Wind Turbine Gearbox Failure Monitoring Based on SCADA Data Analysis

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***Abstract*—A model for monitoring the wind turbine gearbox based on Supervisory Control and Data Acquisition (SCADA) data is developed. A deep neural network (DNN) is trained with the data of normal gearboxes to predict its performance. The developed DNN model is next tested with data of the normal and abnormal gearboxes. The abnormal behavior of the gearbox can be detected by the statistical process control charts via the fitting error. The capacity of the monitoring model for detecting the abnormal behavior of gearbox is validated by two gearbox failure cases.**

***Index Terms*--gearbox monitoring, data mining, statistical process control, deep neural network, SCADA data.**

I. Introduction

Due to the aging of wind farms, the operation and maintenance (OM) cost becomes significant [1]. The main subsystems of the wind turbine, such as gearbox, generator, and bearing, attract the most attentions in studies of condition monitoring and fault detections [2, 3]. The OM cost will dramatically reduce if failures can be detected in advance so that operators can have sufficient time to adjust the generation schedule and prepare replacements [4]. Since gearboxes account for a large proportion of the total cost and their failures may cause excessive downtime, an accurate and effective monitoring model of the wind turbine gearbox is necessary.

The traditional method for monitoring the gearbox is to analyze vibration signals in the frequency domain [5, 6]. Mohanty *et al.* [7] detected a multistage gearbox by utilizing the discrete wavelet transformation for the current signal. Luo *et al.* [8] used spectral analysis and acceleration enveloping techniques to extract the gear damage features and applied the synchronous analysis to accurately detect specific damage features. Recently, data mining algorithms are also introduced to detect the abnormal performance of gearboxes. Rafiee *et al.* [9] used the neural network to model the different gear conditions based on the standard deviation of wavelet packet coefficients. Zhang *et al.* [10] combined the data mining algorithms with control charts to monitor the vibration excitement of the gearbox.

As previous studies typically require the installation of additional sensors, it is difficult to access the vibration data for real industrial applications. SCADA systems connecting wind turbines and meteorological stations have been built in most modern wind farms [11]. Compared with the vibration data, SCADA data in time domain are relatively inexpensive and non-intrusive. Moreover, the monitoring model can be applied under different operation conditions. Feng *et al.* [12] derived the robust relationship between the temperature and power output and utilized the SCADA oil temperature to predict the gearbox failure. Gacia *et al.* [13] modeled the normal behavior of gearboxes with the bearing oil temperature by a neural network algorithm and applied such model to detect the incipient anomalies in the gearbox. Wang *et al.* [14] employed a non-linear state estimation technique to build the oil temperature model and considered the Welch's t-test for the fault detection.

Pioneer studies of monitoring gearboxes with SCADA data have been conducted and the gearbox oil temperature has been considered in all of them as the monitoring objective. The gearbox oil temperature is easily influenced by the environment and noisy data are measured. In our study, an alternative monitoring objective, the gearbox lubricant pressure which is slightly influenced by the environment, is considered. The deep neural network algorithm is employed to build the model for predicting the gearbox lubricant pressure and statistical control charts are introduced to detect the abnormal behaviors existed in the wind turbine gearbox.

II. Monitoring Approach

In this section, the details of proposed monitoring approach are presented. The monitoring framework is composed of two processes, the prediction model development and the monitoring. A semi-supervised learning technique is

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utilized to develop the prediction model. The model is only trained by using the SCADA data of normal wind turbines and the resulted fitting errors only reflect normal behaviors of the gearbox. Based on such fitting errors, the upper and lower limits for monitoring are derived to develop a control chart. The abnormal turbines will produce errors exceeding the monitoring limits and the alarm of the gearbox failure is activated. The proposed monitoring procedure shown in Fig. 1 is composed of following four steps:

Step 1. Generate the training dataset: Collect SCADA data of wind turbine *i*, $i = 1, 2, \dots, N$, in the wind farm and exclude the invalid data and incorporate all valid SCADA data to generate the training dataset.

Step 2. Build the prediction model: Use the data mining approach to develop the prediction model based on the training dataset.

