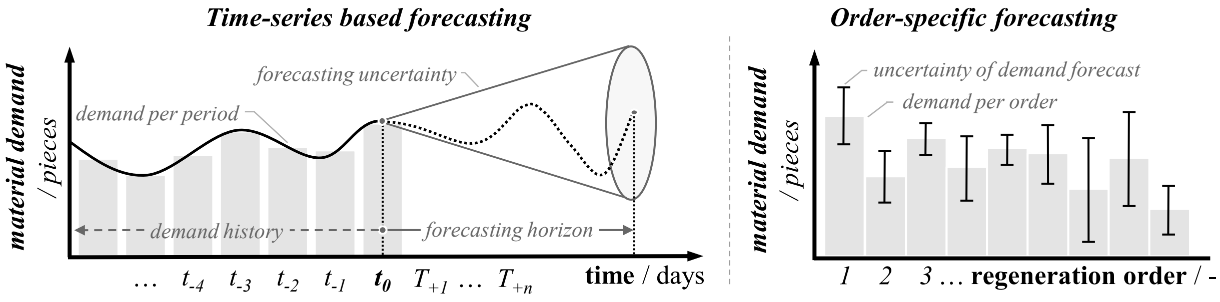

Figure 3 – Types of material demand forecasting

3.2.3 Qualitative approaches

Qualitative approaches are methods based on expert estimates or the analysis of existing information (without causality determination) about the forecasting asset. These can be subdivided in past-based and future-based qualitative forecasting methods. Methods based on past data include, for example, relevance tree analysis. The future-based methods include, among others, questioning, brainstorming, Delphi method, and scenario technique. [17]. Although qualitative methods are widely used for spare parts demand estimation in the MRO sector due to their simplicity, they are still strongly dependent on individual, subjective estimations and thus can neither be proven by data, nor can they be reproduced or even automated. Due to high financial risks, the high variability in demand as well as the complexity of the goods, the quality of the forecasts is often insufficient, which is why they are not the focus of this paper.

3.3 Hybrid approaches to material demand forecasting

Hybrid forecasting approaches combine different forecasting methods to improve forecast accuracy. In [35] hybrid approach for intermittent demand forecasting in the semiconductor supply chain is proposed, which combines RNN-based and time-series-based methods. In this study, the presented method outperforms time-series and RNN-based forecasting methods in terms of demand prediction accuracy. In [36] a hybrid approach for material demand forecasting dedicated to the mining industry is proposed. It combines regression modeling and ANN-based method and which also shows better forecasting performance compared with time-series and ANN-based methods as standalone approaches.

The overview of relevant literature has shown, that advanced ANN MLP-based approaches outperform conventional statistics methods in forecasting accuracy. Hence, in the following section an ANN-based order-specific approach dedicated to the MRO industry is presented. This order-specific forecast could afterwards potentially be distributed over the demand time periods, which could be a topic of further research.

4. Overview of ANN MLP-based approach for material demand forecasting

As mentioned in section 3, ML-based and, especially, ANN MLP-based methods provide better forecasting performance in comparison to the time-series methods. In this section, hence, an approach for systematic application of ANN for order-specific material demand forecasting in the MRO industry is presented. First the approach functionality and general process is presented in section 4.1. Afterwards its software-based implementation based on real dataset provided by MRO service provider is presented in section 4.2.

4.1 Overview of approach functionality

The performance of ANN MLP-based methods can be significantly improved by the selection of relevant input-features (cf. [38,37]). The approach presented in this section (see Figure 4) is focused on sufficient data preparation and feature selection for ANN MLP-based order-specific demand forecasting for the MRO industry. It combines qualitative and causal analysis methods into a two-step process to select relevant features and, by this, increase forecasting accuracy. The structure of the approach is based on typical structure of data analytics project, presented e.g. in [39]. Consequently, the first step of the approach is data preparation based on typical datasets available to MRO service providers. This usually comprises condition parameters, contractual information, customer related data and data from previous regenerations of similar or the same product. To apply ANN-processing this data needs to be prepared accordingly (e.g. through normalization). Afterwards the data irrelevant to the subject area needs to be excluded – usually in corporation with a subject area expert (e.g. internal customer numbers). This may help to decrease computational time and costs for the next FS-step (see Figure 4). After this assessment and basic filtering of irrelevant features, systematic techniques for feature selection have to be applied to avoid redundancy [37], which can not be identified during expert evaluation, as well as to enhance the understandability and to minimize the effort of further data processing [38].

