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Comparative Study of a Simulated and Real Life Reliability of Turbine Gas Path Diagnostics

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ABSTRACT-Enhancing the performance of gas turbine requires the bringing together and optimization of the disciplines and expertise required to acquire an operationally competitive gas turbine engine. This study comprises comparative research between simulated and actual reliability of the gas path of a turbine engine. An innovative idea was introduced to reduce the gap between diagnostics processes via simulation and actual maintenance condition of the engine. The possible sources of errors were investigated by generating real error distribution. This research study explores the comparative investigation conducted to evaluate the reliability of a turbine gas path through simulating varying scenarios and analyzing real-life performance data. The application of simulation tools is to enable the replication of operating conditions and accurately model the gas turbine components, providing insights into potential weaknesses and strength. Real-life performance data provides important information about actual system behavior, including the frequency and nature of failures. Comparative investigations allow for validation of simulation accuracy, refinement of models, and identification of discrepancies. The findings from these investigations contribute to the optimization of gas turbine reliability, leading to efficient, cost effective power generation systems.

KEYWORD- Diagnostics, Enhancement, Gas Turbine, Gas Path Analysis, Simulation.

I. INTRODUCTION

The design and performance of gas turbine components such as turbine gas path reliability has always been acritical area of power generation systems. With the improvement in technologies, engineers are constantly looking for avenues to enhance the design and performance of gas turbine to ensure improved reliability and overall efficiency. To assess the reliability of this complex system, comparative investigations of simulated and actual life conditions have become a common research practice [1]. This research aims to show the comparative investigations carried out to evaluate the reliability of a turbine gas path through through simulating various scenarios and analyzing real-time performance data. Examination of the similarities and differences between simulated and real-life conditions, brought about valuable insight into potential weaknesses and strengths of the gas path, emanating to more effective maintenance and operation methods. The application of simulated tools has revolutionized of studying the reliability of turbine gas path as it allows the replication of operating conditions in a regulated environment. The gas turbine components are accurately modeled, and factors such as temperature, pressure, and flow rates, are adequately taking into cognizance. Simulation provides a comprehensive understanding of the behavior of the system. This will give room to identify potential failure and develop preventive measures to improve the reliability of the gas path [2].

On the other hand, real-life performance data provides important information about the actual behavior of gas paths under varying operating conditions. In monitoring a gas turbine performance over a given period of time, valuable information about the reliability of the system can be gotten, such as, frequency and nature of failures or deteriorations. Real-life data also allows for the identification of any non-simulated factors, which include external disturbances or unforeseen stresses that may affects the reliability of the system. Comparative investigations between simulated and real-life reliability provide a more holistic understanding of the performance of a turbine gas path. By comparing the simulation results with real life data, the accuracy of the simulated is validated and the model is fine-tuned to mirror the actual operating conditions. This iterative process strengthens the predictive abilities of the simulations, which can then be used to forecast potential issues and optimize gas path reliability. In addition, comparative investigations facilitate the analysis of inaccuracies between simulated and real-life outcomes. It is imperative to identify the causes of these inaccuracies as it highlights potential drawbacks or biases in the simulation models. This models can be refined to accommodate previously overlooked aspects or unknown factors, thereby improving the accuracy of the simulation tools [3].

Comparative investigation of a simulated and real-life reliability of a turbine gas path offers invaluable insights seeking to enhance the performance and dependability of gas turbine. A comprehensive method can be developed by combination of the accuracy and control of simulations with the real-world data obtained from turbine operation to optimize it performance reliability. Through this research, the field of gas turbine reliability will continue to make significant advancement, leading to more efficient, safer, and cost-effective power generation system.

