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Procedia CIRP 23 (2014) 252 – 257

www.elsevier.com/locate/procedia

Conference on Assembly Technologies and Systems

Reliable capacity planning despite uncertain disassembly, regeneration and reassembly workloads by using statistical and mathematical approaches – Validation in subsidiaries of a global MRO company with operations in Asia, Europe and North America

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Abstract

The MRO industry faces substantial challenges with regard to the capacity planning of disassembly and reassembly work. This is due to the unknown workloads when regenerating complex investment goods and is caused, in particular, by the uncertain degree of disassembly and the complex challenges of reassembly. Forecasting techniques based on Bayesian networks are developed along with mathematical models which optimize capacity utilization, job order and the resulting costs. The approaches are tested and validated in conjunction with an MRO company with global operations. The results show possibilities for enhancing the planning processes and are found to be transferable on an international scale regardless of sociocultural and process differences.

Selection and peer-review under responsibility of the International Scientific Committee of 5th CATS 2014 in the person of the Conference Chair Prof. Dr. Matthias Putz matthias.putz@iwu.fraunhofer.de

Keywords: Bayesian networks, capacity planning, complex capital goods, damage library, data mining, disassembly, forecast, maintenance, mixed-integer linear programming, MRO, reassembly, regeneration

1. Introduction

The maintenance, repair and overhaul (MRO) of complex capital goods is afflicted with challenges with regard to several processes [1]. Complex capital goods include diesel locomotives, aircraft engines, industrial gas turbines and wind turbines. The employees working in this field are highly qualified and specially accredited. Therefore, the supply of new employees is limited [2]. At the same time, the wages for such labour are high. Consequently, the capacities have to be planned as accurately as possible. This is one key challenge for MRO companies because the planning of regeneration processes is much more complex than for customary production processes due to high diversity of parts and damage. The process cannot be standardized as easily because every new regeneration job is unique in its damage set [3]. Thus, the workload of upcoming jobs is unknown beforehand, which makes them even harder to plan [4]. The capacity planning in the field of MRO has hardly been studied

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doi:10.1016/j.procir.2014.10.097

scientifically. Currently no practical relevant, rule-based and thus transparent method or software application that is suitable for planning or controlling the regeneration of complex capital goods exists [5,6,7].

In this paper, aircraft engines are chosen as an example of complex capital goods. Aircraft engines consist of a vast number of components with special geometries and materials, which makes the regeneration process itself very complex [4]. Fig. 1 shows an aircraft high bypass turbofan engine. Special tooling and machines are needed to disassemble, repair and reassemble an engine. Aviation legislation calls for the company and its employees to have particular qualifications and accreditations in order to work on an aircraft engine [4].

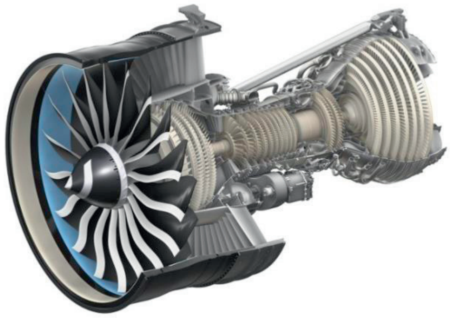

Fig. 1. Schematic high bypass turbofan engine [8]

The regeneration process for an aircraft engine begins after its removal from the wing. The engine is transported to a designated facility, where an incoming inspection is carried out to determine the damage to the engine and the work to be carried out. After disassembling the engine, all disassembled parts are inspected again to define the exact damage and the processing of the parts. A decision has to be made as to whether a part is serviceable, repairable or has to be purchased anew. The reassembly of the stored, repaired and purchased parts takes place as soon as the necessary parts are available. The regeneration ends when a test run of the reassembled engine is successful [9]. The regeneration process takes 20–70 days and is shown in Fig. 2.