Step 3. Compute fitting errors: Compute fitting errors of wind turbine *i*, $i = 1, 2, \dots, N$ via the prediction model. The fitting error reflects the modeling capability of the data mining algorithm based on the SCADA data.

Step 4. Develop the monitoring chart: Based on fitting errors of all wind turbines, the statistical process control chart is developed to give the upper and lower control limits. If the fitting error of the wind turbine *i* exceeds the control limits, the alarm of the gearbox failure will be activated.

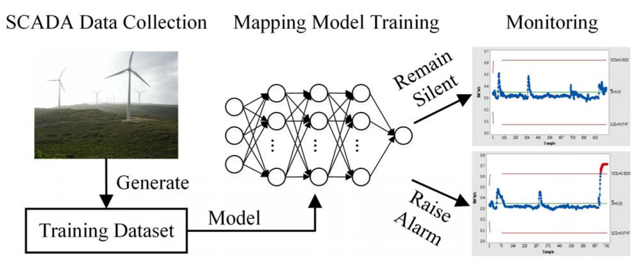

Figure 1. The schematic diagram of DNN

In this study, the DNN is utilized to build the prediction model of the lubricant pressure. As the lubricant is used to cool down the gearbox, the change of the lubricant pressure follows the change of the power output. Compared with the gearbox oil temperature, the lubricant pressure is more resistant to the impact of the environmental temperature. If there is the mechanical wear on the gearbox, the iron scrap will fall into the lubricant oil and the lubricant pressure will change. Therefore, the lubricant pressure, P_l, is chosen as the predictive objective. The prediction model of the lubricant pressure is built by considering three parameters, the gearbox oil temperature, T_o, power output, P_o, and shaft temperature, T_s. A statistical process control method, the exponentially weighted moving average (EWMA) chart, is introduced to obtain the lower and upper limits for monitoring based on the fitting errors *e*, expressed by the absolute percentage error (APE), in (1).

$$e = \frac{\left|P_l^{pred} - P_l^{act}\right|}{P_l^{act}} \times 100\% \tag{1}$$

where P_l^{pred} is the predicted lubricant pressure and P_l^{act} is the actual lubricant pressure.

A. *Deep Neutral Network*

NNs are widely considered in modelling the non-linear relationships among data. However, classical NNs are typically developed with one hidden layer and are lack of the capacity for modelling higher nonlinearities [15]. Compared with classical NNs, DNN deploys multiple hidden layers to model more complicated relationships [16]. In this research, a DNN with three hidden layers is developed to model the mapping from the input, T_o, P_o and T_s, to the output P_l, as shown in Fig. 1 and the trained model can be expressed by (2).

$$\hat{P}_l = f(T_0, T_s, P_o) \tag{2}$$

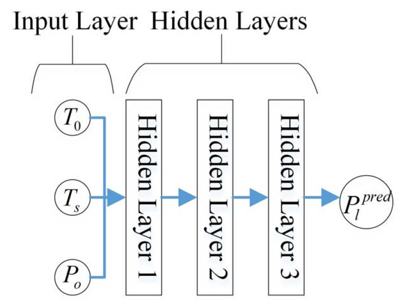

Figure 2. The schematic diagram of DNN

The training process of DNN is to estimate the parameters $\mathbf{W}_n$ and $\mathbf{b}_n$, which are the weights and bias of layer *n*, respectively, by minimizing the average squared fitting errors, shown as (3).

$$\{\mathbf{W}_n, \mathbf{b}_n\} = \underset{\mathbf{W_n}, \mathbf{b_n}}{\operatorname{argmin}} \sum_{i=1}^{N} \frac{1}{2} (\hat{P}_l - P_l)^2, n = 0, 1, \cdots, L \tag{3}$$

where *L* is the number of layers in DNN and *N* is the number of samples in the training dataset.

The activation function used in this research is a hyperbolic tangent function in (4).

$$\tanh(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}} \tag{4}$$

In order to facilitate the training process, the parallelized stochastic gradient descent (SGD) algorithm [17] is utilized to update the parameters of DNN and its procedure is presented by the Pseudo Code, ParallelSGD().

