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Development of Alarm Prediction System for Monitoring Steam Turbine Based on SCADA Data

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ABSTRACT

A steam turbine is a critical machinery in power plants for generating a driving force of a generator. The high reliability of the turbine is a must to guarantee the availability of power plant in producing electricity. Therefore, a turbine condition monitoring (CM) system is needed to access real conditions and the health state of such equipment. Even though many CM systems have been developed, however, the current system was set up manually based on a determined threshold that was adopted from standard or best practice. The CM system that automatically generates the true alarm based on the performance of the generator is still rare. In this paper, an automated alarm system that uses the power output of a generator as a reference has been developed. The data for developing the alarm system is vibration data acquired by the SCADA system that is a very famous data acquisition system used in the industry. Furthermore, the method of developing such an alarm system is machine learning (ML) through a long short-term memory (LSTM) network. Validation of the proposed method has been conducted using a real system of SCADA data for training the LSTM. The trained LSTM is then used to generate an alarm system based on predicted data for turbine condition monitoring. The results show that the alarm generation and prediction give a plausible performance measured by RMSE.

Key words: Vibration, condition monitoring, steam turbine, fault detection, long-short term memory, machine learning.

1. INTRODUCTION

Maintenance is a very important activity in the industry, such as power plant to ensure the reliability of critical machinery and assets. In strategic industries like a power plant, the division of maintenance plays an important role in extending the useful life of engineering assets such as machinery. Furthermore, the issue of reliability is also prominent in ensuring the operational process of the power plant. Recently, condition-based maintenance (CBM) has been implemented by many industries due to its relevance in the prediction of failure. CBM also provides the mitigation of the consequences of failure and can improve the profit and safety of the industry concerned.

One of the critical parts of CBM is machine condition monitoring that can provide the information of a machine's condition through the sensors installed in the machine. Sensors send the information from the machine through related parameters such as vibration, temperature, current, voltage, acoustic emission and so on. A robust CM system should involve observing the component of the machine to identify changes in the operation of a machine that can be indicative of developing faults. According to Stetco *et al*. (2018), CM can be used to fault detection in real-time or in the future, so the CM can be employed as tool for fault diagnosis and fault prognosis [1]. As a diagnosis tool, the CM identify the presence of failure that should be a prerequisite for ML in building model for prognosis. Then, the CM as prognosis tool where the underlying model recognize the patterns in the signal data that are predictive in the future.

The use of ML method for prediction machine condition and prognosis has been listed in many research papers. Degradation assessment of gearbox using vibration signal and extreme learning machine (ELM) have been reported [2]. He used vibration signal and decomposed the signal to become intrinsic mode functions (IMFs) and performed feature extraction using kernel principal component analysis (KPCA). The research of CM using the vibration signal was also reported for detecting the changes in operating conditions of the rotating machine [3]. He constructed a multisensors based for monitoring strategy. He also performed multidimensional time-series analysis using autoregressive integrated moving average (ARIMA) through the regression process.

Another research was reported that recurrent neural networks (RNN) was employed for predicting remaining useful life

(RUL) based on vibration signal [4]. It has proposed a bearing degradation indicator called waveform entropy as the data input for RNN learning to identify the degradation state. However, all the mentioned papers above are investigated based on the vibration signal which had high-frequency sampling during the data acquisition process. So, it was regarded as a full vibration signal with high resolution. Nevertheless, in the case of a real system in the industry, sometimes such data do not exist. That means it is very difficult to find and deals with the vibration data acquired in high-frequency sampling.

Usually, the industry such as the power plant only provides the acquired vibration data from SCADA data acquisition with low sampling and the data has already been converted into feature data such as root-means squared (RMS) vibration. It means a feature extraction cannot be performed anymore from the data. The challenge is how to deal with this data for conducting machine CM that can generate an automatic alarm and predict the future condition of machine. In this paper, both abilities of CM will be used as an alarm generation for monitoring and fault detection based on vibration data acquired from real system. In the case of industrial real system, many experts performed investigation and research on the topics related to wind turbine systems with their own methods. Zaher et al. [5], Feng et al. [6], Zhang *et al*. [7], Zhang *et al*. [8] and Borchersen *et al*. [9] are researchers of wind turbine system who used SCADA for conducting fault diagnosis.

