

Article

Condition Monitoring of Internal Combustion Engines in Thermal Power Plants Based on Control Charts and Adapted Nelson Rules

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Abstract: In thermal power plants, the internal combustion engines are constantly subjected to stresses, requiring a continuous monitoring system in order to check their operating conditions. However, most of the time, these monitoring systems only indicate if the monitored parameters are in nonconformity close to the occurrence of a catastrophic failure—they do not allow a predictive analysis of the operating conditions of the machine. In this paper, a statistical model, based on the statistical control process and Nelson Rules, is proposed to analyze the operational conditions of the machine based on the supervisory system data. The statistical model is validated through comparisons with entries of the plant logbook. It is demonstrated that the results obtained with the proposed statistical model match perfectly with the entries of the logbook, showing our model to be a promising tool for making decisions concerning maintenance in the plant.

Keywords: condition-based maintenance; failure analysis; internal combustion engines; Nelson Rules; statistical process control

1. Introduction

The current stage of evolution of thermal power plants (TPPs), in conjunction with the low reservoir levels of their hydro counterparts (due to longer periods of high temperatures or droughts [1]), has resulted in the dispatch of TPPs in order to fulfill occasional demand [2]. Furthermore, due to the ever-increasing penetration of intermittent renewable sources, in combination with the fact that large thermal generation systems may have limited power ramping capability [3], TPPs using internal combustion engines (ICEs) can be dispatched in less time. However, a great number of ICEs in the TPPs are constantly exposed to stresses [4], increasing the chances of catastrophic failures. Inherent factors to thermal power generators (such as the number of start-ups, average load, variation in load and ambient temperature) can increase the levels of stress on the assets [5,6]. This increase on the stress levels may put the asset on the path towards failure. An accumulation of stresses may lead to wear and an increase in the vibration of the unit, decreasing the energy efficiency, decreasing the insulation resistance, increasing the consumption of replacement items, among other situations [7,8], and decreasing the generation reliability in consequence.

When the failures are identified at an incipient stage, appropriate actions can be performed to avoid breakdowns and the resulting losses [9,10]. The concept of condition-based maintenance (CBM) is based on the continuous monitoring of certain parameters and the evaluation of whether some of these parameters indicate signs of decreasing performance [11].

The in-depth knowledge of the plant environment, with regard to the condition of its main assets, is an important factor to gain information on the stress levels and wear and tear of the assets, as well as to perform maintenance control more effectively, which can reduce costs and postpone investments. Several approaches to the implementation of supervisory systems based on the resources of the environment in which they are inserted have been proposed in the literature, such as the methods presented in [12–15]. In the work of Audas [12], a database scheme was proposed in order to solve issues related with manual workload (spreadsheet-based) of TPP signal data. In Ribeiro et al. [13], a real-time monitoring system was presented in order to identify early failures in the energy generation of the TPPs. In Samtani et al. [14], an approach was presented to rate and identify the vulnerability of an Internet-enabled data acquisition and supervision system (SCADA). In Mayadevi et al. [15], a new technique was proposed that is capable of predicting failures in plants that use SCADA as a supervisory system. In the present context, special emphasis is given to the Wärtsilä Operator's Interface System (WOIS), which is discussed in depth in [16,17].

In WOIS, the operators can control and monitor the generators and related systems through an interface consisting of windows. These windows are classified into three categories: main, process and object. In the main window, the operator has an overview of the set of generators and their states, in addition to access to lists of alarms, graphs and reports. In the process window, operators have access to measurements and graphic symbols that describe more detailed information about the process itself. Finally, in the object window, the operator has access to detailed information about analog measurements [16]. As a result, operators are able to access all important plant data via the WOIS graphical interface.

Another interesting proposition in this context is the Marprime system [18]. With this system, operators can perform both the monitoring and measurement of internal pressure with or without ultrasound data of the internal combustion engines in a portable way. This system also provides the operator with analysis and diagnostic software [19]. Still related to the scope of this article, there are different approaches to maintenance: corrective, preventive and predictive maintenance. A review of these approaches is presented in [20]. However, special emphasis is given to predictive maintenance. This kind of maintenance allows the monitoring of the operational behavior of the generating units and has the ability to foresee a possible failure before the shutdown of the unity [20].

The concept of statistical process control (SPC) can be brought into this context [21] and here is considered as an option to monitor the operative condition of the internal combustion engines of the TPP and indicate a trend of failures in the medium and long term based on the stresses to which the monitored assets were subjected. This concept is based on control charts that enable the tracking of each monitored parameter within certain limits [22]. Lampreia et al. [23] propose the use of the EWMA (Exponentially Weighted Moving Average) on the control charts of the pressure and temperature of a maritime ICE in order to decide when to activate a spare refrigeration system for the engine. However, the EWMA has insufficient rules to consider the behavior of data points that are not very close to the average.

This current paper presents a statistical model (SM) based on SPC and adapted Nelson Rules (which enable the indication of statistically abnormal behavior of variables [24]). The adapted Nelson rules are a set of eight rules that provide for better decisions concerning the behavior of the data points on the entire control chart. Hence, the maintenance personnel of the TPP can benefit from the use of statistical monitoring in order to develop strategies for the maintenance of all its assets, without the need for a complex infrastructure.

The asset sensing method integrates the ability to monitor and locate regions of abnormal operation, allowing for intelligent asset management. When the SM finds such regions, it can issue an alert of the probability of future failure if the asset continues operating under these conditions. However, in order to do so, data need to be available (which originate from the plant's supervisory system itself, field measurements, online monitoring systems and even reports from the maintenance personnel) to allow the interpretation of these data (in order to extract valuable information) and decision making in relation to the events.

In order to improve the performance of the original supervisory system [16], this article analyzes the ability of the proposed SM to present indications of failure probabilities. In order to provide the analysis with practical appeal, the operating data used refer to the history of an internal combustion engine of model 18V46, from the manufacturer Wärtsilä. The rest of the paper is organized as follows: Section 2 presents the fundamental concepts about the development of the SM. Section 3 presents the validation of the proposed SM based on the data of an internal combustion engine operating in a TPP in Brazil. Finally, Section 4 presents the main conclusions of the work and some opportunities for future research.

2. Materials and Methods

This section presents the analytical development of the SM based on thermal power generators (each of them driven by a Wärtsilä 18V46 internal combustion engine) of a TPP in Brazil. Section 2.1 presents a general description of this engine.

The proposed statistical model is based on the assumption that there is no prior knowledge of the operating conditions of the engines nor ideal operating ranges of the monitored variables (a variable is a term used to describe the information from each sensor—a further discussion on the variables is presented in Section 2.2). From this assumption, the goal of the technique presented in this article is to characterize the generating units from a model based on variable control charts, in which the control limits are updated according to the arrival of new data from the sensors.

In order to simplify the analysis, each generating unit is divided into 11 subsystems. Each subsystem has distinct characteristics and modes of operation. A set of 112 variables is distributed among the 11 subsystems, as presented in Section 2.2.

