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CONDITION MONITORING OF WIND TURBINES BASED ON COINTEGRATION ANALYSIS OF GEARBOX AND GENERATOR TEMPERATURE DATA

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Abstract

This paper presents a cointegration-based method for condition monitoring of wind turbines. Analysis of cointegration residuals – obtained from cointegration process of wind turbine data – is used for operational condition monitoring and fault detection. The method has been employed for on-line condition monitoring of a wind turbine drivetrain with a nominal power of 2 MW under varying environmental and operational conditions using only the temperature data of gearbox bearing and generator winding, which were collected by the Supervisory Control And Data Acquisition (SCADA) system. The results show that the proposed method can effectively monitor the wind turbine and reliably detect the gearbox fault.

Keywords: wind turbine, varying environmental and operational conditions, condition monitoring, fault detection, cointegration, SCADA

DIAGNOSTYKA TURBINY WIATROWEJ W OPARCIU O ANALIZĘ KOINTEGRACJI SYGNAŁÓW TEMPERATURY Z PRZEKŁADNI ORAZ GENERATORA

Streszczenie

Artykuł przedstawia metodę kointegracji sygnałów do monitorowania stanu turbiny wiatrowej. Analiza wektorów resztkowych kointegracji wykorzystana została do monitorowania stanu turbiny wiatrowej o mocy nominalnej 2 MW. Diagnostykę turbiny wiatrowej przeprowadzono dla zmiennych warunków środowiskowych i eksploatacyjnych, tylko w oparciu o sygnały temperatury łożyska przekładni i uzwojenia generatora. Sygnały te zostały zgromadzone przez system sterowania, monitorowania oraz wizualizacji SCADA. Wyniki pokazują, że proponowana metoda może skutecznie monitorować turbinę wiatrową i niezawodnie wykryć uszkodzenie przekładni.

Słowa kluczowe: turbiny wiatrowe, zmienne warunki środowiskowe i eksploatacyjne, monitorowanie stanu, wykrywanie uszkodzeń, kointegracja, system SCADA

1. INTRODUCTION

It is well known that unexpected failures of wind turbine components (such as gearboxes, generators, rotors) can lead to costly repair and often months of machine unavailability, thereby increasing operation and maintenance costs, and consequently the total cost of energy. Therefore condition monitoring (CM) and fault diagnosis of wind turbines (WTs), in particular at the early stage of fault occurrence, is an important problem in wind turbine engineering [1].

Many CM techniques have been developed to detect and diagnose abnormalities of WTs, as reviewed in [2,3], such as vibration analysis, oil monitoring, acoustic emission, ultrasonic testing, strain measurement, radiographic inspection, and thermography. Another solution – based on the analysis of Supervisory Control And Data Acquisition (SCADA) data – has been employed in [1,4-7]. This technique is cost-efficient, readily available, and is beneficial for identifying abnormal components because only key process parameters need to be tracked [1,6]. Monitoring of data trends and removing undesired trends from wind turbine data are important when SCADA approaches are used. Various methods have been developed for data trend analysis. Recent years have attracted many applications based on the cointegration technique, which was originally developed in the field of Econometrics [8,9].

The cointegration method has been successfully employed as a reliable tool for dealing with the problem of environmental and/or operational variability in Process Engineering [10] and Structural Health Monitoring (SHM) [11-17]. The previous work in [10-17] has showed that when variables (or data from a monitored process or structure) are cointegrated, the stationary linear combinations of these variables – obtained from the cointegration analysis – are purged of all common trends in the original data, leaving residuals equivalent to the long-run dynamic equilibriums of the process. The common trends removed by the cointegration process in this case are supposed to be the environmental and/or operational conditions that drive the response of the monitored process or structure [11-14]. Because the choice of lag length in cointegration analysis has a strong influence on damage detection results where any wrong selection of lag length can lead to false damage detection alarms, a new approach for the optimal selection of lag length in cointegration analysis used for damage detection has been proposed in [18]. More recently, the research on applications of cointegration for SHM has been moving towards nonlinear extensions, as presented in [19-21].

This paper builds upon previous research work on the cointegration technique for data trend analysis, process monitoring and structural damage detection. The main goal is to investigate the feasibility of applying the cointegration-based approach for condition monitoring and fault detection in wind turbine systems using only the temperature data of gearbox bearing and generator winding, which were collected by the SCADA system. The proposed method is based on the residual-based control chart approach.

