GAS TURBINE FAULT DETECTION USING A SELF-ORGANISING MAP

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Abstract: Turbomachinery condition monitoring and fault detection in the Malaysian oil and gas industry is currently done by monitoring the parameters of the equipment, such as a gas turbine, based on limits provided by the original equipment manufacturer. This is performed in an attempt to avoid any unscheduled downtime and catastrophic failure of the machinery. However, this method has proven to be insufficient and ineffective in providing early information or warning regarding machine faults. This paper presents a case study of a gas turbine that developed a blade fault in an oil and gas plant despite operating within its original equipment manufacturer limits. The parameters used for machinery condition monitoring were then analysed using a self-organising map; a two-dimensional graphical layout consists of neurons arranged in contact with one another. The results demonstrate that such a map is efficient in providing early warning regarding turbomachinery's health conditions.

Keywords: gas turbine; condition monitoring; fault detection; self-organising map

1. Introduction

The unscheduled downtime of turbomachinery in critical industries, such as oil and gas, power generation, petrochemical, and aviation, results in large financial losses to the industries. In addition, component failure, such as blade, bearing, shaft, and gear failure, may lead to a catastrophic failure that threatens human life. Oil and gas plants in Malaysia are implementing machinery condition monitoring and fault detection by observing the equipment parameters, such as temperature, pressure, vibration levels, and operating speeds, at various machine locations. This paper presents a case study of a gas turbine that was operating within its original equipment manufacturer (OEM) limits, but was found to have obvious damage on multiple blades during its periodic and borescope inspection, as depicted in Figure 1. Gas turbine condition monitoring and fault detection solely based on the OEM limits are thus deemed to be insufficient. The hypothesis of this study is that the faulty machine parameters are deemed to be outliers in a self-organising map (SOM) when the SOM is generated by using all historical machine parameters. This paper explores the feasibility of SOM to provide insight into gas turbine health conditions. The SOM concept will be introduced in the following section.

Figure 1: Multiple instances of blade damage were found during the periodic and borescope inspection of the gas turbine

2. Self-Organising Map

A self-organising map (SOM) is an unsupervised machine learning technique inspired by an artificial neural network (ANN), which mimics the human brain in processing signals. This map was developed for clustering applications by grouping data based on their similarity. As the name implies, an SOM, represented in a two-dimensional graphical layout, consists of neurons arranged in contact with one another. It varies from a typical ANN-correlated input-output; using hidden layers via error feedback minimisation, an SOM applies competitive learning with the objective of visualising a high-dimension complex space in a straightforward manner. An SOM consists of a competitive layer, which can classify a dataset with any number of features into as many classes as the layer has neurons. An SOM recognises input data with similar characteristics or patterns and assembles identified groups as neighbourhood neurons. The associated topology-preserving maps are established by assigning a unique weighting factor to each neuron corresponding to the similarities. For every iterative training cycle, an SOM refines the input neuron locations, weighing factor, and weighing equations in expectation of a mature form of cluster mapping. The overview of the SOM training process is displayed in Figure 2.

