A Study on Fault Detection of a Turboshaft Engine Using Neural Network Method

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Abstract

It is not easy to monitor and identify all engine faults and conditions using conventional fault detection approaches like the GPA (Gas Path Analysis) method due to the nature and complexity of the faults. This study therefore focuses on a model based diagnostic method using Neural Network algorithms proposed for fault detection on a turbo shaft engine (PW 206C) selected as the power plant for a tilt rotor type unmanned aerial vehicle (Smart UAV). The model based diagnosis should be performed by a precise performance model. However component maps for the performance model were not provided by the engine manufacturer. Therefore they were generated by a new component map generation method, namely hybrid method using system identification and genetic algorithms that identifies inversely component characteristics from limited performance deck data provided by the engine manufacturer. Performance simulations at different operating conditions were performed on the PW206C turbo shaft engine using SIMULINK. In order to train the proposed BPNN (Back Propagation Neural Network), performance data sets obtained from performance analysis results using various implanted component degradations were used. The trained NN system could reasonably detect the faulted components including the fault pattern and quantity of the study engine at various operating conditions.

Key Word : Fault detection, turboshaft engine, Neural Network, model based diagnose

Introduction

Engine condition monitoring is an effective way to improve safety as well as to reduce operation and maintenance cost of gas turbine engines. Various monitoring and diagnostic techniques are applied to keep track of the health of major components making up the gas turbine engine.

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On−condition performance monitoring techniques of major gas path components using the GPA (Gas path Analysis) methods have been proposed, and they have the capabilities to isolate and to quantify gas path faulted components of the gas turbine. Some of the features of the GPA can identify multiple faults, and quantify the deterioration affecting individual components (Zedda & Singh, 1998) [2]. Performance diagnosis using GPA is carried out using independent parameters such as component efficiencies and mass flow parameters and FCM (Fault Coefficient Matrix). The FCM is the inverse matrix of the ICM (Influence Coefficient Matrix) that gives the relationship between the independent parameters and the measurable dependent parameters such as pressure, temperature, fuel flow etc. The independent parameter is mostly a non square matrix although often difficult to obtain the inverse matrix (Urban, 1972) [1].

AI (Artificial intelligence) techniques have recently been used for gas turbine engines diagnosis, for instance NN (Neural Network), GA(Genetic Algorithms) and Fuzzy [9]. Among them the NN has an inherent feature that makes it particularly suite for diagnostic tasks (Lu et al, 2001, Volponi et al., 2000, and Depold & Gass, 1999) [3, 4, 5]. Changes of the measured parameters in engine gas path reflect the changes of component characteristics. If the interrelationship between them can be built using the NN, the different types of faults may be diagnosed. A lot of research works have been conducted on the engine fault diagnosis using the NN, and as a result some NN approaches have been developed. Among them the BPNN (Back Propagation Neural Network) have been widely used due to its simplicity and well−defined algorithm (Sun et al, 2000, Ledda, 1998 and Tang et al. 1998) [6,7]. The BPNN was created by generalizing the Widrow− Hoff learning rule to multiple layer networks and nonlinear differentiable transfer functions. Input vectors and corresponding target vectors were used 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. Network with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. The BP (Back Propagation) is a gradient descent algorithm with the Widow−Hoff learning rule which the network weights are moved along the negative of the gradient at the performance function (Haykin 1994) [8].

In this work, a model−based diagnostic method using the NN was proposed for fault detection of PW206C turbo shaft engine, which was selected as a power plant for the tilt rotor type Smart UAV (Unmanned Aerial Vehicle). For this model−based diagnostics an accurate performance model is mandatory to have, hence the performance simulation program was developed using SIMULINK. Further more real component maps are required for the performance model. However they are not provided by the engine manufacture, hence a new component map generation method, which can identify component maps conversely from the limited performance deck data provided by the engine manufacturer, was used [11]. Based on the obtained component maps by the above method, the PW206C turbo shaft engine performance model was built. Fault and test databases for building the NN were obtained at various off−design operation conditions such as flight altitude, flight Mach number and gas generator rotational speed. In fault detections by the NN, the component performance deteriorations caused by faults such as compressor fouling, compressor turbine erosion and power turbine erosion were found.

