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STUDY ON FAULT DIAGNOSTICS OF A TURBOPROP ENGINE USING INVERSE PERFORMANCE MODEL AND ARTIFICIAL INTELLIGENT METHODS

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ABSTRACT

Recently, the health monitoring system of major gas path components of gas turbine uses mostly the model based method like the Gas Path Analysis (GPA). This method is to find quantity changes of component performance characteristic parameters such as isentropic efficiency and mass flow parameter by comparing between measured engine performance parameters such as temperatures, pressures, rotational speeds, fuel consumption, etc. and clean engine performance parameters without any engine faults which are calculated by the base engine performance model.

Recently, the expert engine diagnostic systems using the artificial intelligent methods such as Neural Networks (NNs), Fuzzy Logic and Genetic Algorithms (GAs) have been studied to improve the model based method. Among them the NNs are mostly used to the engine fault diagnostic system due to its good learning performance, but it has a drawback due to low accuracy and long learning time to build learning data base if there are large amount of learning data. In addition, it has a very complex structure for finding effectively single type faults or multiple type faults of gas path components.

This work builds inversely a base performance model of a turboprop engine to be used for a high altitude operation UAV using measured performance data, and proposes a fault diagnostic system using the base engine performance model and the artificial intelligent methods such as Fuzzy logic and Neural Network.

The proposed diagnostic system isolates firstly the faulted components using Fuzzy Logic, then quantifies faults of the identified components using the NN leaned by fault learning data base, which are obtained from the developed base performance model. In leaning the NN, the Feed Forward Back Propagation (FFBP) method is used.

Finally, it is verified through several test examples that the component faults implanted arbitrarily in the engine are well isolated and quantified by the proposed diagnostic system.

NOMENCLATURE

COMA	Compressor Mass Flow
COEF	Compressor Efficiency
EGT	Exhaust Gas Temperature
FC	Fault Case
FIS	Fuzzy Inference System
FFBP	Feed Forward Back Propagation
GAs	Genetic Algorithms
GPA	Gas Path Analysis
HTMA	High pressure Turbine Mass Flow
HTEF	High pressure Turbine Efficiency
IFC	Input Fault Cases
ITT	Inter Turbine Temperature (T5)
LRF	Learning Rate Factor
MF	Fuel Flow
MPC	Measured Parameter Change
NNs	Neural Networks
OFC	Output Fault Cases
PTMA	Power Turbine Mass Flow
PTEF	Power Turbine Efficiency
RC	Flight Rating Code
RMS	Root Mean Square
T	Total Temperature
TRQ	Torque
UAV	Unmanned Aerial Vehicle
φ	Activation function
x_i	Input neuron values
y_i	Output neuron values thru activation function applied to the weighted sum of the inputs

INTRODUCTION

In operation of the aircraft propulsion system, high reliability, high availability and low operational cost are very important issues for both engine manufacturer and user. Therefore, development and application of aircraft propulsion condition monitoring and diagnostics are recently generalized. Especially, in case of the propulsion system which is operated for long time in severe operating conditions of high altitude more than 11Km (36000ft), the health monitoring system must be required for precaution and maintenance action against faults or performance degradation of the engine. Therefore, a condition monitoring is needed to enhance reliability and availability of the propulsion system. The model based condition monitoring method which can monitor quantitatively the condition of major gas path components can be realized by analyzing changes of mass flow parameter and efficiency of each component [1]. However, because direct measured of these component performance characteristic parameter changes is impossible during the flight, they can be indirectly obtained from changes of measurable performance parameters such as temperature, pressure, rotational speed, fuel flow, etc. Therefore, a step to monitor the performance trend must be performed before the engine diagnostics. The performance trend monitoring can be realized by using performance differences between the real measured engine performance data and the base performance data calculated by the base engine performance simulation program.

Recently, advanced diagnostic methods using NNs, Fuzzy Logic, GAs, the knowledge and rule based Expert System, etc. have been studied to improve the model based diagnostic methods of gas turbine engines. Among them, the NNs is mostly used in diagnostic systems due to good learning capability, but it has drawbacks due to taking longer learning time and lower accuracy if learning data are increased[2]. Moreover, the NNs structure becomes more complex in effective diagnostics of the multiple component faults.

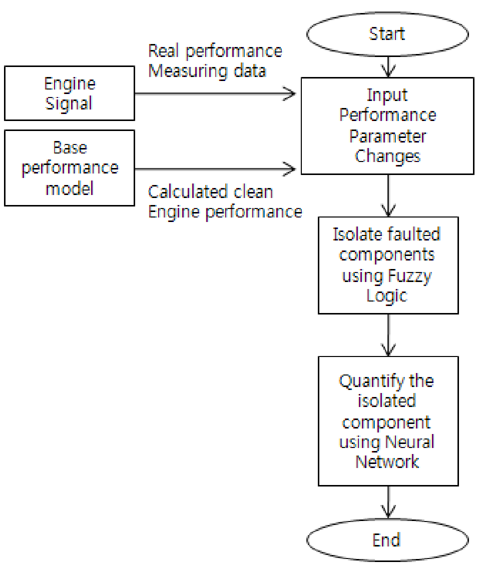


Fig. 1 Flowchart of proposed diagnostic system

Therefore, this work proposes a new effective diagnostic system using the accurate base engine performance model of PWC PT6A-67 turboprop engine, Fuzzy and NN. Figure 1 shows the flow of the proposed diagnostic system in this work.

