Analysis of Potential Wind Farm Profitability Increase by the Application of a Predictive Analytics Approach

Fabio Wagner, Christian Pagel, Urs Steinmetz

STEAG Energy Services GmbH
Rüttenscheider Str. 1-3, 45128 Essen, Germany
fabio.wagner@steag.com, christian.pagel@steag.com, urs.steinmetz@steag.com

1 Introduction

The worldwide installed capacity of wind power assets presented an ever growing trend over the last years (Figure *1*).

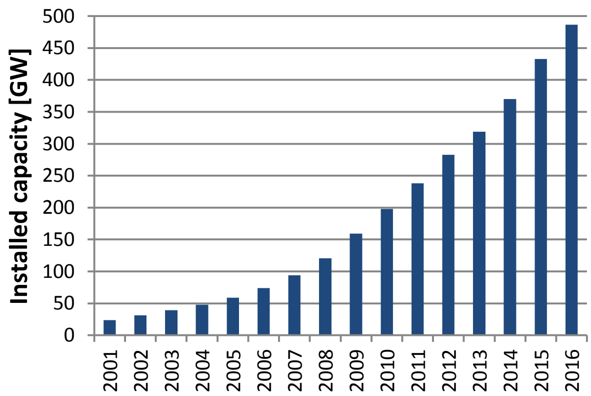

Figure 1: *Worldwide installed wind power capacity (GWEC, 2017, p. 3)*

This trend was supported by subsidies, but with a foreseeable reduction of governmental support, the wind industry has to reduce costs in order to remain competitive (van den Broek, 2014, p. 1).

An alternative to reduce costs is to apply methods and tools that enable an optimized Operation and Maintenance (O&M) approach.

Maintenance could be optimized if there was early knowledge that a given wind turbine component would fail. This would enable a better planning of resources and significantly reduce production loss due to unexpected downtime.

This paper analyses the potential benefits of the application of predictive analytics methods for the optimization of wind farm profitability.

The analyzed object is an onshore windfarm composed of 36 wind turbines of 3 MW each during their first 12 months of operation (September 2014 to August 2015).

The methods applied in this analysis are described in chapter 2, while the results of case studies are presented in chapter 3. Chapter 4 discusses the findings, while chapter 5 presents some concluding remarks.

2 Methods

The proposed benefit analysis was performed based on the results a predictive analytics system and a root cause analysis procedure were able to produce on a 108 MW onshore wind farm.

Those methods are presented in detail in the following sections.

2.1 Predictive Analytics System SR::SPC

The predictive analytics system SR::SPC is used to define performance values of technical processes in such a way that the generated data permits reliable statements about the current status of the monitored component. In addition, these data can be used to detect emerging faults of the monitored components at an early stage, so that, for example, the shutdown necessary for the repair or for preventive maintenance can be planned and carefully prepared.

The purpose of SR::SPC is to reliably detect possible critical deviations of a component or of the process from the nominal or normal condition defined beforehand. For this purpose “Key Performance Indicators” (KPIs) are determined by comparing the actual value with a reference value.

Prior to this, a reference value has to be calculated which is suitable for the particular operation mode and other boundary conditions like e.g. ambient temperature (Figure 2). The calculation of the reference value can be done by data-driven models using powerful neural networks, by polynomial approximation and/or physical models.

There is no need to install any sensors for this approach: SR::SPC analyzes whichever available data. Both high frequency e.g. 1 s data, and low frequency e.g. 10 min data can be used for the analysis. The quality of the data is, however, essential for the quality of the SR::SPC evaluations.

The trends of the KPIs over time are analyzed by the so called “control chart”, a technical tool for quality control established for years in the production of homogeneous goods.

