

Condition monitoring systems: a systematic literature review on machine-learning methods improving offshore-wind turbine operational management

Innes Murdo Black, Mark Richmond and Athanasios Kolios 

Naval Architecture, Ocean and Marine Engineering, University of Strathclyde, Glasgow, UK

ABSTRACT

Information is key. Offshore wind farms are installed with supervisory control and data acquisition systems (SCADA) gathering valuable information. Determining the precise condition of an asset is essential on achieving the expected operational lifetime and efficiency. Equipment fault detection is necessary to achieve this. This paper presents a systematic literature review of machine learning methods applied to condition monitoring systems, using both vibration information and SCADA data together. Starting with conventional methods using vibration models, such as Fast-Fourier transforms to five prominent supervised learning regression models; Artificial neural network, support vector regression, Bayesian network, random forest and K-nearest neighbour. This review specifically looks at how conventional vibration data can be combined with SCADA data to determine the assets condition.

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1. Introduction

The total capacity in Europe of installed wind power sat at 18,499 MW in 2018 which is an increase of 2649 MW from 2017 (WindEurope 2019). The industry has tended away from small clusters of wind turbines where maintenance is more accessible and the overheads of sending a team for regular intervals were not expensive. For offshore wind farms, the cost of maintenance relative to the levelised cost of energy (LCOE) is significantly increased compared to onshore. It is reported in the North-Sea that the operations and maintenance (O&M) cost between 20% and 25% of the LCOE compared to around 12% onshore (Röckmann, Lagerveld, and Stavenuiter 2017; Tavner 2012). The impact of the offshore environment coupled with increasingly expanding machines means that the maintenance strategy of planned, scheduled or responsive regime to incorporate a more proactive, predictive methodology. The key contributor to this shift in the industry is the intelligent monitoring of the structural health termed condition monitoring. Condition monitoring systems (CMS) are being developed by several operators. Companies monitor several parameters including; vibrations, oil quality and temperatures in some of the main assemblies (Martinez-Luengo, Kolios, and Wang 2016). This information is used to infer the health of the assets to determine the remaining useful life or to determine if scheduled maintenance is required based on the monitored irregularities. There is an additional cost of implementing supervisory control systems, which have deterred operators in the past but the financial benefit has eradicated skepticism (Clark and DuPont 2018). All large utility-scale offshore wind turbines have supervisory control and data

CONTACT Athanasios Kolios  athanasios.kolios@strath.ac.uk

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acquisition (SCADA) systems to govern the performance. SCADA systems provide a magnitude of information over the operational life of a turbine providing updates at a resolution of 10 min. This paper is a continuation of Martinez-Luengo, Kolios, and Wang (2016), which is carried out a detailed review of CMS, following the statistical pattern recognition paradigm. Developing this idea, this report seeks to understand the types of maintenance procedures implemented in offshore wind engineering. Focusing on current detection methods incorporating machine-learning techniques. Currently, there is a variety of review papers on how condition monitoring is beneficial when implemented correctly (Artigao et al. 2018; Zhou and Yin 2019). Others look at how predicting the structural health of a component using machine learning methods can determine scheduled maintenance (Scheu et al. 2019; Wan and Ni 2018). Most of which are looking at vibration methods or SCADA methods individually. This article investigates this but develops on the idea that they can complement the results from machine learning methods when used together. One of the major drawbacks of vibration-based methods is that the results are difficult to interpret without the help of an expert. Combining both sets of information compliment the analysis for easier insight and implementation on improving offshore-wind turbine operational management.

The remainder of this paper is constructed as follows: A methodology for the systematic review is portrayed in Section 2. In Section 3 and 4 is a review of 5 different machine learning methods and condition monitoring strategies. Finally, rounding the remaining sections with a discussion and conclusion separately.

2. Method

This review paper conducts a qualitative systematic review providing an exhaustive summary of current systems in place that tackle offshore wind monitoring and maintenance. The purpose of this review style is to restrict confirmation bias.

The systematic review procedure is developed based on Ioannou, Angus, and Brennan (2017). This focuses on assessing what methods have been applied towards maintenance and monitoring. This study is only looking into five different regression type models. Refining this search helped manage the large volume of literature and streamline the process. The top five most commonly integrated regression methods are implemented in this paper. Observing that there are other regression methods such; Tobit, Cox, Poisson, Lasso and linear to name a few but they are less commonly applied in recent papers.

The process is as follows; both Google Scholar and Scopus were used to initialise the database, searching specifically for condition-based maintenance for offshore-wind turbine operational management. Then a limitation of the top five most used types of machine learning applied to SCADA data, and all vibration-based methods were included. Secondly, a limit from 2013 is set, removing duplicates from both searches. After this process was completed the initial screening process, with titles and abstracts are checked against a predetermined criterion for relevance. The thorough search screening for this paper ranks papers with higher citation having more recognition and importance in the community. At this point, a full paper consideration is taken. Noting, some significant works older than 2013 and other with limited citation works that have a large impact in this field are still included. Following the exhaustive search, a review of the most relevant information will be transcribed.

3. Machine-learning

Machine-learning is the application of artificial intelligence (AI) that provides systems the ability to experience without explicitly being programmed. Nevertheless, machine learning is referred to as an area of artificial intelligence that is solely concerned with identifying patterns from data for predictions on unseen information. One of the most common definitions, by T. M. Mitchel (1997) 'A computer program is said to learn from experience E with respect to some task T and some

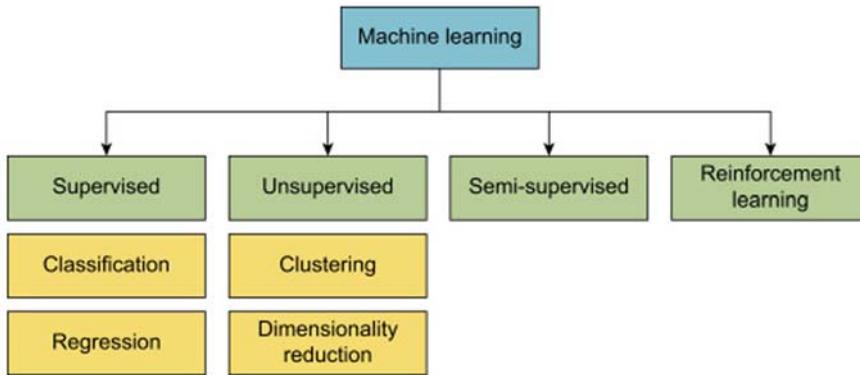


Figure 1. The types of machine learning. This is achieved by supervised learning, unsupervised learning, semisupervised learning, or reinforcement learning. Both Supervised and unsupervised can be further distinguished with classification and regression for supervised learning. Finally clustering, dimensionality reduction and Clustering in unsupervised learning.

performance measure P , if its performance on T , as measured by P improves with experience E' . In this section the types of machine learning methods will be discussed, detailing the nuances and how they are incorporated into the industry. Following that, a more in-depth discussion on 5 specific regression models that are both most commonly applied and are widely applicable at time-series data predictions are discussed. These are support vector regression (SVR), K-Nearest Neighbour, Bayesian Network, Gaussian Process Regression and Artificial Neural Networks (ANN).

