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AIRCRAFT ENGINE OVERHAUL DEMAND FORECASTING USING ANN

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Abstract
Due to the unpredictable nature for aircraft maintenance repair parts demand, MRO (Maintenance, Repair, Overhaul) business perceive difficulties in forecasting and are currently looking for a superior forecasting solution. This paper deals with techniques applicable to predicting spare part demand replacement during helicopter PZL 10W engine overhaul – operating according to hard – time. The experimental results show new forecasting method based on hard – time as the predicted time of required demand and ANN technique as forecasting models predicted numbers of spare parts. The evolution for a new forecasting method, which will be a predictive error-forecasting model which compares and evaluates forecasting methods, based on their factor levels when faced with intermittent demand show as possibility of big changes in MRO lean manufacturing. The results confirm the continued superiority of the new method, whereas, most commonly leveraged methods such as moving average used by MRO business are found to be questionable, and consistently producing poor forecasting performance.

Keywords
Artificial Neural Network, Maintenance, Repair, Overhaul, Spare Parts Forecasting.

Introduction

Prices of aircraft engine parts, repair, and storage costs are so high that it is impossible to guarantee that the stock will cover the whole specification during overhaul, which may be reported to the demand. In addition, purchasing too many overtime spare parts is causing loss to the freezing of capital and the probability of loss due to changes in the functional properties during storage. This makes the provision of accurate demand forecast exchanged during a replacement helicopter engine overhaul is for the production and procurement one of the most important information. Improving the forecast accuracy of demand for spare parts is directly related to the reduction in operating costs of helicopter, and this is due to additional costs incurred in overhaul business as result in the accumulation of excess inventory. Significant costs are also accrued in the case of shortage of spare parts resulting from underestimation of the forecast. These costs appear as resulting from the need to maintain a greater number of spare engines or short-term lease and the financial penalty for repair facilities. These costs are difficult to estimate, due to the individual provision of contracts between users and the repair facilities as well as an immeasurable loss resulting from leasing credibility condition. Therefore, one overarching goals in the process of production and purchasing planning is to avoid the problem of shortage of spare parts during the engine overhaul. This paper documents the new forecasting method for predicting spare part demand during aircraft engines overhaul.

Spare Parts Forecasting Methods

The issue of spare parts planning has been studied for many years, which has resulted in the development of numerous methods and techniques of forecasting [1]. Traditional statistical methods, such as exponential smoothing and regression analysis are used in forecasting demand for spare parts for a long time. These methods, however, are unreliable when intermittent demand [2], as is the case with requests for spare parts demand during aircraft overhaul engines. The first who proposed the new accurate methodology was Croston [3], called the CR method, which allows you to determine independently the time of demand and value of demand during the period. The CR method was studied by many researchers who have demonstrated the effectiveness, or proposed to introduce some modifications to it. The most important proposals for changes published Syntetos and Boylan, who pointed out error in the CR algorithm [4]. The result of this research was to develop a new forecasting method called the SBA [5]. Despite the many studies on methods of forecasting intermittent demand, still the results of the prediction return inaccurate numbers. This provides the rationale to search for more accurate methods of forecasting demand for spare parts required during the overhaul aircraft engines.

Aircraft Engines Overhaul Planning

According to the most popular trends, as the most rational maintain aircraft engines treated repairs and overhaul. Typical repairs are limited to the replacement of individual components or subassemblies which are technical conditions to prevent further engine exploitation. Aircraft engine overhauls are performed in specialized repair facilities and are strictly connected with operating systems. In the operation on aircraft engines the two most commonly used are condition and hard-time. The second one allows relatively easy planning of overhaul, especially when the aircraft are operated in accordance with the plan [6]. Figure 1 shows typical hard-time oper-

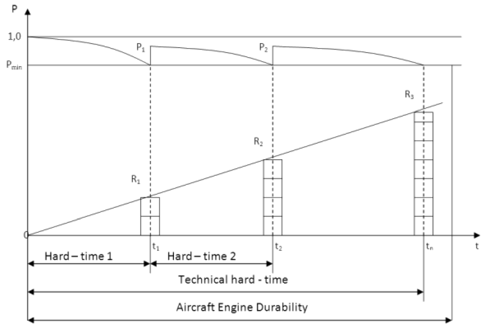


Fig. 1. Dependence of the probability(P) of work without failures and reliability (R) for hard – time operation of the aircraft engine.

ation of aircraft engines. The level of engine reliability, the probability of work without breakdown at a given time and under certain operating conditions is reduced to the minimum.

