Adedipe, Tosin, Shafiee, Mahmood and Zio, Enrico (2020) ***Bayesian Network Modelling for the Wind Energy Industry: An Overview.*** **Reliability Engineering and System Safety, 202 . ISSN 0951-8320.**

Journal Pre-proof

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PII: S0951-8320(20)30554-8
DOI: https://doi.org/10.1016/j.ress.2020.107053
Reference: RESS 107053

To appear in: *Reliability Engineering and System Safety*

Received date: 9 August 2019
Revised date: 5 May 2020
Accepted date: 25 May 2020

Please cite this article as: Tosin Adedipe , Mahmood Shafiee , Enrico Zio , Bayesian Network Modelling for the Wind Energy Industry: An Overview, *Reliability Engineering and System Safety* (2020), doi: https://doi.org/10.1016/j.ress.2020.107053

RESEARCH HIGHLIGHTS

- To review the state-of-the-art and future developments on adoption of BN models in wind energy;
- To identify relevant academic publications, best practice documents and software user guides;
- To identify and evaluate various applications of BNs in wind energy;
- To discuss the applications of BNs to risk management, degradation analysis, fault diagnosis, reliability analysis, and O&M planning and updating;
- To analyse a number of case studies to show the applicability of BNs in practice.

AUTHORS STATEMENT

Tosin Adedipe: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data curation, Writing - Original Draft, Visualization, Project administration.

Mahmood Shafiee: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Writing - Review & Editing, Visualization, Supervision.

Enrico Zio: Validation, Formal Analysis, Writing - Review & Editing.

Bayesian Network Modelling for the Wind Energy Industry: An Overview

Tosin Adedipe [1], Mahmood Shafiee [2]*, Enrico Zio [3,4]

[1] *Department of Energy and Power, Cranfield University, Bedfordshire MK43 0AL, UK*
[2] *School of Engineering and Digital Arts, University of Kent, Canterbury CT2 7NT, UK*
[3] *MINES ParisTech, PSL Research University, CRC, Sophia Antipolis, France*
[4] *Department of Energy, Politecnico di Milano, Via la Masa 34, Milano 20156, Italy*

** Corresponding author. Email: m.shafiee@kent.ac.uk*

Abstract

Wind energy farms are moving into deeper and more remote waters to benefit from availability of more space for the installation of wind turbines as well as higher wind speed for the production of electricity. Wind farm asset managers must ensure availability of adequate power supply as well as reliability of wind turbines throughout their lifetime. The environmental conditions in deep waters often change very rapidly, and therefore the performance metrics used in different life cycle phases of a wind energy project will need to be updated on a frequent basis so as to ensure that the wind energy systems operate at the highest reliability. For this reason, there is a crucial need for the wind energy industry to adopt advanced computational tools/techniques that are capable of modelling the risk scenarios in near real-time as well as providing a prompt response to any emergency situation. Bayesian network (BN) is a popular probabilistic method that can be used for system reliability modelling and decision-making under uncertainty. This paper provides a systematic review and evaluation of existing research on the use of BN models in the wind energy sector. To conduct this literature review, all relevant databases from inception to date were searched, and a total of 70 sources (including journal publications, conference proceedings, PhD dissertations, industry reports, best practice documents and software user guides) which met the inclusion criteria were identified. Our review findings reveal that the applications of BNs in the wind energy industry are quite diverse, ranging from wind power and weather forecasting to risk management, fault diagnosis and prognosis, structural analysis, reliability assessment, and maintenance planning and updating. Furthermore, a number of case studies are presented to illustrate the applicability of BNs in practice. Although the paper details information applicable to the wind energy industry, the knowledge gained can be transferred to many other sectors.

Keywords: Wind energy; Bayesian network (BN); Reliability; Probabilistic methods; Operation and maintenance (O&M); Fault diagnosis and prognosis; Structural analysis; Risk assessment.

1. Introduction

Wind energy is one of the fastest-growing and most cost-effective means of power generation worldwide. A large number of wind energy farms are currently being built or are planned to be built – either on land (onshore) or at sea (offshore) – in different countries throughout the world. As reported by the Global Wind Energy Council (GWEC), the global capacity of onshore wind energy reached over 600 GW at the end of 2019, with China contributing the highest proportion of the total, followed by the USA and Germany (Global Wind Energy Council, 2020). In the offshore wind sector, the United Kingdom has the highest installed capacity of 9.95 GW, followed by Germany with the cumulative installed capacity of 7.45 GW. The total capacity of onshore and offshore wind power in Europe has increased from 77GW, as of the end of 2009, to more than 205GW, as of the end of 2019 (see Figure 1). Among the European countries, the UK ranked first in terms of new installations in 2019 (with 16% of the total installed capacity), followed by Spain (with 15%), Germany (with 14%) and Sweden (with 10%) (WindEurope, 2020). The total wind power capacity in Europe is estimated to reach 342GW and 840GW by 2030 and 2050, respectively.

In recent years, there has been a significant growth in the number of wind energy projects deployed in remote, deep-water locations (Presencia and Shafiee, 2018). These locations have more space available for installation of large-scale wind turbines as well as larger wind resources for production of electricity. Nevertheless, wind energy projects in deepwaters often involve a lot more complexities than their onshore or shallow water counterparts. The operating conditions in deepwater environments are highly dynamic and often change very rapidly over time. Any variation in operational and environmental conditions may alter the behaviour of offshore wind turbines or their support structures, and also impact the accessibility of operation and maintenance (O&M) personnel to offshore sites. Therefore, the performance metrics used in different life cycle phases of a wind energy project must be updated on a very frequent basis.

According to the European Technology and Innovation Platform on Wind Energy (2018), O&M is a key priority for improvement in the European wind energy sector in order to reduce the levelised cost of energy (LCOE). Wind farm O&M is attracting more and more attention from industry and policy-making organizations due to its huge potential in increasing safety, efficiency, and power production. In general, there are two strategies adopted for O&M of wind energy farms: corrective and preventive. The corrective maintenance (CM) is a type of maintenance carried out after a failure has occurred. This strategy may lead to large production losses due to potentially long system downtime when a failure occurs. The preventive maintenance (PM) strategy, on the other hand, refers to scheduled maintenance (SM) and condition-based maintenance (CBM). The former requires scheduling of maintenance activities at predetermined time intervals, as estimated based on system's reliability, environmental conditions and other factors. The latter uses equipment condition – as assessed based on inspection reports, interpreted Supervisory Control and Data Acquisition (SCADA) data, or information gathered by sensors embedded in different parts of the wind turbines – to identify maintenance requirements. The sensor readings are recorded, inspection information is analysed, and a maintenance decision is made to address degradation before it causes a failure within the system (Shafiee, 2015).

The reliability analysis and O&M planning of wind energy farms, in particular in deep water locations, is a complicated task as it is a function of several contributing factors such as meteorological conditions (e.g. wind speed, wave height, visibility, and sea state), failure rate of wind turbine components, distance to shore and water depth, availability of resources required to execute maintenance tasks (e.g. transport vessels, service crew, spare parts and special tools), etc. In order to optimise availability of wind energy farms at the lowest operating cost, an efficient planning and reporting system is crucial. Correspondingly, several quantitative and qualitative decision-making methods for reliability analysis and O&M planning of wind energy farms have been developed in recent years. The most common methods include: Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Event Tree Analysis (ETA), Markov Chain Analysis (MCA), Monte-Carlo Simulation (MCS), Petri Net (PN) and Fuzzy Logic (FL) (for more see Shafiee and Sørensen, 2019).

Advanced methods for prediction of reliability and remaining useful life (RUL) of various wind farm assets (including turbines, foundations and transition pieces, export and inter-array cables, offshore substations, etc.) can contribute to the strategic O&M planning and efficient resource allocation in wind energy farms. Thus far, reliability assessment and RUL modelling have been performed using accelerated life testing (ALT) data and failure mode analysis. However, with the development of advanced sensor technologies and condition monitoring systems in the wind energy industry, a great volume of information about the mechanical loadings to wind turbine structures as well as conditions of the surrounding environment (such as temperature, humidity, wind speed, etc.) has been made available in continuous time (Shafiee and Finkelstein, 2015; Martinez-Luengo and Shafiee, 2019). Therefore, it is necessary to develop advanced computational tools/techniques that are capable of incorporating (near) real-time data obtained from inspection results, condition-monitoring sensors or SCADA systems in order to optimise reliability and improve O&M planning of wind energy farms. In this context, the use of Machine Learning (ML) algorithms in various applications has grown enormously in the past few years.

ML methods are capable to learn from training datasets, capture complex interactions that are difficult to model through analytical methods, as well as to predict possible outcomes based on new observations. Of all the ML tools and techniques, the Bayesian Network (BN) seems to be the most promising framework for updating the information in the event of any changes. This can be useful in situations where there is limited information about a complex system at early stage but more information becomes available at later stages of development and the decision makers will need to update their estimates. BNs have been adopted in many industries, particularly because of their ability to cope with uncertainties present in organizational operations and decision-making. As wind turbines are complex machines functioning under a high degree of uncertainty, the wind energy industry can benefit from employing BN models by a significant reduction in inherent uncertainties of the wind turbines' operational conditions or their surrounding environment. It is proposed that the use of Bayesian models in assessment of wind turbines' reliability or scheduling of wind farm O&M activities can bring benefits in terms of increase of power production and thereby reduction of LCOE (levelized cost of energy).

The aim of this paper is to review the state-of-the-art of BN models and identify and classify their application areas in the onshore and offshore wind energy sectors, with a focus on the areas related to risk analysis and reliability assessment. Relevant databases have been searched using appropriate keywords and the studies investigating the use of BNs in the wind energy industry have been identified and reviewed. The researches included in this review range from journal articles and conference papers to university dissertations, industry reports, best practice documents and software user guides. Our review findings show that the applications of BN modelling in the wind energy industry are quite diverse and involve a number of areas such as: system design, wind speed forecasting, power output modelling, data analytics, risk management, degradation modelling, fault diagnosis, cost optimisation, system reliability evaluation, and O&M planning and updating. Further supporting evidence will be provided via a number of case studies found in the literature.

The organisation of this paper is as follows. Section 2 presents an overview of BNs and describes different tools that can be used for Bayesian model development and analysis. In Section 3, we discuss the review methodology adopted in this study to identify the most and least researched areas to date. Section 4 describes the case studies reported in the literature. Section 5 discusses the BN models and their application areas in the wind energy sector and, finally, Section 6 concludes the review with a discussion of major findings and additional suggestions of future research.

2. Overview of BN

2.1. Fundamentals of BN

Bayesian networks (BNs) are directed acyclic graphs (DAGs) which encode relationships among random variables represented by nodes and links (Jensen and Nielsen, 2007; Baraldi *et al.*, 2015). The mathematical background of a BN relies on Bayes' theorem. This theorem supports the fact that the belief regarding the outcome of a system has to change when new evidence (to make probabilistic inference based on available information and quantify uncertainty when information) becomes available. Thus, BNs are also known as Belief networks (Pearl, 1988). BNs are used to solve decision-making problems based on recorded or prior knowledge about the system dynamics and their resultant effects. Bayes' theorem can be expressed in terms of prior probability, likelihood function and a normalisation constant to produce the posterior probability. With reference to the probability of occurrence of events, this can be expressed mathematically as:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}, \tag{1}$$

where $P(A|B)$ is the posterior probability (it is the conditional probability of event A given the observation of evidence B), $P(A)$ is the prior probability distribution of event A, and $P(B|A)$ is the likelihood function of observing evidence B when event A has occurred.

A simplified BN model for events A and B is presented in Figure 2. The prior probability distribution is dependent on the inputs provided by experts or collected from inspection reports, SCADA or condition monitoring systems, that represent stochastic or uncertain variables. Hence, the accuracy of the model depends on the quality of the input data and for updating terms, on the quality of the newly acquired data. BNs also offer a graphical way to represent a problem space in which conditional relationships exist between two or more parameters of a system. This is also useful for making informed inferences based on the output information (i.e. posterior probability distribution). For further reading, the readers can refer to some useful references in the literature, e.g. Compare *et al.* (2017); Li *et al.* (2017) and Fan *et al.* (2019).

When developing a BN structure, some important steps should be followed. These steps include: identifying the key variables and classifying the variables, obtaining *prior* data, and establishing links between different nodes to construct the model. The development of a BN can be facilitated using some well-established techniques such as systematic requirements engineering, ontologies, design patterns, refactoring, object-oriented and component-based techniques (Baclawski, 2004). Different BN structures can be developed that are explained below.

2.1.1. BN structure and learning

In principle, a BN is made up of nodes and arrows which represent the system states/events and their relationships with one another, but not necessarily causality. The quantitative part of a BN is made up of conditional probability tables (CPTs) which express the quantitative relationships between the events. These CPTs represent the dependence structure within a system. The nodes in a BN represent random variables, which can be either discrete or continuous but mutually exclusive in nature. A node may take the form of a parent node (referred to as a root if it has no preceding nodes) or a child node (it will be referred to as a leaf node if it is the last node in the chain of events). The arrows, on the other hand, depict the direction of relationships within the system, where the child node is conditionally dependent on the parent node with the CPT showing the conditional relationship between a child node and a parent node (Cai *et al.*, 2016). The nodes are connected via links to form different structures, including serial, converging, and diverging. Fundamentally, Bayesian reasoning is used to revise beliefs based on updated evidence; thus, when a variable/node receives an evidence, it is said to be *instantiated*. There are two stages involved in the BN learning process (i.e., learning the manner in which BN distributions can be obtained from complete or incomplete datasets): (*i*) learning the network structure, and (*ii*) learning the parameters of the distributions. Further details about BN structures can be found in the following references: Ibe, 2011; Boudali and Dugan (2005a) and Jensen and Nielsen (2007).