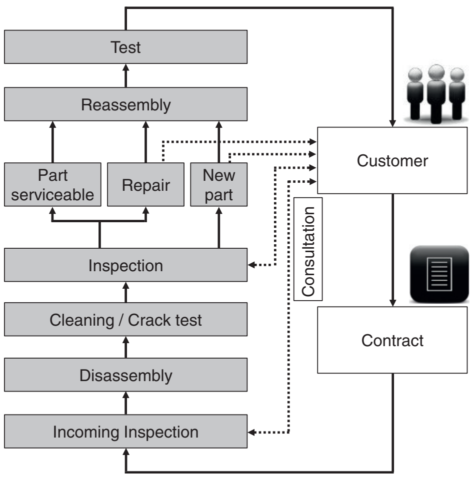

Fig. 2. Regeneration of an aircraft engine [9]

According to Herde (2013), the condition of an engine sent for regeneration is determined by four categories of influences: environment, usage, maintenance and directly triggering incidents. Environmental factors, e.g. the contents of dust or sulphate in the air, differ regionally. These factors can cause specific damage, e.g. burning or erosion. Therefore, the region in which an aircraft is operated has a great influence on the damage to its engines [4]. Whether an engine is used mostly on short- or long-haul flights is seen as a usage factor. Stresses on an engine are highest during starts and landings. Thus, operations over short distances cause more wear and potential damage [4]. Although all regeneration work has to be performed by accredited service providers, the exact regeneration processes can differ. For example, the cleaning method or the policy on life limited parts can have a substantial influence on the engine [4]. A bird strike is one example of a directly triggering incident; others are the sale of the engine or the necessary exchange of life limited parts. All of these are related to specific damage or work that has to be executed during the regeneration [4].

Although the influencing factors are known, the exact damage to an aircraft engine and the necessary disassembly level are to a large extent unknown beforehand [9]. The uncertain condition of an engine before its disassembly is a major challenge for MRO service providers because most of the planning processes proceed while the engine is still in use. The decision as to whether employees have to be specifically qualified or whether new personnel must be hired has to be made far in advance [10]. The workload for the disassembly department, for example, is highly dependent on the level of disassembly required for an engine. At the same time, environmental factors can have a big influence, too. Heavy erosion on bolts and screws causes more work during disassembly because the standard tools cannot be used. Instead, the employees have to improvise or even build special tools [1]. The information available is imprecise and therefore it is not easy to predict the correct workload for an engine [2].

Nevertheless, customers expect short lead times and good quality at low costs [9]. A delay causes a severe loss of revenue for the owner of the engine. This is why a high service level is a key goal for MRO companies [11]. Additionally, customers can cause delays themselves when unexpected damage is found which needs clarification before the disassembly process can continue. This can only be prevented if as little damage as possible comes under the heading of “unexpected”. The regeneration of aircraft engines has to be profitable. With this in mind, it is the goal of an MRO service provider to meet customer demands with as little capacity as possible. All these reasons mean that a good estimate of the condition of an engine and the workload needed to regenerate it is essential for MRO service providers [12]. The lack of accuracy in information during the regeneration process is illustrated in Fig. 3 together with the potential for additional database usage. A database containing data about former regenerations of similar capital goods can be accessed using data mining techniques in order to increase the information content. Bayesian networks represent one way of using the existing fuzzy information to estimate the potential workload of complex capital goods [2].

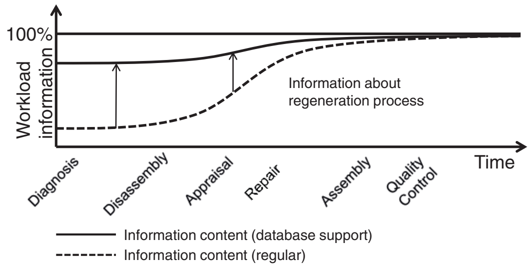

Fig. 3. Accuracy of information during regeneration process [10]