Description of PW206C Engine

PW 206C turbo shaft engine used to demonstrate the diagnostic algorithm chosen for use in the tilt rotor type Smart UAV developed by KARI (Korea Aerospace Research Institute) consists of the gas generator section with single stage centrifugal compressor, reverse flow annular type combustion chamber and single stage axial compressor turbine and the power section with single stage axial free power turbine, exhaust duct, reduction gearbox and output drive shaft.

Table 1. Operating range of propulsion system required by system integration group of Smart UAV of KARI

Gas Generator RPM	65% ~ 100%
Altitude (m)	0 ~ 7629
Flight Mach No.	0 ~ 0.4

Table 2. Design Performance data provided by engine manufacturer

Variable	Values
Atmospheric condition	S/L, Static STD Condition
Mass flow rate (kg/s)	2.004
Fuel flow rate (kg/s)	0.039
Compressor pressure ratio	7.912
Turbine inlet temperature (K)	1254.4
Shaft horse power (kW)	418.19
SFC (kg/kW hr)	0.338
Gas generator rotational speed (100% RPM)	58900
Propeller rotational speed (100% RPM)	6120

System integration group of the Smart UAV R&D Center of KARI (Korea Aerospace Research Institute) provided the following required operating range for the propulsion system as shown at Table 1.

Table 2 shows design performance data at maximum take-off condition, which were provided by the engine manufacturer estimated engine performance parameters(EEPP manual) [12].

Performance Modeling for Model-based Fault Detection

The proposed component map generation scheme mentioned in this study is the hybrid method that refers to the combination of the previously developed System Identification Method [14] and Genetic Algorithm Method [11]. The theory behind its working is scaling is first performed at each engine rotational speed noting that only limited data is available from the engine manufacturers This is followed by a process of deriving component characteristic equations by System Identification Method. The second step involve modifying the initial component characteristic considering component behavior at varying flight Mach number, altitude and atmospheric temperature using G.A (genetic Algorithms).

Component characteristics obtained by the System Identification are used as initial data to reduce the calculation time. And finally the component map is generated by integrating the component the component characteristic equations taken at each engine rotational Speed.

The resulting generated component performance maps by the Hybrid Intelligent Method [11] are illustrated in Fig. 1,2, 3.

