# Data Evaluation to Detect Faults and Problems in Power Plant Operation

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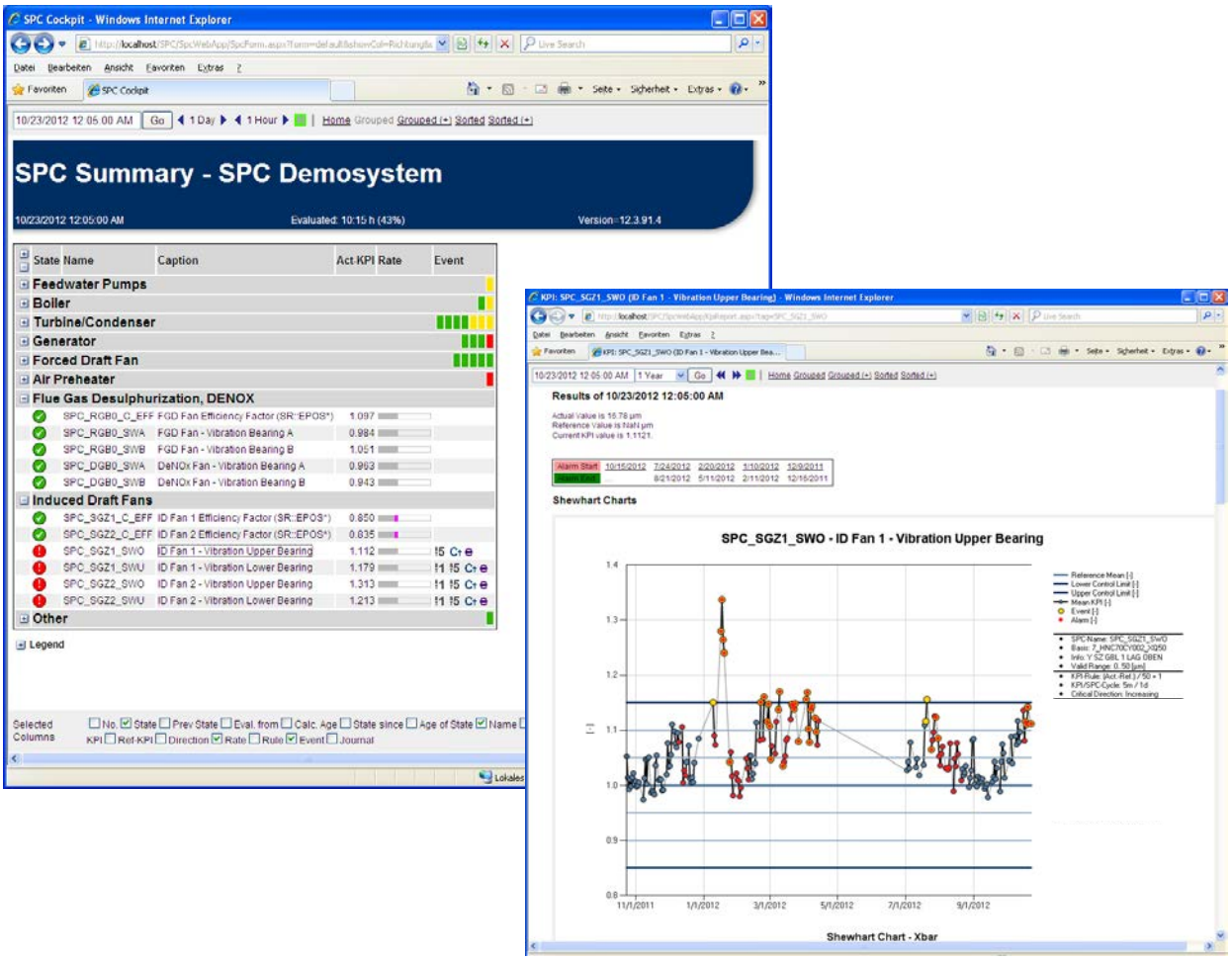


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# 1 Challenges in Power Plant Operation

Power plants and their components are subject to continuous changes in their operating behavior. Such changes have to be monitored continuously as otherwise they regularly lead to undetected deteriorations of the plant efficiency or to seemingly sudden failures of components with economic consequences.

A continuous analysis of the operational data provided by the DCS of each power plant is required for monitoring any changes in the operating behavior at power plants. Due to the vast amount of data in the DCS, however, support by suitable IT systems that allows to derive the most important characteristics for the process and the main components is needed.

The use of statistical methods lends itself for obtaining reliable indications of impending faults by continuously evaluating existing performance values as early as possible. The expert system SR::SPC supports the power plant staff in fulfilling their tasks by continuously analyzing operational data and by reliably detecting changes and automatically reporting them by e-mail.

# 2 Statistical Process Control in Power Plants

The software module SR::SPC has been developed for the qualitative description of power plant processes and components. It combines the classical approach of statistical analysis with reasonable additional tools such as neural networks, trend prediction, and advanced data filtering for maximum usefulness.

At first, SR::SPC calculates normalized quality characteristics in order to determine the current condition of a process or a main component. For this, the reference values belonging to the respective current mode of operation are calculated for important measured and characteristic values.