After this time, engines must to be overhauled, during which a lists of n parts, subassembly and aggregates are repaired or replaced. After a specified number of overhauls the level of reliability can reach the minimum value, which is the signal of problem with the safe exploitation [7]. At this moment in time, the engine should be withdrawn from operation, called technical hard-time.

Spare Parts forecasting by ANN

The demand for spare parts required during aircraft engine overhaul is lumpy demand. Most of the literature shows inefficiency of traditional methods of forecasting based on time series in prediction such phenomena. Traditional methods of inadequately reflect non-linear in the data, which do well artificial neural networks or single artificial neural. The techniques of artificial intelligence, in particular, artificial neural networks are the logical plane for further researches [8–10]. Replacement of individual parts, assemblies or aggregates during aircraft engine overhaul has usually a random character. It is also the phenomenon associated with the technical diagnostics, where the key information of diagnostic symptoms and external condition are recorded during exploitation. This data is used during the construction of diagnostic models. Such models are non-linear, and often have unknown relationships between the selected signal and damage, should be built using advanced tools. In the literature there is a lot of examples effective utilization, the MLP ANN in technical diagnostics [11]. It has been shown in paper [12] as result of researches impacts climatic condition on the turbine gas aircraft engine P&W F117 and the diagnosis of turbine blades aircraft engines, where the parameters in the ANN input layer uses vibration and vibro acoustic signals [13]. MLP ANN play from a mathematical point of view of the role of the stochastic approximation tools for functions of several variables by mapping a set of input variables in the set of output variables. Networks of this type consist of input, hidden and output layer. The task of neurons in the input layer is the pre-processing, which may include normalization or scaling of signals. The main process takes place in the hidden and output layers. Connections between layers are designed so that each element of the previous layer is connected to every part of the next layer. The learning process, which is supervised learning phase, starts with randomly chosen values of weights and as result of learning process weights are modified in order to reduce the value of network error [14].

Research Methodology

Studies on a new method of forecasting demand for spare parts required during aircraft engines overhaul operated by hard-time strategy was carried out on the example of the helicopter turbo-engine PZL 10W. The analysis was performed for selected parts, which makes planning the greatest current problem:

- Turbine Compressor Blades – first stage,
- Compressor Blades – first stage,
- Bearings (P/N 88.06.3276).

The engine consists of a large number of assemblies and components with complex structures. Since the condition of the engines changes are caused by each individual, and or group change condition of its components, and thus the total number of changes to the technical condition is practically infinite. For this reason, providing the possibility of evaluation of all the changes of the technical component condition is practically impossible. Because even the most advanced diagnostic systems are subject to natural limitations of collecting and processing of diagnostic information. Explanatory variables were deigned on the basis of available operational data, most of which are recorded in the logbook. This knowledge is often referred to as the aircraft engines operating characteristics. Operating characteristics can be divided into:

- Internal – used to assess the impact of the motor circuit parameters on the functional characteristics
- External – used to determine the impact of engines operating ranges and flight conditions on the functional parameters: rotation, speed, height, climatic conditions.

The construction of models began to systematize the data and the rejection of less important diagnostic parameters. As a result, variables were eliminated for which there was no cause and effect of potential relationship with engine components, as well as avoiding the problem of redundancy. For the models predicting the demand for compressor blades were assigned variables:

Parameters at helicopter start

VAR8 – NTS turbocharger rotation for a given ambient temperature,

VAR10 – Gas temperature rise.

Nominal input vector ANN predicting the demand for the compressor turbine blades has been built with the variables.

Parameters at helicopter start

VAR5 – t_4 gas temperature at the start [K],

VAR7 – starting time (entrance to a small gas).

For models predicting the demand for bearings assigned to variables

Operating parameters for the take-off power

VAR14 – oil pressure [kPa],

VAR15 – oil temperature [K],

VAR19 – TS overrun time [s].