The data from the 112 variables are processed at a fixed time basis of a few units of seconds. At each update, statistical calculations are performed for each variable (mean and standard deviation). The operational probability regions are updated on the control chart, and the adapted Nelson Rules are applied to the new point of monitored quantities, resulting in a percentage of activation of those rules. Section 2.3 discusses the development of the statistical model, including the control charts and the adapted Nelson Rules.

2.1. General Description of the 18V46 Engine

Figure 1 presents the basic drawings of the 18V46 engine. The 18V46 engine is configured in a V format with 18 cylinders, arranged as 9 cylinders on side A and 9 on side B, as presented in Figure 1a. Figure 1b presents the most important parts of a pair of cylinders (1—crankshaft, 2—connecting rod, 3—piston, 4—exhaust gas valve, 5—inlet valve and 6—fuel injection valve).

The 18V46 has a hybrid fuel mode between Gas–Diesel (GD) or Heavy Fuel Oil (HFO). The cycle starts with the piston (one of the pair) in downward motion and the opening of the inlet valve to fill the cylinder with air. As the pistons are in alternate motion (due to the movement of the crankshaft), as soon as the piston reaches the bottom of the cylinder, it returns in an upward motion. During the upward motion, the injection valve releases HFO in the cylinder in order to ignite the mixture of air and fuel in the cylinder. If the engine is in GD mode, the gas is released in the cylinder through the fuel injection valve. If the engine is in HFO mode, the fuel injection valve also releases the amount of HFO related to the working force of the pistons (apart from the ignition parcel). As the piston moves upwards, the compression of the HFO (both in GD and HFO modes) produces the

combustion of the fuel, which in turn produces the downward movement of the piston. At the same time, the exhaust gas valve opens in order to liberate the hot gases produced in the fuel combustion. As the piston is in downward motion, the cycle repeats. The up and down movement of the pistons is transmitted to the crankshaft through the connecting rod. The rotational movement of the crankshaft acts as a prime mover for a synchronous generator connected at the same shaft, thus generating electricity.

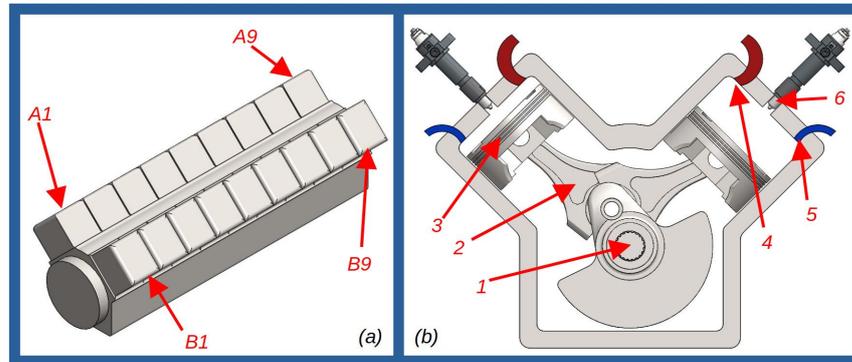


Figure 1. Didactic illustration of the 18V46 engine—(a) positioning of the cylinders—(b) parts of the cylinders.

2.2. Subsystems and Variables

In an ICE, monitoring is established for thermal and hydraulic variables (basically, temperature and pressure, in previously defined locations) accompanied by the angle of the eccentric axis. Failures and consequent damages in unmonitored positions present, in most cases, a delay from their occurrence until their detection by monitoring. In most cases, this delay is of different time scales for thermal changes in relation to hydraulic changes, leading to a great difficulty in assessing the temporal onset and fault location. The use of statistical control over the monitoring process makes it possible to establish a coalition between the thermal and hydraulic data of the control variables throughout the operating journey of the ICE, defining stops and maintenance criteria.

The diagram of Figure 2 presents the division of a generation unit into its subsystems, named as intake air, turbocharger, fuel oil, cylinders, bearings, lubricating oil, cooling water, generator, natural gas, exhaust gases and others. Each subsystem is further divided into several variables (that contain data from a multitude of sensors installed in the system). In total, each generator unit has 112 variables. The sensors are the same as those already installed in the Wärtsilä supervisory system. The variables also follow the same naming convention (tags) of the Wärtsilä system [17,25]. Table 1 presents a description of the variables.

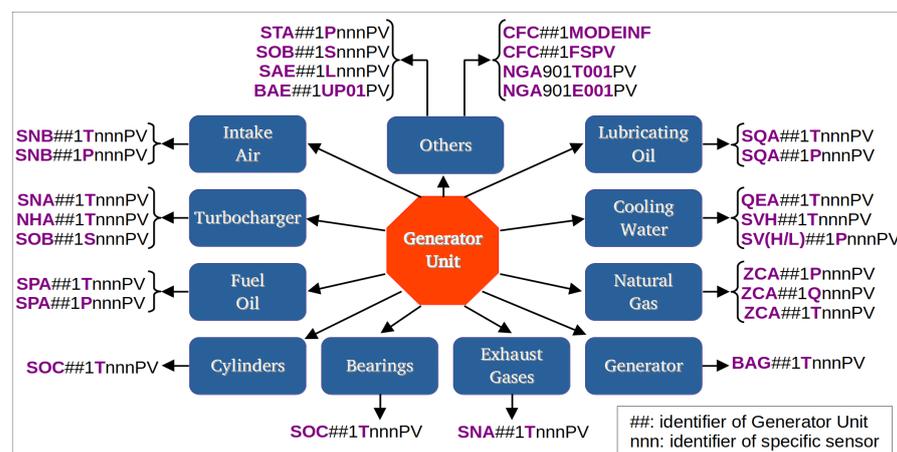


Figure 2. Diagram of a generator unit, divided into 11 subsystems (further divided into variables).

Table 1. Distribution of variables from the subsystems of generator unity number ##.

Subsystem	Variable	Description
Intake Air	SNB##1T001PV	Turbo air inlet temperature
	SNB##1T002PV	Charge air temperature in receiver
	SNB##1P002PV	Charge air pressure in receiver
Turbocharger	SNA##1T055PV	Exhaust gas temperature before turbo A
	NHA##1T001PV	Exhaust gas temperature after turbo A
	SNA##1T056PV	Exhaust gas temperature before turbo B
	NHA##1T002PV	Exhaust gas temperature after turbo B
	SOB##1S002PV	Turbo A speed
	SOB##1S003PV	Turbo B speed
Fuel Oil	SPA##1T002PV	Fuel oil inlet temperature
	SPA##1P004PV	Fuel oil inlet pressure
Cylinders	SOC##1TnnnPV	Cylinder (identified by nnn) liner temperature
Bearings	SOC##1TnnnPV	Main/Thrust bearing (identified by nnn) temperature
Exhaust Gases	SNA##1TnnnPV	Exh.gas. of cylinder (identified by nnn) temperature
Natural Gas	ZCA##1P101PV	Valve skid gas pressure inlet
	ZCA##1P102PV	Valve skid gas pressure outlet
	ZCA##1Q101PV	Main gas flow
	ZCA##1T001PV	Valve skid gas temperature outlet
Generator	BAG##1TnnnPV	Generator winding or bearings (identified by nnn) temperature
Cooling water	QEA##1TnnnPV	Cooling water temperatures (at positions identified by nnn)
	SVH##1TnnnPV	HT water temperatures (at outlets identified by nnn)
	SV(H/L)##1P003PV	(H/L)T water inlet pressure
Lubricating Oil	SQA##1TnnnPV	Lube oil temperature (at positions identified by nnn)
	SQA##1PnnnPV	Lube oil pressure (at positions identified by nnn)
Others	STA##1PnnnPV	Air pressure (at positions identified by nnn)
	SOB##1S001PV	Engine speed
	SAE##1L001PV	Torsional vibration
	BAE##1UP01PV	Generator active power
	CFC##1MODEINF	Fuel sharing (GD/HFO) mode
	CFC##1FSPV	Fuel sharing (GD/HFO) percentage
	NGA901T001PV	Outdoor temperature
	NGA901E001PV	Absolute humidity