By comparing actual and reference value, normalized quality characteristics, so-called KPIs (key performance indicators) are calculated, which are independent of the mode of operation of the plant and the ambient conditions. If an individual KPI deviates from a specified target value at a balancing time, this will be a first indication of an impairment. If this deviation recurs or increases at following points in time, the indication of an impairment will grow stronger.

The chronological behavior of KPIs can be evaluated by means of methods of statistical process control (SPC). The SPC methodology has been developed to detect significant deviations of a process from a reference condition as early and reliably as possible.

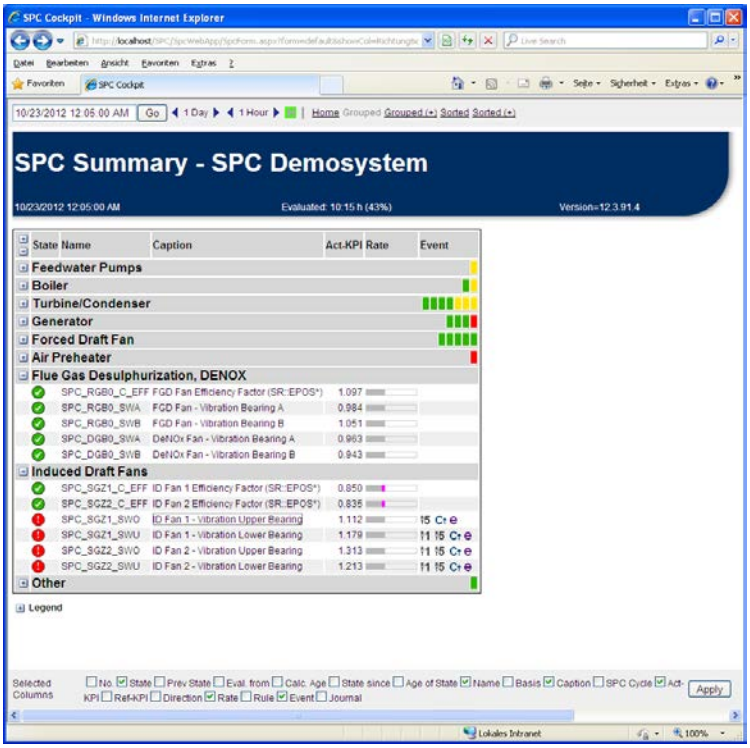


*Fig. 1: SR::SPC Overview*

One important element of statistical process control are so-called control charts. These tools for quality assurance were introduced in manufacturing many years ago. Control charts are diagrams that illustrate the chronological behavior of characteristic process parameters / KPIs. This way, deviations from the expected behavior that point out to faults can be detected earlier and more reliably than if only an isolated value were examined.

KPI behaviors detected as critical are displayed to the user by SR::SPC in a web-capable overview (see Fig. 1) by corresponding color changes in a traffic light system.

In the overview, all monitored KPIs of a site can be conceived at a glance, so that the plant condition can be realized entirely with one brief look. By clicking on the KPIs, the stored control charts can be activated and analyzed in detail.

Furthermore, previously defined e-mail recipients will be automatically informed about the current condition with a brief report (see Fig. 2) in the case of conspicuous KPI behaviors.


*Fig. 2: SR::SPC Example of a control chart*

The continuous monitoring of the KPI behaviors significantly contributes to detecting impending damages or problems automatedly. “Overlooking“critical changes is largely ruled out as the responsible persons are automatically informed about a fault (process quality monitoring) or warned of an impending damage (condition monitoring) by e-mail.

# 3 Statistical Analysis in Continuous Processes

A software solution for a statistical analysis of power plant processes might conduct the following steps of analysis. The goal is to make use of available data in the DCS or data historian to identify whether the component is in a “good condition” or if a current development is leading to a degradation of the component.

## 3.1 First Step: Raw Data

Statistical procurement of operational data starts with digitized measurements. Typically, they can be obtained easily via an interface to the DCS (OPC for example) or a data historian.

An example of raw data – the pressure drop of a flue gas desulfurization scrubber demister – is shown in Fig. 3:

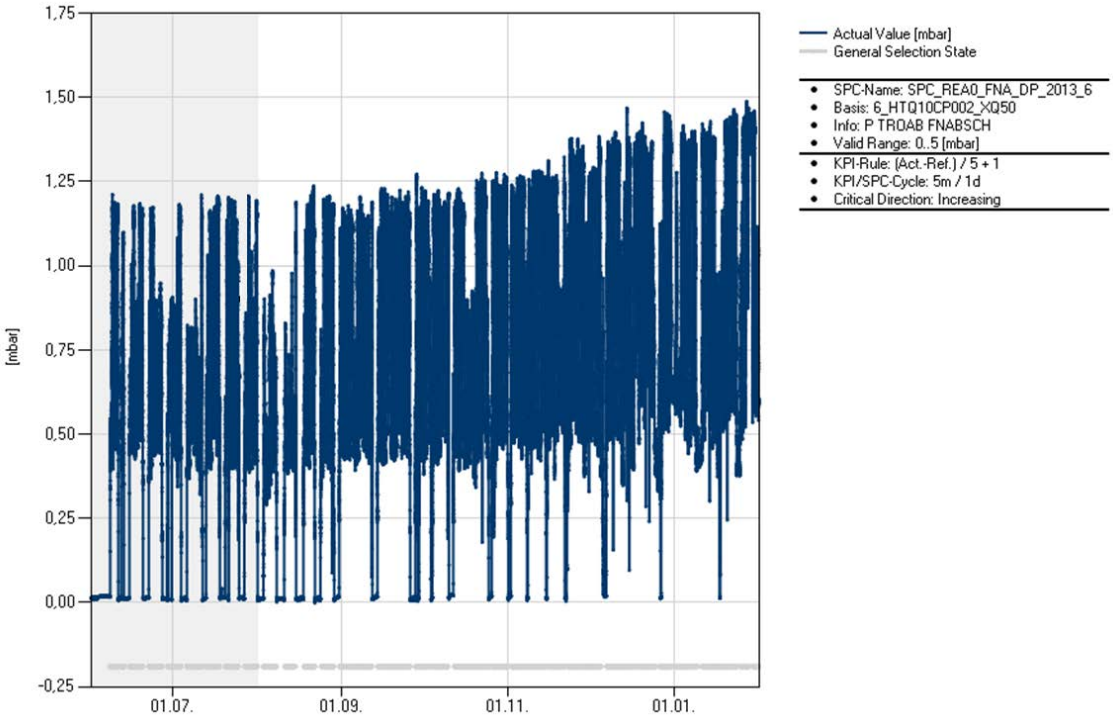


*Fig. 3: Raw data (pressure drop of a flue gas desulfurization scrubber demister) imported from the DCS (actual value)*

First, the raw digital data of a measurement will contain values of times which are irrelevant for a long-term analysis (e.g. periods of very low load, load changes, periods where the crew knows that there were irregularities/damages, outliers from faulty measurements, long-term shutdowns).

Fig. 4 shows the measured raw values for the pressure difference [mbar] as light blue lines, outliers as red triangles, and the filtered values as dark blue lines. The area highlighted by the blue box will be analyzed in more detail in Fig. 5.

Two different kinds of filters can be applied to focus on the relevant data:

1. Selection filter
2. Outlier filter

The selection filter defines which periods of time will not be evaluated. Times of unit shutdowns, extreme part-loads or – for a specific component – times when it was deactivated should not have an influence on a long-term statistical analysis. In SR::SPC, it is easy to define parameters to have the selection filter remove these time frames.

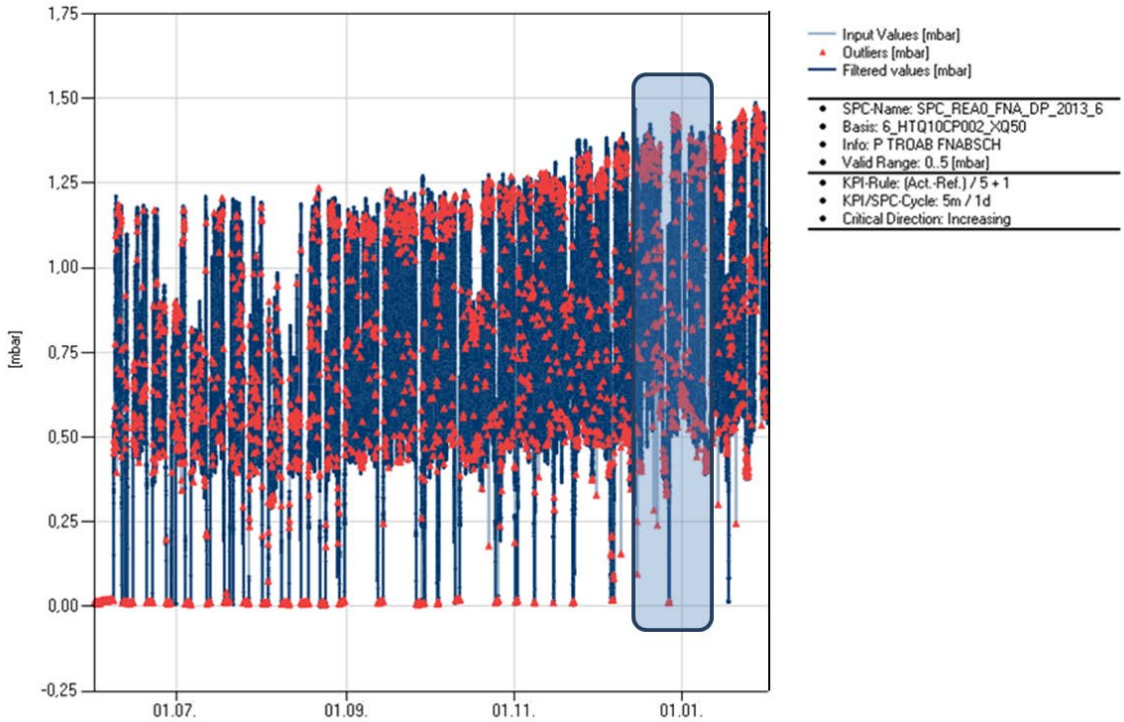


*Fig. 4: Relevant data is prepared for further analysis*

Additionally, the outlier filter identifies measured values which do not fit in with the other measurements in the context of the statistical analysis.