Another group of explanatory variables was developed as a result of the classification of engines due to the current configuration, the method of operating and climatic conditions. These variables were coded classification engines suitable:

VAR20 – the number of overhaul,

VAR21 – series engine,

VAR22 – number of starts,

VAR23 – the number of cycles,

VAR24 – the area of operation, where the engines are classified according to groups:

- Seaside,
- Mountain,
- Lowland,
- Desert,
- Tropical.

VAR 25 operational use:

- Firefighting,
- Tourism services,
- Rescue and evacuation,
- Military and combat tasks.

VAR26 – performed tasks

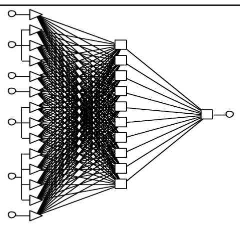
- Civilian,
- Military.

VAR27 – flights distance

- Short distance,
- Long distance.

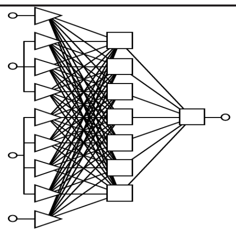
The data was recorded during six years, a collection of 125 regression variables obtain during the first five years was used in the construction of ANN models, and 25 pairs in the last year, called the period of testing, were used to evaluate the ex-post prediction. The study was conducted using the software Statistical Neural Network 4.0. Using the Intelligent Problem Solver was carried out the construction process and analysis of MLP type ANN models. Sensitivity Analysis tool tests were helped during rejection of the regression function of explanatory variables with the smallest significance. Tool “Case Error” tested noise introduced into the model by different patterns. Results were tested by metrics ex-ante S.D. Ratio and Correlation. Prepared forecasted demand models for spare compressor and turbine compressor blades and bearing (PN 88.06.3276) are presented in Tables 1–3.

Table 1
MLP type ANN forecasting demand for spare compressor blades first stage, architecture 7:14-9-1:1, explanatory variables (VAR8, VAR10, VAR20, VAR21, VAR25, VAR26).



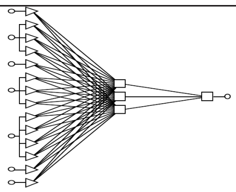
Collection	Training	Validation	Testing
Data S.D.	9.097167	9.06529	8.59304
Error Mean	1.287475	0.2564624	-0.2132
Error S.D.	2.947182	2.976607	3.30523
Abs E. Mean	2.488489	2.416415	2.37739
S.D. Ratio	0.323967	0.3283521	0.38464
Correlation	0.949652	0.9447384	0.92363

Table 2
MLP-type ANN forecasting demand for spare compressor turbine blades first stage, architecture (4:9-7-1:1), explanatory variables, (VAR20 ,VAR24, VAR25, VAR26).



Collection	Training	Validation	Testing
Data S.D.	24.6137	24.7985	23.08246
Error Mean	0.9867655	-1.871755	1.048275
Error S.D.	6.50682	7.727287	8.371041
Abs E. Mean	4.071347	4.87629	5.601794
S.D. Ratio	0.2643577	0.311603	0.3626581
Correlation	0.9647657	0.9516923	0.9327171

Table 3
MLP-type ANN forecasting demand for spare bearings PN 88.06.3276, architecture (5:9-4-1:1), explanatory variables (VAR15 , VAR20, VAR21, VAR24, VAR25, VAR26, VAR27).



Collection	Training	Validation	Testing
Data S.D.	3.415051	3.632884	3.106705
Error Mean	0.09799	0.1090312	0.09582
Error S.D.	1.190276	1.353605	1.151888
Abs E. Mean	0.8314106	0.977919	0.8110796
S.D. Ratio	0.3485383	0.372598	0.370775
Correlation	0.9447259	0.9301645	0.9395406

Findings

In assessing the quality of forecasts used in the ex post forest error, defining the difference between the empirical and estimated. The results of the forecasts quantity spare parts generated by ANN models compared with forecast prepared by moving average method - currently used to planning demand during overhaul engine PZL 10W. The time of demand was determined by hard-time operating system. Comparative results of the forecast errors for the ANN models and moving average methods are presented in Tables 4–6.

Table 4
Spare compressor blades first stage forecast errors.