2. CONDITION MONITORING OF WIND TURBINES USING SCADA DATA

SCADA-based approach has great advantages for developing CM systems for WTs. Firstly, SCADA systems have been installed in the majority of utility-scale WTs for system control and data acquisition so that the data needed for analysis is readily available and no more hardware investment is required when developing a SCADA-based CM system [6,7]. This solution is thus cheap in cost. Secondly, the technique is beneficial for identifying fault components by tracking only key process parameters [1,6]. Because of these advantages, developing CM tools for WTs using SCADA data has become a fast growing research field and SCADA data have been widely used by researchers as the basis for CM systems. As a results, previous work on the use of SCADA data for condition monitoring and fault diagnosis of WTs has established considerable achievements, as reported in [1,4-7].

The main objective of the work presented in this paper is to develop a reliable SCADA data analysis method – based on cointegration technique – that can automatically interpret and analyse a large amount of low-sampling rate SCADA data, and additionally, is able to deal with undesired effects of environmental and operational variability in data used for condition monitoring and fault detection of wind turbines.

3. COINTEGRATION ANALYSIS

In mathematics the concept of stationarity can be introduced using time series analysis. A given time series y_t can be presented in the form of the first-order Auto-Regressive $AR(1)$ process [22], which is defined as

$$y_t = \phi y_{t-1} + \varepsilon_t \qquad (1)$$

where ε_t is an independent Gaussian white noise process with zero mean, i.e. $\varepsilon_t \sim IWN(0,\sigma^2)$. Then three different time series can be distinguished for different values of coefficient ϕ [22]. These are: (1) stationary time series ($|\phi| < 1$); (2) nonstationary time series ($\phi > 1$); and (3) random walk ($\phi = 1$).

Any time series y_t that exhibits the form of random walk without a trend is considered as an integrated series of order 1, denoted $I(1)$ [23]. For such a series Eq. (1) yields

$$\Delta y_t = y_t - y_{t-1} = \varepsilon_t \qquad (2)$$

Eq. (2) shows that, the first difference of y_t, i.e. $y_t - y_{t-1}$, is just a stationary white noise process ε_t. In other words, a nonstationary $I(1)$ process becomes a stationary $I(0)$ process after the first difference. By analogy, a nonstationary $I(2)$ process would require differencing twice to induce a stationary $I(0)$ process.

Next, the concept of cointegration can be introduced using a vector Y_t of $I(1)$ time series defined as $\mathrm{Y}_t = (y_{1t}, y_{2t},..., y_{nt})^T$. This vector is linearly cointegrated if there exists a vector $\beta = (\beta_1, \beta_2,..., \beta_n)^T$ such that

$$\beta^T \mathrm{Y}_t = \beta_1 y_{1t} + \beta_2 y_{2t} + \cdots + \beta_n y_{nt} \sim I(0) \qquad (3)$$

In other words, the nonstationary $I(1)$ time series in Y_t are linearly cointegrated if there exists (at least) a linear combination of them that is stationary, i.e. having the $I(0)$ status. This linear combination, denoted as $\beta^T \mathrm{Y}_t$, is referred to as a cointegration residual or a long-run equilibrium relationship between time series [23]. The vector β is called a cointegrating vector. The action of creating the cointegration residual ($u_t = \beta^T \mathrm{Y}_t$) is considered as the action of projecting the vector Y_t on the cointegrating vector β.

In essence, testing for cointegration is testing for the existence of long-run equilibriums (or stationary linear combinations) among all elements of Y_t. Such tests have two important requirements [23]. Firstly, any analysed time series must exhibit at least a common trend. Secondly, the analysed time series must have the same degree of nonstationarity.

The cointegration test consists of two steps:

1. The first step is to determine the existence of cointegration relationships and the number of linearly independent cointegrating vectors among multivariate nonstationary time series and to form the cointegration residuals.
2. The second step is to perform unit root tests on the cointegration residuals found to determine if they are stationary series (i.e. testing for stationarity).

For the first step, the Johansen's cointegration test [9] has been widely used. It is a sequential procedure based on the maximum likelihood technique, which basically is a combination of cointegration and error correction models in a Vector Error Correction (VEC) model. For the second step, the augmented Dickey-Fuller (ADF) test [24] is the most popular unit root test. The ADF test checks the null hypothesis that a time series is nonstationary against the alternative hypothesis that it is stationary, assuming that dynamics in the data have Auto-Regressive Moving Average structure.

4. WIND TURBINE DATA

The wind turbine data used in this paper originate from a series of experimental measurements on a WT drivetrain with the nominal power of 2 MW. SCADA data were acquired at 10-minute intervals during thirty days in November 2012. A number of process parameters (such as wind speed, rotor speed, generator speed, generated power, generator voltage and generator current, gearbox bearing and generator temperature) were monitored and recorded under varying operating conditions. The collected data were also influenced by environmental conditions (namely, wind speed, ambient temperature variations between day and night, and air humidity). As a result, 4320 data samples were acquired for each process parameter under the effect of both environmental and operational variability. Examples of the SCADA data are illustrated in Fig. 1, in which the wind speed, the generator speed, and the generated power are shown. It should be noted that this study assumed that under the normal operating condition the investigated wind turbine operated at wind speeds varying around 5–11 meters per second (mps) or 11–25 miles per hour (mph).

