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To cite this article: Xide Sun *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **575** 012015

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Research on Condition Monitoring of Key Components in wind Turbine based on Cointegration Analysis

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Abstract. Traditional models based on temperature trend can not comprehensively monitor the condition of wind turbine, besides, the threshold obtained from model can cause fluctuation when wind turbine operates under different conditions. In view of this, this paper presents a novel methodology based on cointegration analysis for continuously monitoring the operating conditions of wind turbine. The first step is to determine the optimal combination of parameters from normal SCADA sample data, by using the cointegration test. Then, perform the method of cointegration analysis to calculate the cointegration residuals and stationary threshold line under normal working space. When wind turbine component is operating out of the normal track, the data sample in cointegration residuals will exceed the stationary threshold line, and send the alert signals. The method is tested using SCADA data of wind turbine with known faults, the results demonstrate the proposed method can effectively monitor the abnormal state of generator and gear box, and provide the function of early warning.

1. Introduction

In recent years, with the development of wind power technology, the number and capacity of wind turbines have increased rapidly. However, due to the adverse operation environment and long time varying load operation, the wind turbines have a high failure rate [1]. Therefore, condition monitoring and fault diagnosis of wind turbines at early stage of fault occurrence is necessary. The most widely used condition monitoring methods are oil monitoring [2] and analysis of current (voltage) signal [3] and so on. These technologies can monitor the operating condition of wind turbine in real time, but there is a certain coupling relationship between each component when wind turbine is operating.

To solve these problem, method of online monitoring based on SCADA data has been gradually developed [4],[5]. This kind of method only needs to process the real-time of SCADA data, and even when the wind speed is changing, the fault information can be accurately judged. Therefore, it has the advantages of high efficiency, low cost and low complexity. At present, the analysis method based on SCADA data has been studied in Ref. [6-7]. These studies focus on two ideas: the first is to determine the fault threshold based on the residuals between the fault and normal parameters, and continuously



monitor the condition of wind turbine, but the actual operating conditions of wind turbine are constantly changing, this can cause the fluctuation of threshold. The second is to predict the SCADA fault data by using the intelligent algorithms (such as neural network, SVM, etc.). However, intelligent algorithms are complicated and require massive training data, but it is difficult to satisfy for those wind farms put into operation for a short time.

This paper proposed a novel methodology based on cointegration analysis for continuously monitoring the operating conditions of wind turbine. The vital idea is to perform cointegration analysis between the monitored nonlinear variables. Besides, we can obtain the cointegration residuals, this parameter can represent the long-term stable equilibrium relationship between variables [8]. When the wind turbine runs normally, the relative SCADA parameters will change in the normal working space. On the contrary, they will have abnormal changes, this will cause some points in cointegration residuals exceed the stationary threshold line, and send the alert signals, indicating the occurrence of the failure. Therefore this method can continuously monitor the wind turbine and reliably detect abnormal problems.

2. Introduction and Model Building of Cointegration Analysis

2.1. Concept of cointegration

Let $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})^T$ denote an $n \times 1$ vector of nonstationary first order single integer time series.

This vector is said to be cointegrated if there exists an $n \times 1$ vector $\beta = (\beta_1, \beta_2, \dots, \beta_n)^T$ such that:

$$\begin{aligned}\beta^T Y_t &= \beta_1 y_{1t} + \beta_2 y_{2t} + \dots + \beta_n y_{nt} \\ &\sim I(0)\end{aligned}\quad (1)$$

Eq. (1) implies that the nonstationary time series in Y_t is cointegrated if there is a linear combination of them that is stationary, the $I(0)$ represents stationary status. This stationary linear combination, denote as $u_{rt} = \beta^T Y_t$, is referred to as a cointegration residual. The vector β is called a cointegration vector.

