퍼지 로직 시스템을 이용한 항공기 가스터빈 엔진 오류 검출에 대한 연구

Fault Diagnosis in Gas Turbine Engine Using Fuzzy Inference Logic

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Abstract : A fuzzy inference logic system is proposed for gas turbine engine fault isolation. The gas path measurements used for fault isolation are exhaust gas temperature, low and high rotor speed, and fuel flow. The fuzzy inference logic uses rules developed from a model of performance influence coefficients to isolate engine faults while accounting for uncertainty in gas path measurements. Inputs to the fuzzy inference logic system are measurement deviations of gas path parameters which are transferred directly from the ECM(Engine Control Monitoring) program and outputs are engine module faults. The proposed fuzzy inference logic system is tested using simulated data developed from the ECM trend plot reports and the results show that the proposed fuzzy inference logic system isolates module faults with high accuracy rate in the environment of high level of uncertainty.

Keywords : fuzzy inference logic, gas turbine engine, engine condition monitoring, fault isolation

I. Introduction

In the last twenty years, gas turbine performance diagnostics has attracted the attention of many researchers. The gas turbine performance diagnostics involve the accurate detection, isolation, and estimation of engine module performance, engine system problems and instrumentation problems using measurements from the engine gas path. Discernable changes in gas path measurements from a baseline "good engine" are used to obtain changes in engine performance from the baseline state. Historically, this type of analysis has been treated as a system identification problem and the analysis performed using Kalman filters. More recently, neural networks have also been used to solve the fault isolation problem. While the Kalman filter literature focuses on long-term deterioration of the engine modules, the neural network literature focuses on single-fault isolation following a step or rate change in engine gas path measurements [1].

Once a trend change has been detected, a trained neural network can isolate the engine fault [2]. The Kalman filter can also be configured to isolate single faults following a trend change [3,4].

In this paper, we focus on the subset of the performance diagnostics problem involving isolation of the faulty module in the gas turbine once a trend shift in one or more of the gas path measurements has been detected. Knowledge of the faulty module reduces maintenance costs as only the faulty module needs to be opened and inspected, and not the whole engine. It is assumed that only one module is defective. The analysis can be looked on as a way to automate the ECM charts to perform module fault isolation.

A typical twin-spool turbojet engine has five modules: fan (FAN), low-pressure compressor (LPC), high-pressure compressor (HPC), high-pressure turbine (HPT), and low-pressure turbine (LPT). Most damages to the engine manifest themselves as changes in either the module efficiency or flow capacity/area. ECM (Engine Condition Monitoring) trend plot reports provided by jet engine manufacturers such as Pratt and Whitney are routinely used by airlines for gas turbine performance diagnostics [5]. These reports summarize the relationships between measurement deviations of gas path parameters from a baseline model to an engine fault. Experienced power plant engineers can often look at a given trend shift in the measurement deviations and isolate the faulty module or component using the ECM trend plot reports. However, automation of the process allows the isolation to be performed as each measurement data point becomes available and may prevent expensive maintenance events.

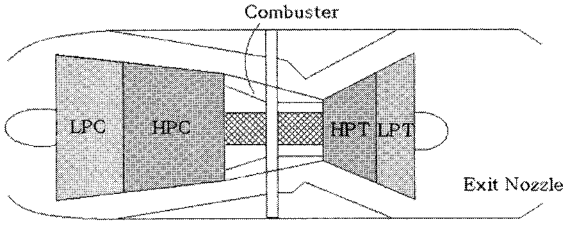

그림 1. 일반적인 2축 터보제트 엔진 구조.
Fig. 1. A typical twin-spool turbojet engine.