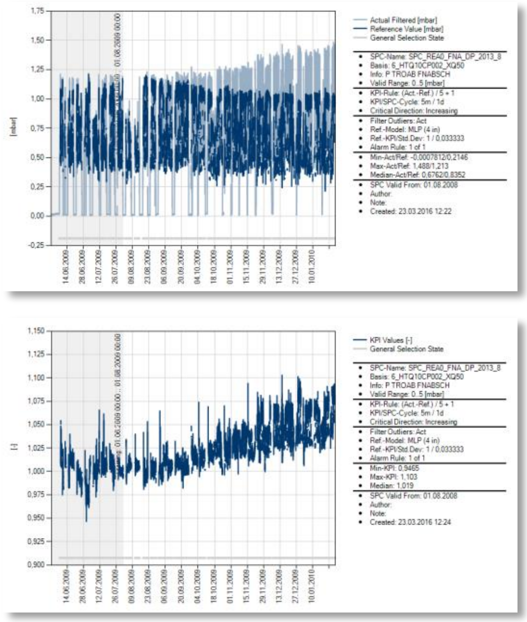

Figure 2: *Actual (light blue) and reference (dark blue) value (top) & KPI (actual / reference) (bottom)*

The control chart is a graph (Figure 3) showing an essential feature of the monitored process, so that, on the basis of the chronological sequence of this feature, deviations from the current reference value and thus emerging faults can be detected early.

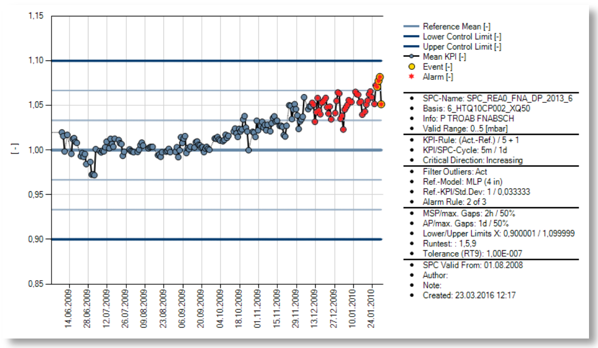

Figure 3: Shewhart control chart

Additionally, the future progress of the KPI can be predicted (Figure 4) and also changes in the trend characteristics (e.g. increasing rate of temperature increase) can be detected by using the trend module.

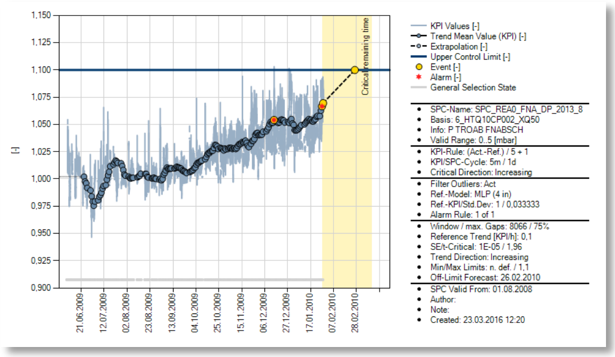

Figure 4: *Example of Trend detection and trend prognosis*

To make the actual control chart and trend evaluation applicable to power plant data, adequate reference values have to be determined by means of additional calculation steps. For this, the SR::SPC software uses the following main steps:

- Data preparation like application of well-defined selection filters (e.g. steady state) and generic outlier filters (e.g. short-time peaks)
- Calculation of the actual characteristic value of the monitored components or process parameters based on measurements (e.g. efficiency)
- Calculation of the corresponding reference values
- Calculation of the normalized KPI as ratio of the first two results that are now independent of the mode of operation and other external influencing variables
- Statistical analysis of the KPI values using pattern detection (e.g. Runtest) and other well established methods (e.g. Shewhart, CUSUM, EWMA)
- Prediction of the future KPI trend and detection of trend changes

By analyzing the KPI time series with the control charts, statistically anomalous fluctuations, patterns, and trends typically caused by critical process conditions are detected early. This procedure – especially the combination of various statistical methods – is also very reliable so that false alarms are negligible.