2.3. Statistical Model

Based on the variables of each subsystem, the control criteria to be used as indicative of abnormalities in monitoring the variables are defined with the objective of indicating the occurrence of abnormal wear. The statistical analysis of each monitored variable is performed through control charts, as illustrated in Figure 3.

Figure 3 presents an example of the expected behavior of a random variable, plotted as the black curve (called x). The red line (called ML) characterizes the middle line; in other words, it characterizes the average (\bar{x}) of the measures of each variable x . The brown lines represent the statistical limits in which the variable is expected to swing in extreme cases, although still under normality. The limits are called the UCL (Upper Control Limit) and LCL (Lower Control Limit) and are determined based on the average \bar{x} and standard deviation s . Three zones (A, B and C) are defined in the figure. Zone C is the region in which the variable deviates from the average in less than one standard deviation (above or below). Zone B is the region in which the variable is between one and two deviations from the average (above or below). Zone A is the region in which the variable is between two and three deviations from the average (above or below). Considering a normal distribution, it is known from probability theory [22] (pp. 119–120) that any random variable has a 68.27% chance to be measured in a region limited between two standard deviations ($\pm 1 \cdot s$),

a 95.45% chance to be measured in a region between four standard deviations ($\pm 2 \cdot s$) and a 99.73% chance to be measured in a region between six standard deviations ($\pm 3 \cdot s$). Hence, if any measurement is obtained outside of six standard deviations, it is considered that this measurement is “outside the control limits”, as this would have only a 0.27% of chance of occurrence.

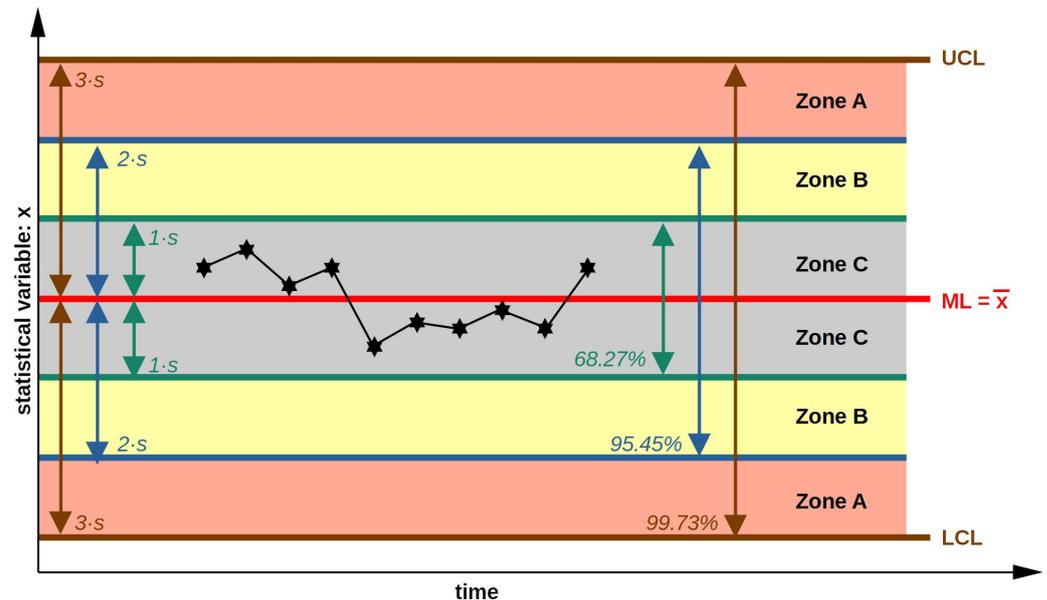


Figure 3. Example of control chart of a statistical variable x , with average \bar{x} and standard deviation s .

It is important to note that the application of the control chart as defined in Figure 3 is able to monitor the behavior of the variables. However, in practice, it is necessary to determine rules that point to the tendency of failures of the measured variables of the generator units and to indicate in some way an abnormality for the machine operator.

Commonly, the performance evaluation of the generating units of TPPs is performed through electronic and automatic monitoring and control systems. However, the reliance of these systems on the obtained parameters and measurements of the process generates increased difficulty in monitoring. Furthermore, the evaluation of all parameters by an operator, given the infinity of available parameters and the complexity of the processes involved, increases the difficulty. In this article, a statistical model is used to analyze the operating states of the generator units and to support the operators of these machines. According to this statistical model, the fault detection of the generator units is given by the activation of the adapted Nelson Rules, described briefly below:

- Rule #0: First point above (or below) the upper (or lower) control limit.
- Rule #1: Second point in the same Zone A, in three consecutive measurements.
- Rule #2: Fourth point in Zone B or A (on the same side), in five consecutive measurements.
- Rule #3: Ninth consecutive point on the same side of the average.
- Rule #4: Sixth consecutive point always below (or above) the previous ones.
- Rule #5: Eighth point outside C zones.
- Rule #6: Fifteenth consecutive point within C zones.
- Rule #7: Fourteenth alternating point up and down in any zone.

