Benefits of Big Data and Machine Learning for the life cycle of wind turbines

New methods for plant monitoring offer many and various potentials across the entire value chain.

Christian Pagel

Kurzfassung

Vorteile von Big Data und Machine Learning für den Lebenszyklus von Windenergieanlagen

Die technische Verfügbarkeit von Windenergieanlagen (WEA) ist bei geringen Kosten zur Optimierung ihrer Wirtschaftlichkeit auf einem möglichst hohen Niveau zu halten. Systeme zur Online-Überwachung wichtiger WEA-Betriebsgrößen nutzen konsequent die Fortschritte der Digitalisierung und damit die Stärken von KI-Methoden, u.a. auf Basis von Big Data und Machine Learning. Solche Systeme ermöglichen durch eine intelligente Analyse von Daten zur Betriebsführung und Zustandsüberwachung nicht nur die Realisierung kosteneffizienterer Instandhaltungsstrategien im laufenden Windparkbetrieb, sondern bieten bereits während der Projektierung sowie im Zuge der Installation und Inbetriebnahme von Windparks vielfältige Vorteile. So liefert die Einbeziehung von Erfahrungen, die durch das Monitoring von installierten Anlagen aus anderen Windparks zur Verfügung stehen, bei der Auswahl eines optimalen Anlagentyps eine wertvolle Entscheidungshilfe und kann darüber hinaus einen nicht unerheblichen Beitrag zu Senkung der Stromgestehungskosten leisten. Mit dem Online-Monitoring von Windparks entsteht überdies für jede WEA ein wertvolle Anlagenhistorie in Form einer digitalen Lebenslaufakte, die mit Blick auf den Weiterbetrieb eine zuverlässige Unterstützung zur Beurteilung der Restlebensdauer ermöglicht. Die Potenziale der in diesem Beitrag beschriebenen Lösungen erstrecken sich somit über den gesamten Lebenszyklus von WEA, von der Windpark-Projektierung bis zum Weiterbetrieb der Anlagen nach dem 20. Betriebsjahr.

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To optimize their economic efficiency, the technical availability of wind turbines has to be kept at the highest possible level at low costs. Systems for the online monitoring of important operating parameters of wind turbines make consistent use of the progress of digitalization and thus of the strong points of AI methods, among other things on the basis of Big Data and Machine Learning. By intelligently analyzing data of operation management and condition monitoring, such systems not only allow to implement more cost-efficient maintenance strategies during wind farm operation but offer many and various benefits already during the development as well as in the course of the installation and commissioning of wind farms. Thus the inclusion of experiences available from monitoring installed plants from other wind farms provides valuable decision support in selecting an optimal plant type and, in addition, can significantly contribute to decreasing the levelized cost of energy. Moreover, the online monitoring of wind farms creates a valuable plant history in the form of a digital service life record that enables reliable support in assessing the residual lifetime with regard to the ongoing operation. The potentials of the solutions described in this paper thus range across the entire life cycle of wind turbines, from the development of the wind farm right up to the ongoing operation of the plants after the 20th year of operation.

In simple terms, with regard to a planned wind farm the levelized cost of energy (LCOE) results from the quotient of investment expenditure, operating costs, and the predicted energy production over the expected lifetime of the wind turbines. In this context, the solutions described here have a positive impact on all factors of the LCOE.

- **Investment expenditure:** decreasing the investment and financing costs by proving a powerful monitoring system to banks and insurance companies for preventing damages on wind turbines and, consequently, costly plant outages.
- **Operating costs:** decreasing the operating costs by means of optimized maintenance due to the early detection of changes in the plants' operating behavior.
- **Energy production:** increasing the energy production by preventing unplanned plant shutdowns and by optimizing the times of service operations, e.g. by shifting them to periods of weak wind.

While the investment expenditure of a wind farm can be determined relatively exactly, its predicted energy production mainly depends on the availability of the wind turbines in the context of the wind conditions prevailing at the site of the plant, where the expected revenues are minimized by the operating costs, among other things (Figure 1).

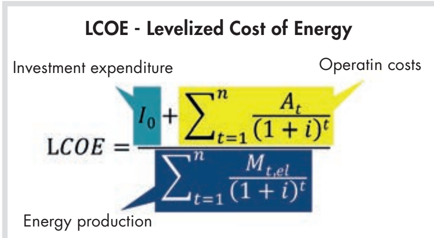

Fig. 1. The LCOE describes the ratio of investment expenditure, operating costs, and the predicted energy production. Source: Stromgestehungskosten Erneuerbare Energien. Studie, November 2013. Fraunhofer-Institut für Solare Energiesysteme ISE.)