To investigate whether the cointegration-based approach – presented in Section 5 – can reliably detect a faulty situation of the turbine, a known gearbox fault (occurred at the data sample 1230 and persisted in 20 minutes until the data sample 1232) has ben used as a case study. This fault is identified from the event logs for the wind turbine and the corresponding data are shown in Figs. 2 and 3, with the fault happening at the moment indicated by the circle marked at the data sample 1230, leading to the turbine being shut down immediately at the data sample 1232. More especially, this fault happened when the generator speed and generated power as well as the generator voltage and generator current were suddenly dropped down to the zero value, whereas at the same time, the wind speed was relatively stable around [5–6] mps (i.e. it was varying within the specified normal operating condition). It was assumed that this fault might be caused by a bearing failure in the gearbox. It is thus important to accurately detect this fault at the early stage of its occurrence.

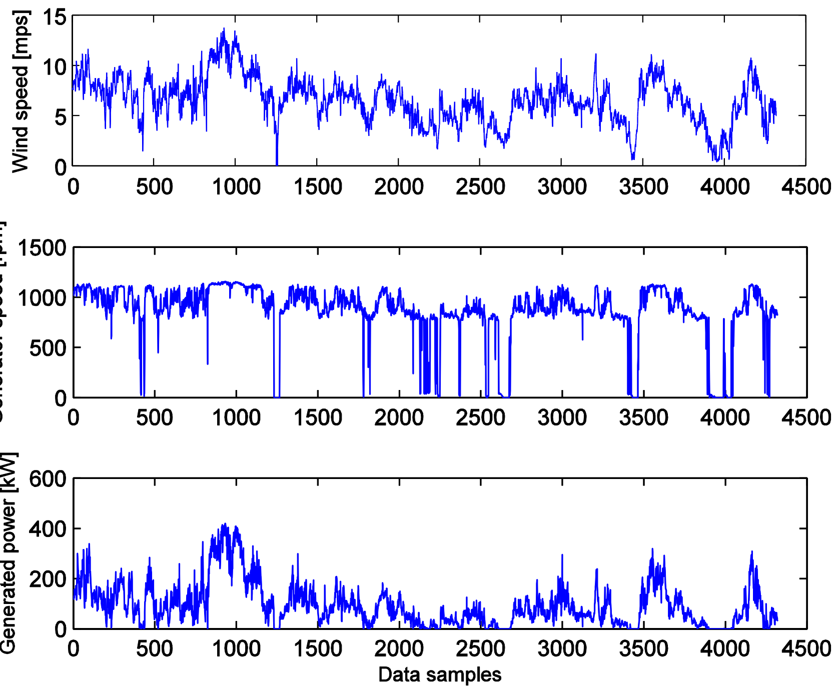

Fig. 1. Examples of wind turbine data

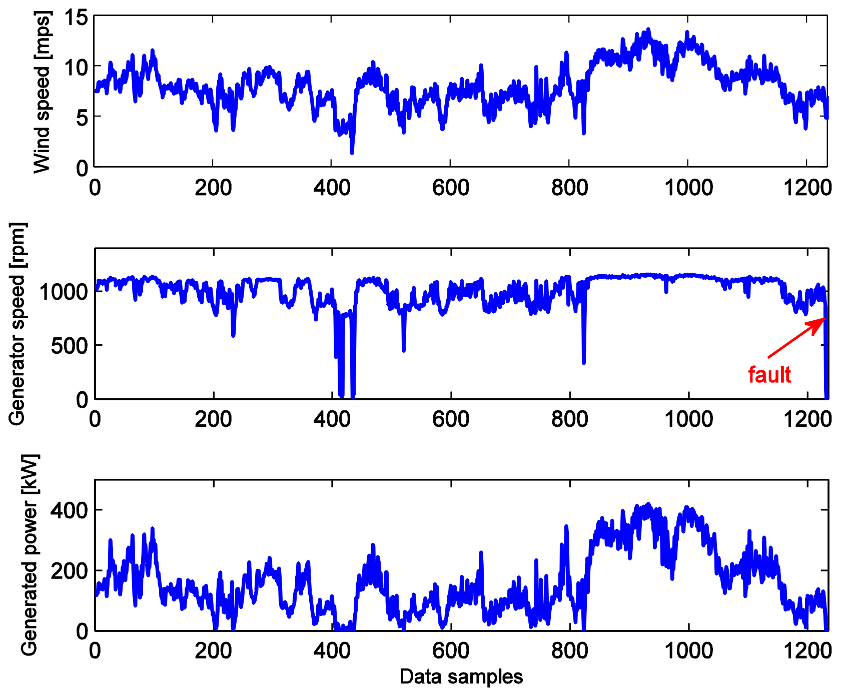

Fig. 2. Wind turbine data displaying the occurrence of the gearbox fault.