The unknown workloads of the different engines in combination with strict deadlines from the customer and the need for efficient capacity usage represent the main challenges for capacity planning in an MRO company. Additionally, most of the work has to be performed directly when a job comes up and therefore cannot be stored as in a production company [1,5]. Capacities have to be utilized according to the existing workload. As the capacities consist mainly of highly qualified, accredited personnel [4], it takes time to augment the workforce because the number of available employees is limited [2]. Capacities can be adjusted by moving personnel from one department with too much capacity to another with a temporary lack of capacity. If employees have a wide range of qualifications and skills, it is possible, for example, to move them from the reassembly department to the disassembly department. The other way around is not as easy because of the higher qualifications needed for reassembly. At the same time, it is nearly impossible to move employees from disassembly or reassembly to repair work because of the totally different skill set necessary. Mathematical models are needed to determine how and when to adjust capacities in the most efficient way [13].

Another factor that influences the capacity planning of an MRO service provider is the sociocultural environment of the company. The regional labour market determines how easy the workforce can be enlarged and the labour legislation determines the flexibility. Furthermore, the acceptance of planning strategies and tools is dependent on the sociocultural background [14]. These influences have to be taken into account during the development of a methodology that provides reliable capacity planning.

2. Methodology for capacity planning

As explained above, estimating the regeneration workload is a key aspect in the planning and control of capacities [3]. Due to the influencing factors, described by Herde, the damage to an engine and the resulting workload should be predictable to a certain extent. The available information about an engine has to be used in the best possible way and merged into an estimate of the total workload. Bayesian networks have proved to be suitable for this kind of problem. It has been shown that for this approach Bayesian networks are superior to artificial neuronal networks, Fuzzy logic and other potential techniques in the field of data fusion [2]. Bayesian networks use the statistics of conditional probabilities to calculate an estimated value, which is dependent on input parameters. The input parameters used in the Bayesian networks are based on the influencing factors and include the operational region as well as information about the use of the engine. The database for the development of the networks is a damage library that consists of historic data of engines regenerated previously. The Bayesian networks are used to estimate the regeneration workload and the severity of the damage. A validation of the method was carried out with an industrial partner and showed very promising results for both networks [2].

Operations research methods, e.g. linear programming, can be used to plan the capacities in the best possible way. The capacity planning problem of an MRO company can be modelled as a system of equations with parameters, constraints and decision variables. The abstract structure of one of the mathematical models with its input and output parameters is presented in Fig. 4.

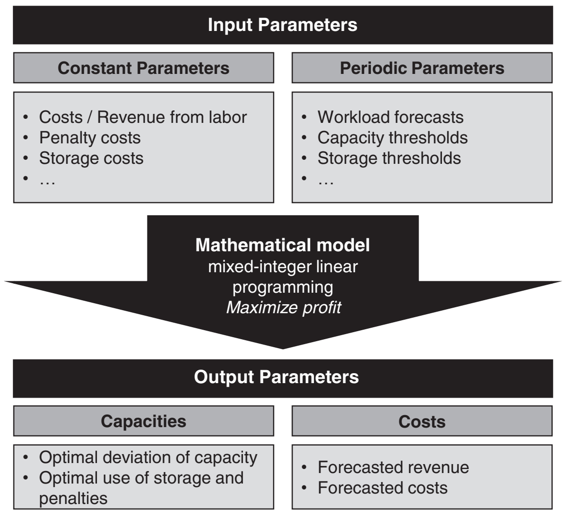

Fig. 4. Abstract structure of a mathematical model for capacity planning

Capacity planning is executed with different time horizons, usually distinguishing between long-, medium- and short-term plans. Thus, three different models are necessary to describe the entire planning problem [13]. The models also differ in the section of the company to which the plans apply. The long-term model plans the whole facility, the medium-term model individual cost centres and the short-term model particular workstations [13]. The different models and their properties are presented in Table 1. Instead of a direct integration the models are indirectly linked. Decisions based on the results of the long-term planning model, such as ordering new machines, influence the amount of capacity available for cost centres of the medium-term planning and consequently the number of workstations which have to be optimal assigned by the short-term model. A rigid connection of the three models would be impractical because of the continuous changes in the regeneration environment due to the market situation or employee fluctuation.