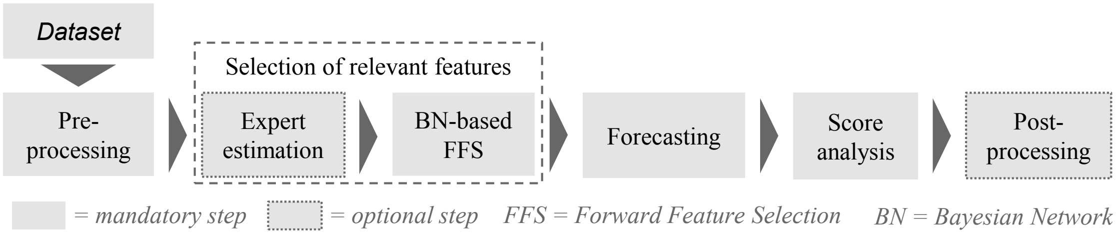

Figure 4 – ANN MLP-based approach for material demand forecasting in the MRO industry

This paper focuses on Forward Feature Selection (FFS) only as one of the most popular feature selection methods. This represents an iterative approach, that progressively adds features that improve the model's forecasting accuracy the most until no additional accuracy can be gained [40]. Due to the increasing number of features available in regeneration this needs to be supported systematical. To do so, BN are chosen as a model learner, due to their good performance in the identification of interdependencies as reported in [3] and [34]. After relevant features have been selected, forecasting can be performed and analyzed using statistical failure rates. This assessment allows for a preliminary evaluation of forecasting results. If the applied forecasting method did require the normalization of data during pre-processing, data has to be denormalized to obtain forecast values usable in practice.

4.2 Software-based application of ANN-based order-specific demand forecasting

For validation of the proposed approach functionality, it was applied to a real data set, provided by an MRO service provider. The data provided comprises more than 600 datasets with 22 qualitative and quantitative parameters each. The data preparation and forecasting method were implemented using the open-source visual-programming tool *KNIME Analytics Platform v4.5*. Using above described two-step-FS the following features were selected: cycles since new and last regeneration and (partially) product owner, region of operation, regeneration project type. To analyze the forecasting accuracy the results obtained by forecasting with one-step (only expert estimation) feature selection is compared with results obtained using the presented two-step (expert estimation and FFS) feature selection based on typical statistical measures: Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) (see Table 2). In this comparison the normalized values are used for better understanding of the range of the forecasted value. The training algorithm was repeated ten times to determine the achievable range of forecasting accuracy.

Table 2 – Comparison of forecasting accuracy of ANN MLP with one-step and two-step of feature selection

Error	MAE	MSE	RMSE
ANN MLP (1 St.)	0,292…0,300	0,115…0,135	0,339…0,367
ANN MLP (2 St.)	0,288…0,299	0,112…0,120	0,340…0,346

The comparison confirms that ANN MLP-based approach with two stages of feature selection outperforms the similar order specific approach with only one step of feature selection (expert evaluation) in forecasting accuracy. It needs to be mentioned, that in this example only required demand for serviceable components were forecasted, as there was no information on capacity demands per regeneration order, which have to be included for demand forecasting and demand-oriented inventory dimensioning of repairable spare parts. For comparison with conventional time series-based approaches, it also has to be taken into account that the prediction results obtained with the ANN-MLP approach so far only forecast order-specific demands without their demand timing. Consequently, it requires a scheduling of the demands based on the probability of occurrence of the regeneration events as well as the delay in demand based on the date of occurrence of the regeneration events. A potential approach to this estimation is described in [41] that uses a hybrid approach of data mining and logistics models to predict throughput times of regeneration orders. As mentioned in section 4, this coupling should be focused next to allow for an application in the MRO industry.

5. Summary and outlook

Despite various research regarding the prediction of mostly intermittent or lumpy spare parts demand in the MRO-industry service providers still lack suitable and applicable approaches to spare parts demand forecasting using available quantitative and qualitative information. In this paper, different methods for material demand forecasting are analyzed, compared and systematically structured. Here it needs to be differentiated between time-based and order-based forecasting. The literature review has shown, that ML- and especially ANN-based forecasting methods significantly outperform conventional time-series methods in terms of forecasting non-stationary demand. Taking into account MLP as the best performing approach among other ANN-based methods, a systemic approach for application of ANN MLP to forecast material demand in the MRO industry was proposed afterwards. Further this approach was applied to a real dataset provided by an MRO service provider for the prediction of required quantity of serviceable components with two stages of feature selection (expert estimation and FFS). Its performance was compared with the similar approach, using one-step feature selection (expert estimation) only, afterwards. This comparison has shown, that using two-stage feature selection with FFS technique, based on a BN learner, better forecasting accuracy can be achieved. Further research needs to be dedicated to the hybridization of time-based and order-based forecasting approaches with the purpose of distributing precise ANN-based demand forecasts over time periods. In this context, the material demand forecast must also be extended to include the expected demand for repair, so that inventories of repairable components can also be systematically taken into account for the purpose of meeting the total material demand. An additional direction of research is the comparison of alternative feature selection methods and different selection model learners to further improve forecast accuracy.

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Biography

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