Study on Condition Monitoring of 2-Spool Turbofan Engine Using Non-Linear Gas Path Analysis Method and Genetic Algorithms

Changduk Kong, Myoungcheol Kang, and Gwanglim Park

***Abstract*—Recently, the advanced condition monitoring methods such as the model-based method and the artificial intelligent method have been applied to maximize the availability as well as to minimize the maintenance cost of the aircraft gas turbines. Among them the non-linear GPA(Gas Path Analysis) method and the GA(Genetic Algorithms) have lots of advantages to diagnose the engines compared to other advanced condition monitoring methods such as the linear GPA, fuzzy logic and neural networks. Therefore this work applies the linear GPA, the non-linear GPA and the GA to diagnose AE3007 turbofan engine for an aircraft, and the GA method shows good diagnostic results on all the fault cases not only single and multiple fault cases but also consideration of sensor noise and biases.**

***Index Terms*—Engine condition monitoring, non linear GPA, genetic algorithms, 2-spool turbofan engine.**

I. Introduction

The aviation gas turbine is composed of lots of expansive and highly precise parts and operated in high pressure and temperature gas. When its breakdown or performance deterioration due to the hostile environment and component degradation occur, it gives severe influences to the aircraft operation. Recently to minimize this problem the third generation of predictive maintenance known as condition based maintenance has been developed. This method monitors and diagnoses the engine condition and gives a proper maintenance action. Therefore it maximizes the availability and minimizes the maintenance cost [1]. The engine condition monitoring method is classified into the model based diagnosis such as observers, parity equations, parameter estimation and Gas Path Analysis (GPA) and the soft computing diagnosis such as expert system, fuzzy logic, neural networks and genetic algorithms.

Among the model based diagnostic methods, the linear GPA method was firstly proposed by Urban in 1967 [2] and it has been widely used but it is severely limited to use in high level of faults. Therefore to improve this limitation the non-linear GPA method was developed by Esher [3]. This method can solve the non-linearity by the repetition technique.

However, this method does not manage the sensor noise and bias problem. Based on the GPA method Rolls-Royce developed COMPASS diagnostic system in 1987 [4], Pratt & Whitney developed SHERLOCK diagnostic system in 1991 [5], and General Electric developed TEMPER diagnostic system in 1994 [6].

Among the soft computing diagnostic methods, the intelligent diagnostic methods such as fuzzy logic, Neural Networks (NN) and GA have been developed to solve the problems of the model based diagnostic methods. Patel et al. studied on the diagnostics using SIMULINK model and NN in 1995 [7], Zhou studied on the diagnostics using fuzzy logic and NN in 1998 [8], and Tayler studied on the diagnostics using GA in 2000 [9]. However, Zedda pointed out that NN training is typically performed in cases where the input-output relationship is already known and it is very difficult to provide any level of confidence on the results obtained through the use of NNs [10].

GA has some distinctive features compared with typical calculus-based optimization methods, i. e. no derivatives are needed so any-non-smooth function can be optimized, constraints can be dealt with penalty functions, global search is used to avoid getting stuck in a local minimum, and probabilistic rather than deterministic transition rules are used to create the next generation of strings from the current one [1].

Therefore this work shows that the comparative study of the condition monitoring results for AE3007H turbofan engine of a conceptually designed HALE UAV(High Altitude Long Endurance Unmanned Aerial Vehicle) using the linear GPA, the non-linear GPA method and the GA method is performed, and it is found that the GA method is better than the GPA methods specially in case of consideration of sensor noise and biases.

II. Performance Modeling of AE3007H Turbofan Engine

A. Operating Envelope

The AE3007H turbofan engine is mounted on the conceptually designed HALE UAV that has the required mission performance such as both civil and military use, payload of 1000kg, maximum operating altitude of 65,000ft, cruising speed of Mach number 0.65, and endurance of 24 hours shown at Table I [11].

TABLE I: HALE'S REQUIRED MISSION PERFORMANCE

Payload	1000kg
Mission altitude	Above 50000ft
Endurance	24hr
Take-off weight	12203.5 kg
Cruise speed	M = 0.65
Propulsion system	Rolls Royce/Allison AE3007H 2 shaft turbofan

Manuscript received January 19, 2013; revised March 3, 2013.

