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A HYBRID EKF-FUZZY APPROACH TO FAULT DETECTION AND ISOLATION OF INDUSTRIAL GAS TURBINES

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ABSTRACT

Based on the Gas Path Analysis (GPA) method, nonlinear estimation and fuzzy classification theories, a comprehensive fault diagnosis system has been developed for an industrial Gas Turbine (GT). The hybrid method consists of two parts, in the first part noisy sensor output changes are translated to changes in the health parameters using an Extended Kalman Filter (EKF). In the second part the outputs of the EKF are used as the inputs of a fuzzy system. This system can isolate and evaluate the physical faults based on the predetermined rules obtained mostly from experimental data and aero-thermodynamical simulations. The ratios of changes in different health parameters due to different faults and also the areas in the compressor most affected by these faults are the key factors for developing the rules. The Fuzzy Inference System (FIS) gives the fault locations in the compressor or turbine. Also, operator-friendly suggestions for the time of the compressor washing or components repair are provided. This leads to a hybrid fault detection and isolation solution for the GT, and with pre-filtering the data before use as input of fuzzy inference system, the accuracy of the fault diagnosis system is improved. Nonlinear simulation, estimation and classification results are provided to show the effectiveness of the proposed methodology.

1 INTRODUCTION

With respect to ever-increasing power demand in the world and also growing share of power generation by gas turbines, continuous and risk-free performance of these devices is of high significance. Nowadays gas turbine manufacturers try to boost nominal and design performance conditions of their products and also optimize their performance in the site conditions. All types of gas turbines are susceptible to performance deterioration because of the site and working conditions and polluting environment. These deteriorations cause GTs to supply less power than what they are expecting to. As a result, health monitoring and performance improvement are two of the most important priorities of gas turbine manufacturers and users.

Fault diagnosis procedures rely on discernible changes taking place in observable parameters in order to detect physical faults. There are specific physical faults which are responsible for much of the performance loss in the industrial gas turbines, namely fouling, erosion, corrosion, leakage, thermal distortion and foreign object damage (FOD).

These degradations cause changes in the fundamental component performance characteristics of the gas turbine. They can be viewed as the state parameters representing the overall health of their related component, such as high or low pressure compressors or turbines. In most of the gas path analysis methods, two types of health parameters have been mentioned to be crucial in determining health conditions of the GT components, efficiency and flow capacity. Variations in these parameters caused by physical faults directly change the sensor measurements, such as pressures and temperatures in the inlets and outlets of the gas path components, fuel flow and spool speeds.

In this work, in the simulation phase, using accurate 1D, 3D and quasi-3D simulations and analyses with a 3D finite volume solver program and Fortran, different physical faults are mapped to degraded health parameters and then using zero-dimensional modeling of the gas turbine cycle with the help of stage stacking method, these degradations are mapped to changes in sensor measurements. In the diagnosis phase, first, using nonlinear gas path analysis technique and extended Kalman filtering, degraded health parameters are estimated from noisy measurements and then with the help of fuzzy classification and the rules obtained from simulations and experience and validated by experimental results physical faults are classified. The schematic of the proposed method is shown in Figure 1.

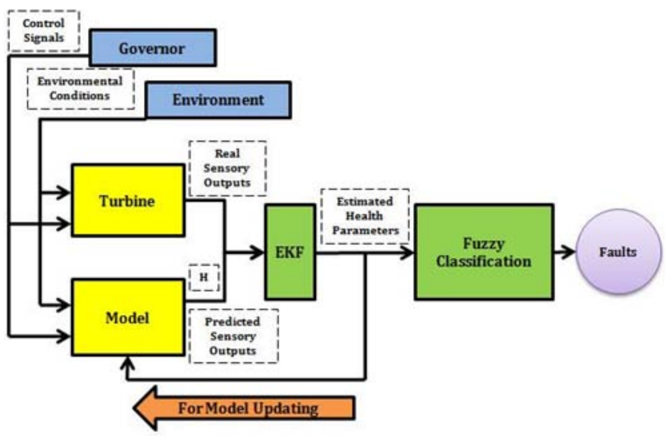

Figure 1: The schematic of the proposed hybrid fault detection and isolation system

In section 2, a specific industrial gas turbine, the Siemens V94.2 modeling is explained. In section 3, GPA technique and EKF theory are briefly reviewed and in section 4, diagnosis system configuration and the results of the health parameter deteriorations estimation by EKF are shown. In section 5, with the help of fuzzy classification physical faults are classified from health parameter degradations and finally conclusions are presented in section 6.

NOMENCLATURE

GT	Gas Turbine
GPA	Gas Path Analysis
EKF	Extended Kalman Filter
FIS	Fuzzy Inference System
FFI	Fuzzy Fault Isolator
ICM	Influence Coefficient Matrix
H	influence coefficient matrix
TET	Turbine Exhaust Temperature
W_f	fuel flow
P_3	compressor outlet pressure
T_3	compressor outlet temperature
Δz	vector of sensor measurement deltas
Δx	vector of health parameter deltas
n	number of sensors
m	number of health parameters
Γ	flow capacity
η	isentropic efficiency

<u>Subscripts:</u>

c	compressor
$c1$	front section of the compressor
$c2$	rear section of the compressor
t	turbine

2 GAS TURBINE MODELING

Any fault diagnosis procedure needs a comparison between the healthy and faulty systems, so a reference for the healthy baseline is needed to detect the existence of the fault. Also for further diagnosis additional references for faulty conditions are required. In the fault diagnosis theory references can be developed by three different ways; hardware redundancy, mathematical modeling (analytical redundancy) and process history data. The first method is costly, space-consuming and not suitable for faulty references, the model-based approach is appropriate if a comprehensive physical and mathematical knowledge of the system is available and the data-driven method is suitable if sufficient process history and experimental data in different operating conditions can be found.

