Development of On-line Performance Diagnostic Program of a Helicopter Turboshaft Engine

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Abstract

Gas turbine performance diagnostics is a method for detecting, isolating and quantifying faults in gas turbine gas path components. On-line precise fault diagnosis can promote greatly reliability and availability of gas turbine in real time operation. This work proposes a GUI-type on-line diagnostic program using SIMULINK and Fuzzy-Neuro algorithms for a helicopter turboshaft engine. During development of the diagnostic program, a look-up table type base performance module are used for reducing computer calculating time and a signal generation module for simulating real time performance data. This program is composed of the on-line condition monitoring program to monitor on-line measuring performance condition, the fuzzy inference system to isolate the faults from measuring data and the neural network to quantify the isolated faults. Evaluation of the proposed on-line diagnostic program is performed through application to the helicopter engine health monitoring.

Key words : On-line Performance Diagnostic Program, On-line Condition Monitoring, Fuzzy Logic, Neural Network, Turboshaft Engine

Introduction

Helicopter propulsion system operates in severe flight conditions such as hot and cold temperature, heavy snow and rain, foreign particles due to dust, sand and birds, etc. This severe operating condition may increase possibility of foreign object ingestion such as sand, dust, birds, etc., which can give rise to damages of engine gas path components.

Types and severities of most engine faults being so complex, conventional model based fault diagnostic approaches like the GPA(Gas Path Analysis) method may not monitor precisely all engine fault conditions [1].

Recently soft computing methods such as Genetic Algorithms, Fuzzy Logic, Neural Networks and Expert System have been applied to the advanced gas turbine HMS (health monitoring system). Moreover, the on-line HMS has been developed for immediate and effective action on identified faults rather than the ground health monitoring system, and most existing HMS are not convenient to use due to difficult input/output data processing of the HMS program. Therefore, this work proposes an effective and user friendly GUI(Graphic User Interface) type on-condition performance diagnostic program which can monitor, isolate and quantify the component faults of the Helicopter turboshaft engine in operation using SIMULINK, Fuzzy and Neural Networks[2].

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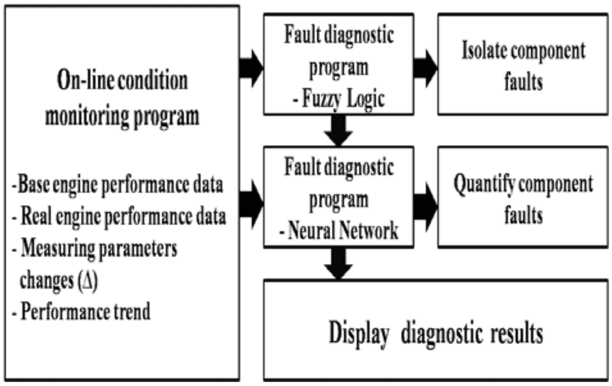

Fig. 1. Schematic diagnostic flow of the proposed GUI-type on-line diagnostic program

Figure 1 shows the schematic diagnostic flow of the proposed effective and user friendly GUI-type on-line diagnostic program, which can monitor, isolate and quantify the component faults, using SIMULINK and Fuzzy-Neuro algorithms for a helicopter turboshaft engine.

On-Line Condition Monitoring Program

The engine for this study is T700 turboshaft engine which will be used for Korean Utility Helicopter. Figure 2 shows the flow path configuration and station numbers of the turboshaft engine that is composed of the compressor with 5-stage axial and single stage centrifugal, the annular vaporizing combustor, the 2-stage axial flow gas generator turbine and the 2-stage axial flow free power turbine. The power turbine is connected to the helicopter rotor through the transmission gears.

Table 1 shows the operating range of the turboshaft engine, and Table 2 shows design point performance data of the model engine at sea level having static and standard atmospheric condition.

