Continuous Process Quality Monitoring and Early Detection of Faults by means of Key Performance Indicators

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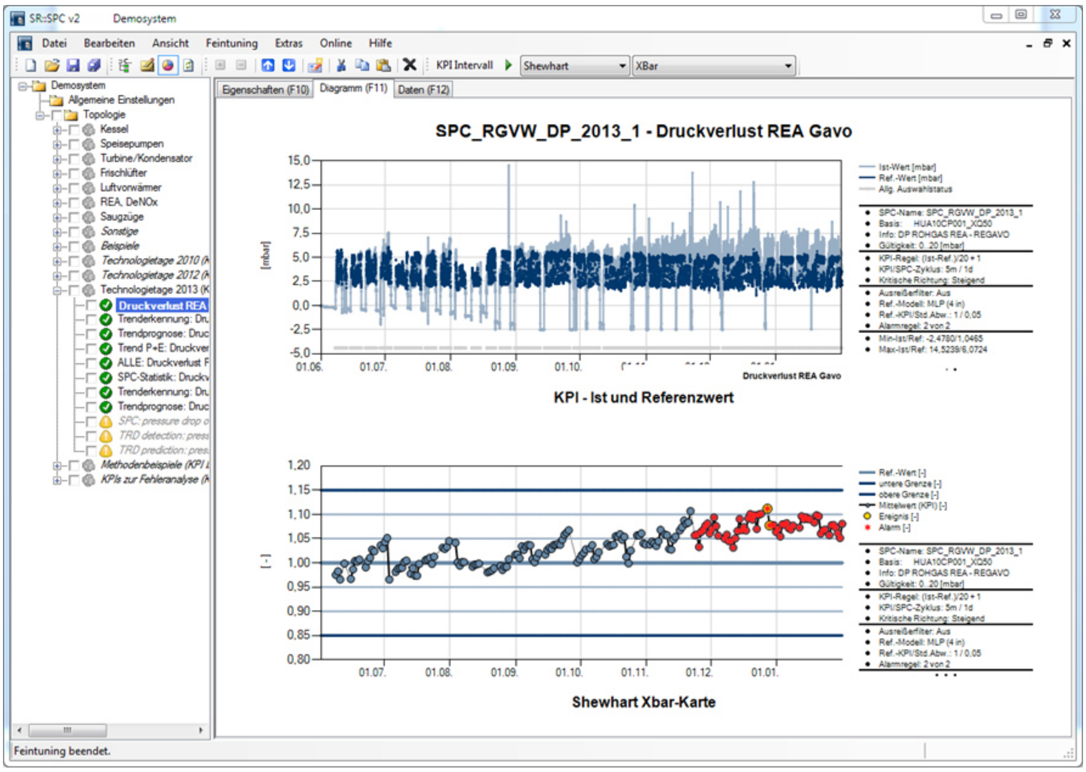

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Abstract

Power plants and their components are subject to continuous changes in their operational behaviours. These changes regularly lead to undetected deteriorations of the degree of efficiency of the plant or to seemingly sudden failures of components with economic consequences. In order to avoid such additional costs, the use of statistical methods lends itself to obtain reliable evidence of imminent failures as early as possible through the continuous evaluation of existing performance values.

1 Boundary Conditions of Power Plant Operation

In an economically difficult environment, it is necessary for the power industry to continuously optimize the entire value chain in the power plant. A comprehensive approach to this task has to account for a range of topics as diverse as improving the degree of efficiency, decreasing the maintenance costs, and efficiently deploying the available human resources in equal measure.

1.1 Improving the Degree of Efficiency

A prerequisite for improving the degree of efficiency is to promptly know the current heat consumption of the power plant unit and to assess the sources of possible losses quantitatively. On the basis of such an analysis, deviations from a reference mode of operation are detected in a timely manner and suitable measures are evaluated regarding their economic efficiency. In daily business, however, the implementation of such an analysis using only the operational data provided in the DCS is complicated by the vast amount of data in the DCS. Without the support of suitable IT systems, it is not continuously possible to deduce the essential characteristics for the process and the main components out of typically 5,000 measured values in the DCS displayed across perhaps 100 views. Only by means of an automated data analysis (fig. 1) can the data flood be condensed into information about the condition of the process and the plant, and the power plant staff be supported in performing their tasks.