One of the possible problems that may arise in the application of the adapted Nelson rules is the requirement of a normal distribution for the data [26]. According to the Central Limit Theorem [22], it can be considered that, for a large number of samples, the probability

distribution of its average will be close to a normal distribution. Hence, the data from the sensors are normalized in terms of a z-score as (1).

$$z[n] = \frac{x[n] - \bar{x}}{s}, \quad (1)$$

where $x[n]$ is the set of non-normalized data of each variable. \bar{x} is the average value of this set, calculated as (2). s is the sample standard deviation of the set and is calculated as (3).

$$\bar{x} = \frac{1}{N-1} \cdot \left(\sum_{n=1}^N x[n] \right), \quad (2)$$

where N is the number of samples in the set.

$$s = \sqrt{\frac{\sum_{n=1}^N (x[n] - \bar{x})^2}{N-1}}. \quad (3)$$

For each of the variables, the control charts of each variable are obtained in accordance with [27]. The zones A, B and C, as well as the control limits, are obtained based on the values of the average (\bar{x} , calculated in (2), which corresponds to the middle line, ML, of Figure 3) and the standard deviation (s , calculated in (3)). The upper and lower control limits (UCL and LCL, respectively) of the chart are based on a spread of three standard deviations from the average, as implied in (4) and (5).

$$UCL = \bar{x} + 3 \cdot s, \quad (4)$$

$$LCL = \bar{x} - 3 \cdot s. \quad (5)$$

In order to apply the Nelson Rules, the total region between the two limits (which comprises six standard deviations) is divided into the zones A, B and C, in accordance with Equations (6) to (11), as shown in Figure 3.

$$ZoneC_{upper} = \bar{x} + 1 \cdot s, \quad (6)$$

$$ZoneC_{lower} = \bar{x} - 1 \cdot s, \quad (7)$$

$$ZoneB_{upper} = \bar{x} + 2 \cdot s, \quad (8)$$

$$ZoneB_{lower} = \bar{x} - 2 \cdot s, \quad (9)$$

$$ZoneA_{upper} = \bar{x} + 3 \cdot s = UCL, \quad (10)$$

$$ZoneA_{lower} = \bar{x} - 3 \cdot s = LCL. \quad (11)$$

The previous equations are evaluated with a dynamic process: as each new piece of is data acquired from the sensors, all statistics (i.e., the average, the standard deviation, the control limits and the zones) are recalculated. To prevent the mean and standard deviation from having extrapolated values, some points are not considered for the calculation, as they are considered outliers by the system. In the development of this work, outliers are considered values greater than a maximum factor or smaller than a minimum factor. If the current value exceeds one of these limits, it is not considered in the calculation of the new mean and standard deviation of the variable. The maximum and minimum values are established in two ways for the variables: the first way is to use the system input data established by the machine manufacturer and presented in the equipment manual, and the second is to use values of $x_{max} = \bar{x} + 10 \cdot s$ and $x_{min} = \bar{x} - 10 \cdot s$. The second option is used whenever there is no information established in the machine's operating manual or if the value established by the manufacturer has a very high operating range.

Regarding the statistical analysis, it is very important to put the fact into perspective that the machine monitoring process started with the ideal operating condition of the

engine, where all the sensors were in good operating condition and the machine was operating as expected by the manufacturer. With all initial operating conditions considered ideal, the mean and standard deviation of the variables become reliable bases in the calculation process.

As the system proposed in the work depends on the operating status of the sensors connected to the ICE, it is necessary to observe the condition of the sensor in operation. Considering the ideal initial operating conditions, if any measurement of a sensor starts to fail after a few months of system operation, the weight of an abnormal value sensor measurement will not abruptly affect the mean and standard deviation value of the analyzed variable. If the damaged sensor continues to provide erroneous measurements, the Nelson Rules judgments would indicate statistical abnormalities that could be associated with sensor malfunctions. As the entire system is based on the statistical analysis of a machine's operating history, the proposed system will indicate events, through the analysis of Nelson Rules, that are outside the historical statistical pattern of the system.

In CBM approaches, as well as the approach proposed in this paper, there must be strategies to deal with the events of failures on the sensors, and the system's users must be notified about these failures. Among these strategies, two forms are observed: measurement redundancy and comparison by measurement similarity. In the present work, the analyses performed according to the Nelson Rules can indicate problems in sensors, since any changes in the sensing of the variable will be shown by the Nelson Rules.

As discussed in Section 2.2, the developed system consists of 112 variables distributed in 11 subsystems that were chosen according to the characteristics and importance of the subsystem. Many of the monitored variables present redundancy in the measurement; i.e., more than one sensor measures the same variable (for example, the cylinder system that has two sensors to measure the cylinder temperature). This redundancy helps to determine possible sensor errors, as it is expected to obtain close values for the same measurement of a monitored quantity. In the case of a defective sensor, the Nelson Rules concerning that particular sensor will indicate changes that do not happen in the redundancy sensor. Whenever these changes persist in a variable and its redundant variable does not show equivalent changes, this is an indication of a possible sensor failure.

Each subsystem has characteristics that are linked to the variables chosen to be monitored. Many subsystems have parts that function similarly, such as cylinder system cylinders, exhaust gas system variables and others. With the proposed technique, it is possible to compare the Nelson Rules patterns between similar parts of the subsystems and identify if there are discrepant values between the triggered rules. These outliers can also be an indication of a possible sensor failure.

3. Results

In order to validate the statistical model (SM), an event that happened on 1 August 2019 at 14:41 in generation unit 05 of a Brazilian thermal power plant (TPP) has been considered. At that time, the proposed monitoring system was not in operation, and the event is used here only in order to validate the model (considering the historical data imported from the plant supervisory database). In that event, there was a shutdown and, after inspection, it was verified that cylinder B7 was locked.

Within selected time windows, the SM generates bar graphs of the triggered Nelson Rules on the control charts as an objective and visual way to display the state of the machine to the operators. Comparisons are made between the events shown in the logbook and the Nelson Rules bar graphs in order to verify whether the SM is capable of displaying the problem described in the logbook. After an analysis of the logbook, it could be found that not only cylinder B7 had issues on 1 August 2019, but also other cylinders were not in an optimal condition (such as the A6 cylinder). Section 3.1 presents the analysis performed with the generation unit under "apparent" normal conditions (with data collected since 14 days before the day of the shutdown). Then, Section 3.2 presents the analysis of this same generation unit on the day of the shutdown event. Finally, Section 3.3 presents an

investigation performed on the disassembled engine and the analysis of the variable related to the root cause of the shutdown during the days of “apparent” normal conditions, which shows that the proposed system could have issued an alert (if in operation by that time) that could have prevented the shutdown and the associated material damage.

3.1. Operation within Normality

In order to obtain the control charts, first, the historical data of the active power provided by the TPP were gathered. Then, the statistical parameters (of all other sensors) were calculated as the average, standard deviation, LCL, UCL and the zones of each monitored variable. The use of the active power was based on the fact that it provides good indications of the load level of the internal combustion engine, and this information can be useful in order to avoid false positives.

Figure 4 presents the control diagram of the active power (variable BAE051UP01PV). The curve in black represents the variation of the active power in the time window from 17 July 2019 until 31 July 2019, which are the 14 days before the day of the shutdown event (as discussed in Section 3.2). The green lines represent the separation between zones C and B and the blue lines represent the separation between tones B and A. The brown lines represent the LCL and UCL.