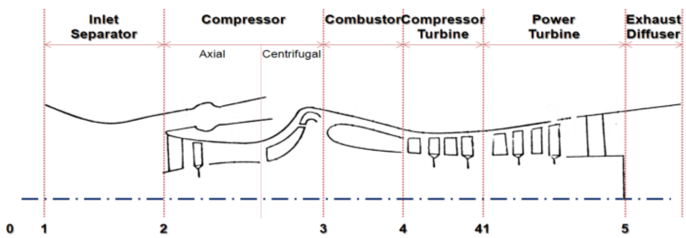

Fig. 2. Flow path configuration and station numbers of T-700 turboshaft engine

Table 1. Operating range of turboshaft engine

Altitude	0 ~ 2 Km
Flight Mach No.	0 ~ 0.3
Atmospheric temperature	-30 ~ +30 K

Table 2. Design point performance data at sea level, static and standard atmospheric condition

Mass flow rate (kg/s)	5.42
Overall pressure ratio	18
Compressor turbine exit temp. (K)	1,154
Exhaust gas temperature (K)	916
Power (Kw)	1,418.5
Specific fuel consumption (kg/kW/hr)	0.287

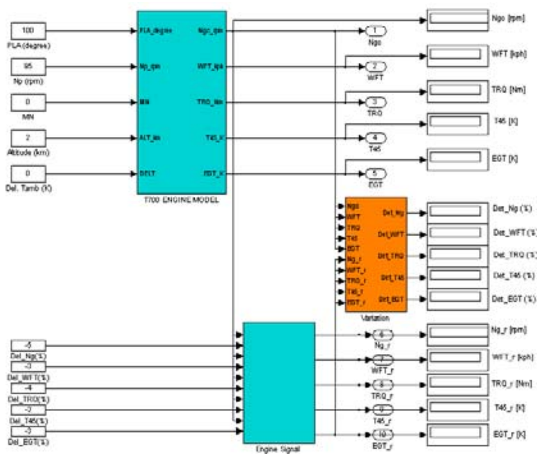

Fig. 3. GUI type on-line condition monitoring program

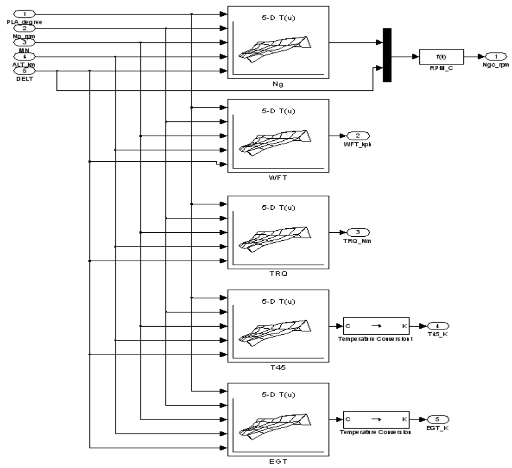

Fig. 4. Look-up table type base performance program module

Figure 3 shows a proposed on-line condition monitoring program. This program is composed of the base engine performance program module, the real engine performance monitoring module and the condition monitoring display module. Here the base engine performance program module is programmed by the look-up table type for improving calculation speed during mass flow and work matching.

During the initial phase of development of the on-condition monitoring program, since the real engine performance data are not available, a signal generation module is proposed for generating virtual engine performance data (See Fig. 5). This module can generate randomly arbitrary measuring performance data within ±5% changes. Measuring parameters provided by KUH turboshaft engine or the signal generator module are gas generator rotational speed (Ng), power turbine inlet temperature (PTT), exhaust gas temperature (EGT), fuel flow (WF), and torque (TRQ). The on-line condition monitoring program displays the differences between real time measuring performance data by engine or the signal generation module and the performance data calculated by the base engine performance module.