2.1.2. Dynamic BNs and influence diagrams

A dynamic Bayesian network (DBN) is a type of graphical model applicable to time-varying probabilistic inference and causal analysis under system uncertainty. The DBN was developed to overcome the limitations of the static networks. A time stamp is used to model a time domain (either finite-horizon or infinite-horizon) at any given time point t; this is referred to as a time slice (Jensen and Nielsen, 2007). The two processing alternatives used to model continuous variables include discretisation and direct use of continuous variables. Also, BNs can be amended to form influence diagrams by including *utility* and *decision nodes*. A node representing a random variable in an influence diagram is called a *chance node*. The influence diagram also contains decision nodes, which have direct influence on other chance nodes. These decisions, represented by the nodes, can have cost implications which can be represented by utility nodes. For further reading, refer to Yang and Frangopol (2018).

2.2. Bayesian inference

Bayesian inference is the use of BNs to compute the posterior distribution within a problem space when new observations or data are available. Owing to the flexibility of Bayesian modelling, a BN can be used to study system behaviour while incorporating new information as they become available. Therefore, the network will be updated whenever any changes are made to the system. The new information may be provided from different sources, including regular inspection measurements or continuous monitoring systems on critical machines. For instance, when a wind turbine is inspected, the information collected from the inspection is inputted into the network and the posterior distribution will be updated. In a problem space where updates are made on only one variable, the influence of other uncertain variables also will change within the network. This will cause a corresponding change in CPTs which quantify the interactive relationships between nodes/variables. In order to model continuous variables, which are inherent in dynamic processes, approximation methods/techniques will be useful. It is also quite challenging to input feedback loops to a BN model as they are fundamentally acyclic in nature. In addition, Bayesian inference can become restrictive when the number of nodes is very large, which can result in a lower level of accuracy in the model. The need to accommodate larger system interdependencies has, therefore, led to algorithmic development in the form of approximations.

When computing the posterior distribution in Bayesian updating, inference algorithms are needed. These algorithms can be of two types: exact or approximate. The exact inference algorithms (such as junction tree algorithm, variable elimination algorithm, arc reversal method, etc.) are used for static BNs with discrete variables; whereas the approximate inference algorithms (such as loopy belief propagation algorithm, etc.) are particularly used for dynamic processes. The approximate inference algorithms are in general divided into two major categories: time-slice methods and event-based methods (Li and Mahadevan, 2018). The time-slice methods include temporal BN, DBN, network of dates, and modifiable temporal BN; whereas, the event-based methods include Temporal Nodes BN (TNBN) and the Net of Irreversible Events in Discrete Time (NEIDT) (Borunda *et al.*, 2016; Boudali and Dugan, 2005b). Different inference approximation techniques have been proposed in literature. These include discretisation, mixtures of truncated exponents, variational approximations, Bayesian search algorithms (BSA), etc. One of the advantages of BN is that it represents systems' behaviour and their interactions including both explicit and implicit connections. By using approximation inference algorithms for continuous variable inputs, two objectives are achieved: the integrity of the BN is maintained, and the model remains capable of making inferences when it is updated with new information. Nevertheless, there still remains gaps in the approximate inference methods applicable to BNs. For further reading on some of these gaps, the readers are referred to Friis-Hansen (2000); Langseth *et al*. (2009) and Luque and Straub (2016).

2.3. BN software tools

A number of software packages have been developed to date for BN modelling. These include: Microsoft MSBNx, Netica, Hugin, WinBUGS, BayesiaLab, OpenBayes, AgenaRisk and Bayesfusion. Some of these software tools have gained more popularity in real life applications, depending on the context for which they are used and the scale to which they can be applied. The most widely used tools are briefly described in the following paragraphs.

2.3.1. Microsoft MSBNx

This is a component-based Windows application for creating, assessing, and analysing BNs (Horvitz *et al.*, 2001). The tool is used to extract information from input database patterns as well as to show dependencies (conditional probabilities) between variables in a network. It can be used to take inspection measurements into account to help asset managers perform fault diagnosis and analyse the costs and benefits of repair actions in a more timely and precise manner. An advantage it offers is that it can be integrated with other programmes to help with inference and decision-making when uncertain parameters or variables are involved. It uses Value of Information (VOI) analysis to estimate the benefit of obtaining improved posterior probabilities (Friis-Hansen, 2000). In the context of the wind energy sector, this software tool was used in Li *et al.* (2015).

2.3.2. Netica

The Netica application is useful for developing belief networks and influence diagrams, which add decision and utility nodes to the Bayesian belief networks. The conditional probabilities in the network nodes can be inputted in two possible ways: either as individual conditional probabilities using equations or from data file inputs. The software uses some fast and modern algorithms to perform Bayesian inference and can help optimise decision-making when influence diagrams are set up (for more see https://www.norsys.com/netica.html).

2.3.3. HUGIN

HUGIN, which stands for Handling Uncertainty in General Inference Network, is used to model conditional dependence in observed data. It has different modules to develop, edit and analyse the BNs. These modules include a graphic user interface (GUI) module, an editor module and a compiler module. HUGIN develops a causal probabilistic network in such a way to support updating with new information for creating improved posterior probability distribution results (Andersen *et al.*, 1989). In the context of the wind energy sector, this software tool was used in Ciobanu *et al.* (2017).

2.3.4. WinBUGS

WinBUGS is an offshoot of the BUGS (Bayesian inference Using Gibbs Sampling) software tool (https://www.mrc-bsu.cam.ac.uk/software/bugs/the-bugs-project-winbugs/). It was developed for processing DAGs such as BNs. It is a user-friendly software that uses different simulation methods or algorithms to analyse the Bayesian models. With Gibbs sampling, when there is new information, each node is assigned an updated value based on the conditional dependence structure of the network. The modules can be extended by adding more components to the network and inputting new distribution functions within the system. The models can be presented by codes (written in BUGS language) or in a graphical form. The modules making up the WinBUGS include graph, updater, monitors, BUGS, samples and Doodle. In the context of the wind energy sector, this software tool was used in Li and Shi (2010).

2.3.5. BayesiaLab

BayesiaLab is a desktop application that uses a GUI to support modelling, diagnosis, evaluation, simulation and optimisation of decision problems (http://www.bayesia.com/). This application is made up of optimised learning algorithms that can execute both exact and approximate inferences with a property called observational inference. It also updates conditional probabilities of variables and analyses how this update may affect the network propagations, allowing the analyst to find explanations of the observations within the network. BayesiaLab discretises all the continuous data inputted by the user. It has the capability to capture the conditional probability of all variables even when the inputs are not defined, no matter how large they are. It has a 'clustering' feature which allows for data and parameter grouping, and this is useful for large input datasets (Conrady and Jouffe, 2013).

2.3.6. AgenaRisk

The AgenaRisk software is used to build BN models for qualitative risk assessment problems (https://www.agenarisk.com/). In order to produce the posterior probabilities, it uses algorithms such as dynamic discretisation algorithm and the ranked nodes method (RNM) which are both useful for modelling the continuous as well as ranked variables, respectively. The software can be used for 'what-if' simulations and sensitivity analysis, because new observations (from, for instance, the inspections) can be inputted into any of the nodes within the network. Even when there is insufficient data, the model can be updated with new information. It is possible that both forward and backward inferences are made for new probability distributions. The output can also show the risk impact of different variables considered in the model. A major advantage of this tool is that it eliminates the need for user-defined discretisation of the continuous variables through its dynamic discretisation feature. This improves the model accuracy for improved risk assessment outputs. It also has an interactive feature, which makes it easy to use. A major drawback to its widespread use is that individual licenses are restricted and they are only available on a large scale for multi-user access (Fenton and Neil, 2004). In the context of the wind energy sector, this software tool was used in Ashrafi *et al*. (2015) and Su and Fu (2014).

3. BN applications in wind energy industry

3.1. Review methodology

In this study, the literature from academic and industry sources including journal articles, conference proceedings, PhD dissertations, industry reports, best practice documents and software user guides was collated for review. Different databases such as Scopus, Web of Science, IEEE Xplore Digital Library and Google scholar were searched to identify relevant studies published on the subject. The search was based on two keywords of “Bayesian network” and “wind energy” and also some inclusion and exclusion criteria were defined to streamline the search content to relevant literature for the review. After reviewing the titles, abstracts and the full texts, 70 documents were eventually considered for detailed analysis. Our review reveals that there has recently been a significant increase in the number of studies applying BNs in the wind energy industry sector. Figure 3 shows the number of studies published between the years 2000 and 2019.

The largest number of publications (13 papers) has appeared in the year 2017, followed by the year 2018 with 12 publications. Among the academic journals, the “Renewable Energy” and “Reliability Engineering & System Safety” journals contained the largest number of articles. Also among the conference proceedings, the “International Conference on Ocean, Offshore and Arctic Engineering” was the most represented conference.

3.2. Applications

BNs have been applied to different areas within the wind energy industry. These areas include: wind speed forecasting, wind power generation forecasting, risk assessment, fault diagnostic and prognostic, system reliability studies, structural analysis, O&M planning, etc. These application areas can all come under the umbrella of improved wind energy systems availability. A brief description of these application areas is provided below.

3.2.1. Wind speed forecasting

Wind speed forecasting is very important to the operation of wind energy farms as it provides information that can help wind farm managers make better-informed decisions about energy production as well as resource planning for maintenance activities. In order to characterise stochastic parameters such as wind speed, different kinds of techniques such as Bayesian model selection and Bayesian model averaging (BMA) can be used. These techniques have been adopted in criteria selection based on input data as well as model selection by taking into account uncertainties. BMA has the capability to predict the maximum attainable wind speed using sparse training data to generate posterior probability distributions. Numerical forecasts, and not raw wind speeds, have been used for generating the prior probability distributions (Sloughter, 2010). The posterior distribution obtained with BMA has an advantage in that it can incorporate parameter uncertainty and model uncertainty from different sets of distributions. This allows BMA to be used for creating models that can show the long-term wind speeds, while maintaining its reliability. Li and Shi (2010) applied the Markov chain Monte-Carlo (MCMC) method as a sampling method for generating wind speed distributions that may be used for wind speed forecasting. The BMA method was used to obtain the weighted average of different probabilistic wind speed forecasting models. The study demonstrated that a model generating the largest relative posterior probability would be the most ideal model to adopt for wind power forecasting.

The hybrid Bayesian-Kalman filtering and sparse Bayesian learning have also been researched for wind speed modelling. In a study by Wang *et al.* (2019b), a sparse Bayesian-based robust functional regression model was proposed to forecast future wind speed for power generation estimation in wind energy farms. The input parameters were optimised using Bayesian inference algorithms for multi-steps ahead wind forecasting in a wind turbine site. The Bayesian learning and variational inference were found to be useful for reduction of 'noise' implication variables in wind forecast outputs and parameter optimisation in wind turbines, respectively. In Du (2019), an ensemble wind forecast was performed by combining three ML algorithms using BMA. This was aimed at improving the grid reliability by improving the forecasting accuracy. Some comparative studies between Bayesian and other methods for wind speed forecasting have been performed in literature. Kumar and Sahay (2018) showed that the BN regularisation algorithm is the best method for wind speed forecasting. Other research papers on this subject are Galanis *et al.* (2017); Pobočíková *et al.* (2017); and Han *et al.* (2018).

3.2.2. Wind power generation forecasting

Although stochastic in nature, accurate wind power generation forecasting in the electric grid supply is essential to reduce operating costs and maximise the revenue from wind energy projects. The power output from a wind farm can be estimated for both the short and long run. Carta *et al*. (2011) used BN classifiers for wind speed and energy output estimation in long-term. Neural Network (NN) combined with Bayesian learning, DBN, advanced Bayesian methods and Bayesian-based regression models have also been applied to wind power generation forecasting. Some studies in this regard include Blonbou (2011); and Wang *et al.* (2017).

Some Bayesian methods such as sparse Bayesian learning can be used in conjunction with numerical methods to improve accuracy and evaluation capacity of wind power generation forecasting (Pan *et al.*, 2015). Park and Law (2016) developed a Bayesian Ascent algorithm composing of two iterative stages: learning stage and optimisation stage. The authors tested their method on a case study to show its capability for improving the targeted power output from a wind farm. In another study, Xie *et al*. (2019) used BNs to forecast the short-term wind power generation by taking into account the uncertainty in stochastic behaviour of wind and also in the model for operational decision-making applications. A review on the applications of BN models to wind energy conversion systems was conducted by Li and Shi (2012). In Otero-Casal *et al.* (2019), the authors used a hybrid Bayesian Kalman filter for improved wind power production forecasting. Other papers on this subject include: Ciobanu *et al.* (2017); Yang *et al.* (2017); Afshari-Igder *et al.* (2018); and Wang *et al.* (2019a).

