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A STUDY ON INTELLIGENT PERFORMANCE DIAGNOSTICS OF A GAS TURBINE ENGINE USING NEURAL NETWORKS

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ABSTRACT

An intelligent performance diagnostic computer program of a gas turbine using the NN(Neural Network) was developed. Recently on-condition performance monitoring of major gas path components using the GPA(Gas path Analysis) method has been performed in analyzing of engine faults. However because the types and severities of engine faults are various and complex, it is not easy that all fault conditions of the engine would be monitored only by the GPA approach. Therefore in order to solve this problem, application of using the NNs for learning and diagnosis would be required. Among them, a BPN (Back Propagation Neural Network) with one hidden layer, which can use an updating learning rate, was proposed for diagnostics of PT6A-62 turboprop engine in this work.

In this study, in order to facilitate application of the NNs as well as to provide user-friendly circumstance a performance diagnostic computer code using MATLAB® was newly proposed. As a result, not only more precise and prompt analysis results could be obtained due to use of the toolbox in MATLAB® on diagnosis and numerical analysis, but also the GUI (Graphical User Interface) platform could be realized.

The proposed engine diagnostics system is able to train the BPN with each fault pattern and then construct the total training network by assembling the trained BPNs. Database for network learning and test was constructed using a gas turbine performance simulation program.

In order to investigate reliability on construction of database for diagnostic results, an analysis was performed with 5 combination cases of 40 fault patterns.

Finally a diagnostic application example for the PT6A-62 turboprop engine was performed using the trained network with database, which represented the best diagnostic results among test sets.

1. INTRODUCTION

Engine condition monitoring is an effective complex way to improve safety as well as reduce operation and maintenance costs of gas turbines. To keep track of the health of various components that make up a modern aircraft engine, a large number of monitoring and diagnostic techniques have to be applied. Among them, the GPA(Gas Path Analysis) is a kind of fault diagnostic techniques that can be used to isolate and quantify gas path faulted components of gas turbines. Some features of the GPAs are the capability to identify the component responsible for the loss of performance, detect multiple faults and quantify the deterioration affecting individual components. (Zedda & Singh, 1998)

Performance diagnosis of major gas path components using the GPA can be carried out by independent parameters, (such as component efficiencies, mass flow parameters, etc.) and the FCM(Fault Coefficient Matrix). Because the FCM, which is a inverse matrix of the ICM(Influence Coefficient Matrix) that is relationship between measurable dependent parameters (such as pressure, temperature, fuel flow, etc.) and independent parameters, is a non-square matrix, there might be some error to obtain the inverse matrix due to numerical treatment. (Urban, 1972)

Recently AI(Artificial Intelligence) and especially the NN(Neural Network) techniques have been applied to gas turbine engine diagnostics. The NNs have inherent features that make them particularly suited to diagnostic tasks. (Lu et al., 2000, Sun et al., 2000, Volponi et al., 2000, Depold & Gass, 1999)

Changes of measured parameters in engine gas path reflect the change of component characteristics. If the interrelationship between them can be built using the NN, the different types of faults can be diagnosed. Lots of research works have been conducted on engine fault diagnosis using the NN, and several NN approaches have been developed. Among them, the BPN (Back Propagation Network) is widely used because of its simplicity and already made algorithm. (Sun et al., 2000, Zedda, 1998, Tang et al., 1998)

The BPN was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. Backpropagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. (Haykin, 1994)

In order to reduce some difficulties of currently used BPNs for gas turbine engine diagnostics, this work proposed a method, which is able to train the BPN with each fault pattern and then construct the total training network by assembling the trained BPN. Fault and test database to build the NNs were obtained using a gas turbine performance simulation program. In order to use easily the proposed diagnostics system, a GUI(Graphical User Interface) program for constructing database, training, test and applying the NNs was developed.

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2. THE DIAGNOSTIC SYSTEM WITH GUI

The proposed gas turbine engine diagnostic system consists of construction of database for training the NN, learning the BPN, verification of the NN using test data, and application for a target gas turbine engine. Figure 1 shows 'main window' for the proposed diagnostic system.