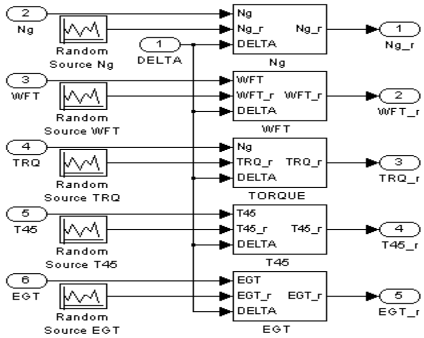

Fig. 5. Signal generation module for virtual measuring performance data

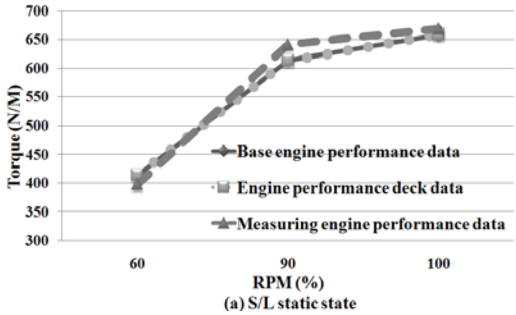

Fig. 6(a). Monitoring results of torque found at sea level static standard atmospheric condition

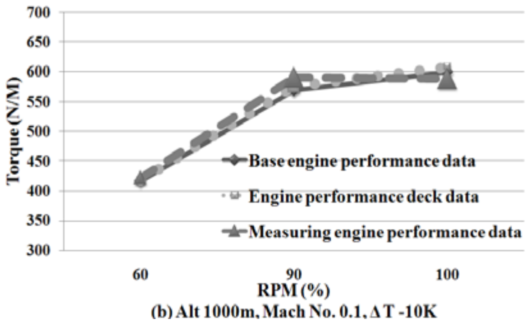

Fig. 6(b). Monitoring results of torque found at altitude of 1000m, MN0.1, T-10K from the standard atmospheric condition

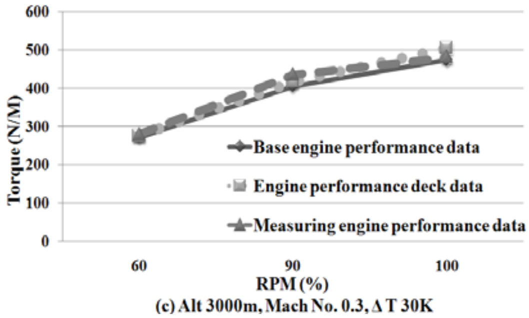

Fig. 6(c). Monitoring results of torque found at altitude of 3000m, MN0.3, T+30K from the standard atmospheric condition

Figure 6 shows monitoring results of torque found by the proposed on-line condition monitoring program at sea level static standard atmospheric condition, at an altitude of 1000m, Mach N0. 0.1 and at ΔT-10K from the standard atmospheric condition and at an altitude of 3000m, Mach N0. 0.3, at ΔT+30K from the standard atmospheric condition. In this graph, it is confirmed that the on-line condition monitoring program monitors well the performance data and moreover, performance results of the look-up table type base engine performance program module agrees well with engine performance deck data.

Fault Diagnostic Program

The proposed fault diagnostic program is composed of the Fuzzy Logic program for isolating faults from monitoring difference performance values and the Neural Network program for quantifying the isolated faults.

3.1 Fuzzy Logic program for isolating faults

Major component fault patterns are classified by single fault patterns of components such as compressor, compressor turbine and power turbine and multiple fault patterns of components where faults occur simultaneously on two or three components. Here fault patterns of gas path component of the KUH turboshaft engine are considered as 7 cases shown in Table 2.

According to Diakunchak's experimental results, the compressor fouling decreases both air mass flow parameter and isentropic efficiency of compressor, and the turbine corrosion or erosion increases air mass flow parameter but decreases isentropic efficiency [3].

Table 3 shows the measuring parameter change (MPC) trend on fault patterns.

Table 2. Considered fault patterns of KUH turboshaft engine.

