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Aircraft engine on-board diagnostics based on neural network

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Abstract

It is offered to employ the neural network (NN) technology in the software of on-board aircraft engines automatic diagnostic system. But first it was necessary to solve the problem related to teaching NN the ability to adequately and certainly evaluate critical shift of an aeroengine technical condition in flight, including engine monitoring system, e.g. in case of one of data channel fault.

Current research recommends to move from trend analysis of gasdynamics parameters measured on the engine during flight to numerical analysis of engines air-gas path defects criteria using neural networks trained by using diagnostic matrix (DM) specifically worked out for this particular engine model with the purpose of deeper diagnostics of fitted on Fokker-50 PW-125B turboprop engine two-shaft gasgenerator. Based on the research results there is recommendation to introduce in the operations the set of neural networks, trained with abbreviated DM, with defined number of input data which will allow to perform more reliable engine diagnostics during flight in real time mode. Also it is noted that for two-shaft gasgenerator 4 parameters are the minimum parameters number below which the diagnostics become unreliable.

Keywords: diagnostics, neural network, failures.

Introduction

The qualitative difference of the fifth generation aircraft engine diagnostics system is the using of the onboard solid-space removable magnetic storage devices (or laser compact-discs) that allows to increase the volume of the flight information to register rapidly, as well as to process this information with the aid of expert systems with artificial intelligence elements such as artificial neural networks [1, 2, 3]. The important requirement for such systems is that for the raising the safety of the flights onboard information system for the estimation of the technical condition of the engine must contain not only facilities for the initial information processing during the flight, but also the local defect recognition system [4]. Primarily it is concerning to such failures and malfunctions that can threaten the continuation of current flight. However the realization of the usual approach to potential engine defective conditions in the onboard computer is difficult because of the limitations to the volume of information that can be stored and processed onboard. That's why, for example, in the onboard engine control system PS-90A (used in Il-96-300 and Tu-204) in the block of operational documentation (BOD) to the CPU tape not the values of parameters themselves, but only the signals signifying their value deviation are recorded [5]. The indications of BOD are checked after every flight and if the tape is clear, then engine had been working without deviations, else according measures must be taken (not in the flight, but on the ground). For the correct decision taking during the flight crew receives the collection of the codes of external failures displayings. Using it the situation with the defect appearing or malfunction during the flight can be analyzed.

For the automation of the decision taking during the flight in such situations another method for initial information about engine working processing using the onboard computer is proposed. It is the apparatus of artificial neural networks, which is more and more widely used in the different humanity activities tasks [3]. However, for its effective usage the problem of neural network's training for adequate and reliable estimation of the critical change of the engine technical condition including the onboard control system must be considered.

Problems of using the diagnostic matrices for the aircraft engine diagnostics

The using of diagnostic matrices [6] is one of the most promising aircraft engine diagnostics method. In current investigations the switching from qualitative estimation of thermogas parameters' (measured on the engines during the flight) deviations to quantitative estimation of the flowpath's defects using the diagnostic matrix (DM). It is offered for the increasing the depth of the diagnostics for the dual rotor turboprop engine's PW125B of the Fokker-50 gas generator, which is exploited in the "Riga" airport. Unfortunately, it is impossible to use DM during the flight because of the limited measurable parameters' count ($n_{LP,}$ $n_{HP,}$ T^*_{LPT} *u* G_F). For the successful diagnostic of the gas generator the complete control of all its nodes (each compressor and each turbine) is required. The existing measurable parameters' count does not allow to carry out the qualitative diagnostic, because the change of the small parameters' count does not point to possible processes taking place in the engine's flowpath. From the mathematical model analysis it can be seen that there is a single connection between the compressor's and turbine's parameters, but in the case of insufficient measurable parameters' count it can not be always discovered – the linear equation system becomes unsolvable.