In order to obtain measured performance parameter changes as input data for the diagnostic system, firstly the base engine performance model, which can accurately estimate clean engine performance, must be needed. Therefore this work generates inversely component maps of the PWC PT6A-67 turboprop engine using limited performance deck data provided by engine user and considering the high altitude engine behaviors, and then develops the base engine performance simulation program using the generated component maps.

Using the obtained measured performance parameter changes, the faulted components are isolated using Fuzzy Logic, and then the isolated components are quantified using the NN learned by the learning data set. The verification is carried out by showing several test examples how well the proposed diagnostic system can detect the component faults due to intentionally implanted faults.

TARGET ENGINE AND INVERSE MODELING

The target engine for this work is PWC PT6A-67 turboprop engine which will be used for a long endurance UAV in the high altitude operation. This engine is composed of 4 stages axial and 1 stage centrifugal compressor, reverse annular vaporizing combustor, 1 stage axial compressor turbine, and 2 stages axial free power turbine with constant speed control. Moreover it has 2 stage reduction gear box, and the power is flat-rated to 1200 hp.

Figure 2 shows the schematic view of PT6A-67 turboprop engine, and Table 1 illustrates design point performance data of this engine [3].

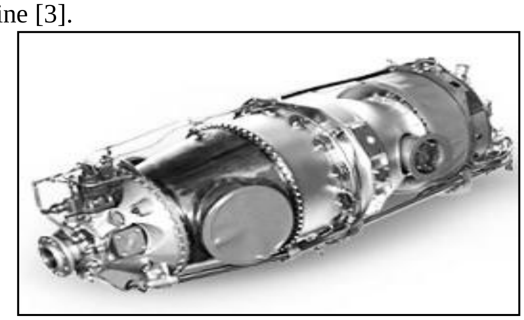


Fig.2 Schematic view of PT6A-67 turboprop engine

Table 1 Design point performance of PT6A-67 turboprop

Operation Conditions	Static Standard
Gas Generation rpm	39,000
Power Turbine rpm	29,894
Propeller rpm	1,700
ITT (K)	1,113
Shaft Power (SHP)	1,726(Flat-rated to 1200)

Gas turbine engine performance relies on its components' performance characteristics. Because component maps can be generally obtained by lots of experimental tests at various operating conditions, it takes long time and needs high cost. Thus, most engine manufacturers do not want to provide component maps to engine purchasers. Therefore engine users, who want to develop the engine performance simulation model, have generated component maps using the scaling method from similar component maps. However this method is generally inaccurate at off-design points. Especially, because the high altitude operation of the engine influences greatly the engine performance due to getting worse compressor surge characteristics by much lower ambient temperature and pressure than design point performance, the scaling method has much greater error.

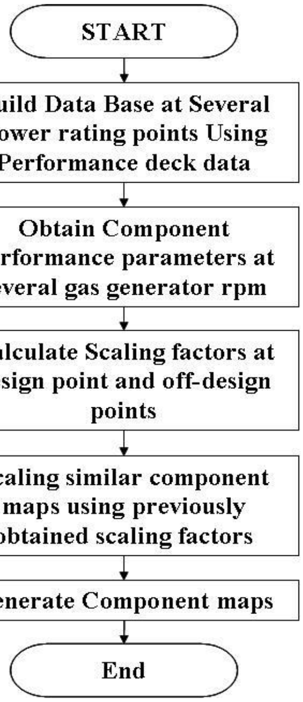
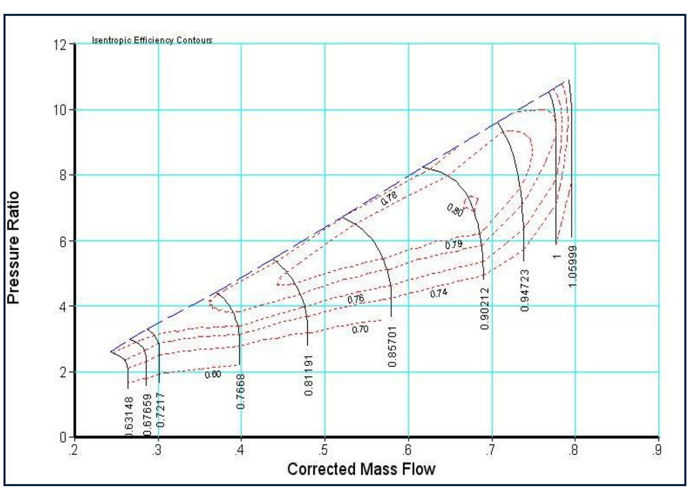


Fig.3 Flowchart of component map generation

Therefore this work proposes a new method which can generate inversely component maps of PT6A-67 turboprop engine using limited engine performance deck data and considering high altitude operation behavior. The previous map generation method using the system identification method was an extended scaling method considered only the shaft rotational speed without consideration of altitude and flight speed variation [4]. Figure 3 illustrates the flow how to generate inversely the component maps from engine performance deck data. Figure 4 shows the inversely generated component maps such as compressor map, compressor turbine map and power turbine map considering high altitude operation behavior using the proposed map generation method.