Other researchers are Schlechtingen *et al*. [10] and Yang *et al*. [11] who conducted research work on condition monitoring of wind turbine based on SCADA data using normal behavior model. Song *et al*. [12] reported a research of wind turbine state health monitoring using SCADA data with Bayesian approach. Zhao et al. [13] studied prognosis of wind turbine based on SCADA data using an anomay index. Bangalore and Patricksson [14] reported a research of analysis SCADA system for wind turbine fault detection.

Recently, Gonzalez et al. [15] conducted research of sensitivity study on wind turbine monitoring based on SCADA data. However, the research used SCADA data implemented on steam turbine for performing fault diagnosis and prognosis are still rare.

The rest of the paper is presented as follows: first, the method of a proposal for generating an alarm prediction system based on SCADA data will be presented. Second, the presentation of vibration SCADA data and its processing are reviewed. Third, the analysis of the results will be discussed including the validation of the proposed method. Finally, the conclusion is drawn to highlight the finding of the present study.

2. EXPERIMENTAL METHOD

A neural network, as so-called long short-term memory (LSTM) recurrent network, has memory function and powerful series processing ability, which attracts much attentions recently. The experts of developer, the recurrent network are Elman networks [16] and Jordan networks [17], in which the activation of nodes calculates not only the current input but also the previous return value. Hochreiter et al. [18] proposed long short-term memory (LSTM) cells, adding three switches to hidden layer nodes. LSTM-RNN achieves a really good performance in sequential data processing because of the recurrent feedback. For instance, Liwicki *et al*. [19] applied LSTM recurrent network to handwritten digital recognition and achieved a state-of-art result. Sutskever *et al*. [20] constructed two multi-layer LSTM networks for machine translation. There are some documented investigations in neural network and signal processing that can be considered as source of reference [21-23].

The LSTM recurrent network employed in this present study is shown as Figure 1, where $x_1, x_2, \ldots, x_m$ are representation of the inputs of the network, and $y_1, y_2, \ldots, y_n$ are the outputs. The inputs are e.g., historian data which is originated from SCADA vibration, temperature and rotating speed signals acquired from turbine bearings and the outputs are the predictions of vibration signals ahead. The notation of $W^{(1)}$, $W^{(2)}$, and $W^{(3)}$ are the weights of the layer connection, which are represented by solid lines. In addition, $W_t^{(1)}$, $W_t^{(2)}$, and $W_t^{(3)}$ are the weights of the time connection, which are represented by dashed lines.

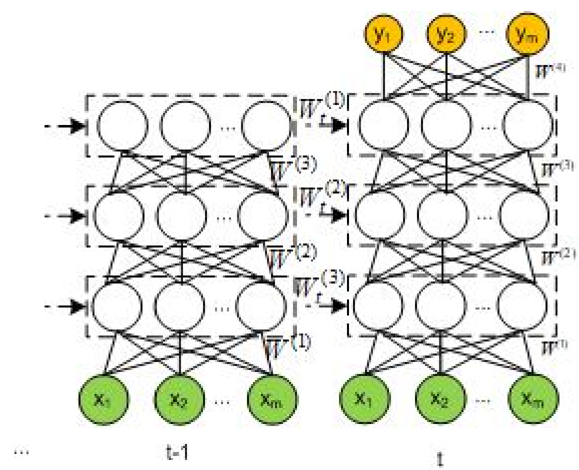

Figure 1: Architecture of recurrent neural network

Figure 2 shows the hidden node of a LSTM cell and its structure, where h_t represents the output of LSTM cell at current time t, x_t denotes the inputs of LSTM cell at current time t and A is another LSTM network [24]. Conceptually, an LSTM has three gates, to protect and control the cell state. The first gate is shown as Figure 3, called the "forget gate layer", decide what information that would be throw away from the cell state using *sigmoid* layer from Eq. (1). The second gate is shown as Figure 4, called the "input gate layer", decides what new information that would be store in the cell state. There two steps in the "input gate layer". First, decide which values that would be update using *sigmoid* layer from Eq. (2), then second, create a vector on new candidate values $\tilde{C}_t$ that could be added to the state using *tanh* layer from Eq. (3). We can update the old cell state C_{t-1}, into a new cell state C_t using Eq. (4). Finally, the third gate is shown as Figure 5, called the "output gate layer", decide what parts of the cell state that would be the output using *sigmoid* layer from Eq. (5), then decide the chosen output using *tanh* layer using Eq. (6) by multiply it with the result from Eq. (5).

