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# From monitoring to maintenance support: a critical review of wind turbine condition monitoring systems and their integration into maintenance practice



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## Highlights:

- Analyze why condition monitoring system outputs cannot provide actual help to site maintenance.
- Develop a Data-Model-Decision Gap framework to describe the mismatches between them.
- Discuss the misalignment between data, models, and decisions in practice.
- Propose a decision-driven design for next-generation condition monitoring systems.
- Illustrate how the future condition monitoring systems benefit wind turbine maintenance.

**Abstract:** Although condition monitoring systems (CMS) provide detailed information about the health of critical wind turbine components, their practical application in wind farm operations and maintenance (O&M) remains limited, significantly diminishing their value. The reasons for this situation are not merely technical issues, rather, a complex interplay of various factors besides the condition monitoring algorithms themselves. The purpose of the paper is to investigate these reasons and propose a potential solution. Through in-depth analysis, two gaps are identified. The first gap is the Data-Model Gap, in which operational wind turbine data do not adequately satisfy the assumptions and quality requirements of condition monitoring algorithms. The second is the Model-Decision Gap, where the CMS output fails to provide sufficient information to support maintenance decisions. Based on this, a Data-Model-Decision Gap (DMDG) framework is further developed to explain how maintenance requirements can be used to determine the CMS outputs and, subsequently, the wind turbine condition monitoring data that are needed to produce these CMS outputs. Such a CMS design logic reverses the usual data-to-model development sequence by starting from understanding what kind of CMS outputs can actually support decision-making in practical wind farm O&M. This new CMS design approach emphasizes the alignment of data, models, and decision processes through an iterative and integrated design strategy. Research findings indicate that merely improving algorithm accuracy is insufficient to enhance the practical value of CMS. Bridging the aforementioned gaps is the key to transforming the



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CMS design from “monitoring-oriented” to “decision-oriented” and in the end, providing “prescriptive maintenance solutions”. This change is critical for unlocking the full potential of CMS in wind farm O&M.

**Keywords:** wind farm; condition monitoring system; operation and maintenance; decision making

## 1. Introduction

With the continual growth of wind turbine size and their increasing deployment offshore, wind farm maintenance costs and downtime risks have greatly risen [1]. Traditional maintenance strategies, primarily based on regular inspections and corrective repairs or replacements, are no longer sufficient enough to ensure economic and reliable operation of wind farms. This is why condition monitoring systems (CMS) have been widely adopted today as a key tool for condition-based maintenance (CBM) [2]. By analyzing wind turbine operational data, these systems detect anomalies and assess health of critical turbine components (e.g., blades, gearboxes, bearings, generators, *etc.*), enabling early fault detection and timely intervention prior to catastrophic failure.

In practice, wind farm Supervisory Control and Data Acquisition (SCADA) systems are also frequently applied to performing some wind turbine monitoring tasks. However, CMS and SCADA systems serve fundamentally different purposes and operate at different levels of resolution and functionality. To be specific, SCADA systems are primarily designed for supervisory control and operational monitoring, providing low-frequency (typically 1–10 min intervals) measurements of key wind turbine operational variables, such as wind speed, power output, temperatures, and system states. So, SCADA can support anomaly detection but mainly at the system level, because their low rated data lacks the sensitivity to incipient fault [3]. In contrast, CMS are specialized diagnostic systems focused on the health assessment of critical components, utilizing high-frequency data (such as vibration, acoustic, electrical current) to detect “early-stage” faults. Herein, “early-stage” faults refer to degradation condition in which a condition-monitoring indicator exhibits a statistically significant and persistent deviation from the established healthy baseline, while the component has not yet reached a critical condition requiring immediate corrective intervention or shutdown. They can be quantitatively defined by  $z = (x - \mu_H) / \sigma_H \geq z_0$  and the value of threshold  $z_0$  is dependent on the monitored component, operating conditions and historical baseline. Therefore, CMS and SCADA complement each other but cannot replace one another. However, how to use them together remains a key challenge today.

In spite of the critical role and wide application of CMS as well as the significant advancements in condition monitoring algorithms, a fundamental issue remains unsolved today, *i.e.*, “CMS outputs are underutilized as decisive inputs for planning maintenance”. This is because most existing relevant studies focus on improving diagnostic accuracy, while overlooking the practical challenges of integrating CMS outputs into operational decision-making. Motivated by this perspective, this paper proposes to shift CMS design from algorithmic performance to engineering applicability. Specifically, it will introduce a Data-Model-Decision Gap (DMDG) framework to analyze the disconnect between data acquisition, model inference, and maintenance decision-making. Herein, it is necessary to clarify that the proposed DMDG framework is intended to improve the design of CMS from the perspective of maintenance decision support, rather than to automate maintenance decisions or replace human expertise.

Rather than seeking to provide an exhaustive catalogue of publications or a quantitative bibliometric analysis, this paper synthesises existing evidence to examine the extent to which wind turbine CMS research supports real-world maintenance decision-making. The literature is considered across three connected levels, *i.e.*, decision, model and data. Studies are examined according to the maintenance or operational decision being supported, the modelling approaches used to generate condition information, and the data characteristics and assumptions underlying those approaches.

The remainder of the paper is organized as follows. Firstly, it reviews the current deployment and use of CMS in wind turbines. It then examines the practical limitations of existing data-driven monitoring and diagnostic approaches, before defining the Data-Model Gap and Model-Decision Gap in greater detail. Subsequently, the DMDG framework is formulated and compared with established approaches such as prognostics and health management (PHM) and digital twin-based systems. A decision-driven design methodology is then developed to translate the framework into a workflow of CMS design. Finally, an illustrative cost analysis is used to illustrate the potential economic benefit of aligning CMS outputs more closely with maintenance requirements. It is necessary to note that the cost analysis here is only an illustration rather than an empirical validation of the proposed framework.

## 2. Current status of CMS deployment and usage

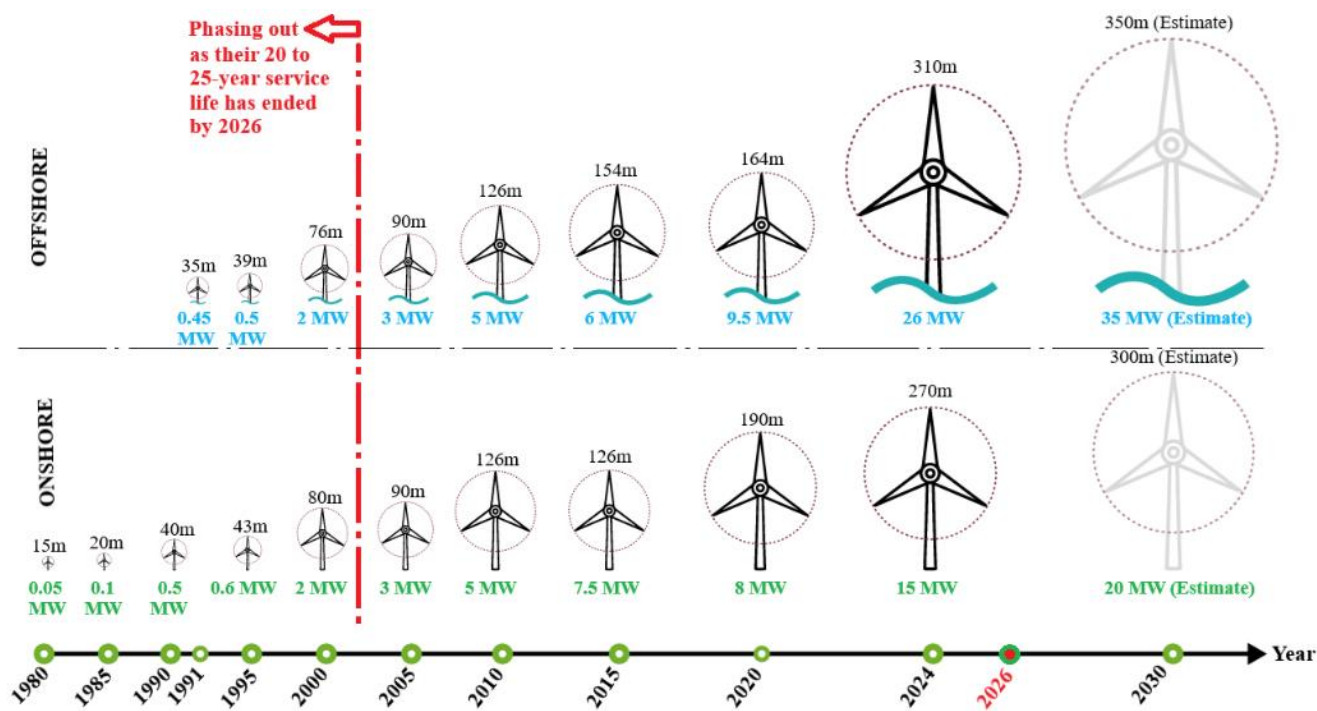
### 2.1. Deployment characteristics

SCADA has become a standard source of operational data for modern wind turbines, while dedicated CMS are installed selectively according to turbine design (e.g., gear-driven or direct drive), component criticality, and the O&M strategy being adopted (e.g., corrective, preventive, condition-based) [4,5]. This difference in deployment directly affects how much information the two data sources can provide for condition assessment.