Fault Pattern Cases (FPC)	Causes of faults
FP1	Compressor fouling
FP2	Compressor turbine erosion
FP3	Power Turbine Erosion
FP4	Comp. Fouling & Comp. turbine erosion
FP5	Comp. Fouling & Power turbine erosion
FP6	Comp. turbine erosion & Power turbine erosion
FP7	Comp. Fouling & Comp. turbine erosion & Power turbine erosion

Table 3. Measuring parameter change (MPC) trend depending on fault patterns

MPC / FPC	⊿Ng	⊿PTT	⊿EGT	⊿WF	⊿TRQ
FP1	−	+	+	+	−
FP2	−	+	+	+	+
FP3	+	−	−	−	−
FP4	−	+	+	+	+
FP5	−	+	+	−	−
FP6	−	+	+	+	+
FP7	−	+	+	+	+

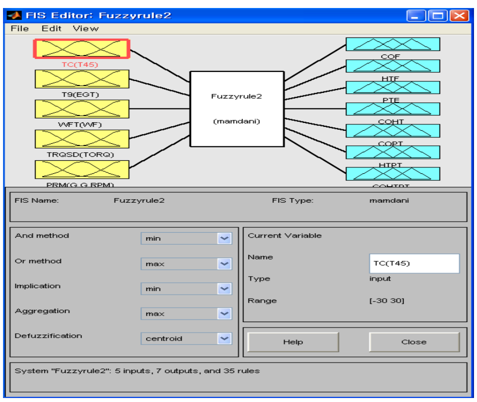

Fig. 5. MAMDANI type Fuzzy inference system for isolating faulted components.

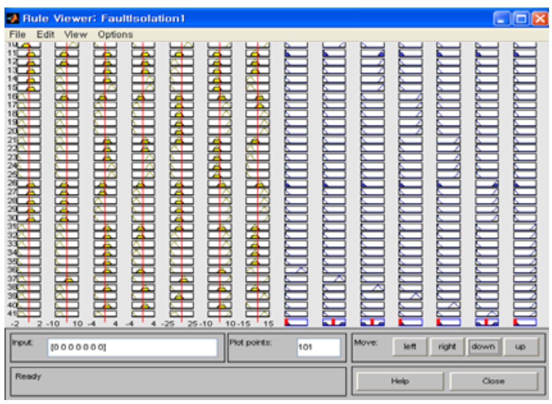

Fig. 6. Fuzzy rule generated by measuring parameter change trend

Here the single fault pattern case FP1 of the compressor fouling has the following trend of measuring parameters; increases of power turbine inlet temperature change, exhaust gas temperature change and fuel flow change, and decreases of gas generator rotational speed change, torque change. However the multi fault pattern case FP7, which is compressor fouling, compressor turbine erosion and power turbine erosion, has the following trend of measuring parameters; increases of power turbine inlet temperature change, exhaust gas temperature change, fuel flow change and torque change, and decrease of gas generator rotational speed change.

In order to isolate the faulted components, the MAMDANI type Fuzzy Inference System is developed using FIS editor of MATLAB [4][5]. This program can identify the faulted components from data base of measuring parameter changes and trends (See Fig. 5).

Input data for fuzzyfication of the inference system are changes between measuring engine performance data due to faulted components and calculating base performance data, having output for 7 fault pattern cases. The MAMDANI theory is applied to fuzzyfication, and the Centroid method is applied to defuzzyfication. The fuzzy rule depending on measuring parameter change trend is generated as Fig. 6[6][7].

4.2 Neural Network program for quantifying faults

In the proposed Neural Network program, the FFBP (Feed Forward Back Propagation) algorithm is used for training Neural Networks using measuring performance data changes and component performance characteristic parameter changes due to faulted components. The Neural Network is composed of an input layer with 5 neurons, a hidden layer with a neuron and an output layer with 6 neurons. The 5 neurons of input layer are measuring parameter changes of Ng, PPT, EGT, WF and TRQ, and the 6 neurons of output layer are changes of mass flow parameters and isentropic efficiencies of compressor, high pressure turbine and power turbine, respectively.

