A Survey of Deep Learning Approaches on Wind Turbine Condition Monitoring

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Abstract. Current physics-based wind turbine monitoring methods often need extra sensors installed on wind turbines, thus increasing the operation and maintenance (O&M) cost. Besides, physical methods are only effective under some constraints. The real effectiveness needs to be further checked in real conditions. Recent advances in data acquisition systems allow collection of large volumes of operational data of wind turbines. Learning knowledge from the data allows us to do monitoring in another direction. In this paper, a survey of deep learning algorithms applied to wind turbine condition monitoring is given. Compared with original data, more meaning features were extracted through feature extraction of deep learning. Monitoring these new signals, outliers were detected by applying suitable control charts. Several industrial cases confirmed the effectiveness and efficiency of these frameworks.

1. Introduction
With explosive population and economic growth worldwide, many countries rely on the consumption of energy to improve people’s living conditions. This kind of consumption results in an over-reduction of fossil fuels because of the big proportion of fossil energy in the energy industry. However, due to the limitation of fossil energy [1], many governments show great interest in renewable energy, for instance, solar, wind and hydropower energy [2-4]. Among these energy resources, wind energy is the most attractive because the cost of wind energy is comparable to the power from coal and gas fired power plants [5]. A typical wind farm is shown in Figure 1.

Figure 1. Wind Farm Example
Condition monitoring of wind turbines is of great importance for wind energy as wind turbines are located at remote locations [3,6-9]. As a consequence, it is difficult for maintainers to access these turbines. Therefore, unexpected faults may cause excessive downtime, causing thus operational costs. Besides, more and more wind energy companies show great interest in making wind turbines working at a good state and performance optimization of wind turbines become a more and important job of wind energy companies and wind turbine manufacturing companies [10]. A suitable condition monitoring system (CMS) can help to detect turbine faults at their early stage, preventing the turbine accidents [5]. Meanwhile, condition monitoring system benefits related companies by keeping wind turbines working efficiently.

In the literature, the condition monitoring has been intensively investigated by many researchers. The proposed methodologies can be categorised as physical methods and data-driven methods. Physical methods often need to install additional sensors for monitoring. Acoustic Emission (AE) sensors [11], fibre optics displacement transducers [12] and Fiber Bragg grating (FBG) sensors [13] were installed on wind turbines to monitor the key components of a wind turbine, such as blade, gearbox and nacelle, shown in Table 1. In order to handle those sensor signals, signal transformation methods were also introduced [5]. Unlike physics-based methods, data-intensive methods focus on analysis of current operational data. The large amount of operational (SCADA) data can be used to give an indication of wind turbine monitoring. This fact is confirmed in many researches [14-16]. These methods usually utilise historical operational data to learn normal behaviour models. Residual analysis is often applied to check wind turbine conditions. These normal behaviour models can predict some output targets when given some input features. As a result, the prediction errors of these models can be used as indicators for turbine faults. In order to have a better performance, many different models are studied.

| Component   | Downtime of Failures |
|-------------|-----------------------|
| Blade       | 6 days                |
| Gearbox     | 5 days                |
| Generator   | 9 days                |
| Nacelle     | 7 days                |

Among them neutral network models accounts for a large proportion and their performance is overall good [14,17-19]. Researchers applied neutral networks (NNs) based model to monitor different components of wind turbines, such as wind turbine generator bearing [18] and wind turbine drive trains [16]. Instead of using NNs, adaptive network-based fuzzy inference system (ANFIS) models are used for wind turbine monitoring [20].

Although wind turbine condition monitoring was studied in literature, several shortcomings are worthy noted. Current physics-based methods need extra sensors installed on wind turbines, thus increasing the operation and maintenance (O&M) cost. Besides, physical methods are only effective under some constraints. The real effectiveness needs to be further checked in real conditions. Another shortcoming is that the features monitored by current methods are relatively few as current SCADA system can provide more than 40 parameters. Partial monitoring may cause the loss of information for wind turbine conditions. Furthermore, blade monitoring by data-driven methods is rarely reported.

As one of the most successful data-driven or machine learning algorithms, deep learning [21] has transformed the whole society in multiple fields, such as image recognition, machine translation, power markets [22], and fraud detection. However, researches on the application of deep learning on wind turbine condition monitoring were few. Current wind turbine O&M requires a high-level condition monitoring and main components failure prognosis. As a results, more advanced and useful techniques need to be developed. Since deep learning’s success in recent years, it is valuable to investigate its application on wind turbine condition monitoring.
A brief introduction of deep learning method in wind turbine condition monitoring is presented in this paper. The remaining parts of this paper is organized as follows. In section 2, wind turbine blade failure monitoring framework is introduced while the gearbox failure identification framework is described in section 3. In the last section, some conclusions and future prospects are illustrated.

2. Wind Turbine Blade Failure Monitoring Framework
As a pioneer study of deep learning on wind turbines, Wang et al. [23] proposed a wind turbine blade failure monitoring framework based on deep auto-encoders. The following steps summarize the framework:

Step 1 Collect SCADA data of all wind turbines in a wind farm. Next, combine SCADA data of normal wind turbines into one dataset.

Step 2. Based on the training dataset, learn a deep autoencoder model to represent the normal behaviors of wind turbines in this wind farm. It is noticed that all SCADA parameters are utilized in the training process.

Step 3 Compute the reconstruction errors using the squared errors for both healthy and failed wind turbines.

Step 4. Develop exponentially weighted moving average (EWMA) charts to monitor these reconstruction errors. If any alarms are issued, then a possible blade failure may happen.

The above-mentioned framework was validated with three wind turbine failure cases. The alarm time ahead of the failures is listed in the table 2.

| Failures | Time prior to breakages |
|----------|-------------------------|
| 1        | 7 hours and 20 minutes  |
| 2        | 6 hours and 10 minutes  |
| 3        | 8 hours                 |

It can be observed from table 1 that enough time is given before the failure actually happened, which will leave operators enough time to stop the wind turbines.

3. Wind Turbine Gearbox Failure Identification Framework
With only four parameters, Wang et al. [24,25] introduced a novel framework for wind turbine gearbox condition monitoring and failure identification. The key component of this framework is a prediction model of lubricant pressure for wind turbine gearboxes. The independent variables are shaft temperature, oil temperature, and output power. The detailed steps of this framework are listed below:

1. Collect SCADA data from a wind farm and clean the invalid and missing data. Next, group the preprocessed data into the training dataset;

2. Apply data-driven algorithms to learn the prediction model which is utilized for the lubricant pressure modelling.

3. Select the model with the best performance from all these models for wind turbine gearbox monitoring;

4. Develop EWMA control chart to monitor the prediction errors and issue alarms for gearbox failures.

During the development of the prediction model, the deep neural networks with drop-out offered the best prediction performance, which further confirmed that deep learning is powerful in wind turbine condition monitoring.
4. Conclusion
A very brief survey of deep learning methods on wind turbine condition monitoring was given in this paper and mainly two monitoring frameworks were introduced. These frameworks were utilized to monitor failures of sub-systems, including both gearbox and rotor blade. SCADA data were employed to develop the related condition monitoring framework. The feasibility and effectiveness of the discussed monitoring approaches were examined with real data collected from commercial wind farms.

The application of deep learning on wind turbine condition monitoring actually provides a new direction for the O&M of wind farms. Besides of traditional sensors, SCADA data now can be viewed new resources for wind farm operators in the field of O&M. The future research can be conducted from the three aspects: 1) Develop more advanced deep learning algorithms for wind turbines; 2) Extend the data from SCADA data to images; 3) Integrate all frameworks to build an intelligent monitoring system.

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