Fig. 1 Main window for diagnostic system

In the stage of data base construction, a performance simulation program calculates base engine performance and measurable parameters for various faults. Engine performance degradation is saved at a file through normalization using the following equation. Figure 2 shows 'in/out window' for the stage of data base construction.

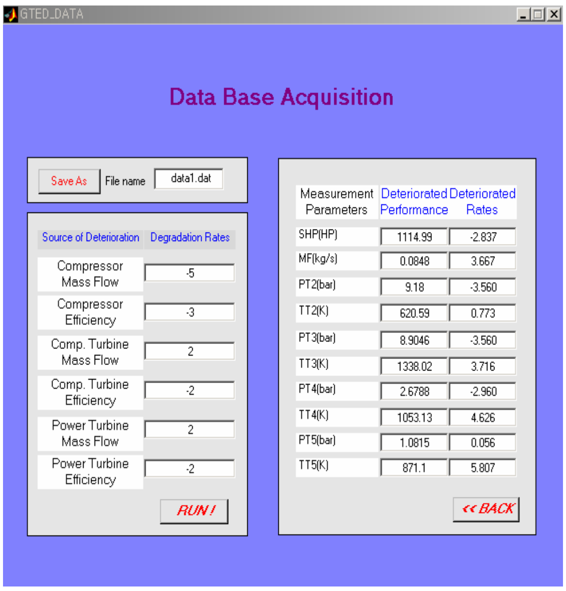

Fig. 2 Window for database acquisition

$$\Delta Z = \frac{Z_b - Z}{Z_b} \times 100 \qquad (1)$$

Where Z_b is the value at the established baseline condition and Z is the measured or calculated value respectively.

In the stage of training stage of the BPN, the training is performed using input data (such as training error goal, number of neurons in hidden layer, number of maximum iterations, etc.), and database obtained in the previous stage. Figure 3 shows 'in/out window' for the stage of training.

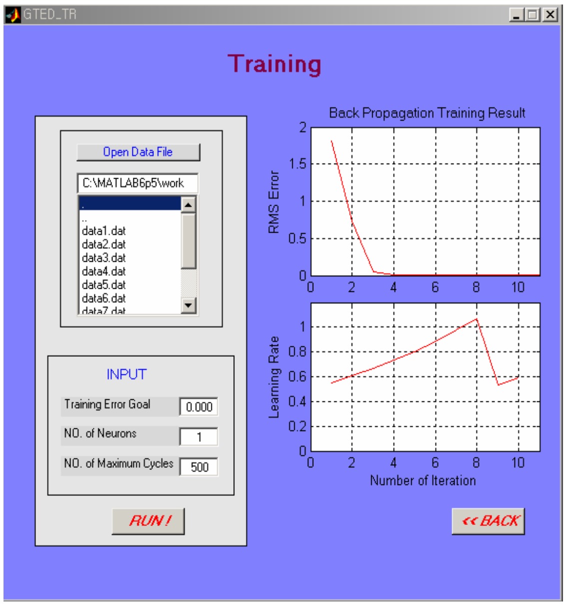

Fig. 3 Window for BPN training

In the stage of test and application at the target engine, the types of faults and their severities are quantitatively indicated using the trained NN with input data such as test and measured data. Figure 4 shows 'in/out window' for the stage of test and application.

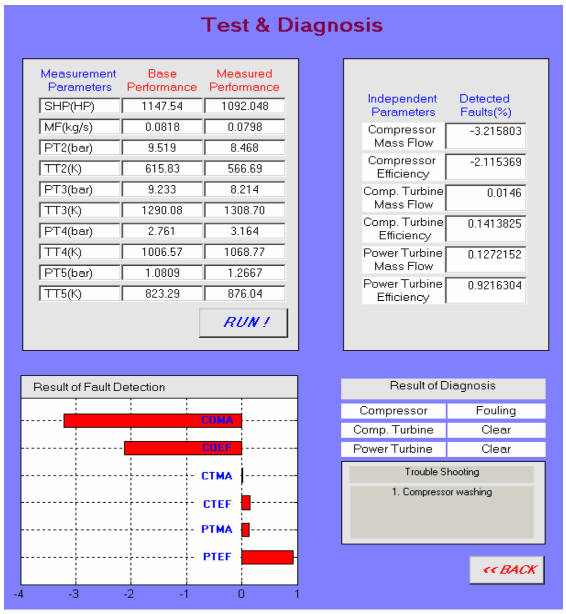

Fig. 4 Window for NN test/diagnosis

3. NEURAL NETWORK APPROACH TO GAS TURBINE PERFORMANCE DIAGNOSTICS

An engine selected for diagnostics system is the P&WC PT6A-62 free-turbine turboprop engine. The engine shaft horsepower is 857.9kW(1150 hp) at sea level, but flat rated at