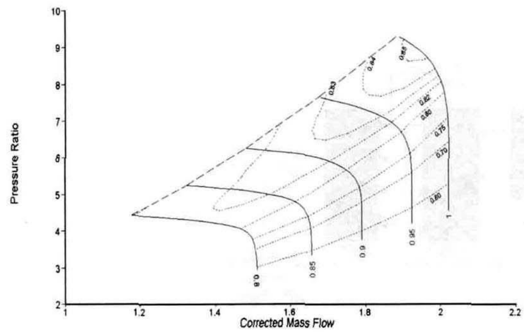


Fig. 1. Generated compressor map by Hybrid Intelligent Method

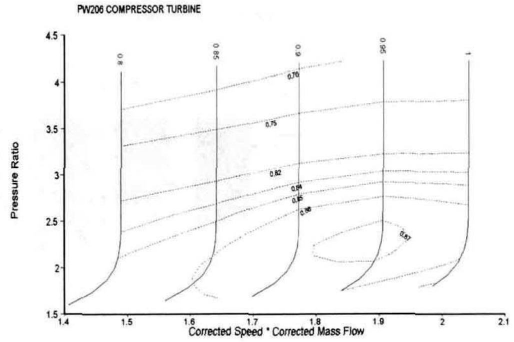


Fig. 2. Generated compressor turbine map by Hybrid Intelligent Method

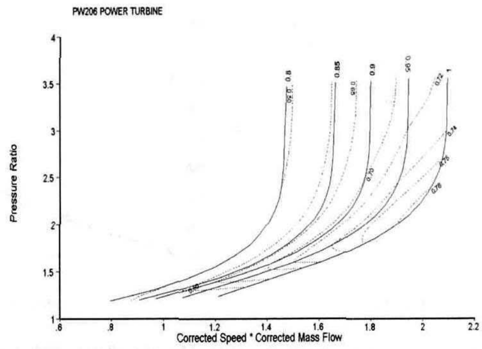


Fig. 3. Generated power turbine map by Hybrid Intelligent Method

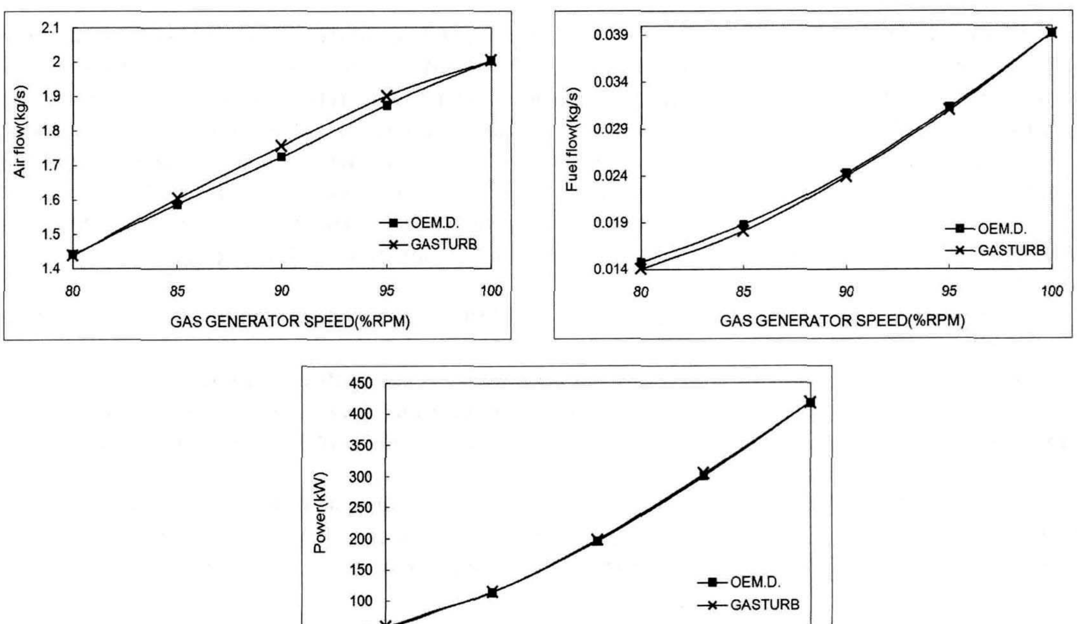


Fig. 4. Evaluation results of newly generated component maps

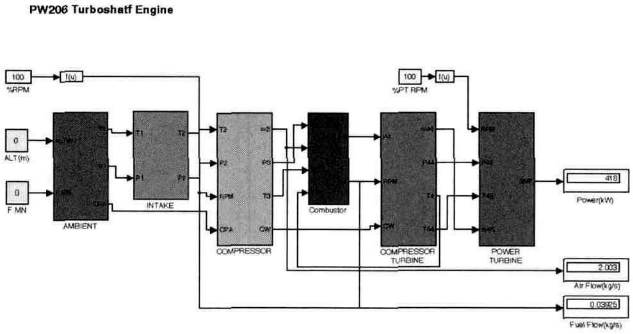


Fig. 5. SIMULINK model of PW206C turboshaft engine

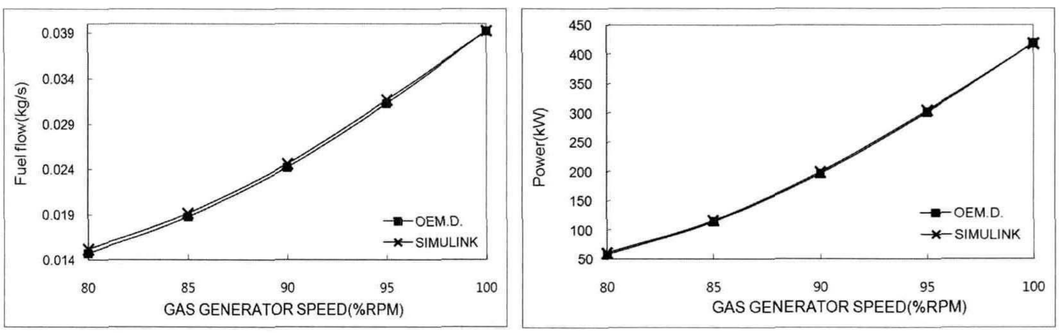


Fig. 6. SIMULINK Model analysis results for varying gas generator speed at Sea level static standard atmospheric Condition (Represented engine component maps were generated by hybrid scheme)

Figure 4 shows the comparison between performance analysis results with component maps using the proposed hybrid intelligent method and manufacturer' s performance deck data at various generator rotational speeds and at sea level static condition. A Commercial program GASTURB 9 [13] was used to evaluate proposed component map, Part load performance analysis of the studied engine. The resultant part-load performance analysis results were then compared with the manufacturer' s performance deck data. [12]

The results shows that compressor map generated by the present study agree well with the performance deck results even though the off design calculation points are far away from the design point.

The overall SIMULINK® model of the PW206C turbo shaft engine configuration is represented in Fig. 5.

The overall model is composed of modular blocks represented by individual components as ambient subsystem for flight environment condition, intake subsystem, compressor subsystem, combustor subsystem, and compressor turbine subsystem and finally power turbine with rotor dynamics.

The part load performance analysis results were compared with the manufacturer's performance deck data to verify the proposed model as seen in Fig. 6. Result of the analysis of the proposed model closely matches those from the performance deck data.

Neural Network Algorithms for Fault Detection

