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Improving MRO order processing by means of advanced technological diagnostics and data mining approaches

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Abstract

Production planning based on uncertain load information may lead to low schedule adherence or low capacity utilization. Thus, maintenance, repair and overhaul (MRO) service providers are striving to improve their business processes to achieve high logistics efficiency. To estimate repair expenditures and material demands as early as possible, different approaches may be pursued. In this paper, the advancement of technological diagnostics to enable condition assessment without prior disassembly and the use of data mining to generate reliable forecasts are discussed. Thereby, the potential for planning MRO order processing is focused using the example of aircraft engines and rail vehicle transformers.

Keywords: MRO, Complex Capital Goods, Order Processing, Condition Assessment, Data Mining

1. Challenges in planning MRO order processing

Particularly for complex capital goods, the aim is to increase service life and thus value-adding potential by means of maintenance repair and overhaul (MRO) measures [1,2]. Since MRO measures are usually only feasible when the superordinate system is out of service, the rapid recommissioning of an inoperable capital good is a key objective when contracting a MRO service provider [3]. In addition, high reliability and adherence to delivery dates are essential decision criteria from the customer's point of view [4].

Consequently, the reliable planning of the necessary capacities and materials is required to achieve the above-mentioned objectives of short throughput times and high schedule adherence in order to realize high logistics efficiency in MRO processes [3,5,6]. Due to the fact that the type and expenditure of necessary MRO measures can only be determined very inaccurately in advance [7], the planning of capacity and material demands for MRO processes is very challenging [2,6]. Subsequently, the earlier the damage pattern is known, the higher is the potential to reduce the

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throughput time of MRO orders and thus the downtime of the processed complex capital good [8,9] as well as to achieve a high schedule reliability [5,6].

2. Information accuracy in MRO order processing

The generic MRO reference process comprises seven phases, see Figure 1. Until a damage incident occurs, the complex capital good remains in the service-life phase. The MRO process then begins with an initial diagnosis to identify the first available information relevant for planning the order processing. On the basis of this information as well as comparable MRO orders from the past, a first work schedule is roughly estimated. [10,11] In order to precisely determine the extent of damage within condition assessment, most capital goods first need to be disassembled for reasons of accessibility [12,13]. In contrast to the prior rough estimation, the required MRO measures and material demands are reliably known after having finished this condition assessment. The following MRO measures include all necessary steps to restore or improve the functionality of the complex capital good [6]. When all components and subassemblies have been reconditioned, the assembly and quality assurance complete the MRO reference process [12,13].