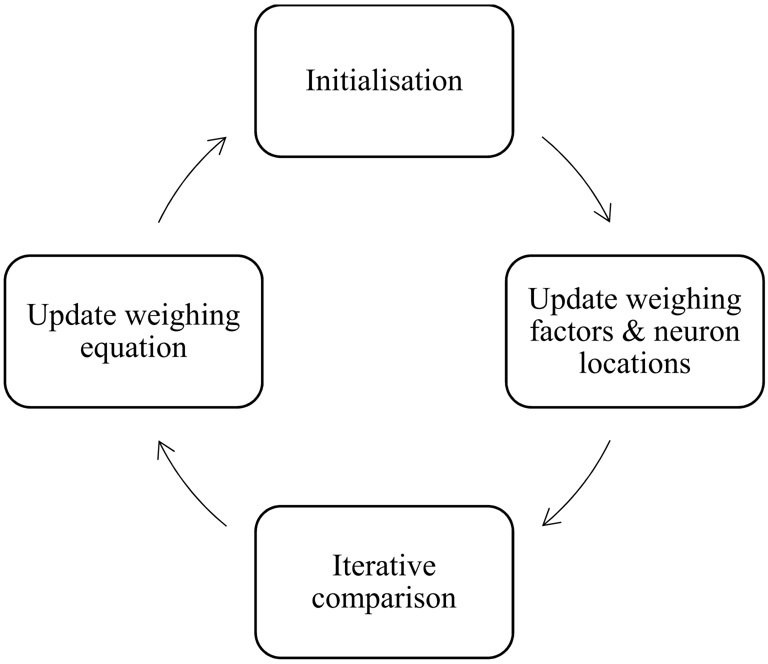

Figure 2: Overview of SOM training cycle

Self-organising maps have been implemented in various applications such as machinery health assessments [1–6], as well as in the fields of medicine [7–9], finance [10], and energy [11]. On the one hand, the adaptive nature of an SOM has recently been recognised in a range of applications, particularly in non-linear structure mapping, dimensional reduction, and clustering illustrations. On the other hand, an unsupervised SOM could not only potentially reduce premature output class labelling, but could also be capable of generating feature maps for visual aid purposes. For instance, an SOM has been found to be notably effective in candidate evaluation for genetics pool, topological collaborative clustering, and harmony memory embedded multi-layer deep learning [12–14]; cost-effective data collection tracking [15]; intrusion dynamic systems accommodating dynamic vehicle ad hoc networks model [16]; potential disaster risk assessment [17]; and contaminated water image processing corresponding to Caenorhabditis elegans activity [18].

3. Data Collection and Machine Trending

This section provides a brief summary of the data collection methodology relating to the data used in this research. The machine parameters used in this study and their corresponding measurement units are listed in Table 1. The parameters were logged half-hourly into the turbomachinery condition monitoring system from 1st October, 2016 to 31st October, 2017.

Table 1: Machine parameters used in this study

Machine Parameter	Labelling	Unit
Gas generator rotor speed	GG SPEED	RPM
Power turbine rotor speed	PT SPEED	RPM
Compressor vibration (displacement)	GG VIB (DISPL)	micron
Compressor vibration (velocity)	GG VIB (VEL)	mm/s
Compressor inlet temperature	T2	°C
Compressor discharge temperature	T3	°C
Compressor discharge pressure	PCD	bar(g)
Power turbine inlet temperature	T5.4	°C
Exhaust temperature	T EXHAUST	°C

Figure 3 illustrates the measurement locations of each machine parameter, and Figures 4–6 present the trending of various machine parameters recorded in a year. The gas generator rotor speed at 0 RPM shown in Figure 4 represents machine outage during that particular period of time. In addition, the green lines in Figures 4–6 denote the upper and lower limits suggested by the OEM, whilst magenta and red lines represent alarm and trip limits respectively.