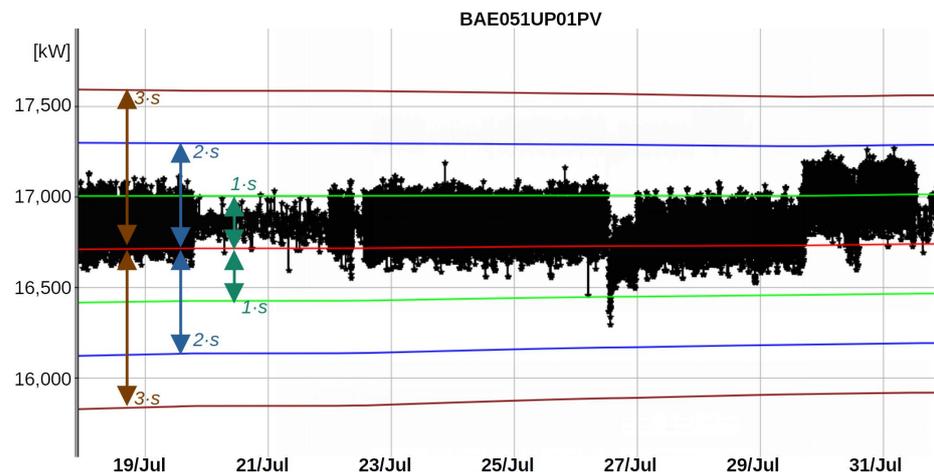


Figure 4. Control chart of active power of the generation unit 05 between 17 July 2019 and 31 July 2019.

Similar graphs were also obtained for all other monitored variables. Conventionally, the maintenance personnel would have to analyze several control charts (for each monitored variable) in order to find a possible trend of failure. Figure 5, for example, presents the trend of the z-score of the variable SOC051T027PV (one of the two temperature sensors in cylinder A6 at the Cylinders subsystem) within the same time window as Figure 4.

As the complete analysis of a machine with 112 sensors is not practical, this paper proposes a visual indication in the form of bar graphs, displaying at once the activation percentage of each of the Nelson Rules for all variables. Figure 6 presents the bar graph of the cylinder subsystem. The horizontal axis of the figure presents the tags used in the Wärtsilä system for this subsystem (2 temperature sensors for each of the 18 cylinders) and the vertical axis presents the rules being triggered:

- Rule #6 is well activated for the majority of variables in this subsystem. This is an indication that their data points are inside the $\pm 1 \cdot s$ region (as seen for variable SOC051T027PV from the control chart of Figure 5, where the majority of data points are between the green lines).
- Rules #5 and #2 have some percentage of activation. This is an indication that these variables have points that are outside the $\pm 1 \cdot s$ region, although they are still statistically in normality.

- Rule #1 indicates some very small percentage of data points (for variables SOC051T019PV, SOC051T021PV, SOC051T022PV, SOC051T034PV and SOC051T058PV) in the regions either between $+3 \cdot s$ and $+2 \cdot s$ or between $-2 \cdot s$ and $-3 \cdot s$, which are still statistically in normality as long as these percentages are below 4.28%.
- Rule #0 indicates that none of the variables have points outside the control limits of $3 \cdot s$.

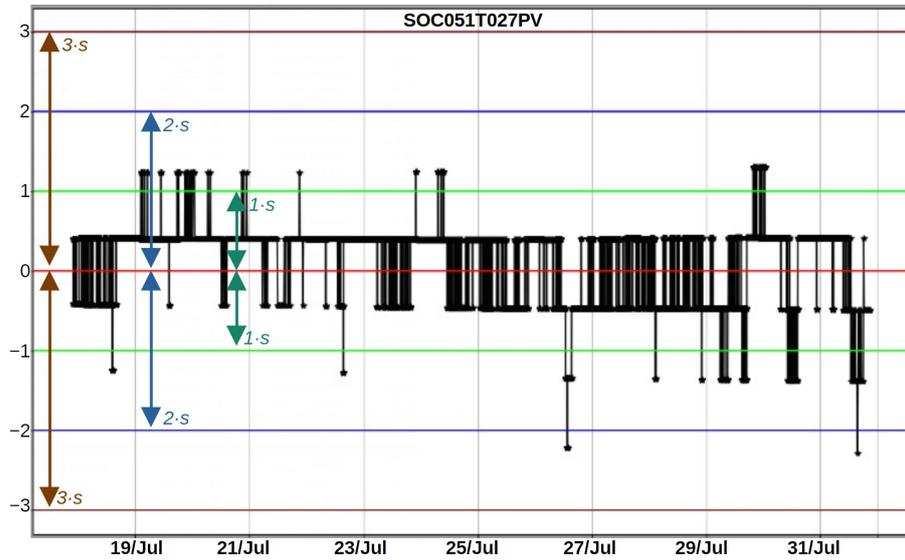


Figure 5. Trend of the variable SOC051T027PV (one of the two temperature sensors of cylinder A6 in the cylinders subsystem) between 17 July 2019 and 31 July 2019.

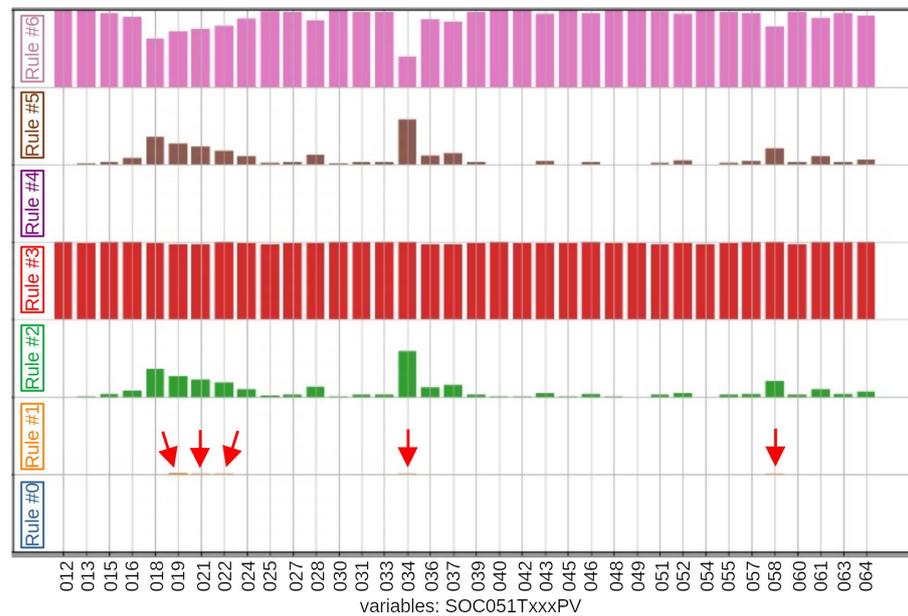


Figure 6. Bar graph of the cylinders subsystem between 17 July 2019 and 31 July 2019.

3.2. Operation on the Day of the Shutdown Event

The same generation unit that presented a statistical behavior under normality in Section 3.1 suffered a series of events, including a shutdown, hours after that period. Figure 7 presents the control diagram of the active power (variable BAE051UP01PV). The curve in black represents the variation of the active power in the time window from midnight of 1 August 2019 until 16:00 (4:00 p.m.) of the same day. In order to carry out the validation analysis of the SM, the dates, times and descriptions of the events that occurred in the unit were collected from the logbook (which has manual entries written by the TPP

personnel—the most relevant are shown in the figure). The figure also indicates two time windows in which the analyses were performed.

