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# An integrated operational system to reduce O&M cost of offshore wind farms

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ABSTRACT: Offshore wind is a relatively new industry and it is generally more expensive to generate electricity than many alternative renewable sources. Operation & Maintenance (O&M) makes up a significant part of the overall cost of running Offshore Wind Turbines (OWT). Since the O&M associated responsibility is shared among turbine manufacturers, wind farm operators and the offshore transmission owners, this has inevitably led to lack of information, duplication of effort and less efficiency. Big data analytics is one great technique that will drive future growth. In this paper, an integrated operational system of offshore wind farm is proposed deploying big data analytics. Firstly, the current state of the O&M of offshore wind farm and the big data analytics are introduced. Afterwards, a predictive maintenance model and a maintenance implementation model are proposed, and an integrated operational system is developed incorporating those two models in order to optimize maintenance planning and implementation. Finally, the possible contribution of such a system to a more effective O&M of offshore wind farm is discussed.

## 1 INTRODUCTION

The future development of Dutch wind energy will for a large part take place in the sea: the Dutch government plans to realize an offshore wind energy capacity of 3,450MW by 2023 (Gebraad, 2014; Broek, 2014).

The size of wind turbine has been enlarged continuously to increase the power output, see Figure 1 (Chemnews); Wind turbines are being placed further offshore, see Figure 2 (Rohrig, 2014).

The harsh offshore environment leads to more intense mechanical stress within the turbine (Ribrant, 2006), and the annual failure rate of wind turbines has arisen substantially as shown in Figure 3 (Echavarria et al., 2008).

The operational unavailability reaches 3% of the lifetime of WTs. Statistics show that the O&M cost makes up a significant part of the overall cost of running offshore wind farms(Nabati & Thoben, 2017), ranging from 10%–20% of the total cost at the initial stage to 35% at the end stage of a wind project (Tchakoua et al., 2014)

In general, the O&M efficiency of offshore wind farms can be improved from three aspects, namely wind turbine monitoring, supply chain

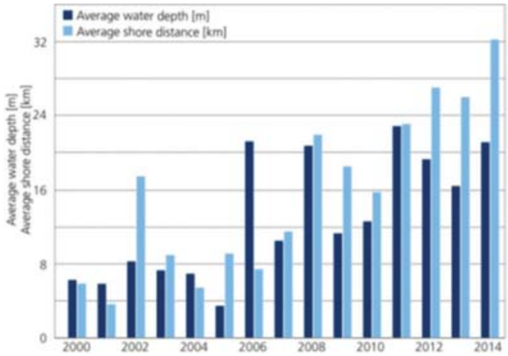


Figure 1. Wind turbine size and power output.

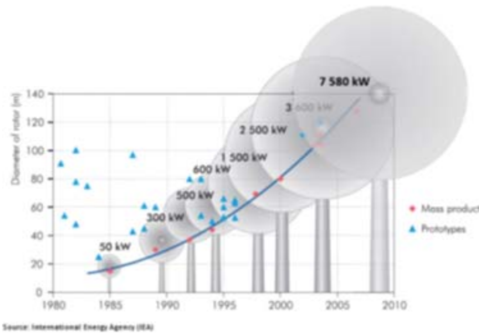


Figure 2. Wind turbines are placed further offshore.

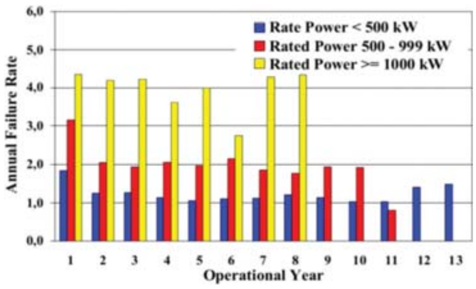


Figure 3. Annual failure rate of different rated power.

management and marine operations (Coronado & Fisher, 2015) To date, academic research on O&M of offshore wind tends to concentrate on the wind turbine monitoring. (Márquez et al., 2012; Kusiak & Li, 2011) However, although abundant data becomes available, the data itself is not identical to useful information. There are remaining challenges about how to extract valuable information from a large number of data. Comparatively, supply chain management and marine operations have received little attention. The supply chain management is more a business specific activity on a top level, it will not be covered in this paper. The marine operation contributes 12.5% to the total cost of O&M, it presents a potential for immediate efficiency gains and offers significant cost savings for minimal investment (Koopstra, 2015; Zheng H et al., 2016; Wang K et al., 2017a). In those regards, it is valuable to develop an integrated system to improve the effectiveness of O&M by accounting for both conditional monitoring of WTs and the marine operation.

