Why wind O&M needs AI grounded in physics

AI is becoming increasingly important in wind O&M, but data alone cannot explain why a turbine is behaving differently. Liam Sharkey, SVP of AI & Innovation at ONYX, examines why combining AI with engineering physics can provide operators with more useful answers.

As the wind industry looks for better ways to manage assets and improve the profitability of operational projects, interest in AI-powered operations & maintenance (O&M) tools has grown. Faster processing of asset data is useful, but operators also need to understand why a system has reached a particular conclusion. For wind O&M, that means combining data analysis with tools grounded in the physics of the turbine.

Operators have to balance a wide range of O&M demands. These include managing mixed OEM

fleets and ageing assets, making performance and derating decisions, forecasting remaining useful life, monitoring asset health and meeting commercial obligations. They must also manage factors outside their direct control, including weather, supply chain pressure and equipment availability.

This leaves operators with plenty of opportunities to improve efficiency and has encouraged more autonomous O&M models, with operators taking greater control of maintenance activities. AI is increasingly becoming part of that approach. Major OEMs, utilities and fleet operators are already incorporating it into asset management systems to improve yield, reduce unplanned downtime and help prevent serious failures.

The wind industry is ready for AI, but what does it need most from new O&M tools? Looking at the practical needs of an operator, the limitations of black-box statistical models quickly become apparent. They can improve routine monitoring, but are less effective when operators need to understand an output, prove a diagnosis or apply the same quality of analysis across larger fleets. To deliver its full value in wind O&M, AI needs to be informed by the physics that govern turbine behaviour.

Explainability

The value operators require most from AI-powered O&M tools is explainability. Identifying a mechanical fault early is important, but the finding is only useful if engineers can understand the diagnosis and verify the maintenance decision that follows. Every decision made by engineers and site managers carries physical and financial risk. Without supporting evidence, few will take the costly decision to derate or shut down a turbine.

Statistical AI models are good at identifying patterns in performance data, detecting anomalies and alerting operators to potential mechanical issues. In an environment full of noisy alarms, that ability to pinpoint and prioritise problems is valuable. Their limitation is diagnosis: they can identify that something is changing without necessarily explaining why. For serious issues such as a potential gearbox failure, that distinction matters.

By contrast, physics-informed AI can help identify the mechanism driving a change in operational data. Engineers often lose time verifying an alarm diagnosis. If the system can also provide evidence for that diagnosis, engineers can monitor larger turbine fleets more effectively while devoting more time to work that requires engineering judgement.

Reducing the risk of catastrophic failure

Catastrophic failures can have a significant impact on profitability. According to ONYX Insight, replacing a single wind turbine can cost more than $5 million, while business interruption can amount to $100,000 per day in lost revenue.

Turbine condition monitoring systems (CMS) are commonplace in the industry and can identify issues before they escalate. However, CMS can show that a component is faulty and track the progression of a fault without necessarily telling an analyst when failure will occur. Deciding when to intervene still relies heavily on experience. One of the opportunities for AI is to turn fault data into better informed recommendations about when action is needed.

Statistical AI models can struggle most with the unusual events that lead to catastrophic losses, such as gearbox failure, because affected assets may behave outside the training data on which the model relies. When a new failure mode appears, a model based primarily on historical patterns may produce only a generalised prediction or, in the worst case, a misleading one.

Physics-informed models are better placed to identify unusual issues in their early stages because the fundamentals of structural dynamics, vibration analysis and physical loading do not change simply because performance data is incomplete or unfamiliar. With limited standardisation across turbine models, O&M predictions need a physical basis as well as historic data.

Immediate functionality

Operators also need AI tools to be useful from day one when new turbine models enter service. Manufacturers have pushed turbine capacity beyond 25 MW, but the rapid introduction of new machines also means that operational track records can be based on relatively small samples. At the same time, newer machines have also experienced recurring defects.

This creates a problem for statistical AI models. They may need at least 12 months of operating data to establish a useful baseline for anomaly detection. Fault diagnosis can require an even longer history because enough failures must first occur to provide valid examples. That can leave operators with less support during the early operating period, when understanding unfamiliar behaviour is particularly important.

Physics-informed models can work with smaller or irregular data samples, without relying on OEM proprietary design data, because they assess behaviour against established mechanical principles and a broader history of turbine failures. The underlying principles of turbine operation remain broadly consistent across different machines. That gives these models a basis for analysing new assets before a long operating history has accumulated.

Lifecycle adaptability

As more fleets approach the later stages of their operational lives, operators are paying greater attention to how much value can still be extracted from existing assets. The challenge is no longer simply to process more data, but to turn it into decisions with a clear operational and commercial consequence, such as derating an asset to extend its useful life until a planned service visit. Operators increasingly want to understand how those decisions affect remaining useful life (RUL).

Statistical AI models can flag a potential issue before a service visit, but they are less effective at optimising the period between visits or adapting predictions as operating conditions change. Physics-informed models can reduce some of that uncertainty by testing observations against physical behaviour rather than relying only on patterns in historical samples.

Without accurate RUL information, operators may be left choosing between early replacement and continuing to operate with limited evidence about what should be prioritised. AI grounded in engineering principles can combine performance data with industry failure datasets and physical behaviour, supporting decisions

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throughout the asset lifecycle, from warranty periods to end-of-life, life-extension or repowering decisions.

Over an asset's life, better forecasting can improve uptime and give engineers more control over costly maintenance activities such as crane visits. The wind industry now has large volumes of operating and failure data, but those datasets are most useful when they are interpreted within a mechanical framework rather than treated as statistics in isolation.

Physics-informed AI does more than process data. It gives engineers a way to relate an alert or prediction to the behaviour of the turbine itself. That engineering context is important if operators are to trust automated processes and use their outputs in maintenance decisions. The aim should be practical recommendations that remain useful throughout the life of the fleet.

The industry has recognised that AI can help maximise power production, reduce downtime and make complex asset management more efficient throughout the life of a turbine. Those potential benefits matter at a time when operators are dealing with tighter economics, supply chain pressure and permitting constraints, while extracting more value from existing assets is becoming increasingly important.

Statistical AI models can make a useful contribution to operational efficiency, but they do not answer every O&M question. If the industry expects AI to support more consequential engineering decisions, advanced data science alone is not enough. The models also need to reflect the physical behaviour of the machines they are analysing.

ONYX Cortex has been developed around that principle. It combines physics-based models derived from more than 50,000 failure events with AI to support explainability, earlier identification of serious failures, functionality from the outset and lifecycle management across larger fleets. The objective is to give owner-operators recommendations that can be traced back to engineering evidence, rather than asking them to rely on statistical probability alone.

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