3.2.3. Risk assessment

The purpose of risk assessment is to systematically identify all hazards which can potentially lead to major incidents, assess the risks arising from the hazards, and decide on suitable measures for eliminating or reducing the risks. Several researchers have conducted risk assessment studies using either a single tool or a combination of two or more tools in order to combine the advantages of different tools and make up for areas in which one of them may fall short. For example, Hazard

Identification (HAZID), Failure Mode, Effects and Criticality Analysis (FMECA) and BN have been combined for risk assessment studies, as reported in Kougioumtzoglou and Lazakis (2015).

In order to carry out a well-detailed risk assessment and determine an effective risk management strategy, wind energy managers employ advanced tools and techniques for decision-making regarding system safety (Shafiee *et al.*, 2019). BNs have been adopted in recent years to assess the risks and make strategic O&M decisions in the wind energy industry. Real-time risk assessment and management analytics can be developed using BNs. A BN model has the capability to take into account dependences of structural, electrical, mechanical components of wind turbines as well as complex interactions between natural, political, social and environmental factors. BNs can also provide information on the effect of changes in one of these factors when there is an update in another factor, e.g. the changes in conditional reliability when there is a change in safety factors (Ashrafi *et al.*, 2015). An observed limitation to BNs' ability to combine as many complex factors as possible lies in the presentation / graphic user interface (GUI), which has had very limited improvement thus far. Safety assessment needs to be made without the difficulties related to the GUIs in order to ensure improved wind turbine reliability.

In hybrid Bayesian Network (HBN) models, the variables associated with both static and dynamic systems can be considered. The AgenaRisk is a useful tool for creating HBN models, which provides posterior probability distribution of the wind turbine system reliability based on some information such as time to failure of different components within the system. Different factors affecting the wind turbine reliability can be incorporated in a HBN model and the risks associated with different elements can be quantified (Ashrafi *et al.*, 2015).

3.2.4. Fault diagnosis and prognosis

In order to ensure wind energy system reliability, faults must be effectively diagnosed and corrected. The faults found in wind turbines can be caused by inherent material defects in components, cyclic fatigue or mechanical damage. Some wind turbine components such as generator and drivetrain components are more failure-prone than others and it is crucial to adequately diagnose faults in these components for optimal maintenance planning. When a fault occurs, it can be detected either by inspection techniques such as non-destructive testing (NDT) or using advanced analytics on SCADA-based condition-monitoring data. Critical components whose failure can lead to significant downtime on a wind farm, especially the mechanical and electrical subsystems, are often continuously monitored.

With the growing use of condition monitoring and predictive maintenance for wind turbines, there has been an increasing interest in the use of BNs for fault detection and diagnosis (see Asgarpour and Sørensen, 2018a). BNs are useful in detection and diagnosis of faults in different wind turbine components. One of the early studies done on the subject of fault diagnosis and prognosis of wind turbine gearboxes using BNs is Chen and Hao (2011). BNs can also be applied to train SCADA data in order to perform fault diagnosis with the aim of lowering O&M costs. Plumley *et al*. (2012) conducted a fault diagnosis and prognosis study on wind turbine gearboxes by means of DBN. The authors used the lubricant condition as an input data to model the gearbox degradation. Chen *et al.* (2012) applied BNs for diagnosis of failures within the pitch system of a wind turbine. They utilised SCADA data to train the BN model for determining root-causes of service failures in the wind turbine pitch system.

In a study by Stutzmann *et al.* (2017), BNs were used to improve the detectability of fatigue cracks in an offshore wind monopile support structure using the inspection outcomes. The fatigue life after each inspection was estimated using a Bayesian updating method. In another study, Sinha and Steel (2015) proposed a BN model to incorporate qualitative information into the estimation of failure probability. They considered four major factors, namely, system faults, operational factors, human factors and external factors (environment) in the analysis. Jing *et al.* (2017) matched possible fault modes with the outputs of a BN model to detect anomalies in a faster and more accurate manner. The model was a two-layer Probabilistic Signed Directed Graph (PSDG), which was made up of sensor data input and a possible-fault list input. Two sets of possible fault rankings were collected from the two layers of data input until they match. The authors used stochastic techniques to convert qualitative data into quantitative data, for ease of running the model. The method, then, uses a ranking technique to select the main faults from both layers to select the most appropriate fault type. These steps are iterated for a number of times to ensure a right fault is selected. Using real-time data collected from the wind turbine operation leads to a significant improvement in fault diagnosis and prognosis. This will in turn improve the safety assessments, especially if it leads to less false positives or false negatives. Other references in this field include: Asgarpour and Sørensen (2018b); Fernández-Cantí *et al.* (2015); De Bessa *et al.* (2016); Joshuva and Sugumaran (2018); Zhong *et al.* (2019); Moghaddass and Sheng (2019); and Cai *et al.* (2016).

3.2.5. Reliability assessment

BNs have garnered attention in recent years as an efficient tool for assessing the reliability of wind turbine systems. Reliability improvement is closely linked with lowering O&M costs of wind turbines and thereby reduction of LCOE. In one of the studies reviewed, Mardfekri and Gardoni (2013) used the BN technique for reliability assessment of offshore wind turbine support structures. The analysis showed that fatigue life estimation of support structures would benefit from Bayesian updating. BNs have found applications also as a RUL estimation tool. Accurate estimation of RUL is important for wind farm owners and operators as well as wind turbine manufacturers. RUL estimation must be updated when inspection data is collected or new information from wind turbines is provided. DBNs are useful for incorporating updates when new information is obtained from inspections. An application of such model to wind turbine blades can be found in Nielsen and Sørensen (2017). BNs can also be used as a decision-making tool for cost-benefit analysis as well as reliability analysis of repair/replacement actions on different wind turbine components. They can be used either as a standalone tool or in conjunction with other tools such as FTA (see Herp *et al.*, 2018; Lazakis and Kougioumtzoglou, 2019; Reder and Melero, 2018). The application of Bayesian classification methods to wind turbine health state monitoring has also been studied in Song *et al*. (2018).

Reliability assessments are dependent on the quality of NDT techniques, which have inherent uncertainties. These techniques will not be able to detect cracks within structural members if the length of cracks is below a certain limit. Reliability assessments are also dependent on the type of system's deterioration mechanisms, environmental factors, etc. These all will pose uncertainties to the reliability assessment, making BNs the most ideal method to quantify and update decisions when there is additional information. Condition monitoring data can be incorporated into structural reliability analysis by fatigue failure models. Rangel-Ramírez and Sørensen (2009) presented a BN model to incorporate information from the second year of operation of an offshore wind turbine support structure into fatigue life assessment. The fatigue life updates helped operators improve their risk-based inspection (RBI) plans for fatigue prone components of offshore wind turbine structures. The wind turbine components that have mostly been studied in the past include: generator, blade, gearbox and support structure. Other papers that addressed reliability assessment of wind farms include: Sørensen and Toft (2010); Wang *et al.* (2013); Su and Fu (2014); Li *et al.* (2015); Mardfekri and Gardoni (2015); Tatsis *et al.* (2017); Ding *et al.* (2018); Song *et al.* (2018); and Valeti and Pakzad (2019).

3.2.6. Structural analysis

The wind turbines should be designed with sufficient strength and stiffness to withstand the forces to which they may be subjected during operation. The typical forces on wind turbines include: wind and wave forces, forces due to current acting on the sea, tides, temperature forces, ice forces, and earthquakes. During wind turbine design, advanced tools are required to model the components' behaviour under real environmental conditions. These models are often subject to uncertainties due to inputted data, assumptions, or prediction errors. BNs can therefore be used as a tool for structural analysis of wind turbines during the design phase to compare different alternatives. This potential of BNs as a decision-support tool is seen in studies on damage growth modelling for structural reliability analysis, which have been carried out using Bayesian updating in order to analyse the impact of new inspection data on structural integrity (Garbatov and Soares, 2002).

Bayesian analysis methods and Bayesian spline models can be applied to compute the effects of potential extreme events on wind turbines (see Cheng *et al.*, 2002; Lee *et al.*, 2013). Bayesian analysis has also been applied to study the effect of uncertainty in lifetime distribution parameters on structural integrity of wind turbines so as to select the most suitable distribution model for use in extreme response analysis (Cheng *et al.*, 2002). The design of wind turbines will benefit from the use of probabilistic methods such as BNs. The ultimate limit state (ULS) and fatigue limit state (FLS) of wind turbine components can be modelled by Bayesian updating methods. Bayesian methods have been used to update the ULS and FLS estimates for wind turbine blades. Also, Bayesian statistics and maximum-likelihood (ML) methods have been applied to update the reliability of wind turbine components (such as blades) after obtaining design data or inspection test results (Toft and Sørensen, 2008; Toft and Sørensen, 2011). Bayesian updating has been studied and shown to have the potential to help decision makers improve RUL predictions (see Nabdi *et al.*, 2017; Ziegler, 2018). Improvements in RUL prediction will lead to increased reliability and safety of wind energy system operations.

3.2.7. O&M planning and updating

O&M planning has a significant impact on avrbiailability as well as operating expenditure (OPEX) of wind farms (Shafiee *et al.*, 2016). Effective O&M planning is not only crucial for increasing the power generation of wind farms but also plays a key role in reducing the cost of electricity production. Risk-based O&M planning using Bayesian decision theory and DBNs have been studied in the offshore wind energy industry (see Nielsen and Sørensen, 2010a; Florian and Sørensen, 2017). Sørensen (2009) proposed a framework for risk-based O&M planning of wind farms using BNs. This framework is illustrated in Figure 4.

As can be seen, there are three types of decisions, namely, the initial design $\mathbf{z}$, inspection/monitoring $\mathbf{S}$, and maintenance/repair plan $d(\mathbf{S})$. This corresponds to a pre-posterior decision problem, where the state of nature at one point is affected by previous decisions. For instance, the reliability of components is influenced by the decision on initial design, $\mathbf{z}$, and the O&M cost of wind turbines is influenced by the decision on how and when to carry out repair tasks, given by the decision rule $d(\mathbf{S})$.

Some Bayesian methods such as Bayesian Ascent algorithms have also been applied in order to maximise wind energy production from improved O&M (Park and Law, 2016). Bayesian classifiers have been used in conjunction with multivariate higher order moments to assess the performance of wind turbines. Herp *et al.* (2016) showed possible application of Bayesian classifiers in performing reliability assessment whilst updating inspection plans to make risk-informed O&M decisions (Pattison *et al.*, 2016). Wind farm power optimisation can also be performed using Bayesian method and Bayesian inference functions, as proposed in Park *et al.* (2017) and Mahmoud and Oyedeji (2018). The O&M planning of wind turbines can also be carried out by combining subjective techniques such as expert judgment with BNs (see Uzunoğlu, 2018). Additional references on O&M

planning using BNs are: Sørensen (2009); Nielsen and Sørensen (2011a); Nielsen and Sørensen (2011); Nielsen and Sørensen (2014); Florian and Sørensen (2017); and Nielsen and Sørensen (2017).

3.3. Comparison between BNs and other tools

In some reviewed papers, the results obtained from BNs were compared with those determined by other methods. In Fernández-Cantí *et al.* (2013), the performance of Bayesian approaches in fault detection of wind turbines was compared to a set-membership model and it was found out that the BN method performed better in terms of runtime. Wang *et al.* (2019b) also compared the performance of conventional models in wind speed forecasting with functional regression models. The conventional models included the linear regression (LR), multi-output least square support vector machine (MLSSVM) and variational Bayesian-based linear regression (VBLR), whereas the functional regression models included Bayesian robust functional regression (R-FR) and sparse Bayesian-based functional regression (S-FR). The Bayesian robust functional regression model was shown to have the best performance rating compared to the other techniques.

In Galanis *et al*. (2017), the performance of Kalman-Bayesian (K-B) filtering was compared with the conventional Kalman filter and it was found out that the K-B model produced more reliable predictions. In Carta *et al.* (2011), the performance of BNs were compared with linear regression (LR) and vector regression (VR) methods. BNs were found to be more superior to the other two methods because the output from BN had the least line of best fit with the cumulative wind frequency histograms. In Wang *et al.* (2017), the accuracy of Bayesian models was compared with prediction interval forecasts and it was shown that BNs performed much better due to their ability to generate an interval forecast at any confidence level. The authors concluded that variational Bayesian methods can be used to optimise variables and generate continuous probability density functions (PDFs) for wind power forecasting. In Friis-Hansen (2000), the results for risk analysis using the BN model were compared with those obtained using FTA and ETA and it was concluded that the BN model is more efficient and flexible method. BN was also found to be a good technique for inspection planning. Influence diagrams (IDs) are found to be superior to decision trees, as they do not require a supplementary tool when performing probabilistic fatigue crack growth and probabilistic risk modelling. BN was also compared with neural network (NN) and linear regression models for vessel design. It was observed that BNs, being iterative in nature, reduce the solution space for design parameters. Also, compared to NNs, the BN does not need to be relearned when new queries are made.