1.2 Reducing the Maintenance Costs

Maintenance is another effective lever to optimize the value chain. However, an optimization at that point has to factor in the attainable plant availability and the costs of unplanned shutdowns. Thus an intelligent combination of reactive, preventive, and state-oriented maintenance in order to minimize the life cycle costs will become an increasingly important task in the time to come. At the same time, the relevance of state-oriented maintenance will rise in the future. This requires that changes in the condition of a component are detected early on and reliably. Then a quantitative analysis of the trends is the basis for choosing the appropriate action and determining the cost-optimal point in time for its implementation. This task, too, cannot be fulfilled on a continuous basis in day-to-day operations without the support of suitable IT tools. Without such IT tools, not all main components can be evaluated promptly and based only on the data flood of the DCS; even more so, as with increasingly varying load demands, the change of an individual measured value does not necessarily indicate changes in the plant condition. It can also result from differing operating conditions. So mostly, the actual state of the component can only be deduced from the interaction of various measured values.

1.3 Utilizing Resources Efficiently

To some extent, staff members experienced over many years have developed a "procedural feeling" for such complex coherences. Based on their jobs, they know which combinations of measured values are normal and which ones are exceptional. However, these skills are not equally distributed across all shifts. Also, in times of demographic change and at the same time scarce human resources, there is the risk that when such high performing staff members leave the company, the valuable know-how gets lost and can only be rebuilt in the medium term. Here, too, the knowledge from experience can be quantified through the use of IT tools for data analysis. Thus the "Best Practice" becomes secured in an IT system independently of individual experience and can then be developed further in a continuous improvement process not just site-specifically, but company-wide.

Irrespectively whether the necessity for optimizing the value chain in the power plant is regarded from the point of view of improving the efficiency, of state-oriented maintenance, or of the efficient deployment of human resources: In any case, the use of IT systems for continuous data analysis is indispensable for condensing information out of the variety of data. On the basis of this information, a more efficient work is possible.

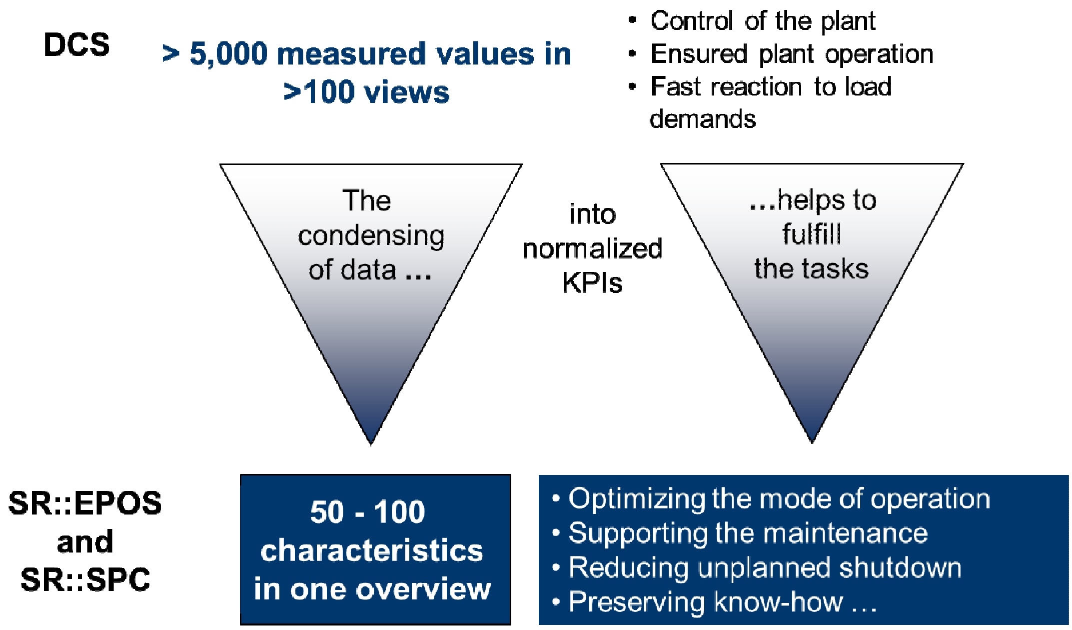

Fig. 1 Data are condensed into information by means of expert analysis

2 Methods of Data Analysis for Process Quality Monitoring and Early Detection of Damages

The analysis of the requirements for optimizing the value chain shows that the data analysis of in-service measurements has to cover various ranges of tasks. On the one hand, the point is to determine the current status of the process or the main components. To do so, key performance indicators (KPIs) have to be defined that only depend on the status but not on the current operating conditions and ambient conditions.