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The HALE's mission profile is composed of basically take-off, climb, cruise, loiter, descent and landing [11].

B. Engine Performance Modeling

The performance modeling engine is AE3007H 2 shaft mixed flow type high bypass turbofan engine manufactured by Rolls-Royce/Allison, and it is composed of 1 stage axial fan with bypass ratio of 5, 14 stage axial high pressure compressor with pressure ratio of 23, 2 stage axial high pressure turbine and 3 stage axial low pressure turbine. The engine produces 36.9 kN at take-off condition. Figure 1 shows the cut-down view of AE3007H turbofan engine [12].

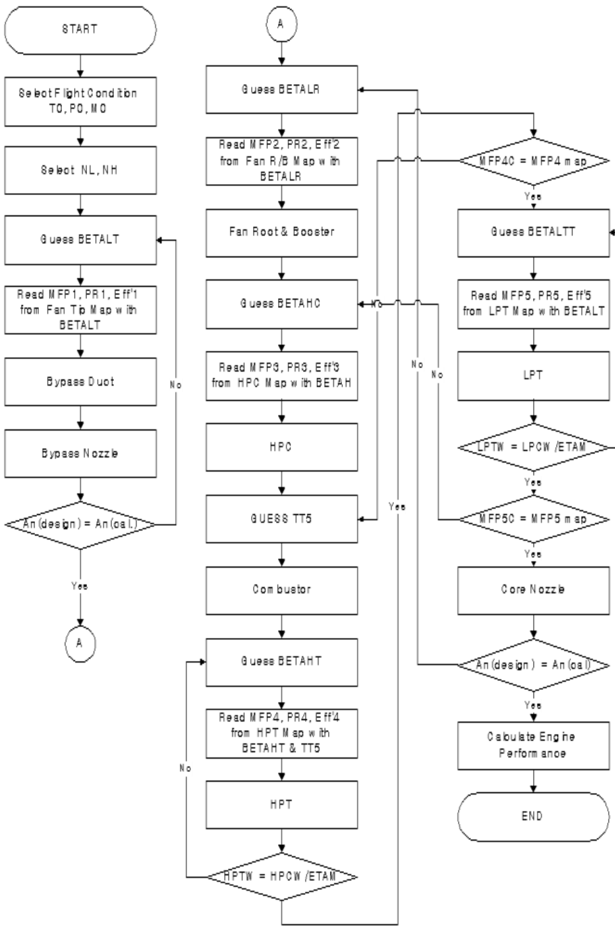

Fig. 1. Rolls-Royce/Allison AE3007H turbofan engine.

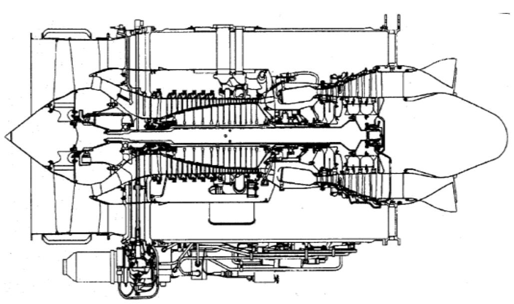

Fig. 2. Flow chart of performance model of AE3007H turbofan engine.

The study engine model is the similar type engine as BR715-56 2-spool turbofan engine which has been previously studied by authors. Therefore the BR715-56 turbofan engine's performance model [13] is slightly modified for the AE3007H turbofan engine's performance model with the newly generated component maps and some other engine characteristics.

The developed performance model can make input data such as altitude, Mach number, standard atmosphere temperature change, and gas generator speed using constant blocks and output data such as net thrust, specific fuel consumption (SFC), and specific thrust. Fig. 2 shows the proposed performance model's flow chart of AE3007H turbofan engine. The component maps are generated from similar known component maps using the scaling law because they are not provided by the engine manufacturer. The scaling is firstly performed based on the design point, i.e. the HALE UAV's cruising condition, and then it is performed at other off-design conditions.

C. Performance Analysis Results

Off-design performance analysis is carried out at the major mission profile such as take-off, climb, cruise, loiter, descent and landing. The rated power setting conditions are max take-off, max continuous, max climb and max cruise.