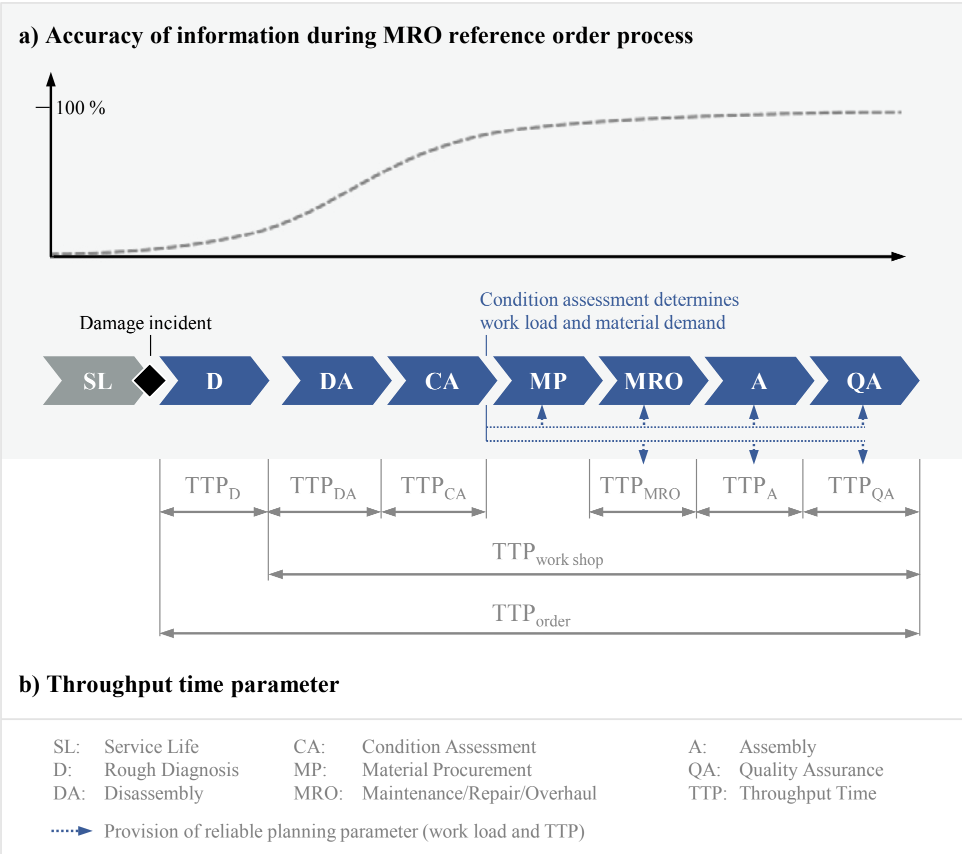

Fig. 1. MRO reference process with related information accuracy based on Eickemeyer and Nyhuis 2010 (a) and throughput time parameter (b)

There are different approaches to meet the challenge of low information accuracy when planning the capacities and material demands for MRO order processing. On the one hand MRO service providers focus on the further development of technological diagnostics to be able to assess the condition of the complex capital good as early as possible. In this context, particularly condition assessment approaches without prior disassembly are promising [8,9,14–16]. Conducting the condition assessment before disassembly enables a precise determination of the damage and therefore required MRO measures before the capital good is physically transferred into the work shop. This increased accuracy for all process steps improves planning processes, especially in short and medium-term planning.

On the other hand, the progressive digitalization allows the application of data-driven approaches. Since process data of completed MRO orders is increasingly recorded, the evaluation of this data by means of data mining offers great potential for improving the information basis regarding MRO order processing [17–19]. According to the taxonomy developed by Hippner et al., data mining methods are categorized according to their goals into describing or predicting issues. Methods that describe issues are aimed at revealing significant structures in the available data, whereas those that predict issues use known characteristics about an object to generate information about unknown or future characteristics [20]. In terms of this data mining taxonomy, the estimation of expected capacity loads as well as material demands to support MRO order processing may be defined as a forecasting problem.

3. Potentials analysis of specific MRO order processes

There are different possibilities to design MRO order processes for complex capital goods [21]. The improvement of MRO order processing by further development of technological diagnostics as well as the selection and implementation of suitable data mining methods to support capacity and material requirements planning is highly dependent on the capital good to be serviced and the specific MRO measures. Thus this research work is based on two examples of application. The first describes the improvement of technological diagnostics and the implementation of Bayesian networks to derive load forecasts in order to improve MRO order processing for rail vehicle transformers, whereas the second focuses on the potential for the regeneration of aircraft engines.

3.1 Improving MRO order processing using the example of rail vehicle transformers

Current research activities deal with the improvement of order processing for the reconditioning of rail vehicle transformers in cooperation with Siemens AG as an industrial manufacturer that also offers MRO services.

In the regarded sample of application there is no exclusive workshop for MRO orders. Instead, these are integrated into ongoing production. As these orders compete with production orders for available capacity, a reliable estimation of the required MRO workload is particularly important for the medium- and short-term planning of processing MRO orders. Subsequently, a difference between the planned and actual workload of an MRO measure per workshop area has a direct effect on the entire production plan and thus on schedule adherence for all orders to be processed [19].

In recent years, the industry partner has therefore invested in the continuous improvement of technological diagnostics. In order to reliably determine the various influencing variables and thus the current state of the transformer, numerous supplementary analysis methods have been developed [15]. In particular, electrical measurements and various analyses of the insulating oil can be applied to assess the condition of a rail vehicle transformer. In the incidence of damage, gases, acids and sludges may be generated in the insulating oil of the transformer due to complex interactions. By analyzing these dissolved gases or particles, the extent of a damage or a progressive aging process can be reliably determined. Essential analyses can already be carried out at the customer's site. (Siemens 2018). Thus, these results can already be considered in the medium-term planning of MRO order processing. If necessary, further in-depth analyses can also be carried out at the manufacturer's site [16]. The results of these tests can also be integrated into medium- or short-term planning.

