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AN IMPROVED TURBOMACHINERY CONDITIONMONITORING METHOD USING MULTIVARIATE STATISTICAL ANALYSIS

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ABSTRACT

Industrial practitioners require a well-structured, proactive and precise conditionmonitoring package in order to optimize turbomachinery operation. Typically, conventional condition monitoring uses built-in software to capture faults or degradation processes based on threshold limits recommended by the Original Equipment Manufacturer (OEM). However, because OEM manual concurrent monitoring involves abundant information parameters, it is dependent on human intervention, insensitive to the development of machinery faults and tends to generate error-prone outcomes. This study proposes a simplified and advanced health-monitoring method for turbomachinery using a multivariate statistical analysis (MSA) technique. By exploiting mathematical relationships between OEM recommended variables, the significance of input parameter is identified based on weighting factor. With a highly-correlated input subset, the revised condition monitoring method delivershigher sensitivity and a more accurate performance in investigating machine assessment mode.

Keywords: Turbomachinery, Condition Monitoring, Multivariate Statistical Analysis.

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1. INTRODUCTION

Turbomachinery is a type of machinery which transfers energy between rotors and fluids. Governed by Newton's second law and the thermodynamics conversion rule, turbomachinery serves as a common power solution provider for aircrafts, ships, compressors and power generators [1]. Standardized turbomachinery packages consist of a centrifugal compressor, mechanical gearbox transmission system, power-generated turbine, gas generator and various accessories. Consequently, the machine involves 100,000 rotating components that function together continuously with high pressure and temperatures, to process liquids to deliver the desired performance [2].Nevertheless, rigorous operation execution inevitably induces a process of degradation. Typical faults linked to turbomachinery include: gas turbine blades delamination; rubbing tips; foreign object damage (FOD); fuel burner erosion; seal wear; gear tooth pitting; bearing rolling contact fatigue; rotor crack; misalignment; imbalance; sensor errors; clogging, leakage and lubricant contamination that result in a drop in efficiency for the compressor.

Current monitoring practice utilizesstandard limits recommended by the original equipment manufacturer (OEM) in observing individual machine parameters. Individual parameters are sorted according to assessment modes for every subsystem by referring to an OEM manual [3, 4, 5, 7, 8, 9], empirical studies and industrial consensus [6, 7, 8, 10].In simple terms, an assessment mode targets the appearance of unique anomalous situation by gathering a set of parameters connected to specific subsystem. For a typical turbomachinery package, there can be up to 500operating parameters gathered from built-in instrumentation. For instance, thirty three feedback signals are registered and monitored in parallel for a single subsystem package, as shown in Figure 1. This method often failed to proactively identify any subtle health degradation of the machine if the operating parameters were still within OEM-specified threshold level since parameter integration and correlation monitoring were absent. Also, excessive data size is beyond the capability of manual interpretation. Moreover, significant parameters will be overlooked in the dataset and will unavoidably contribute to false alarms, ineffectiveness, and increase operator workload. Under such circumstances, it is impractical to introduce an ad-hoc auxiliary sensor and hardware unit during a mid-operation schedule.

From the above reasoning, it is obvious that the exquisite system requires a responsive conditionmonitoring method to ensure optimum operation and safety in a hostile environment. To overcome the above difficulties faced during real-world turbomachinery condition monitoring, one of the effective yet convenient methods is to simplify the conditionmonitoring process via input selection. Theoretically, identifying relevancy-redundancy among peers is achievable by studying the qualitative and quantitative measures of turbomachinery parameters. From a statistical point of view, the selection of highly-correlated parameter subsets and the elimination of irrelevant parameters can be delivered together via determining the associated weighting factors.

