ANOMALY DETECTION IN POWER PLANT DATA OF A LARGE COAL FIRED POWER PLANT – EXPERIENCE FROM THE RECENT PROJECTS

Dr. Peter Deeskow

Dr. Tomasz Kaminski

Urs Steinmetz

STEAG Energy Services GmbH, Essen, Germany

ABSTRACT

Today utilizing resources in an efficient way is a key aspect of the power plant operation. That includes natural resources such as fossil fuels as well as human resources in the power plant. Reducing fuel consumption means improving the heat rate of the unit and limiting the degradation of the unit in a cost effective way. Efficient employment of staff means focusing the manpower on assets, which do show indications of damages or degradation and it means using planned outages to fix the faults.

Both aspects require an early detection of changes in the plant behavior in order to identify the critical assets or process parameters. Advanced pattern recognition has been applied as a tool for that purpose. Recently the development of Big Data and Machine Learning technologies and their introduction into the industry within the Internet of Things has extended that toolbox by new technologies for anomaly detection. Especially Deep-Learning has proven to be a flexible, powerful tool to build large scale autoencoders for anomaly detection in power plant data.

This paper describes an implementation of this approach for a 800MW coal fired supercritical unit and demonstrates the benefits. Results from anomaly detection are compared with recorded failures and maintenance measures to demonstrate the potential of the method.

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.

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DEEP LEARNING - RECENT PROGRESS IN ADVANCED PATTERN RECOGNITION METHODS

For many years neural networks have been a proven and valuable tool for advanced pattern recognition. In applying this tool to power plant data to build a solution for an early detection of possible faults in the plant some key aspect have to be handled: Key parameters have to be identified that are informative with respect to the fault to be detected and causal relationships of this parameter with other measurement have to be identified. This requires some expert domain knowledge and some engineering efforts, but will finally result in a highly sensitive and reliable solution for an early detection of faults in critical assets or deviations in process parameters.

In the last few years the availability of comparatively cheap hardware for high performance computing has boosted the development of machine learning algorithms that allow to go beyond that classic approach. We do not need to identify the key parameters that are informative by expert knowledge because we can monitor simply every tag that is available in the DCS? And among all these measurement we can identity the (much smaller number of) key factors that fully describe the actual operational conditions of the plant as well as their correlations with the other measurements automatically.

The tool that enables this progress is deep learning, an algorithm that has boosted the progress of many AI applications. Speech recognition and picture processing for robitic technologies are among solutions that benefited from this development. Deep learning is an application of neural networks. However it uses network topologies which utilize a high number of hidden layers and complex training algorithms. A special implementation of deep learning that is most valuable for anomaly detection in power plant data are deep autoencoders.

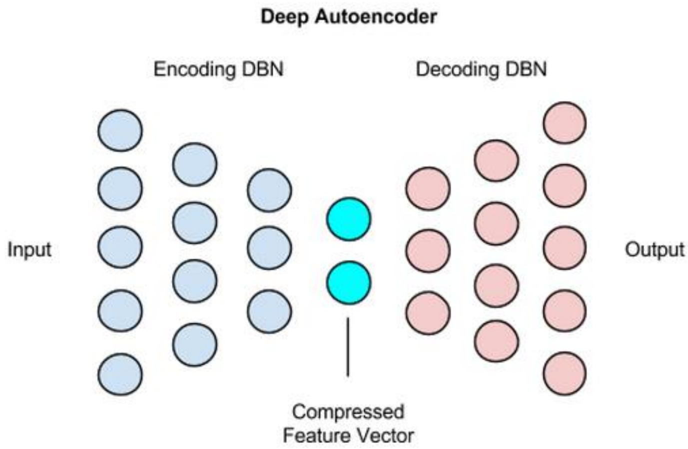

Figure 1: Deep Autoencoder

A deep autoencoder is a neural net which is trained to map the inputs to themselves. So e.g. in case of power plant data all the input will be all the available measurements for the water / steam cycle and the output will be a reference value for each of the measurements. An autoencoder has a symmetrical topology in the hidden layers with a "constriction" in the center layer (see above). That prevents the training algorithm from simply "memorizing" the data but forces a generalization. It will automatically identify a number of key features (corresponding to the number of neurons in the center hidden layer) and learns the relationship between these key features and the input data. In our example of the power plant data from the water steam cycle this topology will force the autoencoder to "learn" that there is a small number of key features that fully describe the operating condition of the plant, such as load, ambient temperature, certain extractions and others. It will further learn how the DCS measurements depend on these features during the training period.

