THE APPLICATION OF ONTOLOGY IN FORECASTING THE DEMAND FOR SPARE PARTS

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Abstract. The intermittent demand for spare parts of an aircraft engine which results from their random wear and tear during operation makes it difficult to manage logistic supply chains in MRO company. The supply chains indicate the need to develop information technology to support resource planning in an enterprise. The response to that are studies on new methods of forecasting the demand for spare parts replaced in engine overhaul using artificial neural networks. The article presents the concept of using OWL AEDO ontology in selecting independent variables for regressive SSN models. Such a solution allows to implement a systemic approach to SSN construction, and in effect to use SSN in forecasting for a wider range of spare parts. Due to the high requirements of flight safety, aircrafts are equipped with numerous data acquisition systems, data analysis and comprehensive diagnostics of their components, and aircraft engines undergo particular scrutiny. The data is collected in specialist bases, which after processing with artificial intelligence methods may bring significant economic gains for the MRO business.

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1. INTRODUCTION

Managing a logistic supply chain in enterprises concerned with aircraft Maintenance, Repair and Overhaul (MRO) is a complex issue which requires particular support from modern information technologies. Most products appearing in the overhaul are at the last stage of the product life cycle – the decline. Also, often the production of new engines for a given series is halted. Frequently the repair services themselves are individual in nature, and the demand for spare parts is intermittent (irregular).

The process of repair and overhaul of aircraft engines has several characteristic stages. Those are activities related to forecasting the need to repair or overhaul the engine, logistic service connected with delivering the engine to specialised MRO company, disassembly and verification of parts and subassemblies of the product repaired. It is often only at the stage of verifying the parts and subassemblies that real information about the need to replace or renovate any parts of the engine is obtained. That results in disruptions in evaluating repair costs and disruptions in the whole logistic chain. Spare parts for aircraft engines are mostly very expensive, produced against individual order and characterised by a long production lead time of several months. Thus appears the risk of not having a spare part available during the overhaul or the risk of freezing the capital in excessive inventory.

2. BACKGROUNDS

Research conducted in 2006–2012 brought about the development of a new method of forecasting demand for spare parts (Kozik&Sęp, 2012). It is composed of a forecast interval of demand appearance and the quantity of the demand for particular spare parts. Implementing it in one of the MRO companies considerably improved enterprise resources planning. The Artificial Neural Network (ANN) models of Multilayer Perceptron (MLP) and network with Radial Basis Function (RBF) were used for forecasting the demand quantity for selected aircraft engine parts. Experiments were done on a demand forecast for compressor blades and compressor turbine blades. Regression models were built with ANN, and the external and internal performance operation characteristics registered during normal flight of an aircraft before it undergoes general overhaul were selected as independent variables.

There are many studies (Carter, 2005; Gosiewski et al., 2011) which indicate high usefulness of diagnostic symptoms in recognising the technical condition of particular parts of an aircraft engine in normal flight. An important information carrier is e.g. the turbine engine case. It has two roles: it shapes the engine's flow channel and constitutes a load-carrying unit transferring the loads resulting from the rotor's reaction to bearing supports and further to the aircraft's clamping joints. The case assembly is affected by forces resulting from the impact of the stream of gasses in the engine's main channel, in the form of pressure and temperature, inertial forces resulting from overload occurring while the aircraft manoeuvres and from the rotor's reaction in the form of longitudinal and transverse oscillations. The vulnerability of the cases' structure and their flanged connections has significant impact on critical speeds. Support rigidness and degree of utilization of the bearings influence frequency values and oscillations amplitude level. The longitudinal force is transferred on the outer structure through the compressor's front bearing. Its work has a large impact on the value of the clearances on turbine blades. In the inner structure and on the outer fastenings of turbine engine housing there are fuel, oil and air system pipes. Both on the pipes and directly on the blocks, pressure, temperature, oscillation level sensors or "magnetic caps" are mounted, which give information both to the diagnostic system that allows to assess the engine's wear, and to the failure warning system installed in the cockpit. Oscillation sensors are mounted on the housing near main rotor supports, in a place which provides convenient access during operation and measurement of rotor oscillations without the additional influence of the construction's spring and damping elements. Frequency and oscillation amplitude measurement allows to assess both the rotor's condition and the degree of utilization of the bearing nodes (an increase in oscillation amplitude level is caused by excessive clearance in the bearing). Experiments show that frequencies corresponding to the rotor's double speed indicate the utilization of bearings on which it is mounted. The system of internal flows carries compressed air of appropriate parameters, taken from various parts of the compressor case through channels and tubes outside the cases and within their structures, both in order to warm the construction elements in the compressor inlet, and to lower the temperature of cases in the hot section and enforce flows through rotor elements by ensuring the right pressure difference. Control of the process of warming and cooling particular sections of the cases is of particular importance when the engine accelerates and decelerates (Rowiński, 2011). Another source of information is analysis of oil samples. It is possible to take oil samples and conduct tribological analysis and to combine those results with measurement of block oscillations. Among others, endoscopic measurements of engine elements are done, as well as engine block oscillation measurements, engine parameter record analysis, or oil samples tribological analysis. Degradation of the tribological system of aircraft engines can be considered a random process. A linear relation between cumulative wear of the examined tribological system and the values of wear products concentration can be noted (Gosiewski et al., 2011). Based on oscillation measurements, the timing of a possible failure can be predicted. By conducting an analysis spectral composition of the oscillations as compared to rotational frequency and knowledge of the engine's kinematics one can define the element (unit) to be repaired or replaced, or as it happens in aviation, decide to temporarily stop using the given engine so as to avoid a disaster. The course of the start-up on the ground can be analysed by observing at least the signals of speed and exhaust temperature and the signals of switching the voltage of power for the dynastarter and the start-up fuel valve on and off (Balicki, 2011). Such knowledge is the key element in selecting independent variables for ANN models. It allows for preliminary verification of how useful a given performance characteristic is, and also facilitates the process of selecting redundant parameters. However, knowledge in operating and diagnosing an aircraft engine presented in the above given form is difficult to apply in a systemic solution. The process of selecting independent variables significantly limits and inhibits work on new forecasting models. That issue was noted as the weakness of Kozik&Sep's method (Rosienkiewicz, 2013). Yet the key argument for using it is a smaller forecast error as compared to other methods (Kozik, 2012). Facilitating the process of selecting independent variables for ANN to forecast the size of demand for spare parts thus became the challenge for further studies. An additional argument for continuing the method's development is interest in adapting it to other industry branches (Rosienkiewicz, 2013).

