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SCADA-Based Offshore Wind Turbine Monitoring: A Review of Methods of Addressing Marine Environmental Challenges

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ABSTRACT

Offshore wind turbines could be an important aspect of the global green energy transition, but their implementation is challenging due to the harshness of marine environments. Compared to onshore structures, offshore wind turbines are exposed to stronger loads from waves and more turbulent atmospheric conditions, while salt-laden air accelerates structural degradation. These variable environmental conditions also make diagnostics difficult. Supervisory control and data acquisition (SCADA) systems, which are already embedded in all turbines, provide a cost-effective source of operational data for performance assessment and condition monitoring. Although experience of SCADA-based onshore testing over recent decades has provided valuable knowledge, these insights cannot be directly applied to offshore monitoring. This review summarises the current state of knowledge of SCADA-based monitoring for offshore wind turbines, compares it with onshore approaches, and highlights offshore-specific challenges arising from the marine environment.

Keywords: offshore wind energy, monitoring, SCADA, digital twin

INTRODUCTION

The European Union is intensifying efforts to scale up offshore wind energy, as a cornerstone of its drive towards industrial competitiveness and clean electrification. New “tripartite contracts” have been signed between governments, wind developers and industry, with the aim of stabilising investment and accelerating the development of grid infrastructure and permitting processes. Although challenges remain, including project delays, underbidding in auctions and grid bottlenecks, recent decisions have signalled that there are plans to raise Europe’s capacity from 37 GW today to 80 GW by 2030, giving rise to an urgent need for reliable monitoring and diagnostic solutions to sustain large-scale offshore operations [1].

Condition monitoring (CM) systems for offshore wind farms are often cost-effective because they help to mitigate the increased energy loss during the downtime of a turbine. In a marine environment, the downtime of offshore turbines may rise due to harsh weather conditions and the longer distances to the turbines. In addition, the larger components needed for high-capacity offshore turbines, which are designed to withstand the marine environment, have higher costs for operation and maintenance (O&M) [2].

All offshore wind turbines (WTs) are equipped with supervisory control and data acquisition (SCADA) systems as standard. These systems collect extensive amounts of data during the operational lifetime of a turbine, and provide updates, usually every 10 min. When used with robust algorithms, data from these systems can enable control, predictive maintenance, and alerts [3].

SCADA-based monitoring technologies have lowered O&M costs and improved wind power generation, thereby enabling more effective maintenance planning and operational decisions for offshore wind farms. However, the current lack of standardisation and open sharing of SCADA data remains a major limitation of offshore systems. Differences in technology, operating environments, and data collection practices make it difficult to compare studies in this field. In particular, offshore reliability is less well understood than onshore reliability, as access to detailed and flagged datasets is limited [4]. This paper highlights the value of SCADA data for monitoring, identifies gaps in extant research, and presents key insights into its benefits for offshore WT applications. The purpose of this review is to identify ways of improving the use of SCADA data within the offshore wind energy sector.

CHALLENGES OF OFFSHORE WIND TURBINE MONITORING

The marine environment presents certain challenges for the SCADA-based monitoring of offshore wind turbines. Offshore turbines operate under strong, turbulent winds [5], and this issue is compounded by wind-wave-current loadings, which increase fatigue of offshore support structures [6] and drive frequent yaw and pitch adjustments. Furthermore, humidity and salt accelerate corrosion, cause sensor drift, and reduce the reliability of data. Another factor is the marine-specific biofouling that modifies the hydrodynamic loading, while the subsea cables introduce additional modes of failure.

SCADA data from offshore wind turbines is often incomplete and noisy, due to the harsh marine environment. This results in, relative to onshore WT data, increased errors in data and a lower signal-to-noise ratio. Furthermore, the maritime environment for offshore WTs imposes unique logistical maintenance constraints, such as limited weather windows for access to turbines via vessel or helicopter, and very high downtime and maintenance costs that demand highly reliable predictive alarms with minimal false positives and false negatives.

When taken together, these factors mean that offshore diagnostics requires more tailored, robust, and environment-aware monitoring strategies. In Table 1, we summarise the key issues related to offshore turbine diagnostics arising from the marine environment, and compare them to those affecting onshore turbines.