The tangent sigmoid function (1) is used as a transfer function of the hidden layer, and the linear (2) function is used as a transfer function of the output layer [8].

$$y = \frac{e^{\alpha x} - e^{-\alpha x}}{e^{\alpha x} + e^{-\alpha x}} \tag{1}$$

$$y = x \tag{2}$$

In order to increase learning speed as well as to maintain stability during training process, LRF (Learning Rate Factor) is increased by 10% of the previous LRF if the error is decreased, but LRF is decreased by 50% of the previous LRF if the error is increased. Here the error is defined in the form of RMS (Root Mean Square) value (3). Where T is target value, y is the output value calculated by Neural Network, and n is the number of output layer neurons. The target maximum RMS error is fixed as 1.5%, here.

$$RMS\ error = \sqrt{\frac{\sum_{i=1}^{n}\left(y_n - T_n\right)^2}{n}} \tag{3}$$

In order to build database for training the Neural Work, 1~5% decreases of both mass flow parameter and isentropic efficiency due to compressor fouling are assumed, and 1~5% increase of mass flow parameter and 1~5% decrease of isentropic efficiency due to turbine erosion are assumed. In addition, engine operating conditions are assumed as 1000m, 2000m and 3000m of altitudes, Mach No. 0.1, 0.2, 0.3 0f flight speeds, and ±10K, ±20K and ±30K changes from standard atmospheric temperatures. Database of faulted components for training Neural Network with operating conditions mentioned as the above are obtained by GASTURB program [9].

Verification of Proposed Diagnostic Program

Through the following example, the proposed diagnostic program is verified. Measuring parameter changes shown as Table 5 are obtained by implanted faults assumed as Table 4 using the base performance module of the on−line condition monitoring program. If the diagnostic program can identify the implanted faults with the measuring parameter changes and trends, it is confirmed that this diagnostic program is verified.

Firstly, measuring parameter changes due to 7 component fault pattern cases are entered as input data of the Fuzzy Inference System program. This Fuzzy Inference System isolates 7 component fault pattern cases from input data though fuzzyfication and defuzzycation using the previously generated Fuzzy rules. Table 6 shows results of faulted components isolated by the proposed Fuzzy Inference System. Here, if the largest value among fault pattern results calculated by given measuring parameter changes using the Fuzzy Inference System is approaching to 1, the largest value becomes a possible component fault pattern. As shown in Table 6, because the diagonal values are larger than other values, the fault patterns related to diagonal values is the isolated fault pattern result. Therefore, it is confirmed that the isolating fault patterns obtained from fault monitoring program are same as the implanted fault patterns.

In the next step, measuring performance parameter changes of the faulted components isolated by Fuzzy Inference System are given as input to the Neural Network diagnostic program learned by training database.

Table 4. Implanted fault values (IFV) of engine major components

IFV FPC	COM A	COE F	HTM A	HTE F	PTM A	PTE F
FP1	−2	−3	0	0	0	0
FP2	0	0	4	−2	0	0
FP3	0	0	0	0	4	−2
FP4	−2	−3	2	−3	0	0
FP5	−2	−2	0	0	2	−3
FP6	0	0	2	−3	2	−3
FP7	−2	−3	2	−3	2	−3

Table 5. Measuring parameter changes due to implanted faults (%)

MPC FPC	Ng	PTT	EGT	W F	TR Q
FP1	4.04	5.025	3.828	0.6	−1.9 2
FP2	7.348	7.328	11.432	8.8	−2.3 5
FP3	−1.73 5	−1.73 1	−4.33 2	−7.9	1.08
FP4	14.529	14.503	17.241	9.9	−4.7 7
FP5	4.598	4.585	1.494	−5.6	−1.3 5
FP6	7.988	7.966	9.814	2.4	−2.1 4
FP7	13.759	13.735	14.359	3.1	−4.1 4

Table 6. Results of faulted components isolated by Fuzzy Inference System (IFPC: Input fault pattern cases, OFPC: Output fault pattern cases)

OFPC IFPC	1	2	3	4	5	6	7
IFP1	0.55	0.29	0.13	0.20	0.17	0.17	0.28
FP2	0.25	0.53	0.20	0.41	0.10	0.10	0.10
FP3	0.24	0.24	0.64	0.09	0.35	0.08	0.08
FP4	0.25	0.45	0.23	0.53	0.09	0.09	0.09
FP5	0.11	0.11	0.11	0.11	0.89	0.11	0.11
FP6	0.13	0.22	0.11	0.15	0.09	0.80	0.20
FP7	0.16	0.16	0.16	0.3	0.09	0.44	0.56

Figures 7, 8, 9, 10, 11, 12 and13 show degraded characteristic values of the single and multiple faulted components found by Neural Network diagnostic program.
Figure 14 shows RMS errors of estimation of 7 fault pattern cases using the proposed Neural Network diagnostic program Through these comparisons, it is confirmed that the degraded characteristic values of the faulted components are well agreed with the implanted degraded characteristic values of the faulted components with less than 1 % RMS error.

