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Reliability assessment of wind turbine bearing based on the degradation-Hidden-Markov model

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ABSTRACT

Wind power develops very quickly in last decade to overcome the energy crisis and environment crisis. Mechanical components of wind turbines usually have characteristic with performance degradation that results in the declining reliability over time. Generally, the reliability data of equipment come from statistical analysis based on extensive experiments and operations. However, wind turbines, as expensive large-scale equipment with long lifetime, face with the dilemma of lacking enough statistical data, and leads to insufficiency reliability data for field operations and thus results in frequent wind turbine faults. A new reliability assessment method based on Hidden-Markov model considering performance degradation, called degradation-Hidden-Markov model, is proposed in this paper. The performance degradation rule of wind turbine component is derived using the monitoring data of performance parameters. Hidden-Markov model is improved by the performance degradation rule of the component to create a new time-correlated state transition probability matrix with degradation feature. The reliability curve is obtained using the state probabilities of the degradation-Hidden-Markov model. Thus, the presented method realizes the reliability assessment of component based on small sample data of wind turbine. Finally, the reliability assessment of a gearbox bearing of a 1.5 MW wind turbine by the degradation-Hidden-Markov model proves its validity.

1. Introduction

Nowadays wind energy plays an increment significant role in providing electricity all around the world due to its advantages of renewable and clean source of energy. According to the data released by the Global Wind Energy Council (GWEC) in Global Wind Report: Annual Market Update, the cumulative wind power capacity installed in world was 487 GW with a global growth rate of approximately 12% at the end of 2016, and will be over 800 GW by the end of 2021 [1].

Coal is the dominant form for power generation in China and it is the main contributor to the current environmental crisis. China has been working hard to develop wind energy to reduce the use of coal these years. By the end of 2016, the cumulative wind power capacity installed in China was 169 GW, who has been the biggest producer and consumer of wind power in the world [1]. However, the first Chinese commercial wind farm was installed in 1986 [2] and the MW level wind turbine (WT) began to develop in 2003. The design period for most of WTs was short while the wind power capacity grew extremely quickly in China [3], which results in the lack of operation experiences for most of Chinese WT operators.

The Chinese wind energy provided 4% of the total power generation while the wind power capacity installed accounted for 9% of the total, and the mean operation hours of WTs is only 1742 h in China during 2016 [4]. There are two main reasons for the short mean operation hours of Chinese WTs: WT faults and weak renewable power grid-connection.

Generally, the designed life of WTs is normally 20–25 years for onshore and 25–30 years for offshore. However, it is reported that current operating lifetime for a large number of turbines is only between 5 and 13 years that is much lower than the initial expectation [5]. The performance of WTs inevitably degrades and results in the unpermitted deviation of characteristic property from the acceptable condition over time during the service period, thus finally results faults. With the large-scale development of wind energy, the reliability of WTs becomes more important. On the one hand, frequent premature failures result in high downtime,

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Nomenclature

a_{pq}	transition probability from hidden state S_p to hidden state S_q
A	state transition probability matrix of HMM
b_{qm}	probability of observable parameter being G_m while hidden state being S_q
B	observable parameter probability matrix of HMM
$F(t)$	partial fitting exponential function of performance degradation
$\widehat{F}(t_j)$	dimensionless performance degradation function
G	grade of performance parameters
O	observable parameter sequence of HMM
R	reliability
S	hidden state of HMM
t	time
U	residual error
y	performance parameter

Abbreviations

WT	wind turbine
DHMM	degradation-Hidden-Markov model
HMM	Hidden-Markov model
CBM	Condition-based maintenance

Greek symbols

Δ	increment
ε	deviation
ζ	performance degradation rate
λ	HMM of WTs
π	hidden states probabilities of HMM
σ	standard deviation

Subscript

d	degradation
f	failure

Superscript

*	threshold of parameter
-	mean value
′	time-correlated

production loss and maintenance cost. Feng quantified the total costs of WFs and found that the annual average O&M (operation and maintenance) cost as a percentage of the total cost of energy of a WT is 18% for offshore wind farms and 12% for onshore in UK [6]. On the other hand, the large-scale wind energy grid-connected has potential negative impacts on the safety of power grids because of the intermittent character of wind.