SCADA can often provide a larger number of low-rated operational variables, including wind speed, power output, temperatures, and other operating-state measurements (e.g., nacelle yaw angle, blade pitch angle, *etc.*). These variables and their correlations show the long-term performance of the turbines, so they are excellent indicators for performance monitoring and anomaly detection. A systematic review of more than 95 recent studies found that over 70% of published work on wind turbine condition monitoring utilizes SCADA data [6,7]. This does not mean that SCADA can replace dedicated CMS. Rather, it suggests that SCADA is indeed a reliable and highly valuable data source for wind turbine performance monitoring.

Under the pressure of persistently high O&M costs [8,9], dedicated CMS are gaining increasing popularity in recent years for large wind turbines, particularly those deployed offshore. Dedicated CMS usually require additional sensing hardware and data-acquisition systems as well as additional communication and storage systems. As a consequence, their deployment is less uniform than that of SCADA due to the unique design of individual wind turbines.

For the above reasons, the resulting deployment landscapes of dedicated CMS and SCADA are heterogeneous. Newer turbines are more likely to be equipped with CMS, whereas some older turbines still rely mainly on SCADA because of retrofit cost, limited available instrumentation or restrictions associated with existing control and data architecture. Figure 1 illustrates this change in turbine generations.



**Figure 1.** Continual growth of wind turbine size [1].

From Figure 1, it is seen that newer and larger wind turbines are gradually replacing older machines, the adoption of dedicated CMS will increase correspondingly. Nevertheless, the availability of additional measurements does not mean that these measurements will be converted into useful information for supporting maintenance. Then, an interesting phenomenon is present. That is a wind farm may have extensive SCADA records and high-frequency CMS measurements while still lacking the information needed for supporting maintenance decision making, for example, whether an observed anomaly represents a developing fault, how serious the fault is, or when an intervention should be planned.

### 2.2. Gap between deployment and effective utilization

The increasing availability of monitoring data has not accelerated their integration into routine maintenance planning. Table 1 summarizes several differences between the expected role of CMS and the way monitoring information is commonly used in practice.

**Table 1.** Expected capabilities and practical performance of CMS in wind farm O&M.

| Aspect                                  | Expected Capability                              | Reported Practice                                                 | Implication                                            |
|-----------------------------------------|--------------------------------------------------|-------------------------------------------------------------------|--------------------------------------------------------|
| Data integration                        | SCADA + CMS fully integrated                     | Two data streams are often analyzed separately                    | Incomplete condition assessment                        |
| False alarm rate                        | Low false positives to ensure trust              | Repeated or non-actionable alarms can occur                       | Increased verification workload and reduced confidence |
| Fault detection timing                  | Early detection of incipient faults              | Some faults detected late or missed entirely                      | Limited predictive maintenance benefit                 |
| Remaining useful life (RUL) utilization | Used for maintenance scheduling                  | Rarely used in operational planning                               | Model outputs not decision-ready                       |
| Decision support                        | CMS outputs directly guide maintenance decisions | Decisions continue to rely on schedules and engineering judgement | Weak integration with O&M workflows                    |

One reason for this situation is the separate use of SCADA and CMS data. The two data sources are often handled through different platforms and analytical procedures [10]. SCADA provides information about turbine-level operating behaviour, whereas CMS provides more detailed information about component condition. Analysing the two streams independently can make it difficult to distinguish a genuine component abnormality from a change caused by operating conditions. It also limits the opportunity to use information from one source to interpret the other. In this sense, having more data does not necessarily mean having more useful information for supporting maintenance.

False alarms and missed detections are a second practical problem [11–13]. A false alarm does not necessarily indicate that the condition monitoring algorithm is technically poor. It may be because an abnormal signal has several possible causes or because the monitoring system does not have enough contextual information to distinguish a fault from a temporary operating condition. However, their impact on O&M can be significant. Frequent alarms require investigation. Once repeated checks fail to reveal an actual fault, O&M personnel may gradually become less attentive to subsequent alarms. On the other hand, missed detections lead to a completely different set of issues. Even if the monitoring system performs well usually, an unexpected failure can still decrease people's confidence in the system. During the preparation of this review paper, the authors had the opportunity to visit an onshore wind farm, where we held an informal discussion with the wind farm manager. We asked 'In your experience, how do repeated alarms or false alarms from the wind-turbine monitoring system affect the way operators respond to alarms?'. The manager explained 'We receive a lot of alarms, and many of them are transient or do not require immediate action. After seeing the same alarms repeatedly without finding a real fault, operators tend to prioritise alarms based on experience and may not respond immediately to every alarm'. Although this was an informal discussion rather than a formal interview study, the observation provides a useful real-world illustration of how repeated and non-actionable alarms can influence operator attention and alarm prioritisation. It is necessary to note that this anecdotal evidence is presented here solely as an illustrative industrial observation and should not be interpreted as a statistically representative assessment of operator behaviour across the wind industry.

A third issue concerns the depth of information supplied by CMS. In many implementations, the CMS output remains an alarm, threshold exceedance or anomaly indicator [14]. Such an output can be useful for directing attention to a turbine or component, but it does not necessarily identify the underlying fault, quantify its severity or indicate how quickly the condition is likely to develop. Consider gearbox monitoring as an example. An abnormal vibration pattern may indicate that something has changed in the gearbox, but the signal alone may not distinguish between a bearing defect, gear-tooth damage, lubrication-related behaviour, or a change associated with operating conditions. Additional inspection is still needed before a maintenance decision can be made. The similar issue appears in prognostics as well. A model may estimate the RUL of a defective component, but the estimate is only one input to a maintenance decision. The decision may also depend on the confidence in the estimate, the next available maintenance opportunity, weather conditions, spare-parts availability, vessel or technician availability and the possible consequence of continued operation. Consequently, a technically reasonable RUL estimate may still be difficult to directly use in maintenance planning.

Finally, CMS data may be controlled by the original equipment manufacturer (OEM) or a third-party service provider depending on contractual and service arrangements [15]. For this reason, turbine operators may have access to alarms or processed indicators, however, cannot full access to the original

high-resolution measurements, historical fault annotations or maintenance records. This issue matters for both operation and research. Without original data and sufficient context, it is very difficult to verify an alarm, investigate a false detection, improve the condition monitoring algorithms or evaluate whether a monitoring method remains reliable after turbine ageing or component replacement.

These observations suggest that the limitation is not simply insufficient deployment of monitoring hardware. The more fundamental issue is the path followed by information after it has been acquired. SCADA and CMS data may exist, diagnostic models may be available, and alarms may be generated, but the links between these stages and the subsequent maintenance decision are often incomplete. The following sections therefore examine the performance of the analytical methods themselves and then consider how their outputs are connected to maintenance practice.

### 3. Algorithmic performance vs. engineering reality

The discussion in Section 2 shows that the practical application of CMS is largely affected by the quality and usability of the information they can provide. To date, lots of condition monitoring methods and algorithms that can be adopted by CMS have been proposed. However, their performance reported in controlled experiments does not necessarily translate into equivalent performance after deployment on operating wind turbines. So, this section is specially designed for reviewing the recent development of data-driven monitoring methods and the conditions that can limit their practical reliability.

#### 3.1. Advances in data-driven condition monitoring algorithms

Machine learning and artificial intelligence have considerably expanded the range of methods available for wind turbine condition monitoring [16,17]. Deep learning can learn fault-related features directly from raw measurements, unsupervised anomaly-detection methods can reduce dependence on labelled fault data, and probabilistic approaches can provide information about prediction uncertainty. These developments have also encouraged the use of multiple data sources rather than relying on a single monitoring signal. In the following, several methodological directions will be reviewed as they have become particularly common nowadays.