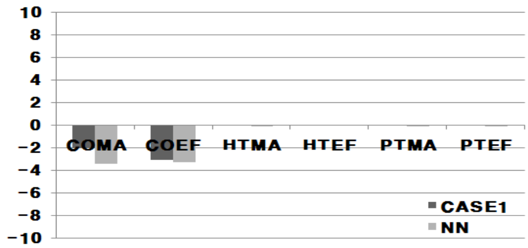

Fig. 7. Degraded characteristic values of the faulted compressor found by Neural Network diagnostic program (FP1: single fault)

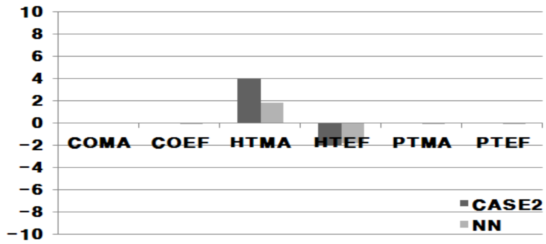

Fig. 8. Degraded characteristic values of the faulted compressor turbine compressor turbine found by Neural Network diagnostic program (FP2: single fault)

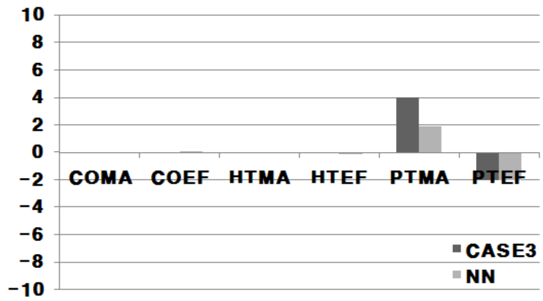

Fig. 9. Degraded characteristic values of the faulted power turbine found by Neural Network diagnostic program (FP3: single fault).

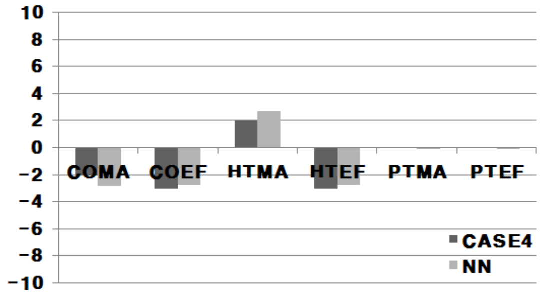

Fig. 10. Degraded characteristic values of the faulted compressor and compressor turbine found by Neural Network diagnostic program(FP4: double fault)

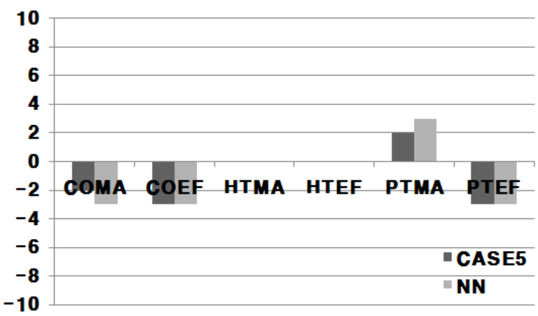

Fig. 11. Degraded characteristic values of the faulted compressor and power turbine found by Neural Network diagnostic program (FP5: double fault)