A team of research engineers in Turbotec company developed a nonlinear simulator for the Siemens V94.2 gas turbine in recent years and using that a nonlinear model has been developed for use in the fault diagnosis procedure. This gas turbine has 16 compressor and 4 turbine stages. For more accurate analysis this compressor is divided into four groups. The classification has been done on the basis of the place of the bleed valves and cooling extractions. In the zero-dimensional modeling of the gas turbine cycle, the maps of all groups of the compressor and turbine and also the combustion chamber are assumed as inputs. The advantage of zero-dimensional modeling is its high speed computation ability, so it is appropriate for the evaluation of the whole cycle performance and control system design. But the maps of the compressor and turbine must be generated from higher order models using one, two, three or quasi-three-dimensional models. Component maps in this paper are the results of accurate quasi-three-dimensional analyses, by knowing the geometry of the compressor, turbine and combustion chamber. The streamline curvature methods as described by [1] and [2] can be used together with the blade-to-blade models in order to generate compressor and turbine maps. For more details readers are referred to [3] developed by one of the authors.

Fault diagnosis is conducted in the steady state mode in our work because most gas turbine diagnosis procedures can be carried out in this mode [4]. As a result, the GT model used in this research has been designed in the steady state, off-design conditions. Off-design conditions are conditions which include various ambient temperatures, pressures and loads on the contrary to the design condition which is ISO environmental condition and full load.

The faults mentioned in this paper are related to different stages of the compressor and turbine and are simulated by displacing the input maps of gas turbine health parameters. These maps are mainly the maps of efficiency-mass flow and pressure ratio-mass flow. In order to simulate a fault in GT, the amount of deviations of the faulty maps from their healthy counterparts can be set as the inputs of the program. In the next stage, the cyclic analysis of the gas turbine can be done and sensor measurements of the faulty turbine will be obtained.

3 GPA AND EKF THEORY

The main parts of any gas turbine are gas path components such as the compressor, combustion chamber and turbine. A large portion of the faults which cause problems in the GT performance, safety and health, happen in these parts, so determining the health conditions of the gas path components is a priority for the turbine manufacturers and users.

In this work, the aim is to detect and isolate the physical faults which threaten the health of compressor and turbine sections. These parts are susceptible to different kinds of degradations such as fouling, leakage, erosion, corrosion, thermal distortion and foreign object damage. These physical faults cause some principle independent parameters in the compressor and turbine sections to change. These parameters which are indicative of the overall health conditions of their corresponding components are mainly efficiency and flow capacity. It is obvious that performance based fault diagnosis methods like GPA can only detect faults which their occurrence changes the sensor measurements.

Urban in [5] introduced the GPA method, and explained how health parameter variations directly change sensor measurements (dependent parameters) like pressures and temperatures, fuel flow and spool speeds. It is shown in [6] that a general influence coefficient matrix (ICM) may be derived for any particular gas turbine cycle, defining the set of differential equations which interrelate the various dependent and independent engine performance parameters. The influence coefficient matrix imply that

$$\Delta z = H \Delta x \tag{1}$$

In (1), Δz is $n \times 1$ vector of turbine sensor output deltas, Δx is $m \times 1$ vector of turbine health parameter deltas and H is $n \times m$ influence coefficient matrix which consists of partial derivatives interrelating the two sets. Usually in gas turbines due to limitations in the number of instruments, the number of measurements (n) is less than the number of health parameters (m) [7], as a result the amount of available information at a single operating point may not be sufficient for the derivation of all unknown health parameters and in this case the system has fewer equations than unknowns.

According to Figure 2 introduced in [6] physical problems result in degraded component performance which produces changes in measurable parameters explainable by ICM. This is the natural chain of events in gas turbine faults. On the other hand in order to diagnose the fault the procedure should be reversed. From the changes of available measurements, estimation of degraded component performance parameters can be done which permits classification and usually correction of the physical problems.

There are a number of methods which solve the inverse problem, especially in the presence of noise and other uncertainties, among them weighted-least-square [8,9] and Kalman filter methods [10-12].

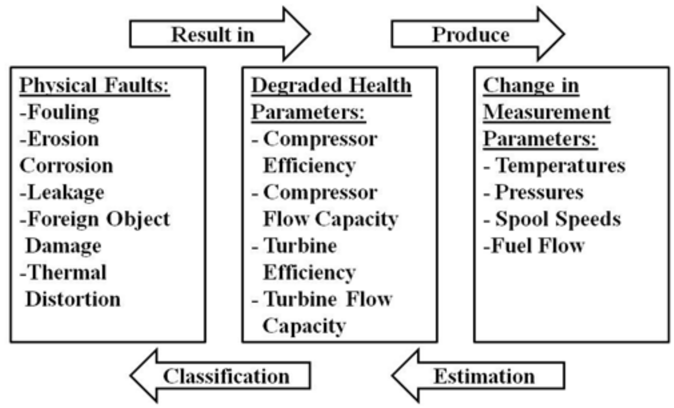

Figure 2: Gas turbine fault diagnosis approach

Kalman filter method, especially in its extended form, has been used widely in fault diagnosis and health monitoring of gas turbines due to highly nonlinear characteristics of these systems [10-12]. Its ability to estimate the state variables of nonlinear systems or health parameters in this case, accurately in the presence of noise and other uncertainties with its prediction-correction procedure has proved itself in many empirical situations.