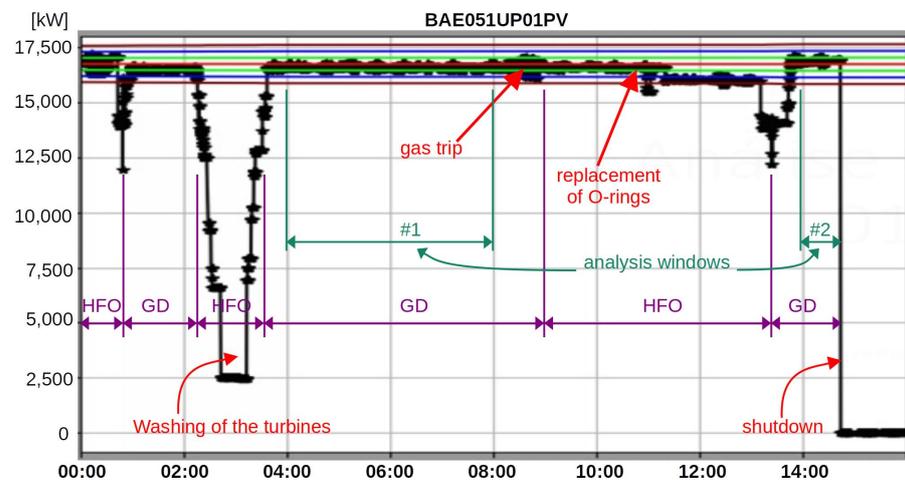


Figure 7. Control chart of active power of generation unit 05—on the day of the shutdown event.

The first analysis window (from 03:57 until 07:58) started after the washing of the turbines (it is important to note that the washing of the turbines is a usual procedure and had no relation to the events on that day) and ended before a gas trip event. Within this time window, the SM generated the bar graphs of the triggered Nelson Rules. Figure 8 presents the bar graph of the cylinder subsystem (the same subsystem presented earlier in Figure 6). This subsystem had two temperature sensors for each of the 18 cylinders (A1 to A9 and B1 to B9). The horizontal axis of the figure presents the tags used in the Wärtsilä system for this subsystem, and the vertical axis presents the rules being triggered. As indicated in the figure, the sensor SOC051T027PV (one of the two temperature sensors in cylinder A6) showed that rule #0 (blue) was activated for about 90% of the time in that time window, and about rule #1 (orange) was applicable for about 10% of the time. The statistical interpretation is that this variable was outside three standard deviations from its average value for 90% of the time window and in the zone between two and three deviations for 10% of the time. This characterizes a statistical anomaly, which might be associated with a failure on that cylinder.

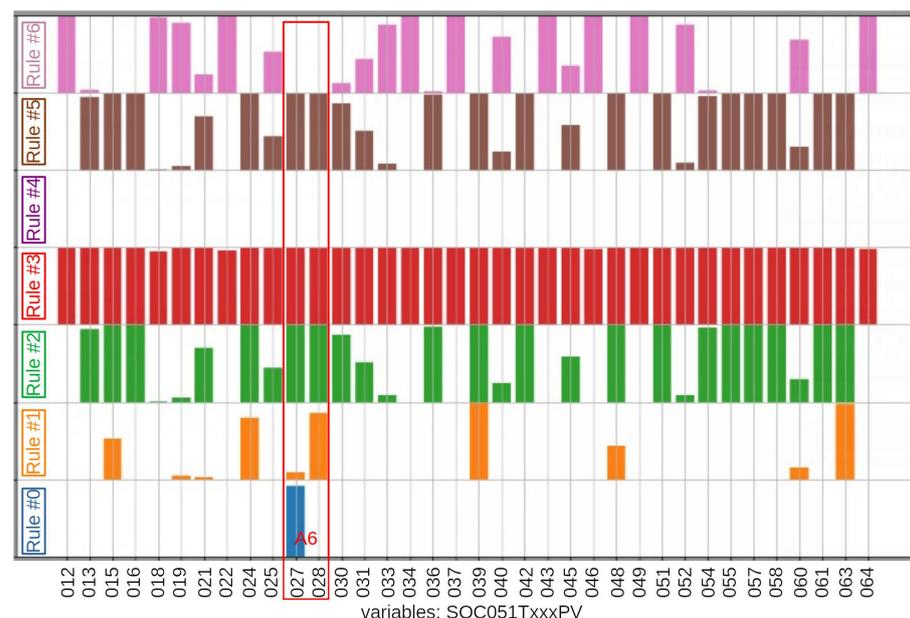


Figure 8. Bar graph of the cylinders subsystem during time window #1 (between 03:57 and 07:58).

Figure 9 presents the trend of the z-score of the variable SOC051T027PV (the same variable presented earlier in Figure 5) within the time window between 03:57 and 07:58. As expected from Figure 7, within this time window, that variable was outside of the three standard deviations limit for 90% of the time.

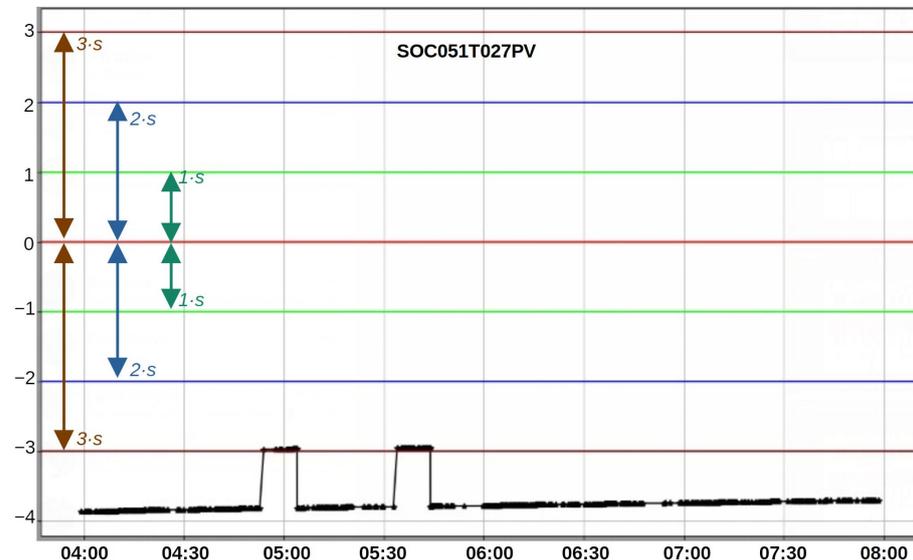


Figure 9. Trend of the variable SOC051T027PV (one of the two temperature sensors of cylinder A6 in the Cylinders subsystem) during the time window #1 (between 03:57 and 07:58).