As a result, the MRO process for rail vehicle transformers (see Figure 2) differs from the reference process previously described in Section 2. The MRO process of a rail vehicle transformer also starts in the service life phase with the occurrence and reporting of a damage incident. Due to the technological developments described above, the condition assessment can be carried out at the beginning of the MRO process. The process element of the first rough diagnosis can therefore be omitted. In addition, no disassembly is required for executing the condition assessment. This is the most significant difference to the generic reference process. Following, a comprehensive condition report is prepared for the assessed rail vehicle transformer. This forms the basis for the subsequent quotation costing and coordination with the customer. The decision regarding the order assignment is then made by the customer. As soon as the required materials and components are provided, the MRO order is physically introduced into the production workflow [19].

This design of the MRO order process makes it possible to plan throughput times and completion dates for MRO orders more reliably. The throughput times for executing the condition assessment as well as for quality assurance testing are almost constant for each specific analysis and thus almost easy to determinate. The throughput times for the work shop based process phases, such as disassembly, MRO measures and assembly, can be reliably planned based on the condition assessment report. Hence, disruptions to ongoing production orders can be reduced.

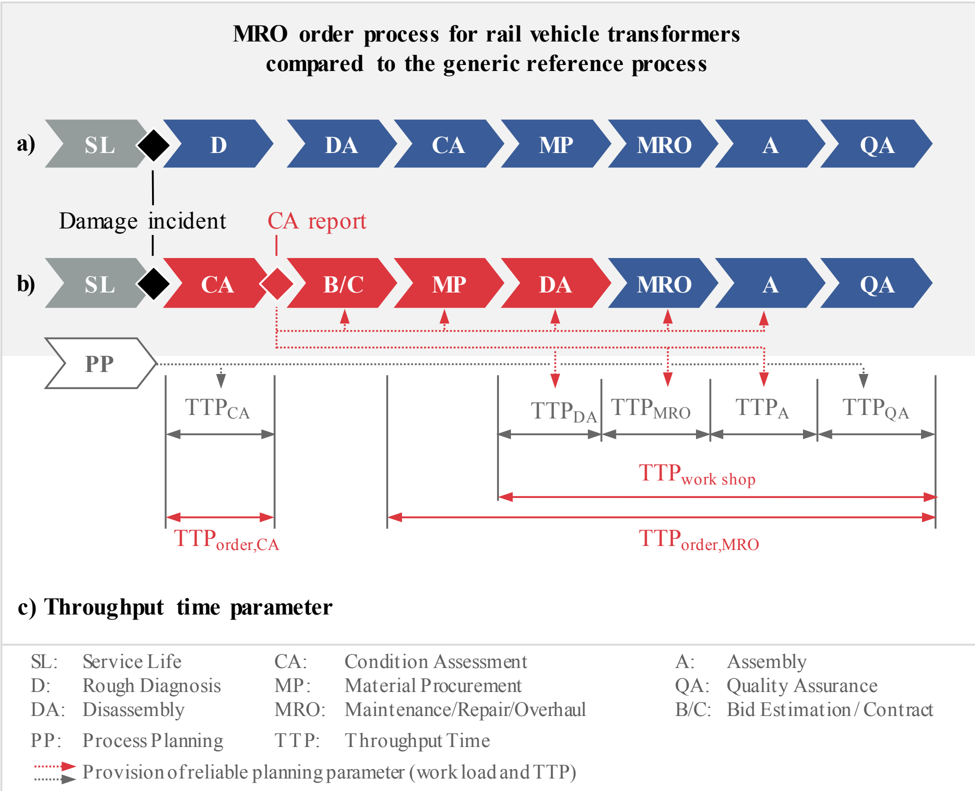

Fig. 2. Generic MRO reference process based on Eickemeyer and Nyhuis 2010 (a) in comparison with MRO order process for rail vehicle transformers based on Seitz et al. 2018 (b) with related information flow and throughput time parameter (c)

Furthermore, the potential of data mining methods to derive load forecasts was examined to provide additional support for medium- and long-term planning of MRO order processing [19]. The basis for this is an MRO order database, which contains information on already completed MRO orders [18]. Due to their significant advantages, such as high transparency and adaptability [22] as well as an expected good forecasting quality even with a low or incomplete data basis [23–25], Bayesian Networks were selected as a suitable data mining approach for the generation of load forecasts when regenerating rail vehicle transformers [18].

In recent research activities, this forecasting approach has been applied and reflected within a case study. Recently completed repair orders that are not included in the database were used to evaluate the forecast quality. Medium-term available information about the transformer project, e.g. service life duration or operating area, were used to generate the forecast with the Bayesian Network.