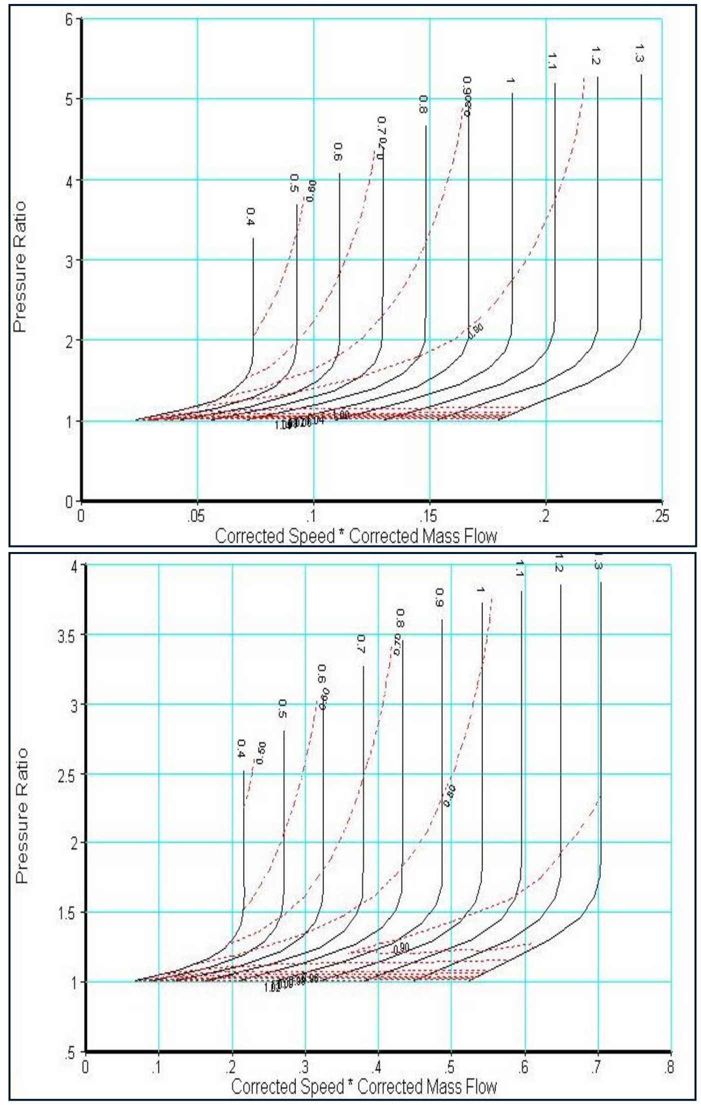


Fig. 4 Component maps generated by the proposed inverse method

Figure 5 shows the steady-state base performance model of the turboprop engine and the compressor subsystem using SIMULINK. The performance model is composed of Ambient & Intake subsystem for analyzing flight and ambient conditions and intake losses, the compressor subsystem for analyzing compressor performance, the combustor subsystem for analyzing combustor performance, the compressor turbine subsystem for analyzing compressor turbine performance, the power turbine subsystem for analyzing power turbine performance, and the matching subsystem for matching work and mass flow rate between components.

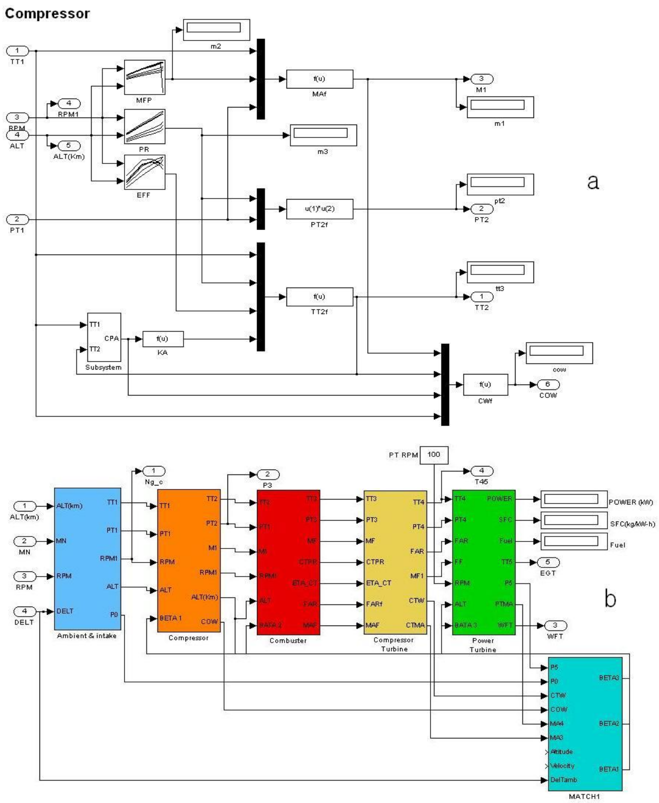


Fig. 5 a : Compressor Subsystem module, b : Base performance simulation program using SIMULINK

FAULT DIAGNOSTIC PROGRAM

The proposed fault diagnostic program is composed of the Fuzzy Logic program for isolating faults from the monitored performance parameter changes and the Neural Network program for quantifying the isolated faults.

Major component fault patterns are considered as the single component fault patterns such as compressor fouling, compressor turbine erosion and power turbine erosion, and multiple component fault patterns combinations of two or three single component faults. Table 2 shows seven fault component pattern cases of the turboprop engine considered in this work.

Table 2 Considered component fault pattern cases

Fault Cases (FC)	Causes of faults
FC1	Compressor fouling
FC2	Compressor turbine erosion
FC3	Power Turbine Erosion
FC4	Comp. Fouling & Comp. turbine erosion
FC5	Comp. Fouling & Power turbine erosion
FC6	Comp. turbine erosion & Power turbine erosion
FC7	Comp. Fouling & Comp. turbine erosion & Power turbine erosion

According to Diakunchak's experimental results [5], the compressor fouling give rise to decrease both air mass flow parameter and isentropic efficiency of the compressor, and the turbine corrosion or erosion give rise to increase air mass flow parameter of the turbine but decrease isentropic efficiency of the turbine. These component performance parameter change trends due to several types of faults are directly applied to the proposed fault diagnostic program.