For example, an $O_2$ measurement behind a coal-fired boiler might usually output 2-4 percent of $O_2$ within the flue gas. In order to reduce fouling, that sensor is cleaned every few hours, and the content of $O_2$ might temporarily amount to 21 percent. This is a technically necessary process and should never lead to an alarm. To avoid misleading interference, the statistical outliers are discarded and will not be used for further evaluation. That approach helps to improve the quality of the analysis.

At a higher zoom level (Fig. 5) it is possible to verify the benefit of filtering outliers: all outliers were identified and only few non-outliers were eliminated. Due to the large amount of non-outliers, it does not do any harm to filter a few too many – as defined by the priority to avoid false alarms.

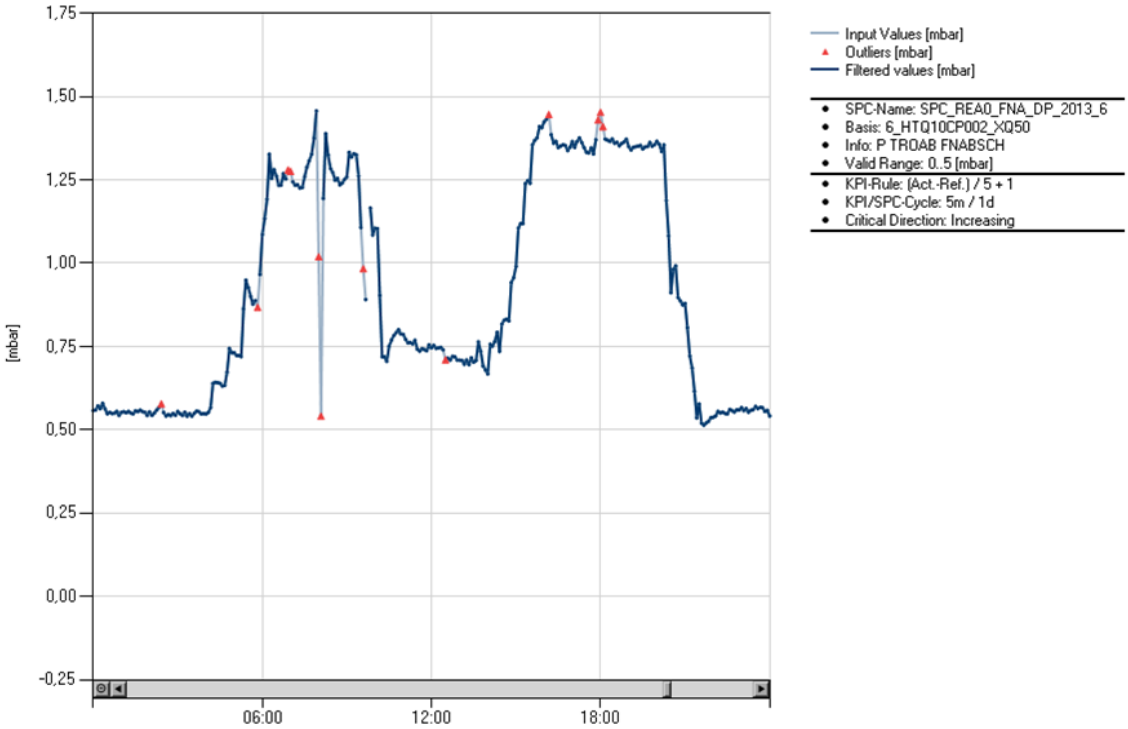


*Fig. 5: Measured values, outliers, and filtered values at a higher zoom level*

For both filters the sensitivity can be configured according to the specific requirements by adjusting the parameters.

## 3.2 Second Step: Comparison with a Reference Value / KPI

In plants where base load scenarios with long periods of same output values prevail, experienced shift members can determine the quality of a measured value to some degree.

Additionally, there are other operators whose everyday business in their plant is defined by constant load changes. Therefore, these staff members experience a wide range of possible process values; thus it is very hard to make an assessment which is true independently of the current load.

For both types of operators it makes sense to use a neutral point of reference in order to achieve the highest possible level of evaluation.

A good approach is to generate a reference value for the current load (as shown in Fig. 6). This can be achieved by a physical approach (e.g. models according to the second law of thermodynamics) or based on operational data (e.g. neural networks).