Machine learning demands learning relevant patterns from data to make predictions. There are various ways in which this can be achieved from a vast variety of learning algorithms to select from (Figure 1). Common taxonomy organises the different approaches into learning styles, based on this there are main categories of learning; supervised, unsupervised, semi-supervised and reinforcement. Supervised learning can be further coupled into classification or regression depending on either categorical or continuous targets respectively. The main task of unsupervised learning involves clustering and reducing the dimensionality of the input information.

3.1. Supervised learning

For supervised learning, the algorithm must have input variables and the target variables could be; severity of symptoms, the presence of credit card fraud or future clinical outcomes. The aim here is to develop an algorithm to determine the optimal function that captures the relationship between input and output target variables. This type of learning is often related to learning with a teacher, in this situation the teacher knows the correct answer and corrects the algorithm when a mistake is made. Therefore, requiring an iterative process of predictions and adjustment until the output prediction and targeted value has reached a maximal efficiency. The performance is estimated by comparing targeted values against unseen information.

3.1.1. Classification

The main aim of classification is to predict group membership, labels or classes, from observations. This type of algorithm is common in brain disorder research. Classification is advantageous for this problem since it can be broken into a categorical decision; for example, should the patient be medicated with A, B or C. In this case, the algorithm learns to distinguish the patient with a particular disease from healthy controls. There are a plethora of published articles that have used neuron-imaging data to determine disorders (Scheu et al. 2019; Wan and Ni 2018; Ioannou, Angus, and Brennan, 2017; Mitchell 1997; Kambeitz et al. 2015, 2017). A small niche is using motor signals to identify Parkinson's disease (Koutsouleris et al. 2015). This motion can be extended to a multi-

disorder diagnosis, where the algorithm can predict the probability of a patient having a particular disease (Schnack et al. 2014).

3.1.2. Regression

For a regression problem, the aim is to determine a score on a continuous scale. There are questions that cross-over with classifier and regression algorithms, but the outcome is continuous rather than a categorical variable. This characteristic is useful, when, predicting outcomes such as stock market trends or predicting meteorological trends, both follow a continuum.

There is a collection of survey articles related to the energy industry, for example (Voyant et al. 2017), applies regression models to determine the solar radiation to make predictions for photovoltaic panels (Heinermann and Kramer 2016), similarly makes predictions on wind power forecasting (Zemene and Khedkar 2017), has applied various methods to determine consumer electric power consumption.

The level of functioning is completely different, in the clinical trials for classification models the output is distinguished between true and false. For the regression models applied to the energy market, the output has a quantitative value that can be ranked.

3.2. Unsupervised learning

As appose to supervised learning, in an unsupervised learning environment, there is no target value. The aim is to uncover underlying structures in data. There are two main approaches to unsupervised learning: clustering and dimensionality reduction.

3.2.1. Clustering

Clustering is an analytical technique to develop meaningful subgroups from large samples, such as subgroups from published journal papers. In this type of situation, the individual articles could be classed into smaller mutually exclusive, from non-defined, groups based on the similarities amongst them. Grid-mapping, used in image recognition or pattern recognition, is another area where clustering is effective. Noise from uncertain sensor measurements can be reevaluated (Zhu et al. 2019), have highlighted effective results.

3.2.2. Dimensionality reduction

In a situation where the number of features substantially outnumber the number of observations, a dimensional reduction can be useful. The greater amount of features increases the visual complexity, a dimensional reduction is a process where reducing the number of random features under consideration replacing it with a principal set.

A dimensional reduction study on three-dimensional shape retrieval carried out in (Wang, Lin, et al. 2019) aims to gather the most pertinent shapes from two-dimensional images. Another study takes conventional household objects in CAD, uses ResNet library in Python, which is a deep neural network, to retrieve the original shape and alleviating computational demand, omitting redundant information. Shape descriptors are commonly used in text recognition software, A.A. Mohamed (2020) has reviewed various Dimensionality reduction text recognition methods. The handwritten text has considerable amounts of ambiguity and redundancies. These methods seek to retrieve the most relevant information to determine the text.

3.3. Semi-supervised learning

As the title suggests, when target variables are only available for a portion of the data. Semi-supervised learning addresses the issue by allowing the model to integrate the available unlabelled features for supervised learning. This approach is effective when it is unpractical or expensive to attain the measured target data.

Soft sensors or virtual sensors are used in chemical plants, where several measurements are processed together where the interaction of the signals can be used to determine quantities that need not be measured. The process of predicting important, difficult-to-measure quality variables is investigated by Shao, Ge, and Song (2019). Melt index, concentration and octane numbers are determined using semi-supervised learning to determine the quality of the ammonia extraction. This approach maximised the amount of input data in the context of this study with the finite amount of information from labelled samples.

3.4. Reinforcement learning

Reinforcement learning aims to build a system whereby it can learn from the interactions from its environment, much like the operant conditioning Sutton and Barto (1998). For this type of learning, the algorithm's conduct is shaped by a sequence of rewards and penalties, which are dependant on whether the decision is towards the final goal, that is set by the programmer. As opposed to supervised learning, where the examples are given to model the behaviour, reinforcement learning is allowed to develop its path, based on trial and error. This is one of the most promising areas of machine learning for autonomous control of vehicles. A model-free reinforcement algorithm developed by Chen-Huan Pi et al. (2020) has a quad-copter tracing a predetermined path subjected disturbances. The algorithm rewards the system when the trajectory is as efficient at following the predetermined path subsequently minimising the error.

Machine learning is an emerging topic within artificial intelligence that is gaining momentum in all research fields. With each individual industry developing different topics within the AI field. The nature of this, for the most part is open source which allows an easy transfer of knowledge between industries. Machine learning is concerned with identifying patterns from data and subsequently using these patterns to make predictions for unseen data. This is a stark contrast from inferential statistics that seek explanatory power. Contrary to popular belief, classical statistics is not capable of making inferences at a singular level. It is important to understand that there are significant challenges with regards to machine learning, it requires a larger number of observations, whereas as some statistical inferences require less. This issue is being addressed with major developments in transfer learning or domain adaptation, among other methods.