Against this backdrop, practice shows that operators of wind farms have to put up with losses of revenue due to production limitations or even outages of wind turbines again and again in spite of regular inspections, servicing, and maintenance measures. In order to prevent limitations or plant outages, solutions like e.g. the WINDcenter of STEAG Energy Services thus, among other things, address precisely the field where the relevant operating costs are caused, i.e. maintenance.

Dominating reactive maintenance processes

Taking a closer look at today's maintenance processes in the field of wind energy, the surprising result is that the majority of the service operations are reactive, i.e. action is taken only when a damage has already occurred. This is remarkable in so far as, due to legal requirements and also according to manufacturers' specifications, wind turbines have to be inspected regularly for the purpose of damage prevention.

It is true that preventive maintenance measures like e.g. regular visual inspections can provide an overview of the plant condition. In spite of this, relevant abnormalities like e.g. increased bearing temperatures or changes in the power electronics often go unnoticed.

As a result, even checked components often develop problems shortly after inspections because their causes were not identified in time. One of the main reasons for this is that the control system monitors the current operating values only on the basis of fixed limits and thus is basically unsuitable for an early detection of changes in the plant process.

Systematic optimization by means of continuous online monitoring

Therefore a crucial objective must be to enable operators of wind farms to implement an economically efficient predictive maintenance strategy instead of a maintenance reactive/preventive in character by means of the combination of IT systems, expert knowledge, and services. The basis for this mainly consists of data management systems, IT solutions for a continuous online monitoring of wind turbines, and in this context the application of procedures considering digital technologies like Big Data and Machine Learning.

A powerful data management system is able to collect, visualize, and permanently store the operating data provided by a SCADA system and a CMS (condition monitoring system) so that also the historical plant data is preserved as a valuable element of a digital service life record. An IT system for a continuous online monitoring of wind turbines, in turn, analyzes the information provided by the data management system on the basis of key performance indicators (KPIs) for the early detection of process changes in the plant operation.

For a better understanding of the implementation of predictive maintenance strategies and thus the early detection of process changes during wind turbine operation, we will take a closer look at the significance of Big Data and Machine Learning for the configuration of KPIs in what follows.

Big Data, Machine Learning, and Digital Twins

Machine Learning has meanwhile become an essential component of software solutions that support predictive maintenance with data-based, Digital Twins of processes and plant components. Additionally, developments in the environment of Big Data have the potential to reduce the engineering effort for setting up a solution for such a maintenance strategy by means of Digital Twins.

After all, a Digital Twin is a mathematical model showing how relevant process parameters depend on the ambient conditions and actuating variables or parameters of a plant. The model is derived from historical data with methods of Machine Learning. The current values of operational measurements can then be compared with the projections of the Digital Twins to particularly detect also creeping changes in the plant condition early and reliably at all times.

On the basis of this information, it is possible to act predictively in terms of predictive maintenance in order to reduce losses of performance by using the resources efficiently and increase the plant availability. The prerequisite, however, is to detect deviations in the operating behavior of a wind turbine really reliably in order to prevent false alarms. This requires highly precise Digital Twins.

"High-quality KPIs" – Highly precise Digital Twins

Different but complementary approaches are possible for creating data-based models:

- Modeling by combining expert knowledge with supervised learning
- Modeling by autonomous, unsupervised learning, largely based on mathematical algorithms with minimal engineering groundwork

An expert knows the significant key variables for the condition of a plant section or of plant processes. He also knows which influencing variables are required for describing the expected behavior of a key variable and which periods of time in the historical data are suitable as reference, i.e. which causalities exist in the data. Thus an expert selects the corresponding input and output variables for his model.

Supervised learning methods will then form the model. This way, Digital Twins with a high accuracy emerge ("high-quality KPIs"). Owing to the selection of particularly informative measured values by engineers, significant changes detected by the system can easily be attributed to possible abnormalities in order to subsequently decide about further examinations and specific maintenance measures respectively (Figure 2).

Autoencoder learns autonomously

In autonomous learning, in contrast, there is no specification of causalities in the data by an expert. It is the task of "Machine Learning" to identify existing correlations and to form corresponding models. In doing so, the algorithms detect that the data from a plant are not independent of each other but are determined by a few key values. Thus algorithms like e.g. the "deep autoencoder" identify such variables autonomously and learn the correlations between those and the measured values of a plant in an "unsupervised" way (Figure 3).