Let $Y_t = (y_{1t}, y_{2t})^T \sim I(1)$, it is a non-stationary time series with Gauss white noise, and the $I(1)$ represents stationary status. Suppose that Y_t is cointegrated with $\beta = (1, -\beta_2)^T$. This cointegration relationship is represented as

$$\begin{aligned}y_{1t} &= \beta_2 \sum_{s=1}^t \varepsilon_{1s} + \varepsilon_{1t} \\ y_{2t} &= \sum_{s=1}^t \varepsilon_{1s} + \varepsilon_{2t}\end{aligned}\quad (2)$$

where the only common stochastic trend is $\sum_{s=1}^t \varepsilon_{1s}$.

It shows there is a common trend among nonstationary data, but by using cointegration analysis, we can remove it, and obtain stationary cointegration residual, such that

$$\begin{aligned}u_t &= \beta_t^T Y_t = y_{1t} - \beta_2 y_{2t} \\ &= \beta_2 \sum_{s=1}^t \varepsilon_{1s} + \varepsilon_{3t} - \beta_2 \left(\sum_{s=1}^t \varepsilon_{1s} + \varepsilon_{2t} \right) \\ &= \varepsilon_{3t} - \beta_2 \varepsilon_{2t} \sim I(0)\end{aligned}\quad (3)$$

2.2. Implementation of proposed method

The condition monitoring of wind turbine cointegration-based are as follows:

- Determine the optimal combination of parameters from normal SCADA sample data, using the cointegration test in the off-line training stage.

- Carry out the method of cointegration analysis to calculate the cointegration residuals and stationary threshold line under normal working space.
- Calculate cointegration residual using the cointegration analysis and SCADA data required from the real-time monitoring of wind turbine.

When the points in cointegration residuals exceed the stationary threshold line, it will send the alert signals.

3. Experimental Verification of Wind Turbine SCADA Data

The SCADA data for wind turbine in this paper is derived from a wind farm of Jilin. The nominal power of wind turbine is 1.5MW, the cut-in wind speed is 3m/s, the SCADA data is acquired at 10-min intervals, during thirty days of September 2017, with two known faults as the generator fault and the gearbox fault. Six days data when wind turbine is operating under abnormal operating conditions were selected from them, and another six days normal data as the train dataset. After processing (eliminate the data when wind turbine shut down and those singular data), we can get two group datasets, each size of it is 963.

3.1. Selection of sample characteristic parameters

A vital parameter in wind energy systems is wind speed, it is closely related to other parameters. By observing the tendency changes between wind speed and other parameters, we can find out those key parameters, and the selected parameters are shown in the fig 1. It presents there is a nonlinear relation between the generator speed, the generated power, the generator temperature, the gearbox temperature and wind speed. Thus, those parameters can be used as the sample characteristic parameters.

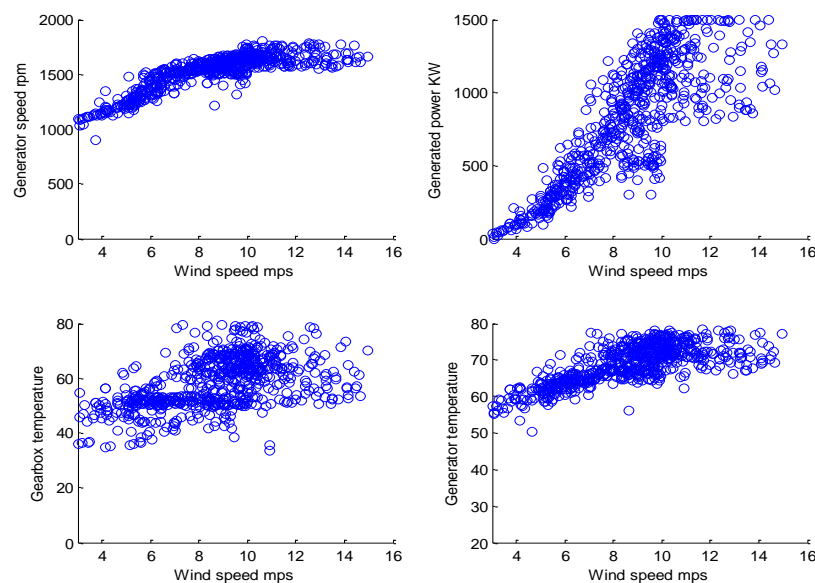


Figure 1. Nonlinear relationship between characteristic parameters and wind speed.