Once the autoencoder is trained, online measurements from the DCS can be propagated through the neural net and the result will the expected values which all the measurements would have under the given operating conditions (if the plant is in the same condition as in the reference (training) period). If there are significant deviations between measured and expected values an anomaly is detected in the online data. This anomaly will give an early warning for changes in component health condition and will be a valuable input for predictive maintenance and performance optimization.

A few years ago this approach would have been beyond the scope of affordable hardware if applied to the entirety of all measurements in a power plant. Today it is in the reach of powerful workstations.

DEEP LEARNING BASED ANOMALY DETECTION IN POWER PLANT DATA

The method described above has been implement and tested first using data from a 350MW coal fired supercritical unit. A number of 1200 measurements describing the behavior of the unit were taken from the DCS for a period for 5 years from 1/2009 to 12/2013. An autoencoder as described above was trained for a reference period. Then the deviations between measured and expected values where calculated and statistical analysis was applied to detect significant deviations ("anomalies").

The results are represented in a number of heat-maps as shown below.in figure 2

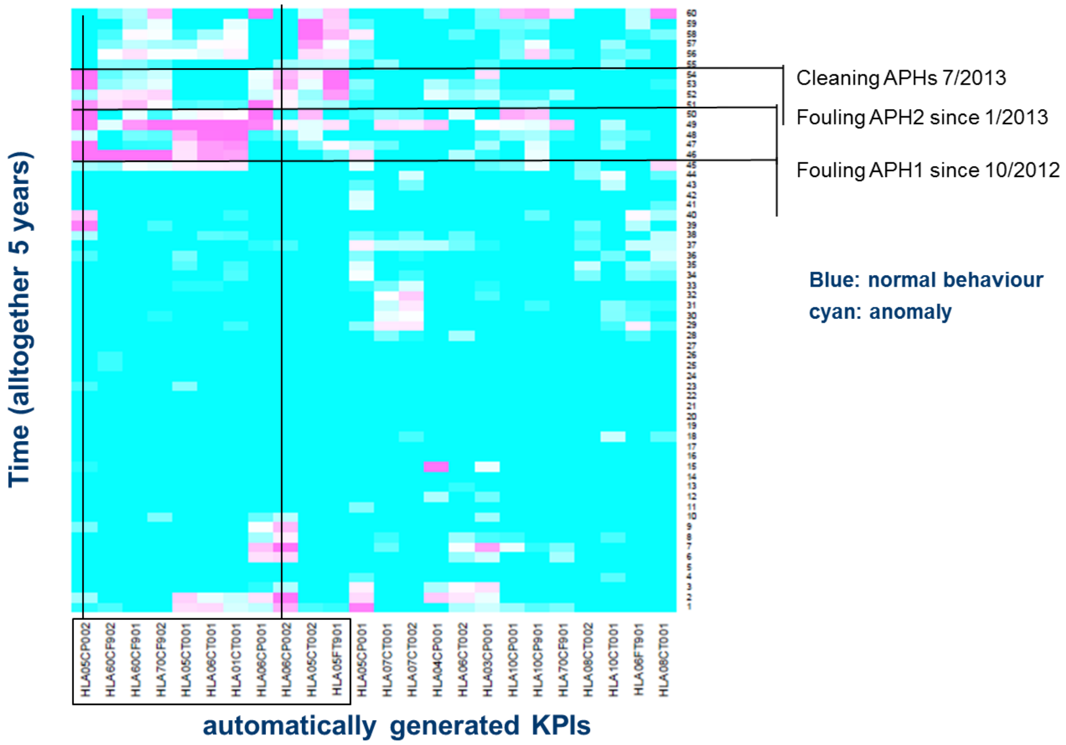

Figure 2: Heat Map for 350 MW unit

Because of the high number of measurements which are considered, a visualization is choosen that shows subsets of them in one diagram, in the example a number of measurements from HLA*** (fresh air system, ducts). To make the huge number of data manageable the representation is highly compressed. There is a column for each measurement and each row represents a time bucket. The autoencoder has been applied to 5min data but in the diagram time buckets of a month (5 years thus mean 60 time buckets) are used. For each time bucket the algorithms has counted how often the combination of deep autoencoder and statistical analysis has detected a significant anomaly for the measurement. The time bucket is colored in blue if there has been no anomaly at all in that month and magenta if there has been abnormal behavior all the time. The color map is from blue over white to magenta, so white means anomaly for 50% of the time.