Again, the models were verified and validated together with an industrial partner. The models were fed with real world data and the output was compared with the reality. The long- and medium-term models both calculate the optimal disposition of the capacities in order to maximize the profit while taking the restraints into account. The short-term model optimizes the assignment of jobs to individual workstations. The validations of all the models show good results and the potential added value for the industrial partner [13].

After achieving good results with both methods, a combined approach is carried out. The workload estimates of the Bayesian network are used as input parameters for the mathematical model, which then calculates the optimal capacity utilization. In this way, the two methods, which are found to be beneficial separately, can multiply their potential to create a reliable capacity planning approach [6].

With respect to the international organization of the industrial partner with subsidiaries on different continents, a North American subsidiary was chosen to carry out the combined approach. The Bayesian networks and mathematical models were adapted to take into account the fact that the processes and sociocultural aspects differ from those relevant to the facility in Europe.

Table 1. General properties of the mathematical models [15]

	Long-term model	Medium-term model	Short-term model
Decision variables	Domain: binary, integer and non-negative real number range → MILP		Domain: binary and integer number range → ILP
Workload	Regeneration tasks forecast derived by Bayesian networks		
A unit	Entire complex investment goods unit	Assembly of complex investment goods unit	Individual part of a complex investment goods unit
Planning period	1 year	12 weeks	1 week
Time steps	1 month	1 week	1 day
Planning domain	Whole company	Individual cost centre	Single workstation
Capacity adjustment	Recruitment or dismissal of employees	Movement of employees between cost centres	Increase or decrease in overtime
Workload adjustment	Outsourcing jobs or accepting external jobs	Outsourcing jobs or accepting external jobs	Outsourcing jobs or accepting external jobs
Time compensation	Preponing or postponing jobs	Preponing or postponing jobs	Preponing or postponing jobs

3. Results

The North American plant considered has a strong focus on the disassembly and reassembly processes of the regeneration process; most of the repair work is outsourced. So the capacity planning also focuses on the disassembly and reassembly of aircraft engines. Nonetheless, the repair of parts has an influence on the scheduling and planning process because the lead times of the repaired parts determine when the reassembly process can start. A delivery delay of a single part can cause a delay for the whole engine. The focus on disassembly and reassembly entails some other challenges as well. It is, for example, nearly impossible to give parts of an assembly job to an outside company in order to balance capacities. So basically the entire backlog has to be processed within the strict deadlines. Otherwise, financial penalties ensue and customer satisfaction suffers.

Bayesian networks are developed with the Netica software by Norsys and are based on historic engine data. The Bayesian networks estimate the in-house workload to regenerate a specific aircraft engine. Estimation work is carried out with two different time horizons with respect to the planning horizons. The Bayesian network for long-term planning works with information that is basically known as soon as a regeneration contract is signed. So the workload can be estimated long before the engine to be regenerated arrives at the facility. The network for the medium-term planning works with information that is available directly prior to the regeneration process. So a workload estimate and accurate capacity planning is possible before the incoming inspection of the engine. The input parameters of both networks are based on the influencing factors described by Herde. A schematic Bayesian network is shown in Fig. 5.

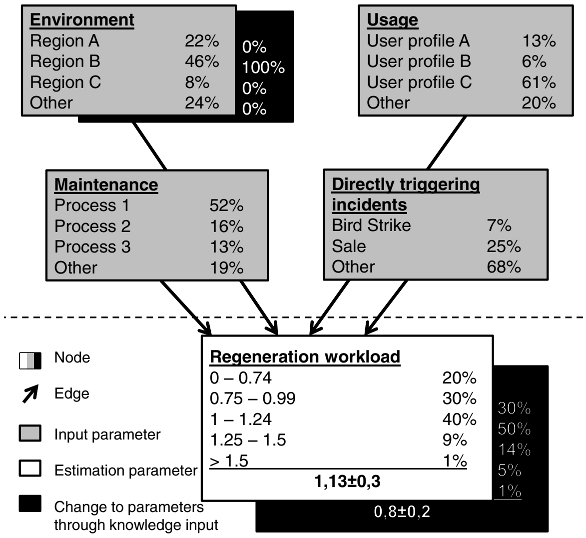

Fig. 5. Schematic Bayesian network [6]