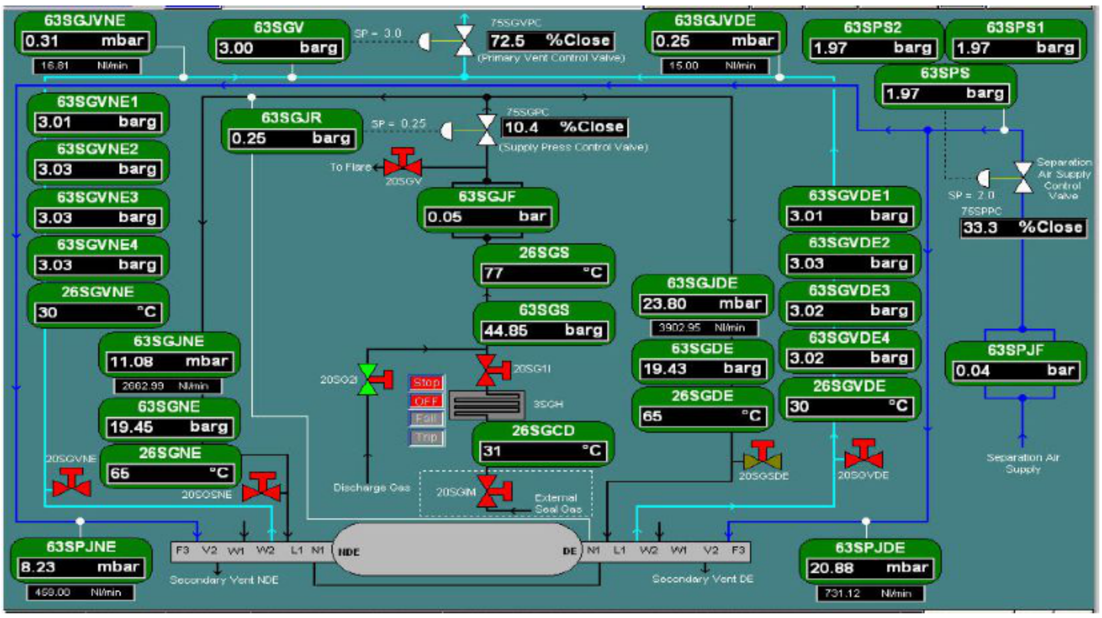

Figure 1 Shows a turbomachinery subsystem control panel interface

2. DEVELOPMENT OF TURBOMACHINERY CONDITION MONITORING TECHNIQUES

Typically, the condition monitoring data-interpretation strategy is categorized into three major groups: baseline fault referencing simulation modelling [11]; signal processing statistical analysis in frequency, time-domain or time-frequency function [12]; and machinelearning algorithm for self-tuning pattern recognition [13]. Each technique has its own characteristics and advantages; design modelling aims for improving performance efficiency while signal processing and machine learning are responsible for fault diagnosis during operating terms. Nonetheless, [14] identified research direction has been focusing on hybrid fault diagnosis design in tackling noise reduction, multiple fault detection, probabilistic function, computational ease and accuracy-wise.

In turbomachinery practice, numerous improvement efforts have been done in recent years. For example, the start-up behaviour of gas turbine signals using Principal Component Analysis (PCA) is analysed by an extracting feature and subsequently integrated into Artificial Neural Network (ANN) classifier [15]. The classification result shows that the transient-driven examination managed to pick up an incipient fault which compensated by feedback response during steady-state condition. The feature of singular value decomposition matrix is utilized by Kalman filter technique to estimate an engine thrust measurement and state parameters [16]. The least square tuned vector proved to be capable of equalling actual engine outputs and practical for diagnostic purposes. Adopting a high-pressured turbine as the simulation target, detailed documentation on gas turbine on-line condition monitoring procedures are outlined [17]. The simultaneous verification of a Gas Path Analysis (GPA) variable scatter plot and state of machine successfully gathers information on frequent compressor fouling. [18] displayed matrix pencil decomposition formed unified filter generated from initial fault detection model, aiming to decouple turbofan engine output noise. The updated triangular matrices are subjected to fault detection and isolation control system design which exceed unknown input observers (UIO's) and the Kalman Filter. The implementation of cascaded optimization and artificial neural network into mistuned identification of assembled bladed disk is presented [19]. The mistuning parameter diagnosis performance is significant, though under the influence of incomplete, low signal-noise-ratio (SNR) information.