Table 3 shows the measured parameter change (MPC) trends depending on various component fault patterns. Where +, ++ and +++ mean low, medium and high increase of parameter changes respectively, and -, -- and --- mean low, medium and high decrease of parameter changes respectively.

In order to isolate the faulted components, the MAMDANI type Fuzzy Inference System (FIS) shown as Figure 6, which is developed using FIS editor of MATLAB. The detail of the FIS editor and SIMULINK are explained in references [6][7]. This program can isolate the faulted components from measured performance parameter changes and trends. Moreover, it can link easily with the proposed health monitoring system for the PT6A-67 turboprop engine using MATLAB and SIMULINK.

Table 3 Measured parameter change (MPC) trends depending on component fault patterns

MPC / FC	ΔITT	ΔEGT	ΔMF	ΔTRQ
FC1	+	+	++	+
FC2	+	+	+++	+
FC3	-	-	-	--
FC4	++	++	+++	++
FC5	++	++	++	+
FC6	++	++	+++	+
FC7	+++	+++	+++	+

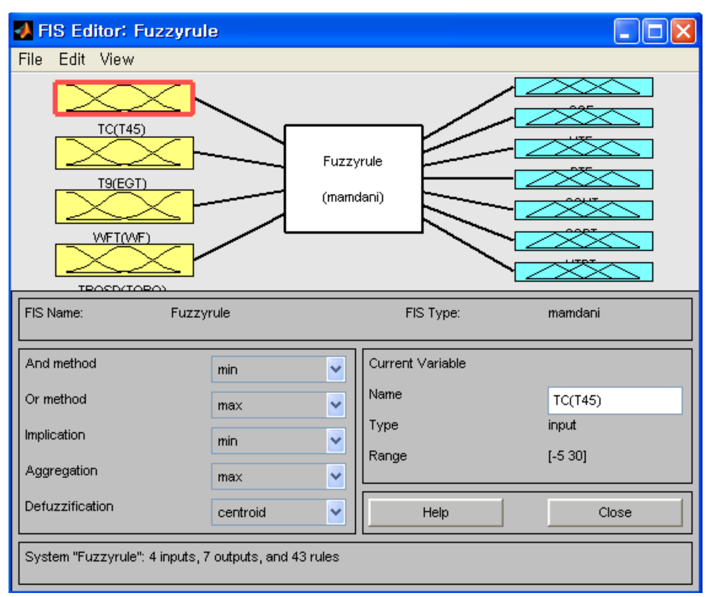


Fig. 6 MAMDANI type Fuzzy Inference System for isolating faulted components

Input data for fuzzyfication of the inference system are deltas between the measured engine performance data with faulted components due to 7 fault pattern cases and the calculated clean engine performance data. The MAMDANI theory is applied to fuzzyfication, and the Centroid method is applied to defuzzyfication. The fuzzy rule following measured parameter change trends is generated as Figure 7 [8][9].

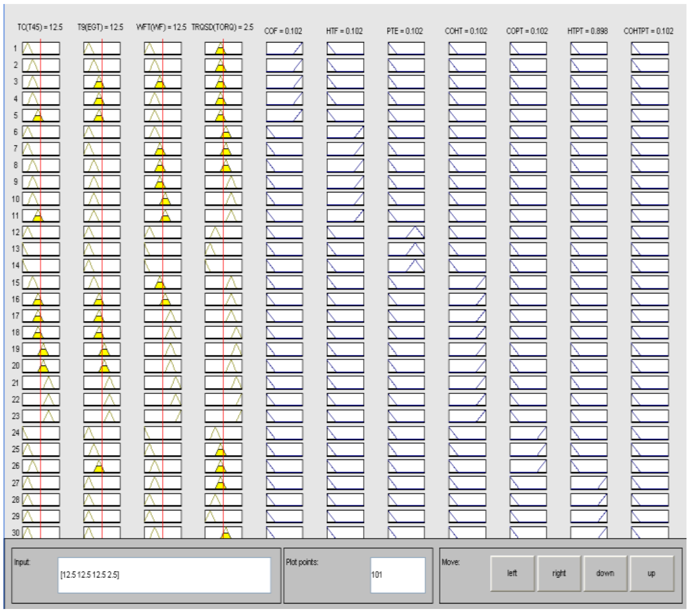
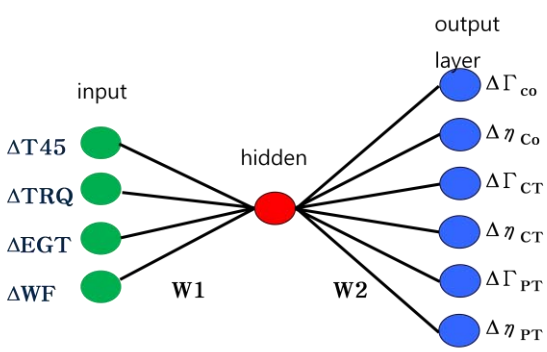


Fig. 7 Fuzzy rule generated by measured parameter change trend

The Feed Forward Back Propagation (FFBP) algorithm shown as Figure 8 is used for learning the proposed NNs using measured performance data changes and component performance characteristic parameter changes due to faulted components. The NN is composed of an input layer with 4 neurons, a hidden layer with a neuron and an output layer with 6 neurons. Because the proposed fault diagnostic system can isolate the faulted components using Fuzzy Logic prior to using the NN, the proposed system is simplified by a hidden layer to avoid the computational complication. The 4 neurons of input layer are measured parameter changes of ITT, EGT, MF 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.