4. Relevant case studies

In this section, a number of relevant case studies from the reviewed literature are identified and described in detail. Some authors demonstrated BN applications with software tools using input data from different sources. Other authors focused on generating posterior probability density distributions based on large datasets.

- *Case studies in wind speed forecasting*

Li and Shi (2010) used the BMA method for wind speed forecasting in nine wind farm sites. They applied eight distribution functions (including Weibull, Log-Normal, etc.) to generate the prior distribution sample data. In order to generate samples for the posterior inference estimation, the MCMC simulations were performed. The samples were then used for each distribution model to calculate the average posterior probability distribution for all the models, the combined likelihood of the prior distribution data to fit each model, and the posterior mean and variance of the BMA posterior probability model. The BMA posterior probability distribution curve was found to have a greater standard deviation than when only one model was considered. The posterior probability of each distribution for the nine sites was also calculated. The results included curves and histograms showing the best fitted model as well as the PDF of the BMA model. The PDF when superimposed with the individual PDFs for each site showed a complete overlap with the appropriate distribution model(s). This makes the method a reliable and robust tool for modelling the wind speed distributions.

- *Case studies in wind power forecasting*

In a study by Xie *et al.* (2019), the wind power output was forecasted using hourly input data from a wind farm, and then the results were compared with those obtained by other models. Gibbs sampling was used to produce different data scenarios for probabilistic wind power forecasts, in order to quantify the estimation uncertainty. The authors used two step-by-step algorithms to generate the posterior probability samples for the forecasting model and also scenarios to quantify the estimation uncertainty. Posterior probability distributions were estimated using different approaches. The non-parametric Bayesian method was found to perform better than other models when there is additional prior distribution data. The R software was used to execute the algorithms and the average runtime was calculated for different volumes of data. In a dataset containing 100 variables, the average runtime was 6 seconds and standard deviation was 0.6 seconds, whereas a dataset with 500 variables had an average runtime of 29 seconds and a standard deviation of 1.6 seconds. The Bayesian method was found to be a more accurate forecasting tool when considering wind speed fluctuations.

- *Case studies in risk assessment*

In a case study about risk assessment of wind turbines, Ashrafi *et al.* (2015) captured both continuous and discrete parameters using the AgenaRisk BN software and presented several factors for a more robust analysis. The environmental, organisational, human and technical factors were considered to improve the conditional probabilistic output. The continuous nodes represented the time to failure whereas the discrete nodes represented the system states. The BN technique was used to make inference regarding the system's reliability given the different contributing factors. The case study showed that the BN analysis is a useful tool for monitoring the risk level and calculating the system's reliability and safety in continuous time. Kougioumtzoglo (2015) performed a study where BNs were used for ranking the criticality of wind turbine components based on their probability of failure. The results generated by the HUGIN software were compared with the results obtained by the FMECA analysis and some differences were observed. A reason for such difference may be because the BN model permits adding more details when performing the analysis. Based on the study outcome, the authors further proposed applying BNs to HAZID analysis.

- *Case studies in fault diagnosis and prognosis*

In a study, Plumley *et al.* (2012) applied the BN method to diagnose failures in wind turbines. The method was tested by simulating different failure modes of a wind turbine gearbox using the LabVIEW software (http://www.ni.com/en-gb/shop/labview.html). The input variables included the parameters associated with lubricant condition within the system, e.g. temperature, ferrous particle count and viscosity. Three sensors were used for data collection, which underpinned a condition monitoring method for estimating the system condition given input data. The reporting was done based on a traffic light system to help maintenance decision-makers. The second case study generated a DBN to determine the degradation rate of a wind turbine gearbox system under different conditions. The GeNIe software tool (https://www.genieonline.com/program/) was used to create the DBN model. The condition monitoring data from the sensors were used to estimate the degradation state of the gearbox. The DBN probability estimates were updated with new measurements (temperature and particle count), which were fed into new time slices of the continuous model. It presented the application of probabilistic model updating to PM scheduling and decision-making.

In another study by Stutzmann *et al.* (2017), the fatigue crack size distribution of an offshore wind turbine monopile structure was calculated based on inspection data collected by eddy current (EC) technique. An analysis was performed to reduce the uncertainty posed by the inspection method. The probability of detection (POD) of a defect by EC technique was found to be higher than that by other NDT techniques. A Bayesian analysis was then performed to estimate the fatigue crack propagation based on the crack size distribution and inspection results. From the distributions generated, the fatigue life of the structure with crack sizes between 0.03–0.06mm was estimated to be about 30 to 40 years. The median and the standard deviation of the fatigue life were estimated as 33 years and 47 years, respectively. The standard deviation of the fatigue life estimation was compared for two cases, including: (*i*) when the defect is detected, and (*ii*) when the defect is not detected. The standard deviation showed a large decrease when the defect is detected irrespective of the inspection method. The study, therefore, concluded that the inspection reduces or eliminates the failure risks only when the crack length on the structure is sufficiently large.

- *Case studies in reliability assessment*

Song *et al.* (2018) applied a Bayesian approach to assess the health state of two 1.5MW wind turbines. The 10-minutes data was obtained from SCADA system for a period of two month. The three input variables of the model included wind speed, power output and generator speed. Two case studies were provided – including a classical case involving the use of wind speed and power output variables and another case involving all three input variables – to evaluate how reliable and robust the results from Bayesian approach are. The second case involved splitting the dataset into five subsets. Four subsets were used to develop the model, and the fifth one was used to test the model accuracy. The models were run five times and their performances were compared with each other. The collected input data was pre-processed to identify abnormal data points. Three methods were used for this purpose, namely, the bin method, the multivariate normal distribution, and the copula method. The copula method was found to be the most robust of the three. The BN model demonstrated good health state monitoring capacity; however, the authors focused on binary health state monitoring (i.e., normal and abnormal states). Since the accuracy of BN method is dependent on the input data, the authors applied Bayesian updating to reduce uncertainty arising due to lack of data. The study concluded that the multivariate and copula methods are best to be used for 1-hour ahead predictions.

- *Case studies in structural analysis*

In order to illustrate the use of Bayesian analysis in studying the wind turbine's rotor blade displacement, Cheng *et al.* (2002) presented a case study of conditional probability distribution for blade tip deflection caused by vibration. Four distribution functions including a Gumbel distribution, a three-parameter Weibull distribution, a log-normal distribution and a generalised extreme value (GEV) distribution were used in the study to estimate the posterior probability values. It was observed that after plotting the probability of deflection by each of the distribution functions, the three-parameter Weibull distribution and GEV distribution were the best fitted models to the input deflection data. The authors argued that the accuracy of the results would improve if well-fitted conditional distributions were used to estimate the maximum deflection of wind turbine blades. The authors estimated the deflection probability over 100 years using different distribution functions and compared the results with those calculated by Bayesian analysis. The blade tip deflection was found to be larger when a deterministic method is used. This was mainly because the Bayesian approach accounted for data uncertainty and distribution model uncertainty.

- *Case studies in O&M planning*

In a case study that compared the efficiency of CBM with risk-based maintenance (RBM) strategy, Florian and Sørensen (2017) adopted BN updating to model the degradation of wind turbine blades subjected to fatigue cracking. Random input variables were generated for the BN model for a period of 25 years (the expected lifetime of a typical wind turbine system). The maintenance decision-making parameters included: the time to first inspection, time interval between inspections, and the repair threshold. MCS was used to generate the cost estimate distribution by taking into account different factors. The simulation procedure entailed identifying the maintenance strategies based on different inputs and then estimating the probabilities of failure and the associated repair/replacement costs. The expected number of blade failures under a CBM strategy was evaluated and the failure categories with the highest potential impact were identified. The number of preventive repair required during the blades lifetime was also calculated. The total lifecycle cost was estimated using a pre-posterior Bayesian decision tree, assuming that an inspection is carried out only when the risk of failure is high. The RBM strategy, on the other hand, was chosen to determine an optimal repair policy after each inspection. Two hundred simulations were run to estimate the average annual cost of O&M. It was shown that CBM and RBM strategies resulted in different number of preventive repairs on wind turbine blades. It was estimated that under CBM strategy about 96% of the wind turbine blades required a preventive repair during their expected lifetime, whereas this percentage under RBM strategy was 62%. This led to a reduction in total lifecycle cost by 23%.

Dinwoodie (2013) presented a case study on an offshore wind farm consisting of 60 wind turbines deployed at 45m water depth. The failure rate distributions for wind turbine components such as gearbox, generator, blade and bearings were calculated. Three decision points during the lifecycle were considered: (*i*) early life strategy, (*ii*) strategy at year seven, and (*iii*) strategy for the remaining lifetime. In the case study, the uncertainties upon which the BN was built were primarily the failure rate and the electricity price. The analysis relied on both the inspection data as well as subjective expert opinions. A risk profile was also generated and the variables causing the highest level of risk were identified.

Table 1 presents the case studies of different wind turbine components that have adopted Bayesian inference techniques. As can be seen, in the reviewed literature the wind turbine blades and gearbox have been studied the most (each with 8 papers). This is followed by pitch system with 7 papers, generator with 6 papers, and support structure with 5 papers.

5. Results and discussion

Table 2 presents the classification of reviewed literature according to their application areas, including: structural analysis, reliability, wind power forecasting, wind speed forecasting, O&M, fault diagnosis and prognosis, and risk assessment. All the classifications are centred around a common theme: *improving the availability of wind farms*.

As can be seen, the field of fault diagnosis and prognosis has received the most attention in the literature. This is closely followed by wind power generation forecasting, reliability analysis, O&M planning, and structural analysis. The field of risk assessment with two publications has been researched the least. In what follows, the results of the literature review for some of the most addressed application areas are briefly discussed.

- *Wind speed forecasting*

Wind speed forecasting is useful for estimating the annual energy production from wind farms. However, due to the stochastic nature of wind, it is difficult to estimate accurately a wind farm's energy output. For this reason, it is required to design and develop short- and long-term wind speed forecasting tools. One of the ways to forecast wind speed is by looking into the data collected from other geographically similar wind energy projects. In some cases, there is no historical data available for deepwater locations; thus, it is important to use tools through which wind farm managers can update their initial decisions when some information becomes available. This makes the case for the use of probabilistic models such as BNs. BNs have the capacity to learn based on new information inputted into the model and may be used in the BN classifier. Bayesian classifications help to determine the most probable value among a set of variables such as wind speed profile at a particular location. Beyond that, BNs also allow multiple locations to be accounted for in the estimation of wind speed and direction within the model. Although the results from BNs are found to be superior to those obtained using linear regression (LR) and vector regression (VR) models, it is still inconclusive as to whether BNs hold true when different correlation coefficients are considered (Carta *et al*, 2011). Thus, there is a need to do further research work about the accuracy of BN models in the case when different correlation coefficients are used.

Wind speed forecasting can also be useful for predicting periods of energy shortfall, so as to have measures in place to compensate for low energy output from wind turbines. Given that BNs are used as a training tool, there is huge potential for use in a wide range of hybrid applications. Generating a probability distribution of weights is valuable for probabilistic modelling, but one key reservation regarding the applicability of this model lies in the fact that the prediction is expected to operate in real-time (Blonbou, 2011). However, the majority of the existing prediction models use pre-recorded wind speed data and evaluate the power output offline. Therefore, further research needs to be conducted on real-time based BN prediction models. Also, since the power predictions can only be reliable when there are no abrupt changes, it is difficult to state how ready this technology is to be applied to real scenarios outside of the modelling environment. If this can be improved, assumptions need to be validated for accurate results in practical terms for wind farm managers.

BNs are useful for short-term probabilistic wind power forecasting and are also suitable for optimising model parameters when other tools are used to forecast the wind speed. The Bayesian models can easily incorporate both unimodal and bimodal wind speed frequency distributions. One key benefit of adopting Bayesian models is that they increase computational efficiency, which may promote their applicability to wind energy systems. The only limitation is that to maintain computational efficiency, there is a trade-off in the power curve used in the estimations. The use of deterministic power curves is known as a way to make BNs more computationally efficient. This reasoning is flawed, however, the technologies using BNs have not been developed to manage the problem yet and more research needs to be conducted in this area (see Bracale and De Falco, 2015; Wang *et al.* 2017).

- *Risk assessment*

Risk assessment is at the heart of reliability and availability improvement in wind farms as wind turbines can only be efficient and available if they maintain high reliability and safety levels. Risk assessment is carried out in order to estimate the likelihood of occurrence and severity of hazards that may damage the integrity of wind farms or cause harm to the life of personnel. A number of tools and techniques are used for risk assessment, e.g. FMECA, HAZID, etc. In order to carry out risk assessments, it is more suitable to use a HBN, which has the capability to model dynamic states within the nodes. Some particular properties of BNs as they relate to risk assessment are as follows (Ashrafi *et al.*, 2015):

- Additional information and data about the maintenance activities can be implemented in BNs. This will be useful when there is a need to include other parameters that have to be analysed for risk assessment.
- BNs can be used for both the forward (top-to-bottom) and backward (bottom-up) risk assessment approaches.

- Risk analysis can be performed to quantify the system's reliability conditioned on the impacts of environmental factors, human activities, and the selected maintenance strategy. This shows how different factors interact with each other and provides optimal strategies for resource deployment by risk analysts and O&M planners.
- The BN tool also allows for updating the system's reliability when there is an improvement in any of the factors considered in the network.
- Depending on the parameters to be quantified, a continuous or discrete node may be used.
- BNs can be used to represent and quantify conditional probabilities with considering different situations.