Typical gas path measurements are exhaust gas temperature (EGT), low-spool rotor speed (N1), high-spool rotor speeds (N2), and fuel flow (WF). These four measurements are often called the four basic parameters and the instrumentation to measure them is available on most new and old engines. However, for a fault isolation system to be widely applicable, it should be able to function with only four measurements [6]. The typical ECM trend plot reports can show any relating changes in measurement deltas for the four basic parameters with the faulty module. Since ECM uses steady state cruise in-flight data taken either automatically by the aircraft computers or manually by the flight crew. This data is

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written into computer files, corrected to sea level static condition, and compared with the baseline of a particular engine/aircraft configuration. The difference between the in-flight data and the baseline is referred to as a "raw" delta. Since these deltas are plotted in the form of trends to identify possible engine malfunctions and the results of the module by module performance analysis of changes in efficiency and flow capacity relative to a baseline engine, they are only approximately correct because they do not account for uncertainties in the measurement process. In this paper, we focus on isolation of the faulty module in the gas turbine engine once a trend shift in one or more of the gas path measurements has been detected [7,8].

II. Fuzzy Logic System

The objective of this paper is to show how a fuzzy logic inference system can accurately isolate the module faults from measurement deltas, while accounting for uncertainty. There are several reasons for selecting fuzzy inference logic system for this application [8]. First, the fuzzy logic system is a knowledge based system that has ability to handle uncertainty. Second, the fuzzy logic system does not require estimation of the system parameter. Third, the fuzzy logic rule base contains control strategies that are applicable to a wide range of qualitatively- similar scenarios. Conventional fault isolation techniques may indicate them differently in the engine performance criteria. However, with system simplicity the fault isolation strategies for both cases remain the same qualitatively, the rule base determines proper control actions based on the magnitude of the input/output relationship. A typical multi-input single-output (MISO) fuzzy inference logic system performs a mapping from $V \in R^m$ to $W \in R$ using four basic components: rules, fuzzifier, inference engine and defuzzifier [9].

The Inputs to the fuzzy inference logic system are measurement deltas and outputs are engine module faults, and the inputs have four measurements represented by y and five engine faults represented by x. The objective is to find a functional mapping between y and x. Mathematically this can be represented as $X = F(y)$ where $X = \{FAN, LPT, HPC, HPT, LPT\}^T$ and $Y = \{\Delta EGT, \Delta WF, \Delta N1, \Delta N2\}^T$. Each measurement delta has uncertainty. FAN, LPC, HPC, HPT, and LPT are fuzzy sets denoting the five engine modules. Each fuzzy set has degrees of membership ranging from zero to one. In this paper, we are only

표 1. 퍼지 세트.

Table 1. Fuzzy sets.

Linguistic Measure	Midpoints			
	EGT	WF(%)	N1	N2
High(H+)	20	4	1.5	1.5
Medium(M+)	13.3	2.7	1	1
Low(L+)	6.6	1.3	0.5	0.5
Negligible	0	0	0	0
Low(L-)	-6.6	-1.3	-0.5	-0.5
Medium(M-)	13.3	-2.7	-1	-1
High(H-)	-20	-4	-1.5	-1.5

interested in the module containing the fault. Therefore, we do not further decompose the module fuzzy sets using linguistic variables.

The measurement deltas $\Delta EGT, \Delta WF, \Delta N1, \Delta N2$ are also treated as fuzzy variables. To get a high degree of resolution, they are further split into linguistic variables. For example, consider ΔEGT as a linguistic variable. It can be decomposed into a set of terms $T(\Delta EGT)$ ={High-, Medium-, Low-, Negligible, Low+, Medium+, High+} where each term in $T(\Delta EGT)$ is characterized by a fuzzy set in the universe of discourse $U(\Delta EGT)$ = {-20°C, 20°C}, which is selected to include values in the vicinity of the ECM trend plot reports.

The other three measurement deltas are defined using the same set of terms as ΔEGT, spanning the following universes of discourse: $U(\Delta WF)$ ={-4.0%, 4.0%}; $U(\Delta N2)$ ={-1.5%, 1.5%}; $U(\Delta N1)$ ={-1.5%, 1.5%}. Since the influence coefficients on which the ECM trend plot reports are based on a linear model, the diagnostic system should be limited to small measurement deltas. In addition, measurement deltas larger than covered by the universe of discourse will represent a large fault indicative of a catastrophic failure.