(1) Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to extract information from CMS and SCADA time series. CNN-based methods have, for example, been applied to vibration signals and spectrograms for gearbox fault diagnosis [18–20], while long short-term memory (LSTM) networks have been used to learn temporal behavior in SCADA data [21–23]. These methods are useful where fault information is distributed across time or frequency domain rather than contained in a small number of manually selected features.

(2) The limited availability of labelled fault data has encouraged the use of unsupervised and semi-supervised machine learning approaches. Autoencoders and variational autoencoders can be trained mainly on healthy operating data and use reconstruction behavior to identify deviations [24,25]. Support vector machines and Isolation Forests have also been applied to SCADA data for anomaly detection without requiring large numbers of labelled fault events [26–28]. Such approaches are particularly relevant to wind turbines because normal operation usually occupies the most service life of the turbines, whereas confirmed fault conditions contribute only a very small portion of their time.

(3) Researchers have increasingly combined information from SCADA and CMS. The former can provide the operating context in which a fault may occur, while the latter can provide high-frequency measurements that give more detailed information about component behavior. So, hybrid and two-stage approaches have been tried to combine system-level anomaly detection with component-level diagnosis [29,30].

(4) Probabilistic models provide an approach to representing uncertainty alongside a prediction. For example, Gaussian process regression and Bayesian approaches have been used for power-curve modelling and anomaly detection [31]. This is important for maintenance, especially when the consequences of a wrong decision are significant. It is well known that an estimate without an indication of its uncertainty can be difficult to interpret.

(5) Prognostic models have been developed to estimate the degradation of components and their RUL. For example, LSTM and temporal convolutional approaches have been applied to wind turbine bearings and gearboxes using historical or simulated degradation data [32–34]. These methods extend the capabilities of CMS, enabling them not only to detect the presence of faults but also to predict how these faults might evolve over time.

(6) Transfer learning and related domain-adaptation approaches reduce the dependence on data from the same turbine on which a model is deployed [35–37]. Federated learning offers another route where raw data cannot readily be pooled between turbines or wind farms [38,39]. All this kind of method allows us to use information from several turbines to train a shared model while retaining local data at their original sources. This provides a potentially effective way to overcome current ownership or governance restriction issues in the field.

(7) Physical knowledge has increasingly been combined with data-driven methods. Physics-informed approaches can introduce constraints based on known system behavior [40,41], while digital twin approaches can provide virtual representations or simulated data for model development and fault analysis [42–44]. These approaches are particularly relevant where real run-to-failure data are scarce.

In summary, these developments have increased the analytical capability available to CMS. Under controlled conditions, these advanced methods can detect anomalies, diagnose faults and estimate component degradation with much higher accuracy than conventional threshold-based monitoring techniques. However, a more difficult question is whether the controlled conditions under which these results are obtained remain valid when the model is exposed to the variability of a real wind farm.

### *3.2. Limitations in practical applications*

The difference between experimental performance and field performance is not caused by a single weakness in machine learning. Several characteristics of wind turbine operation interact with the assumptions made during model training. Studies have reported lots of cases where methods achieving high accuracy under controlled conditions do not maintain the same level of performance in operational environments [45–47]. The underlying causes are analyzed below.

First, most data-driven algorithms are developed and validated under simplified assumptions that do not fully reflect real operating conditions. Training datasets are often curated, preprocessed, and balanced, whereas real-world data are characterized by noise, missing values, sensor faults, outliers, and changing operating regimes [48–50]. As a result, the algorithms that perform well in offline studies may suffer significant degradation when deployed online.

Second, the non-stationary nature of wind turbine operation introduces substantial challenges to algorithm reliability. Wind speed variability, turbulence intensity, seasonal effects, time varying marine & offshore conditions, control system responses, and the increased nonlinearity and structural flexibility of large turbine structures can cause substantial changes in the condition monitoring data [51–53]. These changes should be distinguished into different forms of distributional shift. In particular, virtual drift occurs when the distribution of input variables or features,  $P(X)$ , changes while the conditional relationship between the inputs and the target,  $P(Y|X)$ , remains approximately stable. In wind turbine monitoring, changes in wind conditions, operating regimes, turbulence and environmental conditions can therefore produce virtual drift without necessarily indicating a change in the underlying fault mechanism. By contrast, real concept drift occurs when  $P(Y|X)$  itself changes, such that the relationship between monitoring observations and turbine health is altered. Component degradation and ageing, maintenance or component replacement, and changes in control or system configurations can contribute to such changes. These two forms of drift have different implications for condition monitoring algorithms. Virtual drift primarily requires robust feature normalization, operating-condition compensation or domain adaptation, whereas real concept drift may require model updating or retraining because the underlying mapping between observations and health states has changed. Consequently, treating all non-stationarity as concept drift may obscure the specific source of model degradation and lead to inappropriate adaptation strategies. These factors violate the implicit assumption of stationarity in many machine learning models, leading to concept drift and reduced predictive accuracy over time. For this reason, models require frequent retraining or adaptation. However, it is rarely implemented in practice.

Third, it is well known that wind turbines spend most of their operating life in healthy states, while confirmed fault events are rare. As a consequence, the wind farm datasets are highly imbalanced [54–56]. Additionally, fault records often contain uncertain events or incomplete labels because the precise onset of degradation is not always known. This makes supervised learning particularly difficult when the objective is to identify an incipient fault rather than a developed failure. Synthetic or simulation-generated data can increase the number of available examples, but the resulting data inevitably depends on the assumptions made by the simulation or degradation models.

Fourth, some wind turbine components, such as main bearings and low-speed shafts, operate at low rotational speeds while carrying substantial loads. For a 20 MW turbine, its rotational speeds may be in the range of 4–10 rpm [57]. So, their fault-related features can be weak compared to the background vibration or other operating variability. At the same time, mechanical, electrical and control subsystems of the wind turbine interact with one another [58]. A measured ‘abnormality’ may have more than one reason. It has no doubt that this further complicates fault isolation and increases the possibility of both false alarms and missed detections.

Finally, sensors themselves can also be a factor affecting the reliability of condition monitoring results. This is particularly true for sensors installed on offshore wind turbines. Prolonged exposure to extreme temperature changes, high humidity, and a highly corrosive marine environment can definitely accelerate sensor performance degradation and failure [59–62]. Communication problems can further affect the integrity of the acquired data [63]. If sensor health and data quality are not considered explicitly, the condition monitoring algorithms based on degraded or failed sensors may interpret the measurement problem as a change in turbine condition, thereby leading to false alarms. So, the resulting uncertainty is not simply a hardware issue, it can further affect the subsequent analysis.

From the above discussion, it can be concluded that improving the condition monitoring algorithm may reduce one source of uncertainty, but it does not automatically resolve uncertainty in the data or the other requirements by decision making that uses the CMS output. The reliability of a CMS should be considered across the complete chain from measurement to model output and ultimately to maintenance use.

## 4. Integration of CMS with maintenance practice

### 4.1. Expected role of CMS in CBM

Condition-based maintenance (CBM) changes the basis on which maintenance is planned. Instead of relying only on waiting for failure, maintenance timing of CBM is informed by the observed condition of the component. In such a process, CMS provides evidence on which the assessment of conditions is based. Therefore, the role of CMS will extend from detecting abnormal conditions to providing information that helps maintenance personnel decide what to do next [64]. To be specific,

- At the first level, CMS should be capable of detecting changes in the condition of critical components such as gearboxes, bearings and generators. Detecting a developing abnormality before a major failure occurs creates an opportunity to investigate the condition while there is still some time left to the maintenance response.
- Following fault detection, the next requirement is diagnosis. CMS should, where the available evidence permits, distinguish between possible fault types and identify the affected component or failure mechanism. For example, a change in gearbox vibration may be associated with bearing degradation, gear-tooth damage, lubrication problems or an operating-condition effect. Reliable diagnosis can reduce unnecessary inspection and help maintenance personnel focus on the relevant component. However, signal coupling and time-varying turbine operating conditions make this requirement difficult to achieve sometimes [65–67].
- A further requirement is prognosis. If degradation can be tracked with sufficient confidence, the CMS may provide information about how the condition is expected to evolve and, where appropriate, an estimate of RUL. Data-driven and physics-informed prognostic methods have been investigated for wind turbine bearings and gearboxes [68–70]. Their practical value, however, depends on more than the numerical accuracy of the RUL estimate. Maintenance personnel also need to know how much confidence can be placed in the estimate and whether the prediction horizon is useful for the planning problem at hand.
- The final requirement concerns the use of CMS outputs in maintenance planning. A condition indicator or RUL estimate does not by itself determine the maintenance action. The response may depend on failure consequences, inspection requirements, available resources, weather, access, production requirements and the timing of other planned work. Decision-support approaches can combine condition information with such constraints, for example through risk-based or cost-based maintenance models [71,72].