The deterministic risk analysis methods are limited in being able to incorporate environmental, organisational and human reliability factors. Although these factors are subjective in nature, a closed system is needed to capture them within the nodes. In an attempt to increase objectivity, the BNs can be combined with other risk analysis tools to create a hybrid method. In the BNs, the subjective elements like the organisational factors can practically be inputted as a binary variable (best mode or worst mode), because it takes a long time for changes in these factors to take effect. However, this may be one of the limitations of BNs in practice because organisational/cultural changes take place gradually and are not easily measurable.

- *Fault diagnosis and prognosis*

Depending on the wind turbine subsystem being analysed, different failure mechanisms may be involved. Using BNs, the failure mechanisms can be represented by nodes along with their probability of occurrence, considering other nodal probability distributions. Improved fault diagnosis and prognosis will have a positive impact on wind farm maintenance since the available resources can be effectively deployed to address any concerns based on continuously updated information. Some of the advantageous properties of BNs related to fault diagnosis and prognosis include (Chen *et al*, 2012; Plumley *et al*., 2012):

- BNs can be used to effectively determine the fault position (location).
- Component/system faults can be detected once the posterior probabilities of nodes are calculated. It is helpful to model the most critical stochastic parameters that are required for performing fault diagnosis and prognosis on the wind turbine subcomponents.
- BN is a flexible tool for online fault diagnosis and prognosis, for which the O&M planners aim to embrace in large-scale wind farms in the future. This shows the potential of Bayesian methods in real-time decision-making and updating.
- BNs have the potential to lower O&M costs in the long term as they can help wind farm asset managers quantify different variables and their relationships so as to make risk-informed O&M decisions.
- BNs can be used to develop real-time condition-monitoring systems, which will be very useful for PM planning across the wind farm.
- Data regularisation can be used to train prediction models and improve their accuracy, and this can be achieved using HBNs. Also, if updates are carried out at a higher frequency, fault diagnosis and prognosis can be improved.
- The components that have been studied for fault diagnosis and prognosis in the reviewed literature include gearbox, pitch system, bearing and support structure.

- *Reliability assessment*

High reliability of wind turbines ensures continuous system operation for energy production to meet the growing demand for electricity and to lower the LCOE. When performing reliability assessment, there might be some unknown parameters or parameters with little to no prior information involved in the analysis. Reliability assessment can benefit from the Bayesian updating approaches in cases where there are unknown parameters, uncertain assumptions or latent variables. In such situations, the estimations can be obtained using the pre-obtained data from SCADA or monitoring systems (Mardfekri and Gardoni, 2013). Depending on the number of parameters involved in the reliability assessment, the BNs may be sufficient to accurately compute the overall conditional probability. When the problem becomes too complex, the BNs can be used in combination with other models for reliability studies. BNs can also be used as a validation tool for other reliability assessment techniques. Since the main limitation in using the BNs is on the presentation of the nodal relationships and model uncertainties, one of the improvements is related to the GUI of the Bayesian modelling tool. In terms of the computational efficiency, the BN is believed to have capacity for updating, which should be an addition for its use in reliability assessment (Li *et al.*, 2015). The Bayesian reasoning can show any weak connections within the system when calculating reliability at the design stage. The weak connections are identified by the BNs' backward reasoning capability (see Jin and Liu, 2017). Besides using BN as a verification tool, other tools and techniques such as FMECA can be used to verify the results. When there is new information, the BN model will be updated to show the most accurate state of the system, thus making more informed maintenance decisions. Even though BNs have the capacity to update the results, there has to be more efficient means of data collection and processing so as to maximise the BN capacity (Lazakis and Kougioumtzoglou, 2019). The components that have been studied for reliability assessment in the reviewed literature include generator, blade and gearbox.

- *O&M planning*

Improving the O&M practices is vital to optimise wind farm availability as well as maximise wind power output. Many tools are used by wind farm asset managers to optimise O&M strategies, but Bayesian methods have shown huge potential for improvement in O&M planning. Some of the properties that make BNs attractive for use in O&M planning include (Nielsen and Sørensen, 2010b; Cheng *et al.*, 2002):

- Both logical and stochastic nodes can be incorporated by BNs. This results in a more robust O&M planning model.
- Continuous nodes can be included in BNs when an approximate inference is used (e.g. discretisation of distribution parameters).
- Condition monitoring data and inspection outputs can be incorporated by BNs to update the O&M decisions when needed.
- Bayesian learning approaches can be used to incorporate different parameters such as defect (crack) size into predicting the degradation rates. This informs O&M planners about the optimal time to repair or replace the failed parts, especially in deepwater locations where accessibility is restricted.
- Besides being able to model stochastic processes with limited information and very minimal data points, approximation methods such as Bayesian Ascent algorithm can model complex relationships between system components, and when more information is obtained, more data points can be added to improve the estimation accuracy.
- The prediction of probability of failure will be more accurate if all observations are incorporated into the model. Thus, a strong case is made for when monitoring results are included in a model, as it will increase the confidence levels of failure predictions.

BN-based O&M planning tools can be useful for more accurate estimation of RUL using real-time updates of critical subsystems. This will result in reduced cost of repairs as well as improved availability of wind turbines. As BNs have the capability to process limited data and to update the results when new information becomes available, they prove to be very useful for deepwater sites where floating wind farms will be developed in the future.

A detailed analysis of the reviewed studies in terms of their model inputs, outputs, specifications, challenges of the solutions, advantages and limitations is presented in Table A in Appendix.

6. Conclusion and future work

Wind energy systems often operate in highly dynamic and ever-changing environments; thus, their condition may change very rapidly over time. In such environments, reliability becomes a major concern and it is receiving more and more attention from wind farm owners and operators. It is crucial for decision makers to update their reliability predictions and maintenance actions continuously, taking into account changes in operational/environmental conditions and/or newly collected data. The new data is usually provided from the inspection reports, Supervisory Control and Data Acquisition (SCADA) systems or the sensors fitted to different parts of the wind turbines. Among all data-driven techniques that allow to update probabilistic estimates, Bayesian networks (BNs) are the most promising method for real-time decision making and optimization. This is because BNs can be used to quantify uncertainty when solving a decision-making problem, based on recorded or prior knowledge about the system dynamics and their resultant effects. BNs are useful in situations where there is limited information about a complex system (e.g. at design stage) but more information becomes available at later stages of development (e.g. operation) and the decision makers need to update their reliability estimates, is the case for the majority of wind energy systems.

In this paper, we conducted a systematic literature review on the use of BN models in the onshore and offshore wind energy industry sectors. Several documents were identified and analysed for the purpose of this review. It was found that the major applications of BNs in the wind energy industry include: wind speed forecasting, wind power generation forecasting, risk assessment and management, fault diagnosis and prognosis, system reliability studies, structural analysis, and operation and maintenance (O&M) planning. An overarching theme was observed in all these applications and it was *the need for improved availability of wind farms*. If the wind speed forecasting and power output prediction are improved using an updating method such as BNs, there will be more reliable grid supply data to adequately meet energy demand and at the same time to reduce the cost of electricity produced by wind energy. Also, improving risk assessment and management protocols will ensure increased system availability and better O&M planning and decision-making. Improved fault diagnosis and prognosis and structural analysis are also central to wind energy system reliability. A detailed review of the publications showed that the areas of fault diagnosis and prognosis, reliability analysis, O&M planning, wind power generation forecasting and structural analysis were the most researched areas, whereas the risk assessment field is least researched.

In spite of various applications of BN modelling in the wind energy industry, future work is needed to improve the prediction performance of BN algorithms, particularly the newly developed cyclic Bayesian approximation models. BNs and their approximation models have the potential to help wind farm asset managers move towards 'real-time' predictive analytics. The uncertainties lying within the system performance, stochastic environmental conditions and model can be quantified and subsequently modified with field information to facilitate improved decision-making processes. Hybrid models like the Bayesian-Kalman filtering, sparse Bayesian learning, etc. were more common in different studies, in order to compensate for the current limitations of BNs. A common trend in Bayesian method applications are seen in its use because of its good optimisation and model averaging properties during wind forecasting, to improve the confidence levels of posterior probability outputs. Although BNs have the capacity to combine different complex combinations of wind turbines' structural, electrical, mechanical, natural, political and social environmental factors, the GUI development of BN tools have not improved at the same rate.

The uncertainty caused by the selection of the inspection technique can also be incorporated into BNs, which shows a usefulness of the method, especially because not all inspection methods have 100% detectability in every instance. BN model demonstrated good health state monitoring capacity and because the reliability of BN method depends on the input data, Bayesian updating will help manage issues arising due to insufficient data. An advanced reliability and RUL prediction tool like BNs will be able to take advantage of the real-time data from condition monitoring improvements in the wind energy industry. The potential that Bayesian updating can have on decision-support optimisation for improved system structural analysis, RUL and reliability predictions has also been discussed; this can address issues in predictions caused by insufficient data. When data can be updated using BNs, it will be easier to estimate with higher confidence levels the reliability, risks/safety associated with the wind turbine systems and structures. Some areas that show potential for future research direction include:

- More models need to be developed using BN algorithms in order to make tools more robust, reliable and efficient for different wind energy applications;
- Damage growth models using Bayesian statistics still require improvements, especially, for small size defects on wind turbine structures;
- A future outlook in fault diagnosis and prognosis is expected to bring application improvements when monitoring data is collected in real-time;
- Bayesian inference techniques must be improved in order for models to combine corrosion effects along with fatigue deterioration in reliability studies;
- Because wind power predictions with BNs to-date are reliable when there are no abrupt changes, the technology readiness is difficult to state for application in real scenarios outside of the modelling environment. For this to be improved, assumptions for wind power predictions using BNs need to be validated for accurate results in practical terms for O&M managers (Blonbou, 2011).
- BNs can be used as a decision support tool for modelling life extension strategies in wind farms (for more see Shafiee and Animah, 2017).

Acknowledgement

The authors acknowledge the funding support from the EPSRC on Supergen Wind Hub (EP/L014106/1) in a project titled "Stochastic Methods and Tools to Support 'Real-Time' Planning of Risk-based Inspection for Offshore Wind Structures".

AUTHOR DECLARATION

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.
We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.
We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing

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We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author and which has been configured to accept email from m.shafiee@kent.ac.uk

Signed by all authors as follows: Tosin Adedipe, Mahmood Shafiee, Enrico Zio; 6th May 2020

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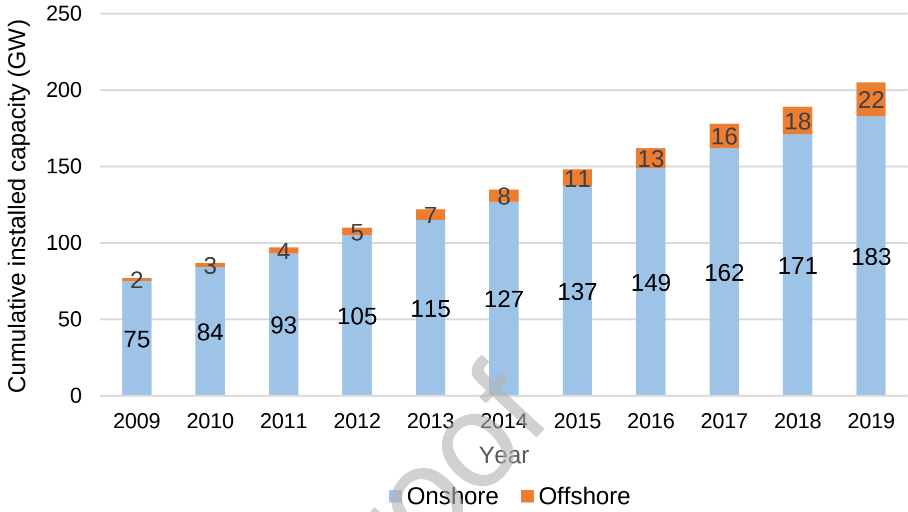

Figure 1. Total installed capacity of onshore and offshore wind power in Europe between 2009 and 2019.

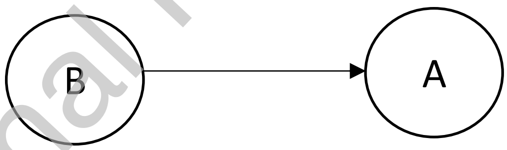

Figure 2. A simplified BN model for events *A* and *B*.