This paper aims to propose such an integrated system to optimize O&M deploying big data analytics. This system would take the wind turbine monitoring as well as marine operation into account, promote information sharing and finally improve the overall O&M effectiveness of offshore wind. The remainder of this paper is organized as follows. The current state of O&M of offshore wind and the remaining issues/challenges are explained in Section 2. Big data analytics and its applicability for offshore wind are illustrated in Section 3. A predictive maintenance model and a maintenance implementation model are proposed and integrated into an operational system in Section 4. The implication of this integrated operational system is discussed in Section 5.

## 2 CURRENT STATE OF O&M OF OFFSHORE WIND

Maintenance strategies in the WT industry can be roughly classified into: 1) Corrective maintenance; 2) Preventive maintenance; 3) Predictive maintenance. Corrective maintenance is a kind of reactive repair after occurrence of a failure. Its main drawback lies in the consequent failure cost can be extremely high. Preventive maintenance is mainly a time-based periodic repair, and its weakness would be relatively high operational cost induced by unnecessary inspections and maintenances. Predictive maintenance is a kind of condition based preventive maintenance. It can improve the reliability, availability and maintainability of OWTs while simultaneously reducing the O&M cost (Byon et al., 2016). A comprehensive knowledge of the actual condition of WTs and thereafter estimation of the remaining useful lifetime (RUL) of critical failure components are essential in order to develop a feasible predictive maintenance strategy (Karyotakis, 2011).

Nowadays, various types of sensors, new measurement methods have been generated and applied to monitor the condition of WTs. A Supervisory Control and Data Acquisition (SCADA) system collects information extensively using sensors mounted on the WTs.

Normally a turbine contains 20–30 sensors, resulting in 60–100 different SCADA signals. With a sampling rate of 1 second with 8 byte values, around 1.8 GB raw data per turbine per month are produced. Upon analysis of those information, it is possible to identify critical failure components in terms of high probability of failure and/or severe failure consequence. Some studies have indicated that the electrical system, control system and rotor blades contribute more than 50% of number of failures, as shown in Figure 4 (Hahn et al., 2007).

Meanwhile, gearbox, drive train and generator cause the severest failure consequence in terms of annual downtime (Fischer et al., 2012), see Figure 5 (Crabtree et al., 2010).

From risk assessment viewpoint, it is reasonable to consider those six subsystems as critical failure components and the RUL estimation can be restricted to them in order to reduce O&M cost of WTs maintaining sufficient reliability level.

The failure modes of the critical components could generally be assigned to either mechanical or electrical associated failure. Mechanical failure is characterized with an increasing failure rate caused by aging factors, i.e., erosion, corrosion and fatigue, etc. An electrical failure rate is not necessarily increasing with age but could be relatively constant even decreasing, referring to a decreasing failure rate of electronic control system in Figure 6 (Faulstich et al., 2011).

Among above mentioned critical subsystems, rotor blade, gearbox and drive drain are mainly subjected to a mechanical failure. The evolution of

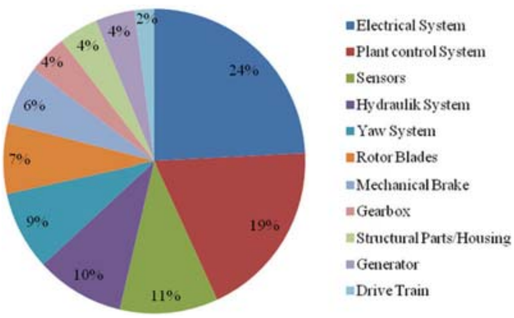


Figure 4. Failures percent of the main components.

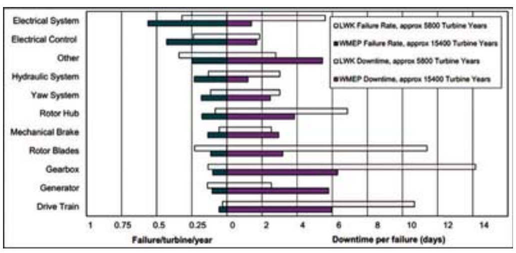


Figure 5. Failures rates and downtime from two large surveys of European WTs.

a mechanical failure can be monitored using various techniques, as shown in Figure 7.

It can be noted that the sensitivity of various techniques to the failure prognosis is quite different. Vibration based technique can detect a potential mechanical failure a few months in advance but heat sensors can do the work days prior to the failure (Madsen, 2011).

Generator, electric system and control system are prone to mechanical failures as well as electrical failures. In general, electrical signals and the thermography based technique are used to detect failures occurring to those subsystems. However, different failure modes could lead to similar abnormality in signal, it is hard to tell one failure mode from another. And the abnormality can only be detected as early as days prior to the failure, thus in general, the condition monitoring of those subsystems are less effective from predictive maintenance strategy perspective.