To make the using of the DM in the ground conditions the placement of additional sensors of pressure and temperature in the flowpath is needed. The required count of them is theoretically founded basing on the count of variables needed for the solving the equation system containing 16 equations of the modified LMM (linear mathematical model) of the engine [6]. The solution of the system of the linearized equations describing the gas flow in the flowpath of the turboprop engine (physical mathematical model) is obtained for the case of the permanent capacity and turning moment with the constant propeller's turbine rotor rotation frequency ($\delta N_e = \delta M_T = \delta n_{TP} = 0$), that's why these parameters are not considered. Using the LMM of the engine the diagnostic (localizing) matrix was formed. It allows to calculate the deviations of some calculable parameters by the determination of the measurable thermogas parameters' relative deviations [7]. Some of these parameters, in particular, additional compressor's characteristics shifts are the criteria (diagnostic indications) of the defects' appearance in the flowpath of these gas generator modules. At the same time the count of the measurable parameters must be equal to the criteria count in the DM. The rest of the determined using DM parameters carry information about the changing of engine's characteristics on account of it's mode of work change.

It is necessary to note that the main task for the automatic regulation of concerned engine is to keep constant capacity in the present flight conditions. In such situation gas generator's parameters can oscillate in some defined limits. In the case of the defect development automatics of one of the nodes on the defined mode has to compensate the loss of capacity in only possible way by increasing the feed of fuel G_F. In return, it will increase the temperature of the gas in front of turbine T^*_G and accordingly rise the work of the turbine which has no defect. Similar situation appears in the case of the compressor's defect. In the case of airflow or efficiency factor reduction in consequence of pollution or mechanical damages the increasing of required horsepower takes place. It must be compensated by the increasing of the turbine's work, which, in return, is accomplished by the gas temperature raising and is leading to T^*_{LPT} и G_F increase and n_{LP} decrease. The determination of the allowable parameter's deviations limits is the separate very important task in the diagnostics based on the defect development statistics gathering, which will guarantee the goal of the prediction of the engine's future secure exploitation.

Resting upon this analysis the following additional measured parameters were chosen: π^*_{LPC} - compression ratio of low pressure compressor; π^*_{HPC} - compression ratio of high pressure compressor; T^*_{LPC} - temperature behind the low pressure compressor; T^*_{HPC} - temperature behind the high pressure compressor; π^*_{LPT} - expansion ratio of low pressure turbine.

During the exploitation process the direct problem must be solved. It consists in the localizing the node's defect directly by the measured parameters values changes. At the same time for each defect the typical combination of the measurable parameters' deviations exists. For the defect localizing using the DM it is necessary to use the diagnostic equations that consist of measurable parameters' deviations multiplied by according coefficients of influence (in the DM rows). For example the change of the consumption characteristic of the LPC is defining as follows:

$$\begin{aligned}\delta\overline{G}_{LPC} &= a_1\delta n_{HP} + a_2\delta n_{LP} + a_3\delta T^*_{LPC} + \\ &+ a_4\delta G_F + a_5\delta\pi^*_{LPC} + a_6\delta\pi^*_{HPC} + \\ &+ a_7\delta T^*_{HPC} + a_8\delta T^*_{LPC} + a_9\delta\pi^*_{LPT}\end{aligned} \qquad (1),$$

where a_i – coefficient of influence that according measurable parameter has on required parameter (criterion of the defect).

Real defects of the turbo-compressor appear as the specific set of measurable parameters' deviations peculiar to the according defect. But even an experienced engineer (expert) can not estimate all the variety of these parameters' deviations' combinations. DM give an opportunity to localize the defect in the flowpath by defining the quotient fault criteria (for the compressor it is quotient change of the efficiency factor $\delta\overline{\eta}^*_C$ and air consumption characteristic's $\delta\overline{G}_A$ shift; for the turbine – changes of the efficiency factor $\delta\eta_T^*$ and nozzle exit sections' area δF_N). Quantitative values of the criteria pair can be presented as the defect's vector field and to analyze these defects' development trends from flight to flight, but if allowance borders are taken into consideration it is possible to predict the time of these defects' dangerous development and of the engine faults. Of course, arrays of the measurable parameters' deviations are the average statistical sets received after the processing of the recorded and gathered flight information as well as after binding to some engine work mode (rated, cruise, etc.). Unfortunately DM loose their ability to localize the defect during the flight in the case of even one sensor (or data carrier) failure.

