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Predictive Analytics and Decision Support for Improved Plant Efficiency

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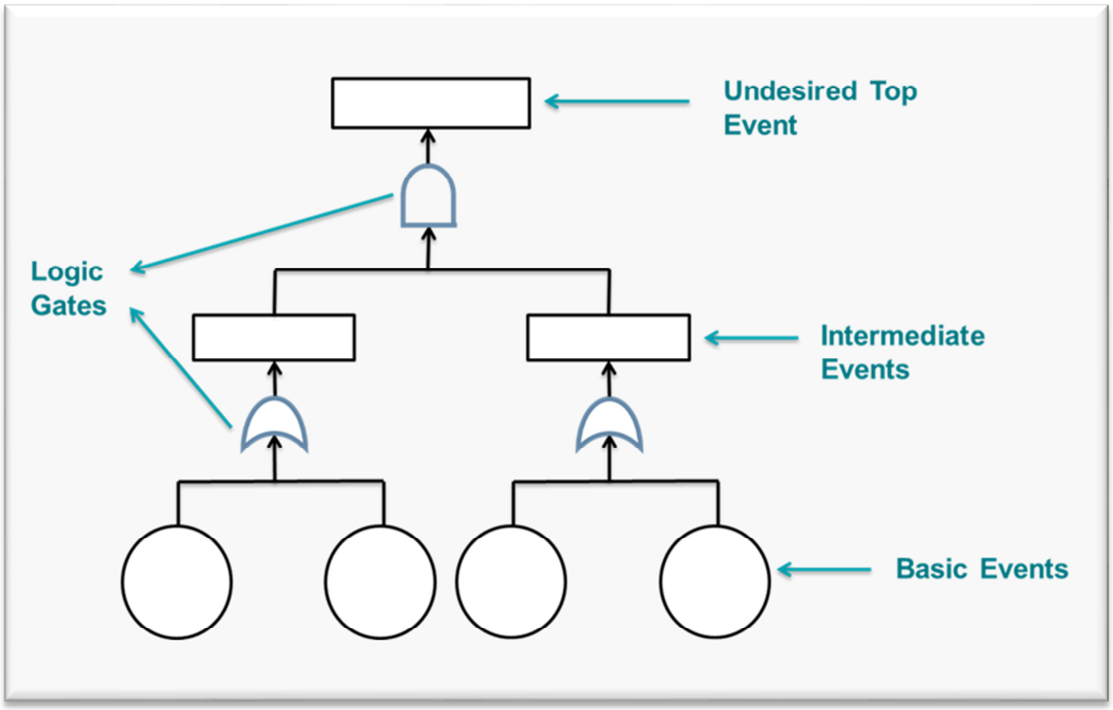

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1 Abstract

With increasing economic pressure on power plants it becomes more and more important to ensure that the operation follows the best practice and that the available knowledge and experience is shared and available at any time. In the past solutions for performance monitoring have been developed and widely implemented in many power plants. These solutions are valuable and helpful tools that provide insight into the thermodynamic processes of the plant and use KPIs for an early detection of changes. However, it requires some engineering knowledge and experience to use this information to identify faults or to derive the best possible corrective action. The next generation of IT solutions supports the operators in these engineering tasks. Predictive analytics allow deriving quantitative models of the plant behavior from power plant data. Such models enable the operator to make a reasoned estimation of the trends of key parameters of the plant and their cost implications. They are complemented by decision support systems which uses plant data together with a-priori knowledge about the plant to identify the root causes of increased losses and to propose corrective action. For tasks such as soot blowing or finding the best possible settings for a combustion system the corrective action can even be done directly through a control mechanism avoiding the human interaction and ending up with decision automation. In this paper concepts and solution are presented that implement these approaches for the operation of power plant. It is shown how this leads to the automation of knowledge in the plant and ensures continuous best practice operation. Operational experiences with such solution are presented.