Table 1. Key issues for offshore vs onshore WT monitoring

Factor	**Onshore WT**	**Offshore WT**	**Main consequences for offshore WT**
Wind conditions	More predictable, lower turbulence, affected by hills, forests, obstacles	Stronger but more turbulent winds, gusts and rapid direction changes	More frequent yaw/pitch activity offshore leads to higher loads and failure rates in pitch and yaw systems
Loads	Only wind and terrain-induced turbulence	Combined wind- and wave-current loading on foundations	Extra dynamic stresses on support structures make them harder to model and influence SCADA vibration signals
Air composition	Dust, sand, insects, occasional icing	Salt-laden, humid air; icing in some seas	Salt accelerates corrosion and sensor failures
Temperature variations	Larger daily and seasonal swings inland	More stable but humid marine climate	Fewer thermal cycles offshore, but constant humidity leads to corrosion
Biofouling	Not relevant	Marine organisms (algae, barnacles, mussels) on foundations and cables	Increased hydrodynamic drag and mass, shifted vibration modes, cable overloading
Cables and grid	Underground or overhead land cables; stable substations	Subsea cables and offshore substations	Cable faults unique to offshore turbines, costly and hard to repair
Maintenance and logistics accessibility	Fast response possible; easy road access; requires road vehicles, cranes	Slower response; limited weather-dependent access; requires vessels, jack-ups, or helicopters	Delayed maintenance for offshore WTs; higher cost of downtime; false positive alarms lead to wasted vessel trips; false negatives can lead to catastrophic failures
Downtime cost	Lower; easier delivery of spare parts	Much higher due to vessel hire, delays and lost production	Offshore SCADA monitoring must prioritise early, accurate prediction

SCADA-BASED METHODS FOR OFFSHORE WIND TURBINE DIAGNOSTICS

The following subsections provide a detailed overview of the three main categories of SCADA-based monitoring methods for offshore WTs, which are shown in Fig. 1. The first category is knowledge-driven approaches, in which physical understanding and expert rules are used to interpret SCADA signals. The second category is data-driven approaches, which include statistical indicators and machine-learning models that extract patterns directly from operational data. Finally, there are hybrid methods that combine the strengths of both knowledge-driven and data-driven strategies to improve diagnostic accuracy under varying marine conditions.

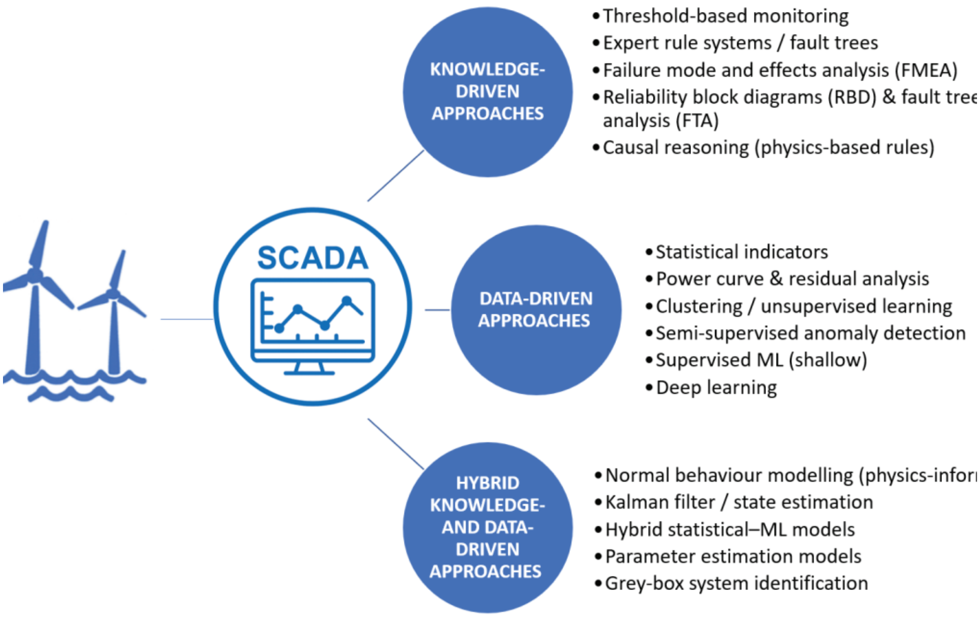

Fig. 1. Three classes of SCADA-based monitoring methods for offshore wind turbines.