708.7kW(950 hp). Table. 1 shows the performance data at maximum take-off condition, which were provided by the engine manufacturer. (Kong & Ki, 2001)

Table. 1 Performance data by engine manufacturer

Variable	Values
Atmospheric condition	Sea Level Static Standard Condition
Mass flow rate (kg/s)	4.18
Fuel flow rate (kg/s)	0.0818
Shaft horse power (hp)	1150
S.F.C (kg/kw·hr)	0.3433
Gas generator rotational speed (100% RPM)	37468
Propeller rotational speed (100% RPM)	2000

Measurable parameters for this model were SHP(shaft horse power), MF(fuel flow), PT2(compressor exit pressure), TT2(compressor exit temperature), PT4(compressor turbine exit pressure), TT4(compressor turbine exit temperature), TT5(power turbine exit temperature). Flow capacities and efficiencies of gas path components were used for detection parameters for their performance degradations. It means that the six performance parameters, which are flow capacities and efficiencies of compressor, compressor turbine and power turbine, used for detecting single or multiple faults such as compressor fouling, turbine erosion, and so on.

40 patterns of training data and 15 patterns of test data were obtained using the performance simulation program of the PT6A-62 turboprop engine. (Kong, 2001) Fault patterns for training and test have various cases of compressor fouling, turbine erosion, and simultaneously combined faults of gas path components with the performance degradation range of 1% to 5%.

Learning algorithm used the BPN with one hidden layer. The hidden layer used the tangent sigmoid transfer function, and the output layer used the linear transfer function.

3-1. DATA SET CONSTRUCTION

Data set for learning was composed of 40 patterns of faults. Compressor fouling causes decrease of both flow capacity and efficiency, and it was considered that the degradation rate due to this fault has the maximum range of 5%. However turbine erosion causes increase of flow capacity and decrease of efficiency, and it also was considered that the degradation rate has the maximum range of 5% like the compressor fouling case. Various cases for fault patterns were assumed that there are single fault pattern such as compressor fouling, compressor turbine erosion or power turbine erosion, and multi patterns with simultaneously combined faults.

If variation rates of component flow capacities and efficiencies are input at GUI window, each component performance map is scaled by them. Therefore the engine performance can be matched at a new operating point with this scaled map. After measurement parameters (such as SHP, MF, P2, T2, P4, T4 and T5) of the degraded engine are compared with them of clean engine and calculated using equation (1), they will be saved as a data file.

With the same procedure as construction of the learning data set, 15 patterns of faults were constructed for test data set. Table 2 shows fault patterns for learning data set. (Diakunchak, 1992)

Where Γ is component flow capacity, η means component efficiency. Subscripts of CO, CT, PT present compressor, compressor turbine, power turbine.

Table. 2 Fault patterns for learning data set

	Γ_{CO}	η_{CO}	Γ_{CT}	η_{CT}	Γ_{PT}	η_{PT}
1	1	1	0	0	0	0
2	-2	-2	0	0	0	0
3	-3	-3	0	0	0	0
4	-4	-4	0	0	0	0
5	-5	-5	0	0	0	0
6	0	0	1	-1	0	0
7	0	0	2	-2	0	0
8	0	0	3	-3	0	0
9	0	0	4	-4	0	0
10	0	0	5	-5	0	0
11	0	0	0	0	1	-1
12	0	0	0	0	2	-2
13	0	0	0	0	3	-3
14	0	0	0	0	4	-4
15	0	0	0	0	5	-5
16	1	-1	1	-1	0	0
17	2	-2	2	-2	0	0
18	3	-3	3	-3	0	0
19	4	-4	4	-4	0	0
20	5	-5	5	-5	0	0
21	0	0	1	-1	1	1
22	0	0	2	-2	2	2
23	0	0	3	-3	3	3
24	0	0	4	-4	4	4
25	0	0	5	-5	5	5
26	1	-1	0	0	1	-1
27	2	-2	0	0	2	-2
28	3	-3	0	0	3	-3
29	4	-4	0	0	4	-4
30	5	-5	0	0	5	-5
31	-1	-1	1	-1	1	-1
32	-2	-2	2	-2	2	-2
33	-3	-3	3	-3	3	-3
34	-4	-4	4	-4	4	-4
35	-5	-5	5	-5	5	-5
36	-5	-3	3	-3	3	-3
37	-3	-2	2	-2	2	-2
38	-4	-2	1	-1	1	-1
39	-5	-3	2	-2	2	-2
40	-1	-1	2	-2	2	-2