2 Introduction

With increasing economic pressure on power plants it becomes more and more important to ensure that the operation follows the best practice and that the available knowledge and experience is shared and available at any time. Higher flexibility in the plant operation and fuels used in the plants make the components prone to failure earlier than their expected lifespan. To increase the availability of components a close monitoring and diagnostic system is of great help. This includes a monitoring of individual component performance as well as a heat rate degradation monitoring. Through these two monitoring focuses a low maintenance schedule is accomplished while maintaining high plant efficiency.

On-line performance monitoring in power plants has become widely used in the last ten years. This involves data archiving, thermodynamic and mechanical data analysis with first principle models on-line and off-line, neural networks for data-driven approach on data analysis, and a variety of diagnostic tools to evaluate historical data of performance data and perform trend analysis. An important feature of the monitoring systems is the possibility to define key performance indicators (KPI) which only depend on the status but not on the current operating and ambient conditions. KPIs incorporate a reference value that as dependent on the operating and ambient conditions as the actual value. This reduces the ‘noise’ that metered values and efficiencies calculated from these usually have and, thus, yields a clear picture of the component and plant conditions.

In discussions with users it is obvious that in times of demographic change and at the same time scarce human resources and higher load flexibility the time to analyze the results of these systems is limited and the complexity of the plant makes the analysis more complicated. Therefore pre- or self-defined fault trees are used to get a better hindsight on what is source for an incident or loss in power or heat rate. Handling these trees off-line can be cumbersome. But with the on-line performance monitoring system and an on-line statistical analysis for early warning already in place the fault trees can also be automatically evaluated and through this give the operator valuable information on the state of the plant without the necessity of searching for the information by hand. Additionally the on-line fault tree has the advantage that is possible to define personalized trees for plant-specific phenomena; one is not limited to pre-defined trees.

Classic fault trees use a binary approach for the evaluation of the root causes. This approach works fine as long as there cannot be more than one cause for an incident. For certain events like e.g. a raised heat rate the reason can also be multiple smaller causes that sum up to result in an alarm for the top event. To see this effect the tree needs to be able to calculate contribution to the top event for all bottom events and weigh the severities to provide an advice to what has the largest contribution and needs to be looked at first. Due to this advanced requirements STEAG Energy Services GmbH has further developed its line of performance monitoring and early warning tools to provide a thorough insight into the plant detecting gradual changes and non-scheduled operation with a detailed fault analysis.