KNOWLEDGE-DRIVEN APPROACHES

One example of a knowledge-based monitoring approach is threshold-based monitoring, in which fixed upper or lower limits are used for SCADA signals. This method offers fast, straightforward anomaly detection, but it often produces false alarms, especially under offshore conditions, due to turbulence, humidity and marine variability. An extension of the classical threshold method for offshore WT diagnostics was successfully applied by Agarwal and Kishor [7], who developed a flexible threshold selection approach combined with a fuzzy inference system-based fault detection method, known as the Flexible Threshold Selection and Fuzzy Fault Detection System (FTSFFDDS).

Other knowledge-driven approaches such as expert rule systems and fault trees use "if-then" logic or hierarchical fault structures based on engineering knowledge (for example, low power combined with yaw misalignment indicates a yaw fault). These methods are transparent and interpretable, but often lack robustness under variable marine conditions, which limits their transferability between offshore sites [8].

Failure mode and effects analysis (FMEA) is a structured, knowledge-driven, risk-based method in which failure modes are ranked by severity, occurrence, and detection. FMEA is widely applied to WT components, including pitch actuators, converters, and gearboxes, but its effectiveness for offshore turbines is limited by missing or unreliable SCADA data and its strong dependence on expert judgments. Extensions of this method have been used to address offshore-specific challenges; for instance, Dinmohammadi and Shafiee [9] proposed a fuzzy-FMEA approach that enabled more accurate risk prioritisation of failure modes. One application for offshore wind turbine systems was demonstrated on 16 mechanical, electrical, and auxiliary assemblies. Furthermore, Li et al. [10] applied an analytic hierarchy process approach to determine the weights of FMEA risk factors for floating offshore wind turbines.

Reliability block diagrams (RBDs) and fault tree analysis (FTA) methods model subsystem reliability and failure relationships, thus allowing for the estimation of downtime impacts such as pitch or converter faults in offshore farms. They are valuable for availability assessment and O&M planning, but are static methods that cannot be adapted to the fluctuating SCADA signal quality specific to offshore environments. For this reason, an extension, a fuzzy FTA (FFTA) model was established by Zhang et al. [11] to quantify the information uncertainties for a floating offshore WT.

A causal reasoning approach involves the application of engineering cause-and-effect rules [12]; for example, a power drop at a constant rotor speed may be linked to a pitch or sensor fault. Methods of this type, which are grounded in physics, enhance the interpretability of faults but may oversimplify the complex, multi-factor interactions in the marine environment. A summary of knowledge-based diagnostics for WTs is given in Table 2.

Table 2. Knowledge-driven approaches for offshore WT SCADA diagnostics

Approach	Description	Pros	Cons	Reference(s)
Threshold-based monitoring	Fixed upper/lower limits for SCADA signals	Simple, widely implemented, fast detection	Possible false alarms due to turbulent winds, humidity, marine variability	[7] (offshore)
Expert rule systems/fault trees	"If–then" rules or hierarchical fault logic built on expert knowledge	Transparent, interpretable, codifies human expertise	Rule transferability is weak, and not robust in changing marine conditions	[8] (review of the method)
FMEA	Structured method to rank failure modes by severity, occurrence, detection	Systematic, risk-based, accepted in industry	Offshore SCADA data often missing/unreliable, heavily expert-dependent	[9] (offshore), [10] (floating offshore)
RBD & FTA	Reliability models of turbine subsystems and failure relationships	Good for availability assessment and O&M planning	Static, cannot be adapted to varying SCADA signal quality	[11] (offshore)
Causal reasoning (physics-based rules)	Uses engineering cause-effect rules rather than pure statistics	Physics-based, helps distinguish between environment and component faults	Simplifications may miss complex multi-factor marine interactions	[12] (offshore)

DATA-DRIVEN APPROACHES

One straightforward data-driven approach to SCADA diagnostics involves monitoring statistical features such as the mean, variance, or coefficient of variation of key signals; for example, an abnormal variance in rotor speed or pitch activity may serve as an early flag. These methods are easy to compute and highly interpretable, although in offshore environments, they often give false alarms due to turbulence and humidity [13].

Another data-driven approach is residual analysis, in which measured curves, such as the power curve, are compared with a modelled or expected baseline [13]. Deviations can indicate several issues, such as blade soiling, pitch misalignment, or icing. Since power is a standard SCADA signal, this approach provides a useful baseline check. Its main limitation for offshore use is that wakes, turbulence, and curtailment events are frequent, and can create residuals unrelated to faults.