In summary, the expected role of CMS in CBM can therefore be represented as a progression of ‘detection → diagnosis → prognosis → maintenance support’. This progression should not be interpreted as a requirement for every CMS to perform all four functions autonomously. Rather, it describes the increasing information required if CMS outputs are to become useful inputs to maintenance planning.

#### 4.2. Observed practice in wind farms

Compared to the expected role envisioned in Section 4.1, the practical CMS application in wind farm O&M is still limited today. SCADA remains an important source of operational monitoring because of its wide availability in wind farms. However, its low sampling rate limits it mainly for turbine-level performance monitoring and anomaly detection rather than for component-level diagnosis [73–75]. Dedicated CMS can provide much more detailed information, but this does not necessarily mean that the data are incorporated into the daily workflow of the wind farm. Some monitoring information is analyzed by OEMs or third-party service providers, sometimes offline, rather than being interpreted directly by the operating team [76,77].

Another practical problem is the separate analysis of SCADA and CMS information. When the two data streams are considered independently, the condition indicated by a high-frequency condition monitoring signal may not be interpreted together with the corresponding turbine operating condition. This can make it harder to judge whether an ‘abnormal measurement’ is due to component degradation or a change in turbine operating conditions [10].

The form in which information presents to the operators is also important. In many operational systems, the immediate CMS output remains an alarm or threshold exceedance. Such an output can be useful as a trigger for further investigation, but it does not necessarily contain the information required to determine the scope or urgency of that investigation.

Finally, some other factors, such as data governance issues (e.g., OEM ownership, limited access, *etc.*), sparse and heterogeneous data, lack of standardized workflows, and difficulty in model updating and validation, further limit CMS utilization. These challenges have been repeatedly identified as key barriers to translating monitoring results into reliable O&M actions.

To highlight the discrepancies between the expected and observed roles of CMS, Table 2 is presented below to facilitate a clear comparison.

**Table 2.** Expected vs. observed CMS roles.

| Function          | Expected (Section 4.1) | Observed (Section 4.2) | Example                                                                                                                                                                                                                                                                        |
|-------------------|------------------------|------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Anomaly detection | √                      | √                      | -                                                                                                                                                                                                                                                                              |
| Fault Diagnosis   | √                      | Limited                | A gearbox vibration alarm may indicate abnormal behaviour, but the CMS may not reliably distinguish whether the underlying cause is a bearing defect, gear-tooth damage, lubrication problem, or an operating-condition effect. Further inspection is therefore required.      |
| Prognosis         | √                      | Rare                   | An increase in gearbox or bearing vibration may trigger an alarm, but the CMS often cannot reliably estimate the RUL or predict when the component will reach a critical failure condition because sufficiently long run-to-failure data are unavailable.                      |
| Decision making   | √                      | Limited/largely absent | A CMS may generate a high-severity gearbox or bearing alarm, but the system typically does not determine whether the turbine should continue operating, be derated, inspected at the next scheduled visit, or shut down immediately. Such decisions remain with O&M personnel. |

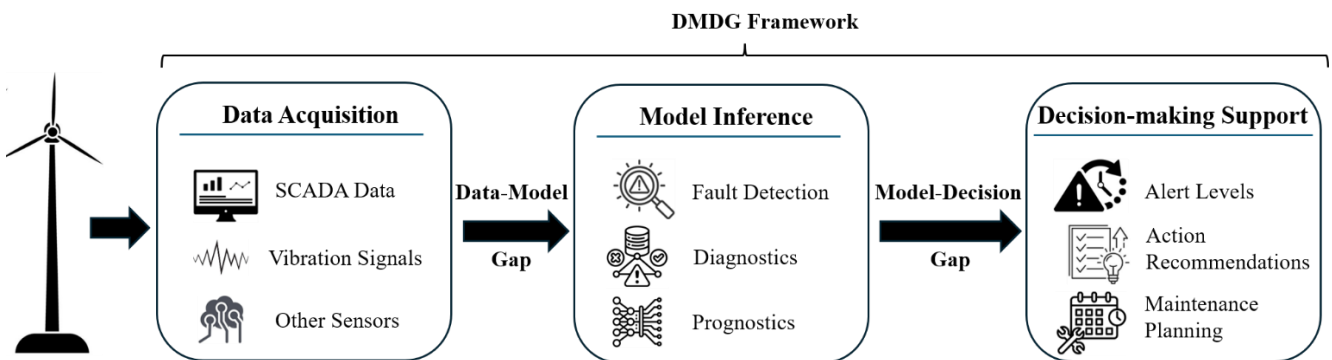
The difference between the two columns is not simply a question of whether the algorithms are sufficiently accurate. Consider a gearbox alarm as a simple example. The alarm may correctly identify that the measured vibration is abnormal, yet the operator may still need to establish what component is responsible, whether the condition is developing, whether an inspection is required immediately, and what operational consequences would follow from continued operation. These questions require information beyond the alarm itself. The same issue also arises when a CMS provides an RUL estimate. Even a technically credible estimate does not automatically specify the maintenance date. The maintenance team may have to consider vessel availability, weather windows, spare parts, technician availability and planned access to the turbine. Therefore, the CMS output is just one input to the decision rather than the decision itself. In a certain respect, this explains why maintenance practice still remains dependent on scheduled plans and engineering experience even when condition-monitoring data are available. Monitoring information can identify where attention is required, however without suggesting how that attention should be translated into an intervention. In other words, the CMS may perform its monitoring function while remaining only loosely connected to the maintenance planning function.

There are also organizational and data-governance barriers. CMS information may be distributed between turbine operators, OEMs and service providers, while the corresponding maintenance records may be stored in separate systems. Differences in data ownership, access rights and information formats make it difficult to construct a continuous link between a measured condition, the model output, the subsequent inspection and the eventual maintenance outcome. Sparse data, heterogeneous turbine populations and difficulties in model updating further increase complications.

All these distinctions motivate the development of the framework in the next section. The problem is not that wind turbines lack monitoring data or that existing condition monitoring models have no value. Rather, the data available to a condition monitoring model, the information produced by the condition monitoring model, and the requirements by the maintenance decision are not always considered during the design process of a CMS. Therefore, a DMDG framework is introduced in Section 5 to make these relationships more explicit.

## 5. DMDG framework

The DMDG framework describes the problems identified in above sections through three connected stages, *i.e.*, data acquisition, model inference, and decision-making support, as illustrated in Figure 2. Its aim is to bridge two critical technical gaps, namely the “Data-Model Gap” and the “Model-Decision Gap”.



**Figure 2.** The DMDG framework.

### 5.1. Data-model gap

The data-model gap describes the mismatch between the characteristics of operational wind turbine data and the assumptions made when developing condition monitoring and prognostic models. Although machine learning and other data-driven methods have developed rapidly, the data available from operating wind farms do not necessarily satisfy the conditions under which these models are developed and validated. This has been a great challenge when laboratory or simulated results are transferred to field applications. The effects of data quality, non-stationary operating conditions, and the limited availability of fault data have already been discussed in Section 3. The following additional issues are also particularly relevant to the data-model gap.

(1) Limited observability of critical components. Some important failure modes occur in wind turbine components such as main bearings and low-speed shafts, where the corresponding fault features are weak and easily masked by background vibration or changes in operating conditions. Even with high-frequency vibration measurements, an early degradation may not produce a sufficiently distinctive feature for reliable detection. In such cases, on the one hand, the condition monitoring model is not simply dealing with noisy data. On the other hand, part of the physical degradation process may not be directly observable from the collected signals. This limits the information that can be extracted by the condition monitoring model and, consequently, its ability to detect the actual degradation status.

