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Reducing sensor complexity for monitoring wind turbine performance using principal component analysis

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ABSTRACT

Availability and reliability are among the priority concerns for deployment of distributed generation (DG) systems, particularly when operating in a harsh environment. Condition monitoring (CM) can meet the requirement but has been challenged by large amounts of data needing to be processed in real time due to the large number of sensors being deployed. This paper proposes an optimal sensor selection method based on principal component analysis (PCA) for condition monitoring of a DG system oriented to wind turbines. The research was motivated by the fact that salient patterns in multivariable datasets can be extracted by PCA in order to identify monitoring parameters that contribute the most to the system variation. The proposed method is able to correlate the particular principal component to the corresponding monitoring variable, and hence facilitate the right sensor selection for the first time for the condition monitoring of wind turbines. The algorithms are examined with simulation data from PSCAD/EMTDC and SCADA data from an operational wind farm in the time, frequency, and instantaneous frequency domains. The results have shown that the proposed technique can reduce the number of monitoring variables whilst still maintaining sufficient information to detect the faults and hence assess the system's conditions.

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1. Introduction

Distributed generation (DG) systems comprising of renewable energy generation technologies will play a significantly increasing role in future power systems [1,2]. A distributed generation system normally consists of hybrid renewable energy generation units embedded in the system. An example of wind-turbine-based DG system is shown in Fig. 1, where turbines are interfaced with the grid at a point of common coupling (PCC). Two of the major challenges for deployment of a DG system are its reliability and maintainability, which can be overcome by condition monitoring. The condition monitoring process can be divided into several components including data acquisition, signal processing and diagnosis and prognosis [3]. To achieve effective condition monitoring, accurate and reliable measurements are crucial. Fig. 2 shows the architecture of a distributed condition monitoring system that was originally developed for conventional power plants but has been used for wind farm condition monitoring for some time. In this system, a large amount of condition monitoring data and SCADA (supervisory control and data acquisition) data need to be transferred to a local CM server for processing and storing or, alternatively, to a remote support centre for further fault analysis.

A condition monitoring system can incorporate present and past data monitored by the sensors to diagnose and predict potential failures. By doing so, the performance, availability and reliability of wind turbines can be improved. Studies have shown that operation and maintenance (O&M) cost plays a significant role in calculating the cost of energy (CoE); a higher-quality O&M regime can achieve higher availability, lower through-life costs and hence a lower CoE [4]. Moreover, the deployment of condition-based maintenance has been proven to be far superior to the conventional preventive and periodic maintenance strategies [5,6]. However, handling, processing and transmitting a huge amount of data will lead to more complex CM systems being built up and hence result in a negative impact on the performance, maintainability and cost of the CM systems [7]. For a typical wind turbine, there can be more than 250 sensors required to monitor most subsystems; it is envisaged the number of sensors will be significantly increased for a wind farm [8,9]. Therefore, if the number of sensors or measurements installed can be reduced whilst still maintaining a necessary number to assess the system's condition, the data acquisition

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Nomenclature

Acronyms

DG	Distributed generation
CM	Condition monitoring
CoE	Cost of electricity
O&M	Operation and maintenance
PCC	Point of common coupling
HHT	Hilbert-Huang transform
EMD	Empirical model decomposition
IMF	Intrinsic mode function
PCA	Principal component analysis
Cppv	Cumulative percentage partial covariance
PMSG	Permanent magnet synchronous generator
SCADA	Supervisory control and data acquisition