The purpose of the reliability analysis is to describe a failure and its impact on components and systems, thus help to improve design or prevent unacceptable impacts to build a safe and reliable WT system [7]. WT reliability data includes failure distributions, downtime distributions, failure rates as failures per turbine per year, downtime as hours lost per component per WT per year et al. [8]. Probability and statistics, such as the Gaussian (normal) distribution, the log-normal distribution, the Rayleigh distribution, the exponential distribution, and the Weibull distribution, are applied to evaluate the reliability and failure characteristics of a WT [7]. Moreover, there are different mathematical models such as point processes, Poisson processes, homogeneous Poisson process (HPP), and non-homogeneous Poisson process (NHPP) to model WT reliability [9].

Most WT failures are due to the following components and systems: frequency converter, generator, gearboxes, main bearing, blades, tower, pitch systems, yaw systems and braking systems [3,10]. It is concluded that blades, control and electrics are components with the highest failure rates [8]. Rademakers investigated the downtime distribution of WT components and found that more than 85% of the total downtime of WTs was due to the blades, generator and gearbox [11]. Especially, gearbox's downtime per failure is highest in WTs with approximately 20% of the wind system downtime [12], and the main systems subjected of concern are gearbox bearings, gear wheels and the lubrication [13].

Since large turbines experience higher wind than smaller ones that lead to a bigger deterioration of components, larger WTs tend to appear more failures than smaller ones [7,14]. Tavner found there was a significant cross-correlation between the failure rate and the weather conditions, especially temperature and humidity were more important factors than wind speed [15]. Kim carried out a reliability analysis of jacket type offshore WT support structure under extreme ocean environmental loads [16]. Toft found that the uncertainty in the site specific wind climate parameters accounts for 10–30% of the total uncertainty in the structural reliability analyses [17]. Nejad carried out a long-term fatigue damage analysis for gear tooth root bending in WTs and calculated the reliability considering load and load effect uncertainties [18].

Moreover, Arabian-Hoseynabadi applied a comprehensive Failure Modes and Effect Analysis (FMEA) on a 2 MW WT in design stage, and investigated the relationship between quantitative FMEA results and WT field assembly failure rates [19]. Kang carried out risk assessment by a correlation-FMEA method to obtain the weakest failure of the floating offshore WT, and they found the material corrosion is the key factor of failure [20]. Zhang applied system grading and dynamic Fault Tree Analysis (FTA) to predict the reliability of floating offshore WT [21]. Márquez analyzed failure modes of WT qualitatively by FTA [22]. Li proposed a reliability assessment framework for the generic geared WT systems based on a Goal Tree, Success Tree and Master Logic Diagram [23].

The performance of WTs inevitably degrades over time due to aging effect during the service period. The component has a higher failure probability when it is in the deterioration period, thus its operation quality decreases rapidly and the decrease is proportional to the severity of the potential failure [24]. Supervisory Control And Data Acquisition (SCADA) system collects data from critical components of WTs to understand turbines' operational performance in a long time condition, Dao presented a methodology-based on the cointegration analysis of SCADA data to analyze nonlinear data trends and monitor WTs operation [25]. The degradation assessment of system level metrics is significant for WTs. Based on the statistical analysis of two partly overlapping datasets comprising 1100 monthly and 1300 hourly time series spanning 5–25 years for each in Sweden, Olauson found that WTs lost 0.15 capacity factor percentage points per year corresponding to a 20-year energy loss of around 6% [26]. Staffell used SCADA data to study the ageing degradation of WTs in UK, they found WTs lost $1.6 \pm 0.2\%$ of their output per year and degradation reduced a wind farm's output by 12% and increased the levelised cost of electricity by 9% over twenty years [27].

In order to avoid critical failure and extend the life of WTs, it is