Method of artificial neural networks' training in the task of aircraft engine diagnostics

For the diagnostics task the method of defect's localization relied on non-linear artificial neural networks (NN) is proposed. The main problems of this method relate to the neural network training process [8].

In this paper the information received after LMM transformations to the table of the influence coefficients (that allows to specify the defect node and to receive the set of the measurable parameters' deviations) and DM (using it the criteria characteristics of the defect demonstration during the exploitation process such as length and direction of the vector characterizing the flowpath defect can be calculated) are used in the training set forming process. Approach of using theoretically formed DM for the developing the software for the diagnostic systems is especially significant in the case of new engines because statistics of the flowpath defects' demonstrations has not yet been received.

For the task solution the two-layered perceptrons are considered (Figure 1). This is the most developed and popular topology of the artificial neural network [9].

It is necessary to consider that the main advantage of multi-layered networks is their non-linearity that can be accomplished by the usage of the non-linear activation function. It can be shown that in such case the two-layered perceptron can represent any function with the finite points' of discontinuities count if the size of hidden layer is sufficient. The most commonly used activation function is sigmoidal curve because of its simple derivative:

$$f(x)=\frac{1}{1+e^{-\lambda x}}, \qquad (2)$$

where λ is the shape parameter.

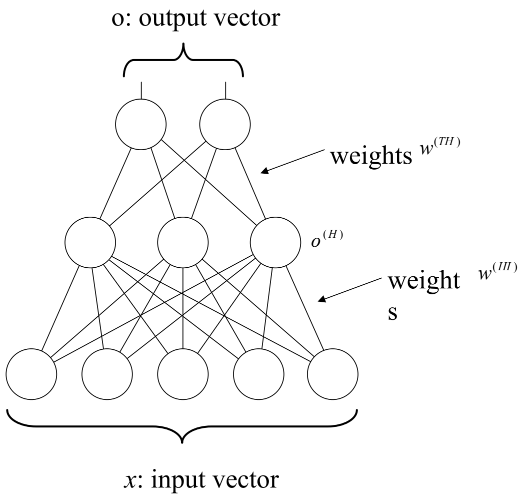

Fig. 1. **Two-layered perceptron scheme**

As the artificial neural network training algorithm the back-propagation is offered. It consists of iterative corrections of output and hidden layers' weights:

$$w_{ij}^{(HI)} = w_{ij}^{(HI)} + \alpha \cdot x_j \cdot \Delta w_{ij}^{(HI)} \qquad (3)$$

$$\Delta w_{ij}^{(HI)} = f^{(H)'}\left(hidden_i\right)\cdot \sum_{k=1}^{n} \Delta w_{ki}^{(TH)} \cdot w_{ki}^{(TH)} \cdot \qquad (4)$$

$$w_{ij}^{(TH)} = w_{ij}^{(TH)} + \alpha \cdot o_j^{(H)} \cdot \Delta w_{ij}^{(TH)} \qquad (5)$$

$$\Delta w_{ij}^{(TH)} = \left(o_i - y_i\right)\cdot f^{(T)'}\left(output_i\right), \qquad (6)$$

where *output*$_i$, *hidden*$_i$ – the outputs of *i*-th output or hidden neuron accordingly before applying the sigmoidal activation function, α – learning rate.

The given algorithm is the sort of gradient descent on the error surface. It means that it doesn't guarantee the discovering of the global minimum of the error function (which depends on weights) or it's convergence in the acceptable terms. Nevertheless many researchers report about successful back-propagation uses in the solution of the number of applied tasks. The weight correction occurs for each observation and in the most cases tens and hundreds of the whole training set presentations is needed for the acceptable results' reaching.