Fuzzy sets with Gaussian membership functions are used. These fuzzy sets can be defined using the following equation:

$$\mu(x) = e^{-0.5(x-m/\sigma)^2} \qquad (1)$$

Where m is the midpoint of the fuzzy set and σ is the uncertainty (standard deviation) associated with the variable. Table1.gives the linguistic measure associated with each fuzzy set and the midpoint of the set for each measurement delta. The midpoints are selected to span the region ranging from a perfect engine (all measurement deltas are zero) to one with significant damage. The fuzzy set corresponding to "high" are defined slightly differently to account for the open-ended nature of the linguistic variable.

$$\mu(x) = e^{-0.5(x-m/\sigma)^2} m_{VH-} < x \quad OR \quad x < m_{VH+} \qquad (2)$$

$$\mu(x) = m_{VH+} < x \quad OR \quad x < m_{VH-} \qquad (3)$$

The Fuzzy logic system employs a series of IF-THEN rules that utilize a strategy resembles to that of a PD controller since the rules are predicated on errors and error rates. Rules for the fuzzy system are obtained by fuzzification of the numerical values in the ECM trend plot reports using the following procedure [10]:

1. A set of four measurement deltas corresponding to a given module fault is input to the FLS and the degree of membership

표 2. 퍼지 추론 논리 시스템의 퍼지 룰.

Table 2. Rules for fuzzy inference logic system.

Module	EGT	WF	N2	N1
FAN	M-	M-	L-	H+
LPC	M+	M+	L+	L+
HPC	H+	M+	N	N
HPT	M+	H+	M-	N
LPT	N	H-	H+	H-

of the elements of $\Delta EGT, \Delta WF, \Delta N1, \Delta N2$ are obtained. Therefore, each measurement has seven degree of memberships based on the linguistic measures in Table 2.

2. Each measurement delta is then assigned to the fuzzy set with the maximum degree of membership.
3. One rule is obtained for each module fault by relating the measurement deltas with maximum degree of membership to a module fault.

These rules are shown in Table 2. The linguistic symbols used in this table are defined in Table 1.

These rules can be read as follows for the HPC module:

IF

ΔEGT is high + AND

ΔWF is medium + AND

$\Delta N2$ is negligible AND

$\Delta N1$ is negligible

THEN

problem in HPC module.

The rules for the other modules can be similarly interpreted. A noticeable drop in N1 speed relative to a baseline can be attributed to a weak LPT. Similarly, a significant drop in N2 speed can be attributed to a weak HPT and/or opened TNGV area. Two other unique parameters are EGT and fuel flow. These two parameters behave proportionally to each other in an approximate ratio of 10°C EGT to 1% WF. That is, for every additional 1 % fuel flow added to the engine, the EGT would rise approximately 10°C regardless of the gas path problem.

This ratio, however may change significantly if there is either an air bleed leak or indication error. Another consideration is the speed of N1 relative to N2, as well as N1 and N2 speeds relative to the baseline. Under normal condition, if the speed increases on a module then the airflow would also increase across the LPC. The LPT drives the fan and LPC together. A weak LPT slows the N1 speed. However since a loss of fan flow capacity would result in an increase in N1 speed, it is essential to assess the condition of the fan before attempting to assess the condition of the LPT.

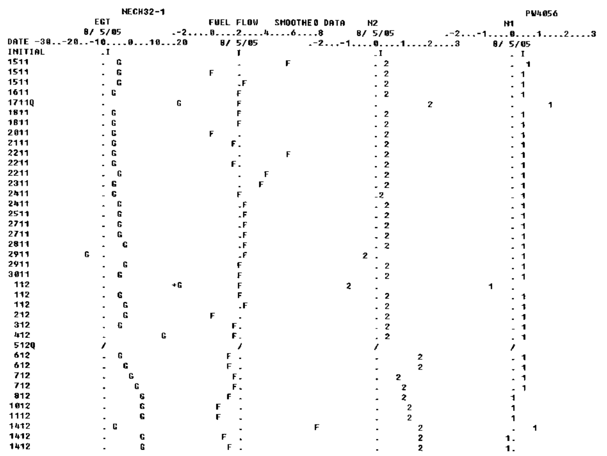


그림 2. N1이 0.6 % 정도 줄어들고, N2 (1.2%)와 EGT (9C) 증가할 때의 ECM 트랜드 플롯 리포트.