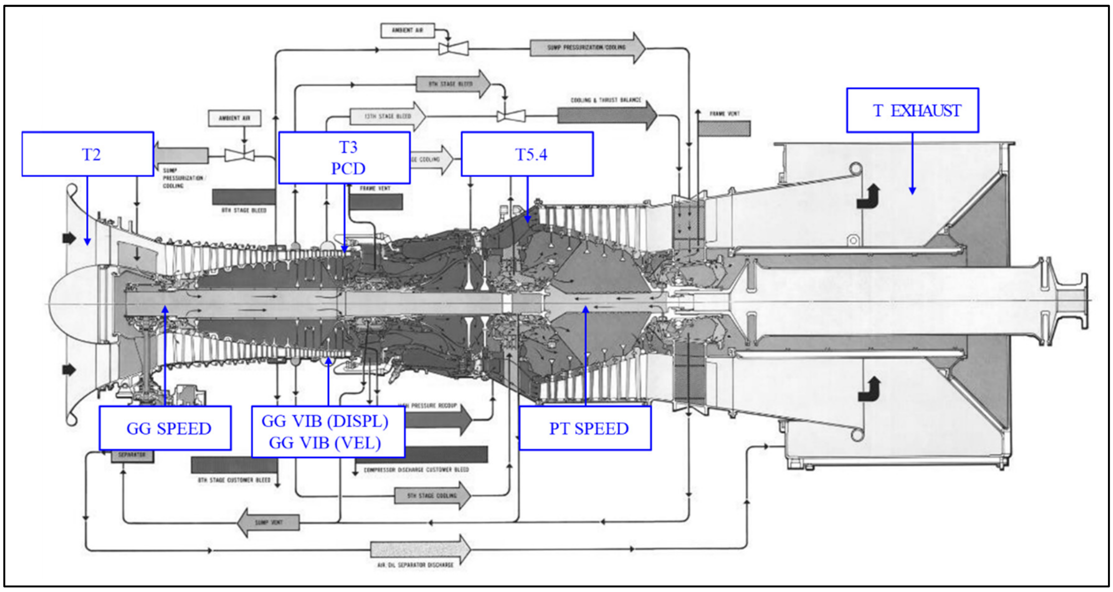

Figure 3: Measurement locations of the machine parameter

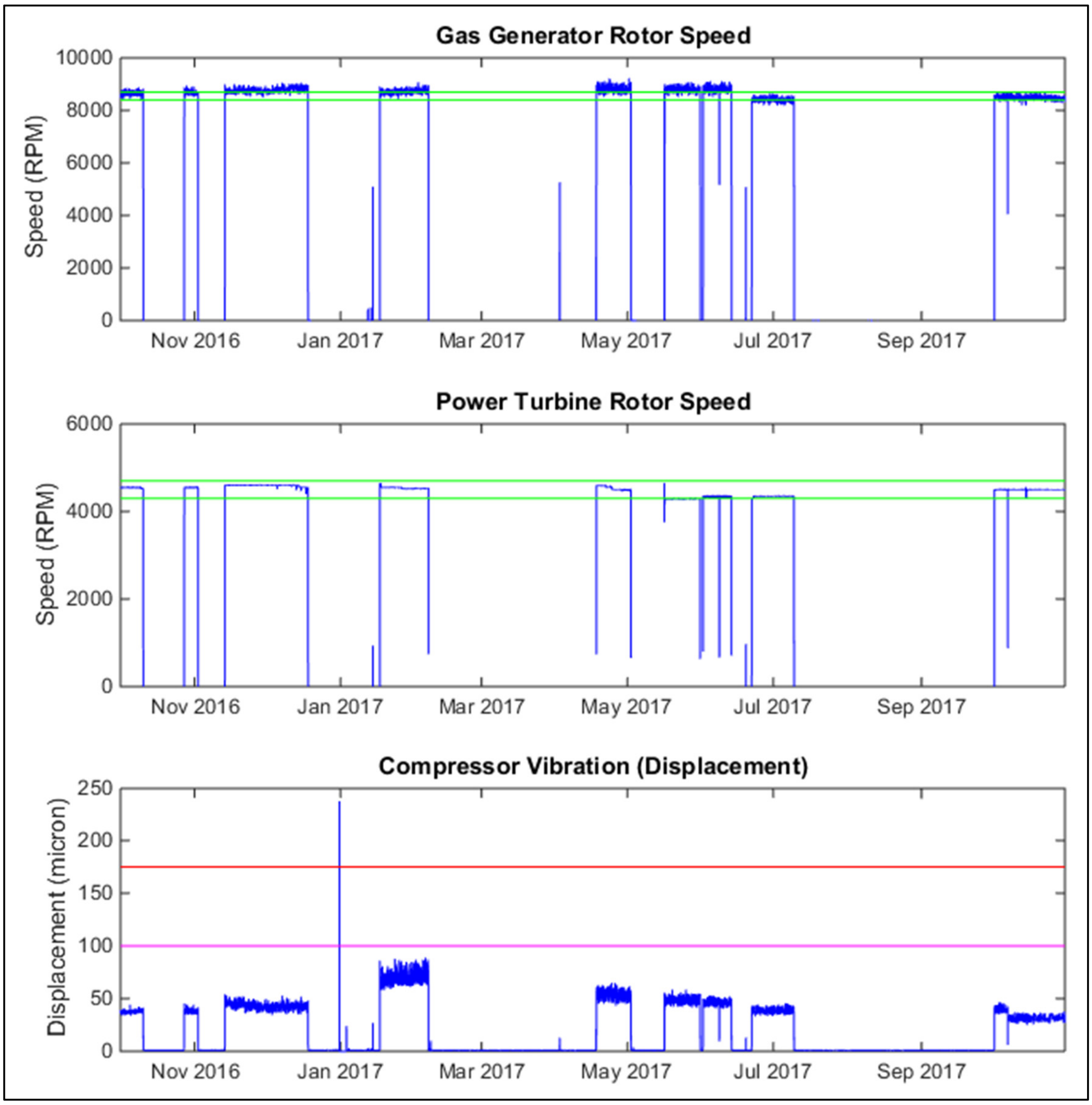

Figure 4: Gas generator rotor speed, power turbine rotor speed, and compressor vibration displacement of a gas turbine (green line: upper and lower limits; magenta line: alarm limit; red line: trip limit)