The concept of wireless data acquisition for three-passage serpentine heat transfer evaluation is introduced [20]. Compared to a typical slip-ring method, an integrated control system is able to cater dense measurement and generate sensitive responses with proposed wireless data transmission. Turbine blade technology advancement and presented future research directions on blade geometry, heat dissipation and material structure designare reviewed [21]. A discussion onthe development of turbomachinery designrevealed that optimization can be categorized in three unique case studies [22]. Fluid dynamics, turbine blade layout, air drag and stall margin performance upgrade are achieved by integrating the Genetic Algorithm (GA) into a design simulation. On the other hand, a block structure adjunct method is rolled out to overcome Computational Fluid Dynamics (CFD) meshing quality in a chained subsystem. Shah et al. demonstrated the noise acquisition of a turbofan engine in detailed resolution using portable microphone set[23]. The novel phase-referencing sound-filtering method is superior in terms of high-sensitivity noise field mapping with faster data processing and limited hardware allocation. The possibility of recognizing the characteristics of debris particles ejected from exhaust gas via electrostatic charge is explored by Addabbo et al. [24]. In that event, an automated tracking system capable of coordinate component defects with state condition setting and particles geometry. Shirazi et al. conducted bearing vibration analysis on a twin shaft gas turbine using a hybrid multi-layer perceptron neural network and cuckoo optimization (MLP-COA) algorithm; the result is more favourable for online prediction than Radial Basic Function(RBF) network and Multilayer Perceptron(MLP) [25]. Last but not least, intuitive wind turbine data visualization based on the random forest technique is tabulated using a PCA scatter plot [26]. The simplified distribution framework provides a clearer overall picture of data interaction and effectively decreases the input dimension.

3. MULTIVARIATE STATISTICAL ANALYSIS (MSA): THEORY AND APPLICATION

3.1. Introduction

From the previous section, it is evident that a turbomachinery system observation emphasizes the degradation process. The deviation from expected performance is typically described by using an acknowledged baseline limit range periodic review, generic curve estimation, or multivariate analysis [27], [28]. With reference to OEM standards, the application of expert systems such as TEXMAS and CASE-based Reasoning (CBR) [29] are comparably favourable to supervisory control and data acquisition (SCADA) [30] since *posteriori* knowledge is acquired without further data collection and model training. Set side by side with the above-mentioned advanced monitoring techniques, OEM's readily-available guideline provides a more direct, fast and compatible approach.

Other than variable set point stochastic tracking, various advanced yet less sophisticated statistical methodsare introduced in an attempt to reduce observational misclassification. For instance, particular signal abruption is disregard as an outlier since it is consistent with Gaussian distribution [31], [32]. Lakshminarasimha et al. opted for Least Squares-Support Vector Regression (LS-SVR) in wind turbine performance response curve estimation as a baseline for residual variance measurement using the central limit theorem in a later stage [33]. As a result,a nonlinear response outline generated by baseline model was free from skewed outliers and shed light on multiple output correlation research. Ogden et al. located a novel pressure inlet fault development involving an air compressor using MSA [34], even though previously the failure mode had not been documented in a library or shown to be causing malfunction in the past. Pozo et al. developed a three-dimensional PCA baseline mapping system in order to deduce the state of wind turbine actuators and sensors under the effect of unsteady wind-speed behaviour [35]. During the investigation period, eigenvector and eigenvalues extracted from the covariance matrix not only functioned for linear transformation, but also served as a score indicator for the principal component selection.

Throughout the examples given, it can be concluded that merging suitable statistical analyses into a standard condition monitoring model could provide better fault prediction performance. In this investigation, least squares (LS)was chosen due to its simplicity and efficiency in estimating coefficient parameters which represent the weighting factor for a particular input vector in a matrix dataset. Elaboration of the LS technique and generation of parameter estimation will be delivered in the next section.

3.2. Multivariate Statistical Analysis: Least Squares Estimation

It is acknowledged that the output dataset $Y = (y_1, y_2, \cdots, y_{n-1}, y_n)$ is recorded during period $t = (t_1, t_2, \cdots, t_{n-1}, t_n)$. Hence, y_k corresponds to a particular time instance t_k at interval n samples, where $k \in n$. The foundation of regression analysis modelling relies on regression equation setting and residual estimation frameworks. In order to achieve the realism stated previously in a simple manner, the observation principal is presumed to be linearly correlated to earlier sampling data (1) and contains the serially uncorrelated random measurement error, v_k (2), which refers to Gaussian white noise.