3.2 Analysis of SCADA fault data

First, we do some simple analysis to the fault sample data. Tendency changes of sample parameters are displayed in fig 2. Including the parameter, the generated power, is varying between 0MW to 1.5MW, which represents the dataset is obtained from different operating conditions of wind turbine. The two faults, in the data sample 84 and 394, are enlarged locally as described in fig 3 and fig 4.

In fig 3, around the data sample 84, this abnormal operation happened while wind speed started to fall from 8m/s, then stayed around 3-4m/s. Consequently, the generator speed dropped down from 1300 rpm to almost stationary state, and then suddenly raised to nearly 900 rpm, but during this period, the generator power is consistent with the wind speed. In fig 4, around the data sample 394, the second fault happened while the wind speed was relatively stable around 5m/s, but the generator speed and

the generator power were suddenly dropped to 0 value, in the same time the gearbox temperature was boosted up to 70 °.

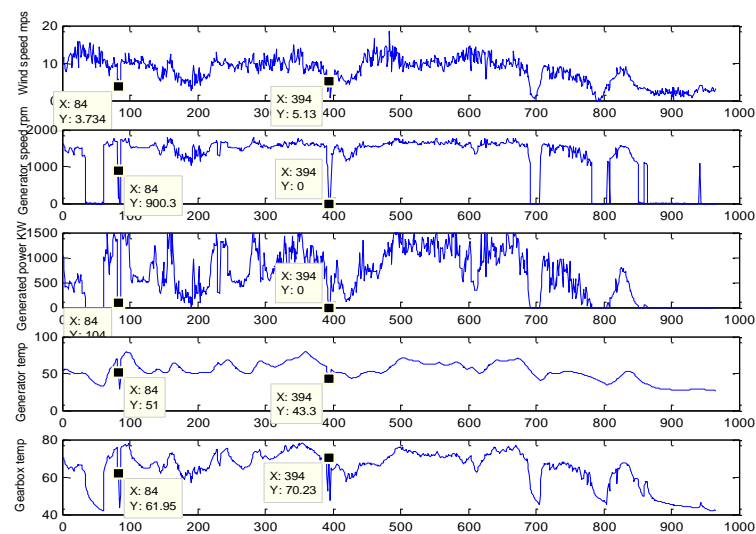


Figure 2. Tendency change of SCADA parameters.

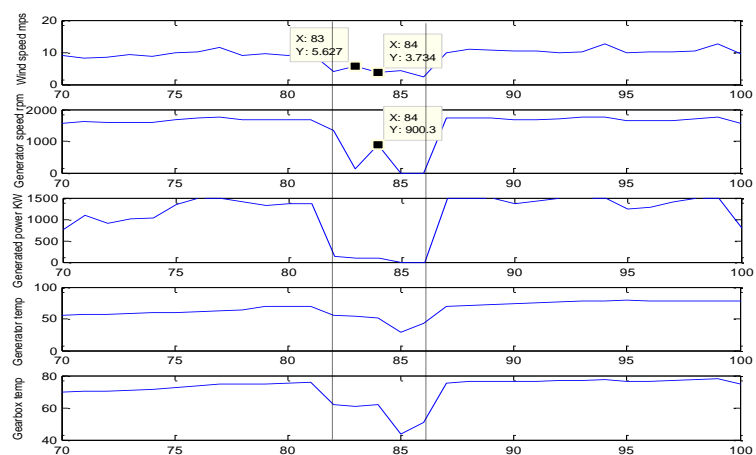


Figure 3. Zoomed data of generator fault.