A particularly prominent example for this is the condenser pressure. This important measurand is not directly suitable as a characteristic for the status of the condenser, because it is raised not only by fouling and ingress of air, but also e.g. by the cooling water temperature, load, and, if applicable, a district heat extraction (fig. 2a). So assessing the status of the condenser is not readily possible from the current value of the condenser pressure alone but only in comparison with an operation-related reference value. This reference value must not be a constant but has to depend on the said influencing variables. It has to represent the condenser pressure that would have to be expected under the current conditions of load, district heat, and cooling water as well as “good” status of the condenser. Then the discrepancy between the current value and the reference value depending on the mode of operation is the measure for the status of the component and can be used as KPI. A similar situation exists for nearly all key quantities of power plant operation, from the power consumption of a fan via vibrations up to the net heat rate.

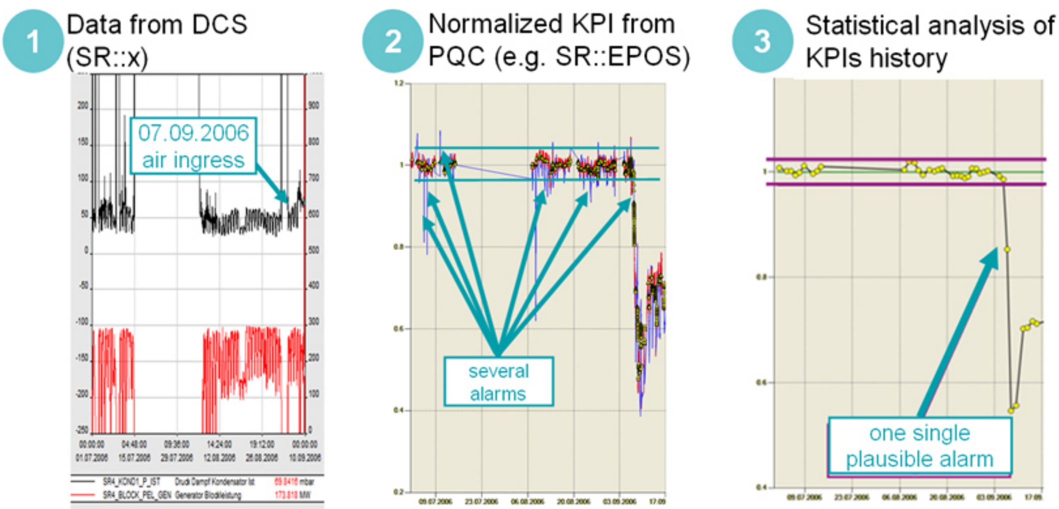

Fig. 2: Detecting critical changes in the process by evaluating available performance data

2.1 Determining the Reference Value

Hence an IT system for the continuous analysis of operational data has to contain a tool for the balancing and simulation of the process by means of which the reference value for important process variables can be established depending on the mode of operation. Here the first choice for those variables accessible for thermodynamic description is a *modeling on the basis of physical base equations(fig. 3a).* Such models “know” the physics of the plant, so they can be adjusted to the condition of the plant with a comparatively limited data pool. This way, they are able to extrapolate with a good degree of accuracy and thus will also yield reliable results if rare or “new” operating conditions arise.

However, numerous measurands defy the modeling with physical base equations. Typical examples are the classical indicators for the status of large equipment units like vibrations or bearing temperatures. Therefore a system for quality monitoring in the power plant would not be complete if it didn't offer the possibility to determine reference values for those in-service measurements, too. Here, *data-based models (fig. 3b)* based on e.g. neural networks or similar techniques can be applied. These methods allow to reconstruct ("to learn") the reference value from historical data (from spaces of time when the component to be monitored was in a good condition) depending on the mode of operation, the load, the ambient conditions etc. The procedure has long been tried and tested but will only yield reliable results as long as no operating conditions arise that did not occur during the learning phase.

