Parametric diagnostics of the condition of a dual-flow turbojet engine using neural network simulation of the operating process

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Abstract. The article presents a method of parametric diagnostics of the condition of a dual-flow turbojet engine (DFTE). The method is based on the identification (determination) of the condition of the DFTE components (the compressor, combustion chamber, turbine) with application of a mathematical model of the operating process which is presented as an artificial neural network (ANN) model. This model describes the relation between the monitored parameters of the DFTE (the air temperatures (T_{lpc}^* , T_{hpc}^*) beyond the low pressure compressor (LPC) and the high pressure compressor (HPC), the pressure beyond the LPC (P_{lpc}), the fuel consumption rate (G_f), the gas temperatures (T_{hpt}^* , T_{lpt}^*) beyond the high pressure turbine (HPT) and the low pressure turbine (LPT)) and the parameters of the condition of its components (the efficiencies of the LPC and the HPC (η_{lpc}^* , η_{hpc}^*), the stagnation pressure recovery factor in the combustion chamber (σ_{cc}), the efficiencies of the HPT and the LPT (η_{hpt}^* , η_{lpt}^*)). The parameters of the condition of the engine components (η_{lpc}^* , η_{hpc}^* , σ_{cc} , η_{hpt}^* , η_{lpt}^*) are the similarity criteria (integral criteria) which enable to identify the condition of the DFTE components to a high degree of reliability. Such analysis enables to detect defects at an early stage, even if the values of the monitored parameters (T_{lpc}^* , T_{hpc}^* , P_{lpc} , G_f , T_{hpt}^* , T_{lpt}^*) are within the permissible limits. We provide the sequence for development of the ANN model and the results of its performance study during the parametric diagnostics of the condition of the DFTE.

1 Introduction

It is known that a considerable part of DFTE faults and failures includes parametric failures which consist in a discrepancy between the values of the monitored parameters of the DFTE and the requirements of the specifications. Parametric methods of diagnostics of a condition are used for monitoring and prevention of similar failures. These methods are based on custom processing and analysis of the values of the thermogasdynamic parameters and other parameters monitored on a running DFTE [1–10,12].

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Nowadays the artificial neural network (ANN) technology is one of the fastest growing fields related to artificial intelligence. It is successfully applied in various fields of science and technology for image recognition, diagnostics of the condition of complex technical facilities, etc. [2,10,11]. In this connection, it is important to carry out research to improve the efficiency of the ANN method for parametric diagnostics of the DFTE condition.

2 Topicality

In the study [1], through the example of a single-shaft aircraft engine and a two-shaft engine, it was shown that diagnostics of the condition based on ANN modeling of the operating process has an advantage over other methods [1,5–9]. At the same time, as the volume of the monitored information decreases, the advantage of this method over other methods increases. The efficiency of parametric diagnostics of the condition depends on the type of engine and other factors. Searching for the optimal structure of the ANN model is a complex problem which can be solved largely due to the experience and intuition of the researcher. This article examines the special aspects of parametric diagnostics of the condition of an aviation dual-flow turbojet engine (DFTE) with application of neural network simulation of the operating process.

3 Problem statement

The goal of the research is the study of the effectiveness of the method of parametric diagnostics of the DFTE condition (Fig. 1) with application of ANN modeling of the operating process.

Fig. 1. Aviation dual-flow turbojet engine (DFTE)

The effectiveness of the method is examined with account taken of the following parameters:

- the ANN model type (MLP, RBF);
- the number of the ANN models (N_{ANN}) which are used for the diagnostics of the DFTE condition (in the study $N_{ANN} \in [1 \dots 100]$);
- the amount of the training set ($N_{train.}$) and the test set ($N_{test.}$) which are used for forming the ANN model ($N_{train.} \in [80 \dots 7700]$);
- the quantity ($N_{qp.}$) and list ($N_{lp.}$) of the monitored parameters, with the respective sensors being serviceable and used for the diagnostics of the DFTE condition.