2.1. The proposed methodology

The use of the right procedure of selecting independent variables for the model allows to considerably reduce the number of the variables, and in effect reduce the model's complexity. An effective procedure allows to improve forecasting precision and also create a ranking of variables as concerns their impact on the dependent variable. In that way the researcher or decision maker obtains a simpler model with smaller forecasting errors, as well as additional information about which variables are the most important for the model.

The independent variables should be strongly correlated with the dependent variable. They should also have weak or no correlation with other independent variables. Technical methods of selecting the variables for the models are used in practice, e.g. the method of optimal predictors choice, or the graph analysis method (Westa, 2008). The Group Method of Data Handling (GMDH) is also used in practice. GMDH model with multiple inputs and one output is a subset of components of the base function (1):

$$Y\left(x_1,\ldots,x_n\right)=a_0+\sum_{i=1}^{m}a_i f_i \tag{1}$$

where f are elementary functions dependent on different sets of inputs, a are coefficients and m is the number of the base function components. In order to find the best solution GMDH algorithms consider various component subsets of the base function called partial models. Coefficients of these models are estimated by the least squares method. GMDH algorithms gradually increase the number of partial model components and find a model structure with optimal complexity indicated by the minimum value of an external criterion. This process is called self-organization of models. The most popular base function used in GMDH is the gradually complicated Kolmogorov-Gabor polynomial (2):

$$Y(x_1,...,x_n)=a_0+\sum_{i=1}^{n}a_i x_i+\sum_{i=1}^{n}\sum_{j=i}^{n}a_{ij}x_i x_j+\sum_{i=1}^{n}\sum_{j=i}^{n}\sum_{k=j}^{n}a_{ijk}x_i x_j x_k+... \qquad (2)$$

GMDH is also known as polynomial neural networks and statistical learning networks thanks to implementation of the corresponding algorithms in several commercial software products.

Three approaches may be distinguished in selecting the explanatory variable operator:

- The rejection method (a posteriori) – it eliminates from the regression function with the largest number of elements the least important elements one by one until all the remaining elements are significant;
- The admission method (a priori) – it introduces to the function one element at a time. The significance of a given element is assessed based on the value of the partial correlation coefficient. The variable with the highest correlation coefficient is introduced in the regression function;
- The admission and rejection method (the step method) starts from the simplest regression function, which is then gradually extended. The essence of the method is examining the significance of the elements which already occur in the regression function. If introducing a new element lowers the significance of an element which is already in the regression function, then the latter is eliminated from it.

Technical methods of selecting independent variables are an important tool supporting the construction work with ANN models. However, they do not guarantee substantive correctness of variable selection. Without proper monitoring of the process of selecting independent, one runs the risk of creating a model with very good, but substantively incorrect ex-ante characteristics. Such correctness can be guaranteed by an expert in the given field or by knowledge collected in ontology.