Despite anonymization, the results depicted in Figure 3 show wide forecast ranges. Therefore the generated forecasts are only of limited usefulness for supporting the planning processes. So the forecasting quality does not meet the expectations of high accuracy. It can be assumed, that this is caused by the fact that the database is not extensive and particularly not sufficiently representative due to the characteristics of small series production in the field of plant engineering as well as the high robustness and long service life of the transformers. Based on the results, it may be assumed that for forecasts based on a limited database, high requirements have to be considered regarding the representativeness of the data to be evaluated. In comparison, more satisfactory results even for medium-term planning can be achieved by early technological diagnostics, see Figure 3. Henceforth, long-term planning will be supported by the charting of aggregated annual KPIs, such as annual number of repairs or annual repair hours per workshop area.

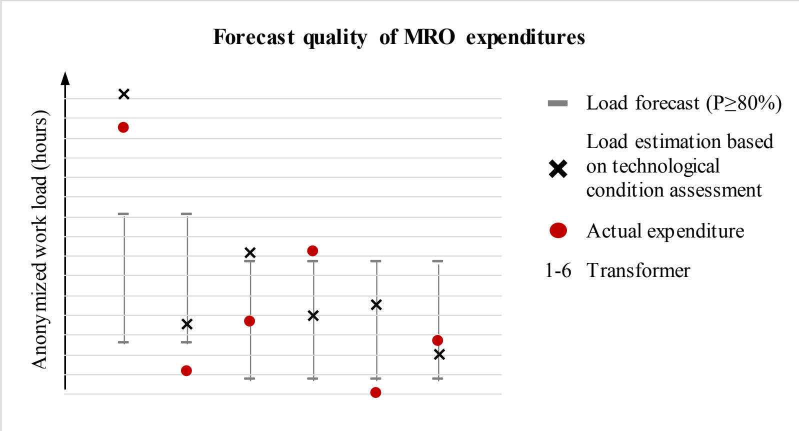

Fig. 3 Anonymized case study results for evaluating the forecast quality of MRO expenditures

3.2 Improving MRO order processing using the example of aircraft engines

The maintenance, repair and overhaul of aircraft engines differs in two key aspects from the above example of rail vehicle transformers. Firstly, aircraft engine MRO orders usually do not compete with production for available capacity. In the MTU Maintenance network, all civil aircraft engines are inducted into shops, which are exclusively responsible for MRO. Secondly, some engine parts restrict shop visit planning to certain intervals. These so called life limited parts (LLPs) are rotor and major static structural parts whose primary failure is likely to result in a hazardous engine effect. In order to ensure safety at all times, the manufacturer imposes strict life limits on these parts, usually based on operating cycles. A typical overhaul interval, after which these parts are replaced, is 20,000 cycles (a cycle consists of take-off, cruise operation and landing). Actual applied load is not taken into account.

On the other hand, operational limits are imposed on aircraft engines. One such requirement is that the engine has to be able to deliver maximum takeoff thrust at all times, regardless of outside air temperature and airport altitude, without exceeding engine operating limits. These limits are imposed to keep structural and thermal loads within an acceptable range and limit rotor speeds and temperatures inside the engine. The highest thermal loads occur inside the combustor and the high pressure turbine. Because temperatures in these areas are too high to be measured directly, the temperature of the exhaust gases is measured instead. Therefore, the thermal operating limit is stated in terms of the exhaust gas temperature (EGT) at fixed operating conditions. The difference between measured EGT (scaled to these fixed operating conditions) and EGT limit is called the EGT margin and is a major parameter for monitoring the performance of an aircraft engine. The EGT margin should always be positive. In case of a negative EGT margin, maximum available takeoff thrust would have to be reduced accordingly, so that EGT limits are not exceeded. This in turn restricts maximum allowable takeoff weight and operating condition, so that certain missions may not be executed anymore. In addition to these operating limits, the operator may also put additional restrictions on engine operation. Since fuel consumption constitutes a large part of an operator's expenses, they may require engines not to exceed a certain specific fuel consumption (SFC, fuel consumption divided by thrust). [26]