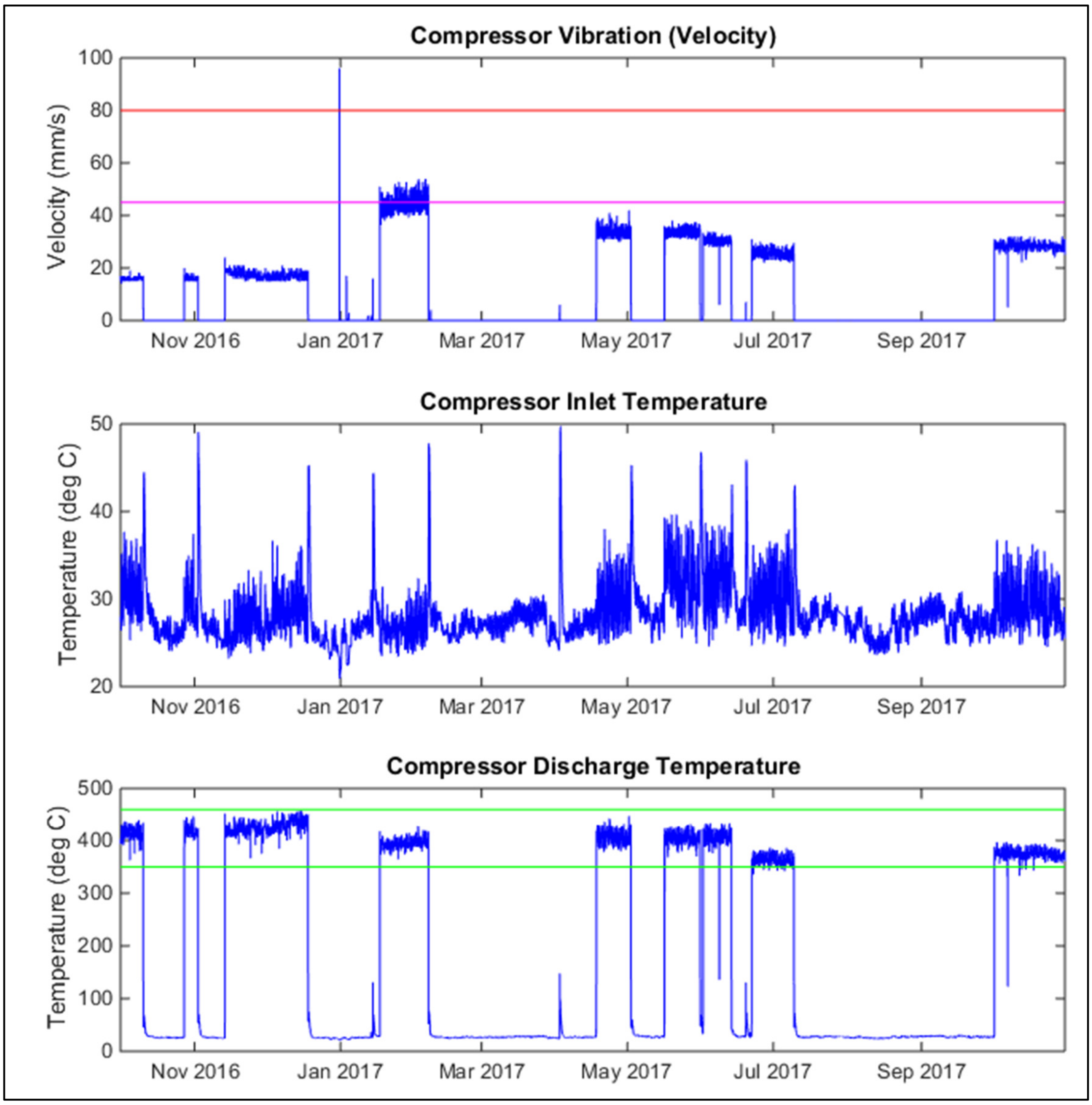

Figure 5: Compressor vibration velocity, compressor inlet temperature, and compressor discharge temperature of a gas turbine (green line: upper and lower limits; magenta line: alarm limit; red line: trip limit)