3 The Decision Support Approach

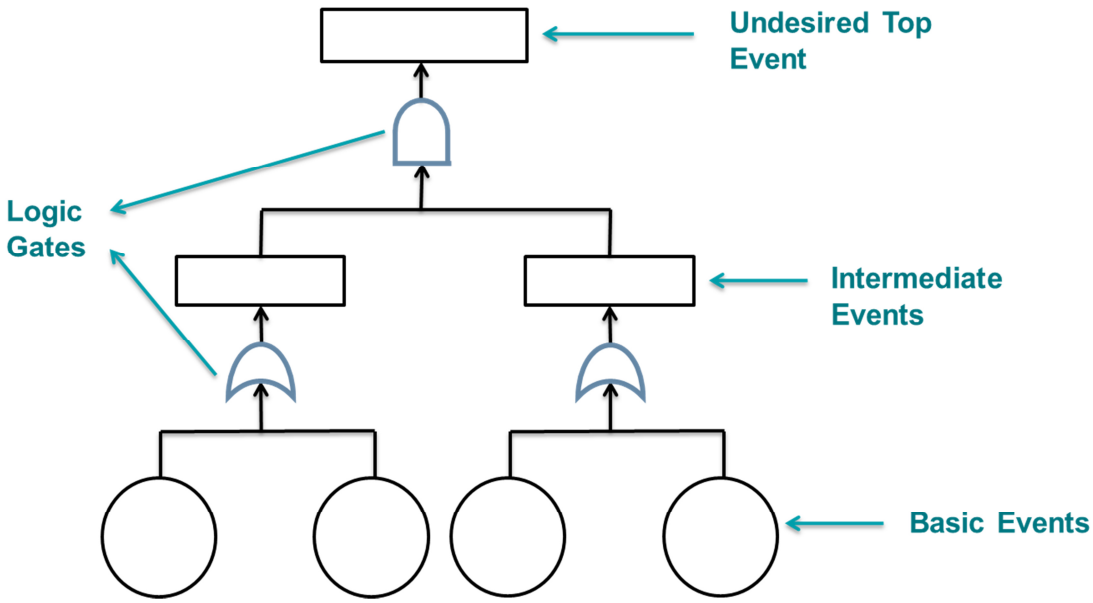

Figure 1: Structure of Decision Support tree

The basic approach for the decision support system that extends the existing performance monitoring systems is software that evaluates the possible causes for an undesirable event. It is organized in a tree structure (see *Figure 1*) with the undesired event at the top and the substantial causes at the bottom. Logic gates (AND/OR) are combining the bottom events towards the top event. Intermediate events are added after logic gates to group the basic events. A top event is for example the boiler loss of the plant next intermediate events are then the dry gas losses, moisture losses, losses due to coal quality, and radiation losses. These are broken down to further intermediate events like faulty heating surfaces ending with causes like leakage and fouling and the respective measurements indicating these causes. Trees can be everything from pre-defined heat rate trees to self-defined trees of specific behaviors of the plant. The alarms can be either triggered through first principle model or a data-driven model.

The attractive nature of the fault tree stems from the fact that it can isolate multiple fault conditions simultaneously. In many cases there are multiple causes for an undesirable event. Fault tree traces all branches of events which could contribute to an accident or failure. The intelligent decision support system based on tree structures is better able to express different levels of the logical relationship between the events and the relevance between them. Thus, it provides an elaborate knowledge of cause and effect relationships existing in the process.

4 Structure of the Decision Support System

The Decision Support System is a logic tree that propagates primary events or faults to the top level event or a hazard. The tree usually has layers of nodes. At each node different logic operations like AND, OR, and INHIBIT are performed for propagation. It is composed of a top event, intermediate events, basic events, and logic gates. The top event of the Decision Support is the undesired event, while the bottom events are the root causes for the undesired event. An AND-gate indicates that all sub-events are necessary to trigger the main event, for an OR-gate only one sub-event is necessary. An INHIBIT-gate states that in addition to the cause stated in the sub-event the condition has to be true to trigger the main event.

The performance monitoring system generates an alarm either from current values or as a result of a certain behavior over a period of time as one of the top or intermediate events this alarm activates the analysis of the possible causes. For the top event a severity is allocated based on its actual value and a possible load dependency. The severity ranges from -1(better than expected) to 1(alarming state). The causes are evaluated using the respective measurements and physical correlations of the components involved. By this the contribution to the top event is calculated. In the visualization the paths with the highest contribution are highlighted to give the user an advice on where to look first (see *Figure 2*).