(2) Heterogeneity of wind turbines and their operating environments. Wind turbines differ in design, control strategy, operating history, geographical location, and environmental conditions. These differences can lead to substantial changes in the distributions of monitoring data between turbines and wind farms. A model trained using data from one turbine or site may therefore not perform in the same way when applied elsewhere. Transfer learning and domain adaptation have been investigated as possible solutions [78,79], but their large-scale application in wind farms remains challenging. Turbine-to-turbine heterogeneity also provides a possible application scenario for federated learning. For example, turbines operating under different wind regimes and with different degradation histories could update a common diagnostic model locally rather than sharing their raw CMS data. Model parameters or updates could then be exchanged and aggregated. This approach could make use of information from several turbines while retaining the original data at their respective locations. This idea sounds excellent. However, its practical value still depends on the consistency of local data, model architecture, communication arrangements, and data governance.

(3) Data accessibility and governance constraints. This issue has been briefly mentioned in Section 4.2. However, a more detailed explanation is necessary to facilitate readers' understanding. Depending on contractual and service arrangements, high-resolution CMS data, historical alarm records, fault annotations, and maintenance information may be controlled by OEMs or third-party service providers, limiting access for wind-farm operators and researchers. This can make it difficult to obtain the combination of data, fault labels, and operational context required for developing and validating site-specific condition monitoring models. This problem is particularly important especially when long-term degradation histories or reliable fault labels are required. Limited access to such information also makes model adaptation and cross-site learning more difficult. A model developed from incomplete or aggregated data may not adequately represent differences in turbine design, operating conditions, sensor configurations, and fault characteristics between wind farms. Data governance therefore affects not

only data availability itself, but also model transferability, generalisation, and the possibility of continuous model updating.

These issues indicate that the data-model gap is not simply a problem of insufficient model sophistication. It results from the interaction between what can be measured from an operating turbine, what information is available for model development, and what assumptions are made by the model. Thus, improving model complexity alone cannot remove the gap. The data used by a CMS need to be considered in relation to the model requirements and, ultimately, to the maintenance purpose for which the model is being developed.

The data-model gap addresses the difficulty of obtaining reliable model outputs from real operational data. Another problem arises after a model has produced its output, *i.e.*, whether that output is sufficiently useful for an actual maintenance decision. This issue is considered below as the Model-Decision Gap.

### 5.2. Model-decision gap

The model-decision gap refers to the disconnect between the information produced by CMS models and the information required to make maintenance decisions. A model may produce an anomaly score, a classification result, a health indicator, or an RUL estimate, but these outputs do not necessarily answer the questions faced by O&M personnel. In practice, maintenance decisions may require information about the affected component, fault severity, likely progression, operational risk, and the appropriate timing of an intervention. For example, a high anomaly score may indicate that a gearbox is operating abnormally, but it does not by itself determine whether the turbine should continue operating, be inspected during the next planned visit, be derated, or be stopped. Similarly, an estimated RUL can provide useful information about expected degradation, but the maintenance timing also depends on factors such as resource availability, weather, vessel access, production requirements, and the consequences of delaying the intervention. The model output is therefore only one part of the decision process.

Another difficulty is that the relationship between a model output and the physical condition of the turbine may not always be clear. Complex models can identify patterns in monitoring data without providing sufficient engineering evidence for the operator to judge whether the result is consistent with the actual turbine condition. In an operational environment, this can lead to additional checks or inspections before the model result is acted upon. The issue is therefore not simply whether a model is accurate in a statistical sense, but whether its output contains enough information to be used within the existing maintenance workflow.

Prognostic information provides another example. As mentioned earlier, CMS models may estimate degradation trends or RUL, but such information is rarely sufficient on its own to generate an appropriate maintenance plan. A practical plan must consider the available maintenance resources, weather conditions, logistics, production requirements, and the risk associated with continued operation. Most existing CMS models do not explicitly represent all of these constraints. Consequently, there remains a gap between the predicted condition of a component and the maintenance action that can reasonably be taken.

The problem is also related to the lack of a clear way of linking CMS outputs with O&M activities. In many wind farms, the CMS runs alongside other operational systems and mainly produces alarms or condition reports, whereas maintenance decisions are made through separate enterprise systems and by O&M personnel. As a result, the information generated by the CMS may not be carried through to the maintenance process. Even when a model provides reasonably accurate predictions, they may

have little practical effect if there is no clear link between the model output and the subsequent maintenance decision.

Uncertainty is another factor that can limit the practical use of CMS outputs. Maintenance decisions are rarely based on a predicted value alone. The operators also need to know how reliable that prediction is and what risks may be associated with it. However, many existing condition monitoring models produce a single predicted value without providing an estimate of its uncertainty. This makes it difficult for the operators to judge whether a prediction is sufficiently reliable for maintenance planning. As a result, uncertainty in the model output can become a barrier to its use in risk-based maintenance decisions.

Finally, as mentioned in Section 3.2, sensor degradation, bias, intermittent failure or complete loss can generate missing or contaminated measurements that no longer accurately represent the physical condition of the monitored component. This creates a mismatch between the data available to the model and the real operating state, thereby increasing the data-model gap. The resulting uncertainty or error can subsequently propagate through the modelling process and affect fault diagnosis, condition assessment or RUL estimation, potentially leading to inappropriate maintenance recommendations and consequently increasing the model-decision gap. Thus, sensor reliability should be considered as part of the decision-driven CMS design rather than being treated solely as a hardware-level issue.

These issues suggest that the limitations of current CMS do not arise only from the modelling itself. An equally important problem is how the results of monitoring and modelling are used in maintenance practice. The model-decision gap can be reduced by designing the CMS around the decisions it is expected to support, rather than treating prediction as the final objective. In this setting, the reliability of the output, its uncertainty, and its connection with maintenance planning all need to be considered when developing CMS.

### 5.3. The DMDG framework

As Figure 2 shows, within the DMDG framework, the data-model gap captures the misalignment between data and models, while the model-decision gap reflects the disconnect between model outputs and decision-making processes. Bridging both gaps is crucial to promote CMS from a merely monitoring tool to a more advanced system that can actually help maintenance planning. From a system perspective, this transition requires the integration of data-driven models with decision-making frameworks. Techniques such as probabilistic risk assessment [80], digital twins [43], and optimization algorithms [81] can play a vital role in this process. In addition, explainable AI methods [82,83] are also essential to ensure that system recommendations are transparent and interpretable to the operators. Attribute to the DMDG framework, the value of CMS is no longer measured solely by algorithm accuracy, but by its ability to support maintenance planning. The contribution of DMDG does not rely on addressing particular technical problems. Rather, it establishes a logic for the decision-driven design of CMS, in which the requirements of maintenance planning determine the required capability and data requirements of CMS.

The DMDG framework can be represented as a three-stage mapping between data, models, and decisions. Given

- Data layer:

$$D = \{x(t), s(t), e(t)\} \quad (1)$$

where  $D$  denotes dataset,  $x(t)$  represents sensor measurements,  $s(t)$  refers to system states (operational conditions), and  $e(t)$  refers to environmental variables (e.g., wind speed, turbulence intensity, wave height, wave speed, *etc.*).

- Model layer:

$$M: D \rightarrow H = \{h_d, h_p, h_u\} \quad (2)$$

where  $M$  refers to data interpretation and prediction models,  $H$  is model outputs,  $h_d$  denotes diagnostic outputs (fault type),  $h_p$  refers to prognostic outputs (e.g., RUL estimation), and  $h_u$  are uncertainty estimates.

- Decision layer:

$$\Pi: H, C \rightarrow A \quad (3)$$

where  $\Pi$  is decision-making models,  $C$  refers to operational constraints (e.g., cost, weather, resources, *etc.*), and  $A$  are maintenance actions (e.g., inspect, repair, replace, defer, *etc.*).

The data-model gap can be expressed as

$$\mathcal{G}_{DM} = \|P_{real}(D) - P_{model}(D)\| \quad (4)$$

where  $\mathcal{G}_{DM}$  refers to the mismatch between real-world data distribution  $P_{real}(D)$  and model assumptions  $P_{model}(D)$ .

The model-decision gap can be expressed as

$$\mathcal{G}_{MD} = \|\Pi(H, C) - A^*\| \quad (5)$$

where  $\mathcal{G}_{MD}$  denotes the difference between model-informed decisions  $\Pi(H, C)$  and optimal decisions  $A^*$ .