Among various neural network algorithms, the back propagation is a common, simple and effective training feed forward neural network scheme. A typical feed forward network is the Multi-Layer Perception (MLP) composed of three layers, the input, hidden and the output layer. Each layer is made of a set of neurons. The hidden and output neurons have an output or activation value computed by equation (1).

$$y_i = \varphi_j\left(\sum_{i=0}^{N} W_{ji} \cdot X_j\right) \tag{1}$$

Where φ_j = activation function applied to the weighted sum of the inputs (Xj), y_j = output neuron j in the current layer, W_{ji} = entering weight from neuron i in the preceding layer to neuron j in the current layer, N = number of neurons in the preceding layer, X_i = input of neuron i in the preceding layer.

In the typical architecture every neuron is connected through weights to all neurons of the succeeding layer and has no connection with other neurons in the same layer, i.e. no intra layer weights in the same layer neurons. Direct connections between non-adjacent layers are allowed but seldom used.

For a certain value of the set of weights, when the net is presented with an input pattern, the neurons' output values are computed layer by layer, from the input to the output one and in this way an output pattern is produced. The name "feed forward" stems from the absence of any feedback when the net is used in recall mode.

The proposed FFBP Neural network is composed of a single hidden layer feed forward back propagation neural network with 7 input measurement parameter changes and 6 output component performance parameter changes.

Fault Detection at Off-Design Point

Fault learning data at various operating conditions are required for fault detection by neural network to be effective but since real engine operating data are not easily accessible simulation data are used for the analysis. 195 learning data sets were considered in this study obtained from the SIMULINK performance Model implanted with virtual performance degradation as shown in Table 4 operating conditions and ranges are represented in Table 3 respectively.

Where independent parameter trend of typical components faults such as compressor fouling, compressor turbine erosion and power turbine erosion are referred to Diakunchak' s experimental results [10].