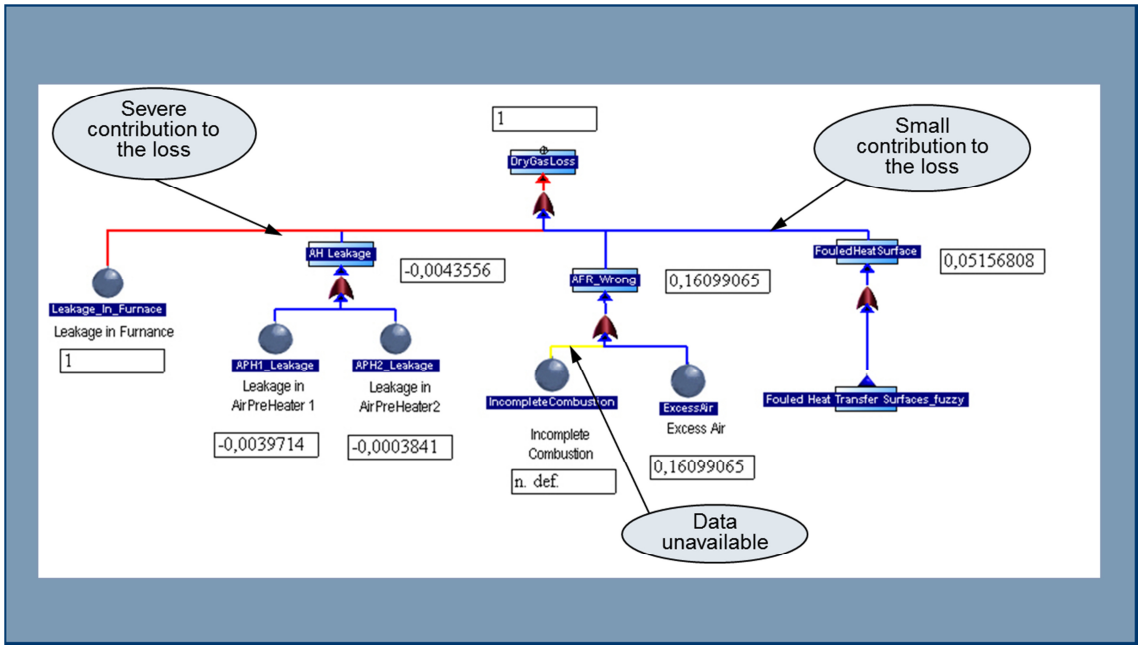

Figure 2: visualization of Decision Support with colored lines indicating the different contributions

For certain events the contribution of the bottom events to the top events might be hard to determine but it might still be sufficient to evaluate which cause is more likely. Therefore in addition to contributions likelihoods have also been introduced to the system. Incorporating the 'procedural feeling' of staff members for these issues can be of great help develop the likelihoods for cases in which no severities can be calculated. Through the Decision Support this knowledge can be transferred between shifts and different plants and saved for the utility. These likelihoods are defined through functions and parameters by the experts and/or through physical correlations or calculated with the help of known branches of the tree.

The likelihood of fatigue of a component usually is proportional to the time since the last overhaul other causes might be triggered by non-time related events. To acknowledge to this fact the system allows the user to implement a time related function and spares him the necessity of re-evaluating the likelihood on a daily base.