1)Take-off performance

The take-off performance analysis results are shown at Table II, and the comparison of the max take-off performance at sea level between the analysis result using the performance model and the manufacturer' s performance data is shown at Fig. 3. Here it is confirm that the take-off performance analysis result is well agreed with the manufacturer's take-off performance data.

TABLE II: TAKE-OFF PERFORMANCE

Mach No.	Thrust (kN)	SFC (mg/Ns)
0.00	36.84	10.88
0.10	33.06	12.18
0.15	31.41	12.83
0.20	29.93	12.67
0.25	28.60	14.26

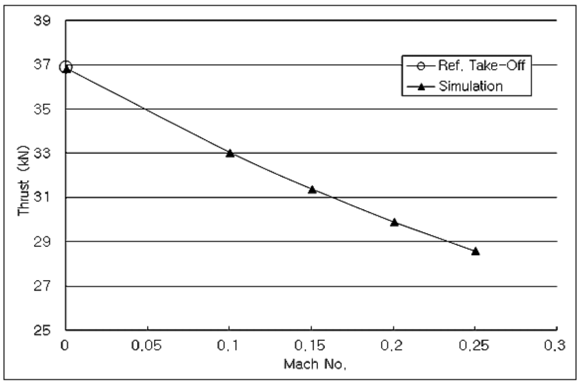

Fig. 3. Take-off performance.

2) Climb Performance

The climb is done between the end of take-off and the beginning of cruise of Mach number 0.65, and the climb performance is set at maximum excessive thrust. It is assumed that the aircraft weight is not changed during climb flight shown as Table III.

TABLE III: CLIMB ALTITUDE

Climb altitude	Aircraft weight (kg)
0 ~ 4,000m	12,200
6,000 ~ 10,000m	12,100
12,000 ~ 20,000m	12,000

TABLE IV: CLIMB PERFORMANCE

Alt. (km)	Time(min)	Fn (kN)	SFC (mg/Ns)	Mn
0.00	0	25.52	14.16	0.27
2.24	4	22.02	12.44	0.30
4.50	8	17.71	13.03	0.35
6.99	12	13.78	13.64	0.42
9.48	16	10.62	14.14	0.50
11.67	20	7.97	14.62	0.59
12.90	22.8	6.58	15.17	0.65

Fig. 4 and Table IV show the calculated thrust and SFC at different altitudes during climb.

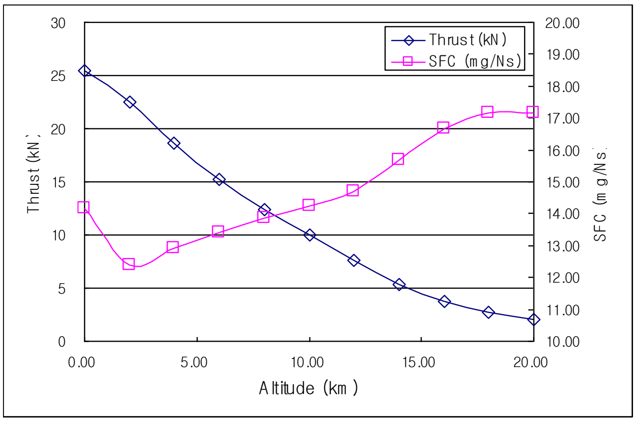

Fig. 4. Climb performance.

3) Cruise performance

The cruise performance analysis is performed from the beginning of cruise to optimal flight Mach number 0.65. The cruise performance analysis result is shown at Table 7.

TABLE V: CRUISE PERFORMANCE

Alt. (km)	Tim (min)	Fn(kN)	SFC (mg/Ns)	Mn
13.76	8.4	2.93	17.77	0.65

4) Loiter performance

The loiter flight can be done at constant altitude and flight speed with minimum drag. The loiter performance analysis results are shown at Table 6.

TABLE VI: LOITER PERFORMANCE

	Alt. (km)	Time (min)	Fn(kN)	SFC (mg/Ns)	Mn
Start	15.24	0	2.51	16.21	0.55
End	15.24	24	1.79	15.67	0.46

5) Descent and landing performance

The power settings at descent and landing are 10% and 5 % of max take-off condition.