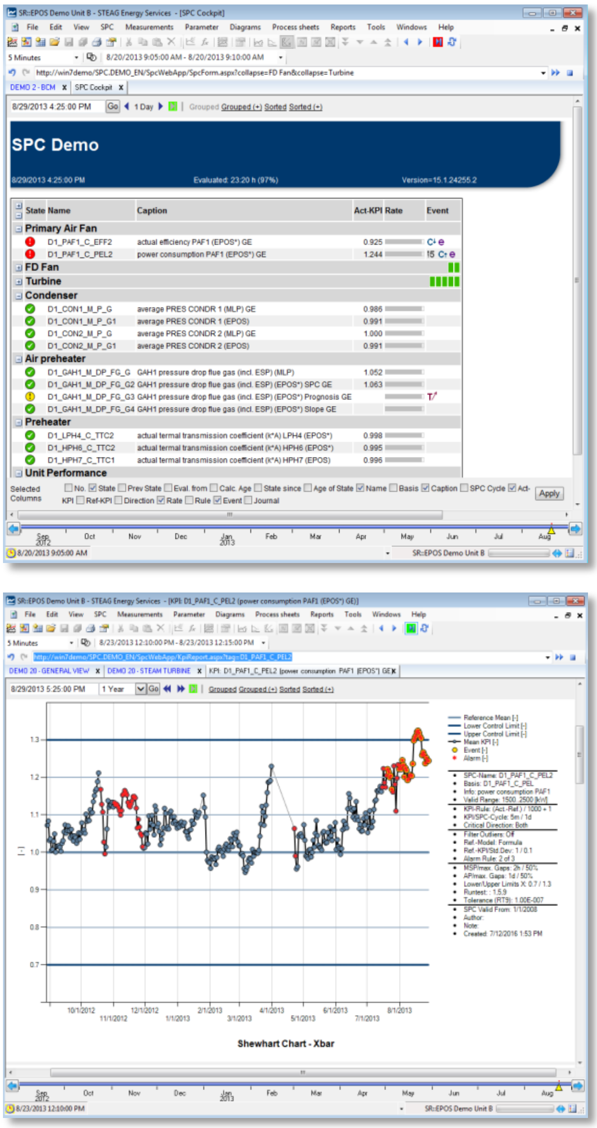

Figure 5*: Overview in SR::SPC Cockpit (top) & detailed illustration of KPI analysis (bottom)*

Due to its high degree of reliability and at the same time low proneness to false alarms, SR::SPC is suited for monitoring a wide variety of process characteristics in a widely automated way. Additionally, plant operators are informed automatically only about critical process conditions (alarms). In this case, the responsible experts are informed via e-mail and can get a quick alarm overview and analyze the root cause of the alarm.

Critical process characteristics are revealed in the corresponding view in the so called SR::SPC Cockpit overview by color changes in the 'traffic light' system. By clicking on the name of the KPI, the appropriate control or trend charts can be displayed on demand (Figure 5) and analyzed in detail. Usually SR::SPC runs in the background. As the software informs the assigned experts independently when required, a manual evaluation of the results is not necessary, so that staff members are not tied up by the system.

In the power plant environment, SR::SPC can support operation management in the following areas (amongst others):

- Process quality monitoring for diagnostics of process quality changes (e. g. increase generator temperature difference due to cooling water system fouling)
- Failure/condition monitoring for early detection of impending defects/failures of components (e. g. increased bearing vibrations due to incipient bearing damages)
- Sensor monitoring for identifying malfunctioning or defective measuring systems (e. g. freezing of a measure due to a damaged sensor)

In the mentioned fields, the procedurally and economically relevant processes are generally well covered regarding existing measuring technology. Thus, suitable characteristics can be deduced continuously to monitor the processes with SR::SPC. The preventive monitoring of the process characteristics and the automatic reporting of critical process conditions thus ensure that, if necessary, the response to the respective incidents can occur at an early stage or can be planned accordingly.

SR::SPC can be applied in any type of plant since the used statistical methods are generally applicable.