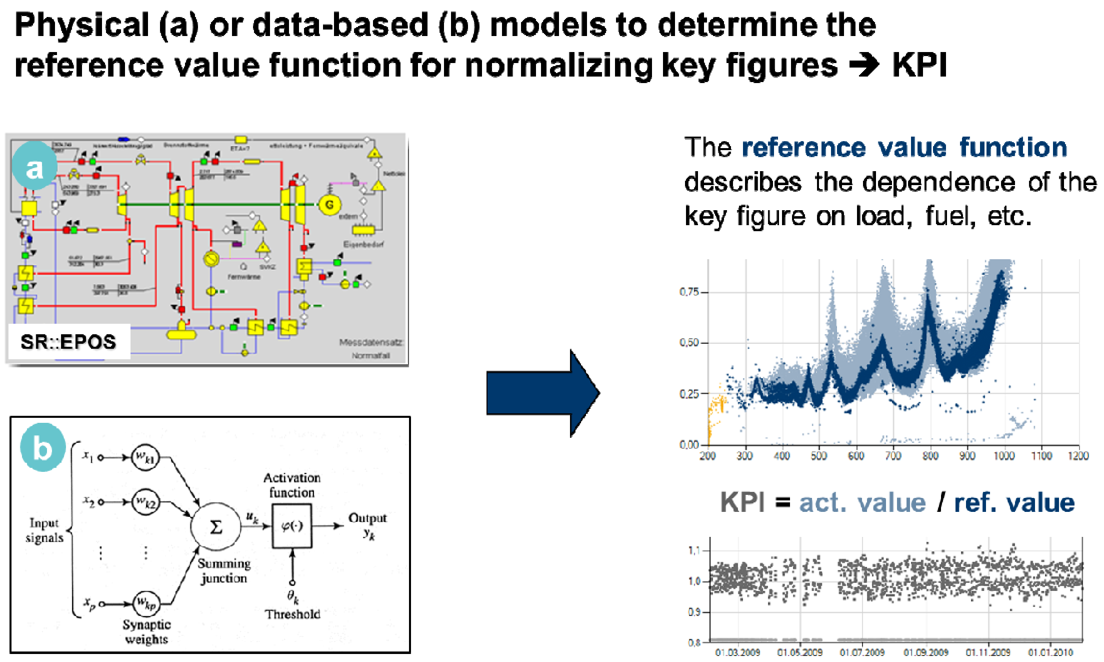

Fig. 3: Data-based or physical calculation of the reference value

2.2 Key Performance" Indicators

For the quality monitoring in power plants, physical models or (if not feasible in any other way) data-based models on the basis of neural networks provide the reference values of key quantities that can be compared to the current value. As KPI, the deviation is then suitable for evaluating the process or a component. Because the KPIs have to be deduced from operational data in a continuous (online) monitoring of the power plant, they are subject to a certain degree of fluctuation due to measurement inaccuracy (fig. 2b). Nevertheless it is essential to automatedly detect significant changes in the condition as early as possible in order to relieve the power plant staff from the regular manual analysis of the KPIs. On the other hand, the acceptance of the system will be seriously affected if changes are signaled due to such fluctuations while no actual cause can be detected in the component or in the process.

2.3 Statistical Data Analysis

Thus the third component of an advanced system for continuous process quality monitoring and early detection of damages from in-service measurements are *statistical methods* that analyze the chronological events of the condition online in an automated way. This tool imitates the engineer's work of analyzing time series and – just like the experienced engineer who looks at a recording strip or history of measured values, but automatically – detects significant trends and patterns or sudden leaps in the monitored characteristic (fig. 2c). By applying various procedures and suitable rules for evaluating the results, the reliability of the statements can be further enhanced.

The "IT toolkit" for process quality monitoring is perfected by modules for deducing optimization suggestions. This module is able to deduce indications for an optimized mode of operation of the plant on the basis of simulation in the context of thermodynamic modeling or also by means of heuristic approaches like fuzzy logic. Prominent examples of such applications are the optimization of the cold end of a power plant regarding the amount of cooling water / the mode of operation of the cooling tower or intelligent sootblowing.

3 The Benefit of Data Analysis in the Power Plant

The operational benefit of such systems is manifold:

Data from the DCS are condensed online into uniform characteristics. The mode of operation and the condition of components are assessed quantitatively and objectively. This leads to a gain in transparency that facilitates a continuous improvement process and allows to learn from the best within an organization.