We consider our state space equations as (2) and (3)

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \tag{2}$$

$$z_k = h(x_k) + v_k \tag{3}$$

in which x_k is the true state vector of the system in step k, f is a nonlinear function which relates the state at the previous time step $k-1$ to the state at the current time step k. u_k is the optional control input in step k. z_k is the measurements vector in step k, h is a nonlinear function which relates the state vector x_k to the measurement vector z_k. And random variables w_k and v_k represent the process and measurement noise respectively. EKF formulation is stated in Table I [13] in which $\hat{x}_k^-$ is a priori state estimate in step k, P_k^- is the a priori estimate error covariance equal to $E[e_k^- e_k^{-T}]$ in which $e_k^- \triangleq x_k - \hat{x}_k^-$, P_k is the a priori estimate error covariance equal to $E[e_k e_k^T]$ in which $e_k \triangleq x_k - \hat{x}_k$ and $\hat{x}_k$ is the a posteriori state estimate in step k. A_k and H_k are the Jacobian matrices of partial derivatives of f and h with respect to x in each step k, Q_k and R_k are process and measurement noise covariance matrices respectively, and K_k is the Kalman gain.

Table I: EKF formulation

$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, 0)$
$P_k^- = A_k P_{k-1} A_k^T + Q_{k-1}$
$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1}$
$\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-, 0))$
$P_k = (I - K_k H_k) P_k^-$

4 HEALTH PARAMETER ESTIMATION

As mentioned in section 2 the model used for this research is a nonlinear model of the Siemens V94.2 Industrial gas turbine. There are measurements of four different sensors available for the fault diagnosis system which are turbine exit temperature (TET), fuel flow (W_f), compressor outlet pressure (P_3) and compressor outlet temperature (T_3). V94.2 is a single-shaft gas turbine and has one compressor and one turbine coupled with a shaft to each other. In [14], using stage stacking modeling technique and combining some of the stage maps, a method is proposed by authors to divide the compressor and turbine into two frontal and rear sections with independent flow capacities for each section but a common efficiency for the whole component. The scarcity of the available sensors limits the number of detectable health parameters and simulations were unable to show any difference between the effect of deteriorations in frontal and rear compressor and turbine efficiencies on the measurements, so we consider the efficiency parameters for the whole compressor and turbine. Mathematically speaking there were almost identical coefficients in the ICM columns for the frontal and rear section efficiencies. Urban in [6] presented an introduction to the fundamentals of turbine engine parameter selection and measurement requirements, and he emphasized there the role of H matrix coefficients in obtaining poor results.

With the configuration described in [14], the result was six independent health parameters, namely frontal and rear compressor flow capacities (Γ_{c1}, Γ_{c2}), compressor efficiency (η_c), frontal and rear turbine flow capacities (Γ_{t1}, Γ_{t2}), and turbine efficiency (η_t). However, the results of simulations by using sensor measurements in several different operating points show that the changes of five out of six health parameters can be estimated correctly and with reasonable accuracy, which are all the parameters except the flow capacity of the rear section of the turbine (Γ_{t2}). The inability to estimate Γ_{t2} deviation is due to presence of small coefficients in the corresponding column of the H matrix. But it is mentioned in [14] that incapability in estimating Γ_{t2} won't affect the results of diagnosis and isolation of the physical fault responsible for the performance deterioration. This is from the fact that turbine fault diagnosis depends less on knowing the whereabouts of most affected area than the compressor fault diagnosis. For example, in compressor, frontal deterioration is a sign of fouling but decline of rear section parameters improves the chance of erosion [15].

Regarding those results, authors have chosen a new configuration and new set of health parameters for the V94.2 gas turbine by considering the turbine section as a whole and allocating one parameter as the flow capacity of the whole turbine (Γ_t), as mentioned earlier this is done by combining the maps of different stages of the component. It leads to the reduction the number of independent health parameters to five which can be estimated correctly using the measurements information of two different operating points. The new configuration is shown in Figure 3.

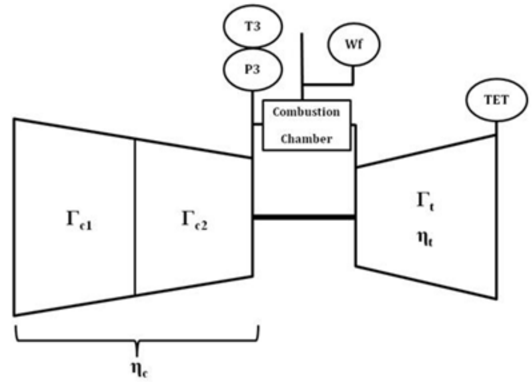

Figure 3: V94.2 fault diagnosis parameter configuration

The concept of multiple operating point fault diagnosis was described by Stamatis et al. in [16]. They explained that, by taking advantage of nonlinearity of the GT model and the hypothesis of having unchanged Δx for different operating points for some of the compressor fault cases the number of useful sensor data can be multiplied by the number of operating points which those measurements are available in. Considering that, for each extra operating point a new set of equation would be added to the problem while the number of unknown and unchanged compressor health parameters would remain the same. For more information readers are referred to [14] and [16].

Because of the fact that the method is validated for the compressor fault cases, we just hold constant the compressor related health parameter deviations. In the configuration used in this work, measurements in two different operating points have been used which means 8 measurements while on the other side there are 5 unknown health parameters of both the compressor and turbine for the first point and two additional which belong to the turbine section for the second point, and their sum is 7 unknown parameters. The results of the estimations with appropriate noise levels are shown in Figures (4-6). It can be seen that the EKF algorithm using measurements of two discrete operating points is able to accurately estimate the health parameter degradations of an over-parameterized problem.

5 PHYSICAL FAULT ISOLATION

As shown in Figure 2 gas path analysis can be divided into two procedures. The first part is estimating health parameter deteriorations using an accurate mathematical model of the gas turbine and noisy measurement data which have done in this work by an EKF algorithm.