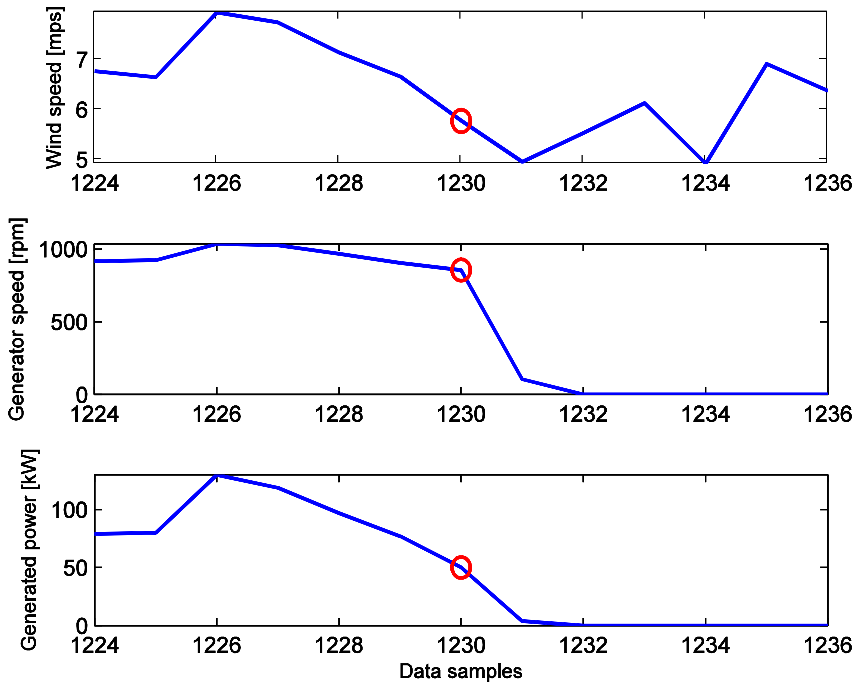

Fig. 3. Zoomed data from Fig. 2 displaying in detail the occurrence of the gearbox fault.

It has been discussed that the temperature data of the gearbox bearing and generator winding may provide an early indication of generator, bearing, and gearbox faults [2-4]. Thus only the temperature data of gearbox bearing and generator winding have been used in the current work for condition monitoring and fault detection of the wind turbine. It is expected that this analysis can effectively monitor the wind turbine and reliably detect abnormal problems. Since the temperatures of the gearbox bearing and generator winding depend not only on the wind speed, but also on the power demand from the grid therefore this study considers the temperatures of both gearbox bearing and generator winding as the functions of wind speed and generated power.

Figs. 4a and 4b illustrate the relations between the gearbox bearing temperature and wind speed and generated power, respectively. One can notice a common nonlinear trend from these characteristics, that is, the temperature of gearbox bearing increases nonlinearly with the increase of wind speed and generated power.

The relations between the generator winding temperature and wind speed and generated power are shown in Figs. 4c and 4d, respectively. Another common nonlinear trend (in the form of a dead-zone saturation nonlinearity) can be observed from these characteristics, i.e. the generator winding temperature increases nonlinearly with the increase of wind speed and generated power; however there exists a dead-zone region in the middle.