4. Models

Machine learning is a growing area with a magnitude of methods to select from. In the previous section, only the basic procedure is explained. Supervised learning is a common type of machine learning for condition-based maintenance. The following section will provide a more detailed discussion on classification and regression models, introducing the fundamental concepts behind them. Before digging into the details of these models it is important to divulge the process of dealing with raw data.

Pre-processing temporal data are mandatory to improve the final model accuracy. The mote of errors could be, incomplete data, noisy or inconsistent. The following process can be implemented:

- Feature extraction involves cases where data sources from multiple databases and it may need to be integrated into a single data set. In the case of offshore wind, one may want to extract vibrational features from the metalogical data.
- Data reduction involves reducing the size of the data through a subset selection, feature selection or data transformation. This can be handled using row reduction and column reduction. This generally improves the efficiency of the algorithm by removing irrelevant records, improving the quality of the data.
- Data cleaning is a widely studied practice that can be carried out using varying methods for time-series data (Burman and Otto 1988) and (Fox 1972) have discussed potential options.

Alternatively, for high dimensional data (Aggarwal and Yu 2001) explores other methods. It involves potentially removing noisy data points or replacing it. This handles missing and incorrect entries.

- Data splitting, consists of three sets; training set, which is used for learning. The Validation set is used to tune the parameters of the model and the testing set is used to assess the performance of the fully trained model. This is most commonly used in ANN, however, it is not employed in all ML process.

This process is carried out to provide more accurate and efficient results. The following subsections discuss the underlying features of; ANN, SVR, K-nearest neighbours, Dynamic Bayesian network and Gaussian regression.

4.1. Artificial neural network

ANN have developed since the 1940s by McCulloch and Pitts (McCulloch and Pitts 1943) and the learning rule of ANN is based on simple neuron-like logic called a perceptron. A single neuron which is a universal approximator of a smooth surface. The connection strength between artificial neurons is called 'Hebbian learning' (Hebb 1949) ANNs took off in the 1980s when; Werbos (1974), Parker (1982) and Rumelhart, Hinton, and Williams (1986) all worked on backpropagation; hence, systematic learning can be achieved. The human brain is a vast network of connections coupled with sensory receptors that perform the simple task of receiving and passing on signals. If the signal is strong enough it passes the information on, otherwise, it is rejected. This is the building block for the ANN, with the structure depending on the architecture. Dendrites are assimilated to the inputs of the signal, collating the information along the cell body. The myelinated axon is the functioning body of the neuron processing the information and at the axon terminal, the information is passed on to the subsequent neuron. Learning in ANNs is commonly carried out using backpropagation optimisation. Originally it was considered that a synaptic signal was either 1 or 0. For an optimisation problem, discontinuous trends are difficult to solve. Rao and Rao (1998) considered the synaptic strength to be a continuous fixed function. Recently have been developments implementing the self-adjusting threshold discussed in Werner et al. (2019). One of the most significant advantages of ANNs is the ability to predict non-linear, complex behaviour effectively. This success is directly proportional to the selected instances. When presented with incomplete information ANNs can still produce results. ANNs are dependant on the samples, with limited information the accuracy is hindered. This also means that large quantities of data are necessarily imposing a hardware requirement. But there are developments in domain adaptation (Wang, Michau, and Fink 2019). This method transfers knowledge from other related data-sets to improve the performance of machine learning methods when there is limited amounts of data for specific tasks.

4.2. Support vector regression

Due to some of the shortcomings from ANN, the so-called SVR was developed in the 1990s for non-linear regression and classification problems by V. Vapnik (1998). There are three main reasons for SVR's success; reliable training efficiency with small samples, the robustness against error models and its computational efficiency compared to other methods such as ANN (Martinez-Ramon and Cristodoulou 2006; Wang 2005). In the training process of machine learning techniques, it is often assumed that the larger the sample, the error function will decrease. This can result in what is known as overfitting (Duda, Hart, and Stork 2002), where a complicated function is designed to reduce the loss of estimated target and desired output. This yields very accurate results in the training stage, but the estimation is poor. This is not consistent with SVRs.

SVRs aim to generate a function by separating the variables with a hyperplane. To determine the two classes separating the hyperplane a suitable regularisation model is required for the training

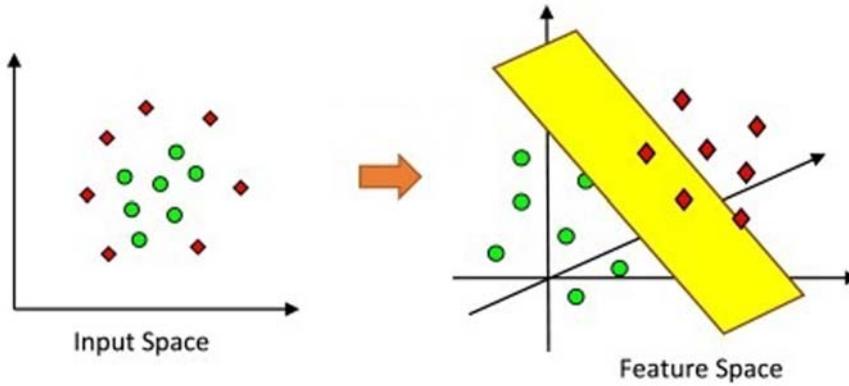


Figure 2. The transformation from input data into feature space for a greater fit (Gholami and Fakhari 2017).

stage. Vapnik-Chervonekis developed the basis of SVR (Cristianini and Shawe-Taylor 2000), the Kernel function (Mercer 1909), this transforms the input space into feature space or Hilbert space so that non-linear input data can be modelled more accurately (Figure 2). An approximation of this can be (Smola and Schölkopf 2004):

$$y = \sum_{i=1}^N (\alpha_i - \alpha_i^*) \langle x_i, x \rangle + b$$

where α_i & α_i^* are Lagrange multipliers for N training variables and b is a constant real number. For this instance a Gaussian radial bias kernel function can be used with σ , a tuning parameter:

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|}{2\sigma^2}\right)$$

4.3. K-nearest neighbour

Similar to the previous machine learning methods, K-nearest neighbour (K-NN) presumes that the current time series will exist in the future. This method differs from the other methods in this article since the training of the algorithm is considered 'lazy learning', where learning is a generalisation of the input data as opposed to training the algorithm before receiving queries in 'eager learning'. The objective is therefore to determine the present value based on a generalisation of past values. This is evolved from Kantz and Schreiber (2004).