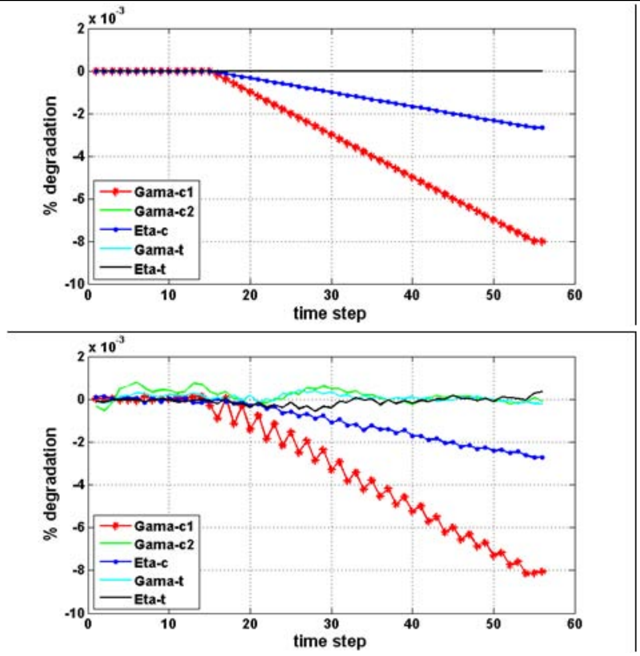

Figure 4: True degradations of Γ_{c1} and η_c (up) and their estimation with EKF (down)

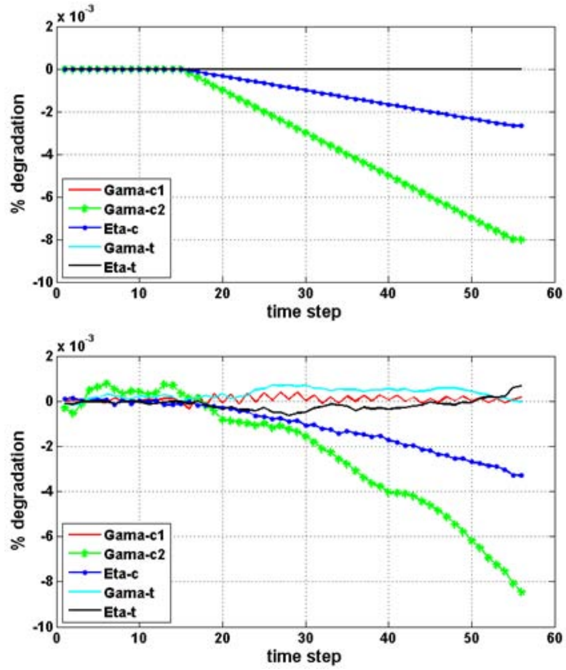

Figure 5: True degradations of Γ_{c2} and η_c (up) and their estimation with EKF (down)

The second part is classification of the estimated parameters to isolate the physical fault or faults responsible. For the first part the precise model and data are available but for the second part, lack of an appropriate model and comprehensive data set is usually the problem. The kind of physical faults threatening the GT is very dependable to its aerodynamic design, site location, environmental and operational conditions, appropriate filtering and maintenance [17-19]. For example jet engines are more vulnerable to foreign object damage than industrial gas turbines due to lack of filtering in the air intake. Or operating in desert conditions or near the sea or ocean where the level of salt and sand particles in the air is high will increase the chance of fouling and erosion problems. Other than that, the size of these particles and the quality and type of the filter used can be important factors for determining the kind of fault [20]. The size and the stage loading of the gas turbine is another factor for susceptibility to fouling [21,22].

Fingerprint Charts

Many researchers have tried to diagnose these physical faults by analyzing representative health parameters and their deviations. The results are usually shown as a table or fingerprint chart describing the signs, magnitudes or ratios of the changes happened in health parameters or sensor outputs due to different physical faults [23-28]. Ecsher in [28] proposed an almost comprehensive table which connects the direction and ratio of changes in the independent health parameters to the physical faults. These mappings are shown in Table II.

Table II and the other similar tables are actually sets of rules with health parameter changes in the "if" part and physical faults in the "then" part. For example:

- If ($\Gamma_C \downarrow$) and ($\eta_C \downarrow$) and the ratio of changes is about (2:1) the fault is (Compressor Erosion)

Table II: Physical faults exspressed as independent parameter changes according to [28]

Physical Fault	Non-dimensional mass flow change A	Isentropic efficiency change B	Ratio A:B
Compressor Fouling	$\Gamma_C \downarrow$	$\eta_C \downarrow$	~3-8:1
Compressor Erosion/Corrosion	$\Gamma_C \downarrow$	$\eta_C \downarrow$	~2:1
Turbine Nozzle Guide Vane Fouling	$\Gamma_T \downarrow$	$\eta_T \downarrow$	~2:1
Turbine Erosion/Corrosion	$\Gamma_T \uparrow$	$\eta_T \downarrow$	~2:1
FOD (Non Severe)	$\Gamma_c \updownarrow$	$\eta_c \downarrow$	0.5:1
Thermal Distortion	$\Gamma_T \uparrow$	$\eta_T \downarrow$	0.5:1

Another theory which we used for further improvement of fault isolation is the one developed in [15] by Mathioudakis and Stamatis. They stated in [15] that "a realistic way to model fouling in a compressor is to assume a linear variation of stage performance drop at the front stages of the compressor" and "when compressor blade erosion is considered, it is possible that the loss of performance in the stages can be more severe in the rear stages of the compressor".

Considering the facts mentioned above and undeterministic nature of the problem, a fuzzy solution seems to be ideal. Fuzzy classification is a nonlinear mapping of an input feature vector into a scalar output [29] and fuzzy systems are now widely used in industries because of their flexibility and ability to handle uncertainties.