Seven measured parameters changes of the PW206C engine were considered they include: ΔSHP, ΔMF, ΔPT_2, ΔTT_2, ΔPT_4, ΔTT_4 and ΔPT_5 and 6 performance parameters listed as mass flow parameter changes and isentropic efficiency changes of compressor, compressor turbine and power turbine (i. e. ΔMFP_{co}, $\Delta\eta_{co}$, ΔMFP_{ct}, $\Delta\eta_{ct}$, ΔMFP_{pt} and $\Delta\eta_{pt}$). (For full meaning of abbreviations refer to Nomenclature)

Table 3. Operating range for learning data set acquisition (For full meaning of abbreviations refer to Nomenclature)

Gas generator rpm (at Alt.=0m, FMN=0)	80%, 85%, 90%, 95%, 100%
Altitude (at 100% rpm, FMN=0.2)	1524m, 3048m, 4572m, 6096m, 7629m
Flight Mach No. (at 100%rpm, Alt.=6096m)	0.1, 0.2, 0.3, 0.4

Table 4. Implanted component performance degradation

Compressor fouling		Comp. turbine erosion		Power turbine erosion	
ΔMFP	Δη	ΔMFP	Δη	ΔMFP	Δη
-1%	−1%	+1%	−1%	+1%	−1%
-2%	−2%	+2%	−2%	+2%	−2%
-3%	−3%	+3%	−3%	+3%	−3%
-4%	−4%	+4%	−4%	+4%	−4%
-5%	−5%	+5%	−5%	+5%	−5%

The error between the network output y_i and the target value T_i was defined as the following RMS error.

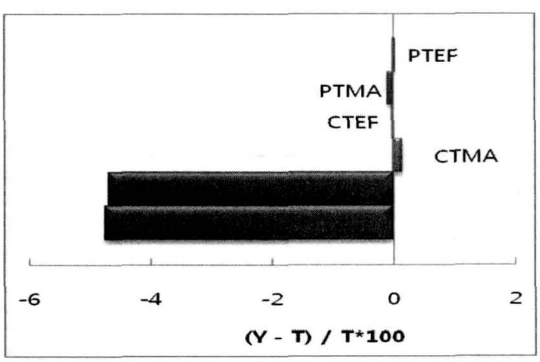
$$RMS_{error} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - T_i)^2}{n}} \tag{3}$$

Using the trained neural networks, diagnose was performed and its algorithms tested at the following operating conditions; 1) sea level, flight Mach number= 0.1 and gas generator rpm= 80%, 2) altitude=6096m, flight Mach number= 0.2 and gas generator rpm= 90%, 3) altitude=6096m, flight Mach number= 0.3 and gas generator rpm= 100%.

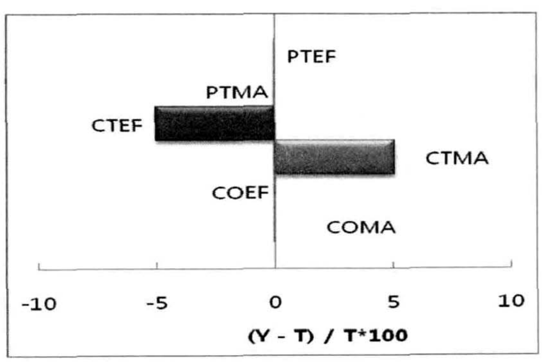
The tested degradation patterns were assumed as a result of compressor fouling with drop of 3% mass flow parameter and drop of 2% isentropic efficiency, the turbine erosion with rise of 3% mass flow parameter and drop of 2% isentropic efficiency.

Figure 7 shows the detected single fault results for the major components at sea level, flight Mach number=0.1 and gas generator rotational speed=80% condition.

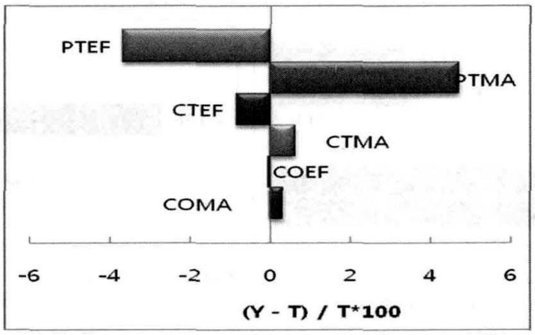
Where COMA, COEF, CTMA, CTEF, PTMA and PTEF means changes of compressor mass flow, compressor efficiency compressor turbine mass flow, compressor turbine efficiency ,power turbine mass flow and power turbine efficiency respectively.