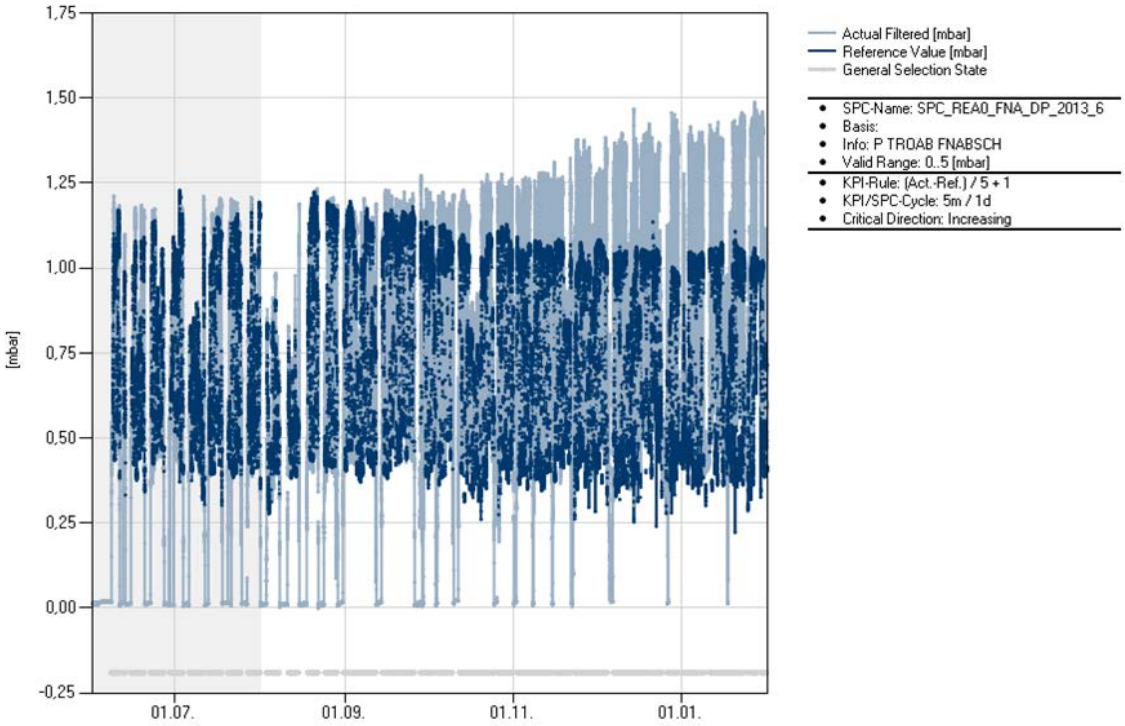


*Fig. 6: SR::SPC calculates the reference value for the current conditions (light blue: actual value, dark blue: corresponding reference value)*

There are different ways of combining the reference value and the actual value. The easiest way is a simple fraction (e.g. reference value / actual value); according to the specific requirements it is important to choose the appropriate way to link the values, while a division by zero etc. has to be avoided.

The goal is to calculate normalized key performance indicators (KPI), i.e. independent of the current load, fuel quality, and environmental conditions. An example can be seen in Fig. 7:

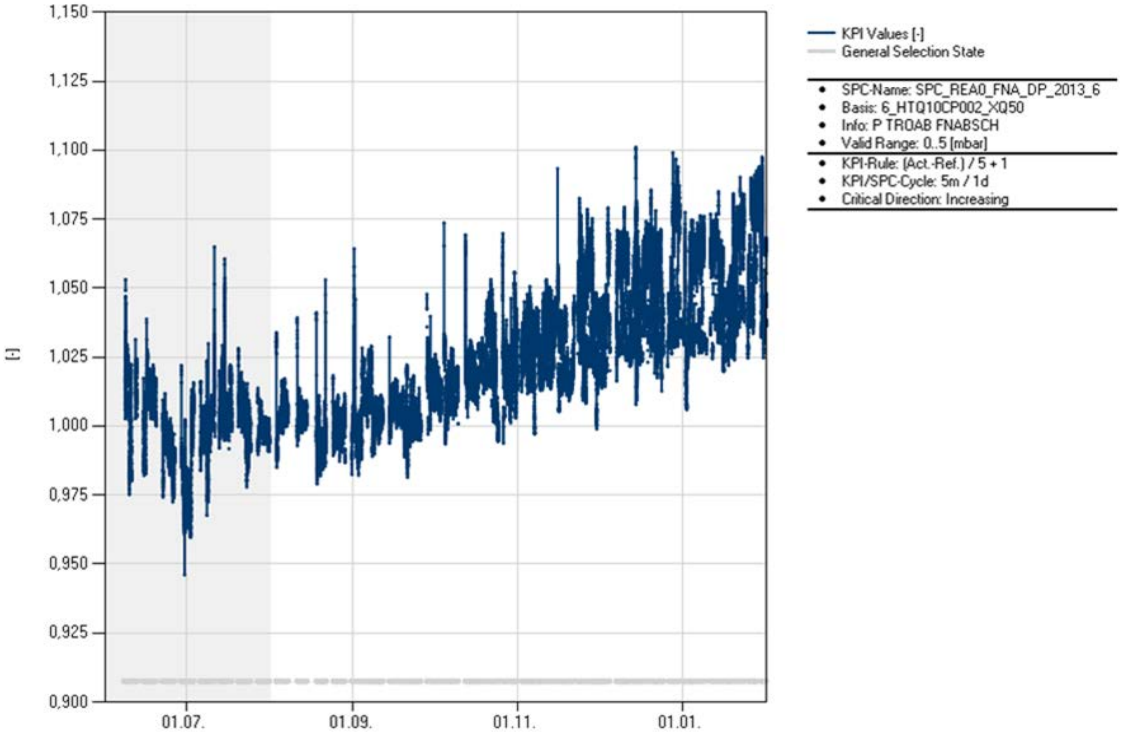


*Fig. 7: SR::SPC creates normalized key performance indicators*

Please note that the vertical axis no longer represents millibars. Now, the vertical axis is dimensionless. As long as a measured value corresponds to the reference value, the KPI is close to one. Any changes can be spotted easily.