The algorithm's aim is to determine the Euclidean distance from the present and past variables, while some other less common distances can also be used (O'Hagan 1978). Locating the closest distance of the variables from the learning data to determine the output. The distance is given by:

$$D(x_i, x_j) = \sqrt{\sum_{l=1}^N (a_l(x_i) - a_l(x_j))^2}$$

where $a_1(x)$ denotes the 1st feature instance of x . To determine the K-NNs the value $\hat{f}(x_q)$ as the estimate of $f(x_q)$ is the most frequent value of f among the K-NN can be represented as:

$$\hat{f}(x_q) \leftarrow \operatorname{argmax} \sum_{i=1}^k \delta(v, f(x_i))$$

with $v(a,b) = 1$ if $a = b$ else $v(a,b) = 0$. This is one of the simplest machine learning methods. Since there is no training necessary it can be considered faster at making decisions. However, with large multidimensional data sets, the algorithm does not perform well since it is more difficult to determine the Euclidean distance.

4.4. Dynamic Bayesian network

Dynamic Bayesian networks (DBN) are directed graphs representing a set of variables and their condition dependence (Pearl 1988). BNs constitute both quantitative and qualitative analysis. The quantitative section involves prior and conditional probabilities for each node and the qualitative section involves acyclic graphs. Each node represents a random variable. The arcs represent the cause-effect relationships or dependence's between the nodes. The joint distribution between variables of vector is X , the network is represented by:

$$p(X) = \prod_{i=1}^N p(x_i | pa(x_i)) \quad \forall x_1 \dots x_N \in \Omega_{x_1} \dots \Omega_{x_N}$$

with values of variable x_i and $pa(x_i)$ denoting an instant of the parents of X .

BNs is a set of conditional independence statements; this is the main consideration when building the model. This can be determined by employing the rules of d-separation. Using this method the joint probability distribution for a set of random variables can be determined using the chain rule. Dynamic BNs are an extension of BNs; typically they partition the variables into input, hidden and output variables for a state-space model. This can tackle discrete-time stochastic models.

4.5. Gaussian process regression

A Gaussian process (GP) is a multi-variable probabilistic approach applied to regression and classification machine learning problems. GP algorithms are stochastic processes, that can model multivariate infinite vectors. The process can be defined for a random set of variables x as mean $m(x)$ and covariance $k(x, x')$ (Rasmussen and Williams 2006):

$$f(x) \sim GP(m(x(x)), k(x, x'))$$

GP regression determines marginal Gaussian distributions from the training data and can describe non-linear trends as an output function. Essentially GP is a non-parametric generalisation of a joint-normal distribution of an infinite set on input variables, defined by the mean and kernel function (Rasmussen and Williams 2006). A typical common kernel is the squared exponential kernel used in Tolba et al. (2019):

$$k(x_i, x_j) = \exp\left(1 - \frac{1}{2}d\left(\frac{x_i x_j}{l}\right)^2\right)$$

with l being a length scale. The function determines a probabilistic accuracy, meaning that the output from this process has a predetermined confidence interval. This is advantageous as there is uncertainty associated with the output function. The Gaussian process is also versatile since there is a variety of covariance functions for varying problems however, this does raise the issue of implementing the correct Kalman filter (Hartikainen and Särkkä 2010).

Machine learning is continually adapting, with huge amounts of investment from large international organisations and research institutions. This article has only selected several models that are suited towards time-series problems but there are vast amounts of other models for different challenges. There is no consensus on what is the most desirable methodology, there are guides and books but no concrete standardisations for confident, accurate model implementation.

5. Data-driven decision making for wind turbine operational management

The maintenance of an offshore wind farm can be categorised into two approaches; preventative and corrective maintenance. The latter applies to the run-to-failure approach, which inherently risks cascading failures with the potential of catastrophic loss. This approach is also likely to cause greater downtimes since planning for maintenance is followed by the failure event.

In contrast, the preventative-based maintenance philosophy aims to repair a component before failure, this is broken into two subcategories: calendar-based maintenance or condition-based maintenance. Calendar-based maintenance is performed by annual or semi-annual visits or scheduled replacements based on the operational life of the component. A more effective approach is condition-based maintenance, where the components are repaired based on the health of the part. This strategy aims to predict failure before it occurs so that the scheduling can be planned earlier in a corrective manner to reduce downtime. Producing accurate predictions of the remaining useful life of an asset is a complex task, especially so in a complex system with multiple failure modes.

There are three main requirements of a condition-based maintenance system according to (Wiglinkhuizen et al. 2008):

- Detection of failure mechanism
- Measurable criteria
- Detection of time

These three steps have been interpreted in a variety of different ways, the creativity within the maintenance sector has resulted in a variety of different models. The following sections will look into Acoustic and SCADA models for the detection of failure mechanisms and how to use the measurable criterion.

5.1. Acoustic condition modelling

In the context of an offshore wind turbine, with mechanical, electrical and structural components. There have been various signals and monitoring tools to determine the structural health of the turbine.

The identification of dynamic system responses has been carried out qualitatively since the introduction of acoustic modelling (Tchakoua et al. 2014), recently with the emergence of condition monitoring, the maturation and cost reduction of digital computer hardware (Crabtree, Zappalá, and Tavner 2014). Condition monitoring is becoming more attractive and the offshore wind industry is becoming an emerging topic. Monitoring of rotating machinery is most competitive in terms of profitability and reliability (Qiao and Lu 2015a; Tavner 2012). The failure detection systems depend on pattern recognition related to displacement, velocity and acceleration time histories.

The sensors are commonly placed on the housing or shafts of the components during the operation. DNV-GL (GL Renewables Certification 2013) codes on condition monitoring state that the minimal amount of sensors of geared turbines shall include at least one vibrations sensor on the main bearing, two on the generator bearing and five for the gearbox sensor. Sensors are predominantly mounted on the housing of the component. The most common sensor used is a Piezo-electric accelerometer because of the large bandwidth, ranging from 0.1 to 30 Hz BSI 13373-1 (BSI 2002). Piezo-electrics sensors, unfortunately, suffer from roll-off at lower frequencies.

Raw vibration analysis is no arbitrary task. The data as a whole needs to be analysed in detail. Common methods are; time-domain analysis, for instance, Hilbert Transform. Statistical analysis, and frequency domain techniques, such as Fast-Fourier Transform or time-frequency domain techniques like the wavelet transform.