The stages of the two-layered perpceptrons training are the follows:

1. Forming of the training and verification sets.
2. The defining of the activation function for the hidden and output neurons.
3. The defining of the hidden neuron count.
4. Consecutive applying of the back-propagation algorithm during some amount of time or until the error of the network becomes permissible (after this stage weights never become changed).
5. Network's performance test on the verification set.

The high efficiency of the network on the training set doesn't guarantee that network has correctly understood the dependence between input and output data. If the errors on the training and verification sets differ significantly, then the network is working incorrectly. In such case the repeated possibly longer training increasing of the training set size or the change of the network parameters defined on second and third stages is needed. Such situation means that network has overlearned.

Method of artificial neural networks' using in the task of qualitative aircraft engine diagnostics

After the training process has finished neural network can be used for the real tasks solving and the weights are not changed anymore. According set of variables is fed to the network and almost instantly the calculated output variables' values appear at output layer neurons. Using the random number generator 250 cases of each node defects (as the field of possible defects' criteria) were added to training and verification sets. It was supposed that single defects are the most probable.

Lower there are the results of the research of the errors appearing during NN usage process while some sensor indication is absent. In such cases zero value was fed to according input neuron. According errors' values are given in the Table 1.

Table 1. **Errors of the nine-input NN for the solution of the qualitative diagnostics task in the case of one input variable absence**

Absent variable	Network error, %
n_{HP}	3.33
n_{LP}	1.06
T^*_{LPT}	0.7
G_F	2.83
p_{LPC}^*	1.18
p_{HPC}^*	0.53
T_{HPC}^*	2.91
T_{LPC}^*	1.98
P_{LPT}^*	0.83

As was said before additional five sensors can be installed only in the ground conditions because the installation and need to process and store additional information in the onboard system is difficult. During the flight there is only information from four sensors. Because of it the possibility of NN usage while only four sensors installed on board was investigated. Toward this end the training of the neural network was made on only four input variables corresponding the information from sensors installed in the engine by the developer firm, but the coefficients from full DM were used for calculations.

The network behavior in the case of one information carrier failure were also investigated. It was done in the same manner like in the example above (see Table 2).

Table 2. **Errors of the four-input NN for the solution of the qualitative diagnostics task in the case of one input variable absence.**

Absent variable	Network error, %
n_{HP}	4.96
n_{LP}	10.6
T^*_{LPT}	5.93
G_F	3.83

As can be seen from the received results the efficiency of the single four-input network is evidently insufficient in the case of one carrier failure. Here it is especially vividly shown that for the each defect there is the definite combination of measurable parameters' deviations and decreasing their count increases the weight for each measurable quantity accordingly to it's coefficient of influence (the ponderability of measured parameters' errors also grow up).

Method of artificial neural networks using in the task of quantitative aircraft engine diagnostics

Two different options are available while realizing the NN for the quantitative diagnostics task solution:

1. NN has as many input neurons as the count of set up sensors is. The count of outputs is defined by the count of the engine's node. Real number characterizing the corresponding node defect's degree appears at each of the outputs.

2. There is a set of NNs - single network for each diagnosable node. The count of input neurons is the same to the previous option, but the output is only one and it defines the degree of the corresponding node defect.

Because the training of the universal network described in the first option is connected with the serious difficulties, we will use the second. Let us use the dataset received for the nine-input network, but the length of the defect vector in the field of possible defects' criteria will be used as output (not 0 or 1 as in the previous section). Results of this experiment are given in the Table 3.

Table 3. **Errors of the NNs for the solution of the quantitative diagnostics task.**

NN specialization	Input count	Abs. error mean	Error standard deviation	Correlation of NN output and error vector length
LP compressor defect	4	0,03	0,04	0,99979
LP compressor defect	8	0,03	0,04	0,99981
HP compressor defect	4	0,03	0,04	0,99976
HP compressor defect	8	0,03	0,04	0,99974
LP turbine defect	4	0,04	0,05	0,99965
LP turbine defect	8	0,03	0,04	0,99983
HP turbine defect	4	0,02	0,03	0,99986
HP turbine defect	8	0,02	0,03	0,99990

Thus the air engine's quantitative diagnostics process consists of two stages:

1. Realization of the qualitative diagnostics using NNs received in previous section.
2. The using of according network defined by the data analysis in the previous stage for the carrying out the quantitative diagnostics.