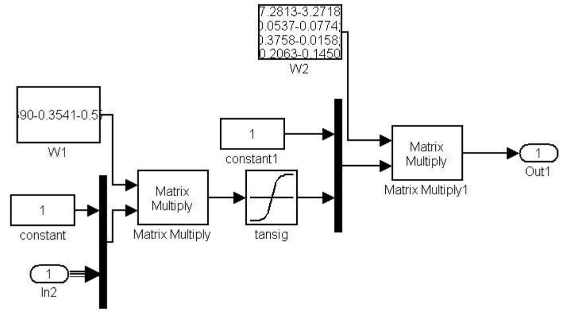


Fig. 8 Feed forward Neural Network program using SIMULINK

The proposed NN is made of neurons, each performing a weighted sum of its own inputs. The sum is the passed through the activation function. The out of the j-th neuron is expressed as:

$$y_j = \varphi_j\left(\sum_{i=0}^{N} w_{ji} \cdot x_i\right) \tag{1}$$

where φ is the activation function applied to the weighted sum of the inputs (x_i). In this step, both bias and noise are not considered because the on-line performance monitoring system linked to the NN which can remove the bias and the noise prior to applying the fault diagnostic system. The weights w_i are updated through Back Propagation learning using equation (2) until satisfying the target RMS error shown as equation (5).

$$W_{ij}(new) = W_{ij}(old) + \Delta W_{ij} \tag{2}$$

where initial weight values are randomly assumed, and they not influencing the learning process because of obtaining optimal values through the following algorithm.

Figure 9 shows the flow of the proposed Back Propagation algorithm.

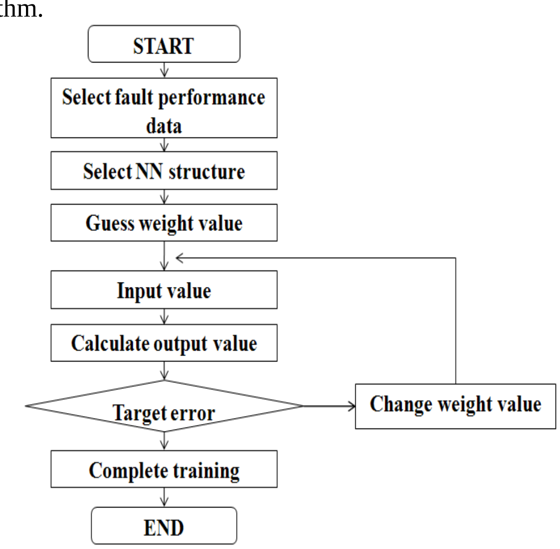


Fig. 9 Back Propagation algorithms for training Neural Network

The tangent sigmoid function (3) is used as an activation function of the hidden layer, and the piecewise-linear (4) function is used as an activation function of the output layer [10], [11].

$$\varphi = \frac{e^{\alpha x} - e^{\alpha x}}{e^{\alpha x} - e^{-\alpha x}} \tag{3}$$

$$\varphi = \mathrm{x} \tag{4}$$

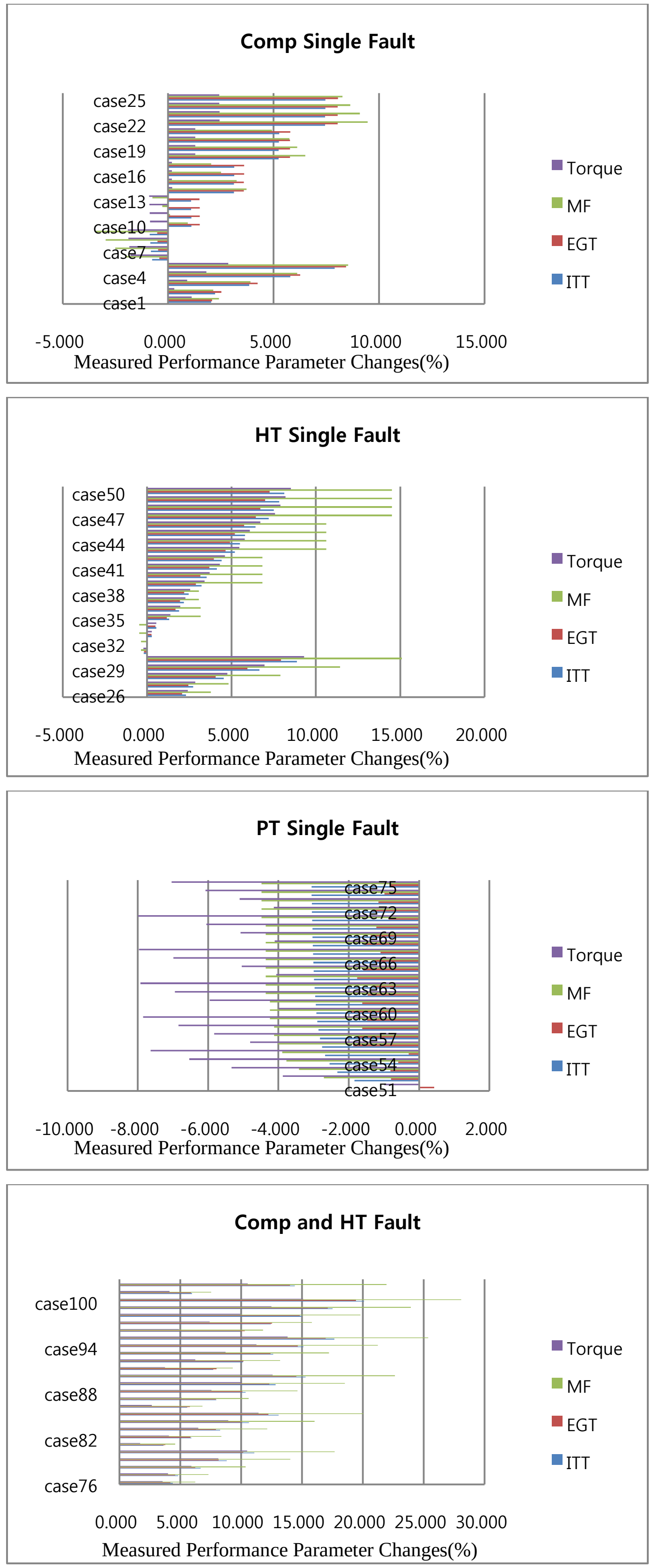
In order to increase learning speed as well as to maintain stability during training process, LRF (Learning Rate Factor) is increased by 10% of the previous LRF if the error is decreased, but LRF is decreased by 50% of the previous LRF if the error is increased. Here the error is defined in the form of RMS (Root Mean Square) value (5). 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.