In ParallelSGD(), *T* is the training dataset, *a* is the learning rate and Avg_m represents the final average weight of local parameters for node *m* to obtain the global model parameters. Besides, the *k*-fold cross-validation technique [18] is employed to overcome the over-fitting issue.

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```
ParallelSGD(T, α)
{
    initialize W and B
    distribute T across nodes
    while not convergence criterion:
        for nodes m with training subset T_m, do in parallel :
            let W_m, B_m = W, B
            partitioin T_m into T_mc by cores m_c
            for cores m_c on node m, do in parallel :
                get training example i ∈ T_mc
                update all weights w_jk ∈ W_m, biases b_jk ∈ B_m
                    w_jk = w_jk − α ∂L(W,B | j)/∂w_jk
                    b_jk = b_jk − α ∂L(W,B | j)/∂b_jk
            end for
        end for
        let W, B = Avg_m W_m, Avg_m B_m
    end while
}
```

B. Maintaining the Integrity of the Specifications

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Since the gearbox failure is a continuous process, early failure can be indicated by the fitting error which needs to be monitored. Continuous large fitting errors in a certain period indicate the anomaly and the alarm can be raised for planning the gearbox maintenance. By considering the error margin and time factors, EWMA control chart is a straightforward solution for monitoring fitting errors [19]. The lower and upper control limits of the EWMA chart are obtained based on the fitting errors of the normal wind turbines. If the fitting errors exceed the control limits and a long-period of high fitting errors in EWMA chart is observed, such pattern can be considered as an alarm of the gearbox failure.

The test static of EMWA, z_t, is computed as (5).

$$z_t = \lambda e_t + (1-\lambda) z_{t-1} \tag{5}$$

where t is the time index, e_t is the reconstruction error at time t, λ is a constant satisfying $0 < \lambda < 1$ and the starting value z_0 is set to the estimate of the process mean. In this study, λ is set to 0.2, which is a typical value for setting the EMWA charts.

From (5), the mean value and variance of z_t are be obtained in (6)

$$\mu_{z_t} = \mu_e, \quad \sigma_{z_t}^2 = \frac{\sigma_e^2}{n}\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right] \tag{6}$$

where μ_e and σ_e are the mean and standard deviation of sample error e.

Control limits for the EWMA control chart are based on $\pm L$ sigma limits, where L usually equals 3 according to the design of Shewart control chart limits [20]. As the upper and lower EWMA control limits depend on time t, they are functions of time t as (7) and (8).

$$UCL(t) = \mu_e + L\sigma_e \sqrt{\frac{\lambda[1-(1-\lambda)^{2t}]}{(2-\lambda)n}} \tag{7}$$

$$LCL(t) = \mu_e - L\sigma_e \sqrt{\frac{\lambda[1-(1-\lambda)^{2t}]}{(2-\lambda)n}} \tag{8}$$