Fig. 2. ECM trend plot report showing change in N2 (+1.2%) and EGT (+ 9°C) are increasing as N1 (- 0.6 %) fall.

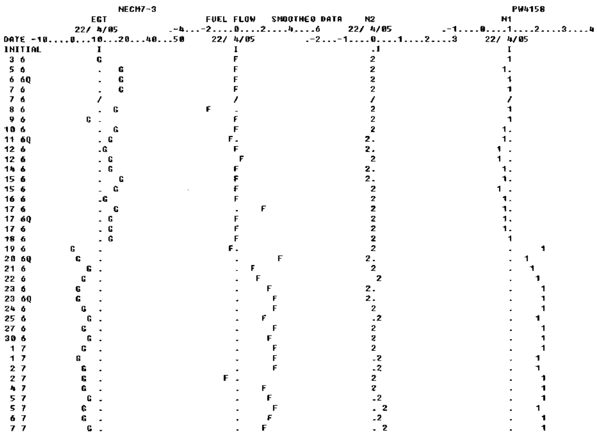


그림 3. EGT는 15도 정도 줄어들고, N1과 연료 흐름이 증가할 때의 ECM 트랜드 플롯 리포트.

Fig. 3. ECM trend plot report showing change in EGT drop (-15°C) and N1(+ 2 %) and fuel flow (+2 %) increases.

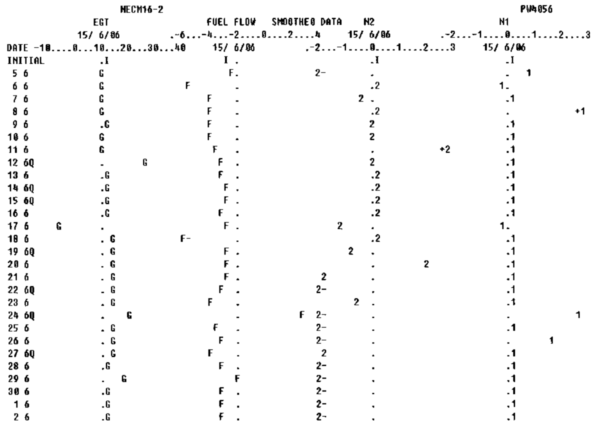


그림 4. N2가 1.5% 정도 줄어들 때의 ECM 트랜드 플롯 리포트.

Fig. 4. ECM trend plot report showing change in N2 (- 1.5 %) drop.

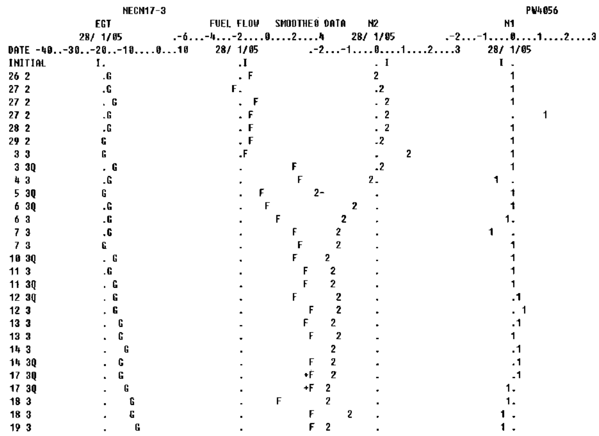
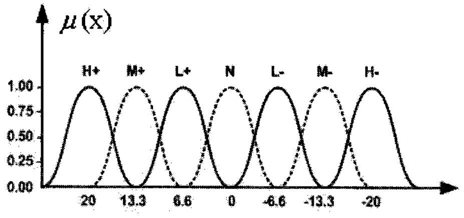
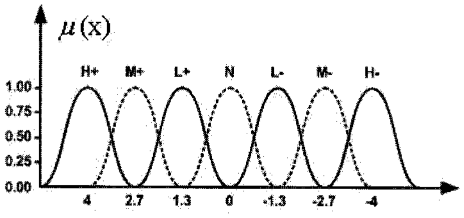


그림 5. EGT와 연료 흐름이 증가하는 반면, N2는 감소, N1은 변하지 않을 때의 ECM 트랜드 플롯 리포트.