III. APPLIED DIAGNOSTIC METHODS

A. *Non-linear GPA Method*

If any effect of measurement uncertainty is neglected, for a given engine operating point the basic equation for gas turbine performance can be expressed as follows:

$$\vec{Z} = h(\vec{X}) \tag{1}$$

where, $\vec{Z} = R^M$ is the measurement vector and M is the number of measurements, $\vec{X} = R^N$ is the component parameter vector and N is the number of component parameters, and h is a vector-valued function, usually non-linear.

It is provided by the performance simulation model.

$$(\vec{X}) = h^{-1}\vec{Z} \tag{2}$$

Equation (1) can be expanded in a Taylor series. For small, higher order terms of expansion can be neglected

The deviation of engine component parameters can be calculated with a fault matrix (or diagnostic matrix) which is the inverse of the influence coefficient matrix H:

$$\Delta\vec{X} = H^{-1} * \Delta\vec{Z} \tag{3}$$

The inverse of the influence coefficient matrix is referred as "Fault Coefficient Matrix" (FCM)

Linear Gas Path Analysis is clearly a very powerful tool for analyzing the health of gas turbines. However, it has the severe limitation that in many circumferences the level of error introduced by the assumption of the linear model can be of the same order of magnitude as the fault being analyzed. One way of improving the accuracy is to try to solve the non-linear relationship between dependent and independent parameters with an iterative method such as the Newton-Ralphson method.

The relationship between engine measurement (dependent) parameter deviation vector and component (independent) parameter vector described by Equation (3) is re-written as follows for convenience:

$$\Delta\vec{X} = H^{-1} * \Delta\vec{Z} \tag{4}$$

The corrections are then added to the solution vector:

$$\vec{X}_{new} = \vec{X}_{old} + \Delta\vec{X} \tag{5}$$

And the process is iterated to convergence. This iterative process has the advantage to overcome the problem that the changes in $\vec{X}$ have to be small. In other words, the process seeks to solve numerically the non-linear set of equation that is defined in Equation (1).

Through each interval the change in the independent parameter becomes smaller and smaller and the process can be stopped when the change in the independent parameter has reached to a convergence criterion that suits your needs:

$$\Delta\vec{Z}_{sum} = \sum_{j}^{M} \left|\Delta Z_{measj} - \Delta Z_{calj}\right| \langle \delta \tag{6}$$

where M is the number of measurements, $\vec{Z}_{meas}$ the actual measured deteriorated measured parameter vector and $\vec{Z}_{cal}$ the calculated deteriorated measured parameter vector that is based on the detected component parameter vector $\Delta\vec{X}$, and δ is the convergence criteria.

B. *GA (Genetic Algorithms) Method*

GA is a stochastic algorithms whose search methods model some natural phenomena: genetic inheritance and Darwinian strife for survival. The idea behind genetic algorithms is to do what nature does.

In the presence of measurement noise and bias, the following relationship for gas turbine component parameters and gas path measurement parameters would hold, as described before:

$$\vec{Z} = h(\vec{x}, \vec{w}) + \vec{v} + \vec{b} \tag{7}$$

where: $h(.)$ is a vector valued function, $\vec{v}$ is the measurement noise vector, $\vec{b}$ is the measurement bias vector.

Usually $\vec{v}$ is assumed to have a Gaussian probability density function (pdf) and moreover to have independent components. Therefore, the joint pdf is the product of the independent pdfs:

$$P(v) = \frac{1}{\left(\sqrt{2\pi}\right)^M} \prod_{j=1}^{M} \left(\frac{1}{\sigma_j}\right) e^{-\frac{1}{2}\sum_{j=1}^{M}\left(\frac{v_j}{\sigma_j}\right)^2} \tag{8}$$

where σ_j is the standard deviation of the j-th measurement.

The idea of gas turbines fault diagnosis with genetic algorithm is shown in Fig. 5. With an initial guess of gas turbine component parameter vector $\vec{X}$, the engine model provides a predicted performance measurement vector $\vec{Z}$. An optimization approach is applied to minimize an objective function. A minimization of the objective is carried out iteratively until the best predicted engine component parameter vector $\vec{X}$ for real $\vec{X}$ is obtained.

The objective function is a measure of the difference between the real measurement vector $\vec{Z}$ and the predicted measurement vector $\vec{Z}$. The basic requirements for the objective function are as follows: It should be a measure of the consistency between actual and predicted measurements, measurement noise should be accounted for, measurement biases should be accounted for, its minimization should reduce the "smearing" effect, and evaluation of the function should not be too burdensome from a computational point of view.