II. LITERATURE REVIEW

A diagnostic analysis of registered gas path variables such as temperature, pressure, fuel consumption, rotating speedetc can be considered as principal component and integral part of the engine. Rao [4] demonstrated an advanced monitoring system which consist of different components intended to cover all gas turbine sub systems. Various types of gas path performance degradation, such as foreign object damage (FOD), fouling, tip rubs, seal wear, and erosion, are known and can be diagnosed. The detailed description of the abrupt fault and gradual deterioration mechanisms can be found in [4,5]. In addition, the gas analysis (GPA) also allows detecting sensor malfunctions and wrong operation of a control system [6]. This analysis allows estimating main measure engine performance such as thrust, shaft power, specific fuel consumption, compressor surge margin, and overall engine efficiency.A lot of applications can be found in literature but not limited to Artificial Neural Network (ANN) [7, 8], support vector machine [9], Genetic Algorithms [8], and Bayelsian approach [10]. A fault classification is an integral part of a fault recognition process irrespective of the technique applied.

Reliability assessment is an important part of gas turbine performance enhancement and maintenance. In traditional methods, tests and analyses with rea-life turbines are carried out, which can be time consuming and cost effective. as such, it has become imperative to develop simulation tools to model and simulate gas turbine behaviors. There has been a growing research body focusing on comparative investigations between reliability and simulation of gas turbine path. This literature review will summarize and discuss some major outcome from these research. Simulation based reliability assessment: simulation-based research has gained significant attention because they are cost effective and able to replicate real-life operating conditions. A comprehensive review of simulation methods for gas turbine reliability assessment was presented by [11]. They presented various methods including Monte Carlo simulation, discrete event simulation, and finite element analysis, showing their pros and coins. The research shows the advantages of accurately modeling turbine components and considering various functional elements for reliable simulation-based reliability assessment.Validation of simulation models: Comparative investigations often involve the validation of simulation models against real-life data, focusing to assess the accuracy and reliability of the simulated gas turbine behavior. A study was conducted by [12] where they compared simulated and measured data of a gas turbine critical components. It was gathered that the simulated matched the real-life measurements, confirming the effectiveness of the simulation model in predicting the gas turbine reliability. They also suggest that simulation-based reliability assessment can be a reliable alternative to traditional real-life testing. Identifying discrepancies and improving models: Comparative investigation also plays a vital role in identifying discrepancies and improving models between simulated and real-life reliability of a turbine gas path. Another research by [13] focuses on the identification and improvement of simulation models for predicting the reliability of gas turbine blades, and they discovered that the simulation models underestimated the fatigue life of the blades compared to real-life measurements, and they concluded that the improvements in the modeling methods, such as more accurate material properties and loading conditions, are required for better reliability predictions. Optimization of gas turbine reliability: comparative investigations contribute to the total optimization of gas turbine reliability according to [14], who conducted a comparative study of simulated and real-life reliability analysis of a gas turbine combustion chamber. It was observed that a good correlation between the simulated results and the real-life measurements enable then to identify and address weak points in the design. It also advised on the improvement of the component redesign, enhancing its reliability and performance.

Comparative investigations of simulated and real-life reliability of a turbine gas path provide valuable details into the accuracy and effectiveness of simulation tools. These demonstrations have shown their potential as a cost-effective and reliable alternative to traditional real-life testing methods. By identifying discrepancies, improving models, and contributing to the enhancement of gas turbine reliability, these studies set the foundation for the development of efficient and reliable power generation system. Further research in this area is required to enhance the simulation models and expand the application of simulation-based reliability assessment methods.

III. RESEARCH METHOD

Comparative investigations of a simulated and real-life reliability of a turbine Gas Path research design employs a two way means to investigate and compare the gas path via both simulated and real-life data. The simulation data is achieved with a software computational tools to model and simulate the behavior of the turbine gas path. The process considered different operational conditions such as load profiles and characteristics of the components. On the other hand, the real-life data is gotten from a gas turbine operator. Thisinvolves operational and maintenance data of existing gas turbine. Data on component failures, operating conditions, inspection and maintenance activities. The reliability metrics such as mean time before failure (MTBF), availability, failure rate, and reliability indices will be considered. This metrics will be determined based on real-life and simulated data to enable a direct comparison. To ensure the accuracy of the model, a validation process is conducted, which involved comparing the simulated results with the rea-life measurement available from gas turbine operations. All discrepancies were identified and reported, and necessary adjustment were put in place to improve the simulation model.

