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Cointegration Modelling for Health and Condition Monitoring of Wind Turbines - An Overview

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Abstract. The cointegration method has recently attracted a growing interest from scientists and engineers as a promising tool for the development of wind turbine condition monitoring systems. This paper presents a short review of cointegration-based techniques developed for condition monitoring and fault detection of wind turbines. In all reported applications, cointegration residuals are used in control charts for condition monitoring and early failure detection. This is known as the residual-based control chart approach. Vibration signals and SCADA data are typically used with cointegration in these applications. This is due to the fact that vibration-based condition monitoring is one of the most common and effective techniques (used for wind turbines); and the use of SCADA data for condition monitoring and fault detection of wind turbines has become more and more popular in recent years.

Introduction

In recent years, with the fast development of wind power technology, the number and capacity of wind turbines (WTs) have rapidly increased. However, due to the harsh operation environment and time-varying load operation, wind turbines have a high failure rate [1]. It is well known that unexpected failures, especially of large and crucial components, can cause costly repair and excessive downtime. This leads to the increasing of operation and maintenance costs and subsequently the cost of energy. Therefore, it is very important to develop wind turbine monitoring systems that can detect turbine faults at the early stage of fault occurrence. Various condition monitoring techniques have been developed to detect and diagnose abnormalities of WTs, as reviewed in the literature [2-4], such as vibration signal analysis, oil monitoring and analysis, acoustic emission, ultrasonic testing techniques, strain measurement, radiographic inspection, thermography. Another solution – based on the use and analysis of supervisory control and data acquisition (SCADA) data – has been recently developed for early failure detection of wind turbines, as reviewed in [5]. This approach is cost-efficient, readily available, and is beneficial for identifying abnormal components because only key process parameters need to be tracked [1, 5].

Changing environmental and operating conditions of wind turbines are well known to create many difficulties in the signal processing of the measured signals. In particular, wind variations can lead to load variations on the gearbox. Condition monitoring in this case is more challenging and difficult. This implies that monitoring of data trends and removal of undesired effects of environmental and operational variability from wind turbine data are important. Many studies have aimed at developing data analysis/processing methods for effective trend removal, continuous condition monitoring, and reliable abnormal detection of WTs.

Cointegration, a technique originally developed in the econometrics field [6, 7], has recently been introduced to Structural Health Monitoring (SHM) and Condition Monitoring (CM) as a promising data-driven method for the removal of common long-term trends – induced by changing environmental and operational conditions – from the measured data. In essence, the theory of cointegration can be used to combine nonstationary variables to create a stationary combination purged of all common trends in the original data. Therefore, cointegration has been seen as an effective solution to the data normalisation problem in SHM. The main idea behind the use of cointegration for SHM is based on the concept of stationarity and nonstationarity. In a brief description, the variables of interest are cointegrated to create a stationary residual whose stationarity represents normal (or undamaged) condition. Then any departure from stationarity may indicate that monitored processes (or data from monitored structures) are no longer operating under normal condition. Since its first application for the condition monitoring of an industrial distillation unit which was reported in 2009 [8], cointegration has been broadly applied to SHM [9, 10]. These applications have demonstrated that the cointegration process can effectively remove such common long-term trends induced by varying environmental and operational conditions from SHM data. Recently, the cointegration theory has attracted considerable research attention from scientists and engineers worldwide for the development of wind turbine condition monitoring systems. This paper presents a short review of cointegration-based techniques developed for condition monitoring and fault detection of wind turbines in order to demonstrate the state-of-art development of the approach. To the best of the authors knowledge, this issue has not been addressed previously in the literature.

The layout of the paper is organized as follows. Section 2 introduces briefly the cointegration algorithm. Section 3 presents the review and Section 4 provides a discussion on the cointegration-based condition monitoring and fault detection techniques for wind turbines. Finally, the paper is concluded in Section 5.