$$RMSerror = \sqrt{\frac{\sum_{i=1}^{n}(y_i - T_i)^2}{n}} \tag{5}$$

In order to build data base for learning 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 9.1Km (30000ft), 12.2Km (40000ft) and 13.7Km (45000ft) of altitudes, Mach No. 0.1, 0.2, 0.3, 0.4, 0.5 of flight speeds, and 100%, 80%, 60%, 30% changes from engine cruise conditions. These operating conditions are provided by the special flight vehicle system requirements. Data base of faulted components for training Neural Network with operating conditions mentioned as the above are obtained by engine model program.

Figure 10 shows changes of measured performance parameters due to 1~5 % degradation of component characteristic values such as mass flow parameter and isentropic efficiency at 13.7Km (45000ft), Mach No. 0.3, 80% cruise condition. The horizontal axis values of Fig. 10 are differences in % between clean engine performance parameters and deteriorated engine performance parameters due to implanted component degradations. These training datasets are used only for training the proposed NN. The validation datasets are separately produced from the training datasets.

All datasets have 4811 by 283 degradation cases with 17 altitude, flight speed and RC (flight rating code) conditions. Figure 10 shows only few cases for demonstration.



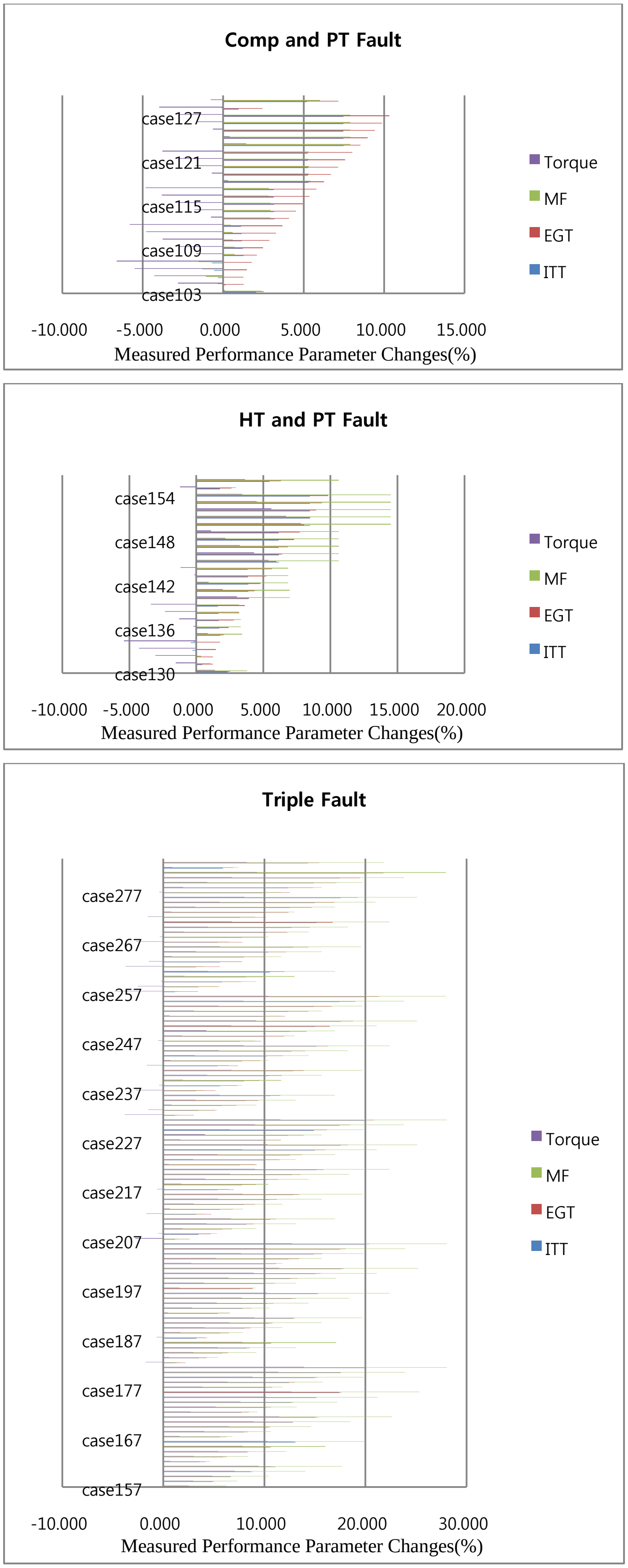


Fig. 10 Measured Performance Parameter Changes due to implanted faults

VERIFICATION OF PROPOSED DIAGNOSTIC PROGRAM

Through the following example, the proposed diagnostic program is verified. Measured parameter changes shown as Table 5 are obtained by implanted faults assumed as Table 4 using the base engine model program. If the diagnostic program can identify the implanted faults with the measured parameter changes and trends, it is confirmed that this diagnostic program is verified.