A steady state nonlinear thermodynamic model operation can be classified as component-based because each gas turbine component is presented in this model by its performance map from the manufacturer. The model is described by the following structural formula as seen below;

$A=F(X,\theta)$ 1

The model considered the effect of operating point on monitored variable A via the vector X of operating conditions, that is, control variablesand ambient air parameters. The health condition of the gas turbine is reflected by a vector θ of fault parameters as indicated in figure 1 below. These parameters shift the performance map of the engine components such as compressors, combustors, and turbines, including other devices, thereby allow simulating different degradation mechanisms of varying severity. The thermodynamic model is a typical physics-based model due to objective physical principles realized.

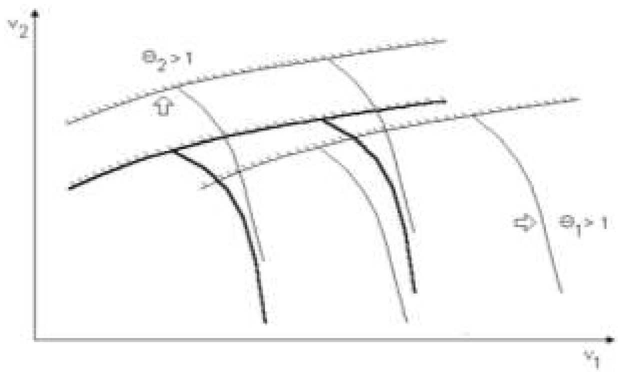

Figure 1: Component Performances (c1, c2) of the Component map shifting by the fault parameters.

The model is capable of simulating baseline engine behavior, and also, since the fault parameters change the component performance involving the calculations, the model is capable to reflect different types of gas turbine deterioration. Mathematically, equation 1 is a result of solving a system of nonlinear algebraic equations reflecting mass and energy balance at steady states. The study by [15] shows the difference between real-life and simulated faults can be visible.

The nonlinear thermodynamics model allows a software to determine a matrix of fault influence coefficient H for linear model

$\delta A=H\delta\theta$ 2

The linear model computes a vector of relative deviations δA influenced by small changes in the fault parameters δθ at a fixed operating condition. A dynamic model can be develop if the nonlinear thermodynamic model is in steady state, since the transient provide more information than steady states and transient analysis allows continuous diagnosis, the dynamic GT model is in increasing demand. With static model case, the dynamic model explains how the monitored variables A depend on the quantities X and θ. However, the vector X is given as a function of time and time variables t is also added as an independent argument. From this explanation, the dynamic model given as in equation 3 below.

$A=F(X,(t),\theta t)$ 3

A separate influence of variable t is explained by inertia of GT rotors, moving gas and heat interchange processes. The dynamic model includes major part of the static model subroutines and these two models tend to form common software package. Though the model presented can simulate a healthy condition and possible faults of GT, the design of monitoring systems cannot based solely on these simulation tools. The equation 4 below shows the steady state GT monitoring and diagnosis.