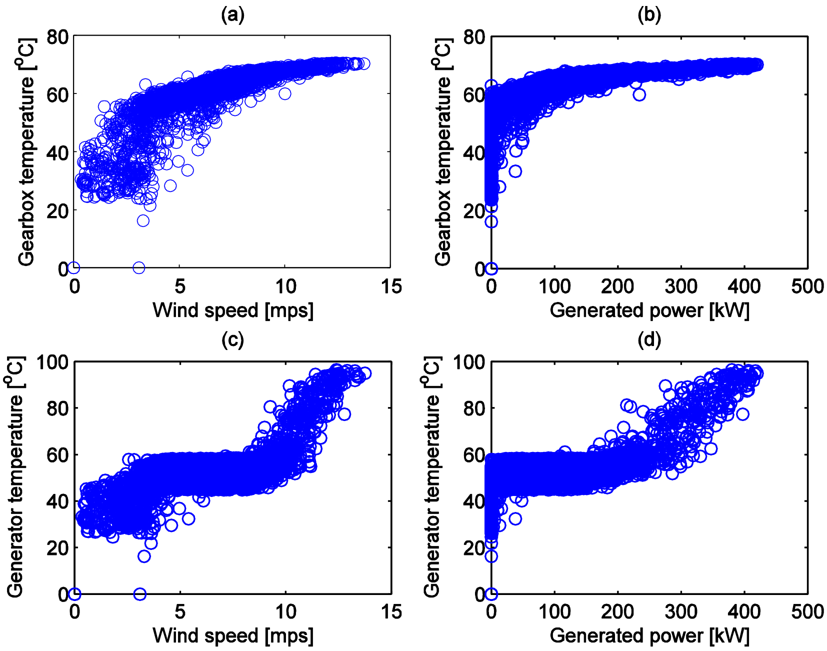

Fig. 4. Gearbox bearing temperature v.s (a) wind speed and (b) generated power; Generator winding temperature v.s (c) wind speed and (d) generated power.

5. CONDITION MONITORING OF WIND TURBINES BASED ON COINTEGRATION ANALYSIS OF TEMPERATURE DATA

The cointegration-based data analysis procedure for condition monitoring of wind turbines using SCADA data employed in this paper involves two steps [17]:

1. Off-line step: calculate (or estimate) cointegrating vectors using SCADA data that are acquired from the monitored wind turbine under normal operating conditions or modes (usually at the beginning of the WT's lifetime when its components are considered "healthy").
2. On-line step: calculate cointegration residuals used for continuous (on-line) condition monitoring using the cointegrating vectors found and SCADA data acquired from the monitored wind turbine under regular operating stage (during electricity production phase).

It is important to note that the main idea of the cointegration-based condition monitoring and fault detection method utilised in this paper is basically similar to the well-known residual-based control chart approach, which is one of the primary techniques of statistical process control. An advantage of control charts is that they can be automated for on-line condition monitoring and SHM applications [25]. More specifically in the context of the proposed method, cointegration is a property of some sets of nonstationary time series where a linear combination of these nonstationary series can produce a stationary residual. Then the stationarity (or nonstationarity) of the cointegration residual can be used in a control chart as a potentially effective damage feature or indicator.

It should be noted here that in the previous work presented in [17] six process parameters of the wind turbine were analysed using the cointegration-based procedure. These are: wind speed, generator speed, generated power, generator temperature (front part), generator current, and gearbox temperature. This means that, in the previous work [17], four different kinds of physical signals (i.e. speed, power, temperature and current) of the wind turbine were simultaneously analysed by the cointegration-based procedure. In the current study, however, only three temperature parameters measured in the gearbox and at the generator (one in the front and another in the back of the generator) have been analysed. These temperature parameters are shown in Fig. 5. Although only three temperature data sets are used, it is expected that the proposed method can effectively monitor the wind turbine and reliably detect abnormal problems. The results are presented and discussed in Section 6.

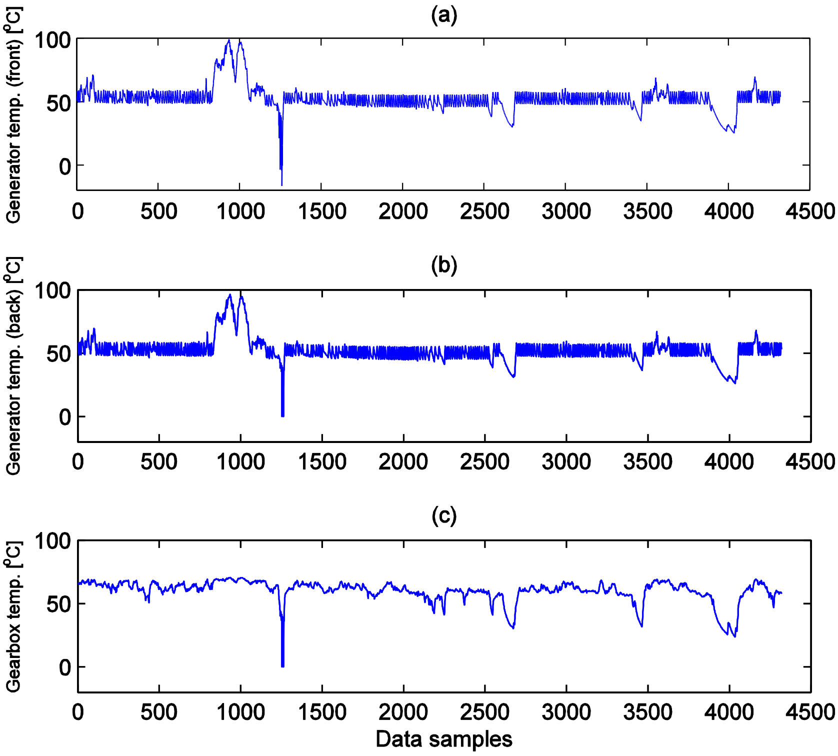

Fig. 5. Temperature data used in this study: (a) generator temperature (front part); (b) generator temperature (back part); (c) gearbox temperature.