III. Case Study

Conference papers are limited to a maximum of five pages. Please use automatic hyphenation and check your spelling. Additionally, be sure your sentences are complete and that there is continuity within your paragraphs. Check the numbering of your graphics (figures and tables) and make sure that all appropriate references are included.

Two gearbox failure cases from two wind farms in Liaoning Province and Hebei Province, China, are analyzed in this section. In the Liaoning wind farm, 9 wind turbines (WT) are considered. One wind turbine has the gearbox failure record and rest ones are normal wind turbines. In the Hebei wind farm, SCADA data of 4 wind turbines including one abnormal and three normal wind turbines are collected. All the wind turbines are equipped with SCADA system and the sampling frequency of the SCADA system was 10 minutes. The SCADA data in Liaoning and Hebei wind farms were separately collected from 1 April to 17 May, 2015 and from 1 April to 2 June, 2015. The details of two wind farms are shown as Table I.

TABLE I. Details Of Two Wind Farm

Wind Farm	No. of Abnormal WT	No. of Normal WT	Failure Date
Liaoning	49	35, 40, 42, 51,53,54, 62,63	May 17th, 2015
Hebei	64	33, 50, 78	June 2nd, 2015

A. Prediction Model Building

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, ac, dc, and rms do

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not have to be defined. Do not use abbreviations in the title or section headings unless they are unavoidable.

In this study, four parameters are chosen from the original SCADA data. To guarantee that the prediction model depicts the behavior of normal wind turbines, the pre-processing of the data is conducted. Based on the knowledge of industrial experts, the gearbox oil temperature T_o should be less than or equals 75 ˚C and lubricant pressure P_l should be within the range of 4 bar and 6 bar. Therefore, two rules, $T_o \leq 75$ and $4 \leq P_l \leq 6$, are utilized to clean data to avoid the influence of erroneous data.

After filtering outliers of the SCADA data, all data of normal wind turbines are combined into the training dataset and the DNN prediction model is trained based on (2). The fitting errors of normal and abnormal wind turbines are computed according to (1). These fitting errors can be utilized to measure the difference between the present behavior and the expected normal behavior of the wind turbine.

B. *Control Chart Monitoring*

EMWA control chart is employed to monitor the fitting errors. To show the performance of the proposed method, the time window, one week before the gearbox failure, is chosen. The UCL and LCL of EMWA chart are computed according to (7) and (8). Representative results are selected and presented in Fig. 3 – 8.