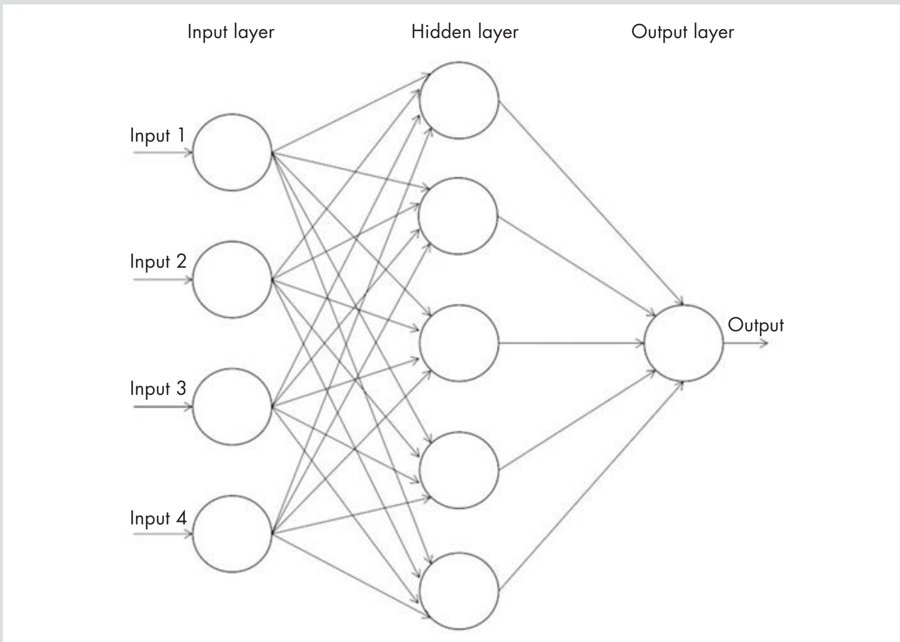

Fig. 2. Supervised learning: expert knowledge on cause and effect is displayed. Engineering in the modeling but simplified evaluation.

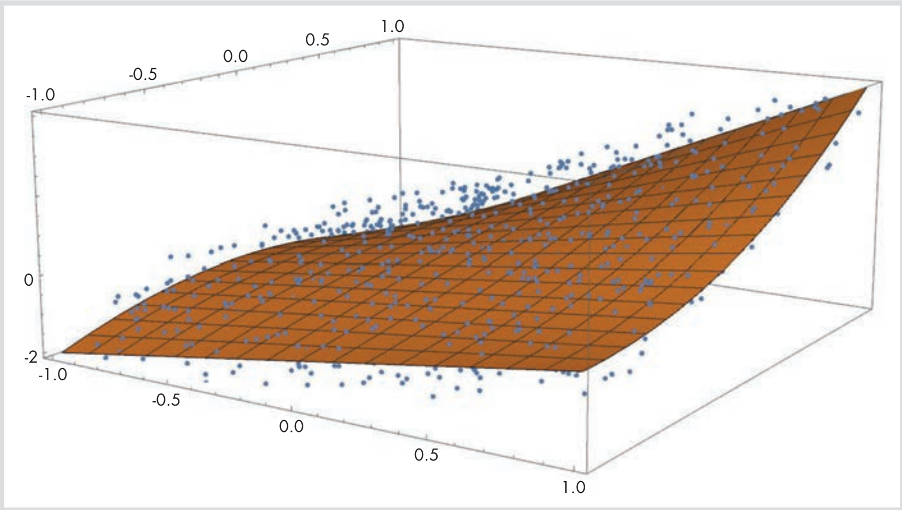

Fig. 3. Unsupervised learning: correlations between the measured values are detected and independent key variables are identified. Automatic modeling but engineers' analysis in the evaluation.

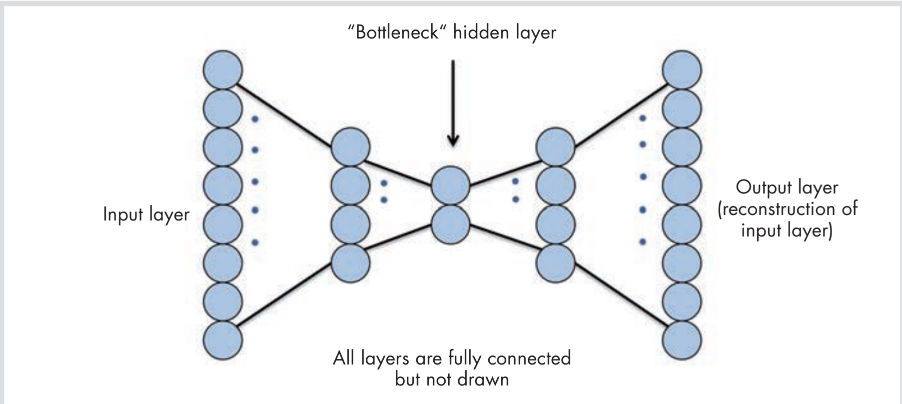

Fig. 4. Structure of an autoencoder.