Fast-Fourier Transform has been the most applied technique in-order to obtain frequency spectrum by converting the time domain signals into the frequency domain. Specific harmonics are directly correlated to the gradation or faults of moving parts. Qiao and Lu (2015b) have explored this for faults specific to wind turbines. Fast-Fourier transforms are effective in stationary signals but, may result in indistinct solutions in non-stationary environments. Offshore wind, and especially floating offshore wind the nacelle oscillates. The IEC-61400-25 (IEC 2011) has suggested binning vibration measurements over the power band of the operational wind turbine, or using log mean composition and applying synchrosqueezing transform (Geropp 1997; Sheng 2013).

Envelope analysis is used in signal processing to detect fault frequencies that may not be represented in the spectrum produced by Fast-Fourier Transform such as shock impulses (Sheng 2012). A Band-pass filter is applied to the time domain signals centreing on the desired energy region. The amplitude is demodulated in the filtered time-domain signal, extracting this repetition rate of impact. Applying this process during Fast-Fourier Transform characteristic impact frequencies and their modulations, side-bands, are determined.

Cepstrum involves taking the inverse Fourier transform of the logarithmic power spectrum. This methodology has been applied in auto-correction ANSIs, which is just performed on the logarithm of the power spectrum, In Cepstrum the correction is mainly focused on the lower harmonics (Geropp 1997).

For rotating machinery, fault detection is usually determined by distinguishing specific harmonics or side-bands. Envelope analysis is carried out to specifically locate side-bands using amplitude demodulation. Cepstrum analysis is carried out to distinguish between different harmonic groups (Spectra Quest 2006). The combination of this collection of techniques can lead to good failure detection. They can identify various forms of failures and are incorporated into commercially available solutions on vibrational analysis for offshore wind turbine condition monitoring. These tools often require experts to interpret the results to determine whether the information is indicative of a fault. Efforts have been put to fully automate fault detection with vibrational analysis using the features such as sideband energy, Koukoura, Carroll, and Mcdonald (2017), deep learning convolution networks (Bach-Andersen, Rømer-Odgaard, and Winther 2018) or using a system that uses vibrations analysis combines with wind and rotor speeds (Ha et al. 2017). There is a need for a more generic approach of fault detection utilising machine learning methods, vibrational analysis with the minimal amount of human intervention as possible.

Offshore wind turbine condition monitoring is an emerging field with various tools emerging. Roller bearing failure detection using vibrational signals by extracting features with SVR modelling (Fernández-Francos et al. 2013). Also, another the same problem using ANN (Ziaja et al. 2016). Gearbox failures are of interest since it has one of the highest gown time, these failures have been diagnosed using Von-Kalman filters during operation and in non-stationary conditions (Feng, Qin, and Liang 2016) also including complex wavelet transformations (Teng, Ding, et al. 2016). Another approach has developed a tool using the angular velocity data (Nejad et al. 2014), investigating jerk', using the rate of change of acceleration (Zhang, Verma, and Kusiak 2012).

CMS have been incorporated in several industries for years, Sky-wise (Airbus 2020) in the Aerospace or Pulse for the Nuclear industry. The Wind industry operators have only recently introduced dedicated CMS. The reason this development requires time is largely dependent on the initial cost being high (Yang, Court, and Jiang 2013), resulting in ambiguity on returns. The benefit of this investment will take years to impact the cost-benefit analysis. Another aspect is there probability of false alarms, hence, unnecessary cost from scheduled maintenance. As some insurance companies dictate that condition monitoring is mandatory the offshore wind industry will develop more effective mechanisms, according to a study carried out in 2014 by Yang et al. (2014) only 60–80% accurate diagnosis is necessary to provide adequate returns to justify the implementation.

5.2. SCADA modelling

CMS based mostly on vibrational analysis can be costly, the appeal of SCADA bases systems for condition monitoring is largely due to the sensors already being installed to track the normal operations of the vessels. This subsection will discuss approaches implemented in the industry using SCADA data for failure detection and condition monitoring. There are six main approaches; trending, clustering, normal behaviour modelling (NBM), damage modelling, alarm assessment and performance monitoring. SCADA data typically records the meteorological data, component temperatures, control variables and electrical characteristics for horizontal offshore wind turbines. The exact configuration is dependant on the manufacture and operator but is most consistent with [Table 1](#). The time-step from SCADA systems are typically 10minute averages of 1 Hz values. Some operators can offer maximum, minimums and standard deviations on each time-step. Some forms of valuable information are start, stop and alarm logs ([Godwin and Matthews 2013](#)), oil pressure levels coupled with filter status ([Yang et al. 2014](#)) and vibrations. There is no standardisation implemented in the wind industry or any industry. The general trend seems to be more sensors in modern offshore wind turbines for more data.

Data cleansing is a technique involving the transformation of raw data into an understandable format. For instance, the data, whether it is missing, inconsistent or noisy data especially in the offshore wind industry. This has a large influence on meaningful reliability assessment ([Farrar and Worden 2007](#)). Two common methods of addressing this issue; Fuzzy-set theory ([Mokhtari et al. 2011](#)). This aims to distinguish the gradual assessment of membership from elements using indicator functions. Dempster–Shafer theory ([Ferdous et al. 2012](#)) is a framework for reasoning with uncertainty applying understood connections. These theories can help mitigate the issue of vague data but do not remove the problem.

There is information that can be utilised from the offshore oil industry or the onshore wind industry that can be utilised in setting up meaningful databases, taking into consideration the different environmental conditions into account ([Zhang et al. 2016](#)). Another issue is the changing technologies of a fast developing industry so the richness of data or cost aspects needs to be tackled in each of the following models.

5.2.1. Trending

As soon as optimising maintenance strategies grew in the wind industry, so did structural health monitoring. One key area of interest in SCADA systems is temperature measurements. Thermal-dynamics of components can directly relate to the efficiency of the system. In the offshore wind, the gearbox has one of the highest down times causing this keen interest.

A study carried out from 2002 till 2007 ([Wiggelinkhuizen et al. 2008](#)), applies SCADA-based monitoring methodologies consisting of trending methods. Implementing regressions on scatter diagrams of temperature, power, as well as three-dimensional graphs including the ambient temperature. Manual interpretation of the filtered results was proven to be beneficial for determining anomalous behaviour. [Yang, Court, and Jiang \(2013\)](#) have concluded that when the gearbox of a horizontal operational wind turbine efficiency decreases, the gearbox temperature will rise (compared to the ambient temperature), with an expected 6 months before failure. [Wilkinson et al. \(2014\)](#) investigated condition monitoring methods. One of which was a trending method that compared the temperature difference of separate wind turbines on the same site tries to determine faults. The authors dismissed the efforts rendering the approach too inaccurate due to the environmental condition disparity between each wind turbine. It could be argued that this method is still valid but a more complex approach is necessary to irradiate the temporal nature of turbines. The binning method, where an average is taken, was applied to; the wind speed, generator speed and output power by [Yang et al. \(2014\)](#). In this case, the trending methods were applied to historic data and current information to detect levels of damage, the added value is the differing scales of damage dictated by the damage mode and dependent parameter.