4 Generation of the data for conducting the research

The initial data for building the ANN model of the DFTE operating process were obtained with the use of the GASTURB software and the mathematical model of the DFTE operating process (Fig. 2) [1,5–9].

The monitored parameters of the DFTE condition are: T_{lpc}^* , T_{hpc}^* , P_{lpc} , G_f , T_{hpt}^* , T_{lpt}^* ; the diagnosable parameters of the condition are: η_{lpc}^* , η_{hpc}^* , σ_{cc} , η_{hpt}^* , η_{lpt}^* .

Fig. 2. Diagram of the DFTE mathematical model in the GASTURB software

Assessment of the inaccuracy of the diagnostics of the condition of the i^{th} engine component was carried out according to the formula [2,3]:

$$\delta_i = \frac{1}{K_i} \sum_{j=1}^{K_i} \frac{1}{m} \sum_{\varepsilon=1}^m \frac{|X_{i,j,DFTE,\varepsilon} - X_{i,j,ANN,\varepsilon}|}{X_{i,j,DFTE,\varepsilon}} \times 100, \% \quad (1)$$

and the assessment for the engine taken as a whole was carried out according to the formula:

$$\delta_\Sigma = \sum_{i=1}^z \frac{1}{K_i} \sum_{j=1}^{K_i} \frac{1}{m} \sum_{\varepsilon=1}^m \frac{|X_{i,j,DFTE,\varepsilon} - X_{i,j,ANN,\varepsilon}|}{X_{i,j,DFTE,\varepsilon}} \times 100, \% \quad (2)$$

where z – the number of the DFTE components ($z = 5$; LPC, HPC, CC, HPT, LPT); K_i – the number of the examined conditions of the i^{th} engine component ($i = \overline{1,5}$); m – the number of the parameters of the engine condition ($m = 5$; η_{lpc}^* , η_{hpc}^* , σ_{cc} , η_{hpt}^* , η_{lpt}^*); $X_{i,j,DFTE,\varepsilon}$ – the value of the ε^{th} parameter which characterizes a defective condition of the i^{th} DFTE component; $X_{i,j,ANN,\varepsilon}$ – the value of the ε^{th} parameter which characterizes a defective condition of the i^{th} engine component, as determined according to the ANN model.

In accordance with the formula (2), the effectiveness of the diagnostics of the DFTE condition was assessed using the parameter E_Σ which is inverse to the value of the error δ_Σ (the lower the error, the higher is the effectiveness of the diagnostics of the DFTE condition):

$$E_\Sigma = (100 - \delta_\Sigma) = \left(1 - \sum_{i=1}^z \frac{1}{K_i} \sum_{j=1}^{K_i} \frac{1}{m} \sum_{\varepsilon=1}^m \frac{|X_{i,j,DFTE,\varepsilon} - X_{i,j,ANN,\varepsilon}|}{X_{i,j,DFTE,\varepsilon}} \right) \times 100, \% \quad (3)$$

The value of $\Delta X_{i,j,DFTE}$ (the deviation of the parameter of the condition of the i^{th} component of the DFTE from its value corresponding to the defect-free condition) varied

within the interval [0...−5] %, inside this interval we selected $N_{\Sigma} = 7700$ values of a defective condition of the DFTE component:

$$\Delta X_{ij,DFTE} = [0; -0.00064; \dots ; -4.99979; -5.0], \text{ \%}.$$

Training of the ANN model was carried out using the amount of the set:

$$N_{\text{train}} = 5390; \left(N_{\text{train}} = 0,7 \cdot N_{\Sigma} \right).$$

Modeling of defects of the DFTE components was carried out within the interval:

$$\eta_{\text{lpc}}^*=[0.81...0.85]; \eta_{\text{hpc}}^*=[0.8...0.84]; \sigma_{\text{cc}}=[0.91...0.95]; \eta_{\text{hpt}}^*=[0.83...0.87]; \eta_{\text{lpt}}^*=[0.82...0.86].$$