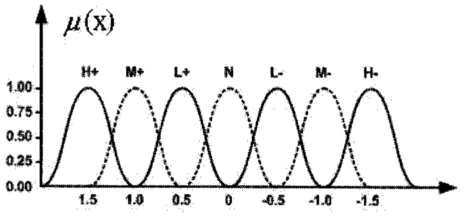
Fig. 5. ECM trend plot report showing change in EGT (+ 10°C) and fuel flow (+2 %) are increasing as N2 (- 1.5 %) shifts down/N1 does not change.



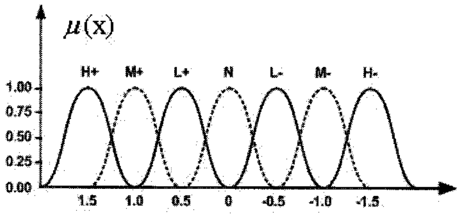
(a) EGT Delta (%)



(b) WF delta (%)



(C) N1 delta (%)



(d) N2 delta (%)

그림 6. EGT, 연료 흐름, N1과 N2 각각에 대한 멤버십 함수.

Fig. 6. Shows the membership functions for each of the seven fuzzy sets for $\Delta EGT, \Delta WF, \Delta N1, \Delta N2$.

For any given input set of measurement deltas, the fuzzy rules are applied using product implication. Once the fuzzy rules are applied for a given measurement, we have degree of memberships for FAN, LPC, HPC, HPT, and LPT. The fault with the highest degree of membership is selected as the most likely fault. The fault with the second highest degree of membership is selected as the second most likely fault.

Fig. 6. shows the membership functions for each of the seven fuzzy sets for $\Delta EGT, \Delta WF, \Delta N1, \Delta N2$. There is more overlap between the fuzzy sets partitioning EGT and WF because these measurements have greater uncertainty, compared to N1 and N2.

III. Simulations

The fuzzy inference logic system is tested using simulated data developed from PW4000-94" Engine ECM trend plot reports. Noise is added to the simulated measurement deltas using the typical standard deviations for $\Delta EGT, \Delta WF, \Delta N1, \Delta N2$ as 2.5°C, 0.5%, 0.25%, and 0.3%, respectively. To observe how the fuzzy inference logic system performs with data at other standard deviations, we define the baseline standard deviation as $\sigma_0 =$ (2.5°C, 0.5 %, 0.25 %, 0.3 %) and test the fuzzy inference logic system with data at standard deviation values which are multiples of σ_0. The success rate for these tests is shown as the scatter in the data σ / σ_0 is increased from 0 to 2 as shown in the Fig. 7. It is clear that the fuzzy inference logic system shows a slow deterioration in performance as the scatter in the data increase. The problem in fault isolation are mostly in the confounding between the LPC and HPC modules, and the other module faults are isolated well even with data with scatter as high as 2 σ_0.

표 3. 퍼지 추론 논리 시스템으로 얻어진 오류 검출 결과.

Table 3. Fault isolation results from fuzzy inference logic system.

Module/Isolation	No.1 choice %	No.2 choice %
FAN	100	100
LPC	95	100
HPC	93	100
HPT	100	100
LPT	100	100
	97.6	100

Table 3. shows the results from the fuzzy inference logic system. For the FAN, LPT, and HPT modules, there is a 100% success rate with the first choice of the fuzzy inference logic system. For the LPC and HPC, there is some confounding and a slightly lower accuracy of 95% and 93%, respectively. The average success rate for the fuzzy logic system is 97 % when only the first choice is considered.