3-2. NEURAL NETWORK TRAINING ALGORITHM

Fault patterns were trained using the BPN algorithm. The BPN consists of one input layer with 7 neurons, one hidden layer with one neurons and one output layer with 6 neurons as shown in Figure 5. Seven neurons of the input layer mean variations of measurement parameters such as SHP, MF, P2, T2, P4, T4 and T5, and 6 neurons of the output layer present degradation rates of flow capacities and efficiencies for compressor, compressor turbine and power turbine.

The tangent sigmoid function (2) was used as the transfer function of the hidden layer, and the linear transfer function (3) was applied as the transfer function of the output layer. (Lee & Mun 1999)

$$y = \frac{e^{\alpha x} - e^{-\alpha x}}{e^{\alpha x} + e^{-\alpha x}} \tag{2}$$

$$y = x \tag{3}$$

Where e means exponential, y and x are output and input values respectively. α is tangential parameter, and it was set as 1 in this work.

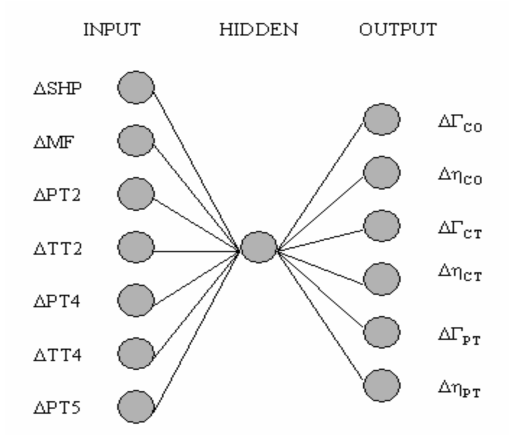

Fig. 5 Architecture of three layer BPN

The BPN needs differential operation of the transfer function for effective calculation in the forward pass. Therefore differential equations of tangent sigmoid and linear transfer functions are respectively as follows. (Lee & Mun 1999)

$$\dot{y} = \alpha\left(1 - [f(x)]^2\right) \tag{4}$$

$$\dot{y} = 1 \tag{5}$$

In the NN learning process, in order to increase the learning speed and maintain the stability the "learning rate factor"(LRF) increases 10 % of the previous LRF if the errors between network and goal outputs decrease, but the LRF decreases 50% of the previous LRF if the errors increase. Moreover the weight factor was only updated in case of decrease of the errors. The errors is defined as the following RMS(Root Mean Square).

$$RMS\ error = \sqrt{\frac{\sum_{i=1}^{n}(y_n - T_n)^2}{n}} \tag{6}$$

Where T is target output, y is output value calculated by the NN, and n is the number of output layer neurons. In this work the target maximum RMS error was set at 0.0001.

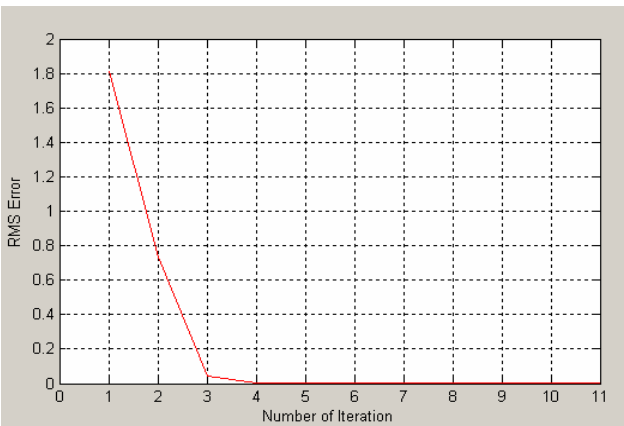

Fig. 6 RMS errors versus number of iterations

Figure 6 shows a trend that the network output is converging to the target output for the 40^{th} fault pattern.