$\delta A=(A_1-A_{oI}\quad X_m)/(A_{oi}\quad (X_m\quad)\quad)$ 4

The baseline model is $A_{0I}\ (X_m)$, the measured values A_1, are computed as relative difference between measured values and engine baseline values. The theoretical analysis of possible errors in real deviations is based on equation 4, and can be re-written as equation 5 below

$\delta A=A^*/(A_o\ (X_m))$ 5

This shows that the inaccuracy of the deviation is completely determined by errors in a term $A^*/A_0\ (X_m)$, in which A_0 denotes estimation of the baseline function for the variable A. the errors can be divided in 4 types. The value A^*differs from A by an error E_A named as error type 1. The true value depends on a vector U of real conditions and on engine health condition given by the vector Δθ, as a consequence, A^* can be written as

$A^*=A(X,\Delta\theta)+E_A\ (X,\Delta\theta)$ 6

The error $E_A$is a function here because, generally, measurement errors may depend on the value A, and consequently on the variables U and Δθ. From equation 5 by vector U_m, the deviation in accuracies is related to measurement errors in operating conditions which represents type 2 errors and is re-written as

$X_m^*=X_m+E_{xm}$ 7

The type 3 error is also related to engine operating conditions, however, it is not obvious.

Given that $X=X_m\cup E_X$, then vector X can be given by $X_m=U\backslash E_u$ and the equation is converted to form. The function has a proper error known as the type 4 error, it can result from systematic error.

$X_m^*=X/E_x+E_{xm}$ 8

Given E_{AO} and a true function A_0 can be re-written as

$A(X_m^*\quad)=A_o\quad(X_m^*\quad)+E_{Ao}\quad(X_m^*\quad)$ 9

By substitution equations 6, 8,. And 9 into equation 5, resulting from the deviation δA^* is written as

$\delta A^*=(A(X,\Delta\theta)+E_A\quad(X_m^*-E_{xm}+E_{(x,)}\quad\Delta\theta))/(A_O\ (X\backslash E_x+E_{xm}\quad)+E_{AO}\quad(X_m\quad)\quad)-1$ 10

A dependency $E_A\ (X_m^*-E_{XM}+E_X,\Delta\theta\ )$ in this expression can be simplified, taking the consideration made into account, we arrive to a final expression for the deviation to be

$\delta A^*=(A(X,\Delta\theta+E_A\ )+E_A\ (X_m^*\ ))/(A(X\backslash E_X+E_{XM}\ )+E_{AO}\ (X_m^*\ )\ )-1$ 11

There are 4 error types in this expression, namely E_A, E_{Xm}, E_X, and E_{AO}. It is assumed that the same sensors were measure currently analyzed values A^* and X_m as well as the reference set data, a systematic error and distribution of random errors in A^* and X_m do not depend on operating time of the engine. and gross errors have been filtered. The normalized distribution equation for real deviation is as seen in equation 12

$$Z^*=(\delta A^*)/a_A \qquad 12$$

The parameter a_A represents an amplitude of random errors deviation variable δA. This type of deviations simplifies fault class description and improve diagnosis reliability. The usual hypothesis applied in the pattern recognition theory state that a recognized object can belong only to one of q classes that are set before recognition itself. This assumption is also accepted in GT diagnostics.

$$D_1, D_2, D_q \qquad 13$$

the deviation produced by the fault that are embedded into the thermodynamic model through a change $\Delta\theta$ can be computed according to the expression 14 below

$$Z_i=(A_I(X,\theta_0+\Delta\theta)-A_i(X,\theta_O))/(A_I(X,\theta_O)\, a_{Ai})+\epsilon_i \quad i=l\_m \qquad 14$$

The vector θ_0 corresponds to a healthy engine. Random error ε, make deviations more realistic. They can be added directly to systematic parts of the deviations or can be through the simulation of random measurement errors in A and U.

The GT diagnosis based on system identification means the thermodynamic models, such as nonlinear static model, linear static model, and dynamic model, as shown in equations 1-3. The technique to identify the nonlinear static model are widely applicable in the GPA. The technique estimates as a result of distance minimization between simulated and measured values of the monitored variables. The equation can be written as 15 below

$$\theta = \arg\min \lVert A^*-A(X,\theta) \rVert \qquad 15$$

The estimate contains information on a current technical state of each engine component. This drastically simplifies a subsequent diagnostic decision. Also, the diagnosis is not limited to by a rigid classification as in the case of the pattern recognition-based approach.