a) Detected performance degradation due to compressor fouling

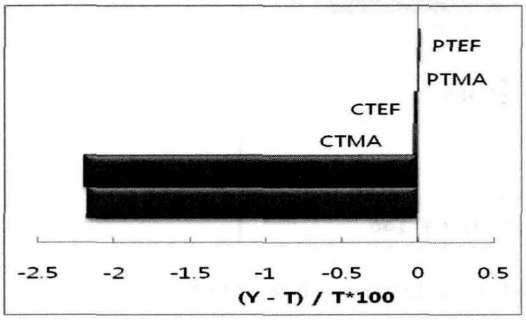


b) Detected performance degradation due to compressor turbine erosion

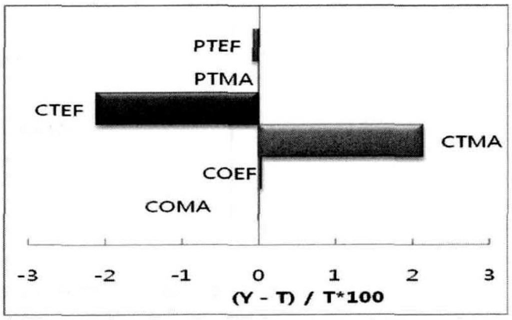


c) Detected performance degradation due to power turbine erosion

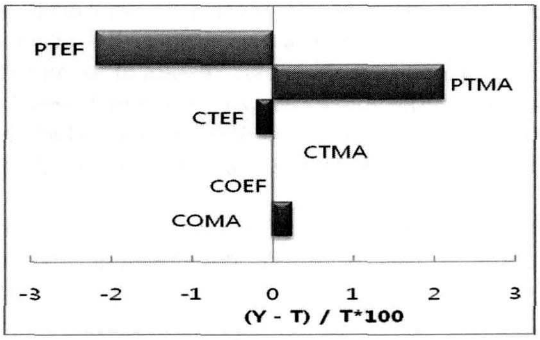
Fig. 7. Performance diagnose results at sea level, FMN = 0.1 and engine rpm= 80%



a) Detected performance degradation due to compressor fouling



b) Detected performance degradation due to compressor turbine erosion



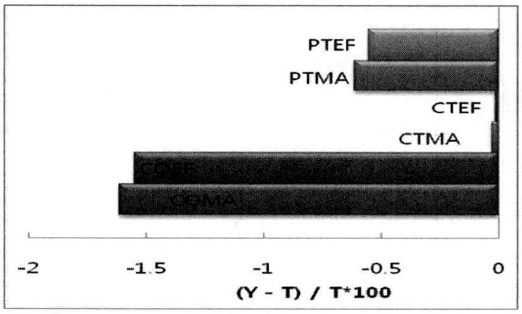
c) Detected performance degradation due to power turbine erosion

Fig. 8. Performance diagnose results at altitude=6096m, FMN= 0.2 and engine rpm= 90%

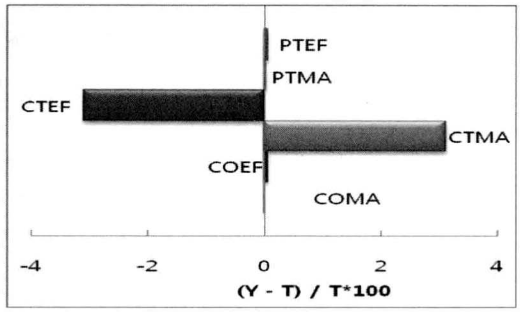
Figure 8 shows the detected single fault results for the major components at flight altitude=6096m, flight Mach number=0.2 and gas generator rotational speed at 90% condition.

Figure 9 illustrates the detected single fault results for the major components at flight altitude=6096m, flight Mach number=0.3 and gas generator rotational speed=100% condition.