Cointegration analysis

Consider a time series y_t presented in the form of the first-order Auto-Regressive $AR(1)$ process, which is defined as

$$y_t = \phi y_{t-1} + \varepsilon_t \tag{1}$$

where ε_t is an independent Gaussian white noise process with zero mean, i.e. $\varepsilon_t \sim IWN(0,\sigma^2)$. With different values of the coefficient ϕ, we have three different time series, which are: (1) stationary time series ($|\phi| < 1$); (2) nonstationary time series ($\phi > 1$); and (3) random walk time series ($\phi = 1$).

A random walk time series without a trend is considered as an integrated series of order 1, denoted $I(1)$ [11]. For this time series Eq. (1) yields

$$\Delta y_t = y_t - y_{t-1} = \varepsilon_t \tag{2}$$

Eq. (2) shows that, the first difference of y_t, i.e. $y_t - y_{t-1}$, is a stationary white noise process ε_t. This implies that a nonstationary $I(1)$ time series becomes a stationary $I(0)$ time series after the first difference. In a similar way, a nonstationary $I(2)$ time series requires differencing twice to induce a stationary $I(0)$ time series.

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

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

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 or has 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 [11]. The vector β is called a cointegrating vector. One can imagine that the cointegration residual ($u_t = \beta^T \mathrm{Y}_t$) is created by projecting the vector Y_t on the cointegrating vector β.

A review of cointegration-based approaches to condition monitoring and fault detection of wind turbines

This section presents a short review of recent investigations on cointegration-based condition monitoring and fault detection techniques for wind turbines in order to illustrate the state-of-art development of the approach.

The work in [12-14] presented a novel data analysis/processing method – based on the concept of residual-based control chart – for condition monitoring and fault diagnosis of wind turbines (WTs). The cointegration-based data analysis/processing procedure proposed consists of two stages, i.e. off-line stage and on-line stage, as illustrated in Fig. 1. The main idea of the proposed method relies on the fact that 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. SCADA data – acquired from a WT drivetrain with a nominal power of 2 MW in 30 days under varying environmental and operational conditions – were used to validate the method. Two known problems of the wind turbine (i.e. an abnormal operating state F1 and a gearbox fault F2) were used to illustrate the fault detection ability of the method. The work in [12, 13] used six process parameters of the wind turbine (i.e. wind speed, generator speed, generated power, generator temperature, generator current, gearbox temperature), whereas the investigation in [14] used only the temperature data of gearbox bearing and generator winding. Some selected results of the work in [12] and [14] are shown in Fig. 2 and Fig. 3, respectively. The results have revealed that both studies could effectively monitor the wind turbine and reliably detect abnormal problems with almost the same quality. This confirms that temperature data of the gearbox and generator can provide an early indication of wind turbine faults. Additionally, the use of only gearbox and generator temperature data helps to reduce the number of sensors needed for monitoring the wind turbine. Also, it simplifies the cointegration-based data analysis procedure. What is more, the method proposed in [12-14] has been motivated by the fact of its simplicity and low computational cost in comparison to other commonly used data-mining techniques, e.g., neural network algorithms.

Following the idea of the method developed in [12-14], the work in [15] also used the theory of cointegration for continuously monitoring the operating conditions of wind turbines. First, the optimal combination of different parameters from SCADA data in normal operating condition was determined by using the Johansen's cointegration test and statistical test. Then, the cointegration residuals and stationary threshold boundaries under normal working space were calculated using cointegration analysis. The method was tested using SCADA data of a wind turbine (with nominal power of 2 MW) with known faults. The results have demonstrated that the proposed method can effectively monitor the abnormal state of generator and gearbox, and provide the function of early warning. In addition, the method can monitor several key components of the wind turbine more comprehensively, and avoids the disadvantage of traditional techniques which can only monitor a single parameter.