Firstly, measured 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 Fuzzy Inference System are given as input to the Neural Network diagnostic program learned by training data based. Here, if the largest value among fault pattern results calculated by given measured parameter changes using the Fuzzy Inference System is approaching to 1, the largest value becomes a possible component fault pattern. In the Table 6, IFC1, i.e. input (or implanted) fault case 1, has 0.51 at OFC1, i.e. output fault case 1, which is the highest value among 7 fault patterns, so this case has high possibility about a single fault with contamination fault of compressor. IFC7 has the highest value of 0.56 at pattern 7; therefore this case has high possibility about a multi fault case with contamination fault of compressor, erosion of compressor turbine and erosion of power turbine. As explanation the above, IFC2, IFC3, IFC4, IFC5 and IFC6 also have highest values at fault pattern 2, 3, 4, 5 and 6, respectively.

Therefore, it is confirmed that the isolating fault patterns obtained from fault monitoring program are same as the implanted fault patterns.

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

IFV / FC	COMA (%)	COEF (%)	HTMA (%)	HTEF (%)	PTMA (%)	PTEF (%)
FC1	-5	-3	0	0	0	0
FC2	0	0	5	-3	0	0
FC3	0	0	0	0	5	-3
FC4	-4	-2	4	-2	0	0
FC5	-4	-2	0	0	4	-2
FC6	0	0	4	-2	4	-2
FC7	-5	-5	5	-5	4	-4

Table 5 Measured parameter changes due to implanted faults (%)

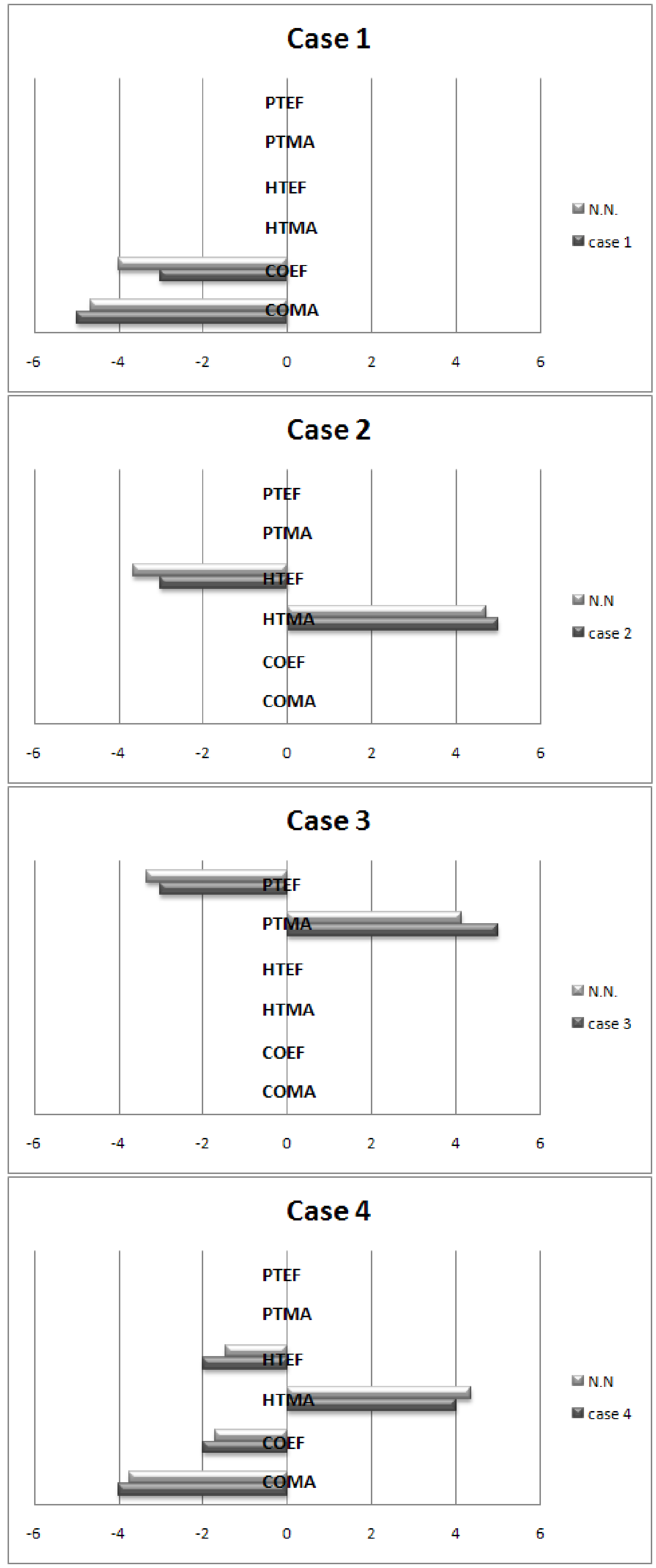
MPC / FC	ΔITT	ΔEGT	ΔMF	ΔTRQ
FC1	7.435	8.067	8.571	2.446
FC2	7.817	7.027	14.367	8.231
FC3	-3.051	-0.933	-4.408	-6.078
FC4	14.385	14.072	21.714	10.588
FC5	5.196	7.226	5.959	-0.762
FC6	5.463	6.372	10.531	3.643
FC7	19.986	21.518	27.755	10.456