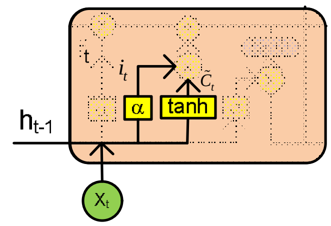

Figure 4: Input gate layer.

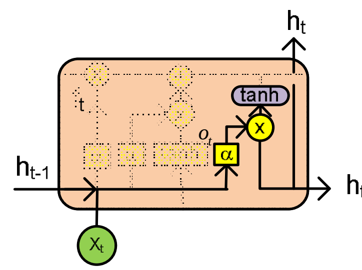

Figure 5: Output gate layer.

Equations:

$$f_t = \sigma(W_f \cdot [h_t - 1, \alpha_t] + b_f) \tag{1}$$

$$f_t = \sigma(W_f \cdot [h_t - 1, \alpha_t] + b_f) \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_t - 1, \alpha_t] + b_i) \tag{3}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, \alpha_t] + b_C) \tag{4}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

$$o_t = \sigma(W_o \cdot [h_t - 1, \alpha_t] + b_o)\ ;\ h_t = o_t * \tanh(C_t) \tag{6}$$

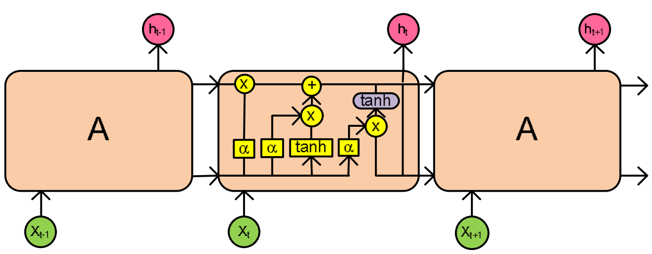

Figure 2: Presentation of LSTM cell.

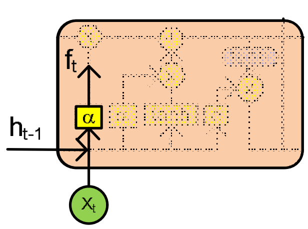

Figure 3: Forget gate layer.

The proposed method is shown as a flowchart in Figure 6. This flowchart is a modification of previous work [25].

There are four steps of the method for alarm generating by means of LSTM neural networks. First, building a model of normal behavior using SCADA data without faults. This step is performed by LSTM training. The testing of a trained LSTM is also performed to validate the model of normal conditions. Second, the determination of the alarm setting is conducted by calculated the deviation of the actual signal and predicted signal. In this step, the threshold is introduced as a reference to alarm prediction in the next step. Third, the online SCADA data comes to the trained LSTM as a new input for prediction. The predicted data is compared with the actual then their deviation is calculated. The final step is a determination of alarm when the deviation reaches the threshold.

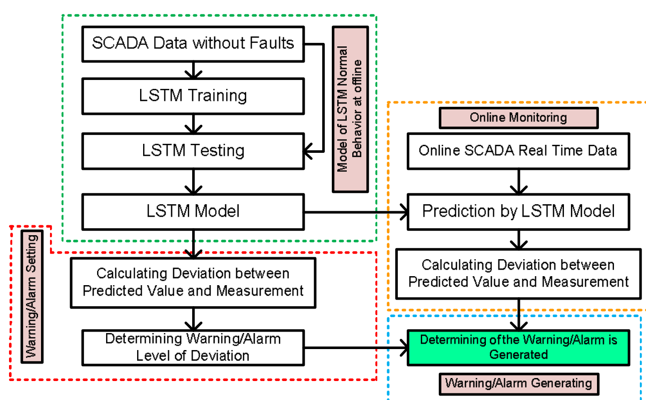

Figure 6: The proposed method for alarm prediction.

SCADA Data

The data used in the present study comes from the SCADA CM system of specific steam turbine in power plant. The measurement was conducted during nine months starting from April 2017 to December 2017. The collected data consists of 47 sensor parameters including vibration, temperature, power output, rotating speed, etc. All data were acquired in 10 minutes average and the total data was 39,600. The turbine is a direct-driven without gearbox which makes the bearing suffer most of the torque and become the vulnerable element. The vibration of bearing is regarded as the main indicator of the turbine condition with a specific threshold of alarm setting which is set up too low to avoid the catastrophic damage. Figure 7 and 8 show the presentation of six vibration signals of turbine bearing and rotating speed (RPM), respectively.