The work in [16] presented a simulation example of the cointegration-based approach for removing environmental or operational trends from one damage sensitive variable (using a single sensor). This research is meant to be applied for on-line wind turbine gearbox condition monitoring under varying load conditions. Simulation of the dynamic response of a three degree-of-freedom (3-DOF) system to a random excitation was used in the study. In order to introduce effects of imitating environmental or operational conditions, a sinusoidal variation in the stiffness was included in the simulated system. Also, damage was introduced by reducing stiffness parameters. The recursive least square (RLS) algorithm with a forgetting factor λ=0.9 was used to fit autoregressive (AR) models to the simulated accelerations at the model's masses. The order of the AR models was chosen to be twenty. The method started with estimating twenty coefficients using the RLS method for each acceleration. Subsequently, the first five coefficients produced were used to perform cointegration analysis. A statistical process control X-chart was used for anomaly detection. The results have demonstrated the method's potential to be applied on vibration data measured from a wind turbine transmission system, where cointegration can be adapted as a solution for extracting the load variation influences in the gearbox vibration signals.

Condition monitoring of wind turbine gearboxes based on the cointegration analysis of vibration signals was intensively investigated in [17]. Vibration signals taken from three different points on a Sinovel1500 wind turbine gearbox were choosen as analysis variables. Acceleration sensors were mounted on both high speed and low speed shaft bearing to acquire vibration signals. The authors have discussed that the three vibration signals sampled from the gearbox have similar trends. So, there must be a linear cointegration relationship among these vibration signals. The key idea of the method is to establish a cointegration model of the gearbox in normal condition and then analyse the stability of residuals calculated by the cointegration model. Once a gearbox failure occurs, vibration features of the testing point which is close to the position of failure will be changed. Consequently, the cointegration relationship is broken and the stability of cointegration residuals changes accordingly. This work also used statistical process control to set the thresholds of residuals as the failure warning level. Through the simulation analysis of gearbox fault data, the results verify the effectiveness of cointegration in monitoring condition of wind turbine gearbox. Selected results of this work are shown in Fig. 4.

A cointegration-based monitoring method for rolling bearings working in time-varying operational conditions was recently developed in [18]. The proposed method was applied to vibration signals measured on an experimental bearing test rig. The signals – acquired during run-up condition – were first decomposed into zero-mean modes called intrinsic mode functions using the improved ensemble empirical mode decomposition method. Next, cointegration analysis was applied to the intrinsic mode functions to extract stationary residuals. The feature vectors were then created by applying the Teager-Kaiser energy operator to the stationary residuals. Finally, the feature vectors of the healthy bearing signals were utilised to construct a separating hyperplane using the one-class support vector machine method. The results confirmed that the method could successfully distinguish between healthy and faulty bearings even if the shaft speed changes considerably.

An interesting application of cointegration to analyse vibration signals for local damage detection in gearboxes was presented in [19]. The work started with the assumption that the correlation of given vibration signal is periodic and its period can be measured. Then, signal was restructured and divided into sub-signals according to the discovered period. Next, sub-signals were checked if they are integrated and the cointegrating vector was calculated by using the least squares method. Finally, in order to test if the cointegrating vector corresponds to healthy or damaged gearbox the authors examined whether it exhibits random (chaotic) behaviour by using the Wald-Wolfowitz test for randomness. The proposed methodology was validated using simulated vibration signals and real data from a two-stage gearbox (with first stage being conical and second cylindrical) used in mining industry. Based on the analysis of cointegrating vectors the damaged gearbox could be detected.

In [20], the authors have explored the use of cointegration in detection of structural damage in the blade of an operating Vestas V27 wind turbine under the effect of certain environmental and operational variabilities (EOVs). The experimental campaign included a measurement period of 3.5 months, in which the blade in question was instrumented with 11 piezoelectric accelerometers (distributed along the leading and trailing edge). The wind turbine was analysed in a healthy/reference state and three damaged scenarios where a trailing edge opening was introduced gradually to the instrumented blade with increasing size from 15 cm long, to 30 cm long, and finally 45 cm long. In addition to acceleration measurements in the different structural states, the study recorded the varying environmental and operational conditions (including wind speed and direction at different altitudes, ambient temperature, atmospheric pressure and precipitation) over the 3.5-months period. The Q-statistics was employed as the damage metric to quantify the discordance between the statistical baseline representing the healthy structural state and realizations from the potentially damaged state. The results have demonstrated that cointegration can be used to successfully detect the introduced damages under conditions not allowing for direct discrimination between damage and EOVs.