Offshore WT SCADA data are rarely made publicly available, especially when labelled, meaning that unsupervised learning methods become particularly useful. Algorithms such as k-means or density-based spatial clustering of applications with noise can cluster SCADA data into groups representing normal operating regimes, while points that do not belong to any cluster are identified as anomalies. These methods can successfully identify unusual states, but the definitions of clusters may drift over time as the sea conditions change, making interpretation difficult. Miraftabzadeh et al. [14] presented a review of unsupervised clustering methods for power systems, including WT applications. Li et al. [15] applied an unsupervised method called Hawkey to multivariate real-world WT data.

In the absence of labelled data, semi-supervised anomaly detection models can only learn from healthy SCADA data and flag any deviations. Examples of this type include autoencoders with reconstruction error thresholds and one-class support vector machines (SVMs). These are particularly attractive for offshore wind applications, where labels for fault data are scarce. Suliaman and Salam [16] successfully applied an autoencoder method to a power curve for onshore WTs. Unfortunately, such methods can be highly sensitive to environmental noise, which can lead to false positive flags.

In supervised machine learning, classifiers or regressors such as SVMs, random forest or gradient boosting are applied to predict faults from SCADA features. For example, Pandit and Infield [17] used a Gaussian process model to onshore power curve data, while Leahy and Hu [18] used SVMs to distinguish faults such as air cooling, excitation, and generator heating from healthy operating states. Methods such as these can achieve high accuracy when labelled fault data are available; their main drawback is that labelled offshore fault data are limited, and there is a risk of overfitting of the model to site-specific conditions.

The most efficient, although time-consuming, methods are deep learning approaches. Recurrent neural networks (RNNs) long short-term memory (LSTM) networks, convolutional neural networks (CNNs), and autoencoders have been applied to offshore SCADA time series [19]. These approaches can capture nonlinearity and temporal patterns, making them powerful for anomaly detection and forecasting. For instance, LSTMs have been used to predict power output or detect emerging faults in offshore turbines. However, these models require large datasets, which are rare for offshore WTs, and their "black-box" nature limits their interpretability. In Table 3, we present a systematic summary of current data-driven approaches.

Table 3. Data-driven approaches for offshore WT SCADA diagnostics

Approach	Description	Pros	Cons	Reference(s)
Statistical indicators	Simple statistical features (mean, variance, coefficient of variation, correlations) monitored over time	Easy to compute, interpretable	Sensitive to turbulence and marine variability, high false alarm rate	[13] (review)
Power curve and residual analysis	Compare measured power to modelled/ expected power from SCADA (baseline regression)	Uses standard signals, good baseline check	Affected by wakes, turbulence, curtailment; common offshore	[13] (review)
Clustering/ unsupervised learning	Identify "normal" operating clusters and flag outliers	No labels required; good for anomaly detection; scalable	Cluster drift due to changing sea conditions, hard to interpret	[14] (review of power systems, including onshore WT) [15] (offshore, tested on real-world data)
Semi-supervised anomaly detection	Trained only on "healthy" data; can detect deviations	Works without fault labels	Sensitive to environmental noise; may confuse turbulence with faults	[16] (onshore power curve data)
Supervised ML (shallow)	Classification/ regression using labelled data (SVMs, random forest, gradient boosting)	High accuracy if labels exist, flexible, time-efficient	Requires fault labels, which are scarce offshore; risk of overfitting	[17] (onshore) [18] (onshore)
Deep learning	Neural networks, LSTM, CNN autoencoders for SCADA time series	Can model nonlinear, temporal dependencies, strong anomaly detection	Data-hungry, limited transparency, risk of overfitting, time-consuming	[19] (review)

HYBRID KNOWLEDGE- AND DATA-DRIVEN APPROACHES

Physics-informed normal behaviour modelling (NBM) methods combine theoretical physics (for example, aerodynamic power curves or thermal balance equations) with SCADA data. By grounding the model in known physical behaviour, this approach can reduce false alarms compared to purely data-driven models. Schlechtingen and Santos [20], [21] demonstrated the use of NBM in the context of WT condition monitoring. Nevertheless, the accuracy of this approach for offshore WT depends strongly on parameter calibration, as wake effects and turbulence can distort the residuals between measured and predicted signals.