As a neural network, an autoencoder is trained to copy input values onto output values. The network has several levels of hidden layers of neurons and consists of two parts with a "bottleneck" in the middle.

It prevents the neural network from just learning input = output and enforces that essential influencing variables ("features") describing the behavior of the input data are identified (Figure 4).

Automatic check of significant deviations

In an online application for supporting the predictive maintenance, all measurements to be monitored are presented to the deep autoencoder. When "learning", the algorithm identifies the most important features that describe the plant behavior and how the measurements depend on it under "normal" conditions.

In "online" mode, the first part of the autoencoder will then at first determine the features describing the current operating condition from the current measured values. From these features, the second part calculates the "normal" values to be expected under the given operating conditions for each measured variable.

For each measurement, statistical methods are applied to automatically check whether possible deviations between the current value and the projection are significant. This way, also large sets of measured values can be monitored automatedly, and changes in the condition of the plant that are reflected in the measured values can be detected very early and, above all, reliably with little engineering effort.

This approach to identify anomalies in measured values has proven itself in practice as it has been successfully applied to data from various wind turbines.

Online monitoring with automatic alarming

Independently of the approaches described so far (supervised or autonomous learning), changes in the operating behavior of a plant are detected by means of deviations from a reference value generated by the system. If this is the case, the IT system for the online monitoring will automatically output an alarm message, whereupon experts can begin with a detailed root cause analysis to systematically recommend remedial actions for a problem.

One crucial advantage of the system described here is that regarding the monitoring, it does not follow fixed limits or alarm thresholds in the process control system, CMS or SCADA system but the actual behavior of a wind turbine taking into account the current operating conditions.

In this context, the system is not just able to monitor a vast amount of process data automatedly but, above all, it enables fast reactions in the event of changes in the operating behavior.

Such abnormalities and consequently impending potential problems are thus detected at a very early point in time, with only relevant warning and alarm messages being generated. Mostly these are changes in the operating behavior of the wind turbine that are noticed by a CMS or SCADA system alone either very much later or not at all, as a case study will show at the end of this paper.

Many and various benefits across the entire value chain

In terms of the cost-efficiency of wind turbines and wind farms, powerful IT solutions using Big Data and Machine Learning in combination with expert know-how have a wide range of potentials that range from the development via the operation right up to the ongoing operation of plants after the 20th year of service life (Figure 5).

Valuable insights for the planning

With a view to future expected revenues, the location of the wind turbines as well as the selection of a suitable plant type are relevant for the development of a wind farm, among other things. Already at the development stage, the deeper insights concerning the specific wind turbine technologies gathered by monitoring already installed plants can offer crucial support in selecting a suitable plant type. In this respect it is advisable to decide for using intelligent monitoring and data management systems very early on, i.e. already at the planning stage of the wind farm, also with regard to the financing and insurance of wind farms. Such IT systems can be implemented during the installation and the commissioning of the plants respectively and require no additional sensors.

All requirements for a power curve examination

During wind farm operation, the IT solutions enable a continuous plant monitoring with the early detection of abnormalities in the operating behavior of the wind turbines, as explained above in greater detail. As a result of this, instead of time- and cost-intensive preventive or reactive maintenance measures, highly efficient and eco-