6. RESULTS AND DISCUSSION

Selected results of the condition monitoring process and fault diagnosis for the wind turbine using the cointegration residual are presented in Fig. 6. The generator speed (previously plotted in Fig. 2) is plotted again in Fig. 6a to ease the observation and assessment of the results. The temperature parameters and cointegration residual are plotted in Fig. 6b and Fig. 6c, respectively.

In order to make the results in Fig. 6c more clear and readable, the 99.7% statistical confidence levels – with respect to the average of the cointegration residual – were calculated as $\nu \pm 3\sigma$, where ν and σ are the mean and standard deviation, respectively. Two pairs of red dotted horizontal lines indicate these confidence intervals. The values of the cointegration residual between these two confidence levels fall into the area representing that the wind turbine is still operating in the normal condition. In contrast, abnormal problems or faults would occur whenever the cointegration residual goes beyond the confidence levels. Briefly speaking, the turbine fault has been detected using the residual-based control chart.

The results in Fig. 6 show that the cointegration residual successfully detects the gearbox fault. One can also notice that another fault (occurred at the data sample 413) has been detected; however this case is not presented and discussed in this paper. To illustrate more specifically how cointegration residuals can be used for condition monitoring and fault detection of the wind turbine, monitoring process of the gearbox fault is enlarged and presented in Fig. 7. By observing the plot results, the gearbox fault was detected by the cointegration residual in the middle of the data samples 1230 and 1231 when the residual goes beyond the confidence level indicated by the dotted horizontal line.

One might argue that this gearbox fault could be detected by directly monitoring the behaviour of wind turbine parameters (such as generator speed and generated power), without using the resulting cointegration residual. This would be the case but the most important result presented here is that the gearbox fault could be detected at the early stage of its occurrence by using the cointegration residual. Fig. 7 shows that this fault really came to effect at the data sample 1232 after the generator speed was dropped down to the zero value. However, as mentioned above this gearbox fault was detected by the residual in the middle of the data samples 1230 and 1231. A conclusion can be drawn from these results is that the cointegration residual predicted in advance the occurrence of the gearbox fault. More specifically, in this case the gearbox fault was detected one and a half sampling intervals (i.e. about 15 minutes earlier) before its occurrence.

Interestingly, the results obtained in this study demonstrates that the proposed method – although applied for only gearbox and generator temperature data – can effectively monitor the wind turbine and reliably detect the gearbox fault with almost the same quality as the previous work in [17] where four different physical signals (speed, power, temperature and current) of the wind turbine were simultaneously analysed by cointegration. This confirms that temperature data of the gearbox and generator can provide an early indication of wind turbine faults. Furthermore, the use of only gearbox and generator temperature data helps to reduce the number of sensors used for the monitored wind turbine and simplify the cointegration-based data analysis procedure performed.