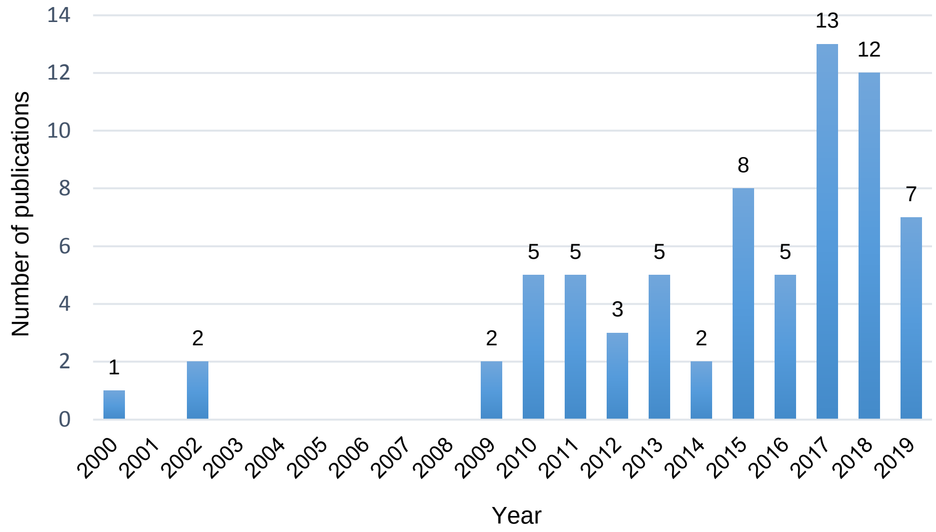

Figure 3. Number of publications about BNs in the wind energy industry.

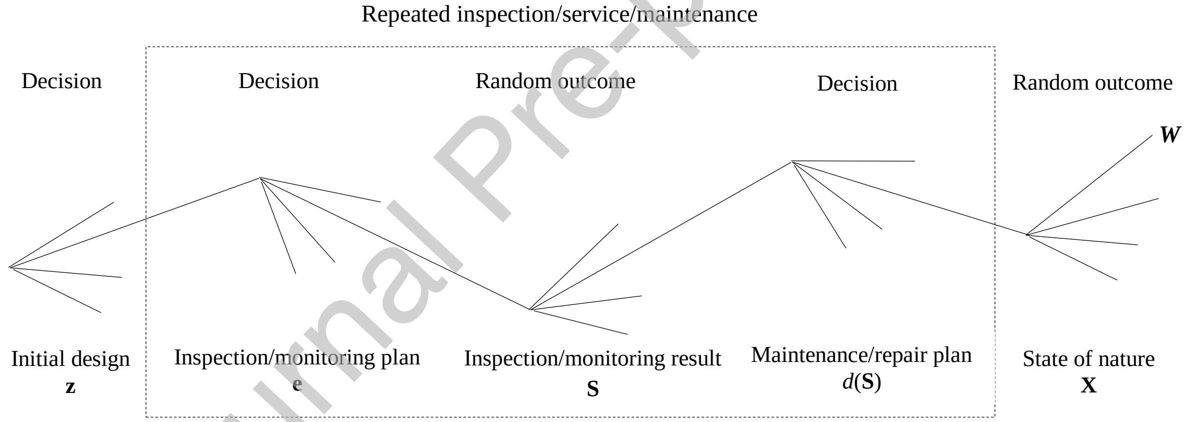

Figure 4. A BN decision model for risk-based O&M planning (Sørensen, 2009).

Table 1. Case studies that have adopted BN model (note: some wind turbine components have been studied in more than one paper).

Component	References
Bearing	Asgarpour and Sørensen (2018a); Asgarpour and Sørensen (2018b); Herp *et al.* (2018); Reder and Melero (2018)
Support structure	Asgarpour and Sørensen (2018a); Kougioumtzoglou and Lazakis (2015); Lazakis and Kougioumtzoglou (2019); Mardfekri and Gardoni (2013); Stutzmann *et al.* (2017)
Gearbox	Chen and Hao (2011); Ding *et al.* (2018); Jin and Liu (2017); Kougioumtzoglou and Lazakis (2015); Lazakis and Kougioumtzoglou (2019); Nabdi *et al.* (2017); Plumley *et al.* (2012); Reder and Melero (2018); Zhong *et al.* (2019).
Sensors	Fernández-Cantí *et al.* (2015);

Pitch system	Chen *et al*. (2012); Fernández-Cantí *et al.* (2013); Fernández-Cantí *et al.* (2015); Kougioumtzoglou and Lazakis (2015); Nabdi *et al*. (2017); Nielsen and Sørensen (2014); Uzunoğlu (2018)
Blade	Florian and Sørensen (2017); Kougioumtzoglou and Lazakis (2015); Lazakis and Kougioumtzoglou (2019); Lee *et al.* (2013); Nabdi *et al.* (2017); Nielsen and Sørensen (2017); Reder and Melero (2018); Sørensen and Toft (2010); Van Buren *et al.* (2013).
Converter	Nabdi *et al*. (2017)
Nacelle	Nabdi *et al*. (2017)
Control systems	Mahmoud and Oyedeji (2018)
Tower	Kougioumtzoglou and Lazakis (2015)
Generator	Fernández-Cantí *et al.* (2015); Kougioumtzoglou and Lazakis (2015); Nabdi *et al*. (2017); Reder and Melero (2018); Song *et al.* (2018); Wang *et al.* (2013).
Rotor	Fernández-Cantí *et al.* (2015)
Cables	Kougioumtzoglou and Lazakis (2015);
Yaw system	Kougioumtzoglou and Lazakis (2015); Reder and Melero (2018)
Hub	Kougioumtzoglou and Lazakis (2015)
Main frame	Kougioumtzoglou and Lazakis (2015)

Table 2. Classification of BN applications to the wind energy industry sector.

Reference	**Year**	**Structural Analysis**	**Reliability**	**Wind Power Forecasting**	**Wind Speed Forecasting**	**O&M**	**F**
Cheng *et al.*	2002	√					
Garbatov and Soares	2002		√				
Rangel-Ramírez and Sørensen	2009	√				√	
Sørensen	2009					√	
Li and Shi	2010				√		
Nielsen and Sørensen	2010a					√	
Nielsen and Sørensen	2010b					√	
Sloughter *et al.*	2010				√		
Sørensen and Toft	2010	√					
Blonbou	2011			√			
Carta *et al.*	2011			√			
Chen and Hao	2011						
Nielsen and Sørensen	2011					√	
Toft *et al.*	2011		√				
Toft and Sørensen	2011	√					
Chen *et al.*	2012						
Li and Shi	2012			√			
Plumley *et al.*	2012						
Fernández-Cantí *et al.*	2013						
Lee *et al.*	2013	√					
Mardfekri and Gardoni	2013		√				
Van Buren *et al.*	2013	√					
Wang *et al.*	2013		√				
Nielsen and Sørensen	2014					√	
Su and Fu	2014		√				
Ashrafi *et al.*	2015						
Bracale and De Falco	2015			√			
Fernández-Cantí *et al.*	2015						
Kougioumtzoglou and Lazakis	2015						
Li *et al.*	2015		√				
Mardfekri and Gardoni	2015	√					
Pan *et al.*	2015			√			
Sinha and Steel	2015						
Cai *et al.*	2016						
de Bessa *et al.*	2016						
Herp *et al.*	2016					√	
Pattison *et al.*	2016			√			
Ciobanu *et al.*	2017			√			
Florian and Sørensen	2017					√	
Galanis *et al.*	2017				√		
Jin and Liu	2017		√				
Jing *et al.*	2017						
Nabdi *et al.*	2017	√					
Nielsen and Sørensen	2017		√				
Park *et al.*	2017					√	
Pobočíková *et al*	2017				√		
Tatsis *et al.*	2017	√					
Wang *et al.*	2017			√			
Yang *et al.*	2017			√			
Afshari-Igder *et al.*	2018			√			
Asgarpour and Sørensen	2018a						
Asgarpour and Sørensen	2018b						
Ding *et al.*	2018		√				
Han *et al.*	2018				√		

Herp *et al.*	2018					√	
Joshuva and Sugumaran	2018						
Kumar and Sahay	2018				√		
Mahmoud and Oyedeji	2018					√	
Reder and Melero	2018		√				
Song *et al.*	2018		√				
Uzunoğlu	2018					√	
Du	2019				√		
Lazakis and Kougioumtzoglou	2019		√				
Moghaddass and Sheng	2019						
Otero-Casal *et al.*	2019			√			
Valeti and Pakzad	2019		√				
Wang *et al.*	2019a			√			
Wang *et al.*	2019b				√		
Xie *et al.*	2019			√			
Zhong *et al.*	2019						

APPENDIX

Table A. A detailed analysis of the reviewed studies about BN application in wind energy.

Reference	Year	Mathematical Problem	Input	Output	Specifications	Challenges of solution	Advantages	Limitations
Cheng *et al.*	2002	Estimation of uncertainties in displacement of WT blades	Sample data of extreme flap moment from 50 simulations	100-year estimate of blade response using different distribution functions	Bayesian Averaging (BA) method is used	Simulation results still have to be analysed statistically	Compared to Maximum deflection theory, BN produced more accurate results	Data was obtained from simulations and not real measurements
Garbatov and Soares	2002	Bayesian updates of model parameters for floating structure fatigue reliability assessment	Material constants, initial crack size, geometry parameter	Posterior probability function of time to crack initiation, and reliability of structure	Uncertainties are associated with time to crack initiation, inspection quality and material properties	There is a need to improve reliability analysis techniques by considering anticipated degradation and accounting for estimation uncertainties	Bayesian updating improves O&M decision-making based on system reliability	Accuracy of BN updating method depends on the posterior function used for the estimation
Rangel-Ramírez and Sørensen	2009	Integration of CM with BN inference	Model uncertainty from wind load effects, posterior density function, design parameters	Accumulated reliability index, lifecycle reliability, RBI information	Fatigue prone hot-spots on WT support structures are analysed. Reliability is assessed by the S-N approach	Offshore WFs require improved maintenance planning methods due to the extreme conditions	Inspection plans are updated with better informed reliability data	N.A
Sørensen	2009	CBM using pre-posterior Bayesian decision theory	Updated damage accumulation model, Design parameters	Probability of failure at a particular time, overall O&M cost	Lifetime probability of failure for WT gearbox was simulated using FORM software	It is complicated to calculate costs, failure rates, and damage models for WT gearbox	Risk-based Bayesian method can be used to make decisions under uncertain conditions	N.A.
Li and Shi	2010	Wind speed modelling with taking into account parameter and model uncertainties	2-year wind speed records at 10m height, prior distributions for each parameter	Posterior mean and variance of BMA predictions given the observed data	WinBUGS is used to obtain the parameter samples for the prior distribution. BMA and MCMC are used for wind speed distributions	Conventional statistical models are not applicable as they only focus on parameter uncertainty but not model uncertainty	The uncertainty can be better accounted for by using an averaged model. BMA produced more robust long-term wind speed distributions for all sites	Candidate models still need to be selected to perform BMA. It is difficult to visually analyse plots from BMA
Nielsen and Sørensen	2010a	Damage size and failure probability updating with new information for RBI planning using BN	Wind load, prior distribution of number of cycles, material parameters, load measurements	Failure probabilities, posterior distribution of damage size	It generates 30,000 samples to calculate posterior distribution. Damage sizes are entered annually in the model	Damage models are used to describe damage development. The uncertain parameters are described using stochastic models	Incorporating inspection results and load monitoring produces more reliable damage models and failure estimates	N.A.
Nielsen and Sørensen	2010b	Probabilistic modelling to update damage size /	SCADA data, wind loads	Updated failure probability, damage size estimates,	Only fatigue cracking failure mechanism is considered. Crack	Damage models have many uncertainties which have to be quantified for more reliable	Incorporating CM and inspection results improves the accuracy of reliability	N.A.

		failure probability with CM / inspection data		expected annual cost of repair	propagation follows Paris' law	and accurate damage size estimation	estimations	
Sloughter *et al.*	2010	Explicit wind speed modelling of full predictive PDF using BMA	Wind speed dataset of observation stations	Verification rank for a raw ensemble forecast histogram and probability integral transform (PIT) histogram	Data is available for 340 days from 35,230 station observations. Discretised wind speed data is rounded to the nearest whole knot	When sparse data is available, fitting of predictive PDF is challenging	BMA produces bias-corrected forecasts. It can produce 48-hour ahead wind speed forecasts by improving predictive PDF sharpness	BMA may not perform well if there is substantial topography at sub-grid scales
Sørensen and Toft	2010	Use of probabilistic models and reliability estimates to improve design based on new test information	Design variables (rotor height, tower diameter and thickness, foundation radius, etc.), stochastic variables (maximum wind pressure, turbulence intensity)	WT design is optimised based on reliability levels. The damage at failure is estimated during amplitude testing	An integrated uncertainty modelling is proposed for optimum WT design based on optimal reliability estimates. Application case study was a model for local buckling failure of support structures	Uncertainties must be incorporated into WT design	Test results and uncertainty can be included in the design process. Both physical and statistical uncertainty and expert judgement can be incorporated into the design	N.A.
Ye *et al.*	2010	Improved fault detection using three tests to detect the system states	SCADA data, power output, rotor speed, blade pitch angle	WT performance features	Tests from the Multi-dimensional Scaling (MDS) method are used as inputs to BN for improved decision-making	N.A.	This method produces better fault detection results because different matrices are used in the fault detection	N.A.
Blonbou	2011	Short term (15-minute ahead) wind power prediction using adaptive Bayesian learning	Wind speed data, wind power production data	Future values of electrical power generated	Wind speed and power production are measured at sampling rate of 1Hz. Neural networks are trained with Bayesian procedure	N.A.	Bayesian framework helps to forecast the interval within which generated power should be observed. It allows for control of the network complexity	N.A.
Carta *et al.*	2011	Estimation of long-term wind speed frequency distribution for a WF site with limited measurements	10-year mean hourly wind speed and direction data from 4 weather stations	Cumulative relative frequency histogram of wind speed, mean wind power density, mean annual energy output	Two commercial WTs of 330 and 800kW were chosen. Model evaluation technique uses 10-fold (cross-validation) method to evaluate the errors	Insufficient data makes it difficult to predict wind behaviours at WF sites.	Allows for the use of wind speed data from different reference stations. Less error between real and estimated energy outputs is obtained	N.A.
Chen and Hao	2011	Gearbox fault diagnosis	Sample data, types of fault (e.g. tooth profile error, broken gear tooth, shaft imbalance, etc.), fault feature	Marginal probability density of a fault node	Sample data is described by a *n*-dimensional vector. Fault features, e.g. RMS, kurtosis, mean are selected and BN is used to calculate the conditional	There are six forms of fault in WT gearbox and it is difficult to correctly recognise and diagnose these faults using traditional methods	Less computation time, good convergence and strong real-time property. State identification and fault diagnosis under uncertainty can be made with BN	N.A.