The Bayesian networks are validated separately before their estimates are used as input parameters in order to make sure that the transfer to the new sociocultural environment has been successful. For the validation, the workloads of engines that are not used to feed the calculations of the Bayesian networks are estimated and compared with the real workloads of the engines. With regard to former validations, the percentage deviation between estimated and real workloads are categorized [2]:

- 0–9.9 % very high quality estimate
- 10–25 % satisfactory quality estimate
- > 25 % unsatisfactory quality estimate

Table 2 lists the results of the validation of the two networks developed as well as the validation results that were achieved in the European plant [6]. The estimates are not only compared with the real workload but also with the existing planning data at the facilities to see if they can be beneficial to the company.

Table 2. Validation of Bayesian networks for workload estimation; BN Bayesian network, IP = industrial partner

Estimate	0–9.9 %	10–25 %	> 25 %
BN Long-term North America	52.0 %	18.0 %	30.0 %
BN Medium-term North America	52.0 %	20.0 %	28.0 %
IP Long- / medium-term North America	8.0 %	50.0 %	42.0 %
BN Long-term Europe	27.0 %	38.1 %	34.9 %
IP Long-term Europe	26.4 %	25.0 %	48.6 %
BN Medium-term Europe	33.8 %	29.2 %	37.0 %
IP Medium-term Europe	26.7 %	45.0 %	28.3 %

The results are regarded as positive and comparable with the validations in the European facility. The estimates of the Bayesian networks are better than the existing planning data. Therefore, the estimates of the networks can be used as input parameters for the mathematical model.

In addition to the estimated workload of the Bayesian networks, several other parameters are used in the mathematical model, which are gathered differently, e.g. data regarding costs, capacity forecasts and revenue. The aim of the mathematical model is to calculate the best way of utilizing the existing capacities in order to cover the workload and maximize the profit at the same time. The model considers the fact that the increase as well as the decrease in capacity is limited by factors such as employees available on the job market and labour legislation. Potential penalties for missed deadlines due to insufficient capacity and storage costs for engines that are finished too early owing to overcapacities are considered as well. The model presented here plans the monthly utilization of the capacities over a period of one year and uses the workload estimates of the long-term network.

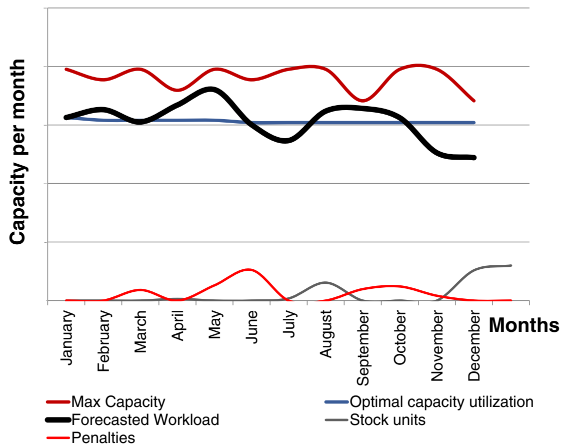

Fig. 6. Results of mathematical model for long-term capacity planning

The calculations are carried out with the solver of IBM ILOG CPLEX Add-in for MS Excel. Fig. 6 shows the results of the model in graphical form, with the proposed monthly utilization of capacities in combination with resulting penalties and stock units.

The model is also validated with real world data from the industrial partner. The proposed capacity utilization of the model is compared with the work that was executed in the planned time period. The planning data from the industrial partner is also compared with the work actually executed. The best result of every planned month is marked in bold type in the following list of validation results (Table 3).