Auto-covariance function of m_k, $C_{yy}(\tau) = \frac{1}{n-1}\sum_{k=1}^{n}(y_k - \mu_k)^2$,

Where$0 < \left|C_{yy}(\tau)\right| \leq \sigma_y^2$ (1)

$y_k = u_k\theta + v_k$ (2)

The coefficient θ is an unknown weighting factor defining the mathematical relationship between input and output. By referencing M, the coefficient parameter is denoted as $\hat{\theta} = (\hat{\theta}_1, \hat{\theta}_2 \cdots, \hat{\theta}_{n-1,}\hat{\theta}_n)$. The hat symbol, $\wedge$ is used to label estimated variables. By rearranging equation (2), the residual illustrating the gap between actual value and measurement for discrete time *k* is described in equation (3). It is noticed that minimal sum square value of residual can be acquired by substitute most probable estimated parameter into $\hat{\theta}_k$.

$\varepsilon_k = y_k - u_k\hat{\theta}_k$ (3)

Linear least squares (LS) approach is adopted for searching element θ via minimization of equation (4)

$L_n(\theta) = \frac{1}{2}\sum_{k=0}^{n}[y_k - u_k\theta]^T w_k[y_k - u_k\theta]$ (4)

While $w_k \in [0,1]$ is the designated probability measure of confidence [36], LScomputes a best fit line with the smallest sum vertical distance from dataset measurement points through the medium of parameter weight assignment. It is worth mentioning that equation L_n resembles cost function minimizers such as *fmincon* and *fminsearch* which available in Matlab software.

Further extension into multivariate setup leads to the following equation:

$$y_k = u_{1,k}\theta_1 + u_{2,k}\theta_2 \cdots + u_{i,k}\theta_i + \cdots + u_{j-1,k}\theta_{j-1} + u_{j,k}\theta_{j+e_k}$$

$$Y = U\theta + e$$

where *i* and *j* represent the element index and total number of involving variables respectively; $Y = [y_1 \quad \cdots \quad y_n]^T$ is denoted as stacked output vector; $U = \begin{bmatrix} u_{1,1} & \cdots & u_{1,j} \\ \vdots & \ddots & \vdots \\ u_{n,1} & \cdots & u_{n,j} \end{bmatrix}$ indicates corresponding input matrix and $e = [e_1 \quad \cdots \quad e_n]^T$ is the assembled error vector.

$$\varepsilon = Y - U\hat{\theta}$$

$$V(\theta) = \frac{1}{2}\left\|Y - U\hat{\theta}\right\|^2$$

$$\frac{dV}{d\theta} = -U^T Y + U^T U\hat{\theta} = 0$$

$$\hat{\theta} = [U^T U]^{-1} U^T Y \quad (5)$$

The product of cost function differentiation in equation (5) yields the estimated parameter vector, $\hat{\theta}$, and the diagonal elements, P_{ii} located within a unique covariance matrix, $[U^T U]^{-1}$ which holds a minimum solution which reflects the estimation's accuracy.

Considering $\hat{\theta}$ as the fractional contribution share of each input equally demonstrates the proportional significance level to the dynamic response of output. Observed engagement of $\hat{\theta}$ or covariance matrix as benchmark for the relevancy-redundancy ratio amongst independent input variables is practical. Hence, the establishment of an LS-based input-selection mechanism for a multiple input single output (MISO) conditionmonitoring model with the intention to identify the usefulness of parameters and enhance observation performance is justified. In addition, input subset selection criteria are defined by coefficient threshold range limits; input associated with minimum values will be discarded.

By applying least squares technique into turbomachinery case study specifically, it is expected a defined input subset from prior OEM guidelines is delivered to an intended intelligent Unit Condition Analyser (iUCA) software package. Later on, the fitness of the newly-estimated parameter vector for modelling purpose will be examined in connection with the OEM limit range. The implementation flow of feature filtering will be tabulated in the following section.

3.3. Methodology

Relating to Figure 2, the development sequence of an MSA integrated desktop application is discussed. The monitoring process emphasizes on using a specialized desktop application, namely an iUCA. Initially, the iUCA employs and processes the entire input dataset as per OEM instructions. The input dataset refers to measured parameters concerning fluid dynamics, tribological and excitation responses, while output suggests three types of machine subsystem state conditions including ‘Acceptable’, ‘Alert’ and ‘Unacceptable’. Notably, the condition list is arranged according to damage severity in ascending order.

Multivariate statistical analysis, in particular the linear LStechnique, is appointed to perform a turbomachinery system conditionmonitoring evaluation according to defined assessment modes. The purpose of assembling MSA into a software implementation sequence is to analyse and identify the mathematical relationship between variables. Specifically, it is employed to indicate and utilize individual parameters that are highly correlated to or heavily influenced by engineered assessment modes, as input subsets instead. The goal of the research is to supply quantitative and qualitative measures for input and output.