Roman symbols

a_i	Instantaneous amplitude at level *i*
c_i	*ith* intrinsic mode function
C	Capacitance, F
C_p	Wind turbine power coefficient
$E(X)$	Information entropy of variable X, bit
h	Sum of the squared correlations
h_{ik}	*ith* temporary IMF at *k* iteration
$H(X)$	Normalised information entropy of variable X
I	Grid current, A
I_{dc}	DC-link current, A
L	Inductance, H
L	Characteristic root matrix
m_{ik}	*ith* envelope of a signal at *k* iteration
r	Pearson's correlation coefficient
r_i	*ith* residual signal in EMD
r_z	Fisher's correlation coefficient
R	Resistance, Ω
$\boldsymbol{S}$	Covariance matrix
$\boldsymbol{S}_{rr}$	Covariance matrix of retained dataset
$\boldsymbol{S}_{dd}$	Covariance matrix of discarded dataset
$\mathbf{S}_{\mathrm{rr.d}}$	Partial covariance matrix of retained dataset
$\boldsymbol{U}$	Characteristic vector matrix
V	Grid voltage, V
V_{dc}	DC-link voltage, V
V_w	Wind speed, m/s
$x(t)$	Real part signal in Hilbert transform
$\boldsymbol{X}$	Input dataset matrix
$y(t)$	Imaginary part signal in Hilbert transform
$\boldsymbol{Z}$	Principal component matrix

Greek symbols

β	Pitch angle, °
η_e	Percentage entropy, %
λ	Tip speed ratio
ω	Angular frequency, rads/s
ω_i	Instantaneous frequency, rads/s
φ	Phase angle, °
ϑ_i	Instantaneous phase angle at level *i*, °

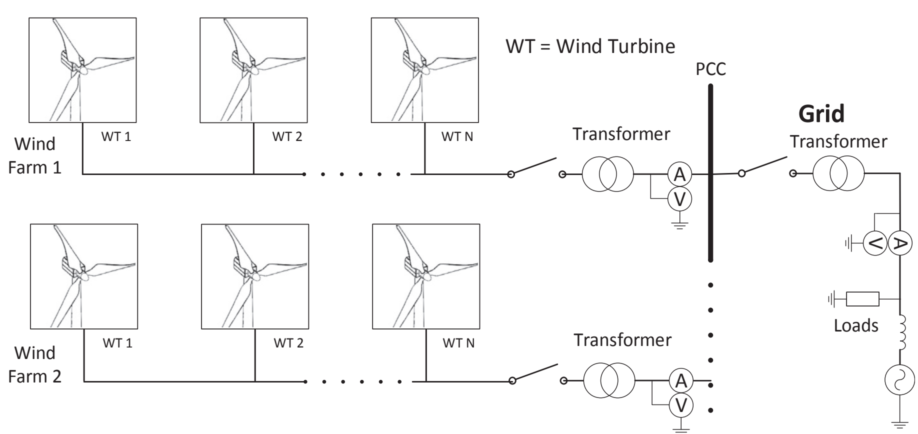

Fig. 1. An example of distributed generation (DG) network, taking the wind turbines as DG units.

system can be simplified and the performance, maintainability and cost benefit of CM systems to be developed can be enhanced.

Currently, data acquisition for condition monitoring systems is implemented mainly based on information maximisation principle, which means sensors are installed to obtain as much data as possible. Due to relationships existing among sensors, there is redundancy within the data collected. Thus, an appropriate sensor selection technique is desirable in order to identify and remove these unnecessary redundancies due to there being too many sensors carrying out similar functions. In the meantime, the method should be able to retain the provision of vital information, which is critical for fault diagnosis, prognosis and maintenance scheduling.

There are a number of researches that have been carried out regarding sensor selection in complex sensor network systems. Information-based techniques are commonly adopted such as mutual information, information entropy, and fisher information. An entropy based sensor-selection approach has been proposed in Ref. [10] for an aerospace propulsion health monitoring system based on quantification of particular fault conditions and diagnostics. Sensor selection schemes were also proposed for tasks like target tracking and mission assignments in order to minimise the number of active sensors in a sensor network and hence reduce the energy use and prolong the lifetime of the sensor network [11]. A stochastic dynamic programming method was proposed to solve the sensor selection problem of robotic systems in real time [12].

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