4. NETWORK VALIDATION

Test data set composed of 15 fault patterns was used to validate the learned NN. Test set consists of various types and severities of component faults similar to data sets for learning. Table 3 presents the applied test data set for validation. (Diakunchak, 1992)

In order to investigate influence on construction of database for diagnostic results, an analysis was performed with 5 combination cases, which were derived from 40 fault patterns. Table 4 shows 5 combination cases for database and their RMS errors.

From diagnostic results, it is noted that the case I with all 40 fault patterns at Table 2 has much greater RMS errors rather than the cases with partial fault patterns. It means that unnecessary data may have inaccuracy diagnostic results inversely. The case II is the results that train the data set using the fault pattern number 1 to 15 at Table 3. These are various types that single fault occurs at each component. It is found that the case II have much less errors rather than the case I including multi-fault types.

Table. 3 Fault patterns for NN validation

	Γ_{CO}	η_{CO}	Γ_{CT}	η_{CT}	Γ_{PT}	η_{PT}
1	-2	-2	0	0	0	0
2	-3	-1	0	0	0	0
3	0	0	2	-1	0	0
4	0	0	3	-2	0	0
5	0	0	0	0	2	-1
6	0	0	0	0	3	-2
7	0	0	2	-2	1	-1
8	0	0	3	-1	3	-2
9	-3	-1	2	-1	0	0
10	-3	-2	1	-1	0	0
11	-3	-1	0	0	2	-1
12	-3	-2	0	0	2	-2
13	-3	-2	2	-2	2	-2
14	-2	-1	1	-1	1	-1
15	-3	-1	2	-1	2	-1

Table. 4 RMS errors for each learning database sets

	CASE I	CASE II	CASE III	CASEIV	CASE V
1	14.935	3.3754	1.9546	1.1734	0.8399
2	14.989	3.3306	1.9488	1.1821	0.8974
3	14.913	3.1191	1.8329	0.8771	2.1929
4	14.603	2.8150	1.8311	1.0011	2.4896
5	14.878	3.3486	1.6566	1.6107	2.0840
6	14.531	3.2175	1.5552	1.9508	2.3483
7	14.399	2.6225	1.4249	1.0443	2.3386
8	14.032	2.5476	1.0592	1.6933	2.5541
9	14.489	2.6804	1.5698	0.6331	1.3279
10	14.516	2.8639	1.7074	0.9074	0.8162
11	14.439	2.9453	1.3681	1.5110	1.1620
12	14.108	2.8278	1.4067	1.6594	1.1662
13	13.425	1.7538	0.8095	1.3505	1.6573
14	14.367	2.6173	1.1718	0.7678	1.3329
15	13.932	2.1884	0.7452	1.1378	1.5194

The case III is the result that trains the data set using the fault pattern number 3, 4, 8, 9, 13 and 14 with component performance degradation rates of 3 and 4%, and the case IV is the result that learns the data set using the fault pattern number 1, 5, 6, 10, 11 and

15 with component performance degradation rates 1 and 5%. As a result of comparison, it is shown that have less RMS errors than the case II, the case III and the case IV with wide degradation rates has the smallest RMS errors.

Finally, the case V constructs learning set using the fault pattern number 1, 2, 3, 4 and 5 (only compressor fouling). This case can detect well the compressor fouling pattern, but it has big RMS errors for other single and multi component fault patterns.

In this test, in order to get better diagnostic results, firstly it was confirmed that unnecessary database may give rise to reduce the diagnostic reliability, inversely. Secondly, the case using the learning database for single component fault patterns has much higher reliability than that for multi component fault patterns, and thirdly, the case using wide range of performance degradation rates has much better than that using narrow range of performance degradation rates. Finally the learned case with a single component fault pattern can detect precisely the same component fault pattern, but it can detect well the other component fault patterns.