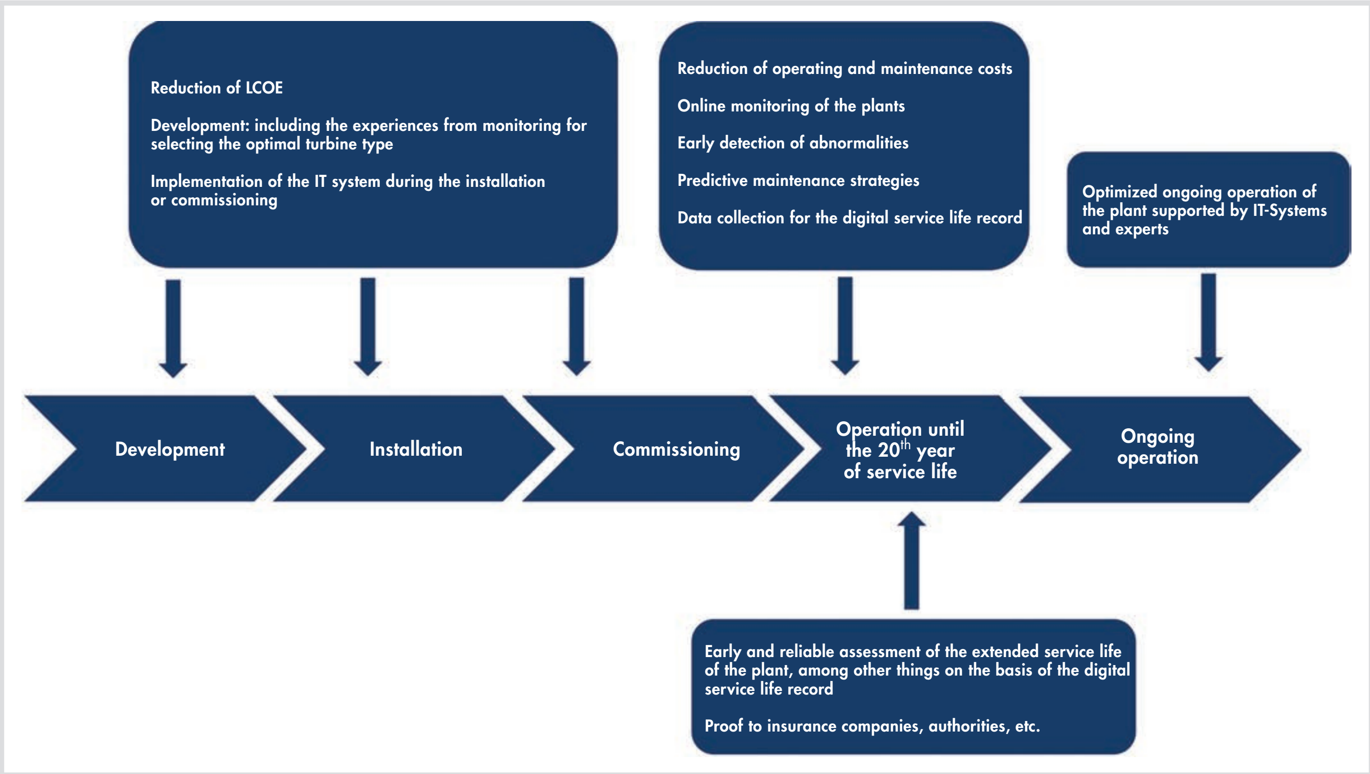

Fig. 5. The potentials are many and various and range from the development right up to the ongoing operation of wind turbines after 20 years of service life.

nomically advantageous predictive maintenance strategies can be implemented that lastingly decrease the operating costs of a wind farm.

In addition, such solutions fulfill all requirements according to IEC 61400-12-1:2017 (Wind energy generation systems - Part 12-1: Power performance measurements of electricity producing wind turbines) and IEC 61400-12-2:2014-02:2013 (Wind turbines – Part 12-2: Power performance of electricity-producing wind turbines based on nacelle anemometry) for the power curve examination, particularly with regard to Technical Guideline 10 (TR10) for calculating the site revenue and thus the site quality on the basis of stored wind turbine operating data (to be carried out after five, 10, and 15 years of operation).

Systematic support in the wind turbine assessment for the ongoing operation

In addition, the continuous data collection during wind farm operation constitutes an important element of the digital service life record of each wind turbine. As a result, the uncertainties in the assessment regarding an ongoing operation can be reduced significantly in good time before reaching the 20th year of a plant's service life on the basis of such data, among other things.

While only the structural stability of a wind turbine has been used as a basis for assessing the residual lifetime of a wind turbine so far, the detailed data records of the plant history additionally allow to reliably assess the residual lifetime of the power-generating components as well. Furthermore, the difficult task of the economic efficiency calculation of the ongoing operation can thus be facilitated significantly in order to achieve the highest possible return for the remaining time of the wind turbine.

The IT systems and procedures described here have been tested at various wind farms and are thus field-tested. In this context, the following case studies demonstrate the enormous potentials of a continuous wind turbine monitoring for use in practice.