3. RESULTS AND DISCUSSIONS

3.1. Training and testing the model prediction

LSTM model prediction was established using selected parameters from a lot of relevant turbine parameters collected by the SCADA system. The selected parameters for input and output LSTM training is presented in Table 1.

Table 1: The selected parameters for input and output of LSTM.

Input	Model output
Bearing vibration (t-1) Bearing oil drain temperature (t-1) Metal turbine bearing temperature A (t-1) Metal turbine bearing temperature B (t-1) Power output (t-1) Rotating speed (t-1)	Bearing vibration (t)

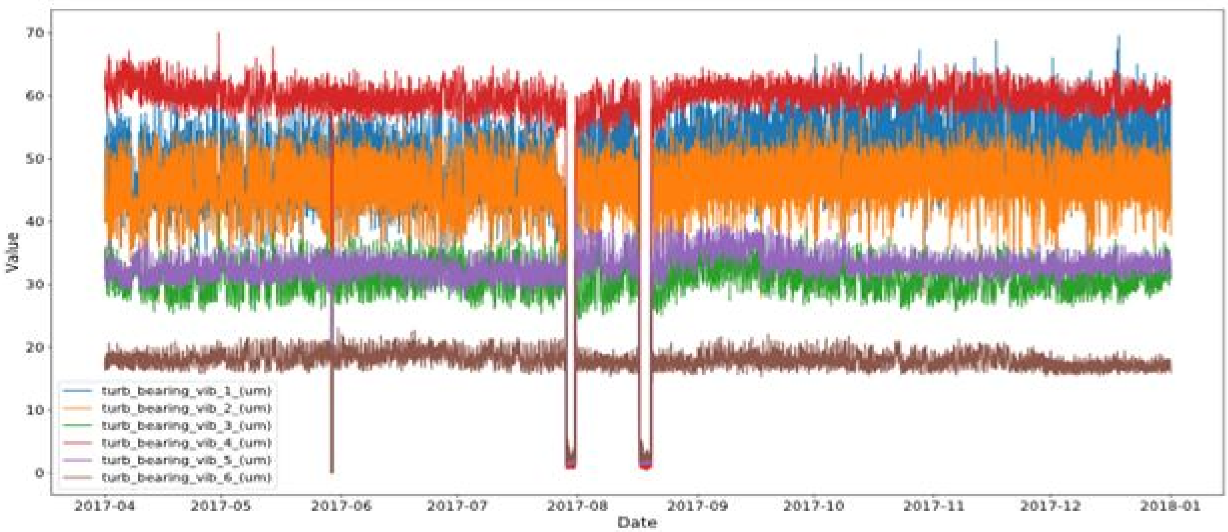

Figure 7: Vibration of six turbine bearings.

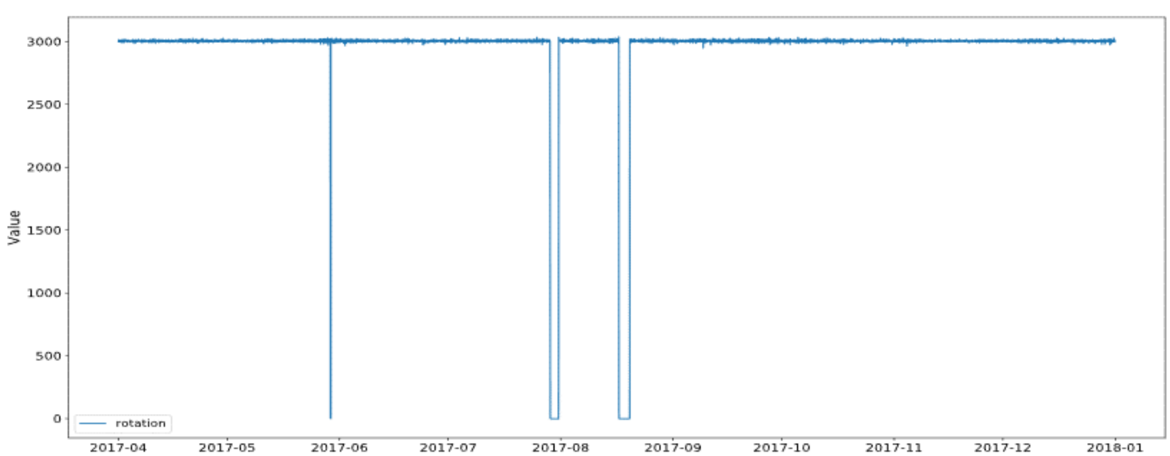

Figure 8: Turbine rotating speed signal (RPM)