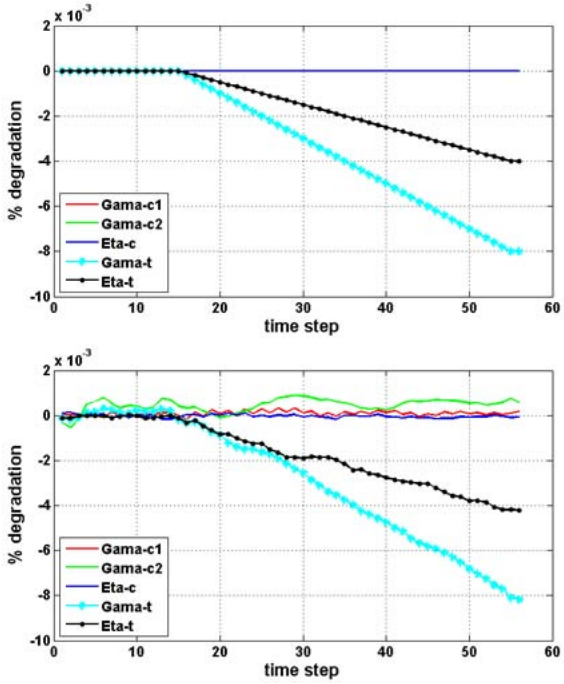

Figure 6: True degradations of Γ_t and η_t (up) and their estimation with EKF (down)

Fuzzy Fault Isolator (FFI)

We use Matlab Fuzzy Logic Toolbox for this part of the project. In some previous works [30], inputs to the fuzzy logic system were measurement deviations and the outputs were faulty components. In our work, inputs of the fuzzy system are the outputs of the EKF at any time step which are health parameter deviations and are more reliable sources of information for fault diagnosis according to [31]. The outputs are also more informative in our work because of indicating the type of physical fault in addition to the faulty component. The EKF estimation procedure observes the trends of changes in the health parameters through time and at any given time a sample of these data can be fed to the fuzzy inference system.

The fuzzy classification part of the work is split into two sections, compressor and turbine FFI. In the first section, compressor health parameter deviations are the inputs and the severity of compressor fouling, oil leakage, erosion and foreign object damage are the outputs. In the second section, turbine health parameters deviations are the inputs and the scale of turbine fouling, erosion and thermal distortion are the outputs.

Fuzzy Inputs and Outputs

First the number and the span of input variables should be determined. The inputs are Γ_{c1}, Γ_{c2} and η_c for the compressor and Γ_t and η_t for the turbine. The efficiency parameters are ranging from -4% to 0% and the flow capacity parameters are ranging from -8% to 4%. Next they are split into linguistic variables and the set is described with the function $L(x)$. Efficiency and flow capacity parameters are decomposed into:

- $L(\Delta\eta)$ = {Very Large-, Large-, Medium-, Small-, Tiny} with the midpoints respectively at: {-4, -3, -2. -1, 0}
- $L(\Delta\Gamma)$ = {Very Large-, Large-, Medium-, Small-, Tiny, Small, Medium} with the midpoints respectively at: {-7.5, -5.5, -3.5, -1.5, 0, 1.5, 3.5} and are shown in Figure 7.

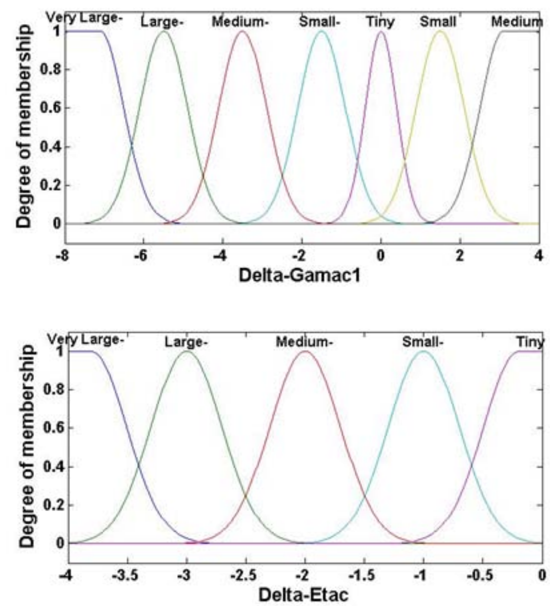

Figure 7: Gaussmf and Gauss2mf functions defining linguistic measures of $\Delta\Gamma_{c1}$ and $\Delta\eta_c$ for input health parameters of the FFI

We have used gaussmf and gauss2mf membership functions from the "Membership Function Editor" panel of the Matlab fuzzy logic toolbox. The outputs for the compressor section are decomposed into: (and are shown in Figure 8)

- L(Compressor Fouling) = {Zero, Next to Wash, Wash, Next to Repair, Repair}
- L(Compressor Oil Leakage) = {Not Happened, Happened, Severe}
- L(Compressor Erosion) = {Zero, Small, Medium, Large, Severe}
- L(Compressor FOD) = {Not Happened, Happened, Severe}

And the outputs for the turbine section are decomposed into: (and are shown in Figure 12)

- L(Turbine Fouling) = {Zero, Small, Medium, Large, Severe}
- L(Turbine Erosion) = {Zero, Small, Medium, Large, Severe}
- L(Turbine Thermal Distortion) = {Not Happened, Happened, Severe}

Fuzzy Rules for the Compressor

After defining the input and output sets, the fuzzy rules must be determined. Using information of the Table II, Figure 9 can be drawn as a classification map for fault isolation of a compressor with the efficiency and one of the flow capacity parameters.