2.2 Root cause analysis

Once the predictive analytics system generates an alarm, the engineering team initiates works on the root cause analysis.

The tools applied by the engineering team are:

- Raw data analysis in a user friendly visualization tool (SR::x), and
- Analysis of OEM's wind turbine documentation

Once the root cause analysis is concluded, the engineering team prepares a report describing the event, the probable cause of the observed behavior, the risks associated with the event and recommendations on further course of action for remediation measures.

3 Results

Ten KPIs per wind turbine were considered[1] in the analysis period, when a total of 12 alarms were generated by SR::SPC. Those alarms were analyzed by the engineering team and respective recommendations were issued to the wind farm owner.

The following two sections present representative case studies where it was possible to assess the benefit predictive analysis has on minimizing production loss.

3.1 Case study 1: high gear oil pressure

In November 2014, an alarm was issued by SR::SPC as the gearbox oil inlet pressure increased significantly in a short time (Figure 6). The measured value (light blue) and the reference value from the system (dark blue line) present a clear discrepancy from November 7th onward.

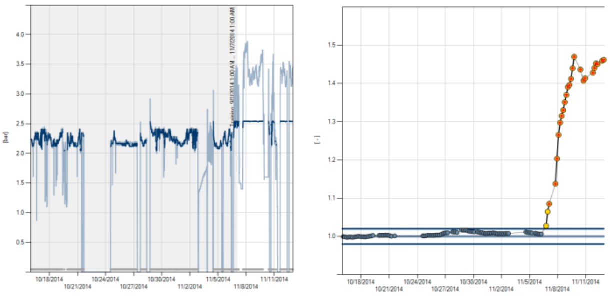

Figure 6*: Actual and reference values (left) and a control chart analysis (right)*

The root cause analysis by the engineering team based on the raw turbine data found that the cooling water temperature was no longer at the usual, regulated level, but has since then correlated clearly with the outside temperature (Figure 7).

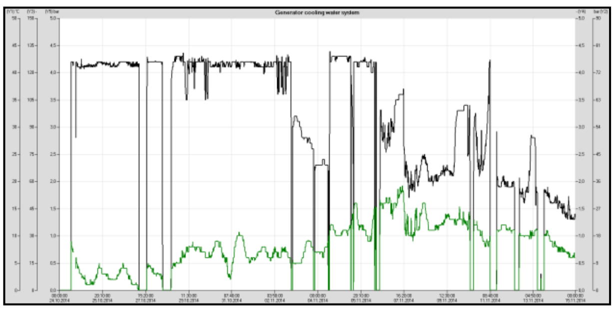

Figure 7*: Cooling water temperature (black) and ambient temperature (green)*

In an effort to explain the observed behavior, the engineering team analyzed the turbine documentation. Figure 8 presents a diagram of the cooling water system.

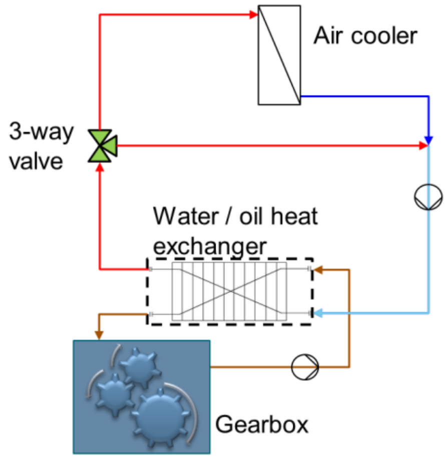

Figure 8*: Cooling water system diagram*

The diagram analysis combined with the raw data analysis lead the engineering team to the conclusion that the 3-way valve in the cooling water circuit was not properly regulated, causing the entire cooling water flow to pass through the air cooler, resulting in the observed dependence of the cooling water temperature on the outside temperature. This caused a significantly lower gear oil temperature which, in turn, resulted in an increased oil viscosity and consequently increased the oil inlet pressure. At the time of the evaluation, no alarm had yet been triggered by the SCADA system itself.