Therefore, the objective of DMDG framework is

$$O = \min (\mathcal{G}_{DM} + \mathcal{G}_{MD}) \quad (6)$$

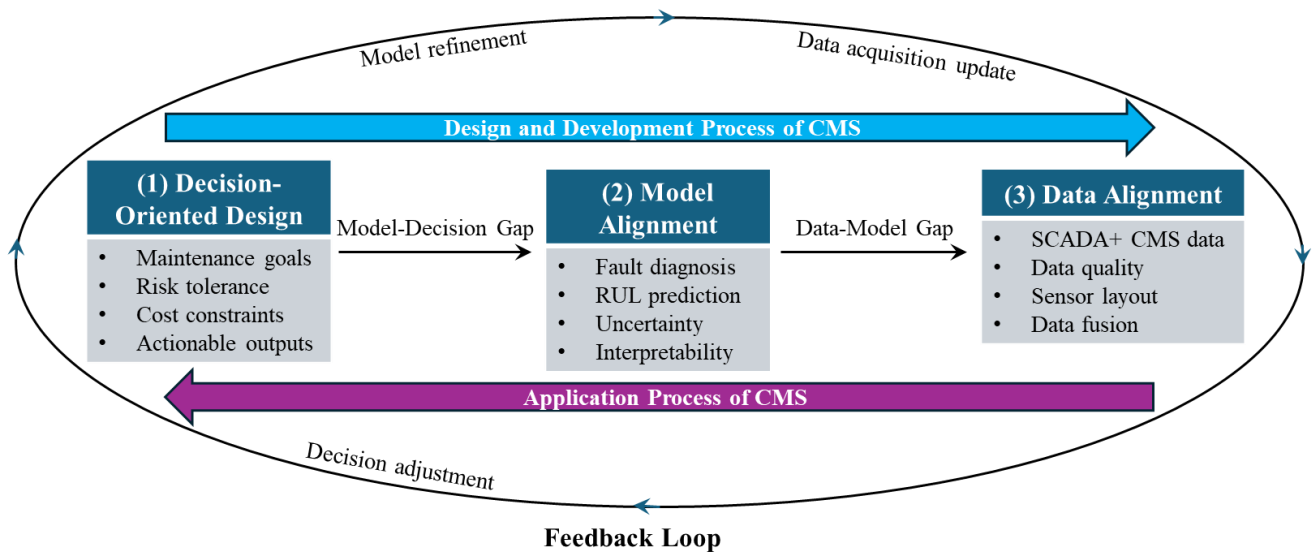
Unlike traditional PHM frameworks that primarily focus on diagnostic and prognostic accuracy [33] and digital twins that emphasize system representation and simulation [43], the DMDG framework explicitly addresses the alignment between data, models, and decision-making processes. It treats supplying essential information to support maintenance planning as the major objective. To better understand the distinct features of DMDG, Table 3 summarizes a comparison with existing frameworks.

**Table 3.** Comparison of the proposed DMDG with existing frameworks.

| Aspect               | Traditional PHM                     | Practical Weaknesses                                                                                                                                     | Digital Twin                                 | Practical Weaknesses                                                                                                                          | Proposed DMDG Framework          |
|----------------------|-------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------|
| Core focus           | Diagnosis & prognosis               | Often centered on predicting component health rather than supporting the complete O&M decision process                                                   | System simulation and virtual representation | Considerable modelling and computational complexity; may focus more on system representation/simulation than actionable maintenance decisions | End-to-end decision integration  |
| Data handling        | Often static or historical datasets | Limited access to representative, labelled and continuously updated field data; turbine-to-turbine variability is difficult to capture                   | Real-time + simulated                        | Requires extensive data integration and synchronization; simulation-to-reality mismatch may remain                                            | Emphasis on data-model alignment |
| Model role           | Predictive                          | Often produces fault predictions without sufficient operational context or actionable recommendations                                                    | Predictive + simulation                      | High-fidelity models can be costly to develop, calibrate and maintain; simplified models may lose diagnostic fidelity                         | Decision-oriented outputs        |
| Decision integration | Limited                             | Final inspection, intervention and shutdown decisions generally remain with human O&M personnel                                                          | Partial                                      | Can support what-if analysis and prediction but does not necessarily provide autonomous or explicit maintenance decision logic                | Central objective                |
| Uncertainty handling | Emerging                            | Prediction uncertainty is often considered separately from operational and decision uncertainty                                                          | Moderate                                     | Uncertainty in sensors, models, parameters and simulations can propagate through the digital representation                                   | Explicitly required              |
| Gap awareness        | Implicit                            | Data quality, representativeness and model-transferability gaps are often treated as implementation issues rather than fundamental modelling constraints | Partial                                      | Data-model mismatch can remain despite real-time data integration and simulation capability                                                   | Explicit (DM + MD gaps)          |
| Workflow             | Data → Model                        | Predominantly model-centric; limited feedback from maintenance decisions to model/data development                                                       | Data ↔ Model                                 | Stronger bidirectional interaction, but decision feedback and continuous model adaptation are not necessarily explicit                        | Decision → Model → Data          |

## 6. Design methodology for next-generation CMS based on DMDG framework

With the guidance of the DMDG framework, the new CMS design methodology adopts a top-down and iterative co-design approach, in which system development is driven by decision requirements, rather than solely by data availability or modelling capability. Specifically, the design process can be structured into three interconnected stages as illustrated in Figure 3.



**Figure 3.** Decision-driven CMS design based on the DMDG framework.

First, the design process should start with the decision-oriented design, where maintenance objectives and operational constraints as well as actionable outputs are explicitly defined. This includes identifying key decision variables, such as maintenance goals, cost constraints, fault severity thresholds, maintenance timing, risk tolerance, and other resource constraints. This stage will ensure that the development of CMS can be aligned with actual needs of wind farm O&M.

Second, based on the requirements defined in the first stage, the model layer is designed to generate outputs that are usable for maintenance planning in the next stage. This requires the models to be able to provide interpretable and structured information, such as fault classification, severity estimation, and RUL prediction. Herein, interpretability is incorporated to ensure that model outputs can be related to engineering evidence and maintenance requirements. For example, when a CMS identifies a potential gearbox bearing fault, the model should ideally provide information indicating which monitoring characteristics or operating variables contributed to the diagnosis. Such information enables O&M personnel to assess whether the prediction is consistent with known component behavior and the prevailing operating conditions before taking maintenance action. If the model relies on inappropriate or physically implausible information, the resulting discrepancy can provide feedback for model refinement or reassessment of the underlying data requirements. Thus, within the DMDG framework, interpretability serves as a link between model outputs and operational decisions rather than being considered solely as an additional model-performance attribute. The selection and implementation of specific interpretability techniques are application- and model-dependent and are beyond the scope of this conceptual review. In addition, models should incorporate uncertainty quantification to support risk-aware decisions. Importantly, model selection and design should be evaluated not only in terms of prediction accuracy, but also in terms of interpretability, robustness, and decision utility.

Third, the data alignment stage should be configured to support the requirements of the models used in the second stage. This includes ensuring data quality, selecting appropriate sensor types and specifications, improving sensor placement, defining sampling rates, integrating heterogeneous data sources (e.g., SCADA and CMS), enabling data accessibility, and addressing data pre-processing and calibration requirements.

The three stages are closely connected rather than operating independently. In practice, information from model performance and maintenance outcomes can be used to update both the data requirements and the model itself. If a model performs poorly under a particular operating condition, for instance, further data collection or changes to the selected features may be needed. Likewise, when the model output does not provide useful information for maintenance planning, the decision requirements should be reconsidered and the corresponding model design adjusted. During CMS operation, these feedback loops can be initiated by problems identified in the wind farm, as illustrated in Figure 3. Repeated false alarms or alarms that do not lead to any useful maintenance action may indicate that the diagnostic model has not adequately captured the effects of certain operating conditions. This may require model refinement or recalibration. In another situation, a confirmed fault may not be diagnosed reliably because the available measurements do not contain sufficient information. The problem could be related to sensor resolution, sensor location, or missing operating variables, in which case the data-acquisition requirements may need to be revised. Similar issues may arise when turbine operating conditions change, components are replaced or aged, sensors deteriorate, or new fault modes are encountered. Persistent differences between predicted conditions and actual maintenance outcomes can provide another indication that the existing data or model requirements need to be reconsidered. These examples show that CMS development does not have to follow a one-way ‘Data → Model’ path. Experience gained during operation can be fed back into the definition of both model requirements and data requirements. In this sense, the feedback loop provides a practical link between CMS development and the conditions observed in actual wind turbine operation.