Case study 1: Systematic root cause analysis

At a wind farm commissioned a couple of years ago, a data base was established by implementing the IT systems to begin with, in order to create first models for monitoring specific operating parameters. Almost two months after the implementation, an automatic alarm message drew the attention of the staff to an abnormality on a wind turbine which, in a first model, showed an increase in the gear oil pressure over the reference value (Figure 6).

In this specific case, the staff members responsible for the plant monitoring determined that the cooling water temperature, which is usually adjusted to approximately 42 degrees Celsius, showed fluctuations from a certain point in time on. Moreover, a correlation between the fluctuations of the cooling water temperature and the outside temperatures at the site of the wind turbine was detected (Figure 7).

The analysis why the behavior of the cooling water temperature followed the ambient temperature of the plant finally revealed a three-way valve in the cooling system of the wind turbine as the cause.

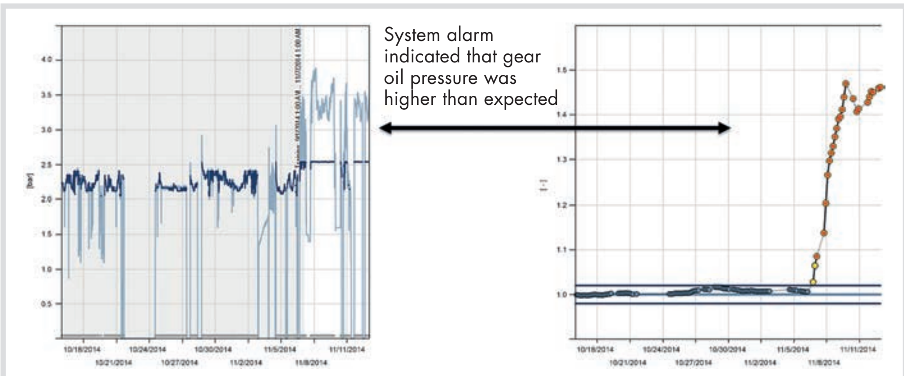

Fig. 6. Shortly after the commissioning of a wind farm, the system reported an increase in the gear oil pressure over the reference value by means of an automatic alarm message.

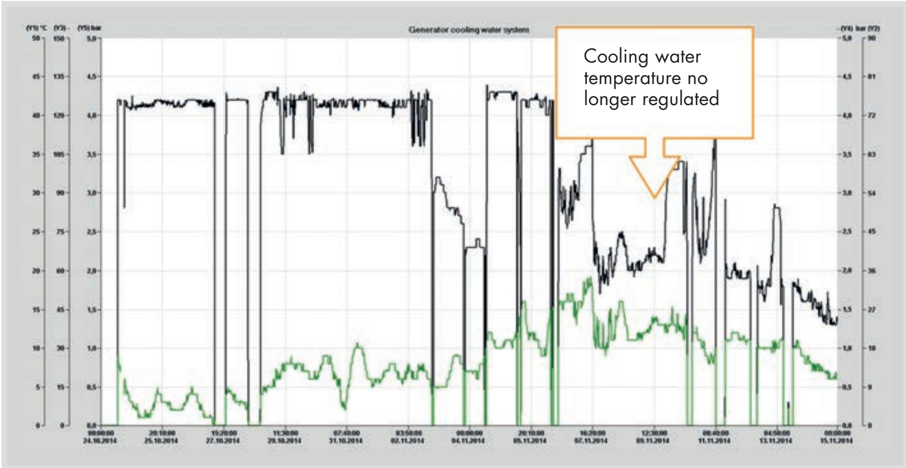

Fig. 7. In the course of the root cause analysis it turned out that the cooling water temperature was no longer controlled.

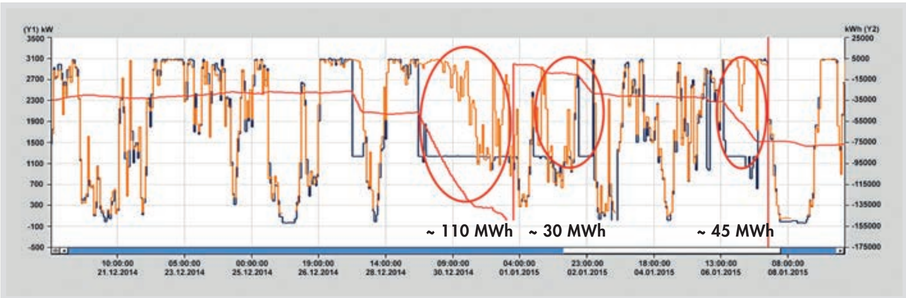

Fig. 8. Due to a defect three-way valve, the wind turbine without data connection to the online monitoring reduced its output several times over a period of less than two months. Finally, the energy production losses added up to approximately 185 MWh.