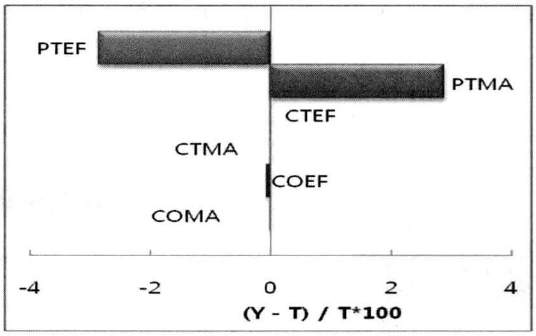
According to performance diagnosis results at sea level, flight mach no=0.1 and engine rpm=80% as shown in Fig.7, the proposed diagnostic system can well identify the faulted components such as compressor fouling compressor turbine erosion and power turbine erosion by distinct fault trends (presented in Diakunchak [10]).



a) Detected performance degradation due to compressor fouling



b) Detected performance degradation due to compressor turbine erosion



c)Detected performance degradation due to power turbine erosion

Fig. 9. Performance diagnose results at altitude=6096m, FMN= 0.3 and engine rpm= 100%

However detected performance deteriorations of each faulted component are a bit different from implanted degradations i.e. drop of 3% mass flow and drop of 2% efficiency due to compressor fouling and rise of 3% mass flow and drop of 2% efficiency due to compressor and power turbine erosion. Performance diagnosis results at an altitude of 6096 meter, Mach number=0.2 and engine rpm=90% have almost the same results as in Figure7. The performance diagnosis result at an altitude of 6096 meters Mach number=0.3 and engine rpm=100% shown in Fig. 9 have almost the same results as those of Fig. 7 except for compressor fouling.

The proposed FFBP NNs for engine fault diagnosis must be modified for accurate identification of degradation as part of future development toward fault detection using neural networks.

Conclusions

A model-based performance diagnostic study for the PW206C turbo shaft engine of the tilt rotor type Smart UAV which has been developed by Korea Aerospace Research Institute was carried out. The FFBP NNs (Feed Forward Back Propagation Neural Networks) was used as the diagnostic algorithms. For this model based performance diagnose, more precise engine performance modeling was performed in order to obtain the component maps that greatly influence on performance simulation, a new component map generation method which may identify component characteristics conversely from the limited performance deck data provided by the engine manufacturer using the system identification method and the genetic algorithms was used. Engine performance modeling with the generated component maps using SIMULINK was carried out, and steady state performance analysis was performed at various operating conditions. According to comparison results to verify the proposed engine performance model, it was found that analysis results using the proposed model well agreed with the performance deck data with an error margin 1.39% even at part load conditions.

In order to build the database for training the proposed BPNN (Back Propagation Neural Network) method, performance degradation data were obtained by performance simulation using virtually implanted performance degradations due to the compressor fouling indicated by drop in mass flow parameter and drop in isentropic efficiency, and the turbine erosion leading to rise in mass flow parameter and drop in isentropic efficiency at various off−design point operating conditions.

Through the diagnose analysis using the trained NNs, it was confirmed that the proposed diagnose system can satisfactorily detect the performance degradations due to the compressor fouling due to drop in mass flow parameter and drop in isentropic efficiency, and the turbine erosion causing rise in mass flow parameter and drop in isentropic efficiency at various off−design point operating conditions.

Further error correction and error reducing studies are underway like the use of fuzzy logic to identify more accurate component faults. Publication and proceedings related to this improvement will be presented in the near future.

Acknowledgement

The authors are grateful to the support provided by the Smart UAV R&D Project.

Nomenclature

ALT	Altitude	PTEF	Power Turbine Efficiency
COEF	Compressor Efficiency	PTMA	Power Turbine Mass Flow
COMA	Compressor Mass Flow	SFC	Specific Fuel Consumption
CTEF	Compressor Turbine Efficiency	SHP	Shaft Horse Power
CTMA	Compressor Turbine Mass Flow	T	Target reference value
FMN	Flight Mach number	TT	Total Temperature
OEM.D.	Original Equipment Manufacturer Data	Y	Neural network output value
MFP	Mass Flow Parameter	n	Number of performance parameter
MF	Fuel Mass Flow rate (kg/s)	η	Efficiency
PT	Total Pressure		

Subscript

2	Compressor exit	co	Compressor
4	Compressor turbine exit	ct	Compressor turbine
5	Power turbine exit	pt	Power turbine

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