An inspection and repair or replacement of the 3-way valve was recommended on November 14th, 2014.

As ambient temperatures fell due to the approaching winter, the gear oil pressure increased further. At the end of December 2014, the oil pressure was so high that the system automatically limited the turbine's output to 40 % of the nominal output. This limitation caused a production loss of 185 MWh (Figure 9).

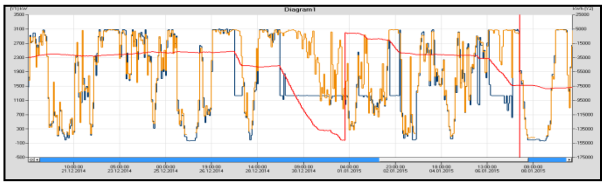

Figure 9*: Measured production (blue), possible production (orange) and production loss (red)*

The 3-way valve was replaced on January, 7th, 2015, i.e. approximately 2 months after the initial recommendation. During the analyzed period, the same problem was identified on two further turbines. In these cases, the valves were replaced without delay due to the experience gained from the initial event, avoiding thus further losses.

[1] Currently over 30 KPIs are being analyzed in the respective wind farm

3.2 Case study 2: high generator temperature

Also in November 2014, an alarm was issued by SR::SPC as the generator temperature increased significantly in a short time (Figure 10). The measured value (light blue) and the reference value from the system (dark blue line) present a clear discrepancy from November 11th onward.

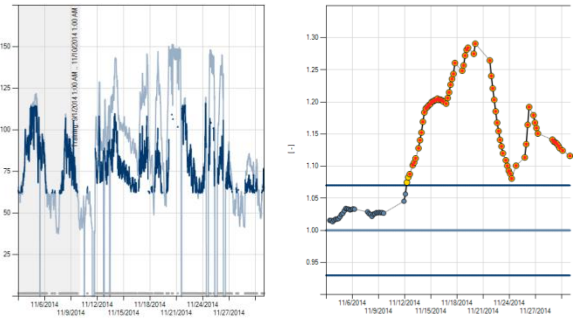

Figure 10*: Actual and reference values (left) and a control chart analysis (right)*

The root cause analysis by the engineering team based on the raw turbine data found that the cooling water pressure was no longer at the usual, regulated level, but has since then been higher than previously observed (Figure 11).

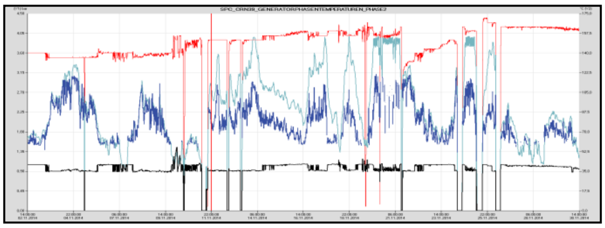

Figure 11*: Actual (light blue) and reference (dark blue) generator temperatures, cooling water temperature (black) and cooling water pressure (red)*

Based on this observation, the engineering team concluded that the cooling water filter was starting to clog and recommended an inspection and replacement of said filter on November 14th, 2014. At the time of the evaluation and recommendation, no alarm had yet been triggered by the SCADA system itself.

This recommendation was not followed promptly, which caused the cooling water flow to reach critically low levels on November 21st. On that day, the generator of the analyzed wind turbine repeatedly reached 150 °C, which caused the turbine to continuously start and stop for 24 hours.

One day later, the filter was replaced, causing the cooling water pressure to fall (Figure 11). However, it increased again quickly and the same behavior could be observed for approximately 12 hours on November 24th.

In this case, a total loss of 75 MWh resulted from the frequent automatic stoppages. Also in this case the same problem was identified on two further turbines during the analyzed period. In these cases, the filters were replaced without delay due to the experience gained from the initial event, avoiding thus further losses.