Table 6 Results of faulted components isolated by Fuzzy Inference System (IFC: Input fault cases, OFC: Output fault cases)

OFC / IFC	1	2	3	4	5	6	7
IFC1	**0.51**	0.09	0.08	0.08	0.43	0.26	0.09
IFC2	0.47	**0.58**	0.08	0.08	0.09	0.45	0.09
IFC3	0.09	0.09	**0.68**	0.08	0.09	0.08	0.09
IFC4	0.09	0.41	0.08	**0.57**	0.09	0.08	0.43
IFC5	0.40	0.09	0.20	0.08	**0.56**	0.08	0.09
IFC6	0.43	0.09	0.22	0.08	0.28	**0.52**	0.09
IFC7	0.45	0.27	0.08	0.45	0.28	0.47	**0.56**

In the next step, measured performance parameter changes of the faulted components isolated by the FIS are given as input to the NN diagnostic program learned by training data base.

Figures 11 shows degraded characteristic values of the single and multiple faulted components found by the proposed NN diagnostic program. In the figures, case 1~7 means implanted degradations respectively, and the N.N. means the identified degradations of each fault pattern by the NN diagnostic program.



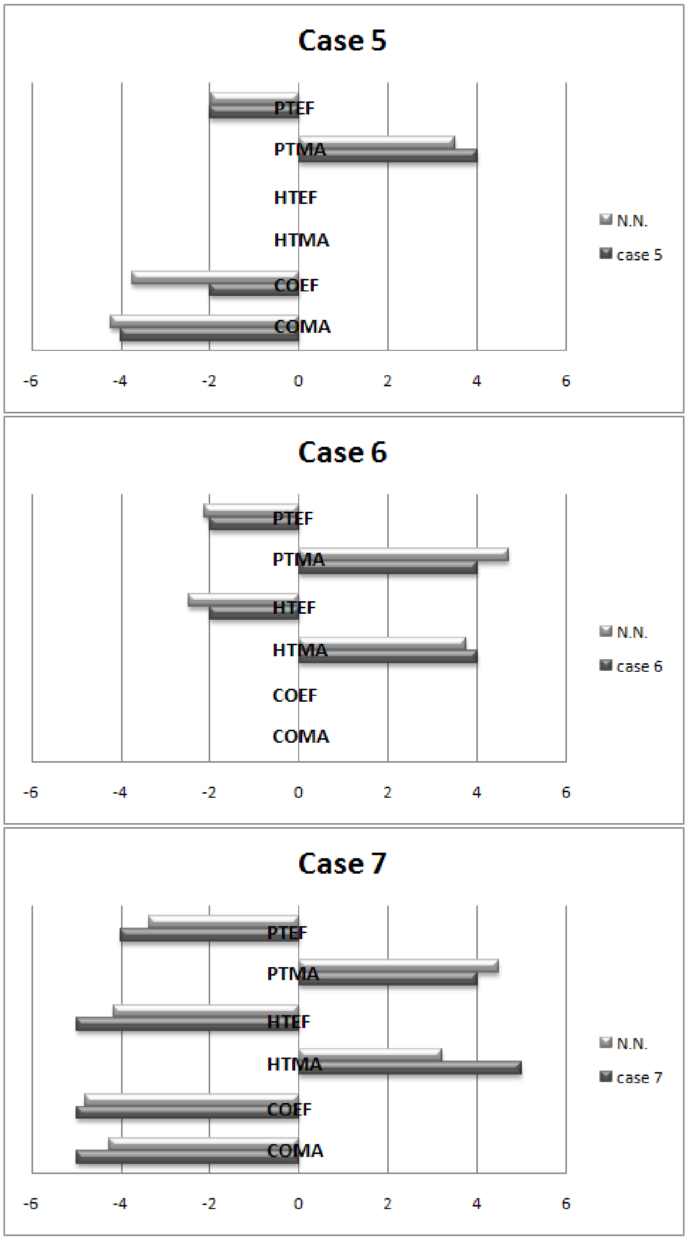


Fig. 11 Results of faulted components quantified by Neural Network diagnostic program

As shown in Fig. 11, the proposed Fuzzy-Neuro diagnostic program isolates exactly the faulted components for all the 7 fault pattern cases, but the degradation results of the isolated faulted components quantified by the program have some amounts of errors. The error will be decreased by leaning with more various case learning data and best selection of measured parameters.

CONCLUSION

The present work develops the performance analysis program using inversely generated component maps and SIMULINK, and the fault diagnostic program which can monitor, isolate and quantify the component faults using Fuzzy-Neuro algorithms for the PT6A-67 turboprop engine of a long endurance UAV in the high altitude operation.

The proposed diagnostic system isolates firstly the faulted gas path components using Fuzzy Logic, and then quantifies the isolated components using the FFBP NN learned by learning data sets of various fault patterns. Through the verification examples, it is confirmed that the proposed diagnostic system can isolate accurately the faulted gas path components as well as quantify the isolated components.

In the next work, the proposed fault diagnostic system will be applied to the real engine under consideration of sensor fault, noise and bias.

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