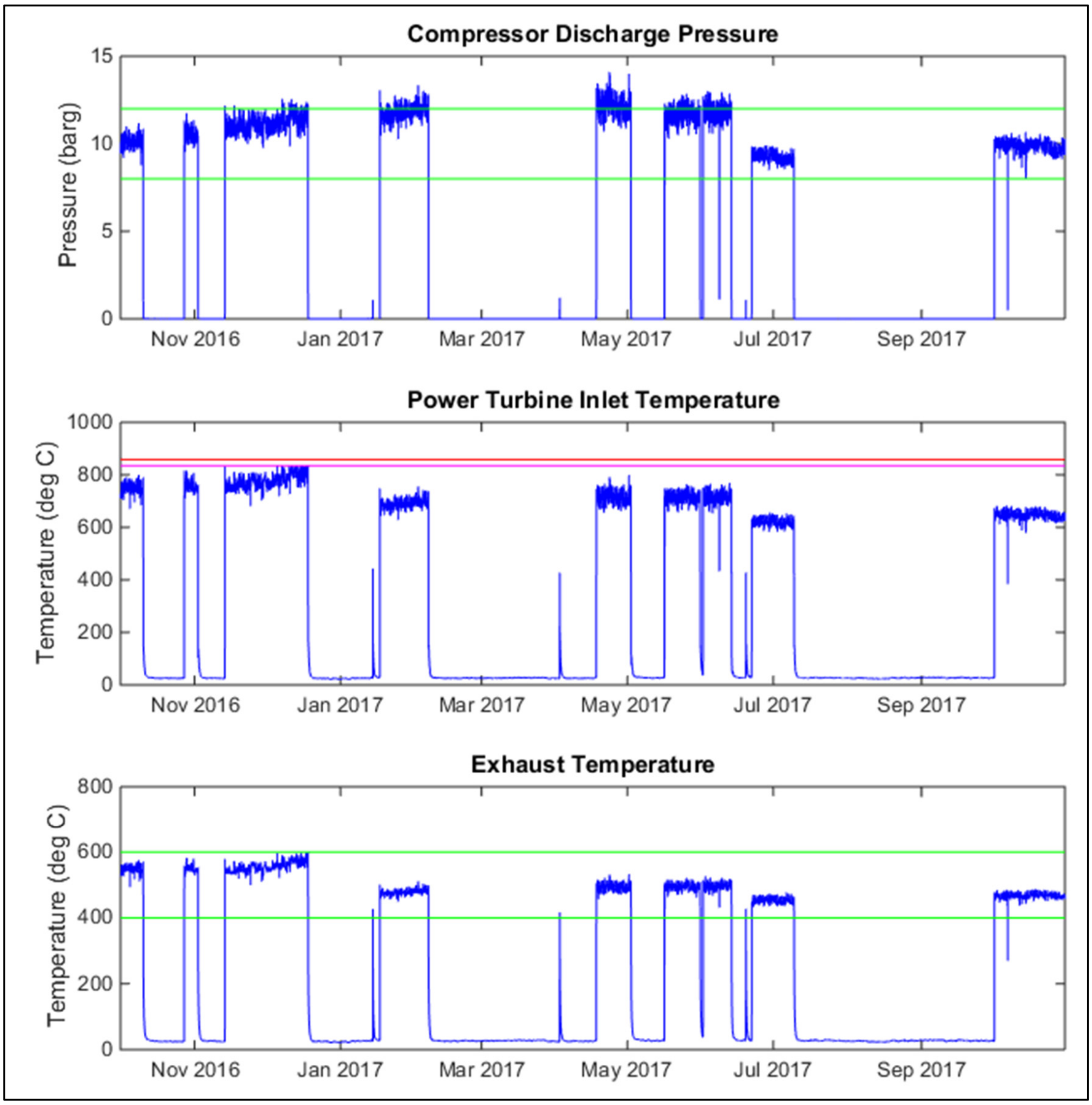

Figure 6: Compressor discharge pressure, power turbine inlet temperature, and exhaust temperature of a gas turbine (green line: upper and lower limits; magenta line: alarm limit; red line: trip limit)

The SOM used in this study consists of 10 neurons in each dimension. The two-dimensional map is capable of classifying the weekly machine parameters collected on a half-hourly basis into 100 categories based on their similarity of characteristics. The machine parameters during machine outage were first omitted. Given that the machine parameters during machine operation fluctuate, and the fluctuation range between machine parameters is rather inconsistent, the machine parameters were then normalised by scaling between 0 and 1 before they were input into the SOM algorithm. The SOM sample hits obtained from the SOM algorithm are described in the next chapter.