Compared to the data in Fig. 3 it is much easier for the operating staff to see long-term developments. But due to the numerous components on site it makes sense to run an automated analysis of the data.

## 3.3 Third Step: Automated Analysis of the Data

To avoid false alarms, SR::SPC conducts different statistical evaluations of the KPIs. Measurements that report faulty data are identified, and statistically significant changes in the components are reliably detected.

The graph in Fig. 8 shows the KPI from Fig. 7 in an analyzed state.

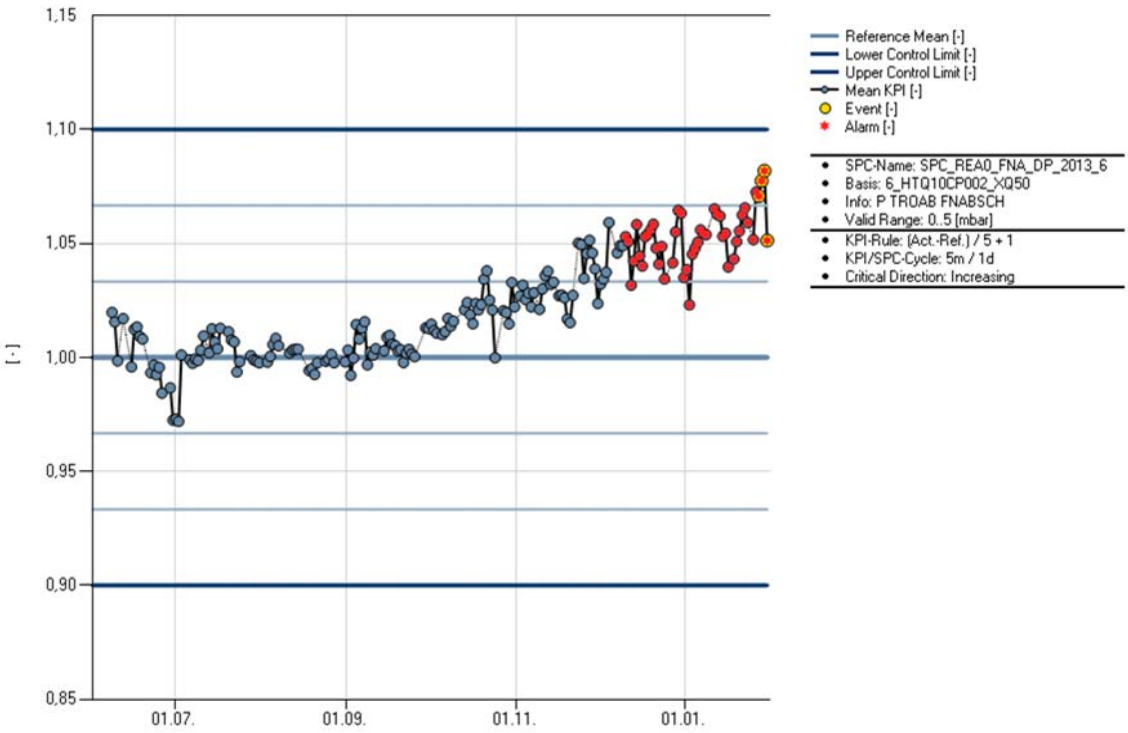


*Fig. 8: SR::SPC uses means of statistical analysis to detect important changes automatically*

Depending on the specific application for one KPI, different ways of analyzing the data can be used: first, statistical control charts (as shown in Fig. 8) can be applied. Secondly, additional statistical methods can analyze patterns and identify e.g. frozen measurements which otherwise would not raise any attention because often the last value is in-between the alarm limits.

Different views and results are available, and useful information can be sent via e-mail to the responsible employees automatically. It is also possible to output this information to the alarming function in the DCS.

## 3.4 Fourth Step: Trend Detection and Prediction

To allow for a better quality of planning the work load, SR::SPC offers a prediction which, by extrapolation, forecasts the date when a limit (defined by the operating staff) will be reached. That makes sense for all long-term developments, e.g. air preheater fouling or worn-out intake filters.

The trend detection and prediction has proven to be very helpful especially for recurrent measures (e.g. air preheater or filter cleaning) when a good knowledge of the upcoming jobs allows to carry out more tasks with own personnel and to reduce the amount of support by external companies.