IV. RESULTS AND DISCUSSION

The options of single, multiple and transient diagnosis were improvised, and the probabilistic criteria $\vec{P}$ and P were applied to compare the recognition techniques. The multiple diagnosis means that measurements from different operating points are united to make a single diagnosis. All the recognition techniques previously described in the application within the single point option can be applied without principal changes. The dimension of the patterns and diagnostic space is only increased because measurements at every operating mode can be considered as a new GT measured variables. In this method, a generalized deviation vector $\vec{V}$, that unites deviations computed at all modes considered, is now a pattern to be recognized. The table 1 below represents the results of the comparison of the single point, and multiple options. The probability P increments contained in the line Difference allow to state that a positive effect from applying the multiple option is very significant. From the mathematical application, the diagnosis under transient condition is similar to the multipoint diagnosis. Every measurement section of a total transient process is considered as a new operating point and the same generalized vector $\vec{V}$ is formed.

Table 1: Probabilities for the Single, Multiple, and Transient Diagnostics Cases of the Gt Data

Choices	Classification by single fault	Classification by Multiple faults
Single point (SP)	0.7308	0.7343
Multiple point	0.8906	0.9435
Transient	0.9024	0.9553
Discrepancy between SP & MP	0.1598	0.2092
Discrepancy between MP & Transient	0.0118	0.0118
Discrepancy between SP & Transient	0.1716	0.2210

This gives room for the comparison of both options as could be seen combined in table 1. It can be seen that the diagnosis at transients has a stable, although not very high, growth of accuracy relative to the multipoint diagnosis. This is related to the higher fault influence under dynamic conditions. Since the growth is not considerable, the actions of diagnosis at transient and multipoint diagnosis are close. Consequently, the most part of the total accuracy growth at transients relative to the single point option is produced by the averaging effect mentioned above. During the simulation diagnosis of the transient condition, some peculiarities such as turbine temperature sensors dynamic error, and an unequal dynamic warm-up of rotor and stator parts that complicated the real diagnosis were not accounted for, that is the reason our conclusions regarding the diagnosis at transients cannot be considered as the sole argument for choosing a proper diagnostic option. Hence, the modes and options to enhance the diagnosis methods based on the pattern recognition theory have been analyzed in details above.

The deviations computed for two monitored variables of GT power plants for natural gas pipelines are as indicated in figure 2 below. Let's assume this plant to be GT 1, with an associated compressor washing time t-7970hours from the behavior of the deviations as well as the former and subsequent compressor fouling periods are well differentiated. In addition, the fluctuations are still relevant here and capable to mask effects of deterioration.

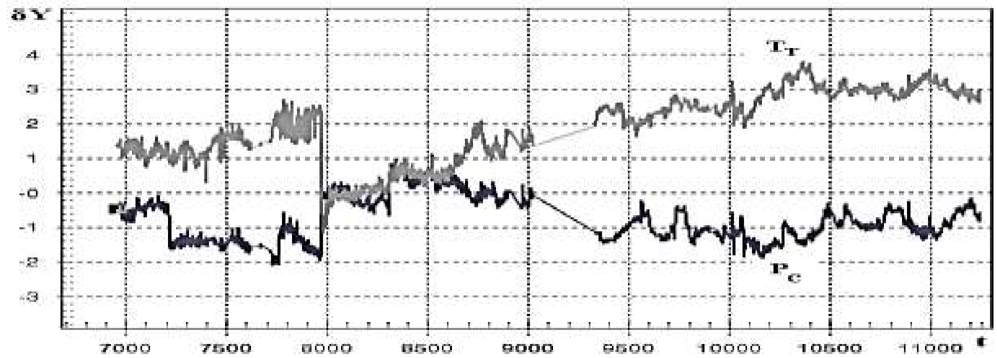

Figure 2: GT deviation δY,% against operating time t,hours (T_T-exhaust gas temperature, P_C-compressor pressure)

The operating conditions of an engine changes from point to another with time, which explains common temporal changes of the curves. Anomalies in behavior of a particular probe can confirm a probe's malfunction. Synchronized perturbations in curves of some probes may be the outcome of a real temperature profile distortion because of a hot section problem.

