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Wind turbines abnormality detection through analysis of wind farm power curves

Shuangyuan Wang, Yixiang Huang *, Lin Li, Chengliang Liu

State Key Laboratory of Mechanical System and Vibration, Shanghai Jiaotong University, Shanghai, China

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ABSTRACT

Abnormality detection and prediction is a critical technique to identify wind turbine failures at an early stage, thus avoiding catastrophes. In this study, we propose a new abnormality detection and prediction technique based on heterogeneous signals and information, such as output power signals and wind turbines downtime event information collected from the supervisory control and data acquisition (SCADA) system. First, discriminant statistical feature extraction is performed on the power signals in both the time-domain and frequency-domain. Then, a sideband expression is derived for normalized statistical data based on quartiles. In addition, a dissimilarity metric is defined to calculate the distances between downtime time intervals, and a higher dimension feature space is obtained. To reduce the dimension of the feature space, the Laplacian Eigenmaps (LE) nonlinear dimensionality reduction method is implemented. Afterwards, a Linear Mixture Self-organizing Maps (LMSOM) classifier is applied to differentiate abnormal types and a cumulative trend difference method is utilized to predict the faults in wind turbine. The method is validated and applied to data collected from a wind farm in north China. The results show that the proposed technique can effectively detect and predict wind turbine abnormalities.

1. Introduction

Worldwide wind generation capacity reached 336,327 MW by the end of June 2014, equaling approximately 4% of the world's electricity demand [1]. Meanwhile, the rapid growth of the wind energy industry has led to significant social, environmental, economic and technical impacts on the operation and maintenance (O&M) of wind turbines (WTs) [2]. One analyzer suggested that O&M costs account for about 10% of the onshore total expenditure, while offshore, the percentage number rises to 30% [3].

Consequently, the demand to lower the cost of wind energy is urgent. Condition-based maintenance (CBM) is regarded as one of the best solutions [4]. Supervisory control and data acquisition (SCADA) systems are used for data collection in wind farms, providing operational and condition information on wind turbines, which is significant for anomaly detection [5]. Among various SCADA data, wind speed and output power have drawn researchers' attention [6] because the failure or malfunction of a wind turbine may dramatically reduce its power generation capability. Supplying power to the grid imposes very strict requirements on the quality of wind turbine power output, which is a complex result of different regimes of aerodynamic, mechanical, electromagnetic and control systems. It has been shown that the quality of power output is strongly related to the wind resource and power output [7]. The challenge of analyzing the relationship between wind speed and active power, which is depicted by the wind turbine power curve, is nonlinear. Thus, the power curve may represent wind turbine performance [8,9]. Many techniques have been developed to study power curves. For instance, empirical copula statistics were used to separate information about the dependency between wind speed and output power [3]. Wang et al. [10] proposed a copula-based joint probability model for wind turbine power curve outlier rejection. They captured the complex nonlinear multivariate relationship between parameters, based on their univariate marginal distributions. An online profile of power curve technology for detecting anomalies in wind turbines was given by Kusiak et al. [11]. They studied the power curve model using a least squares method, a maximum likelihood estimation method and the k-nearest neighbor (k-NN) algorithm under normal operating conditions. A wind farm monitoring system with performance curves based on power curve, rotor curve, and blade pitch curve was proposed by Kusiak [12].

In general, wind speed is usually measured by anemometers installed on the top of the nacelle. Meanwhile, several anemometers are placed at locations on site to measure the average wind speed [13]. However, the highly random nature of wind makes sensor data vary between the measured values and actual wind

* Corresponding author.
E-mail address: david.huangyx@gmail.com (Y. Huang).

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Nomenclature

CBM	condition-based maintenance
DFIG	doubly fed induction generator
FDFs	frequency domain features
GSFs	graded statistical features
k-NN	*k*-nearest neighbor
LE	Laplacian Eigenmaps
LEFs	Laplacian Eigenmaps dimensional reduction features
LMSOM	Linear Mixture Self-organizing Maps
O&M	operation and maintenance
SCADA	supervisory control and data acquisition
SOM	self-organizing map
TDFs	time domain features
WTs	wind turbines

speeds, especially when wind passes through wind blades' swept areas, where the deviation is more obvious. Inaccurate measures of wind speed may raise the risk of failure for abnormality detection, while the output electrical power of a wind farm contains more global information about wind turbines. Besides, the downtime information of wind turbines is merely used in the published literature, which could indicate different types of failures or service with varied time intervals.