In summary, offshore wind farms produce extremely large datasets, such as SCADA. However, not all data has been collected and stored properly, limited by the scalability of traditional databases. Furthermore, even with all data in place, there are remaining challenges faced—converting data into valuable information. Specifically, WTs are complex integrity made up of various sub-systems

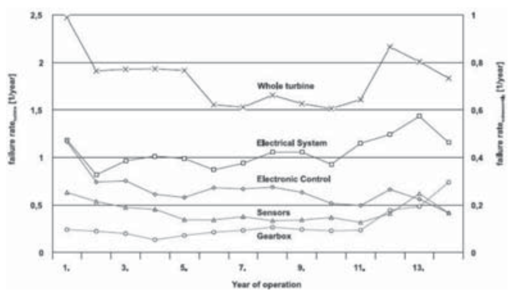


Figure 6. Failure rate with time of operation for onshore wind turbines in the WMEP study.

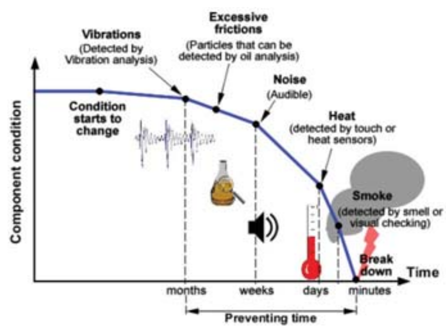


Figure 7. Typical development of a mechanical failure.

and components, one component can suffer from multiple failure modes, and different failure modes can interact with each other. The complication of failure mechanisms make it further more difficult to extract useful information based on traditional data analysis technique.

Last but not least, the maintenance of OWTs is normally implemented by fetching staff and equipment to and from the wind farm using marine vessels. This operation contributes 12.5% to the total cost of O&M and there is a potential to save cost by optimizing associated parameters accounting weather window, operational profile and available resources and deploying advanced data analytics.

## 3 LAYOUT OF TEXT BIG DATA ANALYTICS

Big data analytics is the one that can quickly access to valuable information from various types of data. The related technologies of big data processing generally include big data acquisition, preparation, storage, analysis and mining as well as display and visualization. The significance of big data lies in that the analysis and mining of large amounts of data are conducted through cloud computing and distributed parallel algorithm, etc., in order to obtain the underlying laws and values implied in the data, reveal complex relationships, assist in planning and improve real-time operations. In this respect, big data analytics is very suitable and capable to handle a large number of data, process complex information and achieve high computational efficiency (Wang et al., 2017b).

From O&M of offshore wind farm perspective, big data analytics could have following advantages:

1. to preprocess and visualize complex and diverse data for feature extraction and information mining;
2. to reveal the complex interrelationship between different failure modes so as to achieve a more accurate estimation of rul of critical failure components;
3. to support developing an integrated operational system accounting for both condition monitoring and marine operation by promoting information sharing and utilization.

## 4 AN INTEGRATED OPERATIONAL SYSTEM OF OWTS

Once various data about OWTs has been obtained, including condition of WTs, Wind farm, weather window, marine operational profile, available maintenance resource and its location, etc., an integrated operational system could be developed incorporating both maintenance planning and implementation.

A predictive maintenance model could be developed in order to pre-determine the demanded maintenance of the wind farm. As above mentioned, the big data analytics could make it possible to identify the correlation between different condition indicators (e.g. the speed and temperature of rotor, etc.) and the interaction of different failure modes effectively. Thereafter, the RUL of critical failure components can be predicted more accurately with indicated confidence/reliability level. Based on system reliability analysis (Jiang & Melchers, 2005), it is reasonable to develop a reliability centred maintenance planning. It can facilitate the planner/operator to decide when, where and which components need to be repaired; which maintenance strategies should be taken; and what technicians and resources (material, parts, equipment and vessel) are required to carry out the maintenance (Bajracharya G et al., 2009 & 2010). Santos, Teixeira & Guedes Soares (2015 & 2018) have deployed generalized stochastic Petri Nets (GSPN) method coupled with Monte Carlo to model the planning of O&M activities of an offshore wind turbine. The weather window, corrective maintenance based on replacements and age imperfect preventive maintenance were modeled and compared in terms of the wind turbine's performance and of the O&M costs.