Reliable anticipation data for maintenance are provided and thus a cost- and availability-oriented maintenance strategy is supported. In addition, experiences of the shift personnel are sampled and mapped when implementing the systems. This way, valuable know-how is saved and the mode of operation of the plant becomes independent of the individual experience of the shifts in times of demographic change.

With the SR::EPOS / SR::SPC System of STEAG Energy Services, STEAG STEAG has introduced such a system for continuous process quality monitoring and early detection of damages from in-service measurements comprehensively. Three examples shall illustrate the benefit.

The figures for the three following examples of application are designed identically. To begin with, in each case a characteristic measurand (dark purple) of the examined component that directly correlates with process quality or the condition of the component is shown top left. Additionally, in this illustration a constant threshold value (yellow green) is entered to make it clear that a direct monitoring of the measured value is unrewarding due to the superimposed influences. The figure also contains information about the depicted measurand and the monitoring period. To the right, the normed and averaged characteristic of the measurand, the so-called KPI, is shown. If the value of the KPI is within the limits (light purple) and does not show any statistically significant distribution patterns, it is shown in purple, otherwise in red. The two bottom illustrations show the results of other statistical evaluations. Also for these evaluations applies: if the value of the analysis is between the two shown threshold values, the process or the component is normal; if it is outside, this will be rated as a significant change. Usually, online systems will only trigger an action if one or more analyses show abnormalities. In the examples of application, this point in time is always marked by a yellow green arrow in the first picture – false alarms during the online monitoring did not occur in any of the examples.

3.1 Process Quality Monitoring – Example: Condenser

Figure 3 shows the successful application of SR::EPOS and SR::SPC using the example of a condenser. Here, ingresses of air and thus declines of quality had occurred over a longer period of time due to smaller leakages and a fault of the vacuum system. These ingresses/declines cannot be detected in the measured data concerning condenser pressure (fig. 4, top left), because they occurred only in longer off-design operation and, in addition, were superimposed by other influences like e.g. cooling water temperature and district heat extraction. They become visible only by conversion of the measurand into a KPI (fig. 4, top right), which took place by means of SR::EPOS based on a physical model. The SR::SPC online monitoring downstream detected and signaled the ingresses/declines without major delay directly at the beginning of the increased off-design phases with a high degree of district heat extraction (see arrow).