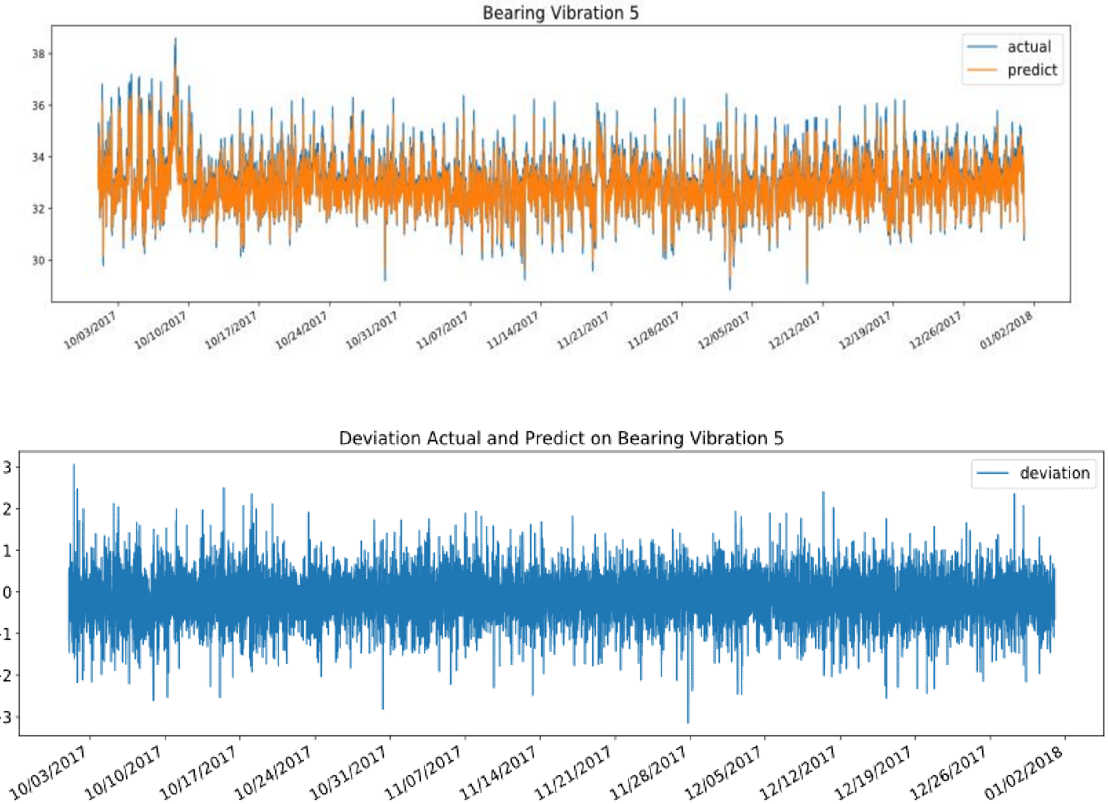

Figure 9: Prediction of vibration parameter of bearing 5.

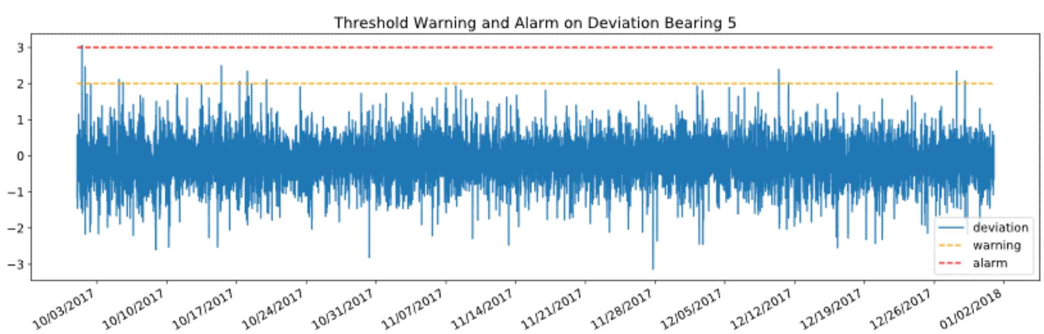

Figure 10: Deviation vibration parameter between actual and prediction of bearing 5.