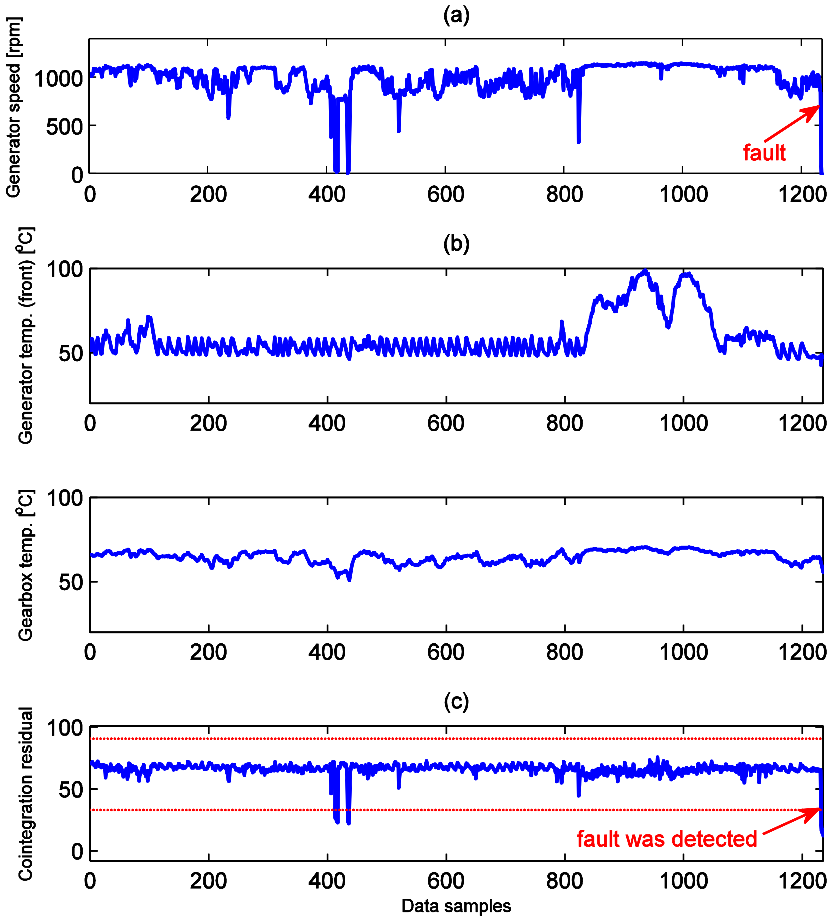

Fig. 6. Condition monitoring and fault detection for the wind turbine using the cointegration residual: (a) generator speed; (b) generator temperature (front part) and gearbox temperature; (c) cointegration residual.

7. CONCLUSIONS

Condition monitoring and fault detection of wind turbines using temperature data of gearbox and generator has been addressed in this paper. Analysis of cointegration residuals – obtained from the cointegration process of gearbox bearing and generator winding temperature data – is used for operational condition monitoring and automated fault detection under the residual-based control chart scheme. The method was illustrated using a case study with a known gearbox fault.

The results have indicated that the proposed method can effectively monitor the wind turbine and reliably detect the gearbox fault as good as the previous study in [17] where different process parameters of the wind turbine were simultaneously analysed by the same cointegration-based method. In summary, this work has contributed a simple, reliable and efficient SCADA data analysis method using only temperature parameters of gearbox and generator for condition monitoring and fault diagnosis of wind turbines.

The work presented is a feasibility study therefore further research work is required to test the method to other wind turbine SCADA database. In addition, the proposed methodology should be investigated for a large number of wind turbines with different types of fault/abnormal components.

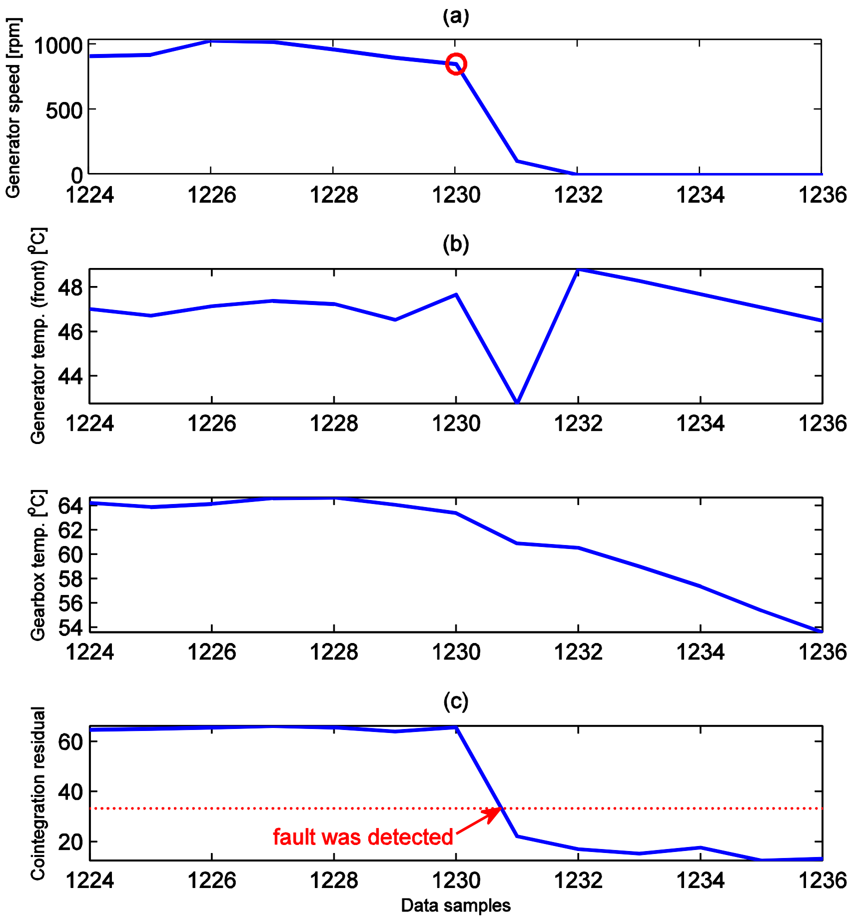

Fig. 7. Zoomed data from Fig. 6 displaying in detail the gearbox fault detection results using the cointegration residual.