It should be noted here that all applications – reported in [8-10] for SHM systems and in [12-20] for wind turbine condition monitoring – have used the linear cointegration theory that was originally developed in [6, 7] and intimately connected with the concept of linear error correction models. However, it is well known that response signals (e.g. Lamb waves, vibration data, SCADA data) acquired from engineering structures or wind energy systems often exhibit not only nonstationarity, but also nonlinear behaviour. Moreover, operational and environmental trends are typically believed to be nonlinearly related with response data used for damage detection or condition monitoring. If this is the case then the conventional linear cointegration theory might be no longer suitable for structural damage detection as well as process condition monitoring and therefore nonlinear cointegration approaches are highly needed.

The work in [21] brought the concept of nonlinear cointegration to SHM. However, a major problem was observed, that is, the variance of cointegration residuals (calculated for a healthy structure) increased with time, although cointegrated variables were mean stationary. This behaviour – known in mathematics as the heteroscedasticity – implied that strictly stationary cointegration residuals could not be obtained. When a cointegration residual with unstable variance characteristics is used in a control chart (i.e. statistical process control) for condition monitoring of a wind turbine, it is not possible to identify accurately that whether a gearbox failure occurs when the residual exceeds a threshold. So, it is clear that reliable condition monitoring methods for WTs based on nonlinear cointegration would require homoscedastic cointegration residuals (i.e. strictly stationary residuals) to prevent false diagnosis results. Recently, the work in [22, 23] has investigated a new approach to nonlinear cointegration, with applications towards SHM and wind turbine condition monitoring – which could solve the problems of heteroscedasticity and nonlinear trend removal. As a result, an approximately homoscedastic nonlinear cointegration method has been proposed for the removal of undesired (environmental, operational or measurement) trends from SHM data in general and wind turbine SCADA data in particular. The method has been successfully applied for condition monitoring and fault detection of a wind turbine drivetrain with a nominal power of 2 MW in the presence of nonlinearity between operational parameters.

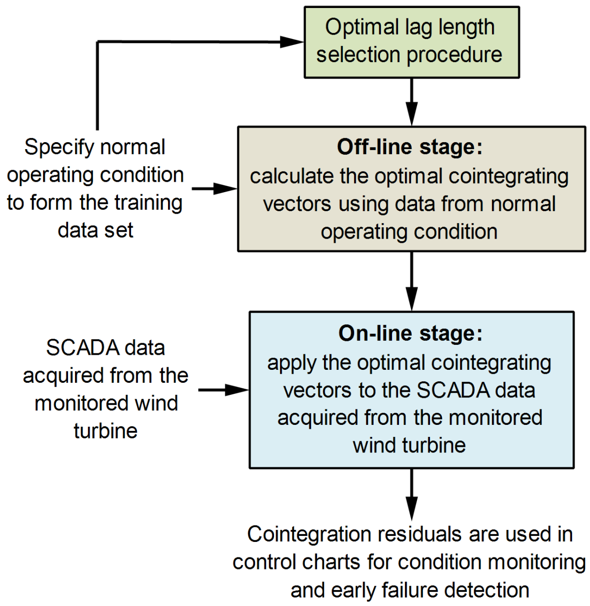

Fig. 1 Cointegration-based data analysis procedure for condition monitoring of wind turbines using SCADA data [12].