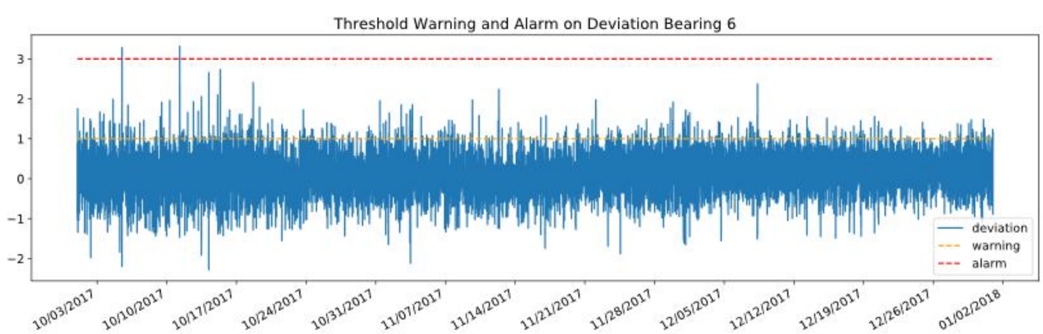

Figure 11: Deviation vibration parameter between actual and prediction of bearing 6.

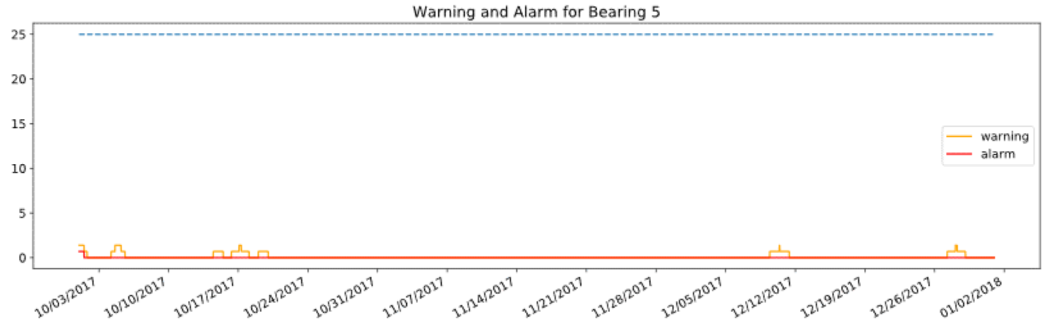

Figure 12: Alarm and warning for bearing 5.

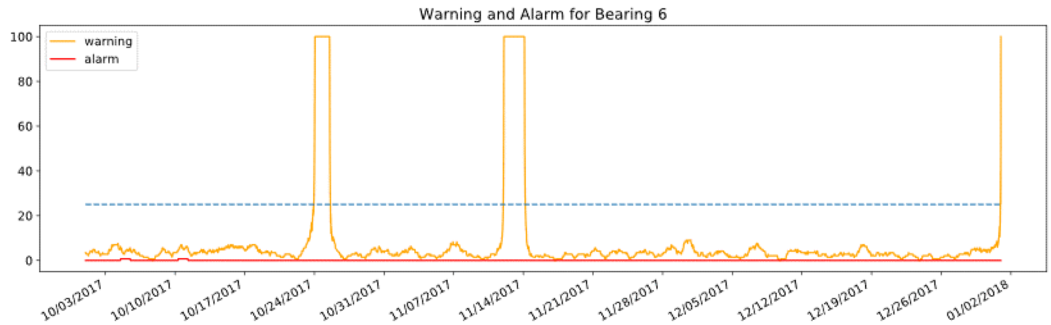

Figure 13: Alarm and warning for bearing 6.

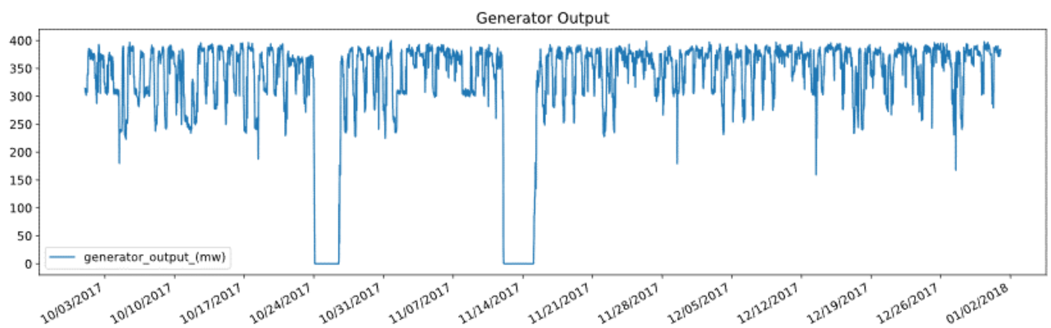

Figure 14: Generator output.