Within the same time window between 03:57 and 07:58, Figure 10 presents the bar graph of the exhaust gases subsystem. This subsystem had one temperature sensor for each of the 18 cylinders (A1 to A9 and B1 to B9). The bar graph indicates that rule #0 was not activated for any of the variables, indicating that all variables worked within the range of three standard deviations from the average. However, in relation to the cylinder A6 (the same cylinder that had rule #0 activated in Figure 8), under the tag SNA051T029PV for the exhaust gases subsystem, it is possible to see that it worked in the region between two and three deviations, since rule #1 (orange) was activated for almost the entire time. It is interesting to note that the logbook had no entries related to this cylinder prior to the gas trip event that happened at 08:19 (after this time analysis window), while the SM already indicated some level of statistical anomaly regarding the behavior of this variable.

At 08:19, the logbook indicates a gas trip event. At 09:15, the logbook indicates that the maintenance personnel identified a leakage in the same A6 cylinder that the SM was indicating with a statistical anomaly.

At 10:40, the O-rings of cylinder A6 were replaced. At 10:50, another test was performed by the maintenance personnel, and the logbook indicates no leakage. Since the gas trip event (at 08:19), the combustion engine (which has a hybrid fuel mode: Heavy Fuel Oil (HFO) and Gas–Diesel (GD)) was switched to HFO mode and stayed in this mode during the O-ring replacement and leakage tests. The operation returned to GD mode at 13:24 (1:24 p.m.). It is important to note that it is preferable to analyze the system under similar conditions. Hence, aiming for a more coherent analysis, the next time window started after the return to GD mode and ended just before the shutdown event (at 14:41).

Figure 11 presents the bar graph of the cylinders subsystem after the return to GD mode, until the shutdown (time window from 13:51 to 14:39). It can be observed in the figure that cylinder A6 (variable SOC051T027PV) do not have rule #0 (blue) activated (in comparison with Figure 8), and rule #6 (pink—a rule that indicates normality) was activated. This is an indication that the statistical behavior of this cylinder returned to normality after the maintenance. However, in this figure, it can also be noted that some other variables (SOC051T025PV (one of the two temperature sensors of cylinder A5), SOC051T051PV (one of the two temperature sensors of cylinder B5) and SOC051T063PV and SOC051T064PV

(the two temperature sensors of cylinder B9)) showed rule #1 (orange) to be activated and rule #6 not to be activated, which is an indication that, although these variables were still inside the three deviations limits, some tendency towards failure might have appeared.

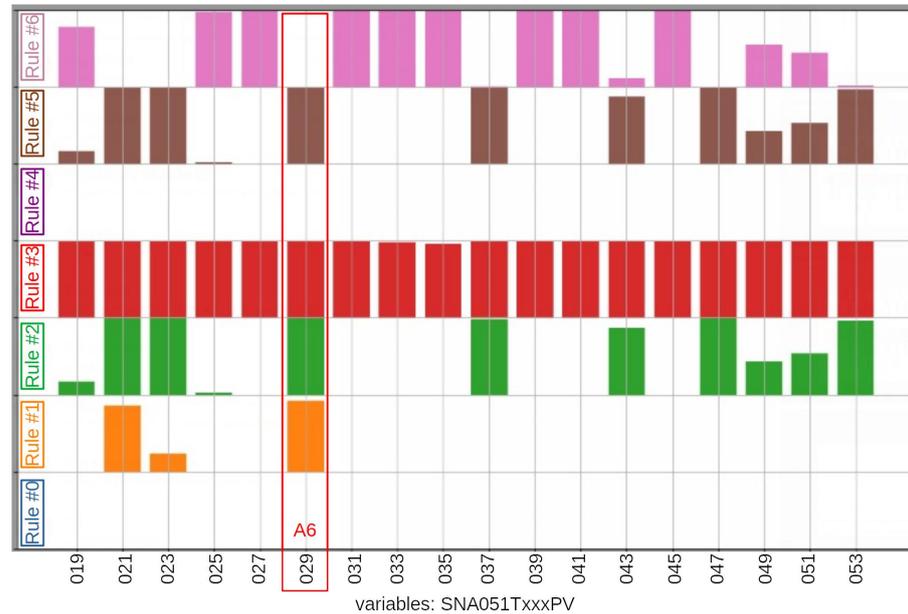


Figure 10. Bar graph of the exhaust gases subsystem during time window #1 (between 03:57 and 07:58).

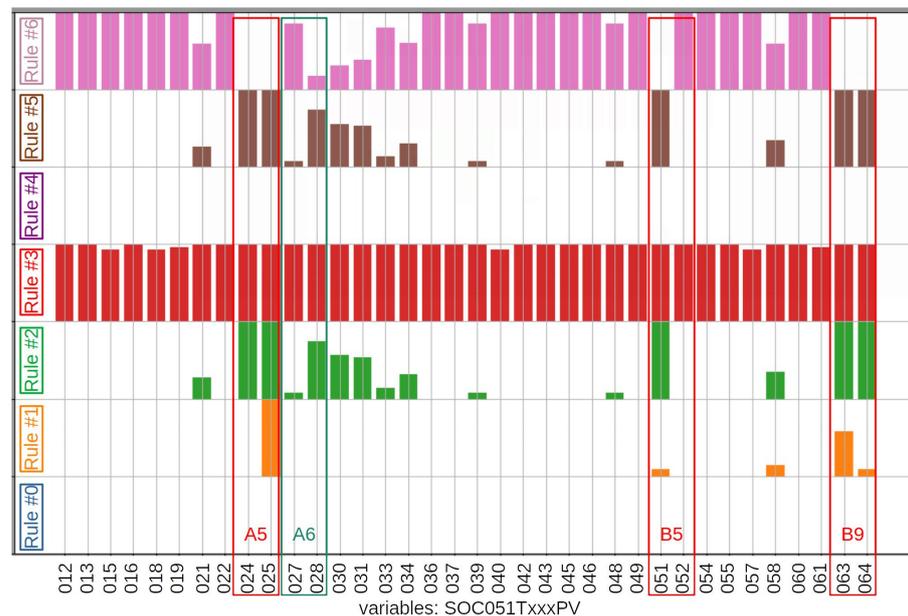


Figure 11. Bar graph of the cylinders subsystem during time window #2 (between 13:51 and 14:39).

Within the same time window between 13:51 and 14:39, Figure 12 presents the bar graph of the exhaust gases subsystem. The bar graph indicates that rule #0 (blue) was activated for variable SNA051T049PV (temperature sensor for cylinder B7), indicating operation outside three deviation limits. It can also be observed that, concerning variables SNA051T031PV (temperature sensor for cylinder A7) and SNA051T037PV (temperature sensor for cylinder B1), rule #1 (orange) was activated while rule #6 (pink) was not activated, indicating that these cylinders (especially A7) might have shown a trend towards failure.