	Moving average	ANN model
Mean Forecast Error	−5.58	0.00
Mean Relative Dev.	−0.46	0.08
Mean Absolute Dev.	8.27	3.44
RMS	9.65	4.35
REL RMS1	0.94	0.40
REL RMS2	1.25	0.57

Table 5
Spare compressor turbine blades first stage forecast errors.

	Moving average	ANN model
Mean Forecast Error	−4.11	−2.12
Mean Relative Dev.	−0.95	−0.12
Mean Absolute Dev.	19.07	6.92
RMS	21.21	11.21
REL RMS1	1.00	0.40
REL RMS2	1.01	0.53

Table 6
Spare bearing P/N 88.06.3276 forecast errors.

	Moving average	ANN model
Mean Forecast Error	−1.11	0.00
Mean Relative Dev.	−0.37	−0.03
Mean Absolute Dev.	2.21	0.88
RMS	3.23	1.17
REL RMS1	0.38	0.14
REL RMS2	1.06	0.38

Another measure which allows the ability to define a superiority forecasting method is the balance of predicted and real demand in the testing period. The balance, the level of short or excess spare parts, is shown in Figs. 2–7. A comparison of the forecasts generated during the testing period by the ANN model and moving average method, was accurate for compressor, and compressor turbine blades of the first stage and bearing P/N 88.06.3276 can be concluded that far better results returns the ANN models. This is proved by lower noise level during balance testing as well as smaller prediction the

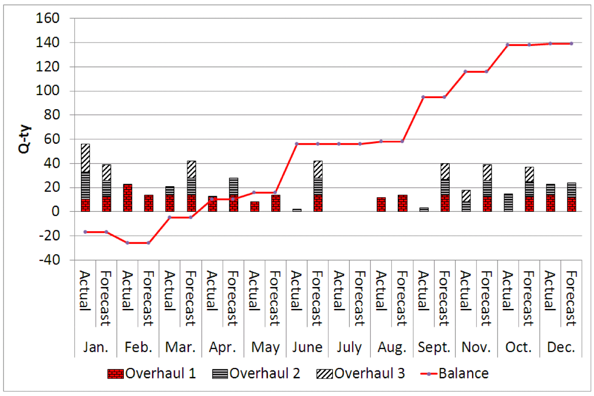


Fig. 2. Execution of forecast (moving average method) for spare compressor blades first stage.

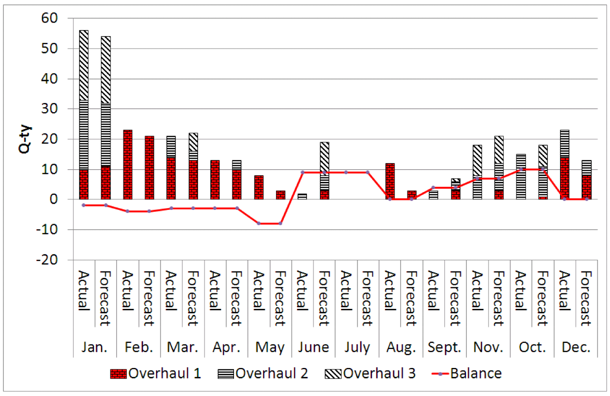


Fig. 3. Execution of forecast (ANN model) for spare compressor blades stage.

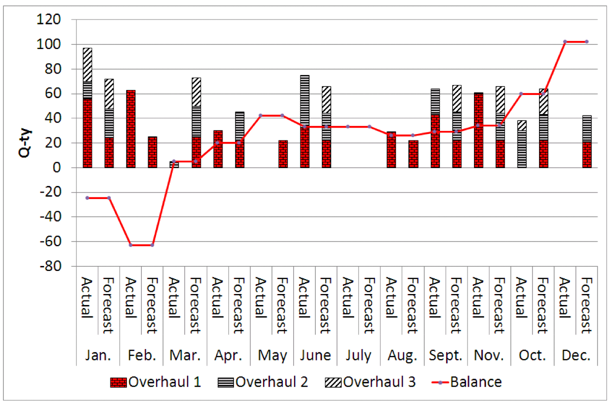


Fig. 4. Execution of forecast (moving average method) for spare compressor turbine blades first stage.

ex-post errors. Assessment of the forecasted demand during the testing period indicates a potential reduction in excess inventory as result of improving the predictability. The ex-post REL RMS errors show the possibility of increasing forecast accuracy and excess inventory reduction for spare compressor blades by 54%, compressor turbine blades by 60% and bearing 24%. Forecast model created using ANN is characterized by more stable balance line then created by moving average method. It indicates the possibility of building stable safety stokes to prevent underestimation shortage.