Table 1. Summary of references relating to the machine learning methods used in the specific types of monitoring and maintenance technique.

	ANN	SVR	K-NN	DBN	GP	Other
Vibrational	Feng, Qin, and Liang (2016)	Ziaja et al. (2016)	Fernández-Francos et al. (2013)			Qiao and Lu (2015b); Sheng (2013); Geropp (1997); Koukoura, Carroll, and Mcdonald (2017); Bach-Andersen, Rømer-Odgaard, and Winther (2018); Ha et al. (2017); Teng, Ding, et al. (2016); Nejad et al. (2014); Zhang, Verma, and Kusiak (2012); Zhu et al. (2018); Lee and Lee (2014); Bouzid et al. (2015)
Trending	Hackell et al. (2016); Wang et al. (2018); Liu et al. (2016)	Kang, Zhang, and Jin (2015)	Kang, Zhang, and Jin (2015)		Skrimpas et al. (2015); Saidi et al. (2018)	Yang, Court, and Jiang (2013); Yang et al. (2014)
Clustering	Catmull (2011); Kim et al. (2011); de Moura et al. (2016); Mazidi et al. (2016); Yu et al. (2019)	Hang, Zhang, and Cheng (2016); Djeziri, Benmoussa, and Sanchez et al. (2019)	Möller, Langenkämper, and Nattkemper (2019); Teng, Wang, et al. (2016)	Herp, Pedersen, and Nadimi (2016); Wang, Wang, et al. (2019)		Djeziri, Benmoussa, and Sanchez et al. (2017)
Normal behaviour modelling	Ciulla et al. (2019); Garcia et al. (2006); Bi, Zhou, and Hepburn (2017); Schlechtingen, Santos, and Achiche (2013)				Aamer Bilal Asghar Xiaodong Liu (2019); Tabib et al. (2017)	
Damage Modelling	Bangalore and Tjernberg (2015); Dervilis et al. (2014)	Li, Liu, and Shu (2019); Regan, Beale, and Inalpolat (2017); Regan et al. (2016)	Ziegler et al. (2019)	Rocher et al. (2014)	Cao et al. (2016); Sarrafi et al. (2018)	Qiu et al. (2015); Borchersen and Kinnaert (2016); Feng and Liang (2014); Joshua and Sugumaran (2017); Shafiee (2015)

(Continued)

Table 1. Continued.

	ANN	SVR	K-NN	DBN	GP	Other
Alarm Assessment	Pliego Marugán and García Márquez (2019); Jlassi et al. (2015); Yang et al. (2019)	Leahy et al. (2016); Yang, Huang, and Yang (2015)		Wang et al. (2014); Zhao et al. (2018)		Qiu and Feng (2020); Fernandez-Canti et al. (2015); Gonzalez, Reder, and Melero (2016)
Performance Monitoring	Sales-Setién and Peñarrocha-Alós (2020)				Pedersen and Fossen (2012); Rogers et al. (2020); Saravanakumar and Jena (2013); Pedersen and Fossen (2012); Song et al. (2018); Astolfi (2018); Simani (2015)	

The trending method applied to SCADA parameters can observe the development of failure using past data comparing to the present information. There are several studies indicated here where the results are case dependant. Particularly in studies using temperature data which is case-specific and requiring manual interpretation. Attempts to visualise the information have not provided more insight. If trending methods are to be used for maintenance, the difficulties of interpretation and variance on individual offshore wind turbines will need to be addressed. If not, this will likely result in uncertainty and the possibility of false alarms.

5.2.2. Clustering

Visualising trends can be problematic, especially in a wind farm with turbines operating individually under dissimilar meteorological conditions. The evolution of trending was clustering SCADA data, where algorithms began to use classification methods to determine either ‘normal’, ‘faulty’ or ‘error’ observations.

One of the original implementations of clustering using ANN was carried out by Catmull (2011), incorporating a self-organising map interpretation of SCADA information. The methods built clusters through the organisation of neurons on a regular grid for the training process such that the neighbouring neurons have similar inputs. To visualise the clustering information a unified distance matrix is used combined with projections of patterns. In this case, only normal operational signals are implemented for training. The fault detection operated by determining the distance between input data and the best-matched neuron, quantisation error, for abnormal behaviour detection. A similarly, a study by Kim et al. (2011) included failures in the training of the algorithm and subsequently was able to determine individual failures.

Reviewing clustering methods highlights again that interpreting this information still requires human intervention. Also developing a tool that requires the faults to have been previously recorded is not always possible. The advantages from clustering are not dissimilar from trending hence more suitable methods are necessary.

5.2.3. Normal behaviour modelling

NBM encompasses the previous detection methods in normal operations of an offshore wind turbine but has incorporated a significant development where the tool aims to empirically model the desired parameter during the training phase. There are two main concepts; full signal

reconstruction, where only the signals no other than the target are used to predict the desired target and Auto-Regressive with eXogenous input modelling, this includes the target value but also incorporates previous values of the target to be used.

There is a magnitude of authors investigating the validity of artificial neural networks' ability to monitor offshore wind turbines. G. Ciulla et al. (2019) have investigated the power curve of a Sen-vion MM92 aero generator from a 2.05 MW wind turbine. They were able to produce results with deviations below 1% for the producibility and below 0.5% for the power curve.

Garcia, Sanz-Bobi, and del Pico (2006) devised a predictive maintenance scheme called SIMAP using Auto-Regressive with eXogenous artificial neural network. This involved gearbox bearing temperatures and oil coolant temperature. Measuring the difference from the coolant temperature before and after the model makes a prediction coupled with selected inputs. Using cross-correlations and the impulse response analysis the scheme can produce results with a confidence level of 95% for the upper and lower bounds. There is no information on the topology of the artificial neural network from this study.