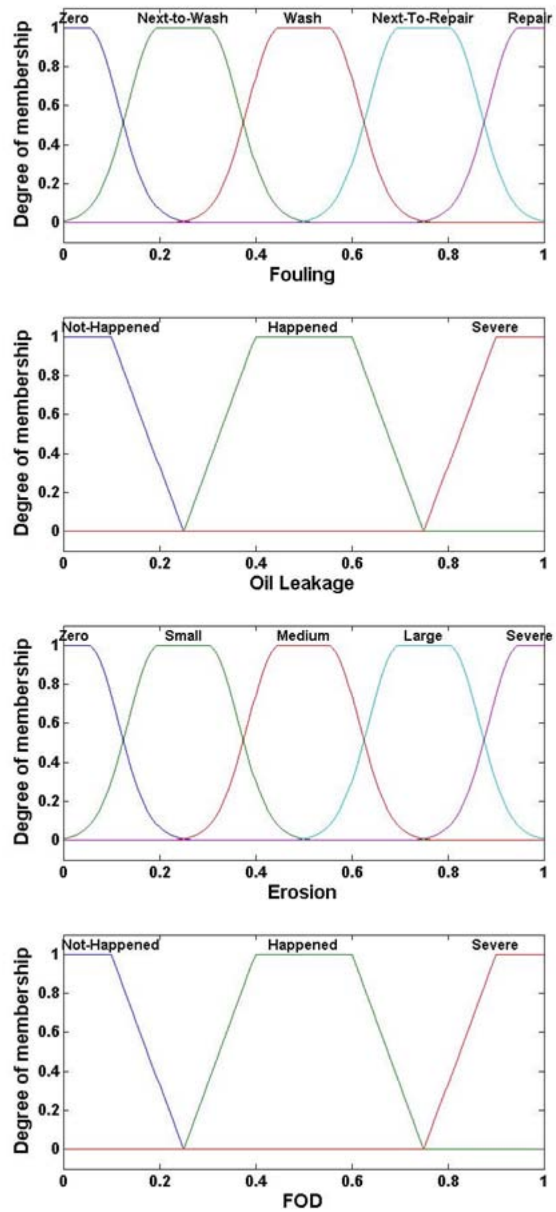

Figure 8: Various membership functions defining linguistic variables of Fouling, Oil Leakage, Erosion and FOD as outputs of the compressor FFI

By adding useful considerations of the effect of different faults in the front and rear sections of the compressor, we can have all three inputs and their modified rules for the compressor section. For example Baker stated in [17] that "compressor deterioration is exacerbated by internal oil leaks near the blade surfaces. Oily substances in the incoming air act as glue to fix dirt particles to compressor airfoil and shroud surfaces. In the high temperature region at the back end, oils bake onto surfaces and form a thick coating". Considering this fact the chance for oil leakage in the compressor will rise if there is considerable decline in rear section flow capacity in comparison to its efficiency and frontal section flow capacity. Unfortunately, we are unable to show the 3 parameter configuration as a classification map on a figure due to its 3 dimensional nature.

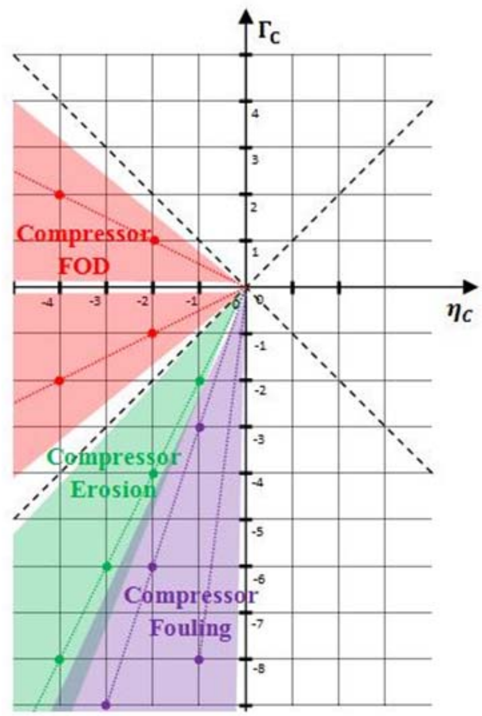

Figure 9: Classification map of the compressor fault isolation

We loaded these rules into the "Rule Editor" panel of the Matlab fuzzy toolbox and completed the procedure. The maximum number of rules is $5 \times 7 \times 7 = 245$ but many of them are not physically possible. For example a small negative change in the compressor efficiency with a considerable positive change in its flow capacity or extreme changes in two compressor flow capacity parameters towards opposite directions. After removing the improbable rules, 145 of them remain. Some of the rules used by fuzzy inference system are as follows:

- If ($\Delta\eta_c$ is Medium-) and ($\Delta\Gamma_{c1}$ in Large-) and ($\Delta\Gamma_{c2}$ is Large-) then (Fouling is Wash) (Oil Leakage is Not Happened) (Erosion is Zero) (FOD is Not Happened).

The above rule indicated that if the ratio of changes of the efficiency parameter to flow capacity is near 1 to 3, the chance of fouling would be high and the time is appropriate for washing the compressor.

- If ($\Delta\eta_c$ is Large-) and ($\Delta\Gamma_{c1}$ in Medium-) and ($\Delta\Gamma_{c2}$ is Very Large-) then (Fouling is Zero) (Oil Leakage is Happened) (Erosion is Large) (FOD is Not Happened).

The above rule indicated that if the extent of deterioration in the rear section is much worse than the front section the chance of fouling would be tiny but there would be a good chance for oil leakage and erosion.

- If ($\Delta\eta_c$ is Large-) and ($\Delta\Gamma_{c1}$ in Tiny) and ($\Delta\Gamma_{c2}$ is Small-) then (Fouling is Zero) (Oil Leakage is Not Happened) (Erosion is Zero) (FOD is Happened).

The above rule indicated that if the change of the efficiency masters the flow capacity deteriorations, foreign object damage would be the primary suspect.

Compressor FFI Results

In Figure 10 the output of the "Surface Viewer" panel of the Matlab fuzzy toolbox for changes of the 2 out of 3 compressor health parameters are shown. $\Delta\Gamma_{c2}$ is kept constant here. The shifting of the prominence of fouling to erosion and then FOD as $\Delta\eta_c/\Delta\Gamma_{c1}$ grows bigger is obvious.