This valve ensures that the correct amount of cooling water is routed through an air cooler. Due to the defect valve, the flow rate of the cooling water was no longer controlled but completely routed through the air cooler; as a result, the temperature of the cooling water adjusted to the ambient temperature of the wind turbine.

As the cooling water exclusively passed through the air cooler, the gear oil temperature was no longer controlled, causing the viscosity of the oil and thus also the gear oil pressure to rise. Finally, the problem was remedied by replacing the three-way valve.

This case study demonstrates how the cause of an abnormality in the operating behavior of a wind turbine can be identified very early owing to a timely alarming and a subsequent systematic analysis in order to prevent a possible output reduction of the plant.

High production losses due to output reduction by the turbine controller

This, for instance, was the case with another wind turbine at the same wind farm which, however, had no data connection at that stage of the project.

On this plant, the same source of defect occurred during the first year of operation as well. However, at this point in time the SCADA system could not detect any deviations yet. At the beginning of winter, temperatures fell and the cooling water temperature decreased to -10 °C at an outside temperature of -20 °C.

As the gear oil pressure increased massively in this case too, the wind turbine reduced its output several times by up to 40 percent in order to prevent a gearbox damage. The result: during a season with particularly strong winds (winter), output losses of approximately 185 MWh occurred before the problem could finally be remedied (Figure 8).

Case study 2: Retrospective analysis of maintenance measures

Regular maintenance helps to keep the technical availability of wind turbines at a continuously high level. If, however, maintenance measures as well as repairs are not carried out properly, this may lead to opposite effects, as the following example shows.

At an onshore wind farm in Germany (12 wind turbines with 1.5 MW output each), abnormalities occurred on the main bearing of a plant. Consequently, the wind farm operator wanted to determine the possible causes by means of a retrospective analysis.

In a first step, the IT systems described in this paper were trained on the basis of the historical operating data of the plant to allow to determine reference values and, in addition, identify deviations from these values. The data from one year were used as training period.

Over the entire observed time period (stored data from more than two and a half years), the temperature trend of the main bearing indeed showed seasonal effects like e.g. a temperature decrease and in-

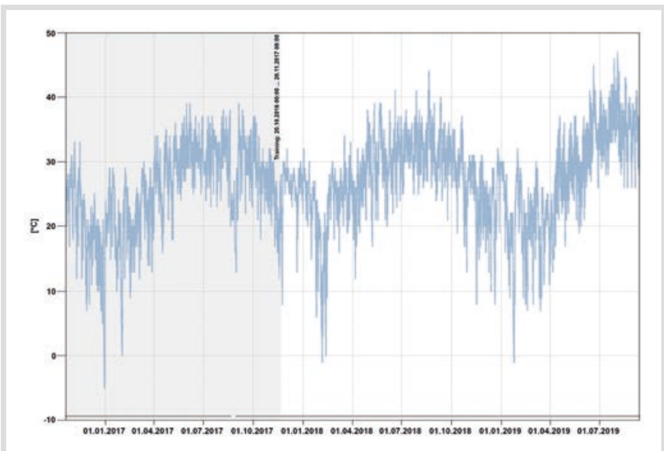

Fig. 9. The data from one year were used as training period (highlighted in gray in the picture). The temperature trend shows seasonal effects over the entire observed time period, but at first no abnormalities are identifiable on the main bearing at all.

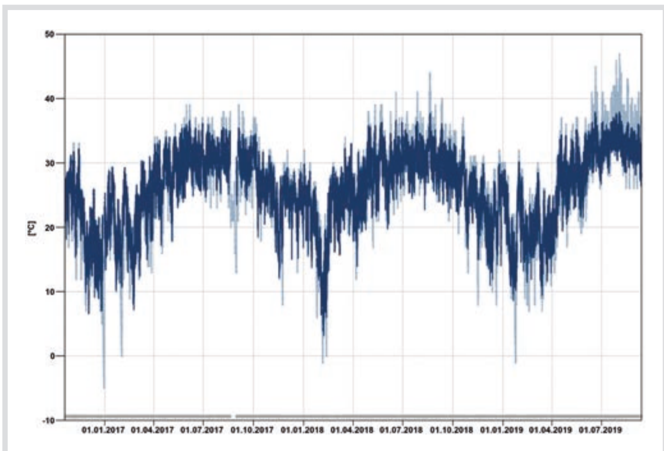

Fig. 10. When comparing the measured values with the reference values, massive deviations in the temperature profile of the main bearing became apparent from May 2019 on.