Another approach using adaptive neuro-fuzzy logic by Aamer Bilal Asghar and Xiaodong Liu (2018) for online estimation of the wind speed from the tip speed ratio. This study is carried out with the NREL 5 MW offshore wind turbine. The wind speed and rotational speed of the rotor are used in the estimator, the neuro-fuzzy logic generates Boolean logic rules. For this example, only 216 rules were determined. This study was able to produce results with a testing error of around 6–7%.

A large number of studies have detailed how NBM is suitable for detecting failure. The concept of evaluating residual measured values minus modelling signals provides an easier interpretation of failure indicators than trending. The large dependency on vast amounts of data for the training stage, coupled with the data pre-processing stage can produce undetected problems or false alarms. There has been a variety of different methodologies discussed but to determine the most effective a more comprehensive study is necessary to evaluate the best solution. Besides, there is no clear universal strategy or consensus on input and output parameters for NBM.

5.2.4. Damage modelling

Effective modelling can be carried out when an entire system can be observed at every detail, unlike NBM, where most of the modelling is considered 'black box'. Damage modelling compares the desired signals with empirical models of normal operation. The interpretation of information involves physical models that can better represent the damage development and provide accurate results.

An electro-thermal analysis of a doubly-fed induction generator in a wind turbine using a geared transition conducted in Qiu et al. (2015) used thermal-dynamic theory and combined it with temperature trending methods. The study made a few assumptions consisting of the rotor aerodynamics are steady-state and the drive-train is considered as rigid body dynamics. This case study used SCADA information of a 1.5 MW wind turbine with gear teeth failures, vibration faults and generator winding imbalances. The diagnostic rules determined faults for power transmission efficiency, generator winding and lubricant temperature.

Switching generators require cooling to sustain the operation. Borchersen and Kinnaert (2016), devised a physics-based numerical model of the coil temperatures. The model was developed using Kalman filters of the actual system. The damage is determined using the values from the physical model on the three coils coupled with a cumulative sum algorithm. This study has used three years of historical data for 43 offshore wind turbines with an 88% fault detection success rate.

The comparison from measured signals and physical turbine damage models has shown success when applied to failure detection, significant challenges still exist with regards to the accuracy. Due to the lack of studies conducted on varying failure modes and from different turbines the full extent of this method of condition monitoring is not yet established.

5.2.5. Alarm assessment

Interpreting the information from complex failure detection strategies is one of the leading causes of discontinuity from development to delivering a condition monitoring system. There are a variety of tools constructed to provide better insight into the outputs of SCADA control alarms or Normal Behaviour Modelling. In general, alarms are usually broken into system operation, environmental and communication/software to indicate system malfunctions.

A fault diagnostic tool for a wind turbine developed by Yingning Qui and Yahuni Feng (2020) used SCADA alarm material and is based on Dempster-Shafer theory. Dempster-Shafer theory is a multidimensional probability theory that takes each alarm as an item of evidence which supports different possible failures. The system verification was carried out using battery failures producing false-negatives and false-positive rates with an accuracy of 76%.

An analysis for detecting false alarms conducted by Pliego Marugán and García Márquez (2019) uses artificial neural networks. There are three trained ANN in this approach, one of which deals with vibration information, the second deals with SCADA data and both of which are fed into a final model which also includes the alarm information. The system verification model involved a fuzzy logic-based methodology, where fuzzification was applied to each input and output variable and was critically analysed in a fuzzy data set. The final results of this tool ranged from 80% to 90% false alarm detection.

Evaluating alarm assessments for condition monitoring has shown benefits for fully autonomous fault detection systems. There is a severe lack of information regarding industrial algorithms for alarm assessment in offshore wind. The lack of clarity, highlighted was the large discrepancy in accuracy of outcomes, for the results status code consistency to increase these articles underline how necessary it is for more work in this area to reach full condition monitoring autonomy.

5.2.6. Performance monitoring

Monitoring the operations of an asset is essential to review the performance. Equally the performance of the turbine can be evaluated in terms of health, assessing the degradation in terms of health has opened up an opportunity to assess the performance in greater detail.

Addressing the performance of an operational wind turbine has been standardised in the IEC 61400-12 (Zhao et al. 2018), discretising the power curve into bins of 0.5 m/s wind speeds and calculating the mean power value for each bin. Applying this method does not consider the non-linear power to wind relationship (IEC 61400-12-2:2013, IEC 2013). There are a variety of probabilistic methods (Pedersen and Fossen 2012; Rogers et al. 2020; Saravanakumar and Jena 2013) and non-parametric (Pedersen and Fossen 2012) that encapsulate the power curve of a wind turbine. This aspect is crucial to effective power modelling.

A robust diagnosis of a wind turbine pitch failure conducted by Song et al. (2018) uses power estimation to diagnose the fault. This method involves a pitch misalignment estimation using a statistically based fault scheme. This model incorporates the wind and wake model to determine the power curve, the fault detection is conducted using a model based observer including a closed-loop. One of the main characteristics of this scheme is the performance improvement by building a bank of observers that lead to the decision to create consensus. This system can determine pitch errors at 0.1 deg at low wind speeds and 1 deg at high.

Another area that affects the output power is the yaw alignment, this is another area that has significant developments for performance monitoring. Sales-Setién and Peñarrocha-Alós (2020) details two favourable yaw control systems. The China Ming Yang 1.5 W wind turbine is assessed in this case. Two yaw control systems are constructed using low pass filters. An Auto-Regressive Integrated Moving Average is used to predict future wind speed and direction. A Kalman filter is then used to determine the manoeuvre of yaw rotation. This method increased the performance by 15% however, the frequency of this SCADA data is every 10 s and would benefit with a higher frequency of results.

Performance monitoring is beneficial, increasing the efficiency of the operational wind turbine and assessing the condition of the turbine. Research has indicated that SCADA data are suitable for this task but a higher resolution is necessary for a more optimal tool. Again there is a limited amount of resources from the industrial sector and the standardisation is not implemented in most academic papers.

6. Discussion

There have been a variety of different machine learning methods' main features discussed. The five popular methods strengths and limitations for; ANN, SVR, GPR, DBN and K-NN are compared:

Given the capabilities and limitations for the above models it is difficult to advise a specific type. They can all provide reasonable results for condition-based maintenance. Whether you are looking to understand the contributions towards the outcome or not would be a consideration among many. One main significant capability all models have is the ability to develop an individual prediction from historical data, something that cannot be carried out with conventional statistical methods or physical models. This comes with the cost of computational effort in comparison to statistical data fitting. Conversely, physical models can be too computationally expensive and hinder productivity but can provide more insight (Table 2).