4 Discussion

In order to assess the potential benefits of the application of predictive analytics methods for the optimization of wind assets, the data of the initial 12 months of operation was analyzed.

Case studies 1 and 2 caused (avoidable) production losses of 185 MWh and 75 MWh respectively. Further 2 cases were reported for each failure mode, which means that the loss of 370 MWh and 150 MWh were avoided.

These 6 events summed up to a total of **780 MWh** of avoidable or avoided production losses.

As mentioned in chapter 3, there were 12 reported events in that period. Whereas it is relatively easy to calculate the avoidable production loss of the already described 6 events, the second set of events never caused any production loss. This happened because the recommendations resulting from the application of the method described in chapter 2 were followed.

In order to estimate the total avoided production loss, it was assumed that the second set of events would have caused similar production losses. This means that the 12 events would have caused the loss of approximately **1,600 MWh**.

Table 1 summarizes the data described above. Moreover, financial losses were also estimated for the Brazilian market by assuming an average energy price of R$100/MWh.

Table 1: *Simulation of production and financial losses based on presented case studies*

Case studies	#	Avoidable production losses [MWh]	Simulated financial losses [R$]
Case study 1	1	185	18,500
Case study 1.1 and 1.2 (estimated)	2	370	37,000
Case study 2	1	75	7,500
Case study 2.1 and 2.2 (estimated)	2	150	15,000
Total (1 year, 10 KPIs, measurable)	**6**	**780**	**78,000**
Total (1 year, 10 KPIs*, estimated)	**12**	**~1,600**	**160,000**

The estimated saving of 1,600 MWh represented an increase of annual energy production (AEP) of approximately 0.56 %.

It is important to notice that Table 1 presents the results achieved by monitoring only 10 KPIs per turbine. Meanwhile, 25 KPIs are being monitored per turbine in the analyzed windfarm, which enables a deeper understanding of the asset's state.

Besides the easily calculable production losses, further benefits of the predictive analytics approach should be mentioned as follows:

- *Detection and enables remediation of underperformance:* because the system knows at each point in time how much each wind turbine should be producing, any deviation is detected. This information can be used to analyze the reasons for underperformance and to recommend remediation measures.
- *Improved maintenance strategy:* by getting early knowledge of upcoming failures, it is possible to shift the maintenance strategy from reactive and preventive to predictive. This is especially interesting for offshore wind farms, where turbine access is difficult and expensive, but it is also important for onshore wind farms.
- *Improved planning of maintenance timing, logistic, and resources:* by getting early knowledge of upcoming failures, it is possible to reduce the stock of spare parts and only order them when necessary. Moreover, it enables a more effective planning of resources such as cranes and specialized personnel. Finally, it enables planned maintenance on periods of weak wind conditions, further increasing AEP.
- *Avoided/minimized consequential damages:* by detecting failures in an early stage, it is possible to apply remediation measures that avoid consequential damages. For example, it is much cheaper to exchange a gear bearing in an initial damage stage than to replace the whole gearbox because of a catastrophic failure.

None of the above described benefits were considered when preparing Table 1 due to lack of reliable date to convert them into financial benefits.

Nevertheless, simulations indicate that these benefits would be of a similar order of magnitude as the AEP increase due to higher availability. In this case, total financial benefits would be twice as high as those presented in Table 1.

5 Conclusion

This paper intended to analyze the potential benefits of the application of predictive analytics methods for the optimization of wind farm profitability.

The presented approach and case studies indicate that that goal is achievable by means increased productivity due to higher availability.

Further financial benefits, such as those listed at the end of chapter 4, remain to be checked during a long-term study.

6 References

GWEC. (2017). *Global Wind Statistics 2016.* Retrieved from http://www.gwec.net/wp-content/uploads/vip/GWEC_PRstats2016_EN_WEB.pdf

van den Broek, T. (2014). *Cost-sensitivity Analyses for Gearbox Condition Monitoring Systems Offshore.* Eindhoven: Eindhoven University of Technology.