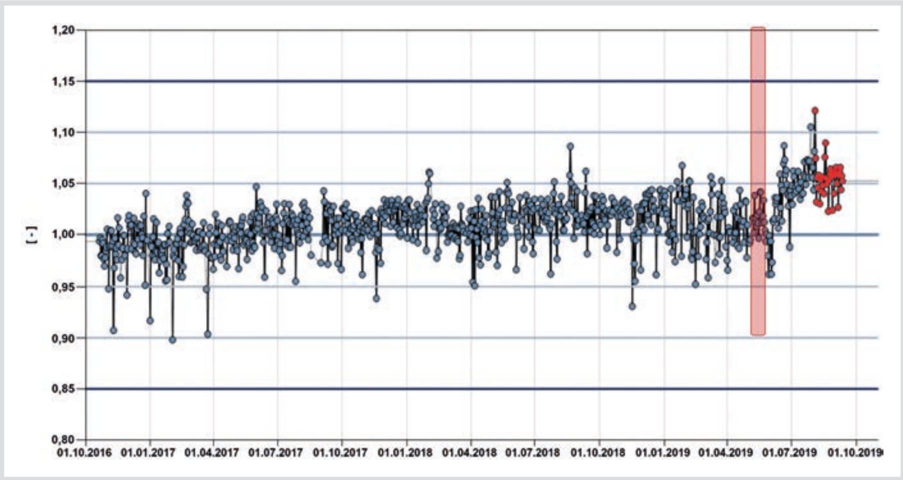

Fig. 11. After the statistical evaluation of the measured results, obvious changes in the temperature behavior can be observed (red tags on the right). Moreover, a correlation of the increase in the main bearing temperature with a semi-annual maintenance (area highlighted in red) can be identified.

crease respectively over the course of the day as well as in the months of winter and summer, but at first no abnormalities at all (Figure 9).

Only when comparing the measured values with the determined reference values, anomalies in the temperature profile became apparent from May 2019 on (Figure 10).

After the statistical evaluation of the measured results, not only obvious changes in the temperature behavior of the main bearing but also a correlation of the increase in the main bearing temperature with a semi-annual maintenance carried out before could be observed (Figure 11).

The root cause analysis finally revealed that repair work had been carried out in the course of this maintenance that resulted in a tensioning of the drive train, leading to a higher stress on the main bearing and an increase in the bearing temperature.

As the wind farm operator identified the actual causes of the abnormalities on the main bearing of the wind turbine owing to the systematic analysis, he was able optimize his future maintenance strategies as a result. In addition, however, further repair measures were required in order not to reduce the lifetime of the main bearing due to the lastingly high stress.

Conclusion and outlook

A high technical availability of wind turbines, especially at times of strong wind, is an essential prerequisite for achieving the expected revenues over the entire predicted service life of wind farms. Therefore it is necessary to detect anomalies in the operating behavior of plants very early and reliably in order to react with suitable measures in a very targeted way. Only this way, also major damage and resulting longer plant downtimes, which may involve high production losses, can be prevented.

In this context, an IT-based early warning system must be able to detect even creeping deviations from the operating behavior of the plant at an early stage of their emergence, especially if such changes are identified by a SCADA system or CMS only later or possibly not at all.

By generating highly accurate Digital Twins (high-quality KPIs), the application of ground-breaking AI methods like e.g. Big Data and Machine Learning provides support in preventing false alarms and detecting only really relevant deviations from the operating behavior of a wind turbine in order to generate automatic alarms.

In addition, for wind farm operators such procedures and methods lay the crucial groundwork for implementing economically efficient predictive maintenance strategies that, among other things, are a prerequisite for shifting possibly required service or maintenance operations to planned downtimes or periods of weak wind. As experience teaches, predictive maintenance strategies lead to a number of benefits, among them a more efficient deployment of human resources, a better availability of spare parts, a more systematic planning of service operations, and thus ultimately considerable cost savings at various levels.

However, the strong points of the solutions described here not only focus on running wind farm operation but become visible already at the planning stage of wind farms, range right up to assessing the residual lifetime of wind turbines after 20 years of operation and, moreover, extend to the ongoing operation of the plants. In this sense, such systems unlock many and various further and possibly hitherto untapped potentials in addition to the obvious benefits for wind energy. l


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