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REFERENCES

1. Kusiak A, Li W. The prediction and diagnosis of wind turbine faults. Renewable Energy 2011; 36(1): 6–23.
2. Hameed Z, Hong YS, Cho YM, Ahn SH, Song CK. Condition monitoring and fault detection of wind turbines and related algorithms: a review. Renewable and Sustainable Energy Reviews 2009; 13(1): 1–39.
3. Garcia Marquez FP, Tobias AM, Pinar Perez JM, Papaelias M. Condition monitoring of wind turbines: techniques and methods. Renewable Energy 2012; 46: 169–178. https://doi.org/10.1016/j.renene.2012.03.003
4. Zaher A, McArthur SDJ, Infield DG, Patel Y. Online wind turbine fault detection through automated SCADA data analysis. Wind Energy 2009; 12(6): 574–593.
5. Qiu Y, Feng Y, Tavner P, Richardson P, Erdos G, Chen B. Wind turbine SCADA alarm analysis for improving reliability. Wind Energy 2012; 15(8): 951–966.
6. Yang W, Court R, Jiang J. Wind turbine condition monitoring by the approach of SCADA data analysis. Renewable Energy 2013; 53: 365–376. https://doi.org/10.1016/j.renene.2012.11.030
7. Schlechtingen M, Santos IF, Achiche S. Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description. Applied Soft Computing 2013; 13(1): 259–270.
8. Engle RF, Granger CWJ. Cointegration and error-correction: representation, estimation and testing. Econometrica 1987; 55: 251–276.
9. Johansen S. Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control 1988; 12(2–3): 231–254.
10. Chen Q, Kruger U, Leung AYT. Cointegration testing method for monitoring non-stationary processes. Industrial & Engineering Chemistry Research 2009; 48: 3533–3543.
11. Cross EJ, Worden K, Chen Q. Cointegration: A novel approach for the removal of environmental trends in structural health monitoring data. Proceedings of the Royal Society A 2011; 467: 2712–2732.
12. Dao PB, Staszewski WJ. Cointegration approach for temperature effect compensation in Lamb wave based damage detection. Smart Materials and Structures 2013; 22(9): 095002.
13. Dao PB. Cointegration method for temperature effect removal in damage detection based on Lamb waves. Diagnostyka 2013; 14(3): 61–67.

14. Dao PB, Staszewski WJ. Data normalisation for Lamb wave–based damage detection using cointegration: A case study with single- and multiple-temperature trends. Journal of Intelligent Material Systems and Structures 2014; 25(7): 845–857.
15. Dao PB, Staszewski WJ. Lamb wave based structural damage detection using cointegration and fractal signal processing. Mechanical Systems and Signal Processing 2014; 49(1–2): 285–301. https://doi.org/10.1016/j.ymssp.2014.04.011
16. Dao PB, Klepka A, Pieczonka L, Aymerich F, Staszewski WJ. Impact damage detection in smart composites using nonlinear acoustics - cointegration analysis for removal of undesired load effect. Smart Materials and Structures 2017; 26(3): 035012.
17. Dao PB, Staszewski WJ, Barszcz T, Uhl T. Condition monitoring and fault detection in wind turbines based on cointegration analysis of SCADA data. Renewable Energy 2017; 116(B): 107–122. https://doi.org/10.1016/j.renene.2017.06.089.
18. Dao PB, Staszewski WJ, Klepka A. Stationarity-based approach for the selection of lag length in cointegration analysis used for structural damage detection. Computer-Aided Civil and Infrastructure Engineering 2017; 32(2): 138–153.
19. Cross EJ, Worden K. Approaches to nonlinear cointegration with a view towards applications in SHM. Journal of Physics: Conference Series 2011; 305: 012069.
20. Zolna K, Dao PB, Staszewski WJ, Barszcz T. Nonlinear cointegration approach for condition monitoring of wind turbines. Mathematical Problems in Engineering 2015; vol. 2015 (Article ID 978156) 11 pages.
21. Zolna K, Dao PB, Staszewski WJ, Barszcz T. Towards homoscedastic nonlinear cointegration for structural health monitoring. Mechanical Systems and Signal Processing 2016; 75: 94–108. https://doi.org/10.1016/j.ymssp.2015.12.014.
22. Tsay RS. Analysis of financial time series (vol. Wiley series in probability and statistics). 2nd ed. New York: Wiley Interscience; 2005.
23. Zivot E, Wang J. Modeling financial time series with S-PLUS. 2nd ed. New York: Springer; 2006.
24. Dickey D, Fuller W. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 1981; 49(4): 1057–1072.
25. Kullaa J. Damage detection of the Z24 bridge using control charts. Mechanical Systems and Signal Processing 2003; 17(1): 163–170.

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