5 On-line application of the Decision Support System

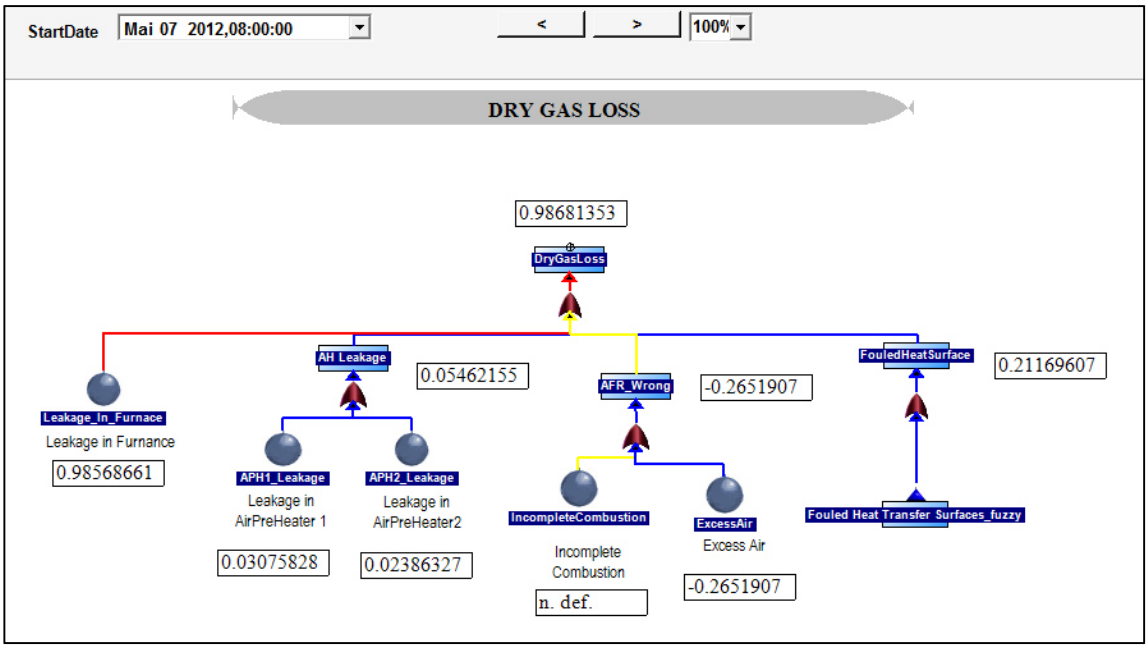

Figure 3: example of the pilot system with high severity for the top event (Dry Gas Loss) and a high contribution to it through an increased leakage in furnace

Real-time evaluation of the Decision Support System is performed in consecutive discrete time steps. The calculation of the bottom events is triggered if the expression of the top event shows an alarm. The diagnosis proceeds within seconds as the severities are calculated instantly form the current process information. The results of the calculation can be observed the visualization provided by the SR::x system as the Decision Support System is part of the SR::Suite. This helps the user to have all measurement data and results of all modules quickly at hand.

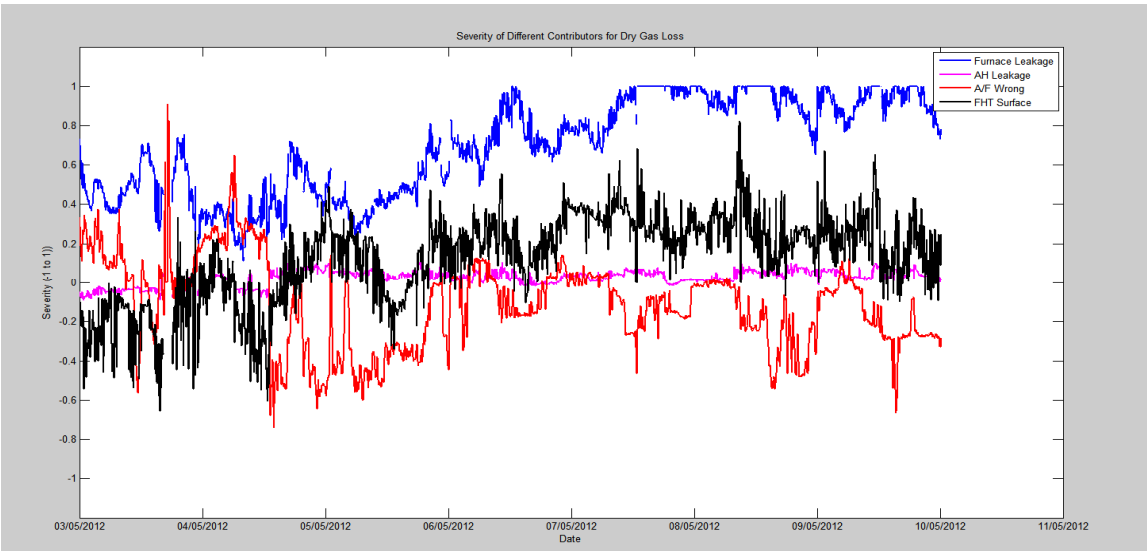

Figure 4: the contributions of the different root causes (furnace leakage, air heater leakage, air/fuel ratio wrong, fouled heat transfer surface) over a period of 7 days corresponding to figure 3

The example in *Figure 3* shows an increased deviation in heat rate that the SR:: system detected. The Decision Support System shows a high contribution for the furnace leakage. A closer look at the data for the furnace leakage reveals that the air ingress mirrors the calculated severity. The decreased severity for the air/fuel ratio is a result of the increased furnace leakage as the controls try to maintain the O_2 level by decreasing the measured air flow (see *Figure 5*).