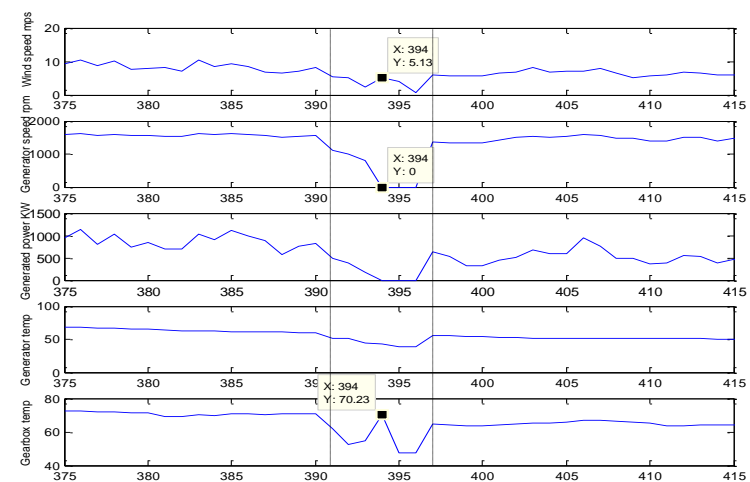


Figure 4. Zoomed data of gearbox fault.

4. Condition Monitoring of Key Components in Wind Turbine

Cointegration analysis can construct stationary relations between nonstationary parameters, when the wind turbine operates abnormally, cointegration residuals will exceed the stationary threshold line, implying a developing fault.

4.1 Cointegration test

Cointegration test is used to find out the cointegration relationships between parameters, those parameters which passed the test can be used to monitor the operating conditions of relevant components. The economics software EViews 8 is used to perform the test by using the common test method, Johannsen cointegration verification (JJ), the experimental object is six days normal dataset. The test results, as shown in table 1, are parameter combinations which has passed the test, the confidence level there is 95%, namely when the test probability is less than 0.05, the hypothetical conditions are invalid.

Table 1. Results after performing cointegration test.

Combinations of SCADA parameters		Cointegration (prob)	Cointegration Vector	Stationary (prob)
Wind Speed	Generator Speed	0.1405	0.305, 1.65E-5, 0.0254	0.0006
	Generated Power			
Wind Speed	Generator Temp	0.0058	0.00059, -0.121, 0.243	0.0024
	Gearbox Temp			
Wind Speed	Generator Speed	0.0229	-0.141, -0.0032, 0.167	0.0001
	Generator Temp			
Wind S	Generator S	0.0075	-0.001, -0.37, 0.57, 0.08	0.0007
	Generated P			
	Gearbox Temp			

4.2 Condition monitoring and fault detection using cointegration residuals

The cointegration residuals can be calculated via the cointegration vector which is obtained from last section, the six days fault data were used to validate. The experimental results are shown in fig 5, the horizontal lines indicate the stationary threshold lines which were calculated as $\nu \pm 3\sigma$ (the 95% statistical confidence levels), where ν is the mean, and σ is the standard deviation, abnormal problems happen whenever the cointegration residuals go beyond them.

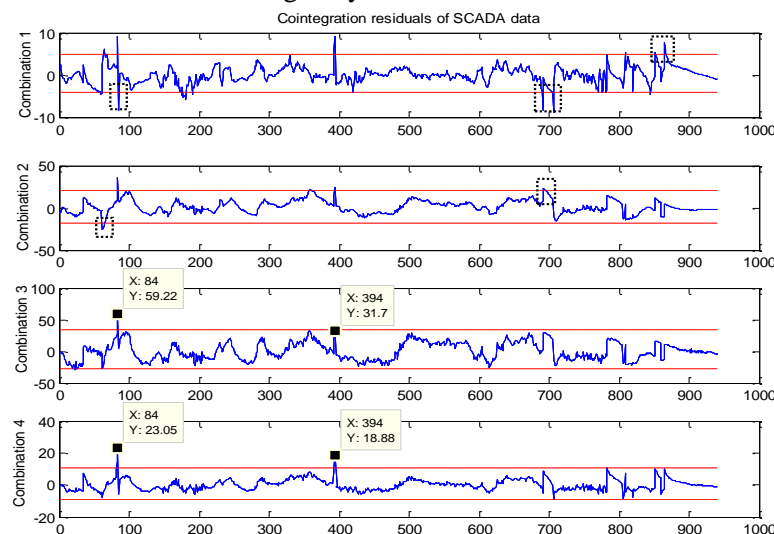


Figure 5. Cointegration residuals of combinations (fault).

