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Structural health monitoring of offshore wind turbines: A review through the Statistical Pattern Recognition Paradigm

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A B S T R A C T

Offshore Wind has become the most profitable renewable energy source due to the remarkable development it has experienced in Europe over the last decade. In this paper, a review of Structural Health Monitoring Systems (SHMS) for offshore wind turbines (OWT) has been carried out considering the topic as a Statistical Pattern Recognition problem. Therefore, each one of the stages of this paradigm has been reviewed focusing on OWT application. These stages are: Operational Evaluation; Data Acquisition, Normalization and Cleansing; Feature Extraction and Information Condensation; and Statistical Model Development. It is expected that optimizing each stage, SHMS can contribute to the development of efficient Condition-Based Maintenance Strategies. Optimizing this strategy will help reduce labor costs of OWTs' inspection, avoid unnecessary maintenance, identify design weaknesses before failure, improve the availability of power production while preventing wind turbines' overloading, therefore, maximizing the investments' return. In the forthcoming years, a growing interest in SHM technologies for OWT is expected, enhancing the potential of offshore wind farm deployments further offshore. Increasing efficiency in operational management will contribute towards achieving UK's 2020 and 2050 targets, through ultimately reducing the Levelised Cost of Energy (LCOE).

Contents

Abbreviations: AE, Acoustic Emission; OM, Operational Management; CB, Carbon Fiber; OMA, Operational Modal Analysis; CM, Condition Monitoring; OWF, Offshore Wind Farm; EOC, Environmental and Operational Conditions; OWT, Offshore Wind Turbine; EU, European Union; O&M, Operations and Maintenance; FBG, Fiber Bragg Grating; RSA, Response Surface Analysis; FEA, Finite Element Analysis; SHMS, Structural Health Monitoring Systems; FMECA, Failure Mode, Effects and Criticality Analysis; SVM, Support Vector Machines; LCOE, Levelised Cost of Energy; WF, Wind Farm; MEMS, micro-electromechanical system; WSN, Wireless Sensor Network; NN, Neural Networks; WT, Wind Turbine

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1. Introduction

Over the past 15 years, Wind Energy has experienced a remarkable growth in the European Union (EU). While in 2000 wind energy contributed 2.4% of the EU's electricity demand, by 2015 this percentage raised to 11.4%, or in absolute numbers, 12.9 GW of installed capacity became 141.6 GW. This rapid development is not only due to the targets set by the EU in 2006 for all Member States [1], but also due to the scalability of wind energy with units of larger capacity been deployed in larger farms, further offshore [2]. According to Renewable UK, Offshore Wind (OW) has officially become the most profitable renewable energy source since, it can produce more renewable energy than all of the other sources combined [3]. In Europe, including sites under construction, there are 84 Offshore Wind Farms (OWF) in 11 countries as of the end of 2015. Furthermore, 3,230 turbines are now installed and operational, reaching a cumulative installed capacity of 11,027 MW. In 2015 only, a grid-connected capacity of 3,019 MW, was added, accounting for almost double of the capacity added in 2014 [4]. Moreover, due to the increased deployment of 4–6 MW turbines in 2015, the average Offshore Wind Turbine (OWT) size became 4.2 MW, constituting a 13% increase over 2014.

Considering wind energy as a mature technology, allows developers and operators to gain confidence to include this energy technology within their mainstream portfolios. Increasing availability of farms and reliability of units, decreasing unscheduled maintenance and eliminating unexpected catastrophic failures, are the targets that attract focus towards deploying the next generation of wind farms. Structural Health Monitoring Systems (SHMS) can contribute significantly towards enhancing OWT's profitability, reliability and sustainability through more systematic operational management approaches. SHM represents the procedure of implementing a damage detection strategy for engineering infrastructures related to aerospace, civil and mechanical engineering [5], being damage referring to the variations in material and/or geometric properties of these systems [6]. Some of the most known structural damage roots are: moisture absorption, fatigue, wind gusts [7], thermal stress, corrosion [8], fire and lightning strikes [9]. Usually, there are two critical aspects that influence SHMS development: the sensing technology (and the associated signal analysis), and the interpretation algorithm [10].

Damage identification is performed through five similar disciplines [11]: SHM, Condition Monitoring (CM) [12], Non-Destructive Evaluation [13], Statistical Process Control [14], and Damage Prognosis [15,16]. Apart from the CM of rotating machines, SHM for OWT remains a research topic which is slowly getting into the field deployment stage. This is due to the early stage of the technology's deployment, the additional challenge that offshore environments pose to these technologies, and associated costs to operators for hardware installation and data processing.

Farrar and Sohn [17] were the first to introduce the Statistical Pattern Recognition Paradigm in the SHM field. This methodology follows four stages:

1) *Operational evaluation:* This stage tries to set the boundaries of the problem by replying to four questions concerning the implementation of the Damage Identification Facility. Questions are related to: the motivation and economic justification for implementing the SHMS, the different Systems' damage definitions, the Environmental and Operational Conditions (EOC) in which the SHMS are used, and the data acquisition limitations in the operational environment.
2) *Data acquisition, normalization and cleansing:* Data Acquisition refers to the selection of the excitation methods, type, quantity and location of sensors, and the Data Acquisition/Storage/Transmittal Hardware [18]. Data Normalization is another crucial aspect for the Damage Identification Process, as there are numerous conditions in which measurements can be taken [19]. Therefore, this Normalization constitutes the procedure of separating variations in sensor readings produced by damage, from those produced by the variation in EOC. Data Cleansing is the procedure of selecting data which is passing on to or rejecting from the Feature Selection procedure [11]. Two examples of Data Cleansing processes are filtering and resampling, which constitute Signal Processing Techniques [20].
3) *Feature extraction and information condensation:* This is the aspect of the SHMS that attracts most attention, as these features allow the distinction between damaged and non-damaged structures [21,22]. Data Condensation is essential when analogue feature sets acquired along the structure's lifetime are envisioned. Due to the extraction of data from a structure during long periods of time, robust data reduction techniques have to be developed to preserve feature sensitivity to the changes of interest.
4) *Statistical model development:* It is related with the implementation of the algorithms that work with the extracted features and calculate the extent of the damage to the structure. These algorithms can be divided into the two categories that are shown in Fig. 1 [23–25]. All of these algorithms assess statistical distributions of the measured or derived features, to enhance the damage identification process.