From a system engineering perspective, the methodology starts with the maintenance decision that the CMS is intended to support and then works backwards to determine the required models and data. This is different from the conventional ‘data → model → decision’ sequence, in which the available data often determines what can be modelled before the intended use of the results is considered. The proposed ‘decision → model → data’ approach therefore provides a basis for linking data collection and model selection to the operational requirements of the CMS. It also leads to several design considerations for the development of next-generation CMS:

- prioritizing interpretability and actionability over purely predictive performance;
- incorporating uncertainty into model outputs to support risk-aware decisions;
- enabling seamless integration of CMS with O&M workflows;
- supporting CMS’ adaptability to changing operating conditions.

These principles are essential for bridging both the ‘Data-Model Gap’ and the ‘Model-Decision Gap’.

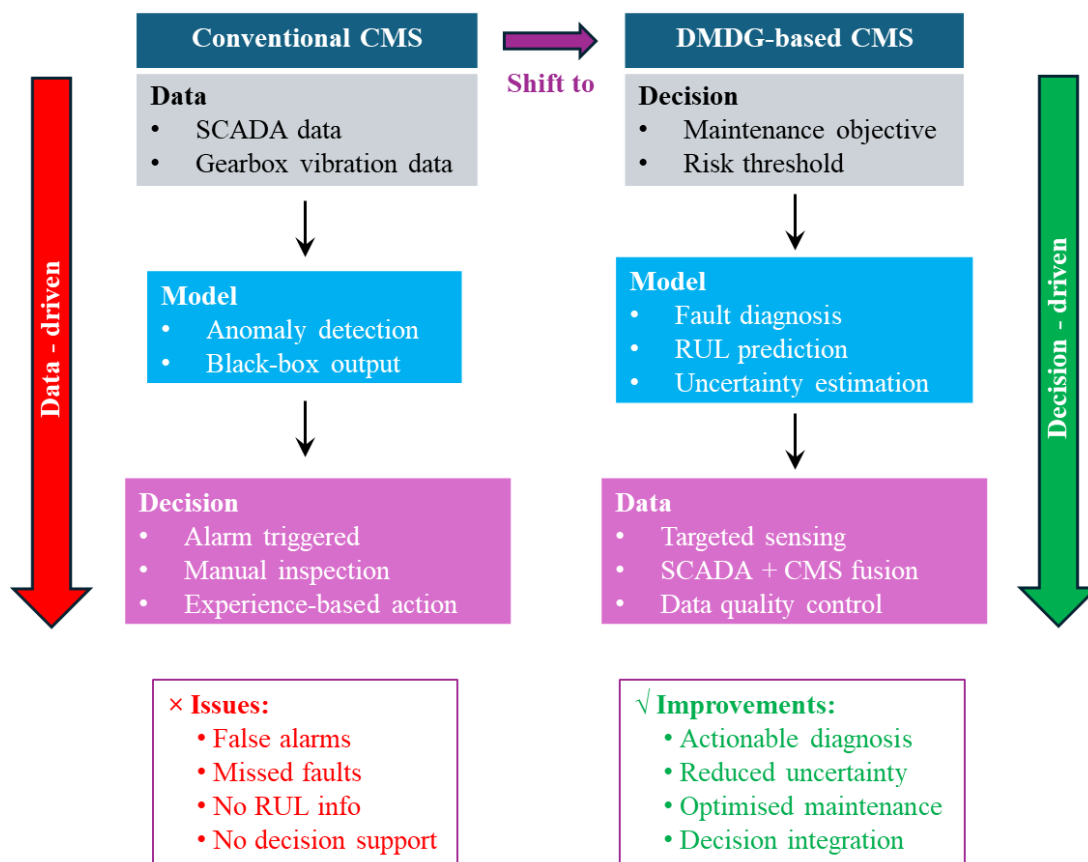
In summary, the DMDG-based CMS design methodology provides a structured pathway for developing next-generation CMS that are not only technically advanced but also operationally effective. By explicitly linking data, models, and decisions, this approach facilitates the transition of CMS from monitoring-oriented systems to decision-oriented, prescriptive maintenance systems.

Herein, it is necessary to repeat again that DMDG is only intended to provide a pipeline for designing a decision-driven CMS, linking the operational decision requirements to the required models and data, rather than to prescribe the subsequent execution or scheduling of physical maintenance activities. Its output does not mean that the subsequent maintenance can be implemented immediately either. This is because, in practice, many operational constraints can affect the implementation of maintenance decisions,

such as adverse offshore weather, vessel availability and access limitations. However, these factors are outside the primary scope of the DMDG framework.

## 7. Case illustration of the potential of DMDG-based CMS in cost reduction

An illustration of DMDG-based CMS design for wind turbine fault management is shown in Figure 4. Where the conventional data-driven CMS (left) primarily relies on anomaly detection and generates alarm-based outputs, leading to limited interpretability and weak integration with maintenance decision-making. In contrast, the proposed DMDG-based approach (right) starts from decision requirements and enables the development of models and data strategies that produce actionable, uncertainty-aware, and decision-oriented outputs. Such redesign envisions how aligning data, models, and decisions can significantly improve fault diagnosis, prognostics, and maintenance planning.



**Figure 4.** Illustration of the design of DMDG-based CMS.

Furthermore, a representative case study is presented in the following to illustrate the great potential of the DMDG-based CMS in reducing wind farm O&M costs. Herein, it is necessary to note that this case is illustrative rather than empirical. It is given just for demonstrating the potential magnitude of benefits when both the data-model gap and model-decision gap are addressed. The case considers a wind turbine subsystem with the following parameters [33,72].

- Failure cost  $C_{failure}$ : £250,000
- Inspection cost  $C_{inspect}$ : £5000
- Downtime cost  $C_{downtime}$ : £10,000 per day

The total cost caused by underperforming CMS can be simply estimated by

$$Cost = R_{false}C_{inspect} + R_{missed}C_{failure} + T_{down}C_{downtime} \quad (7)$$

where  $R_{false}$  is false alarm rate,  $R_{missed}$  represents missed detection rate, and  $T_{down}$  refers to downtime due to delayed inspection, which is in the unit of day.

In conventional condition-based maintenance, fault detection is primarily alarm-driven, without reliable prognostic information or direct decision support (*i.e.*, the utilization of the so-called underperforming CMS). Maintenance actions are triggered through a sequence of alarm generation by CMS, manual inspection, and expert judgment. The key performance characteristics are [11]:

- False alarm rate  $R_{false}$ : approximately 20% (context-dependent)
- Missed detection rate  $R_{missed}$ : approximately 10%
- Downtime due to detection delay  $T_{down}$ : on the order of several weeks (e.g., 20 days)

Given these assumptions, the cost associated with each fault event is estimated as

- False alarm cost

$$R_{false}C_{inspect} = 0.2 \times 5000 = \text{£}1000 \quad (8)$$

- Missed failure cost

$$R_{missed}C_{failure} = 0.1 \times 250,000 = \text{£}25,000 \quad (9)$$

- Downtime cost due to delayed inspection

$$T_{down}C_{downtime} = 20 \times 10,000 = \text{£}200,000 \quad (10)$$

The resulting total expected cost is approximately  $Cost = \text{£}226,000$  per event.

By contrast, the DMDG-based CMS combines SCADA and CMS data, provides interpretable diagnostic information, accounts for uncertainty in RUL estimation, and relates model outputs to maintenance decision criteria. The corresponding results are

- Reduced false alarm rate  $R_{false}$ : 15%
- Reduced missed detection rate  $R_{missed}$ : 5%
- Increased prediction lead time: ~20 days

The corresponding cost becomes

- False alarm cost

$$R_{false}C_{inspect} = 0.15 \times 5000 = \text{£}750 \quad (11)$$

- Missed failure cost

$$R_{missed}C_{failure} = 0.05 \times 250,000 = \text{£}12,500 \quad (12)$$

- Downtime cost due to delayed inspection is reduced to zero with planned intervention.