Choosing a GT for electric generator as a test case to analyze possible malfunctions of EGT thermocouple probes is as could be seen in figure 3. The EGT deviations for 5 probes and for the temperature averaged by 11 different probes. It is observed that the washing took place at the time points t=803, 1919,3098, and 4317. As shown on the figure, deviation plots reflect in a variable manner the effect of fouling and washings. The deviations dTmed does it better than deviations of particular probes. Among deviations dTti, quantities dTt5 and dTt6 for examples. Have almost the same diagnostic quantity as dTtmed, while quantities dTt1 and dTt2 are of little quality. Such deviations can be partly explained by variations in probe accuracy and reliability. For example, elevated random errors of the deviations dTt1 and dTt2 over the whole analyzed period can be included by greater noise of the first and second EGT probes. The dTt1 fluctuations in the time interval 1900-2600 are probably results of frequent incipient faults of the first probe. More so, the shifts of the deviations dTt1, dTt2, and dTt6 around the point t=3351 present the most interest for the current analysis. The shifts looks like a washing result but they have opposite directions.

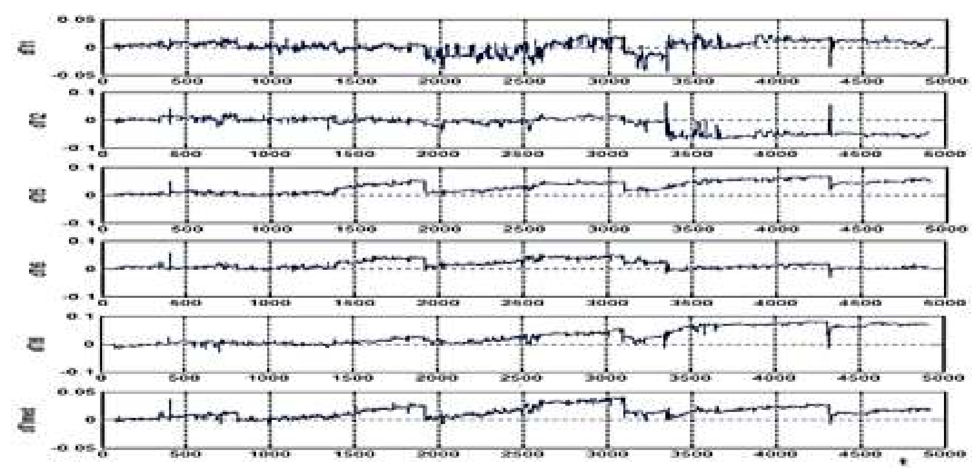

Figure 3: EGT and temperatures deviation dTi for 5 thermocouple probes and a deviation dTtmed of a mean EGT variable

Figure 4 indicates parallel plots of probe measurements themselves which confirms the anomalies in recorded data. Small synchronized shifts can be seen. It is visible in the figure that probe 7 and 8 are synchronized displaced by about 10 degrees during two time intervals t=962.5-966.5, and t=971.7-972.5. More so, the same measurement increase is observed in the probe 1 curve at time t=971.5-972.5. In this case, the considered case presents a correlation shifts in data of some probes and therefore is more complicated. Two explanations can be proposed for this case. The first is related with common problem of the measurement system that affects some probes and alters their data. So the outliers can be classified as data measurement errors. On the other hand, the second supposes that the measurements are correct but real EGT profile has been changed in the noted time points. It can be possible because there is no information that EGT probe profiles should be absolutely stable during engine operation.