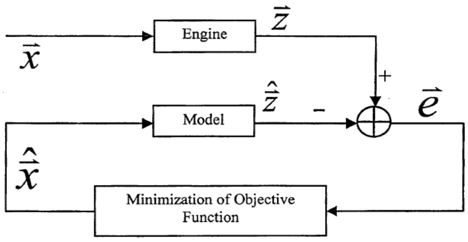

Fig. 5. Non-linear model based diagnostic approach.

A choice for the objective function would be, given a certain operating point:

$$J(x) = \sum_{j=1}^{M} \frac{\left\lfloor z_j - h_j(\vec{x}, \vec{w}) \right\rfloor}{z_{odj}(\vec{w})\sigma_j} \tag{9}$$

where Z_{odj} is the value of the j-th measurement in the off-design un-deteriorated condition.

Minimization of the objective function provides the maximum likelihood solution for the non-linear problem.

C. Sensor Fault Diagnostics

Gas turbine sensor fault diagnostic is achieved with certain types of sensor redundancy.

The approach described previously for gas turbine component fault diagnostics with genetic algorithms can be modified to deal with measurement biases or sensor fault detection. The idea is based on the following criterion: the presence of a bias will introduce inconsistency between actual and predicted measurements.

The way of the optimization-based diagnostic system handles measurement biases relies on the concept of analytical redundancy. If no bias affects the measurement, then the minimization of object function expressed as Equation (9) can be performed

The inconsistency due to a biases measurement would manifest itself with large values of the object function, since no $\vec{X}$ can be found to correspond to predicted measurements fitting sufficiently well the real ones. The problem can be overcome by elimination in the summation of objective function of the *Mbias* terms corresponding to the biased measurements. Then the remaining terms are mutually consistent and the optimized function $\vec{X}$ will reach a low value. For the technique to apply, it is necessary that:

$$M - Mbias > Nperf + P \tag{10}$$

where P is the number of environment and power setting parameters and *Nperf* is the number of component performance parameters.

IV. Condition Monitoring Analysis of AE3007H Turbofan Engine

In order to diagnose the gas turbine engine, the implanted faults are firstly classified, and then a set of the measuring parameters to detect effectively the implanted faults are selected. Depending on numbers and kinds of the measuring parameters, the precision of the diagnostic results is changed.

To evaluate the precision of the detected faults the following RMS(Root Mean Square) error formula is used.

$$RMS = \sqrt{\sum_{i=1}^{n} \frac{\left(fault_{implanted} - fault_{detected}\right)^2}{n}} \tag{11}$$

where, n: number of independent parameters.

To evaluate the condition monitoring analysis results by the linear GPA method, the non-linear GPA method and the GA method, use of known fault data is needed. There is the real faulted engine data or the simulating faulted engine data. The use of real faulted engine data is better, but it is difficult to obtain all kinds of real faulted engine data as well as the data without noise and bias. Therefore the simulating faulted engine data are generally used to verify the developing condition monitoring system. This work also uses the simulating faulted engine data.

In the condition monitoring analysis the single faulted component cases and the multiple faulted component cases are considered with and without measuring noise and bias.

The number of implanted independent parameters must be less than the number of measuring parameters, and the considered faults are the compressor fouling case and the turbine erosion case. The degradation quantities of implanted faults for the analysis are shown in Table VII.

TABLE VII: IMPLANTED FAULTS FOR COMPRESSOR FOULING AND TURBINE EROSION

Compressor fouling		Turbine Erosion	
Fan η	-1.5	HPT η	-3
Fan Γ	-2.0	HPT Γ	+4
HPC η	-1.5	LPT η	-3
HPC Γ	-2.0	LPT Γ	+4

Compressor fouling results in reduced flow capacity and efficiency due to reduction of flow area, and turbine erosion increases the nozzle area and decreases flow capacity and efficiency [14].

The selected measuring parameters are inlet and outlet pressures and temperatures of high pressure compressor, high pressure turbine and low pressure turbines and fuel flow. Here the pressure measuring parameter is related to the non-dimensional flow parameter, and the combination of pressure and temperature measuring parameters is related to the efficiency. The more number of measuring parameters and the better precise diagnostic results are expected, but the measuring sensor error increase and the measuring cost increase.