The defect-free condition of the DFTE corresponded to the following values of $X_{ij,0}$:

$$X_{1,1,0} = \eta_{\text{lpc}}^* = 0.85; X_{2,1,0} = \eta_{\text{hpc}}^* = 0.84; X_{3,1,0} = \sigma_{\text{cc}} = 0.95; X_{4,1,0} = \eta_{\text{hpt}}^* = 0.87; X_{5,1,0} = \eta_{\text{lpt}}^* = 0.86.$$

5 Influence of the type and number of the ANN models on the effectiveness of diagnostics of the DFTE condition

The selection was performed by means of comparison of the type MLP and RBF models [2,4]. The number of the ANN models (N_{ANN}) whose results were used for estimation of the error of diagnostics of the DFTE condition varied from 1 to 100.

The error values for the diagnostics of the condition of the LPC and HPC ($\delta \eta_{\text{lpc}}^*, \delta \eta_{\text{hpc}}^*$), the CC ($\delta \sigma_{\text{cc}}$), the HPT and LPT ($\delta \eta_{\text{hpt}}^*, \delta \eta_{\text{lpt}}^*$) depending on the N_{ANN} are given in Table. 1 and are shown in Fig. 3.

Table 1. The error values for the diagnostics of the condition of the DFTE components

Item No.	N_{ANN}	$\delta \eta_{\text{lpc}}^*, \text{ \%}$		$\delta \eta_{\text{hpc}}^*, \text{ \%}$		$\delta \sigma_{\text{cc}}, \text{ \%}$		$\delta \eta_{\text{hpt}}^*, \text{ \%}$		$\delta \eta_{\text{lpt}}^*, \text{ \%}$	
		MLP	RBF	MLP	RBF	MLP	RBF	MLP	RBF	MLP	RBF
1	1	0.13	1.5	0.46	1.0	1.32	1.4	0.04	1.1	0.06	1.4
2	5	0.18	1.5	0.46	1.3	1.32	1.5	0.09	1.3	0.10	1.0
3	10	0.26	53	0.47	135	1.36	40	0.14	52	0.16	229
4	20	0.22	1047	0.48	689	1.37	1085	0.13	887	0.15	934
5	30	0.22	7946	0.47	4954	1.34	3900	0.12	4101	0.15	4014
6	40	0.26	19780	0.47	18133	1.36	11972	0.14	16130	0.15	15897
7	50	0.22	12804	0.47	10469	1.36	5188	0.13	6081	0.13	11328
8	60	0.25	26974	0.47	14683	1.35	7553	0.15	8463	0.16	7055
9	70	0.24	2589	0.47	5815	1.35	1778	0.13	4090	0.14	3079
10	80	0.25	3429	0.47	4675	1.36	5200	0.15	3076	0.17	2680
11	90	0.28	1148	0.48	1067	1.36	1294	0.15	1659	0.15	1867
12	100	0.13	30190	0.46	49870	1.32	25608	0.04	84287	0.06	35610

It can be seen from the table and the figure that the MLP type models are more accurate for the diagnostics of the engine condition. For example, with $N_{\text{ANN}} = 5$ the error value for the diagnostics of the LPC condition with the application of the MLP model is 8 times less than when using the RBF model; with $N_{\text{ANN}} = 50$ the error is $6 \cdot 10^4$ times less.