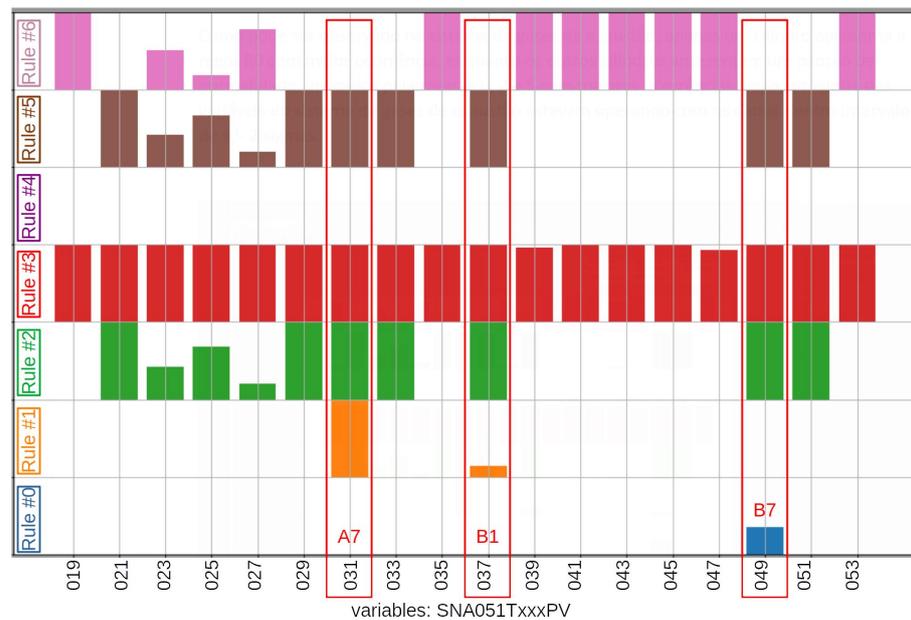


Figure 12. Bar graph of the exhaust gases subsystem during time window #2 (between 13:51 and 14:39).

At 14:41, the logbook indicates a shutdown. At 15:05, the maintenance personnel started an inspection, and at 15:15, it was verified that cylinder B7 was locked.

3.3. Investigation on the Shutdown Event

After the shutdown of the engine, it was disassembled, and it was noticed that the bearing shells of several cylinders (not only B7) presented severe abrasion marks, as shown in Figure 13. Under regular conditions, the movement of the connecting rods in relation to the pistons and the crankshafts occurs under a viscous lubricating oil that prevents this kind of abrasion of a metallic part in friction with another metallic part. After an investigation, it was realized that inadequate lubrication had been an issue for some months before the failure.



Figure 13. Photography of one of the disassembled bearing shells.

Concerning the validation of the SM, it is interesting to note that the bar graphs presented in Section 3.2 show the engine operating outside normality for several variables that were under normal conditions in Section 3.1 only some hours before. However, analyzing the subsystem of bearings during that same interval of “apparent” normal

conditions (between 17 July 2019 and 31 July 2019), the bar graphs clearly indicate abnormal conditions with that system. Figure 14 presents the bar graphs for the temperature variables of the bearings subsystem. It can be noted that three of the main bearings already exhibited a behavior outside statistical normality 14 days before the failure. It is important to note that the proposed system was not in operation at the time of the events described here. If it were, the proposed visualization tool, which concentrates information of several variables, could have given more information to the maintenance team, and the shutdown event could have been prevented.

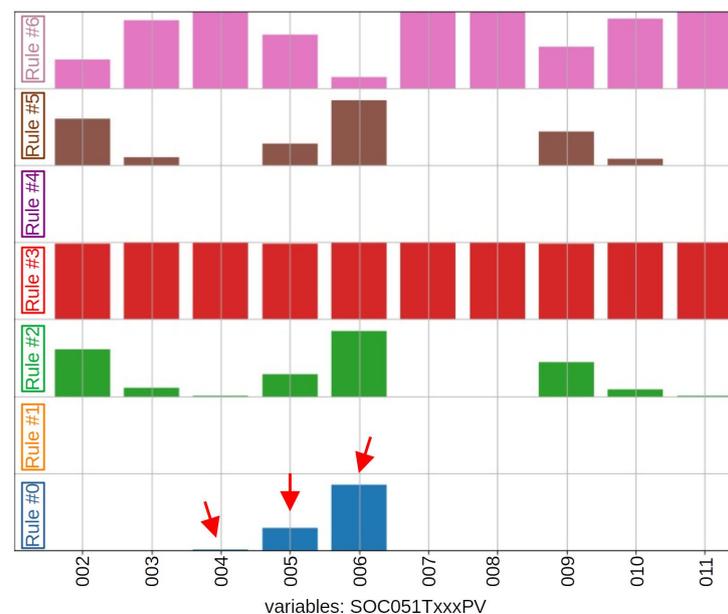


Figure 14. Bar graph of the bearings subsystem—between 17 July 2019 and 31 July 2019.

4. Conclusions and Future Work

This paper presented a statistical model to analyze the operational condition of an internal combustion engine (Wärtsilä 18V46) in operation on a thermal power plant in Brazil. The statistical model has been validated according to entries in the plant's logbook. The model is based on the principles of statistical control processes and adapted Nelson Rules.

Conventional measurement techniques (of temperature, pressure, vibrations, viscosity and others) usually only assign a level of warning and alarm for each of the quantities. However, even if the asset does not reach the alarm levels, its operating cycle goes through moments of greater or lesser stresses, causing a degree of wear that accumulates over time and ends up leading to failures. The originality of this work is the proposition of a methodology that continuously monitors the stress levels suffered by the machine during its operation, even if the alarm limits are not reached. The stress levels can be inferred through the activation degree of the Nelson Rules on the control charts.

A graphical visualization system that takes the Nelson Rules into account for all sensors has been presented in the form of a bar graph. This graph provides a more objective visualization of possible failure trends of a plant to the supervision personnel. The obtained bar graphs of the Nelson Rules have been compared with several events pointed out in the logbook, presenting a good match in the comparisons. However, it is very important to note that the performed analyses must be understood more as a statistical likelihood of failure than an actual physical problem. Hence, the proposed bar graphs are a tool that can be used in order to make decisions concerning maintenance in the plant.

The events presented in this paper took place at a time before the development of the proposed system. The results show that, if in operation by the time prior to the events,

the proposed system could have issued an alert that could have prevented the shutdown and the associated material damage.

The statistical model applies the Nelson Rules based on the data of several sensors connected to the plant's supervisory system. In the current preliminary stage of this project, the analysis has been performed on a time window selected by the operator. Within this selected time window, the model applied the Nelson Rules and displayed a bar graph concentrating the information of all sensors (or selected sensors, if desired). As a future development, an autonomous sliding time window will be implemented allowing for the generation of alarms in the case of a detected trend of failure. Additionally, an inference engine is expected to be implemented in order to concentrate the activation degrees of individual Nelson Rules into a single "early damage index".

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Abbreviations

The following abbreviations are used in this manuscript:

CBM	Condition-based maintenance
CC	Control charts
EWMA	Exponentially Weighted Moving Average
GD	Gas–Diesel
HFO	Heavy Fuel Oil
ICE	Internal combustion engine
LCL	Lower control limit
ML	Middle line (average)
SCADA	Supervisory Control and Data Acquisition System
SPC	Statistical process control
SM	Statistical model
TPP	Thermal power plant
UCL	Upper control limit
WISE	Wärtsilä Information System Environment
WOIS	Wärtsilä Operator's Interface System

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