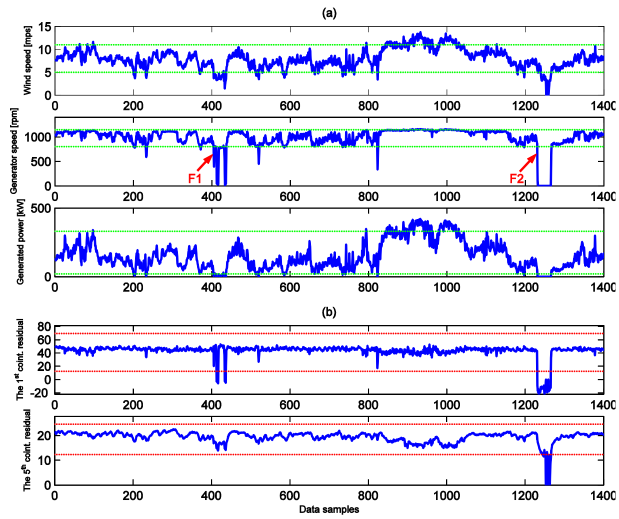

Fig. 2 Condition monitoring and fault detection of the wind turbine using multiple process parameters [12]: (a) abnormal operating state (F1) and gearbox fault (F2); (b) monitoring of F1 and F2 using the 1st and 5th cointegration residuals in control charts.

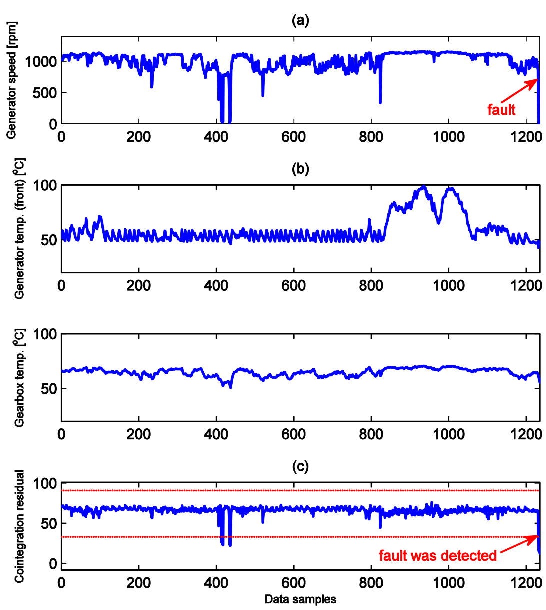

Fig. 3 Condition monitoring of the wind turbine using only the temperature data of gearbox and generator [14].

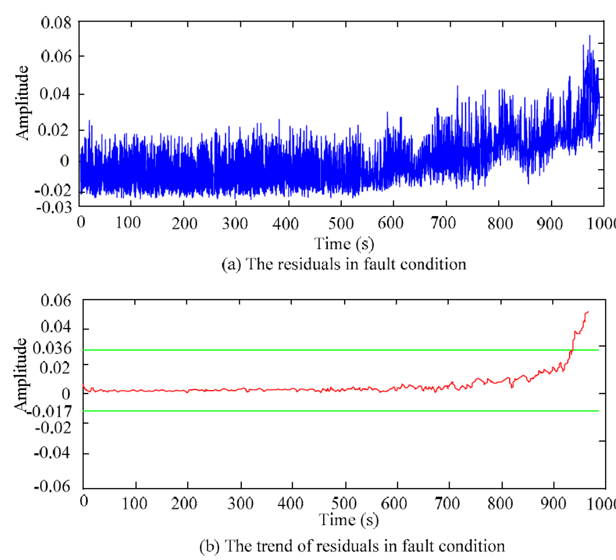

Fig. 4 Monitoring of the wind turbine conditions using cointegration [17]: (a) the residual in fault condition; (b) the residual trend in fault condition.

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Discussion

Some important remarks and a comprehensive comparison between the cointegration-based method and other relevant approaches for condition monitoring and fault detection of wind turbines are presented in the following.

First of all, it should be noted that the major idea of the cointegration-based condition monitoring and fault detection techniques for wind turbines [12-23], as reviewed in Section 3, is basically relied on the well-known control chart approach, which is one of the primary techniques of statistical process control. Basically, control charts plot the quality characteristic as a function of the sample number. The charts have lower and upper control limits, which are computed from the samples recorded when the process is assumed to be in control. When abnormal sources of variability are present, sample statistics will plot outside the control limits and an alarm signal will be produced. An advantage of control charts is that they can be automated for on-line structural health monitoring.