Field data were collected by performing an offshore site visit. The data were captured through historical data stored in the package hard drive or distributed control system (DCS). Parameters measured include flow, pressure, temperature, speed, vibration, level and non-dimensional parameters. The raw data stored were required to be converted into a workable format for detailed analysis. Figure 3 illustrates data acquisition and analysis flow chart.

During analysis stage, the pre-filtered OEM standard limit will be examined by MSA for the purpose of baseline model creation. The process includes discovering multivariate inter-correlation and parameter coefficients which represent the respective weighting factors. The baseline model will select highly correlated parameters as newly filtered input subset to serve as modified baseline standard for further input data in determining variation from normal range by referring to pre-set threshold limit. Because every significant parameter in the MSA display is bounded with individually adjusted limits, the deviation directly reflects the severity of a particular subsystem or component and is critical in defining the acceptable level of condition output. Later on, the newly captured data subset will be observed as a dynamic model and compared to the baseline model. The results of condition monitoring will be determined into three types of health condition descriptions based on the discrepancy between the two models. The overall conclusion will be tabulated with descriptions and graphical representation via the iUCA interface.

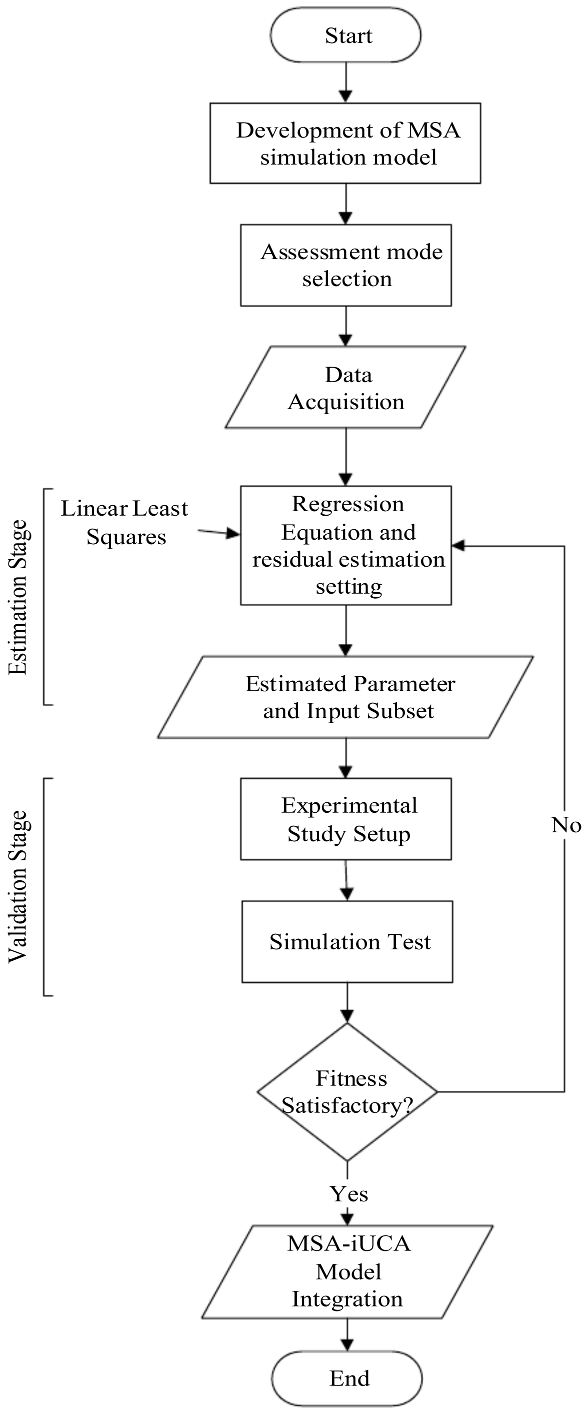

Figure 2 shows MSA Estimation Model Development Flow Chart

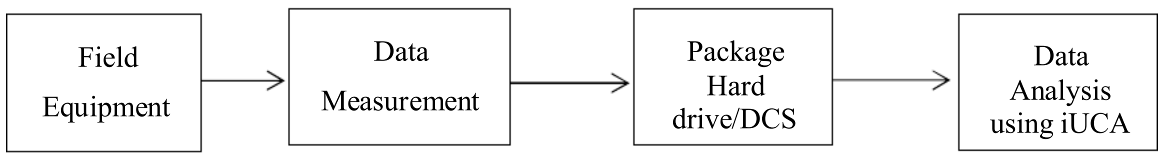

Figure 3 shows Data acquisition and analysis flow chart

4. RESULTS AND DISCUSSION