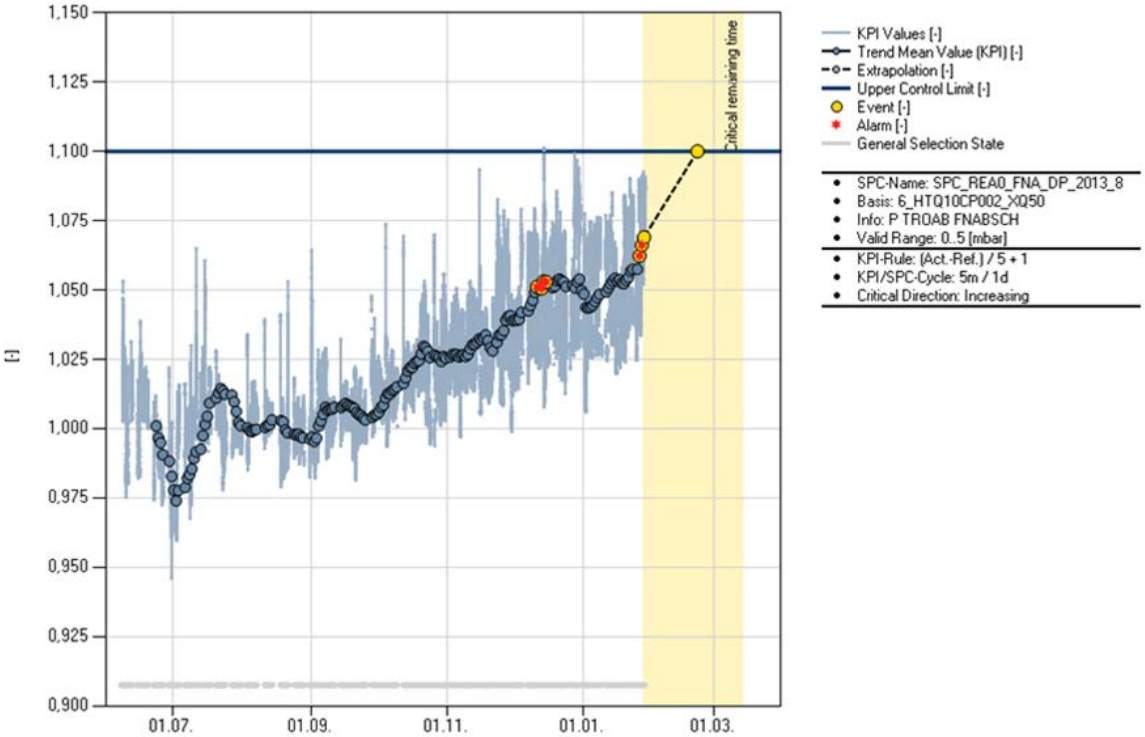


*Fig. 9: SR::SPC detects trends and predicts the remaining time for reaction*

In Fig. 9 the prediction of the latest date for a recurring measure was conducted and a planning time range of approximately six weeks was identified. This gives operating personnel the opportunity to make best use of planned shutdowns.

# 4 Practical Examples: Process Quality Monitoring and Condition Monitoring

## 4.1 Process Quality Monitoring, Example: Condenser

Fig. 10 shows the successful application of SR::SPC using the example of a condenser.

Smaller leakages and a fault of the vacuum system had led to ingresses of air and thus declines in the performance factor over a longer period of time. These ingresses of air cannot be detected directly in the measured data of the condenser pressure (Fig. 10, left) as they occurred only during longer part-load operation and in addition were superimposed by other influences like e.g. cooling water temperature and district heating decoupling. They only become identifiable by converting the measured quantity into a KPI (Fig. 10, right).

The SR::SPC online monitoring downstream detected and signaled the declines in the KPI without greater delay immediately at the beginning of the increased part-load phases with high district heating decoupling (see arrow).

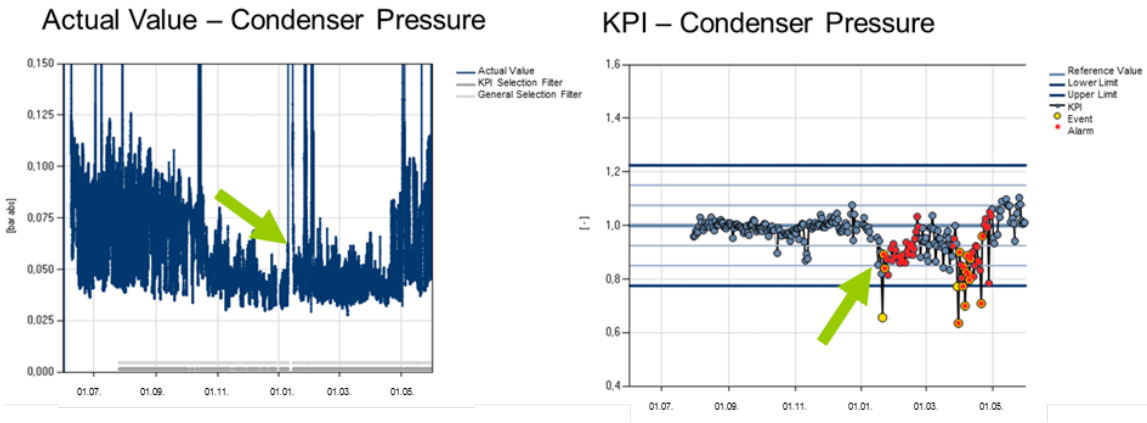


*Fig. 10: Decline in process quality at a condenser in part-load operation*

## 4.2 Condition Monitoring, Example: Boiler Feed Pump and ID Fan

The two following examples (Fig. 11 and 12) show the application of SR::SPC for assessing the condition of a boiler feed pump and an ID fan.

In the two described examples the changes of the raw measured value are quite significant. However, a virtual limit value – e.g. a warning threshold in the DCS (dotted red line) – would have been transgressed unsubstantiatedly several times prior to the occurrence of the damage in both cases or, in the case of the ID fan, would have fallen below several times even after the impairment had set in.

Thus in both cases, no reliable notification could have been effected in a semi-automated way even with an optimal definition of limit values, and several false alarms would have been generated respectively – a monitoring system with such a rate of false alarms would not have been accepted by the operating staff for understandable reasons.