Whenever the LPC module is not identified correctly as the first choice, the fuzzy system confuses it with the HPC module. Whenever the HPC module is not correctly identified as the first choice, the fuzzy system confuses it with the LPC module. However, if the first two choices are taken, the accuracy of the fuzzy system is 100%. The confusion between these compressor modules is because of the similarity in the directions of the ECM trend plot reports, which can be seen in the ECM trend plot reports as well as the fuzzy rules. In the cases where the random error is high, the ECM trend plot reports for the HPC look very similar to those of the LPC, and vice versa.

It is clear that the fuzzy inference logic system is able to identify the correct fault despite the presence of considerable uncertainty in the measurements. In cases where it is confounded, a human expert would also be likely to be confounded.

IV. Conclusion

A fuzzy inference logic system is developed for gas turbine engine fault isolation. It takes measurement deviations from a baseline engine and isolates the faulty module. The fuzzy logic system operates with four basic measurements (EGT, WF, N1, N2) and analyzes deterioration in five modules (FAN, LPC, HPC, HPT, LPT). The fuzzy inference logic system is based on ECM trend plot reports provided by engine manufacturers and used by airline engineers.

Results show that the fuzzy inference logic system has a success rate of almost 100% in isolating the faulty engine module with four measurements. In cases where the fuzzy logic system is confounded, it was due to large uncertainty in the data and an

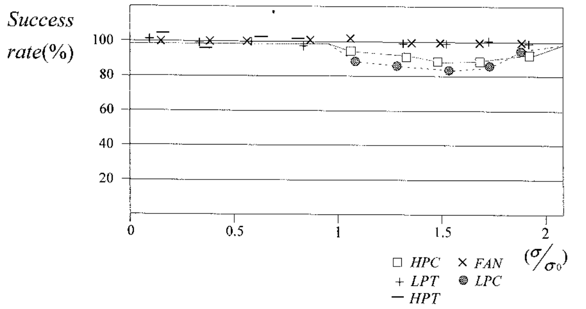


그림 7. 첫번째 시도시 얻어진 결과.

Fig. 7. 1st choice success rate in fault isolation.

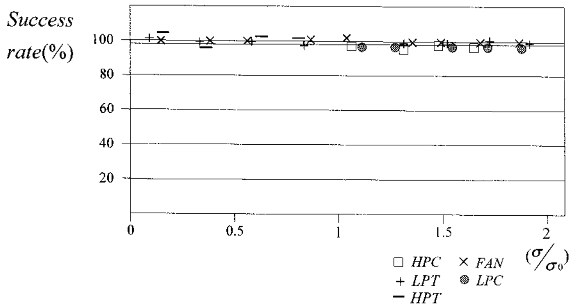


그림 8. 두번째 시도시 얻어진 결과.

Fig. 8. 2nd choice success rate in fault isolation.

airline engineer may have been similarly confounded. The fuzzy inference logic system therefore can be used as an expert system for automating the process of interpreting gas turbine performance data such as ECM trend plot reports or test cell MAP (Module Analysis Program) net charts. The fuzzy inference logic system is sufficiently robust and performs well for fault sizes that considerably different from the implanted faults used to develop the fuzzy rule base.

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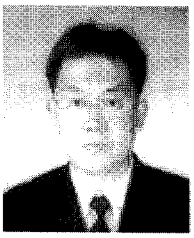

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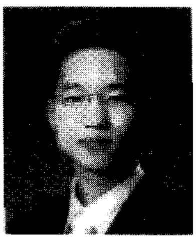

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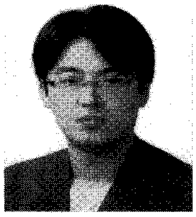

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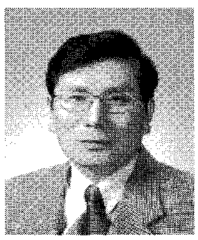

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