In order to fulfil the research target, software was developed with the objective of assessing and determining the health condition of the turbomachinery package according to the last measurement data received by the software, which is described asa dynamic model. For three assessment modes, the MSA equations were embedded in the software to determine the fitness of the dynamic model by comparing the range of the created baseline model and the original OEM standard. If the measurements exceed the range of the baseline model created, this will be highlighted according to the defined health category and an alarm will be prompted. The output of the iUCA for condition monitoring of the turbomachinery package was tested and is explained in this section.

4.1. Case Study 1: Acceptable

In this case study, the compressor drive end journal bearings were evaluated. To determine the condition of the compressor drive end journal bearings, six parameters were assessed, namely compressor drive end “Y” vibration, compressor drive end “X” vibration, compressor drive end bearing temperature 1, compressor drive end bearing temperature 2 and power turbine speed 1. Five out of six parameters were determined to be significant via MSA analysis. Figure 4 explains the assessment result by comparing the baseline model to the dynamic model. Obviously, the MSA result is consistent in comparison with OEM limits, where all readings were also within the OEM limits. Therefore, the final output of the dynamic model is considered to be “Acceptable”. From this case study, it can be concluded that the baseline model generated by MSA obtains similar observation criteria as the OEM limit, even with a lesser parameter subset.

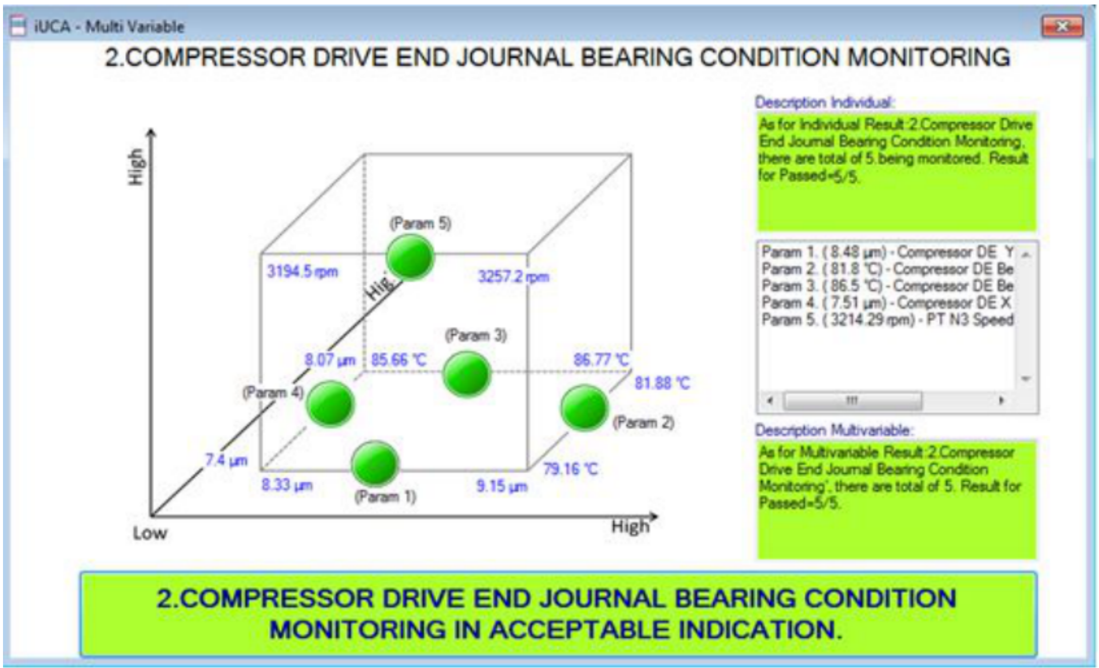

Figure 4 Shows compressor drive end journal bearing condition monitoring using MSA