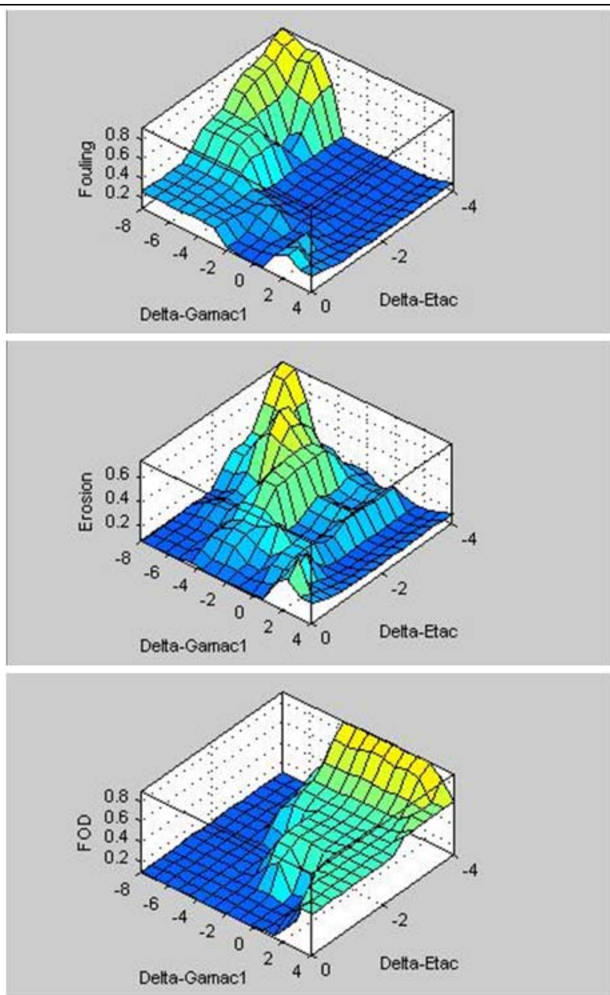

Figure 10: Fuzzy surfaces of Fouling, Erosion and FOD of the compressor with holding $\Delta\Gamma_{c2} = -2$

After developing the fuzzy classifier, output of the EKF estimator at any given time can be classified to the responsible physical fault. To validate our work, we fed the noisy data of 145 different probable set of health parameter deviation estimations as inputs to the classifier. And our Fuzzy Fault Isolator system was able to correctly classify 133 of them, which means correct classification rate of 91.72%. The remaining 12 are those which are on the boundaries of severe changes in the surfaces of Figure 10.

Fuzzy Rules for the Turbine

For the turbine sections, the job is much simpler. There are just two inputs, $\Delta\eta_t$ and $\Delta\Gamma_t$. The maximum number of rules here is $5 \times 7 = 35$ but like the former part some of them are not physically possible. After removing the improbable combinations, 26 rules remain. Once again using information of the Table II, Figure 11 can be drawn as a classification map for fault isolation of the turbine section with efficiency and flow capacity parameters.

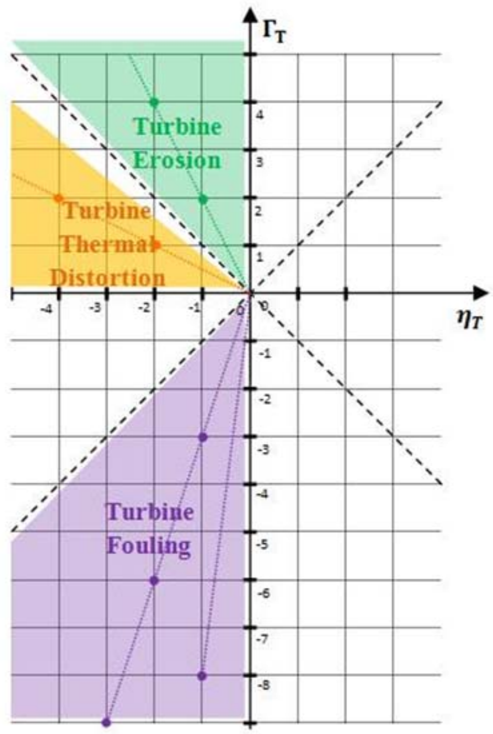

Figure 11: Classification map of the turbine fault isolation

Turbine FFI Results

In Figure 13 the output of the "Surface Viewer" panel of the Matlab fuzzy toolbox for changes of the turbine health parameters are shown. The shifting of the prominence of fouling to thermal distortion and then erosion as the $\Delta\Gamma_t$ sweeps from the extreme negative to the extreme positive is obvious.

Like the previous part, turbine related outputs of the EKF estimator at any given time can be classified by fuzzy fault isolator to the responsible physical fault. To validate our work, we fed the noisy data of 26 different probable sets of health parameter deviation estimations as inputs to the classifier.