The majority of discussion has strictly tackled the individual ML models applied to condition monitoring, but in more recent studies which include multi-agent systems, combinations of algorithms used to gain improved results, is gaining traction in the offshore wind industry. Yin and Zhao (2019) effectively applied this technique using multiple ML methods gaining impressive results in predicting the thrust of the operational wind turbine.

Another interesting aspect is bringing combinations of condition monitoring methods. Multi-agent systems are ones that share features that are used to determine different objectives. M'hammed et al. (2014) applied both clustering techniques measuring the vibrations of multiple components and an alarm assessment to determine the most effective maintenance strategy.

The challenges that arise from CMS of offshore wind turbine systems are discussed. Currently, vibration-based condition monitoring depends on advanced signal processing methods coupled with expert insight. With regard to SCADA-based condition monitoring, there are various techniques addressed. The principal methods in addition to novel ideas are gathered and presented as follows:

- **Trending** methods have demonstrated an effective ability at detecting anomalies. The specific cases have highlighted those specific configurations and interpretations are necessary for different machines. Automated trend monitoring systems are unlikely to provide accurate and adequate alarms.
- **Clustering** a more effective method than **trending** at determining the differentiation between normal operation and anomaly but still has similar limitations. This also requires historical failure information to develop an effective diagnostic tool and it is unlikely that the full extent of faults is determined.
- **Normal Behaviour Modelling** is the main focus for SCADA data condition monitoring because of the simplicity of anomaly detection, by using the trained model modelled versus the measured variable. This article has detailed machine learning methods that can be used to determine failures effectively. But there is no clear comprehensive technique described as the best. From the variety of cases reviewed, it was difficult to determine with certainty if the fault detection technique is lacking or the method used to determine the behaviour. The specific type of configuration of the model also remains unclear to determine if specific issues like overfitting are present. There is also a lack of published standards to understand the performance of individual models to benchmark tools.
- **Damage Modelling** is effective at specifically looking at the physical cause of failure for offshore wind turbines. This will be no easy feat since reliable and accurate damage models encompassing all failure modes are difficult. There is limited information on this with limited studies being

Table 2. Summary of the benefits and limitations for the 5 individual regression machine learning methods.

Method	Capabilities	Limitations
ANN	No Prior knowledge needed: since the algorithm is based only on historical data. Processing incomplete data: A trained network can still produce results with incomplete knowledge. The accuracy is dependent on the importance of the information. Can be updated in real-time: The program can run while updating the firmware reducing downtime.	Unexpected behaviour: One of the major drawbacks of an ANN. When an ANN produces a probing result there is no insight on how these anomalous results are produced. Hardware dependence: ANNs accuracy is directly dependent on the amount of information used to train the network. The network requires a large amount to learn correctly. Black Box: it is incredibly difficult to understand the network within this type of model.
SVM	Rationalisation and training efficiency: As opposed to other methods the probability of local optima during training is unlikely since Quadratic programming is formulated in the development. This is rewarded with the goodness of fit with unseen information. Outlier Suppression: Unlike other methods, SVRs consider trade-off parameters when processing information	Parameter selection: One of the major drawbacks for SVRs is the correct implementation of the Kernel function. The function represents the data in the Hilbert space. Other parameters need to be adjusted to reach the desired fitting. Computational Effort: SVRs usually have good performance with limited data. With an increased magnitude of data, the time required to solve the dual optimisation problem and Lagrange multipliers increases significantly.
K-NN	Simple and effective: This is a well understood methodology. The decision rule is extensively researched. The number of classes reduces the error twice that of a Bayes probability. No assumptions: Unlike other methods K-NN is a non-parametric therefore requires no presumptions to be made. No training necessary: This methodology does not explicitly build a model. It uses previous information to infer new data.	Slow algorithm: As the dataset increases the inverse will happen to the efficiency. Especially with increased dimensionality, the accuracy of the algorithm declines. Outlier sensitivity: The K-NN algorithm is hypersensitive to outliers as the neighbours are selected based on the selected distance criteria. Unknown amount of clusters: It is difficult to determine the right amount that produces the most meaningful results.
DBN	Overfitting control: Since Bayesian statistical methods are encapsulated in the model local maximums can be avoided. Unaffected by parameterisation: DBN looks for interdependence hence they are not adversely affected with more variables.	Unknown amount of arcs: For many cases the number of arcs and nodes could be in the thousands hence a closed-form solution cannot be achievable.
GP	Directly captures uncertainty: in regression models the prediction is given as a value and a distribution. This is not directly captured in other methods. Prior knowledge implementation: when designing the model, if the path of the trend is known a specific kernel function that correlates can be implemented.	Computationally demanding: For more than a few hundred data points the time to process this information is longer than other methods due to the cubic inversion issue.

published. Inferring different models for varying turbines for different environments cannot be examined yet.

- **Alarm Assessment** combined with probabilistic methods and or physical rules has provided promise at reducing the frequency of alarms to more a critical catalogue of alarms. The studies have shown limited industrial developments that back this. Expert systems with fuzzy interference working together can interpret complex information and deliver easily understood information.
- **Performance Monitoring** tools effectively determine the difference in power output from the environmental conditions, operations and health of the turbine. This tool is necessary to determine the performance of the offshore wind turbine, aid the optimisation of power extraction and maintenance.

7. Conclusion

This article has given a systematic review of how monitoring for maintenance can be carried out, detailing specific measures that can be taken for condition-based maintenance. This article has addressed the types of machine learning, providing a review of models suited to condition

maintenance for offshore wind turbines. Bringing both of these components together is a trend across all industries, the offshore wind industry is catching up to the oil sector or aerospace. There are consistencies across all sectors; there are no design principles for implementing these tools and there is no consensus on the best-suited machine learning methodology.

Monitoring and maintenance carried out on an offshore wind turbine are implementing vibrational analysis, but limited studies are incorporating the vibrations analysis coupled with SCADA data to determine faults. This journal paper has discussed in detail how machine-learning can be used to detect faults with a variety of approaches. Another powerful tool of machine-learning is that specific faults can be categorised into alarms for immediate action to be taken.

Common issues when implementing data-driven approaches is the preprocessing of the data. Since there are no specific standards on how this is carried out, each individual producing a ML model may have dissimilar results when using the same architecture. This could be a result of many different approaches to anomaly detection, the variation in the opinion of experts, or the magnitude of dimensional reduction among some possibilities.

Lastly, current methods usually require experts to implement and understand the results of the monitoring systems. Exploring the automation of CMS could remove the complexity of the results decreasing the ambiguity on the condition of the asset.

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ORCID

Athanasios Kolios  <http://orcid.org/0000-0001-6711-641X>

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