Conclusion

The investigations carried out confirm that the usage of NN offer rich opportunities for the diagnostics of the air-engines on board in the real time mode. Starting from the results of the investigation it can be recommended to apply the two stage process: the qualitative diagnostics and after it the quantitative diagnostics. Such approach will allow to carry out the process of the engine diagnostics during the flight reliably. Though it should be mentioned that in the case of two rotor gas generator four meterings are the minimum by decreasing which the diagnostics will lose the credibility. Therefore in the new air-engine (especially the fifth generation and higher) development it is necessary to consider their scheme and in advance to supply the engine with scientifically founded control complexes and diagnostics systems.

References

1. **Кузнецов Н. С., Лабендик В. П.** Проблемы разработок экспертных систем для диагностирования авиационных двигателей. Рига, РКИИГА. 1991. С.10. (Статья депонир. в ЦНТИГА 4.03.91, 836-га 91).
2. **Лабендик В. П., Кузнецов Н. С.** Развитие зарубежных автоматизированных систем диагностирования авиационных двигателей. Рига, РКИИГА. 1991. С. 7. (Статья депонирована в ЦНТИГА 4.03.91, 838-га 91).
3. **Kopytov E., Labendik V., Kabelev N.** Neural network application in aircraft engine diagnostics. Scientific Proceedings of the Scientific-technical Union of Mechanical Engineering, Vol.2 (57). Second International Congress "Mechanical Engineering Technologies MT'01", June 24-26 2001. Sofia, Bulgaria. P..558-560.
4. **Криволуцкий Ю. К., Кузнецов Н. С., Лабендик В. П.** Анализ эффективности контроля технического состояния газовоздушного тракта двигателя НК-86 в АСД "Анализ-86". Рига, РКИИГА. 1991. С.34. (Статья депонирована в ЦНТИГА 4.03.91, 837-га 91).
5. **Пивоваров В. А.** Повреждаемость и диагностирование авиационных конструкций. М.: Транспорт. 1994.
6. **Кузнецов Н. С., Лабендик В. П.** Особенности формирования диагностических матриц для контроля состояния проточной части авиационных ГТД. Изв. ВУЗ "Авиационная техника". Казань, КАИ. 1993, № 3. С.97-101.
7. **Labendiks Vl., Osis A.** Dzinēja PW125B lineāra matemātiska modeļa izstrāde tā diagnosticēšanai pēc gāzdinamiskiem parametriem. RTU Zinātniskie raksti, 6. Sērija "Mašīnzinātne un transports. Transports. Aviācijas transports", 12. sējums. Rīga, ,"RTU". 2003. P.69-75. (ISSN 1407-8015).
8. **Kopytov E., Labendik V., Osis A., Tarasov A.** Method of aviation engine diagnostics in the case of partial loss of information. Abstact collection of II International Scientific and Technical Conference «Aero Engines of XXI Century», 06-09.12.2005, Moscow. M.: CIAM. 2005. Vol. II. P.246-247.
9. **Kopytov E., Kabelev N.** A method of adaptive re-configuration of multi-layer perceptron in real-time learning system. Computer Modelling & New Technologies. Riga: Transport and Telecommunication Institute. 2000. Vol. 4(1). P. 7-14.

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Aviacinių variklių bortinė diagnostika neuroniniais tinklais

Reziumė

Aviacijos varikliams diagnozuoti naudojamos neuroninės sistemos. Remiantis lėktuvo *Fokker-50* tyrimais pateikiamos gedimų nustatymo variklio oro dujų tekėjimo vietose rekomendacijos.

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