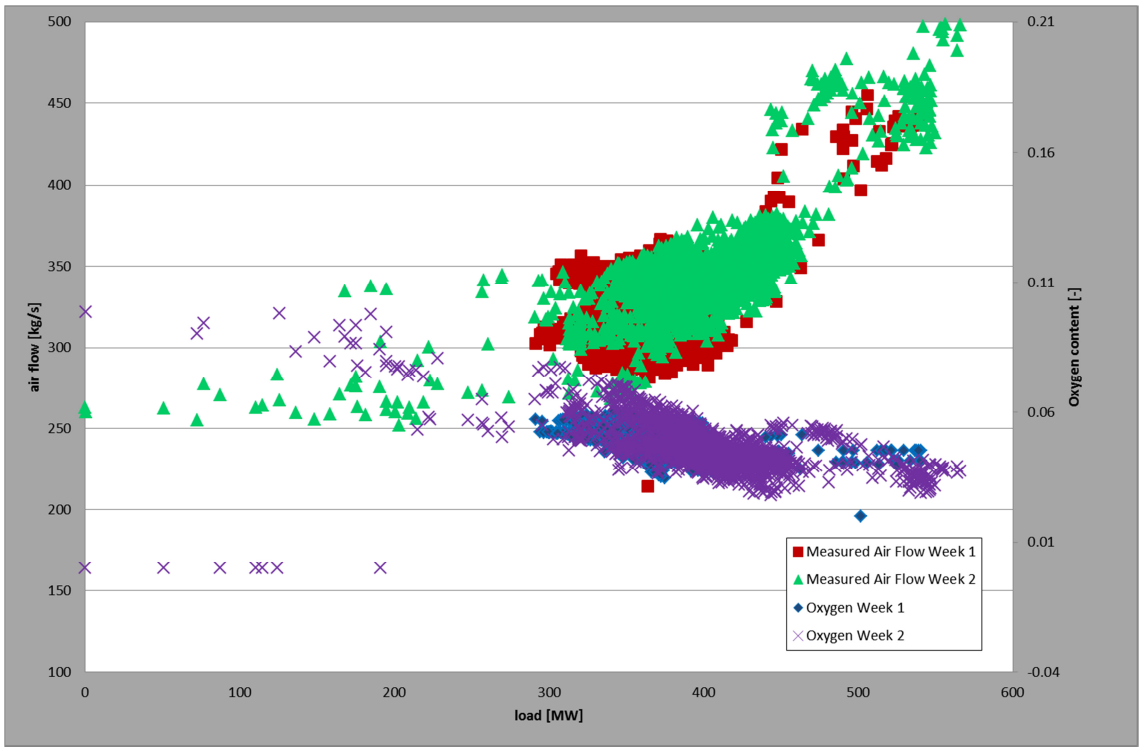

Figure 5: comparison of the measured air flows and the measured O_2 at boiler outlet before (week 1) and while the air ingress was increased (week 2)

6 Summary

Advanced performance monitoring systems provide information on process quality and early detection of faults through key performance indicators. These can be both for process parameters and for component health. Reference values are either calculated by first principle models or by data-driven models to incorporate knowledge on dependencies that would otherwise lead to high variations in results. With the help of statistical procedures information from time series can be gathered to detect changes early and differentiate between spontaneous changes in plant behavior and slow degradation. These calculations make an insight into the health of plant available but the root cause analysis is left to the user. This can at times proof to be quite cumbersome and time-consuming as several potential causes need to be evaluated. Therefore a new module has been developed that enhances the classic binary fault tree to evaluate the possible contributions of several causes at once instead of limiting it to binary answers. This way the tool can be implemented for complex trees that incorporate malfunction sources from different parts of the plant.

The first studies and the implementation of a prototype demonstrate that the new Decision Support System is able to render valuable information for the user. The system provides a thorough insight into the plant and is of help in the planning of maintenance work.

In addition to quantifying severities and the respective contribution of different sources the Decision Support System enables its user to also implement self-defined trees for which it is impossible to quantify the contributions. For these trees the system offers the possibility to handle qualifying information like ‘high if low/high’ and likelihoods derived for example from expert knowledge. Thereby the system works as preservation of treasured expert knowledge.

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