In general, the implementation of the maintenance may not be able to conform to the maintenance plan constrained by actual weather and available technicians, equipment and other maintenance resources. Vessels are usually deployed to transport human and facilities to and from wind farm and the fuel consumption contributes mainly to the total cost of marine operation (Tchakoua et al., 2014; Wang et al., 2017a). The fuel consumption is closely related to the vessel type and size, the sailing route and speed, the weather window and demanded push-on force, etc. Based on big data analysis, it is possible to optimize the maintenance implementation in terms of minimal total cost of O&M, under given maintenance plan determined by the predictive maintenance model, including proper type and capacity of the vessel, proper number of technicians, proper amount of equipment and parts, the right component to be repaired at the right time in the right way, etc. On top of it, an optimal sailing route, speed as well as push-on power under given weather condition would be achieved. In this way, an integrated operational system can be proposed incorporating two models, as shown in Fig. 8.

The framework and the workflow of this system are illustrated in Fig. 9. The system is equipped with hardware, i.e., RAM and Processor etc., and software including Hadoop and Spark etc. The Hadoop consists of MapReduce and HDFS, it can meet the need for off-line batch processing of

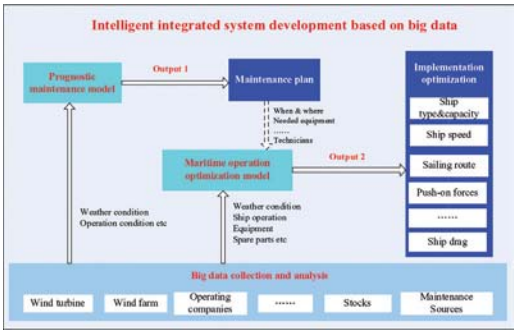


Figure 8. Models and strategies associated with O&M optimization.

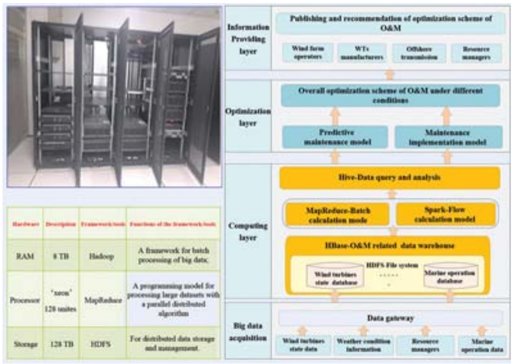

Figure 9. Framework and workflow of the integrated operational system.

big data; The Spark can achieve online real-time processing and support memory computing, which can meet the need for real-time optimization of O&M. Hence, the integrated system is capable to realize real-time parallel processing and effective data storage, and meet the requirement of system's adaptive scalability.

The proposed integrated operational system will work on four functional layers in a sequence, from the bottom to the top, namely data acquisition layer, computing layer, optimization layer and information providing layer, see Fig. 9. The data acquisition layer is responsible for the data collection, including wind turbine condition, weather condition, maintenance resources and marine operational profile. All data will be pre-processed and stored in the computing layer. The maintenance planning and implementation will be integrated and optimized in the core optimization layer. Once a mathematical modeling covering both maintenance planning and implementation is developed, it could be optimized deploying various numerical methods, such as Particle Swarm Optimization (Wang et al., 2017a) or GSPN(Santos et al., 2015 & 2018) among others. The finalized maintenance scheme will be present at the information providing layer in terms of visualized data, statistic result and technical report etc.

## 5 DISCUSSION

As a promising data analysis method, big data analytics has advantages for information extraction and accurate prediction. In this paper, an overall concept based on big data analytics is proposed in order to improve the effectiveness of O&M of OWTs. An integrated operational system is proposed to reduce the total O&M cost from the system-level point of view by incorporating a predictive maintenance model and a maintenance implementation. This big data based integrated system is expected to provide an optimal maintenance scheme with following advantages:

1. No data would be dropped in the data chain, and technical and operational conditions of turbines would be reviewed in detail with improved accuracy.
2. The complicated failure modes would be decoupled, and the root cause of certain failures could be identified.
3. Integrated and shared information can promote a more effective maintenance decision making with respect to both planning and implementation.
4. It is adaptable to a new or growing wind farm relatively easily and less costly.

Big data analytics will break through the limitation of traditional data analysis techniques. It is anticipated to play an significant role in improving effectiveness of O&M of OWTs. The collaboration among turbine manufacturers, wind farm operators and the offshore transmission owners is essential to decrease data blockage, promote information sharing and build up a big data platform in order to reduce areas of inefficiency and duplication of effort. Currently, the data sharing of OWTs among related stakeholders is at initial stage and rather limited. In this respective, a hybrid method combining both physics based failure model and data driven models can be deployed to optimize O&M of OWTs—maintaining acceptable reliability at reduced O&M cost.

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