Six turbine bearings are modeled using LSTM training with six months (April to September) measured input parameters in 2017. The trained LSTM is then used to predict the output parameters from October 2017 to December 2017. Figure 9 presents the prediction of the vibration parameter of bearing 5 and the deviation between two values. It shows the good performance of model prediction that can capture the dynamic patterns of bearing 5. The root mean square error of the prediction is 0.7, which means the model is fair enough to describe the dynamics of the vibration pattern. Furthermore, the trend of deviation can be continuously monitored to indicate the development of bearing faults.

3.2. Alarm and warning setting

Alarm and warning settings are carried out using a deviation of actual and prediction data. Actually, this step needs data parameters included the faults in the system. The data parameter with faults is used to train the LSTM so that it has experience with faults. However, it is very difficult to obtain the real data including faults data in the power plant because the operating condition threshold was setup in safety mode. If the operating condition meets the signal which exceeds the threshold so the system will be trip soon.

Figure 10 depicts the deviation of the vibration parameter between actual and prediction. Observing this figure, the distribution of deviation along time measurement is similar. Furthermore, there is no fault indicated in the distribution of deviation. The red and yellow dashed line represents the fixed thresholds for warning (threshold = 2) and alarm (threshold = 3) generation. A similar phenomenon also exists in other bearings as presented in Figure 11 where the thresholds are 1 and 3 for alarm and warning, respectively.

Based on Figure 10 and Figure 11, the present study proposes an alarm prediction that is not fixed alarm or warning but depending on the distribution of deviation parameter vibration. This idea emerges because in a real system the operating condition sometimes changes rapidly so that the dynamic alarm and warning are needed. To avoid the false alarm and warning, a fixed threshold cannot be directly used. The followings are the process of determining a dynamic alarm and warning based on deviation of vibration parameter and generator power output [25]:

1. Determining the total time interval of measurements (T_{tot})
2. Finding the time for generator when producing power output in the time interval (T_{prod}).
3. Determine T_{alarm} and T_{warn} when the deviation over the fixed alarm and warning.
4. Calculating the percentages of T_{alarm} and T_{warn}:

$$P_{alarm} = \frac{T_{alarm}}{T_{tot}} x100\% \quad (7)$$

$$P_{alarm} = \frac{T_{warn}}{T_{tot}} x100\% \quad (8)$$

Figure 12 and 13 shows the generation of alarm and warning for bearing 5 and 6, respectively. Figure 12 informs that the alarm and warning seem to be dynamic as operating condition changes. Alarm and warning change according to real condition determined by the deviation between actual and prediction of vibration parameter. When the alarm and warning reach the dashed blue line means the turbine indicates some faults.

Figure 13 presents the alarm and warning of bearing 6 indicate the warning over the threshold. It means some abnormalities occur and successfully be captured by the vibration parameter. Such abnormalities make the percentage of warning reach 100% that means there is no power output resulted from the generator as depicted in Figure 14. The proposed method for alarm and warning prediction is established relatively based on the power output of the generator. When the power output of the generator is maximum that means the power plant condition is well. Otherwise, the minimum power output produced by the generator means the system is unhealthy.

4. CONCLUSION

The present study proposes the method of development of alarm and warning prediction for the steam turbine. The data used in this study is vibration data acquired by SCADA system which is a famous data acquisition in industry. A machine learning method so-called LSTM is performed for generating an alarm and warning prediction based on learning from historian data of steam turbine. Six months historian data from April to September 2017 of vibration, temperature of bearing metal, generator power output, turbine rotating speed and bearing oil drain temperature are used for building the bearing model prediction. Then, the trained LSTM is tested using data input from October to December 2017 to predict the output of the vibration parameter of bearing. The deviation of actual and prediction of vibration parameter is evaluated using RMSE for measuring the performance of prediction. The alarm and warning system is calculated based on the generator power output so that the alarm and warning system is dynamic and depends on the real condition of the turbine.

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