For the above reasons, in this paper we propose a new method of graded statistical analysis of power curves. To apply this method, the wind resource must be constant for a certain period of time over a limited flat area, suck as a small wind site, and the performance of wind turbines of the same type must be consistent to a certain extent. These two conditions are easily satisfied for onshore wind farms in plains and most offshore wind farms. Then, outliers are detected to indicate unusual wind turbine performance by a statistical method. Both quantitative values and a qualitative metric are captured by sideband normalizing the distance and direction to the median values. In addition, we propose a dissimilarity measure to survey the wind turbine downtime data. Last a linear mixture self-organizing map is modified for fault classification and abnormality detection, and a cumulative trend difference method is utilized to predict the abnormality and faults in the wind turbine. The data processing flowchart of this paper is shown in Fig. 1.

This paper is organized as follows. Firstly, we describe a graded statistic method for electrical power output of form wind turbines to locate the outlier in eight grades. Sideband normalization is used to regularize the deviation of graded statistical features for abnormality detection. Next, a multi-interval data dissimilarity measure algorithm is proposed with Laplacian Eigenmaps dimensionality reduction method. Besides, linear mixture self-organizing map used for supervised classification is described. Then, we illustrate the original data set used in this paper. And the pre-process and filtering method for the raw data is illustrated. Furthermore, in order to validate effective and accurate of the proposed method, sixteen data sets is constructed to compare the performance of five different combinations of feature sets with basic SOM and LMSOM, respectively. Finally, conclusion and discussion for future work are reported.

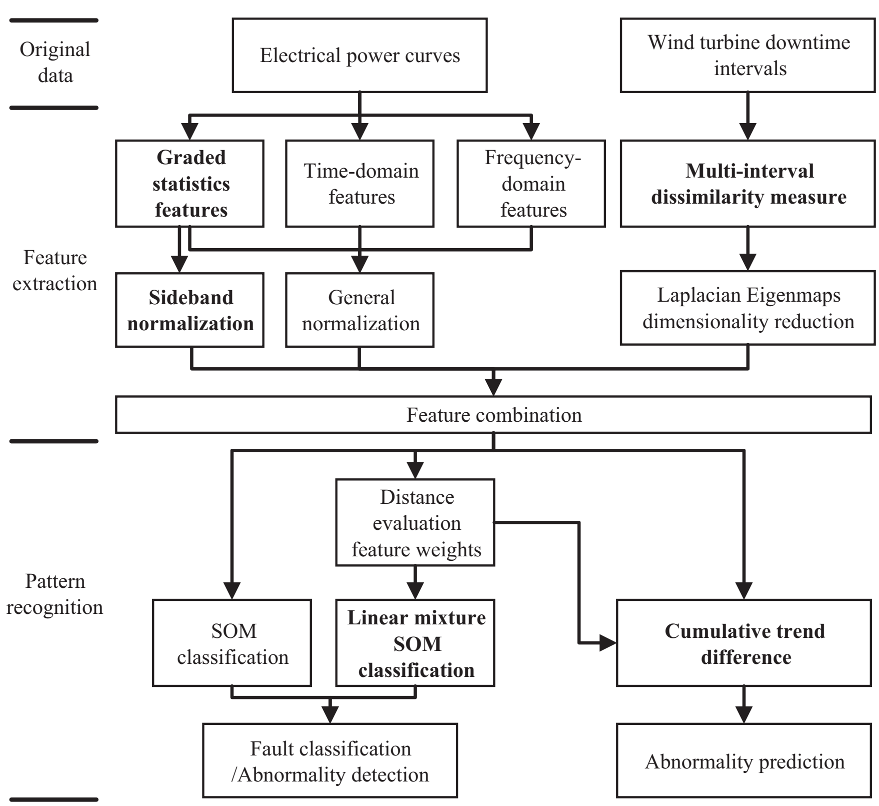

Fig. 1. Flowchart of the data process.