Another example of a hybrid approach to diagnostics involves Kalman filtering and related state-estimation techniques. These methods, as described by Noppe [22] integrate dynamic system equations with continuously updated SCADA measurements. They provide effective noise reduction and can yield estimates of unmeasured states. These methods can be useful, especially when attempting diagnosis in a harsh offshore environment, but they rely on accurate initial models and parameter tuning, which becomes challenging in offshore environments where marine loads are highly variable. Another example of this approach was provided by Branland et al. [23] in regard to floating offshore wind turbines.

Hybrid statistical-machine learning models use physics-derived indicators such as power curve residuals or pitch-to-wind relationships as inputs to machine learning algorithms. An approach of this type was presented by Jamil et al. [24] and validated on an entire offshore farm. Although hybrid models yield improved detection accuracy and a reduced false positive rate, they require site-specific training and can become overfitted to noisy offshore SCADA datasets if not carefully validated.

Parameter estimation models represent one of the most straightforward hybrid approaches. In this approach, SCADA data are linked to physical quantities such as friction coefficients or efficiency factors. Tracking how these coefficients change over time can help in understanding the wear and tear of turbine parts. Ziegler et al. [25] demonstrated how parameter trends derived from operational data could support lifetime extension decisions and be used to identify abnormal wear patterns. However, the reliability of these methods depends on accurate prior knowledge of the turbine's dynamics. In offshore conditions, strong turbulence and wake interactions can cause apparent parameter drift that does not correspond to real structural changes, which can reduce interpretability.

Finally, another hybrid approach is grey-box system identification, in which reduced physical models are combined with optimisation algorithms that fit parameters directly to SCADA data. This method has been applied to offshore WTs, as demonstrated by Liang et al. [26]. Gebel et al. [27] employed a grey-box modelling approach to estimate equivalent wind-wave loads and to update structural dynamics models using field measurements. Grey-box frameworks strike a balance between transparency and flexibility, but their accuracy relies on the quality of SCADA signals and the details of the model. These methods may also overlook the nonlinear effects and subsystem couplings that are characteristic of the marine environment. A summary of hybrid diagnostic methods for offshore WTs is provided in Table 4.

Table 4. Hybrid approaches for offshore wind turbine SCADA diagnostics

Approach	Description	Pros	Cons	Reference(s)
Normal behaviour modelling (physics-informed)	Combines theoretical models with SCADA corrections	Uses physics baseline, reduces false alarms vs. pure data-driven	Still sensitive to turbulence/ wakes, requires careful calibration	[20],[21] (onshore)
Kalman filter/state estimation	Uses physics equations but updates state with SCADA signals	Handles noisy SCADA, bridges physics and data	Requires accurate initial model, tuning difficult in variable marine loads	[22] (offshore), [23] (floating offshore)
Hybrid statistical-ML models	Combine physics-derived indicators with ML classifiers/ regressors	Improve detection accuracy, balance interpretability	Dependent on site-specific training, may be overfitted to noisy offshore data	[24] (offshore)
Parameter estimation models	Estimate degradation of physical parameters using SCADA trends	Link SCADA signals directly to physical meaning	Need good prior knowledge, risk of parameter drift in marine turbulence	[25] (onshore)
Grey-box system identification	Reduced physical model fitted with SCADA using optimisation	Simplified but interpretable, scalable to farm level	Requires high-quality SCADA, oversimplification may miss nonlinear effects	[26] (offshore), [27] (offshore)

CONCLUSION

SCADA data represent the backbone of offshore WT monitoring, but could be more cost-efficient if more robust methods for diagnostics were developed. Of the methods discussed here, it is difficult to identify the single best option, as some are more suited to specific SCADA signals while others address different types of problem. One of the most promising directions for wind turbine monitoring is the development of a digital twin (DT) [28]. Although individual hybrid approaches such as NBM, Kalman filtering, and parameter estimation can improve the robustness of SCADA-based offshore WT monitoring, the concept of the DT represents the most advanced multi-hybrid integration of these methods. This technology combines a physics-based approach with continuous SCADA-driven updates. Furthermore, a DT can adapt to the changes and complexity of the marine environment, thus enabling predictions, simulations, and diagnostics. This technology is still computationally challenging and limited by the accessibility of data, but is widely regarded as the most promising path for offshore WT monitoring.

This review indicates that there are only a limited number of studies in which methods have been validated on actual offshore datasets, and even fewer datasets that are openly accessible. Future progress in offshore WT diagnostics and maintenance, and the adoption of integrated frameworks such as DTs, will rely on improved data sharing within the industry and among scientists.

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