However, the first three combinations can not reliably detect the two faults, and eventually cause

some misinformation, as the rectangle frames mark. In the contrary, the 4th combination can reliably detect two faults without any mistakes, thus, there select the combination 4, generator speed, the generated power, the gearbox temperature and wind speed as the optimal combination, and its cointegration residuals is displayed in fig 6 (normal and fault).

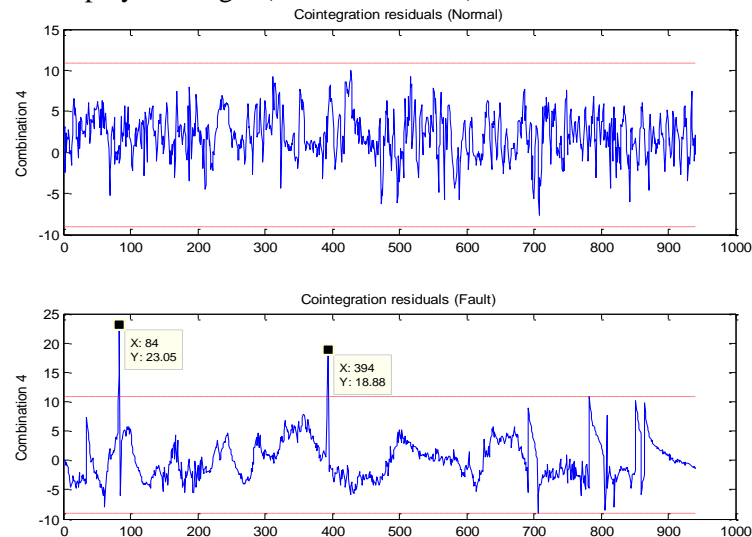


Figure 6. Cointegration residuals of combination 4.

In order to illustrate more specifically, the data sample 84 and 394 of the two faults are enlarged locally is shown in fig 7. It reveals the fault 1, the generator fault, can be detected around the data sample 82, 2 data sample (20min) before the occurrence; the fault 2, the gearbox fault, can be detected around the data sample 392.6, more than 1 data sample (14min) before the fault occurrence.

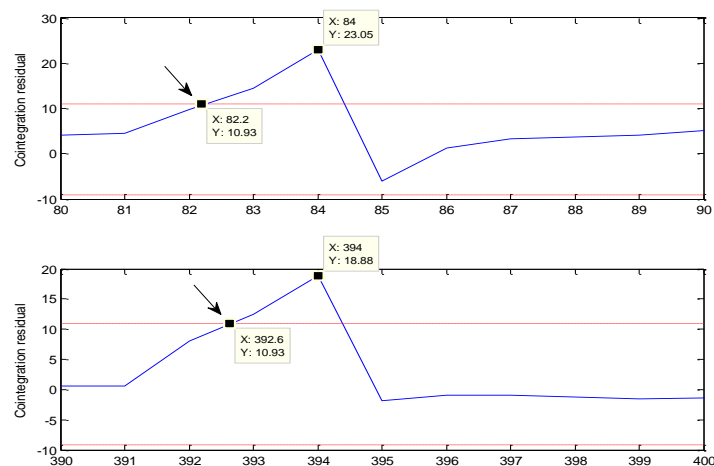


Figure 7. Zoomed data of cointegration residuals.

5. Conclusions

Condition monitoring of key components in wind turbine based on SCADA data can reduce the cost of hardware installation, and diagnose the developing failures in time, especially important for those offshore wind farms which are hard to set up hardware facilities. The proposed method based on cointegration analysis can monitor the key components in wind turbine more comprehensively, avoids the disadvantage of traditional model which can only monitor single parameter. Besides, compared with the current AI technology, this methodology is promising candidate for automated fault diagnosis because of their low complexity, low computation, and cost-efficient. The results demonstrate the proposed method can effectively monitor the abnormal state of generator and gearbox, and provide the function of early warning.

6. References

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Acknowledgements

The research work was supported by Science & Technology Development Plan of Jilin province -Major Science & Technology Bidding under Grant 20180201004SF.