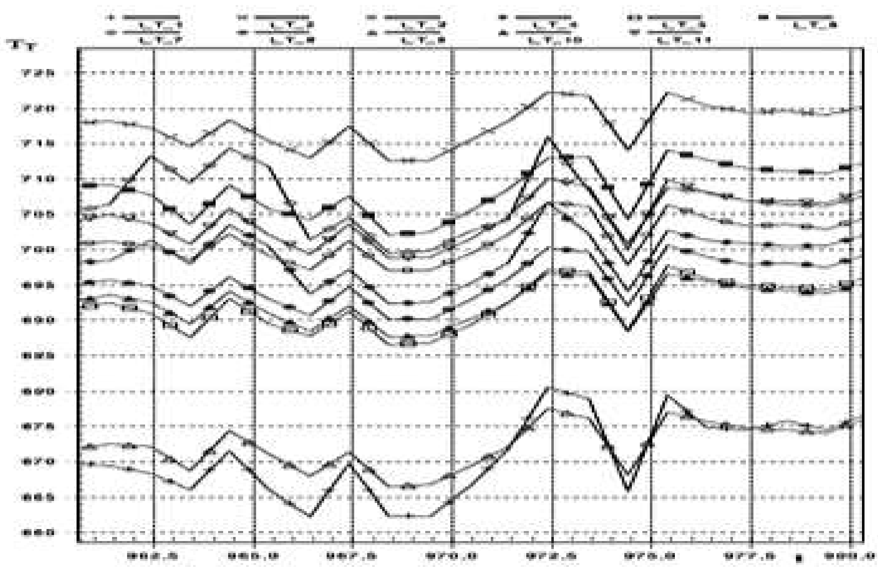

Figure 4: Anomaly cases of deviations in EGT and temperature measurements by 11 thermocouple probes

Distribution of simulated and real deviation errors are as shown in figure 5 and 6 below, normalized deviation from equation 12 are presented here. A parameter denoted an amplitude of random errors in the deviation variable. Such normalization simplifies fault class description and improve diagnosis reliability. Figure 5 demonstrates the deviation errors simulated via the multidimensional Gaussian distribution of sensor errors type 1 and 2. Such simulation is traditionally applied in GT fault recognition algorithms.

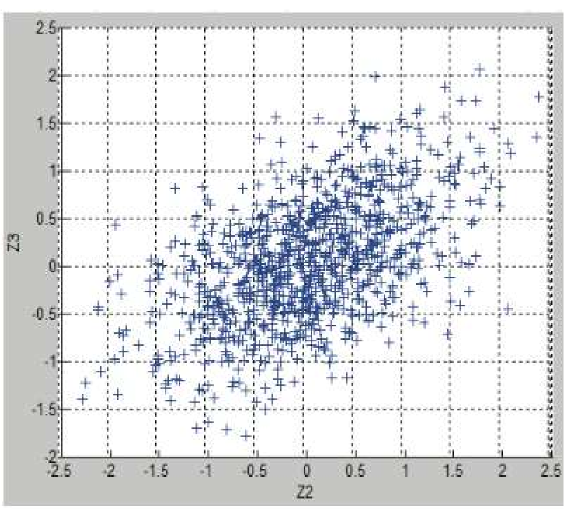

Figure 5: Deviated errors computed via sensor error simulation

Figure 6 shows the errors extracted from real data based deviations. Both figures show visible error correlation between the presented deviations. But there are obvious differences as well, the distribution in real deviation errors is less regular. Not taking into consideration in fault recognition algorithms, these differences can affect the reliability of GT diagnosis. Incorporating noise bias will make the diagnosis more reliable.