Fig. 3. Influence of the type and quantity of the ANN models on the error values for the diagnostics of the condition of the DFTE components: ♦ – η_{lpc}^* ; ■ – η_{hpc}^* ; ▲ – σ_{cc} ; □ – η_{hpt}^* , ● – η_{lpt}^*

6 Influence of the amount of the training set and the test set on the effectiveness of diagnostics of the DFTE condition

During the research the amount of the training set N_{train} varied within the range [80 ... 7700], while the amount of the test set N_{test} varied within the range [7700 ... 80]. The error values for the diagnostics of the condition of the DFTE components ($i=1.5$) were evaluated according to the formula (1) and are given in Table 2, while for the DFTE in general – according to the formula (2) and shown in Fig. 4 (with $N_{\Sigma} = 7700$).

Table 2. The error values for the diagnostics of the condition of the DFTE components (δ_i , $i = \overline{1,5}$; %)

Item	N_{train}	$\delta\eta_{lpc}^*$	$\delta\eta_{hpc}^*$	$\delta\sigma_{cc}$	$\delta\eta_{hpt}^*$	$\delta\eta_{lpt}^*$	N_{test}	$\delta\eta_{lpc}^*$	$\delta\eta_{hpc}^*$	$\delta\sigma_{cc}$	$\delta\eta_{hpt}^*$	$\delta\eta_{lpt}^*$
1	80	0.09	0.05	0.09	0.05	0.06	7700	0.07	0.04	0.04	0.04	0.04
2	770	0.11	0.06	0.09	0.07	0.08	6930	0.11	0.05	0.10	0.09	0.11
3	1540	0.06	0.06	0.06	0.05	0.05	6160	0.04	0.04	0.04	0.03	0.04
4	2310	0.08	0.05	0.07	0.04	0.05	5390	0.06	0.06	0.05	0.04	0.05
5	3080	0.09	0.09	0.11	0.08	0.12	4620	0.06	0.06	0.07	0.05	0.08
6	3850	0.10	0.06	0.07	0.06	0.07	3850	0.10	0.06	0.07	0.06	0.07
7	4620	0.10	0.06	0.07	0.05	0.08	3080	0.13	0.09	0.11	0.08	0.12
8	5390	0.09	0.06	0.05	0.04	0.05	2310	0.09	0.05	0.08	0.05	0.08
9	6160	0.04	0.04	0.04	0.03	0.04	1540	0.06	0.06	0.08	0.07	0.06
10	6930	0.04	0.04	0.09	0.06	0.11	770	0.06	0.07	0.09	0.07	0.08
11	7700	0.08	0.04	0.04	0.03	0.05	80	0.13	0.06	0.10	0.05	0.08

Fig. 4. Influence of N_{train} and N_{test} on the error values for the diagnostics of the DFTE condition

From Table 2 and fig. 4 it can be seen that the error value for the diagnostics of the DFTE condition is minimal ($\delta_{\Sigma} = 0.19 \%$) with a ratio of N_{train} . and N_{test} that amounts to 80:20 %.

7 Influence of the number and list of the monitored parameters on the effectiveness of diagnostics of the DFTE condition

The influence of the number (N_{qp}) and list (N_{lp}) of the monitored parameters on the error values for the diagnostics of the condition of the DFTE components was assessed according to the formula (1) (Fig. 5), while the condition of the DFTE in general was assessed according to the formula (2) (Fig. 6).

Fig. 5. Influence of the number (N_{qp}) and list (N_{lp}) of the monitored parameters on the error values for the diagnostics of the condition of the DFTE components

Fig. 6. Influence of N_{qp} and N_{lp} on the error values for the diagnostics of the DFTE condition

8 Conclusion

The effectiveness of the parametric diagnostics of the DFTE condition is maximum (the estimation error is minimum) with the following values of the influencing parameters:

- the ANN model type – MLP;
- the number of the ANN models which are used for estimation of the error of diagnostics of the engine condition – $N_{ANN} = 5$;
- The ratio of the training (N_{train}) and test (N_{test}) sets – 80:20 %;
- The error of the diagnostics of the DFTE condition is minimum ($\delta_{z6} = 0.07 \%$) when the diagnostics of the DFTE is carried out with account taken of all $N_{qp} = 6$ parameters.

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