The word ontology was taken from Philosophy, where it means a systematic explanation of being. In the last decade, the word ontology became a relevant word for the Knowledge Engineering community. We have read many definitions about what an ontology is and have also observed how such definitions have changed and evolved over the time. One of the first definitions was given by Neches and colleagues (Neches et al., 1991), who defined the term as follows: “an ontology defines the basic terms and relations comprising the vocabulary of a topic area as well as the rules for combining terms and relations to define extensions to the vocabulary”.

According to Neches’s definition, an ontology includes not only the terms that are explicitly defined in it, but also the knowledge that can be inferred from it.

A few years later, Gruber (Gruber, 1993) defined an ontology as "an explicit specification of a conceptualization". This definition became the most quoted in literature and by the ontology community. Based on Gruber's definition, many definitions of what an ontology is were proposed.

A series of approaches has been reported for developing ontologies. In 1990, Lenat and Guha published the general steps (Lenat et al., 1990) and some interesting points about the Cyc development. In 1997, a new method was proposed for building ontologies based on the SENSUS ontology (Swartou et al., 1997). Some years later, the On-To-Knowledge methodology appeared as a result of the project with the same name (Staab et al., 2001). However, all these methods and methodologies do not consider collaborative and distributed construction of ontologies. The only method that includes a proposal for collaborative construction is CO4 (Euzenat, 1996). This method includes a protocol for agreeing new pieces of knowledge with the rest of the knowledge architecture which has been previously agreed.

When constructing Aircraft Engine Diagnostics Ontology (AEDO), the first steps were as follows:

- Explicitly defining: (1) the domain, (2) the use, (3) questions to be answered using the information contained in the ontology (competency questions), (4) the way of using and maintaining it,
- Identifying the possibilities of using the existing ontologies,
- Defining all major concepts,
- Defining class hierarchy. Three approaches were used: (1) top-down – first the general classes were defined, then expanded, (2) bottom-up – first the most detailed classes were defined, then put into a more general form, (3) mixed approach,
- Defining class attributes. Four types of attributes were distinguished: (1) internal, resulting from mere description of the element, (2) external, giving additional description, (3) part attributes when an element is part of a more or less abstract whole, (4) relations with other concepts,
- Preparing a precise description of the characteristics. Among characteristics with a range of parameters, the following were distinguished: (1) cardinality – how many values of a given characteristic can be attributed to the concept. It might be: Min – the minimum number which must be attributed to the concept, Max – the maximum number which may be attributed to the concept, Exact – the exact number which must be attributed to the concept, (2) value admissibility, (3) ranges and domains, meaning what type of objects may appear to the left and to the right of the characteristic,
- Creating class instances, i.e. specific elements without children.

The technology chosen for this project is Web Ontology Language (OWL) and the Protage software. It is a language of ontology designed for applications which process some of the information, not only present it. The OWL is part of the vision of the Semantic Web project. From data described in OWL, new data can be obtained by inference. Pellet is a tool to aid such activities. It is embedded in the Protege software. The tool allows for inference in the OWL layer and creating questions in the SPARQL language (Allemang et al., 2013).

2.2. Application of artificial intelligence in the decision system

The developed concept of using OWL ontology in the process of selecting independent variables for regressive ANN models resulted in a project of AEDO ontology construction. In creating a knowledge base on the cause-and-effect relationships occurring in various operational characteristics of an aircraft engine and their relations with the technical condition of particular parts and subassemblies, the existing domain-specific ontologies were used. In the project, AVIATION Figure 2, Figure 3, MRO (Zhu et al., 2012; RaDEX; Kuofie, 2010) were used.

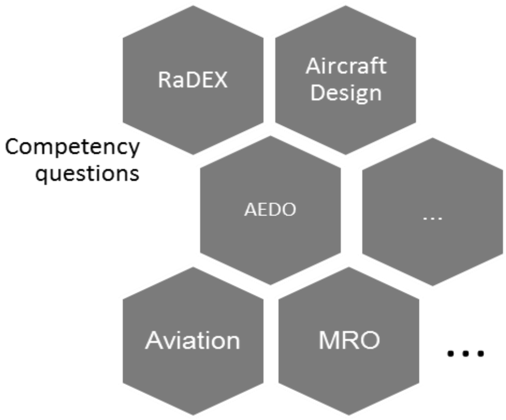

Fig. 1 AEDO environment

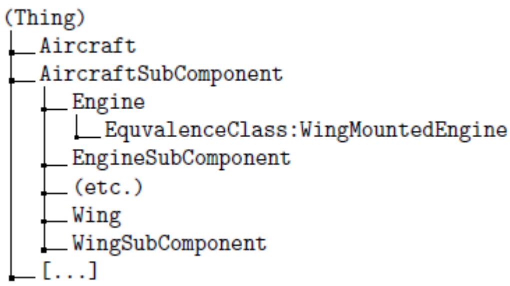

Fig. 2 Class structure composition excerpt

```
(topObjectProperty)
└─hasPart
   └─hasDirectPart
      ├─hasEngine
      └─[...]
```