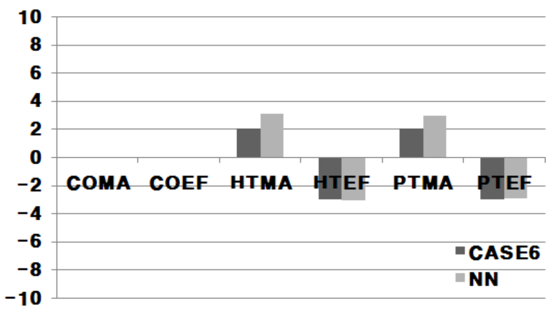

Fig. 12. Degraded characteristic values of the faulted compressor turbine and power turbine found by Neural Network diagnostic program(FP6: double fault)

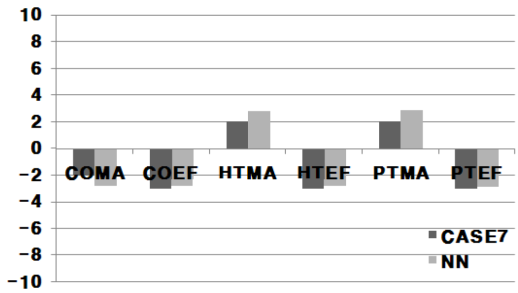

Fig. 13. Degraded characteristic values of the faulted compressor, compressor turbine and power turbine found by Neural Network diagnostic program (FP7: triple fault)

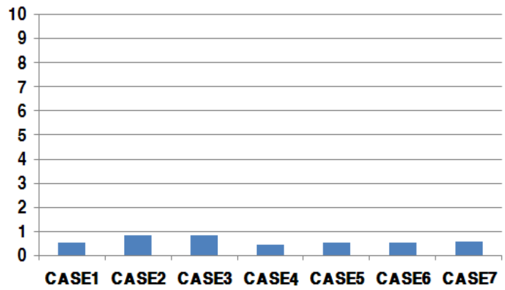

Fig. 14. RMS errors of estimation of 7 fault pattern cases using Neural Network diagnostic program

Conclusion

The present work proposes an effective and user friendly GUI-type on-line diagnostic program, which can monitor, isolate and quantify the component faults, using SIMULINK and Fuzzy-Neuro algorithms for a helicopter turboshaft engine.

This program is composed of the on-line condition monitoring program to monitor on-line measuring performance condition, the fuzzy inference system to isolate the faults from measuring data and the neural network to quantify the isolated faults.

The proposed on-line diagnostic program is performed through application example to KUH turboshaft engine health monitoring. Through this verification, it is confirmed that the degraded characteristic values of the faulted components are compared well with the implanted degraded characteristic values of the faulted components with less than 1 % RMS error.

Acknowledgments

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References

1. Urban, L.A., "Gas Path Analysis Applied to Turbine Engine Condition Monitoring", J. of Aircraft, Vol.10, No. 7, 1972, pp. 400-406.

2. Jayoung Ki, Changduk Kong, Seonghee Kho, Jaehwan Kim, Ieeki Ahn, Daesung Lee, "Development of On-line Performance Diagnostics Program of a Helicopter Propulsion System", ASME TURBO EXPO 2009, 2009-GT-59519.

3. Diakunchak, I. S., "Performance Deterioration in Industrial Gas Turbines", Journal of Engineering for Gas Turbines and Power, Vol. 114, 1992, pp. 161-167.

4. Lee, H. Y., Mun, G. I., 1999, "Fuzzy-Neuro using MATLAB", A-Jin.

5. Changduk Kong, Seonghee Kho, Jayoung Ki, Changho Lee, "A Studys Multi Fault Diagnostics of Smart Unmanned Aerial Vehicle Propulsion System Using Data Sorting and Neural Networks", ASME TURBO EXPO 2008, 2008-GT-50769.

6. Tsoukalas, L.H. and Uhrig, R.E., 1997, "Fuzzy and Neural Approaches in Engineering", John Wiley & Sons, Inc.

7. Lotfi, A. Z., 1998, "Fuzzy Logic Toolbox", MATLAB User's Guide.

8. Heykin, S., 1994, "Neural Networks - A Comprehensive Foundation", Macmilian.

9. Kurzke, J., 2001, "A Program to caculate Design and Off-Design Performance of Gas Turbines", GasTurb 9 User's Manual.