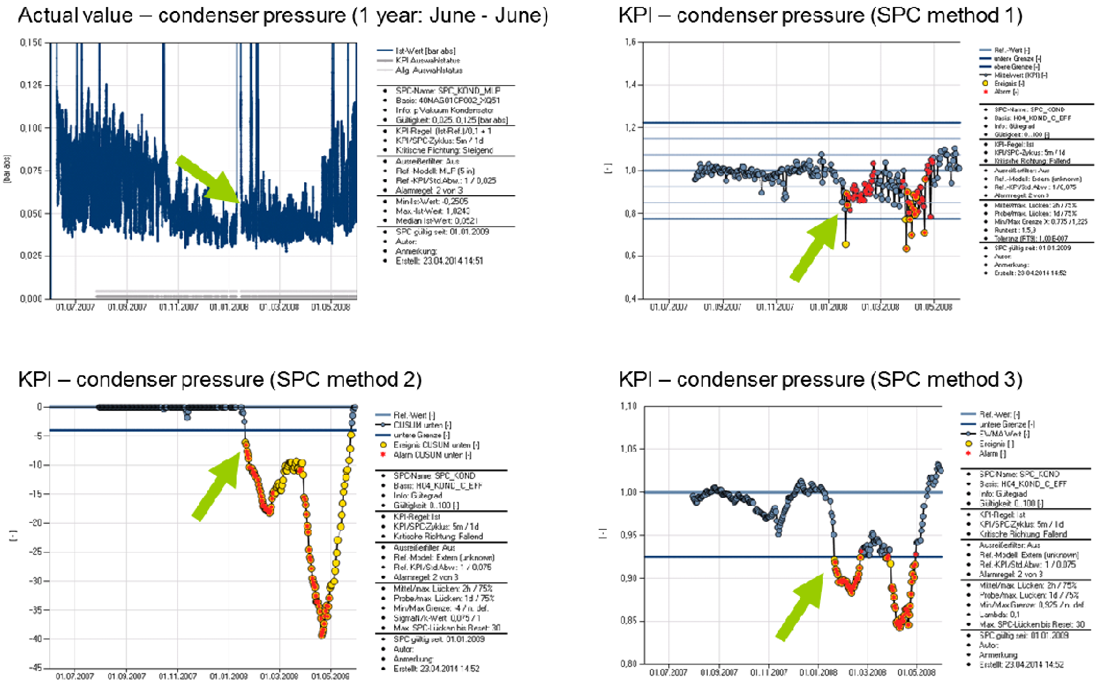

Fig. 4: Decline of process quality: condenser in off-design operation

3.2 Condition Monitoring – Example: Boiler Feed Pump and ID fan

The two following examples (fig. 5 and 6) show the application of data-based models – neural networks were utilized here for KPI determination – that are used for assessing the condition of a boiler feed pump and an ID fan. In both of the illustrated cases, already the changes in the raw measured value are quite significant. Nevertheless, in both cases a fictive threshold value (yellow green) would have been transgressed several times for no reason before the occurrence of a fault. In the case of the ID fan, it would also have been undercut several times after the fault occurred. In both cases, even with an optimal definition of threshold values no reliable notification could have been effected semi-automatedly, or several false alarms would have been generated – a monitoring system with such a rate of false alarms would not have been accepted by the operating crew for understandable reasons. By combining the KPI determination and the statistical analysis of the KPI behaviour, however, it was possible to achieve an unambiguous analysis result and the operator could be informed about the changes online and thus in a timely manner in both cases. In the case of the boiler feed pump, the cause of the changes in the vibrational characteristic was an incipient crack of the shaft, and in the case of the ID fan probably fouling on the blade.

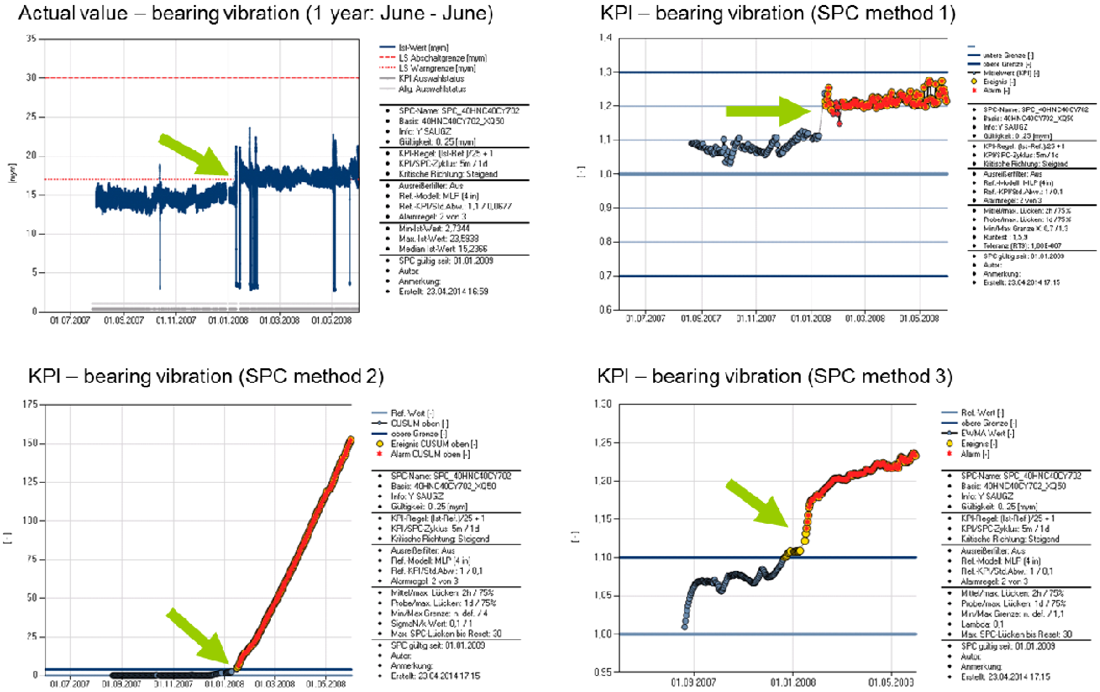

Fig. 5: Incipient crack of the shaft of a boiler feed pump → increased bearing vibrations