4. Results and Discussion

The purpose of this study was to evaluate the collected machine parameters on a weekly basis to identify the change in the data characteristics, thereby allowing for early machinery faults to be determined. The hypothesis of this study is that the faulty machine parameters are deemed to be outliers in an SOM when the SOM is generated by using all historical machine parameters. Figure 7 presents a typical SOM sample hit; the number in each hexagon represents the number of machine parameters that were classified into the neuron. The machine parameters that were classified into a neuron or its neighbouring neurons have higher similarity compared to machine parameters that were classified into neurons located further away. Therefore, a dataset with similar characteristics will be distributed evenly across all neurons, as illustrated in Figure 7.

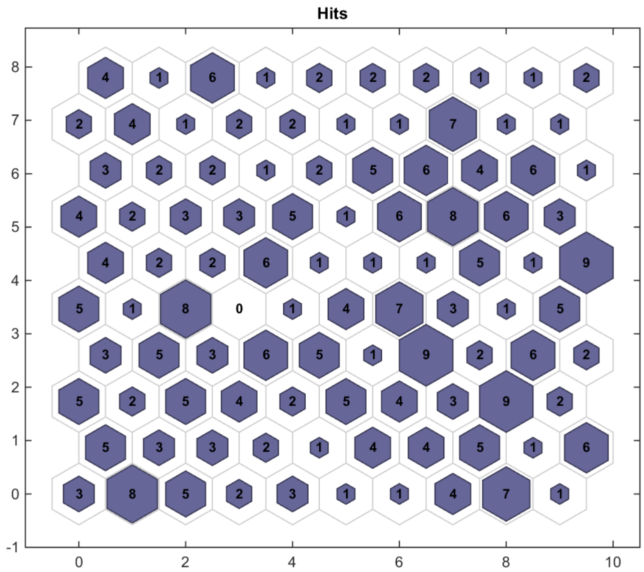

Figure 7: An SOM based on data collected from 1st to 7th October, 2016 (Baseline)

When a dataset consists of outliers, then an SOM shall present a map with the majority of data distributed across most of the neurons. However, some data were concentrated in a smaller number of neurons, as depicted in Figure 8 (lower right corner highlighted in red).

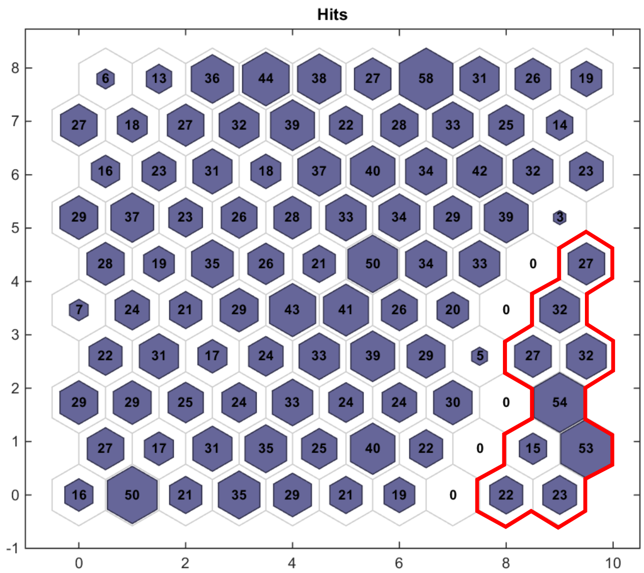

Figure 8: An SOM based on data collected from 1st October, 2016 to 23rd January, 2017

The initial objective of this study was to identify the abnormality of a gas turbine from its trending machine parameters. In the SOM of the first week's dataset shown in Figure 7, the dataset was found to be distributed across all neurons. This indicated that all data in the first week have similar characteristics, and this was assumed to be the baseline of the gas turbine. On the other hand, a significant change in the SOM is observed in Figure 8. The SOM was constructed based on data collected from 1st October, 2016 to 23rd January, 2017. Figure 8 demonstrates that a small cluster was formed in the SOM, and this indicates that outliers existed in the dataset. It can thus be suggested that the gas turbine was operating in a condition that was different from the initial operating condition in October 2016.