A. Diagnostic Analysis Results of Single Fault Cases without Sensor Noise and Biases

Fig. 6 shows the diagnostic analysis results of single fault cases without sensor noise and biases. The analysis results using the linear GPA method have very low precision even though in case of low degradation, and the diagnostic RMS error of the high pressure compressor fouling case approaches to about 2. The analysis results using the non-linear GPA method have more precision in all the single fault cases. However the analysis results using the linear GA method have a bit lower precision in all the single fault cases.

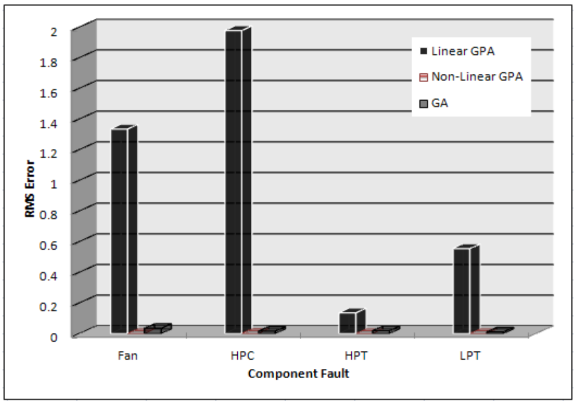

Fig. 6. Single component faults without noise or biases

B. Diagnostic Analysis Results of Single Fault Cases with Sensor Noise and Biases

Fig. 7 shows the diagnostic analysis results of single fault cases with sensor noise and biases to consider real operating condition.

According to the analysis results with noise and biases, the GA method has the lowest RMS error among three methods. The linear GPA method has the RMS error of 9 at the fan fouling case, but the non-linear method has higher RMS errors than the linear GPA methods at other single fault cases. Moreover the GPA methods cannot detect the faults if the noise increases greatly.

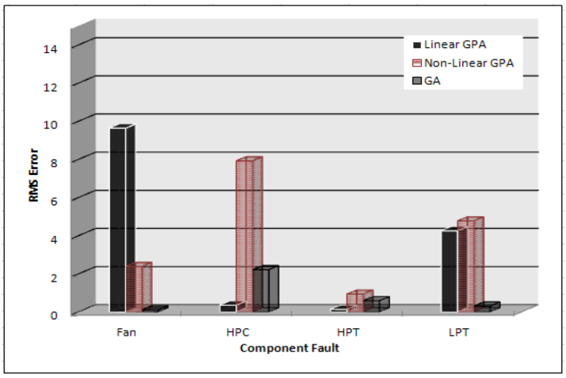

Fig. 7. Single Component Faults with noise and biases.

C. Diagnostic Analysis Results of Multiple Fault Cases without Sensor Noise and Biases

Fig. 8 shows the diagnostic analysis results of multiple fault cases without sensor noise and biases.

According to the analysis results, the linear GPA method has very high RMS errors compared with the non-linear method and GA method, so it is found that the linear GPA method is very weak to use in the multiple fault cases. The non-linear GPA method has good results except for the fan and high pressure turbine multiple fault case.

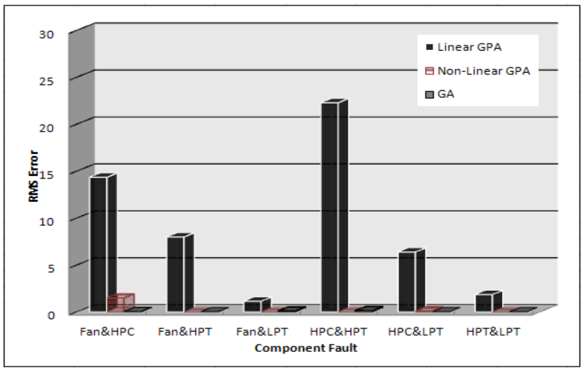

Fig. 8. Multiple Component Faults without Noise and Biases

D. Diagnostic Analysis Results of Multiple Fault Cases with Sensor Noise and Biases

Fig. 9 shows the diagnostic analysis results of multiple fault cases with sensor noise and biases.