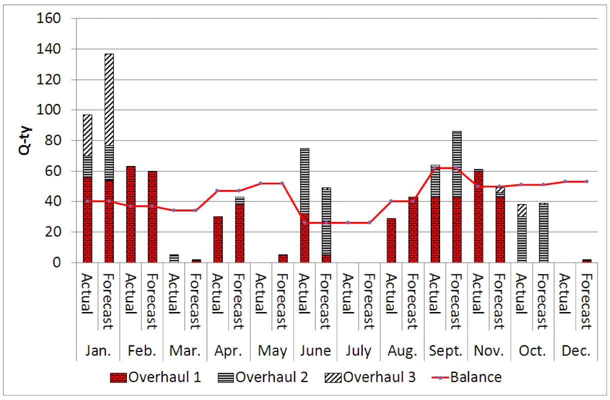


Fig. 5. Execution of forecast (ANN model) for spare compressor turbine blades first stage.

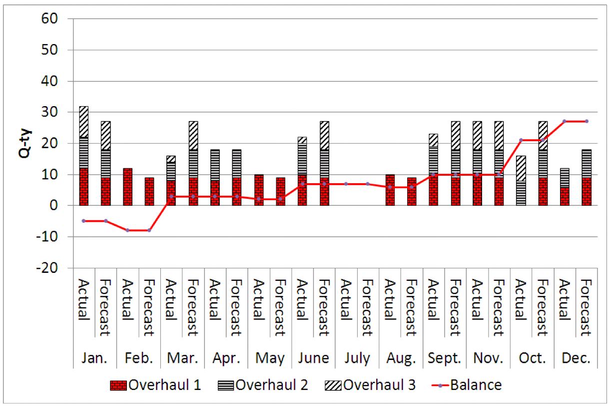


Fig. 6. Execution of forecast (moving average method) for spare bearing P/N 88.06.3276.

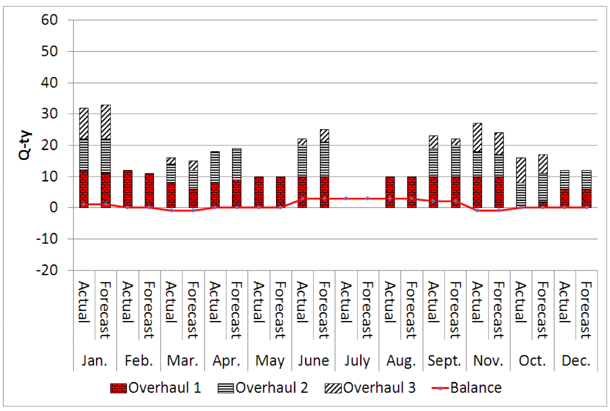


Fig. 7. Execution of forecast (ANN model) for spare bearing P/N 88.06.3276.

Conclusions

Traditional forecasting methods based on time series such as CR, SBA or exponential smoothing method which are implemented e.g. in SAP APO do not apply in forecasting demand for parts and components replaced during engine overhaul. The new forecasting method is composed of the engine's hard-time calculation and value of demand as ANN models prediction should be a power weapon in the implementation of lean manufacturing in MRO facilities. Research results indicate the desirability of building a comprehensive information system that solves the problem described in the article in which will be applied ANN forecasting demand for spare parts replaced during aircraft engine overhaul. This system would by complementary of the functionality Enterprise Resources Planning (ERP) systems as input to Manufacturing Resources Planning (MRP II) algorithm. A prototype of such a solution is developing in MRO facility in WSK "PZL-Rzeszów" S.A. and application compound-forecasts with interval as remaining hard-time and demand size as MA, instead of time series methods used so far, resulted increasing in inventory turnover in March 2011 plus 1.1 turn compare to January 2010.

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