Figure 7 and 8 show respectively application results for diagnostics of the PT6A-62 turboprop engine. Because diagnostic results show reduction of both flow capacity and efficiency of compressor as shown in Figure 7, it can be found that cause of fault is compressor fouling.

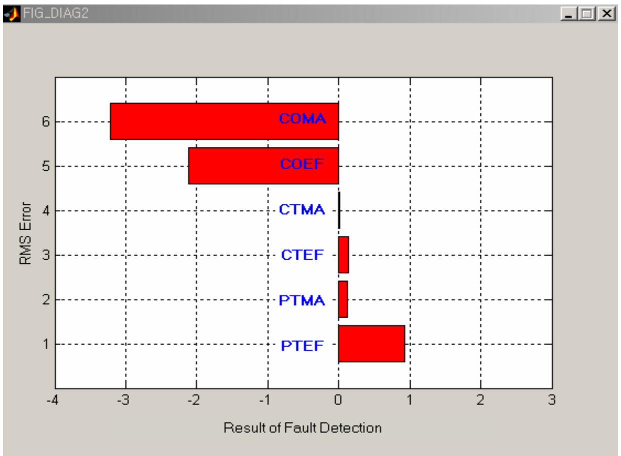

Fig. 7 Application results of the case IV network

Because Figure 8 shows decrease of both flow capacity and efficiency at compressor as well as increase of flow capacitiy and decrease of efficiency at compressor turbine, it presents that causes of combined faults are compressor fouling and compressor turbine erosion.

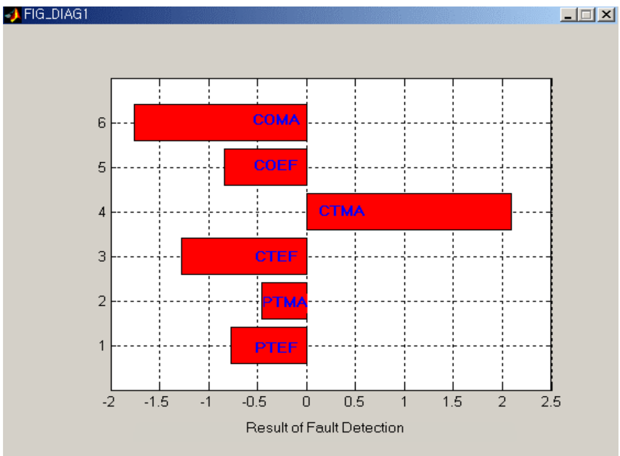

Fig. 8 Application results of the case IV network

5. CONCLUSION REMARKS

In this work, a performance diagnostics system for a gas turbine was newly proposed using the NNs. The proposed diagnostics system was composed with the basis of the GUI platform, which users can use easily for construction of data base, training, test and even application of the NNs.

For learning the NN, a BPN with one hidden, one input and one output layer was used. The input layer had seven neurons of variations of measurement parameters such as SHP, MF, P2, T2, P4, T4 and T5, and the output layer used 6 neurons of degradation ratios of flow capacities and efficiencies for compressor, compressor turbine and power turbine. The tangent sigmoid function was used as the transfer function of the hidden layer, and the linear transfer function was applied as the transfer function of the output layer. After obtaining 55 fault patterns using the performance simulation program of PT6A-62 turboprop engine, 40 patterns were used for network training, and 15 patterns were applied for network validation.

In order to investigate reliability on construction of database for diagnostic results, an analysis was performed with 5 combination cases of 40 fault patterns. From analysis results, in order to get better diagnostic results, firstly it was confirmed that unnecessary database might give rise to reduce the diagnostic reliability, inversely. Secondly, the case using the learning database for single component fault patterns had much higher reliability than that for multi component fault patterns, and thirdly, the case using wide range of performance degradation rates had much better than that using narrow range of performance degradation rates. Finally the learned case with a single component fault pattern could detect precisely the same component fault pattern, but it could detect well the other component fault patterns.

From application results for diagnostics of the PT6A-62 turboprop engine using the learned networks, it was confirmed that the proposed diagnostics systems could detect well the single fault types such as compressor fouling, compressor turbine erosion and power turbine erosion as well as multi component combined fault types.

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