Then, the total expected cost is reduced to approximately  $Cost = \text{£}13,250$  per event, corresponding to a reduction of about 94% relative to the conventional approach. More than 88% of the calculated saving comes from the reduction in downtime-related costs. This is mainly a consequence of the assumed cost associated with prolonged turbine unavailability, rather than an additional cost assigned to missed detections. The downtime saving should therefore be viewed as a potential benefit under the assumed scenario. Its actual value would depend on the available prediction lead time and whether maintenance can be planned before a fault develops into a failure that results in prolonged downtime. Thus, the calculated saving does not represent a guaranteed reduction in cost resulting from the DMDG framework.

Anyway, this illustrative analysis suggests that substantial cost savings may be achievable if the assumed improvements in detection performance can be realised in practice. Although this example is conceptual and intended to show potential impact rather than provide empirical validation, it highlights the magnitude of improvement achievable when both the data-model gap and model-decision gap can be systematically addressed in practice.

To examine the robustness of the estimated cost reduction to variations in CMS detection performance, a two-way sensitivity analysis was conducted by varying the false alarm rate  $R_{false}$  and missed detection rate  $R_{missed}$  of the DMDG-based CMS. The inspection cost  $C_{inspect}$  and failure cost  $C_{failure}$  were kept unchanged from the assumptions in the illustrative case study. For the DMDG-based CMS, the expected cost is calculated as

$$C_{DMDG} = R_{false}C_{inspect} + R_{missed}C_{failure} \quad (13)$$

In Equation (13), the downtime cost is not included because the DMDG-based approach is assumed to enable earlier and planned intervention, thereby largely avoiding the prolonged downtime associated with delayed inspection. Assume the false alarm rate  $R_{false}$  was varied from 10% to 30%, while the missed detection rate  $R_{missed}$  was varied from 2.5% to 12.5%. The resulting expected costs are presented in Table 4.

**Table 4.** Sensitivity of the expected DMDG-based CMS cost to false alarm and missed detection rates.

| $C_{DMDG}$ (£)<br>$R_{missed}$ | $R_{false}$ |        |        |        |        |
|--------------------------------|-------------|--------|--------|--------|--------|
|                                | 10%         | 15%    | 20%    | 25%    | 30%    |
| 2.5%                           | 6750        | 7000   | 7250   | 7500   | 7750   |
| 5.0%                           | 13,000      | 13,250 | 13,500 | 13,750 | 14,000 |
| 7.5%                           | 19,250      | 19,500 | 19,750 | 20,000 | 20,250 |
| 10%                            | 25,500      | 25,750 | 26,000 | 26,250 | 26,500 |
| 12.5%                          | 31,750      | 32,000 | 32,250 | 32,500 | 32,750 |

The baseline case, corresponding to  $R_{false} = 15\%$  and  $R_{missed} = 5\%$ , gives an expected cost of  $C_{DMDG} = £13,250$  per event, consistent with the previous calculation. Across the investigated parameter range, the expected DMDG-based CMS cost varies from £6750 to £32,750 per event. Even at the highest false alarm and missed detection rates considered (30% and 12.5%, respectively), the estimated cost remains below the £226,000 per-event cost assumed for the conventional CMS.

Across the sensitivity range considered, the estimated cost reduction ranges from approximately 85.5% to 97.0% relative to the conventional CMS baseline. This indicates that the principal cost-reduction potential of the DMDG-based CMS is not dependent on a single assumed combination of false alarm and missed detection rates. Instead, it mainly depends on the cost savings achieved by reducing the prolonged downtime associated with delayed inspections. The analysis also indicates that the missed detection rate has a substantially greater influence on the expected cost than the false alarm rate. This is attributable to the much higher economic consequence assigned to a missed failure (£250,000) than to a false alarm requiring inspection (£5000). Consequently, improving the reliability of failure detection, particularly by reducing missed detections, is likely to provide greater economic benefit than reducing false alarms alone.

Herein, it is worth noting that this sensitivity analysis is intended to assess the robustness of the illustrative economic comparison, rather than to provide an empirical estimate of CMS performance or maintenance cost. The assumed costs and performance ranges are therefore retained as representative values for demonstrating the potential economic implications of closing the data-model and model-decision gaps.

## 8. Concluding remarks

The paper has presented a critical review of CMS in wind farm O&M, with a focus on the gap between their intended role in CBM and their actual use in practice. To be specific, despite significant advances in sensing technologies and data-driven condition monitoring methods, CMS remain largely confined to monitoring and alarm generation, with limited influence in supporting wind farm maintenance.

To explain this limitation, the paper introduced the DMDG framework, which conceptualizes CMS as an integrated pipeline linking data, models, and decision support. Two key misalignments, *i.e.*, the ‘Data-Model Gap’ and the ‘Model-Decision Gap’, were identified. These gaps are closely related, and together they can limit the effectiveness of CMS in real-world applications.

This study translated the DMDG framework into a decision-driven design methodology for next-generation CMS. The methodology starts from maintenance objectives and then relates these requirements to the model and data layers, rather than treating model development as the starting point. In this way, the resulting CMS is intended to address both the technical requirements of condition monitoring and the information needed for maintenance practice. The illustrative case study suggests that better alignment between these elements could lead to lower O&M costs, although the estimated savings depend on the assumptions used in the analysis.

The analysis also indicates that the limitations of current CMS cannot be addressed by improving algorithm accuracy alone. Data quality, model interpretation, uncertainty in the results, and the connection between CMS outputs and maintenance activities also affect the usefulness of the system in practice. These aspects are closely related and therefore need to be considered together when developing CMS. This provides a basis for moving from a predominantly model-centred approach towards a more system-level consideration of data, models, and maintenance requirements.

The proposed ‘Decision → Model → Data’ workflow may also be difficult to implement in some existing wind farms. Additional sensors, data acquisition systems, communication links, computing resources, and system integration may be required. This could increase capital and operating costs, particularly for ageing or legacy turbines that have limited digitalisation capabilities. The integration of heterogeneous CMS, SCADA, maintenance and operational data may also require substantial engineering effort and organisational coordination. Furthermore, continuous model updating and decision validation require appropriate human expertise and long-term data governance. These considerations may constrain the immediate adoption of the framework in cost-sensitive wind farms. Therefore, future research should further investigate cost-aware implementation strategies, including incremental retrofitting, prioritisation of high-value sensing and data sources, and quantitative assessment of the economic benefits relative to the required investment.

Finally, it is worth noting that this study is primarily qualitative and conceptual in nature. Quantitative benchmarking across different CMS implementations is needed to validate the proposed framework. Therefore, an important direction for future work is to establish a benchmark dataset specifically designed to evaluate the proposed DMDG framework rather than relying solely on conventional

datasets developed for fault-classification accuracy. A suitable benchmark should contain synchronized multi-sensor measurements from wind turbine subsystems, including vibration, temperature, rotational speed, power and relevant SCADA variables, together with operating and environmental conditions. The dataset should also include normal operation and multiple fault stages, from incipient to developed faults, with time-stamped fault initiation, progression and maintenance events where available. Importantly, the benchmark must include realistic data-quality issues, such as missing data, sensor bias, sensor drift and sensor failure, so that the impact of data quality on the data-model gap can be fully assessed. For each fault event, the dataset needs to provide decision-oriented labels, such as fault severity, recommended intervention urgency, maintenance action and, where available, downtime and maintenance consequences. For example, a representative benchmark may comprise 10–20 turbines, several years of operation, the corresponding SCADA data, higher-frequency condition monitoring data, major fault categories, and time-stamped maintenance records. Such a dataset would enable future studies to evaluate whether a DMDG-based CMS can help achieve reliable maintenance decisions under variations in data quality, model performance and operational conditions.

### Data availability statement

No supplementary or additional data were generated in this study.

### Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used generative AI tools only to improve language and readability. Specifically, the authors used ChatGPT for language polishing only for drafting in limited sections. The authors take full responsibility for the content of the manuscript.

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### Authors' contribution

Conceptualization, R.D.Y. and W.Y.; methodology, R.D.Y.; investigation, R.D.Y., W.Y. and L.Z.; resources, W.Y.; writing—original draft preparation, R.D.Y.; writing—review and editing, W.Y., L.Z., R.Q.Y., G.W. and Z.L.; visualization, R.D.Y.; supervision, W.Y. and R.Q.Y.; project administration, W.Y.; funding acquisition, W.Y., R.Q.Y. and L.Z. All authors have read and agreed to the published version of the manuscript.

### Conflicts of interest

Ruqiang Yan holds the position of Editor-in-Chief for *Mechatronics Technology* and has not peer reviewed or made any editorial decisions for this paper. The authors declare no other conflicts of interest.

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