Engine deterioration can be observed without inspection through a decreasing EGT margin and increasing SFC. Deterioration itself depends heavily on engine operating conditions. These include outside air temperature, actual required takeoff thrust, air pollution, particle concentration (dust and sand) and more [27]. In many cases, an aircraft engine reaches its performance limits long before the limiting cycles of an LLP. Therefore, shop visits alternate between limited performance restoration work scopes, in which some engine parts are repaired, and complete shop visits with overhaul work scopes, including replacement of LLPs. In addition, some small maintenance tasks may be performed on-wing in order to extend engine life and fix minor issues during so called line maintenance. [2] Finally, even if all available data is taken into account, there will always be incidents that are impossible to predict. Unscheduled engine removals may be caused by foreign object damage, bird strikes or other outside influences and have to be accounted for in some way. All of this makes shop visit planning and material provisioning a very complex task. As of today, planning an overall shop visit strategy for a specific customer still heavily relies on experience and expert knowledge. Good knowledge of the customer's operation enables not only reliable planning of shop capacity but also informs pricing strategies. Data taken into account for this includes remaining LLP life, region of operation, cycle/hour ratio (does the customer operate on long or short routes), type of contract etc. The combined prognosis of engine shop visits for all customers including possible unscheduled engine makes up the required shop capacity. The MRO order process for the regeneration of aircraft engines essentially corresponds to the generic process model (see figure 4). While planning overall shop capacity requirements based on these predictions is relatively reliable, the actual workload at a specific work station in time can still vary significantly. Therefore, efforts are being made to improve planning on engine level.

Many maintenance contracts follow the "power by the hour" model, meaning the operator pays for flight hours completed by an aircraft engine. This contract model tries to make long on-wing times beneficial for both the operator and the maintenance provider: While the operator strives for undisturbed continued operation, the shop tries to reduce the number of shop visits, in order to reduce shop visit costs. Care has to be taken though that continued operation of an already heavily worn engine may cause severe additional damage, making a single shop visit increasingly expensive. [28] Thus, it is essential for the maintenance provider not only to reliably predict expected scrap rates (and through this, material requirements), but also to be able to monitor the performance of engines in operation.

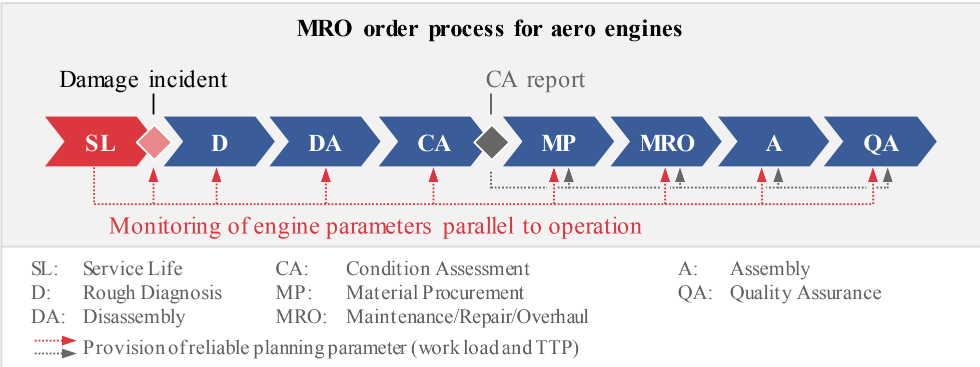

Fig. 4 Provision of service life data for planning purposes along the MRO order process for aero engines

Following the long term goal of usage-based lifing and moving from scheduled maintenance to a maintenance system based on actual demands, several steps are already being taken to improve shop visit planning and material provisioning covering parts of the aspects mentioned above. In the following, a tool already in use at the MTU Maintenance GmbH Hannover will be highlighted in some more detail. Furthermore, an outlook is provided into what can likely be achieved with available data now and in the following decade.

At MTU Maintenance, the Engine Trend Monitoring (ETM) software developed in-house is used to monitor customers' aircraft engines in operation [14]. The ETM system monitors and evaluates a variety of engine parameters at specific points during the flight cycle. Data is sent from the aircraft in-flight or post-flight. After this data is imported, it is first processed by a thermodynamic models for engine performance calculation. The model compares measured and calculated values for several engine parameters, such as EGT, fuel flow and several pressures and temperatures measured within the engine based on several input parameters (outside air temperature, altitude, Mach number and thrust setting). Afterwards, the data is annotated with significant information and alarms are generated based on trend changes and operating limits. The software offers a range of features, including diagnosis, forecasting and analysis features and is highly customizable.