According to Fig. 3-8, it is observable that outliers only appear in the turbines with failed gearboxes (Fig. 4 and Fig. 7). In EWMA charts of normal turbines, all the fitting errors are inside the range of UCL and LCL boundaries. Besides, the failure can be alarmed two or three days ahead of the occurrence of real failures, which can provide the wind farm staff enough time to check the gearbox condition and plan the replacement. If the abnormal gearboxes can be repaired or replaced before the failure, extra cost will be avoided. Therefore, the proposed model is effective to monitor the gearbox and prognose its failures.

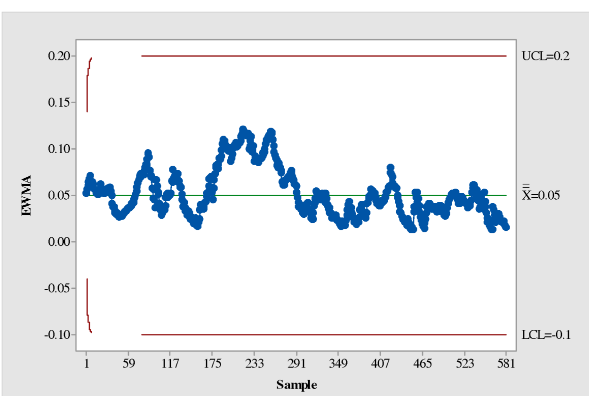

Figure 3. EMWA chart of No. 35 turbine in Liaoning (May 11th - May 17th)

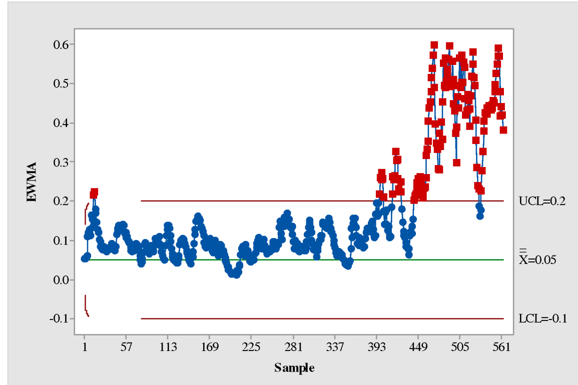

Figure 4. EMWA chart of No. 49 turbine in Liaoning (May 11th - May 17th)

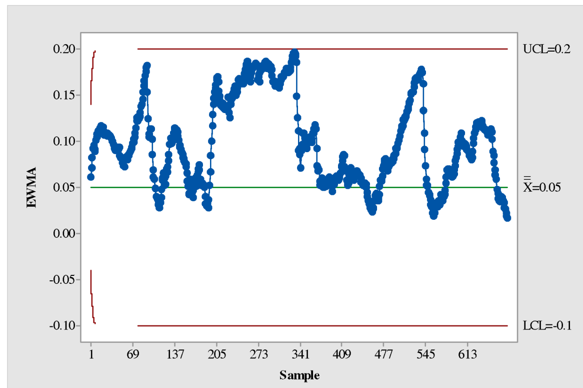

Figure 5. EMWA chart of No. 54 turbine in Liaoning (May 11th - May 17th)

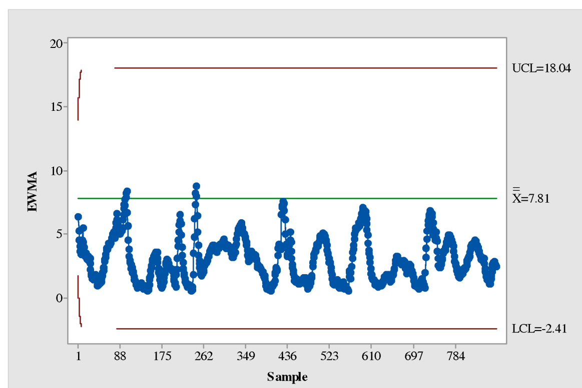

Figure 6. EMWA chart of No. 50 turbine in Hebei (May 27th - June 2nd)

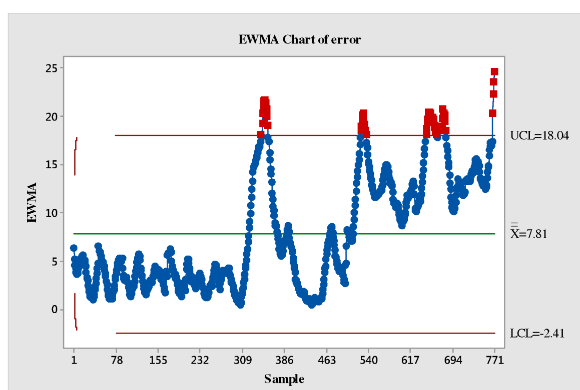

Figure 7. EMWA chart of No. 64 turbine in Hebei (May 27th - June 2nd)

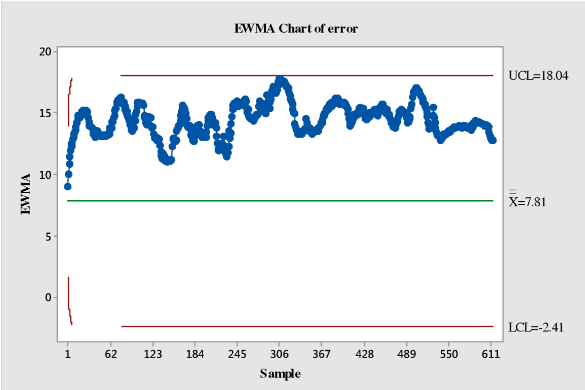

Figure 8. EMWA chart of No. 78 turbine in Hebei (May 27th - June 2nd)

The parallelized SGD algorithm makes the training process of DNN fast, even with cross-validations. For a computer with a CORE I5 CPU and 8GB memory, it only takes less than 3 minutes to train the DNN model with 3 hidden layers. Therefore, it is reasonable and possible to use this proposed model in the industry application concerning the effectiveness and computational time.

IV. CONCLUSION

In this study, a gearbox monitoring model was developed and the lubricant pressure was chosen as the monitoring objective. Two phases of building the monitoring model were introduced. The first phase was developing the lubricant pressure prediction model by using the DNN algorithm. The prediction model was trained based on the SCADA data of all the normal wind turbines which represented the normal behaviors of wind turbines. The fitting errors of normal and abnormal wind turbines were estimated. The second step was constructing the EMWA control chart. The UCL and LCL were utilized to alarm the gearbox failure. The proposed framework was validated through two gearbox failure cases from two different wind farms. In the monitoring results, fitting errors of all normal wind turbines fell within the monitoring boundary while the failure of the gearbox could be alarmed two or three days ahead. Therefore, it provided the wind farm staff sufficient time to examine the gearbox condition and plan the maintenance. In addition, the whole monitoring process could be complete in several minutes via the parallelized SGD algorithm. The previously mentioned results made the proposed monitoring model feasible to be applied in the industry.

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