Second, condition monitoring systems of wind turbines, as reported in Section 3, have employed the cointegration technique for either vibration data [16-20] or SCADA data [12-15, 22, 23]. It is due to the fact that vibration signals of gearbox contain a large number of operating condition information. Hence, it is common to use vibration signals for fault prediction and diagnosis. Regarding SCADA-based approaches, since standard SCADA systems have been installed in the majority of utility-scale WTs for system control, data logging and performance monitoring so that the data needed for analysis is readily available and no additional hardware and sensors are required when developing a SCADA-based condition monitoring (CM) system [5, 12]. Hence, this is a potentially low cost solution. In addition, SCADA-based CM systems can be designed to operate in on-line or off-line mode. Because of these advantages, SCADA data have been used with cointegration to develop monitoring systems for WTs. It is suggested that if gearbox vibration signals of a wind turbine are combined with its SCADA data for cointegration analysis, earlier fault prediction can be achieved with high accuracy.

Next, it should be mentioned that regression analysis can be used for condition monitoring of wind power systems, as illustrated in [24]. However, cointegration analysis has been used in [12-23] instead of other regression techniques is due to two main reasons: (1) to avoid the problem of spurious regression; and (2) to actively deal with the undesired effect of environmental and operational conditions in the analysed data. The former has been discussed broadly in the econometrics literature [25]. The problem arises when standard regression analysis fails while dealing with nonstationary variables, leading to spurious regressions that suggest relationships even when there are none. For example, if two time series show monotonic trends, even if the trends are not causally related, ordinary least-squares (OLS) regression will potentially find a spurious relationship. The later relates to the capability of cointegartion analysis for removing undesired effects of environmental and operational variability from wind turbine SCADA data (SHM data in general), while still maintaining sensitivity of cointegration residuals to faults, structural damage, or abnormal problems. This process is known as data normalisation.

Finally, in comparison with typical data-mining algorithms, such as neural network (NN), support vector machines, adaptive neuro-fuzzy interference systems (ANFIS), decision tree learning, or naive Bayes classifier, cointegration-based condition monitoring algorithms are simpler and requires much less computational resources. For example, in the study [12-14], the calculation of cointegrating vectors in the off-line stage takes only few seconds on a normal computer. Then, the cointegration residual is obtained through projecting the SCADA data – acquired from the monitored WT under regular working phase for producing electricity – on the resulting cointegrating vectors. This is done simply by multiplying a vector of time series variables by one cointegrating vector to form one cointegration residual, or multiplying a matrix of time series variables by cointegrating vectors to obtain cointegration residuals. This computation process can be promptly executed in real-time manner on a computer-based condition monitoring system, thereby providing a simple on-line condition monitoring solution for wind turbines. Furthermore, cointegration can be used in practice to monitor a wind turbine system without the need of analysing many nonstationary variables. Through monitoring a cointegration residual, one can achieve the objective of simultaneous monitoring of multiple nonstationary variables [12, 16].

Conclusions

This paper have reviewed recent investigations on cointegration-based condition monitoring and fault diagnosis techniques for wind turbines. First of all, it is observed that all reported applications have used cointegration residuals in control charts for condition monitoring and early failure detection. This is known as the residual-based control chart approach. Second, only vibration data and SCADA data have been used with cointegration in these applications so far. This is due to the fact that vibration signals are the most common condition monitoring signals and SCADA-based condition monitoring has become more and more popular in recent years.

An important conclusion is that the cointegration-based techniques can automatically interpret and analyse a large amount of low-sampling rate SCADA data and enables a transition from a singular process parameter analysis to automatic interpretation and analysis of a large number of process parameters. Moreover, simplicity and fast computation are the major advantages of cointegration-based techniques, if comparted with other common techniques (such as NN-based and ANFIS-based algorithms). Hence, the cointegration-based condition monitoring algorithm for wind turbines using vibration signals and SCADA data can be computed on-line and deployed on a computer for real-time condition monitoring applications.

Furthermore, the use of cointegration can remove, compensate, or at least, mitigate the effect of environmental and operational variability in vibration and SCADA data used for condition monitoring and fault detection of wind turbines.

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