					probability			
Nielsen and Sørensen	2011	Optimal O&M planning based on Bayesian pre-posterior decision theory	Weather data, failure rate data	Framework for reliability modelling of WT blades	A decision is made on when and how to maintain and repair WT components. Damage models are associated with uncertainties	Corrective maintenance in O&M is flawed because it may lead to failures occurring at times of limited accessibility to the assets	Information from NDI techniques can be used to update reliability model using Bayesian methods	N.A.
Toft *et al.*	2011	Updating reliability assessments with NDI data from WT blades using BN	Data from blade NDI	Updated reliability or probability of failure	Defect positions are generated randomly within the model. Defects are repaired when detected	NDI techniques are still prone to many uncertainties	Reliability can be improved by updating with NDI information	The reliability is dependent on POD of the NDI technique used for inspection
Toft and Sørensen	2011	Probabilistic design and reliability updating of WT blades with test data using BN and ML methods	Material strength coefficient of variation, number of tests	Reliability index in a year given number of tests	Bayesian method was used to estimate ULS function. Only one failure mode was considered in the reliability estimation	Design uncertainties are inherent in WT blades. Full-scale tests contain uncertainties	Estimation of uncertainty of material strength is possible even with little test data. Data from past full-scale tests may be used for prior data used in the analysis	The Bayesian method is dependent on the number and quality of prior test data
Chen *et al.*	2013	Detection and location of faults	SCADA data, outputs from a Venn diagram analysis	Fault probability, root causes depending on the input data	The BN modelled the relationships between the condition of pitch system and sensor readings. SCADA data was used to train the BN	There is a gap for automatic use of SCADA data in failure diagnosis	BNs can make inference about the probabilities of all connected events. The sensor readings are collected online and used to update the BN in fault diagnosis	BN can become too complex. The accuracy of the BN model depends on the quantity of input data
Plumley *et al.*	2012	Degradation modelling of WT systems to determine optimal O&M	N.A.	Probability density functions and updates	The BN was tested by running different failure mode scenarios using changes in temperature and metal particles within the lubricant. LabVIEW was used to show how BNs can be used.	Although condition monitoring systems are effective, false positives increase O&M cost. Thus, a method is required to improve the accuracy and robustness of the results	BN allows evidence to be propagated in the model in order to update the posterior probability of the model	N.A.
Fernández-Cantí *et al.*	2013	Non-linear set membership model estimation and fault detection	N.A.	Feasible dataset and verification that model matches dataset	The faults of pitch system were detected using 50000 sample data generated by a Simulink model	There are some challenges for executing Bayesian estimations	The Bayesian set-membership approach requires less run-time than statistical methods	N.A.
Lee *et al.*	2013	Wind turbine extreme load estimation	N.A.	N.A.	Bayesian spline method is used to extrapolate extreme loading response of WTs. The results are compared with the	The binning method cannot accurately estimate the uncertainty of extreme loads. When the binning method is used, there is an overestimate	The Bayesian spline method produces less parameters than the binning method for extreme response estimation. It is also more	N.A.

					binning method of load estimation	of the extreme loading on WT	flexible in data handling	
Mardfekri and Gardoni	2013	Fragility estimation for a WT support structure using probabilistic models	Deformation capacity, shear capacity (yield stress and ultimate stress), wind speed, wave height	Fragility estimates (in relation to serviceability, yield and ultimate limits) based on wind speed	Fragility estimates were developed for three failure modes: drift, shear and bending failure, based on the wave heights at different wind speeds	Deterministic methods do not account for uncertainties and have inherent biases	Bayesian methods can update the model based on newer information from FEA of the structure	N.A.
Van Buren *et al.*	2013	Reduction of model uncertainty in WT blade dynamics modelling	FE model parameters (trailing edge, spar cap and Z spring)	Posterior predictions of the blade model	The posterior probabilities of five parameters were obtained	N.A.	Parameter uncertainty can be included in the model using Bayesian inference	N.A.
Wang *et al.*	2013	Identification of uncertain and fuzzy vibrational generator fault signals	Data about generator state	Failure rate of generator, mechanical drive system	Feature recognition and Bayesian methods are used to detect faults. The BN structure is created with the fault symptoms and fault layer.	Conventional methods cannot accurately identify fault types and their location in generator	BN has the capacity to estimate system reliability under uncertainty	Bayesian inference quality is dependent on an accurate selection of fault signal events
García *et al.*	2014	Wind power forecasting using DBN for more than 5 hours ahead	2-year wind farm data, including: wind speed and direction, temperature, humidity, pressure	Wind power forecasts from the BN are compared with time-series method	10-minute input data is used for training and testing the model	Classical techniques of wind power forecasting do not account for many variables. Thus, their precision is limited	Methodology for DBN can be used for different forecasting problems. The average error is more acceptable than with other techniques	Daily variable data are not considered
Nielsen and Sørensen	2014	O&M decision updating	N.A.	Optimal O&M decision	Probability of failure and accuracy of monitoring results are calculated	The decisions about repair affect the associated costs of O&M. A method for O&M updating is required	Pre-posterior decision analysis using Bayesian methods can be used to determine the best O&M planning option	Approximation techniques still need to be used in Bayesian analysis
Su and Fu	2014	Reliability model using BN to incorporate uncertain wind speed effects	10-year failure data records	Reliability of WT with varying speed	BN is mapped from a WT submodule fault tree. AgenaRisk tool was used for model reliability	Conventional reliability estimation methods do not account for component interrelationships and dynamic wind speed	The BN method includes the advantages of fault tree, uncertainty and environmental factor impact	N.A.
Bracale and De Falco	2015	Improved accuracy in wind power forecasting with a Bayesian method	Shape and scale parameters for the wind speed distribution	More accurate time series model	A mixture Weibull distribution (MWD) was used to model the wind speed	Uncertainties associated with the wind power resource availability were modelled by probabilistic methods	Probabilistic wind power forecasting is improved with Bayesian inference with incorporating changing environmental conditions	The model used the deterministic power curve provided by the WT OEM
Fernández-Cantí *et al.*	2015	Fault detection and isolation using Bayesian set-membership	Residuals, fault indicator vector and associated indexes	Distributions for the residuals, posterior probabilities of different fault	The errors in the model are bounded by the Bayesian Set-membership framework	Other models use very large detection thresholds, which increase the likelihood of false detections	The method combined the advantages of reduction in model error and false positive. False alarms were	N.A.

		approach		scenarios given the alpha-coefficients			reduced. There was an improved detection time	
Kougioumtzoglou and Lazakis	2015	Risk and cost assessments for improved decision making in WT installation and O&M	Probability of failure (from OREDA Handbook)	FMECA and HAZID matrix, total probability of failure, total cost of failure	The most critical components of WTs were identified. BN was used for the risk assessment and cost analysis for WT O&M strategy	In order to incorporate all risk factors and model uncertainty, a more robust tool has to be developed	BNs can be used for HAZID analysis and include the utility (cost) associated for most critical events	N.A.
Li *et al.*	2015	Reliability assessment of WTs	Initial conditional probabilities of WT states	Predicted WT state and absolute error	BN was used to validate the proposed Goal Tree, Success Tree and Master Logic Diagram (GTST-MLD). BN was modelled in MSBNx	Conventional reliability models do not account for logical and functional relationship between WT components	N.A.	N.A.
Mardfekri and Gardoni	2015	WT structural performance assessment in the event of multiple hazards	Virtual experiment data (obtained from FEM in extreme wind and seismic loads), spectral acceleration, wind speed	Estimation of fragility (as a function of spectral acceleration and mean wind speed), annual probabilities of structural damage	MCS is used to estimate the fragility of WT support structures. All potential hazards are taken into account. Probabilistic seismic demand models are updated.	There are few works taking foundation stiffness into account in WT structural response. The conventional models are computationally expensive and may produce inaccurate structural responses	This assessment can help decision makers optimally design WTs. Uncertainties can be incorporated to reduce result bias. Faster processing time with improved accuracy	N.A.
Pan *et al.*	2015	Presentation of errors in probabilistic wind power forecasting	Wind speed, wind direction, temperature, air pressure and humidity	Predicted wind power curve	Sparse Bayesian Learning (SBL) is used to develop a probabilistic forecasting method for wind power. Parameters of the kernel functions are optimised in order to improve SBL model by using the modified-Gaussian kernel function and Particle Swan Optimisation (PSO)	Probabilistic models focused on non-parametric methods, which need more data and are computational-intensive. Previous methods cannot provide full probability density functions. In order to forecast by minutes, the Gaussian distribution cannot represent the error distributions	With SBL, there is no need to estimate some parameters and thus there is less computation time. The model has better performance than others	The method performs poorly with large datasets. The accuracy of the model is not the best for very short-term or very long-term wind power forecasts
Sinha and Steel	2015	Failure prediction and maintenance planning and execution	Online CM data, inspection reports, service records, component manuals, wind farm information, etc.	Key performance indicators of maintenance regimes in operation	A failure dependency model is developed based on BN taking into account relationships between failures and failure root causes	Failure prediction is difficult because of inadequate understanding of WT behaviour under stochastic conditions. There is a need for a dedicated software tool and relational database for O&M planning	The failure dependency database design is useful for O&M planning when different failures, root causes and their likelihoods of occurrence are interconnected	More failure data is required to improve the reliability of the model
de Bessa *et al.*	2016	Use of time-series and data analysis to	Wind speed, sensor signal database,	Probability indication of each	A two-part fault detection and isolation (FDI)	Using existing data and model-based methods, not all	Fuzz Bayesian method was able to detect and isolate	In some instances, the fuzzy-Bayesian model

		detect and isolate faults in a WT system	probability of fault occurrence from Gibbs sampling	detected and isolated fault	system was used. The fuzzy Bayesian module is used for classifying the detected faults	faults within a WT system can be identified and isolated	multiple faults occurring at the same time by extracting information through Gibbs sampling	confused a wind variation with a fault
Herp *et al.*	2016	Continuous monitoring and performance evaluation of WTs using multivariate statistical model	SCADA data	Prediction of bearing failure (by over-temperature)	Continuous monitoring as a maintenance strategy was used	Threshold detection has been used in the past for WT monitoring. It does not take into consideration the probabilistic events within the system. BN was used because the Hotelling's T^2 approach did not consider the likelihood of the classification	The BN method takes into account the likelihood of the classification, making supervised controls more flexible	Misclassification rates are still high with Bayesian methods, even though reduced
Park and Law	2016	Solving the wind farm control problem by maximising wind power output using the BA algorithm	Wind speed, wind direction, number of turbines, yaw set angles, induction factors	Wind farm power production	The BA method is made of two parts: learning and optimisation. The non-cooperative control solutions are used as the prior data for the BA algorithm. Simulation was performed for validation	Conventional wind farm control strategies are non-cooperative in which the wake effects cannot be accounted for to maximise a collective power output. The proposed method in this study is based on cooperative WF control	The BA algorithm can find improved output values for every input. This method requires limited amounts of data for optimum control estimations. Noisy function values can also be used.	Although BA algorithms can use noisy function values, increased noise levels in data reduces the rate of convergence, slowing down the iteration process
Pattison *et al.*	2016	WT reliability estimation taking into account environment factors, accessibility, failure modes, etc.	SCADA data, CM indications	Probability of failure of WT gearbox, impact of maintenance actions, short-term degradation forecast	DBM method was used for risk assessment and maintenance scheduling of WT gearboxes	Conventional techniques do not account for WT dynamic behaviours	Bayesian methods can help capture the dynamic degradation over time. System state can be estimated based on different maintenance scenarios	N.A.
Ciobanu *et al.*	2017	Power supply reliability assessment using BNs for WTs	Minute-by-minute meteorology parameters such as wind speed and solar radiation	Reliability estimation	Hugin software was used to process the data. The variables used were discretised	BNs are very complex and difficult to synthetically explain and the number of possible structures is exponential	It is a useful tool for monitoring and state diagnosis of the wind power supply network. It has the capacity to predict future availability conditions	More variables need to be included in the probabilistic estimation to ensure robustness
Florian and Sørensen	2017	Impact of using risk-based maintenance on optimal O&M planning of WT blades	Initial crack size, material parameters, mean turbulence intensity	Posterior distributions for mean initial crack size, material parameters, total risk/cost during blade lifetime	Reliability estimates for blade degradation were updated using BNs. Load distribution was obtained by Rainflow counting and fitted to Weibull distribution. Failure time was estimated by MCS	Current maintenance strategies cause higher WT downtimes and increase the LCOE	The degradation model can be updated with inspection results	The method has not taken into account weather prediction for O&M schedules