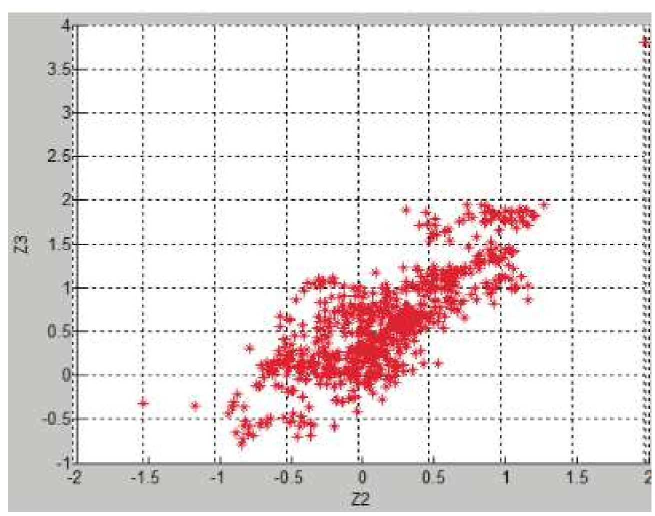

Figure 6: Real Deviation Errors

Random errors in the monitored variables and operating conditions have been considered by most researchers with the application of Gaussian distribution. However, the difference between such traditionally simulated errors and real deviation errors can be significant. That is why it is proposed to draw a noise part from the deviations and integrate it into the description of simulated fault classes. Preliminary calculations have shown that the distinguishability of fault classes can change by up to 6% whenreal errors are replaced by simulated errors. Hence, the diagnostic performance estimated with simulated noise can be inaccurate. The case as also investigated when the errors for the learning and validation set were extracted from different time portions of real data. The loss of diagnosability for this case was found drastic fromP=90%-94% in the validation set increase a lot in comparison with the learning set errors. The increase of the errors occurred because the baseline model is adequate on the reference set data but loses its accuracy on the subsequently recorded data. Such situation is very likely in real diagnosis and we should be careful to avoid or mitigate it.

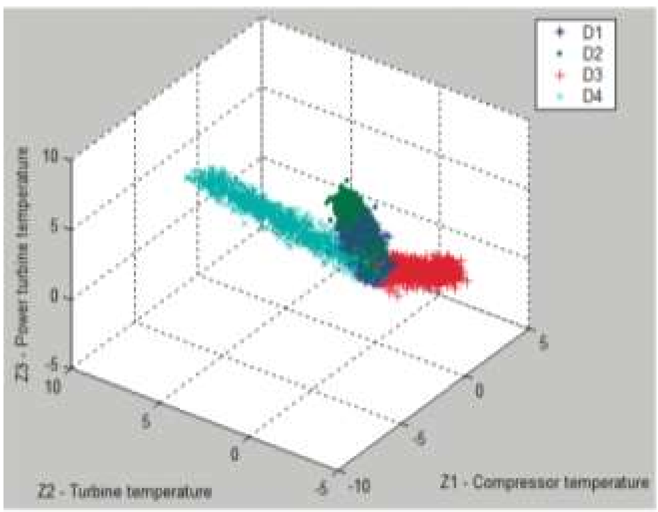

Figure 7: A 3D view of four fault cases with simulated sensor errors

V. CONCLUSION AND RECOMMENDATION

This paper emphasized on the diagnostics and enhancement of the reliability of gas path in turbines. Literatures were reviewed and different methods and trends were evaluated in turbine gas path diagnostics. It was discovered that, many researches have been conducted in this area, as such, a convenient method to optimize the reliability, choosing the best function of approximation while recognizing technique and directing the function and technique, did not produce a significant result. This research introduced a new knowledge gap to reduce the disparity between simulation diagnostics process, and the actual condition of the real engine maintenance. All sources of errors have been examined, and some approaches are recommended to enhance the disparity in accuracy. More so, new techniques were introduced to generate a more realistic fault classification by creating real distribution of error. Some of the major problems recommended to be tackled in the future include but not limited to insufficient adequacy of the baseline, and inaccuracy in fault simulation. The author hope that the recommendation herein if attended to, will help to design and rapidly channel new gas turbine health monitoring systems.

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