By combining the tools for KPI determination and for statistical analysis of the KPI behavior, however, it was possible to achieve an unambiguous result of the analysis. In both cases, the operator was informed about the changes online and thus promptly by the SR::SPC system. In the case of the boiler feed pump, the cause of the changes in the vibration characteristic was an incipient crack of the shaft, and in the case of the ID fan the changes were caused by deposit buildup on the rotor blades.

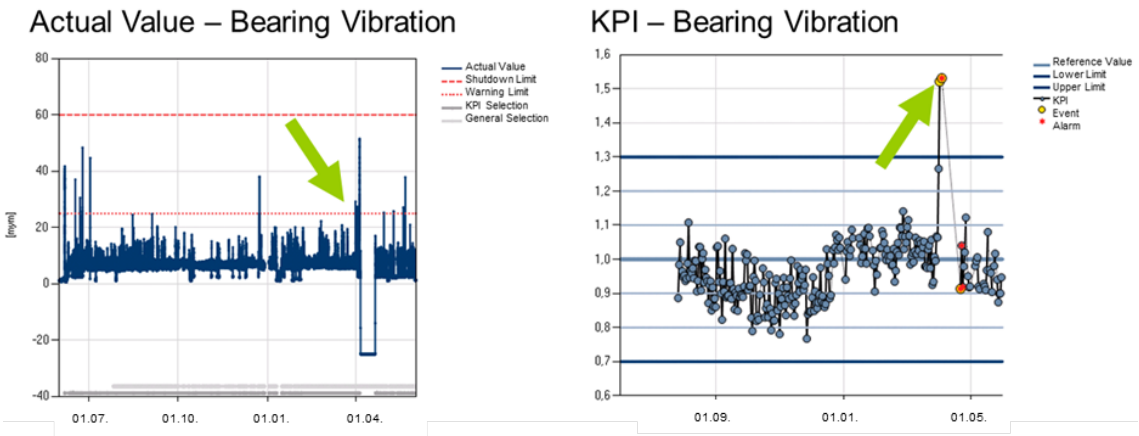


*Fig. 11: Incipient crack of the shaft of a boiler feed pump → increased bearing vibration*

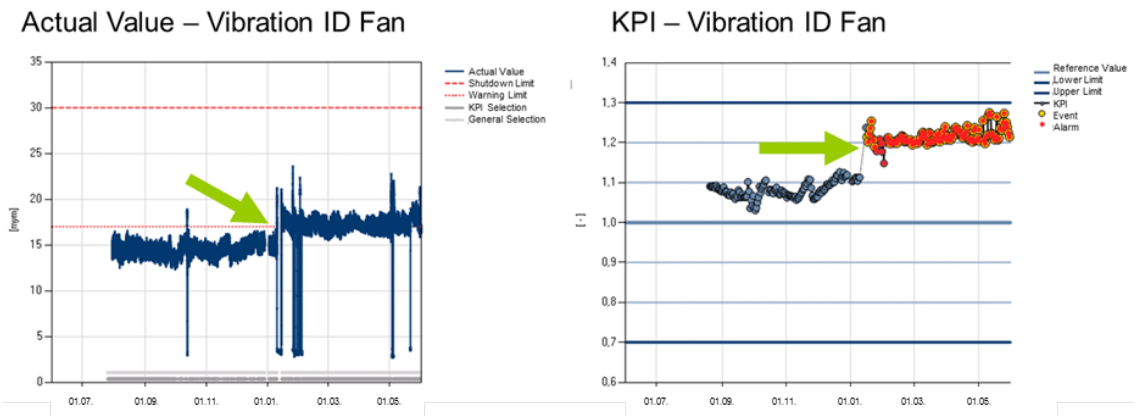


*Fig. 12: Deposit buildup on the rotor blades of an ID fan → increased vibrations*

## 5 Conclusion and Outlook

Modern DCS technology has brought plenty of advantages for power plant owners and operators. Tough market conditions, high demands with respect to operational safety, and declining numbers of operating personnel, to mention only a few influences, have put high requirements on the staff.

Smart software systems can support the staff and ensure that the tremendous available possibilities can be used to prevent damages and efficiency leaks – promptly and even under hectic and stressful everyday working conditions.

Such systems calculate key performance indicators for the condition of the process or of individual components by comparing in-service measurements with reference values for the “good” plant condition. The use of statistical methods allows to continuously evaluate the chronological behavior of the KPIs, to detect changes early and reliably in order to inform the responsible persons autonomously. Our experience has shown that the use of statistical methods is a highly efficient way of condensing operational data to reliable information on the condition of the components of the plant.

SR::SPC offers the opportunity to monitor different departments and production lines as well as several third-party systems in only one clearly laid out view. Without such a compiled view, often several different DCS, which are not interconnected, have to be used in parallel, and it takes a lot of manual effort e.g. to compile reports for managerial or official purposes.

Finally, our internal and external customers' experience indicates that the saying "A small leak can sink a great ship" applies to modern power plants and industrial plants: to manage and master the new load and flexibility requirements, it is crucial to make use of all reasonable options as well as to prevent unnecessary trouble, failures, and downtimes.

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