4.2. Case Study 2: Alert

In this case study, the compressor was evaluated. Thirteen parameters were assessed, namely ASC1 discharge temperature, ASC1 suction flow, ASC1 discharge pressure, ASC2 discharge temperature, ASC1 suction pressure, ASC1 discharge flow, ASC1 suction temperature, ASC2 suction flow, ASC2 discharge pressure, ASC2 suction temperature, ASC2 suction pressure, ASC2 discharge flow and power turbine speed 1. Eight out of thirteen parameters were determined to be significant. It was also found that five out of eight significant parameters were not within the acceptable range. Figure 5 explains the assessment result by comparing the baseline model to the dynamic model. Based on this case study, the MSA result is consistent with OEM, as five readings are out of bounds. Therefore, the final output of the condition monitoring is illustrated as "Alert". The baseline model developed by MSA generates identically stringent criteria compared to the OEM limit. Hence, it can be concluded that the degradation process is less likely to be overlooked when employing an optimal parameter subset.

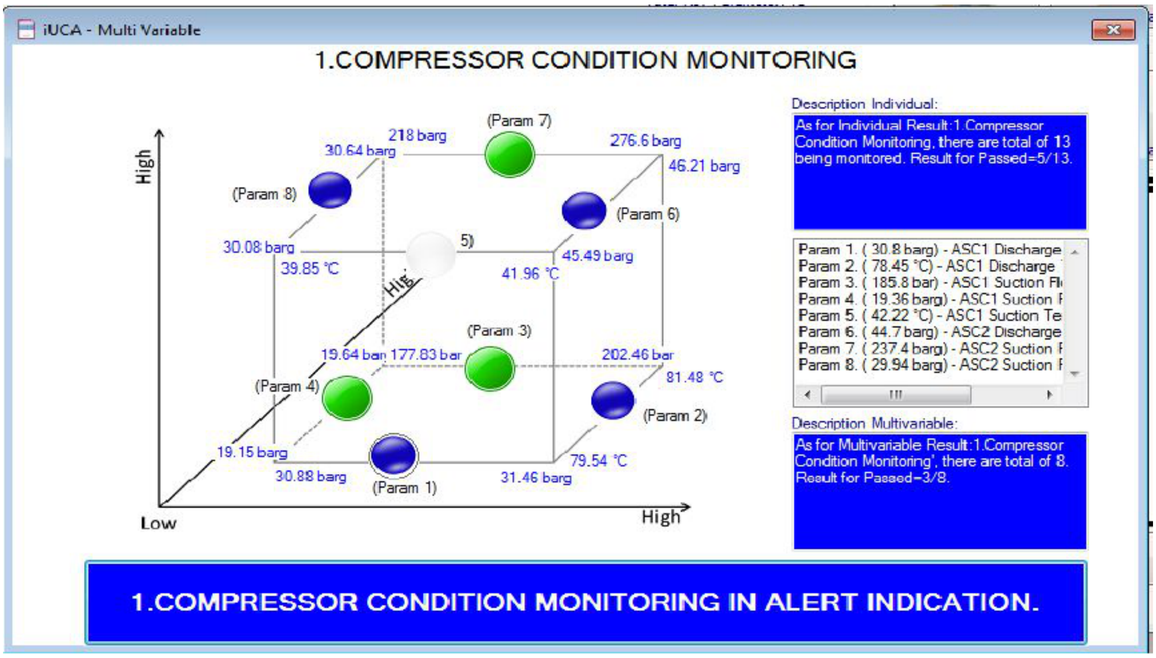

Figure 5 Shows compressor condition monitoring using MSA

4.3. Case Study 3: Unacceptable

In this case study, the gas generator was evaluated. To analyse the condition of gas generator, sixteen parameters were observed: ambient air temperature, combustion filter differential pressure, gas generator 05 module temperature A, gas generator 05 module temperature B, gas generator bearing cooling air pressure, gas generator HP compressor discharge pressure, gas generator inlet flare atmospheric differential pressure, gas generator IP inlet pressure, gas generator IP discharge pressure, gas generator NL speed 1, gas generator NH speed 1, gas generator NL speed 2, gas generator NH speed 2, gas generator enclosure temperature 1, gas generator enclosure temperature 2 and ventilation filter differential pressure. Sevenout of sixteen parameters were determined to be significant by using the MSA equation. It was also found that three out of the seven significant parameters were not within the acceptable range. Figure 3 portrays the assessment result obtained by the comparing the baseline model with the dynamic model. The dynamic model reading contradicts OEM limits, where all readings were well within the OEM limits.