Fig. 3 Object property excerpt on hasPart – relation

As a result of the competency study, additional knowledge was gained, which was then processed in the OWL language. Below are some examples of the knowledge gained through competency questions:

- What might be indicated by lesser rise of combustion temperature of delta T4 in an aircraft engine?
  The power of the compressor turbine is low.
- What may low power of the compressor turbine result in?
  Higher consumption of oil and air.
- What may low power of the compressor turbine result in?
  Higher combustion temperature.
- What may be impacted by higher combustion temperature?
  Quicker wear and tear of compressor turbine blades.
- What may be impacted by higher combustion temperature?
  Quicker wear and tear of circulation turbine blades.
- What does an aircraft engine do when operating with worn compressor blades?
  To maintain the same power, it increases the compressor's speed.
- What is impacted by operation with increased compressor speed?
  Increased wear and tear of bearings.

From the project resulted work on a new model forecasting demand for bearings. The increased rise of combustion temperature of delta T4 at start-up and oil pressure recorded during normal operation are two non-redundant operational characteristics which contain information about the degree of wear of aircraft engine rolling elements. The independent variables admission (a priori) method was used in the experiment.

The size of the training dataset is 120 real cases. It is a set of pairs resulting from acquiring values of characteristics recorded during current operation of the aircraft before overhaul and results of quality assessment of bearings of the type given in Figure 4 operating with the power turbine (1 item) and transmission (4 items) for further operation. The models were built using ANN of the MLP Figure 7 and RBF Figure 5 types. From a mathematical point of view, MLP act as tools for stochastic approximation of the function of many variables, mapping the input variables set into an output variables set. Such mapping of two independent variables and one dependent variable can be presented as a response surface Figure 6, Figure 8 being an answering additional element of model assessment (Farooq et al., 1997).

Fig. 4 Replacements bearing

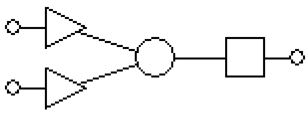

Fig. 5 RBF ANN (2 :2-1-1 :1)

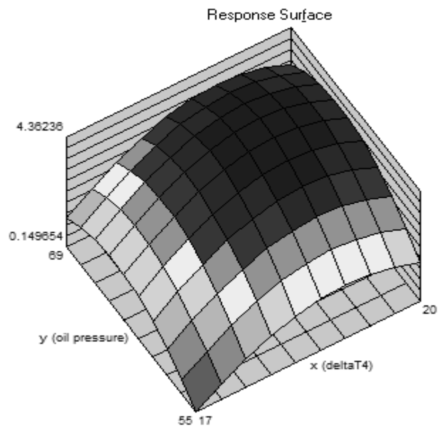

Fig. 6 RBF ANN (2 :2-1-1 :1) response surface

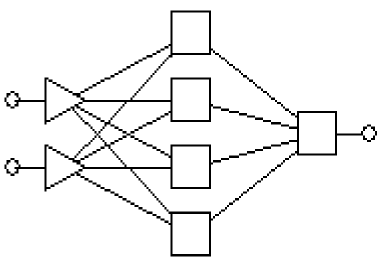

Fig. 7 MLP ANN (2 :2-4-1 :1)

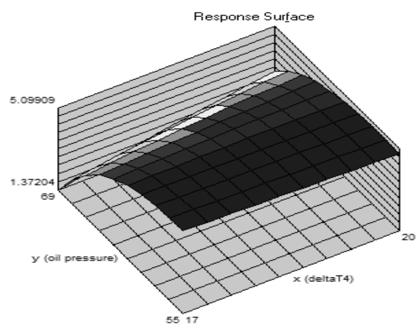

Fig. 8 MLP ANN (2 :2-4-1 :1) response surface

The constructed ANN, both MLP and RBF, are characterised with a low correlation indicator (below 0.9) for training and testing data. It means that the models have insufficient ability for approximation and generalisation. That indicates the need to use ontology to expand the model by further parameters of the ANN input vector.

3. CONCLUSION

In conclusion, the application of ontology in the decision system introduces innovations in the following aspects:

- discovering new knowledge by using competency questions and OWL inference mechanisms,
- ordering and integrating the available ontologies,
- selecting objectively relevant independent variables of the ANN vector forecasting the demand for spare parts,
- expanding Kozik&Sep's method in forecasting the demand for another range of aircraft engine spare parts
- ordering the process of ANN construction using ontology.

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BIOGRAPHICAL NOTES

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