Another major change of the SOM was found in the SOM constructed with data collected up to 29th June, 2017, as shown in Figure 9. The collected data were clearly spilt into two classes. A possible explanation for this might be that the gas turbine was operating in a condition that was different from its baseline and that this continued for a certain period of time. Thus, the number of outliers in Figure 8 was increased and grew into a larger group, as illustrated in Figure 9.

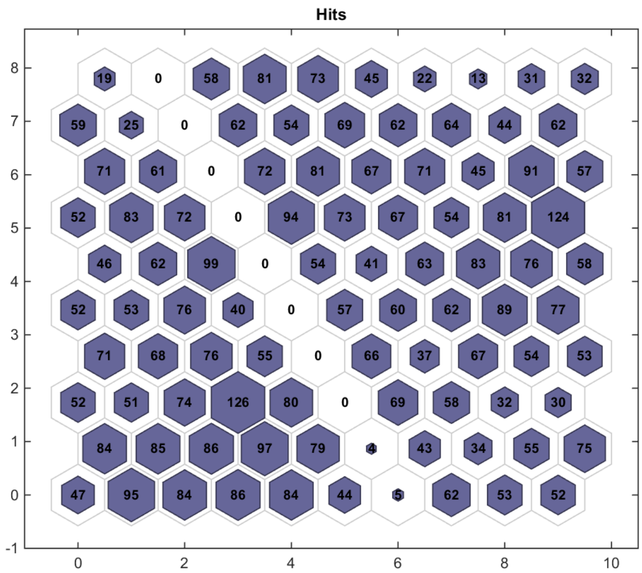

Figure 9: An SOM based on data collected from 1st October, 2016 to 29th June, 2017

Figure 10 presents an SOM constructed with the whole year's dataset; the data were clustered into two groups. These findings suggest that the gas turbine's operating condition was changed as early as 23rd January, 2017, and it may indicate that machine faults were developed at this stage. If the operator was triggered by this change, then the operator may take a step forward to thoroughly analyse the data collected to identify the machine faults, rather than assuming that the machine is running at a normal condition as all collected data were within the OEM limits. This study has been verified by the periodic and borescope inspection that was conducted on 15th November, 2017, when blade damage was found on multiple blades.

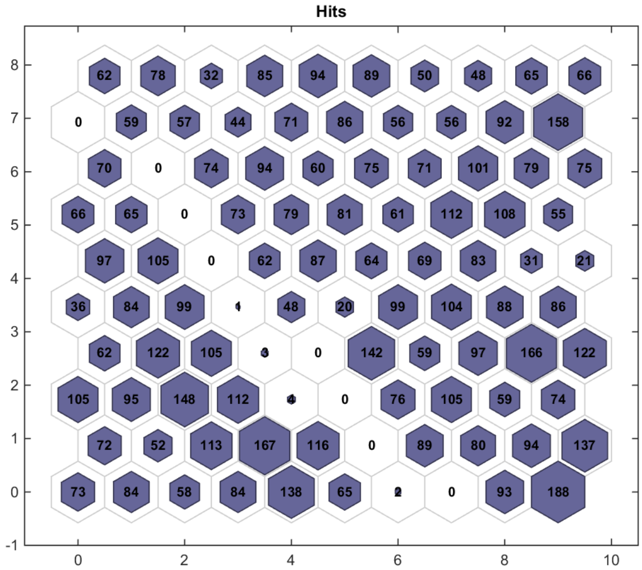

Figure 10: An SOM based on data collected from 1st October, 2016 to 26th October, 2017

5. Conclusion

This study set out to identify significant changes in the data collected over a year, even though all collected data were within the OEM limits. This study identified that an initial change in the characteristics of the collected data took place on 23rd January, 2017. The results of this study indicate that an SOM is capable of machine health monitoring, which would allow an operator to take early action.

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