According to the analysis results with sensor noise and biases, the RMS errors of both the linear GPA method and the non-linear GPA method increase, while the GA method has very low RMS errors compared to GPA methods at all types of fault cases. It means that the GA method is a reliable acceptable diagnostic method for the condition monitoring of AE3007E turbo fan engine.

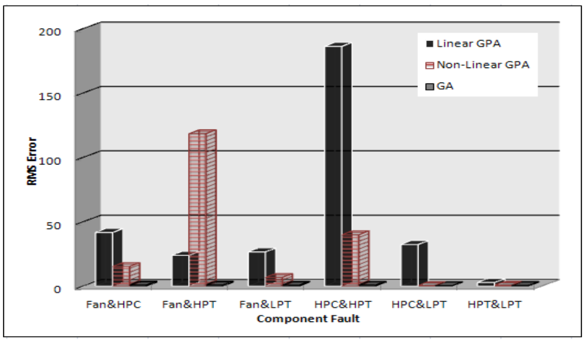

Fig. 9. Multiple Component Faults with Noise and Biases

E. Diagnostic Analysis Results Depending on Changes of Ga's Major Parameter

The influencing parameters to estimation results of the GA method are population size, number of generations, probability of mutation and probability of crossover. The followings show the analysis results depending on changes of Population and mutation effect.

1) Population size effect on maximum fitness

The GA method uses the population of possible strings rather than the use of an improved string through repetition process. To determine the optimal strings within the population, the analysis of changes of max fitness depending on different population size is performed, and its analysis results are shown at Fig. 10.

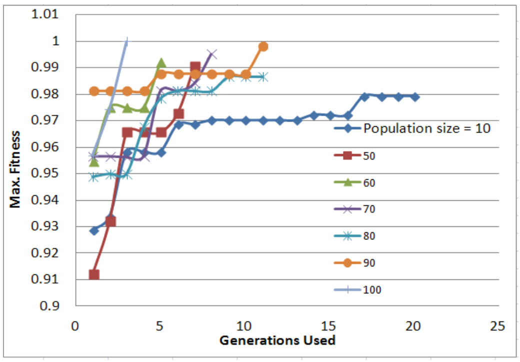

Fig. 10. Population effect

According to analysis results, it is found that if the population size increases, then the max fitness is improved but the conversion time increases. Here the max fitness means the inverse of the RMS error, i.e. if the max fitness increases, then the RMS error deceases.

2) Probability of mutation effect on maximum fitness

The probability of mutation is defined as the occurring possibility or the percentage of probability, and Fig. 11 shows the analysis results depending on changes of the probability of mutation. According to analysis results, it is found that if the probability of mutation increases, then the max fitness is improved.

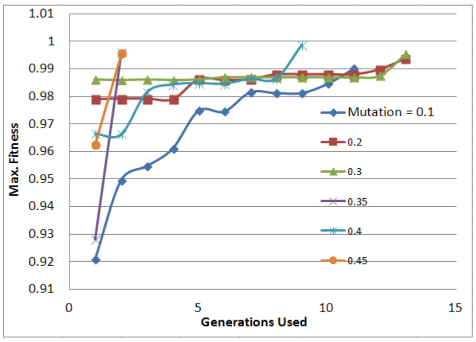

Fig. 11. Mutation effect

V. Conclusion

This work finds that both the linear GPA method and the non-linear method for the condition monitoring of the AE3007E turbofan engine have advantages and disadvantages, so the GPA methods are weak as the diagnostic method of the gas turbine engine.

However the linear GPA has been used together with other diagnostic methods up to now, and this method can be used for the test purpose during development stage of the other diagnostic methods without noise and biases as well as the fundamental model of the non- linear GPA method.

The non-linear GPA method shows much higher precision in the fault diagnostics than the linear GPA but needs more calculation time, and especially it is applicable for large degradation and multiple fault cases.

However the weakness of the GPA methods occurs at consideration of sensor noise and biases. In case of small size of noise, the GPA methods can be used but it is not proper for the large size of noise. Another limitation of the use of the GPA methods is the consideration of biases.

However the GA method has good diagnostic results on all the fault cases not only single and multiple fault cases but also consideration of sensor noise and biases.

In addition if the population size, the probability of mutation and the probability of crossover increase, then the max fitness is improved but the conversion time increases.

Acknowledgment

"This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (No.2012-0001713)."

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