Further investigation on the gas generator showed that it encountered a piping blockage problem, which caused the decrement of pressure and temperature due to low fluid viscosity. Therefore, the final output of the condition monitoring was confirmed to be "Unacceptable". This case study illustrated that the baseline model created by MSA is capable of recognizing fault development at an early stage with a significant parameter subset. Thus, it can be concluded that MSA parameter optimization could improve sensitivity and accuracy due to the absence of data complexity and reduced dependence onOEM guidelines.

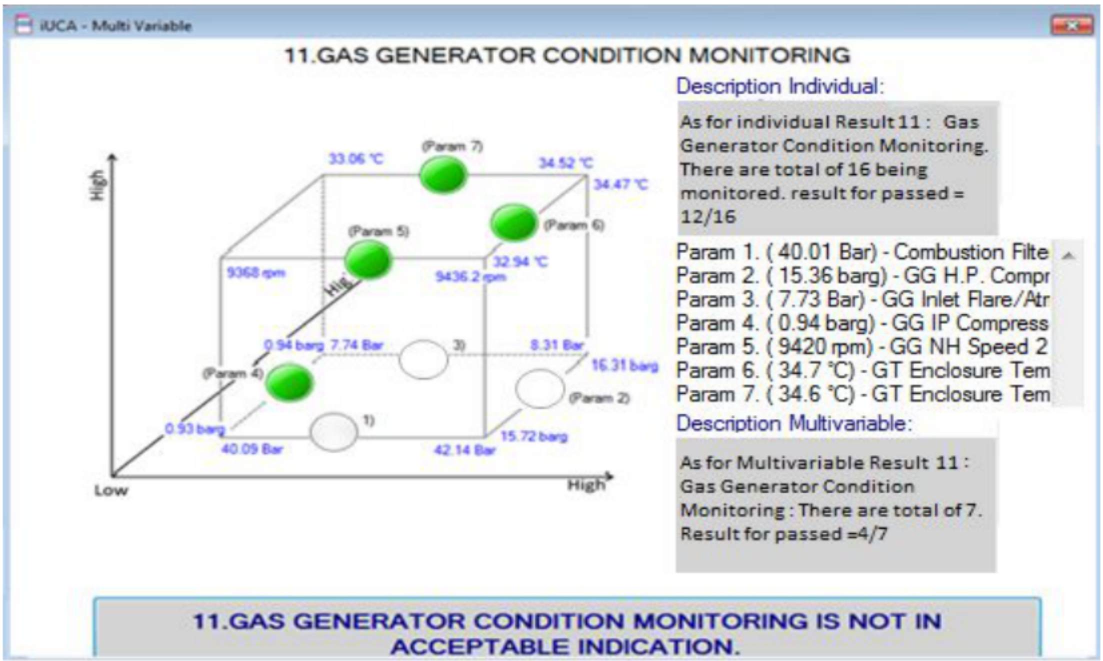

Figure 6 Shows Gas Generator Condition Monitoring using MSA

5. CONCLUSION AND DISCUSSION

Table 1 Case Study Result Overview

No.	Case Study	Verdict		Input Parameter
		OEM Standard	**MSA-iUCA**	**Reduction Percentage**
1	Compressor Drive End Journal Bearing	Acceptable	Acceptable	17%
2	Compressor	Alert	Alert	38%
3	Gas Generator	Acceptable	Unacceptable	56%

Referring to Table 1, it is evident that the efficacy of the MSA-iUCA model condition monitoring process was at least as high as that of OEM limit practice (Case Study 1 and 2). Nonetheless, by adopting statistical analysis, the newly-revised observation model was capable of providing better sensitivity and accuracy compared to the OEM standard, as exemplified in the case study involving the gas generator. The discrimination of a precise fault developing phase is informative in estimating effective maintenance activity and avoiding unscheduled planning. The statistical reassessment of the OEM multivariable list also produced a more straightforward model which emphasizes parameter optimization, simplicity and reduced dependence on human intervention. It provides insight in the direction of cost-saving and compact turbomachinery design. Hence, it can be claimed that this turbomachinery conditionmonitoring method, upgraded with MSA-iUCA model software, is more efficient, reliable and simple compared to the existing conditionmonitoring methodology used for industry purposes.

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