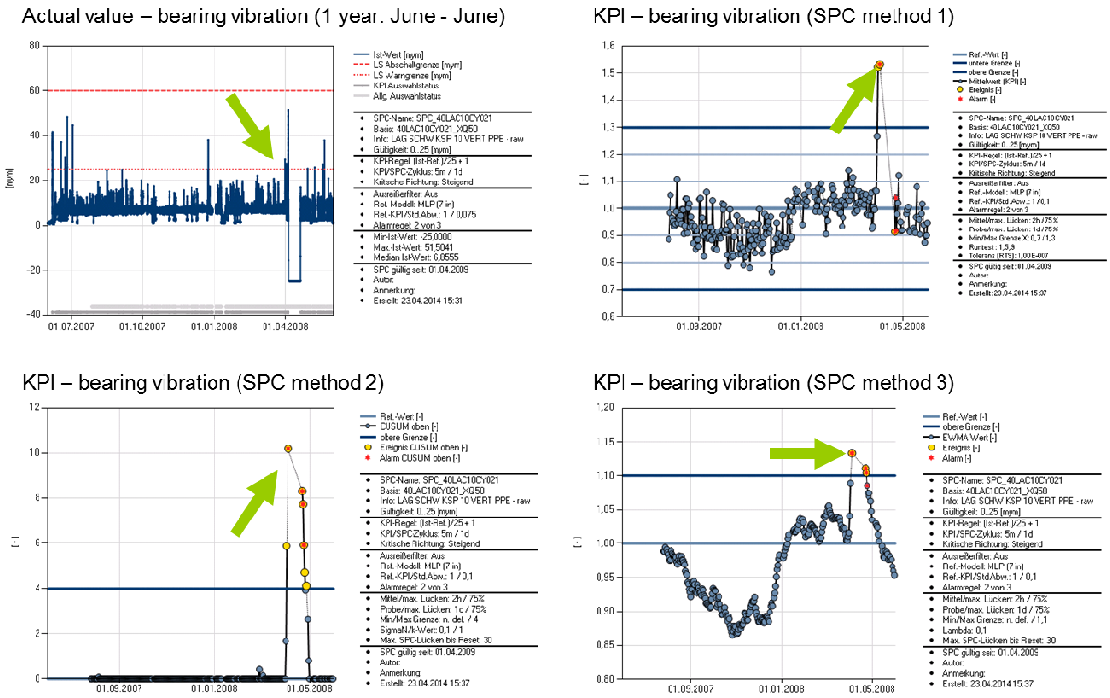

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Fig. 6: Fouling on the blade of an ID fan → increased vibrations

3.3 Status and Development Potentials of Data Analysis

Advanced systems for continuous process quality monitoring and early detection of faults from in-service measurements calculate key performance indicators for the condition of the process or individual components from the comparison of in-service measurements with reference values for the “good” plant condition that result from a thermodynamic or also from a data-based modeling. The complementary application of statistical procedures allows to evaluate the time series of the KPIs automatedly and to detect changes early on and reliably. In doing so, the flood of data from modern DCS systems is condensed into information without burdening the power plant staff with extensive evaluations. The examples have shown that hereby, operational benefit is generated out of an increased transparency of the power plant operation, the support of state-oriented maintenance, and the safeguarding of know-how in times of demographic change.

Early on, reliably and in a partly automated way, the systems available today provide indications that significant changes in the condition of a plant or process have taken place. When such a change has been detected, mostly a first causal research can take place by means of a detailed analysis of the characteristics. In many cases, it will furthermore be requisite that the final analysis of the cause be carried out by an experienced person in charge, if necessary on site. In the medium term, however, additional tools e.g. on the basis of statistical procedures for correlation analysis or of known methods for fault tree description will be integrated, which further facilitate it for the person in charge to conduct this analysis.

Beyond these applications, data analysis in the power plant offers potential for further developments. The described methods and systems are flexible and allow power plant-specific application. E.g. the monitoring of actuating variables and controlled process variables (in addition to the procedural measurands) can provide information about components not collected so far. This way, wear and tear of actuating components, drift in position transmitters or similar events can be detected early on.

It also suggests itself to further examine the potential for early warning in the case of pipe leakages in the steam generator. So far, such damages to the boiler have mostly become obvious only by noise development or a significant increase in the make-up water consumption. Here the application of statistical procedures for analyzing the mass balance in the power plant would be able to indicate such events early on and trigger well-directed inspections. Thereby, the response time before a possibly required shutdown of the unit would be raised and the danger of an extension of the damage would be reduced. First studies and prototypical implementations have already yielded promising results.

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