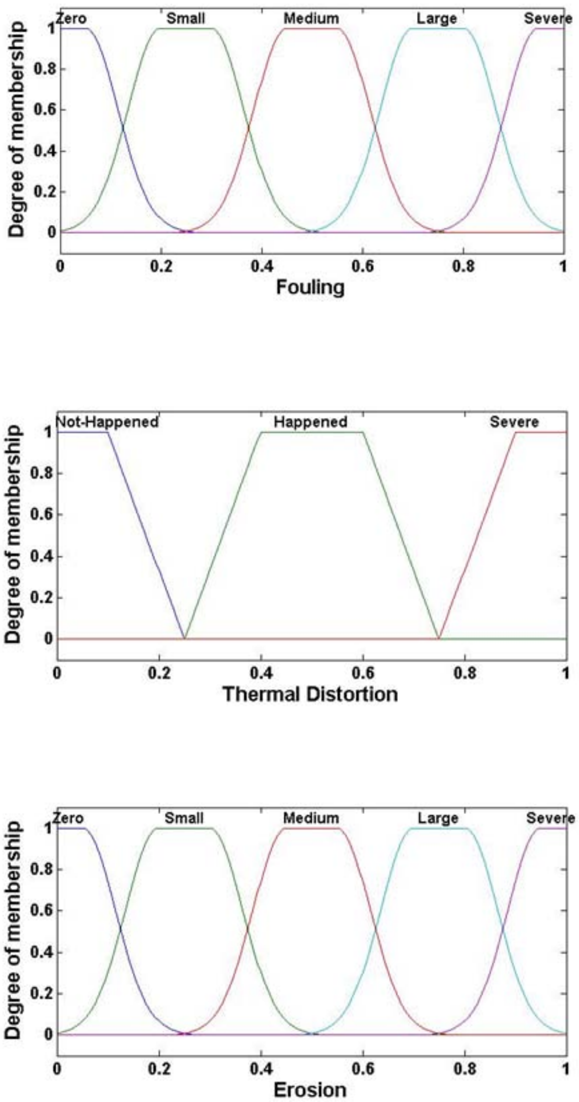

Figure 12: Various membership functions defining linguistic variables of Fouling, Thermal Distortion and Erosion as outputs of the turbine FFI

Our fuzzy fault isolator system was able to correctly classify 25 of them, which means correct classification rate of 96.15%. The only incorrect classification is for the input set of (Large-, Small) which should be mapped to (Zero, Zero, Happened) but the answer of the isolator is (Zero, Small, Happened). In fact the fuzzy system evaluates the erosion as "small" because a block away there is a sharp slope in the surface toward "Large Erosion", shown in Figure 14.

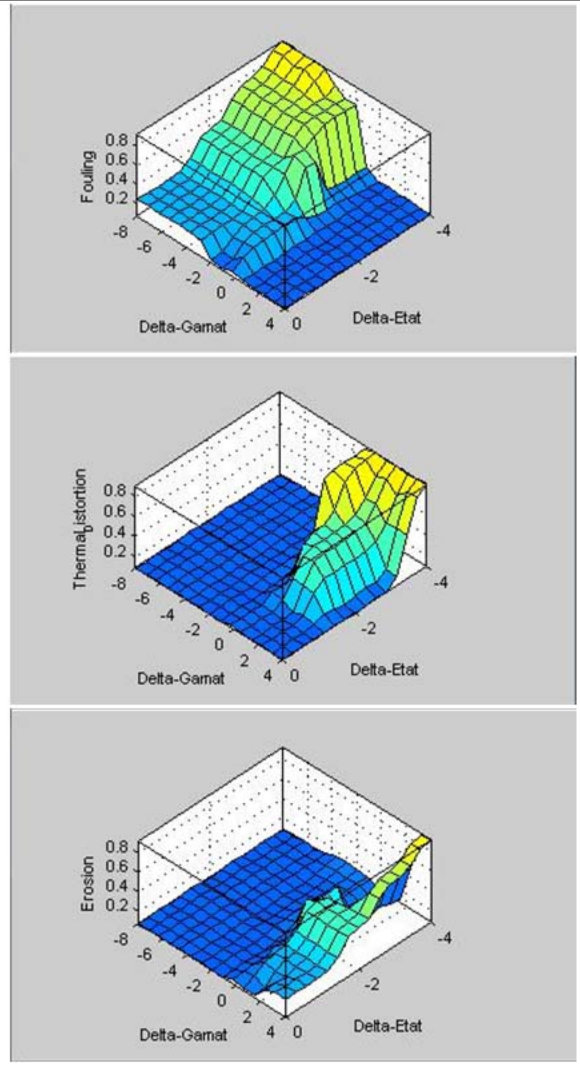

Figure 13: Fuzzy surfaces of Fouling, Thermal Distortion and Erosion of the turbine

6 CONCLUSIONS

A hybrid EKF-fuzzy fault detection and isolation system is developed for the Siemens V94.2 industrial gas turbine. At first using noisy sensor measurements at two different operating points and an accurate nonlinear GT simulator as the model, the deteriorations of the health parameters of both compressor and turbine sections have been accurately estimated. In the next step five health parameters of the gas turbine have been fed to the fuzzy fault isolator system for further classifying the actual physical faults. The FFI system based on the ratios of the changes of different health parameters and the approximate whereabouts of the degradations in front or rear sections of the compressor isolates the most probable physical fault.

This system consists of two parts, the compressor FFI maps the changes of the compressor efficiency and frontal and rear flow capacities of the compressor to physical faults such as, fouling, oil leakage, erosion and foreign object damage.

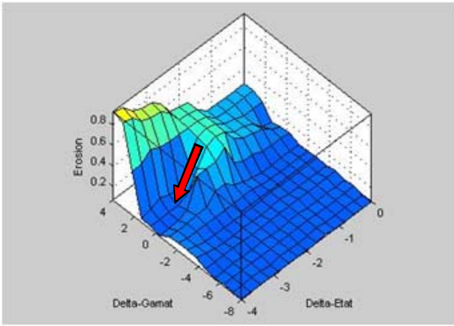

Figure 14: Fuzzy output surface of erosion for the turbine and the sharp slope near the input set (Large-, Small) showed by the arrow

It also gives a user friendly linguistic report of the health situation of the compressor and also a hint for the appropriate time for washing or repairing it. The turbine FFI maps the changes of the turbine efficiency and flow capacity to the turbine related faults such as fouling, erosion and thermal distortion. The method has been validated using data gathered from simulations of the actual faults in different faulty scenarios. Results of the simulations show high correct classification rates for both compressor and turbine sections.

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