With respect to shop visit planning and material provisioning, the ETM forecasting feature is of high significance. While many engines can be reliably operated until the next planned shop visit, some (especially older) engines may require frequent schedule adjustments due to performance decrease. A performance critical engine is removed from the wing due to monitored parameter crossing a limit, typically an EGT margin limit. Initial planning is still done for an expected number of operating cycles, but due to individual differences, actual on-wing duration may vary between engines. The financial impact of being able to order suitable LLPs in advance can amount to several hundred thousand euros. Furthermore, a reliable forecast helps stagger an operator's engine shop visits based on remaining life and thereby level shop load and ensure engine availability.

At the basis of each shop visit forecast is an EGT margin forecast. Combining fleet data with current cycles and average remaining EGT margin of an individual engine, the remaining expected life can be forecast by a simple trained algorithm. This initial estimate can be unstable, because several long and short term events can influence EGT margin calculation. These events range from seasonal influences (low temperatures in winter may lead to less exact EGT margin estimates at reference conditions) to damages occurring in-flight. In order to receive a more reliable forecast, estimates are averaged over several data points in a way that has been found to give good results. An example for a changing forecast over the course of two years is shown in figure 5. This relatively simple approach, that does not take into account individual engine load and operating conditions, already predicts cycles at the time of removal with an error of less than 5% at the time of shop visit scheduling, which in most cases has proven to be enough to avoid later rescheduling of engine shop visits.

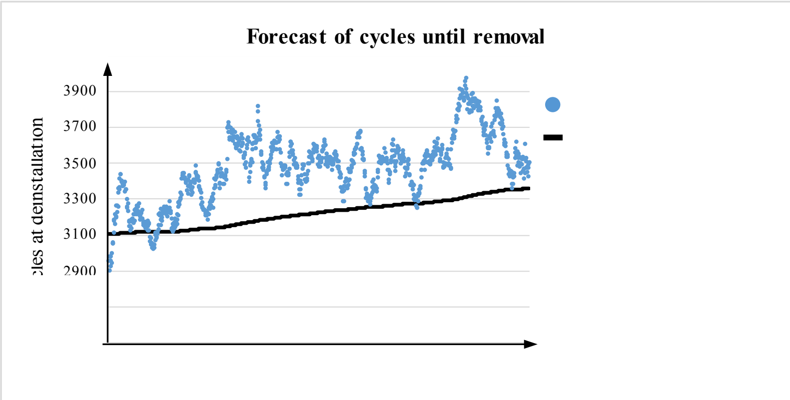

Fig. 5 Change in removal cycle forecast for an aircraft engine over the course of 1000 cycles (two years)

This example shows, that while data based estimates are already quite reliable, under- or overperforming engines require frequent adjustments. In order to make usage based lifing possible, much more data has to be taken into account. Solutions for this are already under development not only at MTU [29], but may require some time to reach productive use. Future applications will make use of full-flight engine operational data, environmental data and positional data and combine those with shop data, in order to further improve shop visit planning, engine reliability and fleet management. Because data points are usually sparse (especially for incidents), even with thousands of engines in operation, the development of algorithms that provide value to the industry and pave the way towards usage based lifing poses a challenges that will likely require industry wide means of data sharing and cooperation.

4. Conclusion

Reliable forecasts of capacity loads and material demands are key success factors to an economical MRO business since absence or errors in forecasting directly influence the logistics efficiency of MRO order processing [5,30].

In order to achieve high logistics efficiency recent research activities focus on the improvement of MRO order processing by means of technological diagnostics or the application of data mining approaches. In this paper, two examples of application for MRO order processing were described. The results presented show that wherever an implementation is possible, technological diagnosis based on known cause and effect relations should be preferred to improve capacity, throughput time and material planning. If early technological diagnostics cannot be executed for the specific complex capital good, correlation-based evaluation methods, such as data mining approaches, may be used to generate forecasts for supporting process and material planning. Therefore data from prior regeneration orders as well as data collected during a components service life can be evaluated. In this context, the selection of data to be processed as well as securing its representativeness and sufficiency of amount are critical factors when developing data-based forecast approaches. Future research activities will focus on the evaluation of data from the entire product life cycle, following the hypothesis that the quality of predicting MRO event dates and expenditures can thus be further improved.

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