Table 3. Validation of mathematical model for long-term capacity planning

Percentage deviation of planning data from **industrial partner (North America)**	Percentage deviation of **mathematical model (North America)**	Month	Percentage deviation of planning data from **industrial partner (Europe)**	Percentage deviation of **mathematical model (Europe)**
19 %	**8 %**	January	**6%**	9%
19 %	**11 %**	February	6%	**4%**
1 %	12 %	March	22%	**17%**
1 %	3 %	April	7%	**3%**
14 %	**2 %**	May	**10%**	17%
19 %	**9 %**	June	0%	0%
14 %	**0 %**	July	4%	4%
7 %	**6 %**	August	11%	11%
11 %	**10 %**	September	3%	**2%**
6 %	17 %	October	11%	**4%**
5 %	17 %	November	**2%**	7%
6 %	**5 %**	December	5%	**1%**
10 %	**8 %**	Total	7%	**6%**

As can be seen, the results are very promising and exhibit a similar quality to the validation results of the long-term planning model developed for the European plant [13]. The mathematical model exhibits a better quality than the existing planning data. High deviations in March, October and November are the result of rigid information used to feed the Bayesian networks which didn't include orders accepted on short notice. It could be demonstrated that it is possible to estimate the workload for the regeneration of an aircraft engine and use this estimate to plan the utilization of capacities in the most profitable way. This has not been demonstrated before and is a milestone for capacity planning with uncertain workload information [7].

4. Conclusion and outlook

This paper has presented capacity planning and coordination models for the regeneration of complex investment goods. In a first step, this article deals with Bayesian networks as an approach to forecasting regeneration workloads for complex capital goods by means of data fusion. Based on the forecasts, algorithms are used in a second step to determine the capacities required based on the regeneration workload forecast. The results of the validation at two sites of a global industrial partner are presented as well.

As could be shown, it is possible to build a reliable capacity planning methodology for the special challenges in the business of regenerating complex capital goods such as aircraft engines. The approach presented here enables job workloads to be estimated when very little information is available. This data is used to optimize the complex problem of capacity utilization. A validation of the combined methodology was carried out. Not only did this show this to be a suitable approach, it also revealed optimization potential for the company in the range of 5–7 %. This is possible regardless of the fact that the idea of the methodology was transferred from a European sociocultural background to a North American one with just a few adjustments. This is perhaps only possible because of the similarity of the two cultures considered. In order to demonstrate the general possibilities of this approach, it is currently being transferred to a third subsidiary of the industrial partner in Asia, which also has a strong focus on disassembly and reassembly. The methodology will be adjusted for this application and also validated afterwards so that it is possible to compare the results with the existing validations for Europe and North America.

Furthermore, the approach presented shows several areas that can be optimized in order to enhance the logistical performance and even shorten the throughput time of the existing regeneration process. The method of forecasting damage also has the potential to be useful for forecasting other parameters in regeneration, e.g. costs or consumption of resources, or to be used in other areas of industry, e.g. for strategic planning processes. The presented research is part of the CRC 871 program which has the goal to improve the regeneration of complex capital goods in general. Therefore the transferability of the approach to other applications and industries was a key aspect in the development. The transfer from one plant to another has already proven its flexibility. A transfer to the regeneration of diesel locomotives has been already applied for. For the transfer a funding period of about two years is calculated.

Future research questions concern the incorporation of capacity demand uncertainties using a scenario approach. Extending the timeframe of the long-term planning horizon to more than one year, considering the net present value (NPV) of investments, e.g. in new machines, and cash flows for sales of machines, for instance, have to be taken into account.

Acknowledgements

The authors would like to thank the German Research Foundation (DFG) for providing funding for this research project within the scope of the CRC 871 program. The authors would also like to thank the Graduate Academy of Leibniz University Hannover for providing funding for the validation of the theoretical results in the global industry.

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