Galanis *et al.*	2017	Improved numerical wind simulations to reduce systematic biases, error and forecast uncertainty	4-year meteorological station data from 9 stations	Time series and percentiles for real and ideal data for different meteorological stations	Tests were performed for both actual and ideal datasets (to test data in a controlled space). Weibull prior distributions were used for the Bayesian-Kalman filter model	Current solutions to wind speed modelling have limitations with errors when performing forecasts	Reduced CPU memory, elimination of systematic prediction errors, reduction of mean bias and real convergence of the modelled probability density function to the observations	Severe changes in data used leads to unexpected discontinuities. Difficulty in matching the modelled and observed data easily
Jin and Liu	2017	Reliability improvement of WT gearbox	Historical gearbox data and expert opinion	Failure probability of each element of the faulty gearbox	Two gearbox failures were considered: tooth surface contact fatigue pitting and toot root bending fatigue fracture	Minimum cut sets need to be solved when using fault trees as the method for reliability calculations	BNs are more suitable than fault trees for reliability analysis as they do not need to solve minimum cut sets for reliability estimations, avoiding the non-cross-computing process	N/A
Jing *et al.*	2017	Fault diagnosis improvement to improve wind energy output	Fault data records	Conditional probability of candidate faults and their diagnosis	First, a sensor data layer is established and then a fault list is used to create the BN. The method was tested using WF fault data	Current approaches focus on data from different components and are difficult to apply to the entire WT. It is challenging to obtain quantitative diagnostic results	Faster fault searches. Improved fault diagnosis accuracy	Limited training data and restricted conditions make diagnosis difficult
Nabdi *et al.*	2017	Decision logic to choose preliminary WT concepts using probabilistic states estimation	Variables of state of different components, failure rate of components, unavailability of components, repair rate of components	Probability of failure of system components for two design concepts	N.A.	Current modelling tools rely primarily on expert judgement, surveys and manufacturing databases to build WT structural models	BN can be used to incorporate numerous design knowledge into a model. BN has powerful analytical and modelling capacity. BN allows for system state to be determined for different operational scenarios	The model presented did not fully account for more criteria for optimisation improvement.
Nielsen and Sørensen	2017	Optimal O&M planning with lifetime cost estimation using CBM	Mean wind speed, wave height	Cost of inspections, repairs and lost production over WT lifetime, power production for 1-hour intervals	Bayesian updating is used to determine posterior probability for the component state. Costs are due to inspection, repair and lost production in the event of a failure	The conventional methods do not include inspection and monitoring information in decision making. Theoretical tools become difficult to handle because of increased decision parameters	Online monitoring can be included into the model	N.A.
Pobočíková *et al*	2017	Wind speed modelling using four probability distributions	Wind speed	Parameter estimation using ML method, histogram of PDF for wind speed	Parameters were estimated with STATISTICA and wind speed was modelled in MATLAB	N/A	N/A	N/A
Tatsis *et al.*	2017	Fatigue damage	Vibration data,	Estimated and	Modelled in FAST	The conventional stress	Improved accuracy of	Using model-based

		estimation (response prediction) of a WT	mean wind speed	actual fatigue damage	software to generate the vibrational data. Bayesian filter was used for noisy data	predictions do not account for uncertain behaviour and response of structures	dynamic response estimation using CM data	techniques for global response analysis is computationally intensive
Wang *et al.*	2017	Wind power forecasting using both deterministic and probabilistic techniques	Wind power dataset	Wind power forecasts using Variation Bayesian method	A new model (ARMKR) is used to process multi-resolution wind power data. A Gaussian mixture model was used to model the error	Conventional methods like quantile regression have discontinuities in the PDF for the wind power forecasts. They ignore some information when dealing with high-resolution data	Bayesian methods produce continuous PDFs even for interval forecasts. The variational Bayesian method is used to optimise all parameters	N.A.
Yang *et al.*	2017	Prediction of wind power using Naïve Bayesian with particle swarm optimisation (PSO) and rough set (RS)	Numerical wind power (NWP), wind speed	Prediction intervals at different confidence levels, segmentation and non-segmentation optimisation prediction intervals	Data (numerical wind power and wind speed) were recorded every 15 minutes. RS theory was used to handle the datasets and Naïve Bayesian classifier was used to establish a power class	The accuracy of conventional methods depends largely on the point forecasting value. Previous methods also require large computational capacity and can be limited for real applications	Higher prediction performance, higher coverage and narrower average bandwidth for wind power forecasting intervals	N.A.
Afshari-Igder *et al.*	2018	Probabilistic wind forecasting	Historical wind power data	Optimal prediction intervals for different times	Approximation methods for prediction uncertainties like Bayesian methods are used to obtain the PI	Uncertainty in wind power forecasting cannot be solved by conventional methods	More reliable PIs of wind power improve forecasting accuracy	N.A.
Asgarpour and Sørensen	2018a	Prediction of maintenance time using a Bayesian-based prognostic model	Average failure rate, operational data like: degradation data and RUL of the components, expert judgements	Posterior degradation model of a component based on updated shape and scale parameters	Posterior degradation model is updated based on updated shape and scale parameters from CM-based observations	Computational complexity limits the use of many prognostic approaches in practice	BN allows more than one threshold and predictive maintenance strategy to be considered. It is applicable to different components and failure modes	N.A.
Asgarpour and Sørensen	2018b	Fault detection for a WT component using a hybrid multi-agent model	Diagnostic model input/agents, SCADA data (vibration, temperature and oil particle), prognostic model input	Posterior confidence levels of diagnostic agents for main bearing, short term O&M planning framework	Both confidence matrix and diagnosis matrix were inputted in the decision model. Faults detected by the diagnosis agents are confirmed by inspections, and the initial confidence matrix is updated by BN	There is no generic diagnostic model suitable for all WTs. Conventional methods result in high O&M costs due to unplanned failures of WT components	Improved fault detection by Bayesian updating of the initial confidence matrix. It can help in short-term O&M planning with significant cost reduction	N.A.
Ding *et al.*	2018	Fatigue life prediction of WT gearbox using varying-load	Material properties, teeth number, Young's modulus, Poisson's ratio,	Fatigue life is predicted and updated with Bayesian methods	CM data and uncertain parameter distributions are used to model the degradation process.	Existing methods use constant loads to approximate external load during fatigue prognosis. When using model-based	Uncertainty is reduced and life prediction is improved by Bayesian updating given the measured crack length	N.A.

		method	diametral pitch, base circle radius, outer circle, pressure angle		Crack is propagated based on stress analysis in FRANC2D programme	methods, it is difficult to model complex components		
Han *et al.*	2018	Probabilistic wind speed forecasting with comparing post-processing methods	Wind speed data	Verification rank histogram of EMOS and BMA forecasts	Six post-processing methods are used for ensemble model output statistics (EMOS) and Bayesian model averaging (BMA) models	Current forecasting methods are subject to bias	Among the forecasting methods, the BMA models had the highest accuracy	Different prediction accuracies for different stations were observed
Herp *et al.*	2018	Bearing failure prediction using Bayesian methods	Temperature measurement residuals	Failure state prediction, RUL prediction given run-to-failure time series	Run-to-failure time of bearings is used to train the prior data used in the model. Hyperparameter are updated to train the model	Other methods of fault estimation do not consider improvement of the model precision	It predicts the bearing over-temperature events. The accuracy improves on a daily timescale while precision improves on a weekly timescale	Convergence is only possible with a large number of time series because of the strong-data-driven nature of the model
Joshuva and Sugumaran	2018	Fault identification in WTs	Vibration data obtained from accelerometer	Classification results and accuracy of different classifiers	Five blade failure features were identified using ML and statistical analysis. Six classifiers, including Lazy Bayesian Rules Classifier (LBRC), were applied	Conventional methods require performance improvements for considering different types of fault parameters	LBRC model requires little running time	LBRC classifier was seen not to be superior to other classifiers. It may require more memory than non-lazy algorithms
Reder and Melero	2018	Predictive failure modelling for improved O&M of WTs	Failure data for components, environmental data (wind speed, rain, temperature), WT data (hub height, diameter, etc.)	Monthly predicted failures, conditional probabilities of failure for different components	Naïve Bayesian classifier was used to incorporate uncertainty. Sensitivity of failures in WT subsystems was analysed based on accuracy and Matthews correlation coefficient	Conventional failure prediction methods assume constant failure rates. Advanced WT reliability models do not always account for the variable environmental conditions of the WTs	Improved prediction accuracy	The technique for the pitch and yaw system had poor performance
Song *et al.*	2018	WT health state monitoring using Bayesian methods	10-minute SCADA data	Distributions of normal and abnormal WT SCADA parameters, variations of SCADA parameter values for WTs	Three Bayesian methods were used (bin, multivariate normal-based, and copula). Data from two WTs were used from 10-minute data for 2 months	Higher resolution diagnosis is required for WT health state monitoring	Bayesian methods are superior to power curve-based monitoring method. The Bayesian-copula method was very effective in one-step ahead prediction	It is challenging to determine the most useful criteria for identifying the normal and abnormal conditions using SCADA data
Uzunoğlu	2018	Development of a BN model for O&M planning using subjective expert	SCADA data, expert opinions	Posterior probability density function updates, fused subjective opinions,	BN is updated with newly available SCADA data. The model is applied to data of pitch control	Current methods do not quantify uncertainties from software reliability, control system reliability, and	The model is updated with new information (SCADA data and expert opinion). Method can be extended to	N.A.

		opinions		and cost assessment	failures from 2009-2015	weather conditions	different maintenance data	
Lazakis and Kougioumtzoglou	2019	Risk and cost analyses of different lifecycle phases of offshore WTs using BNs for installation and O&M	Failure data for each WT subcomponent, failure cause data (from OREDA Handbook)	Failure probabilities for different components, estimation of annual cost of failure	Main system was divided into 11 subsystems. BN was used to validate FMECA and HAZID results	Identifying hazards accurately is a key in decision-making	BN is a more flexible method than FTA/ETA, as it can combine both objective and subjective data. BN improves reliability and criticality analysis for improved O&M planning	N.A.
Moghaddass and Sheng	2019	Cost-sensitive anomaly detection using BN with limited data	Real-time sensor data	Percentage of anomalous sample data removed after parameter estimation	2500 sample data were used (2000 for training and 500 for modelling). MCMC was used for data training	Conventional data-driven anomaly detection methods are inefficient. A trade-of between misclassification errors and detection rates must be defined	The cost sensitive BN decision tool allows for anomaly prediction with lower cost and risk. It can be used with limited data for training and modelling	Intensive computations. During data training, not all anomalous samples can be found
Wang *et al.*	2019a	Improved accuracy in wind power forecasts using inconsistent datasets	Historical wind power data, wind speed data	It estimated power curves to show normal and inconsistent datasets	HSRM and RSRM are optimised by BN methods. 6000 WT datasets are collected at different seasons of the year, collected every 10 minutes	There are inconsistencies in available wind power data. Parametric techniques are limited in modelling the dynamic characteristics of power curves	HSRM and RSRM are considered good methods for improving the quality of wind power forecasts	The methods require more training times for improved accuracy
Wang *et al.*	2019b	Use of sparse Bayesian-based method to improve wind speed forecasting	Wind speed data	The performance of different models was compared using the same datasets	Sparse Bayesian-based robust functional regression model was developed to forecast 10-minute ahead wind speed	There are usually outliers in the dataset that affect accuracy of predictions. Pre-processing accuracy depends on the quality of pre-processed data	The downsides of having outliers within the datasets are reduced. The method is also more robust because of high-resolution data	N.A.
Xie *et al.*	2019	Improved short-term probabilistic wind power forecasting	Historical wind power data, wind ramp datasets	Prediction error for wind ramp datasets, posterior predictive wind power distributions, probabilistic wind power forecasts	1000 datasets of hourly wind power were used. No performance improvement is observed when historical data increases	Conventional methods underestimate uncertainty in wind power forecasts. They do not fully describe the predicted wind power distribution	Reliable for informing regarding real-time risk management	N.A.
Zhong *et al.*	2019	Real-time fault diagnosis using efficient signal processing methods	Vibration signals from online CM system of the gearbox	Identification of faults more quickly and precisely than traditional techniques	Signal data pre-processing and pattern recognition with ML techniques. WT gearbox fault features were extracted using Hilbert-Huang transforms and correlation methods	Conventional fault diagnosis techniques lead to large costs due to big and noisy datasets	Since this method is data-driven, it does not require many parameters. This is a more adaptive and accurate fault diagnosis method	The accuracy of diagnosis depends on quality of input data. It is only designed for binary classification problems (i.e. healthy or faulty)