It is clearly seen that in 9/10 2012 a group of measurements starts to become suspicious. Among them are DCS tags such as pressure drop across APH1 and APH2 and other measurements in the vicinity of the air preheaters. That correlates with an increased fouling of the APHs which started in 9/2012 due to a change in coal quality. The deep autoencoder based anomaly detection has thus identified the beginning APH fouling early and before it would have been obvious to the operators.

This successful detection has been achieved by a fully automated approach without the need for extensive configuration of key performance indicators and without the necessity for detailed domain knowledge. The autoencoder has autonomously learned from the data that there is a relation between the APH pressure drop and other measurements in the vicinity of the APHs and detected that something is changing with increasing fouling.

The method has been recently enhanced and applied to the data set for 800 MW unit. The 5 year data from 1.1.2012 till 1.1.2017 has been examined. Compared to the previous example for 350 MW unit the statistical tests to detect significant anomalies have been improved.

. Apart of that the data models which are the foundation of the method have been optimized to increase the detection rate. Additionally the “false” alarm rate has been significantly reduced without affect the detection of “true” alarms by so called smart data approach where the number of inputs and training sets are optimized. That is the essential feature of the method. The advantage for the user is apparent and that leads to much higher acceptance of the system. Computation routines have been implemented in R-package for statistical computation and graphics.

The results of approach are shown in the next two figures. In the figure 3 all data (> 1200 input channels) were taken for the calculation. The alarm rate is very low but the computational time is relatively high and a rather long period of training data (years of data) is required to set up a proper model.

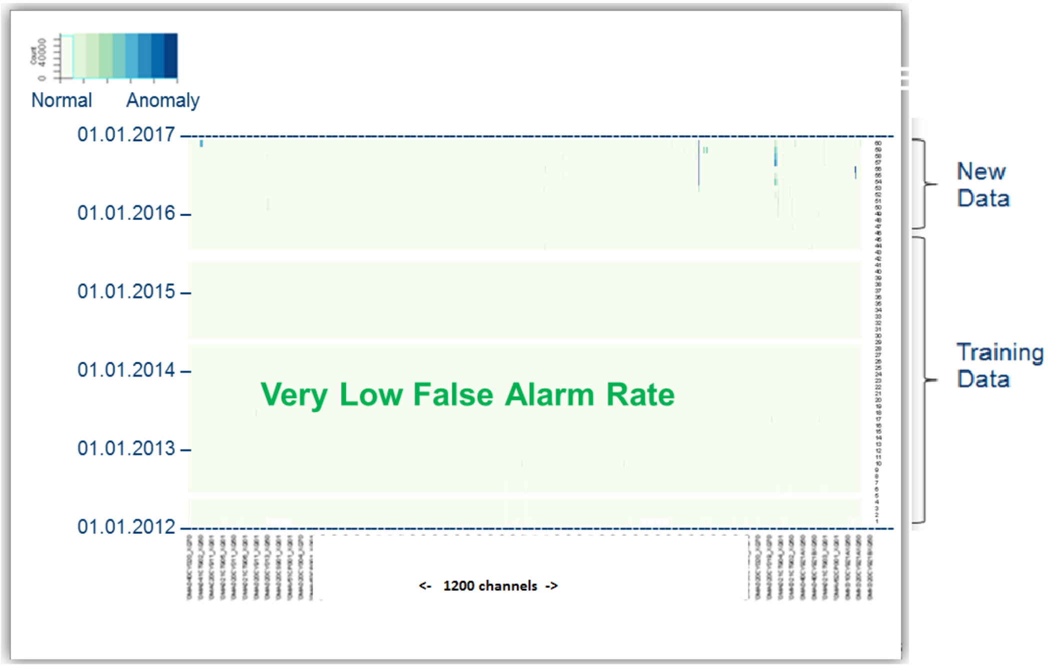

Figure 3: Heat Map for 800 MW unit

In the figure 4 the concept of smart data approach is shown. The number of inputs and the training set have been reduced to 62 channels and 5 months respectively by defining a “smart” subsystem. The computational time and the rate of false alarms have been significantly reduced compared to the conventional approach.

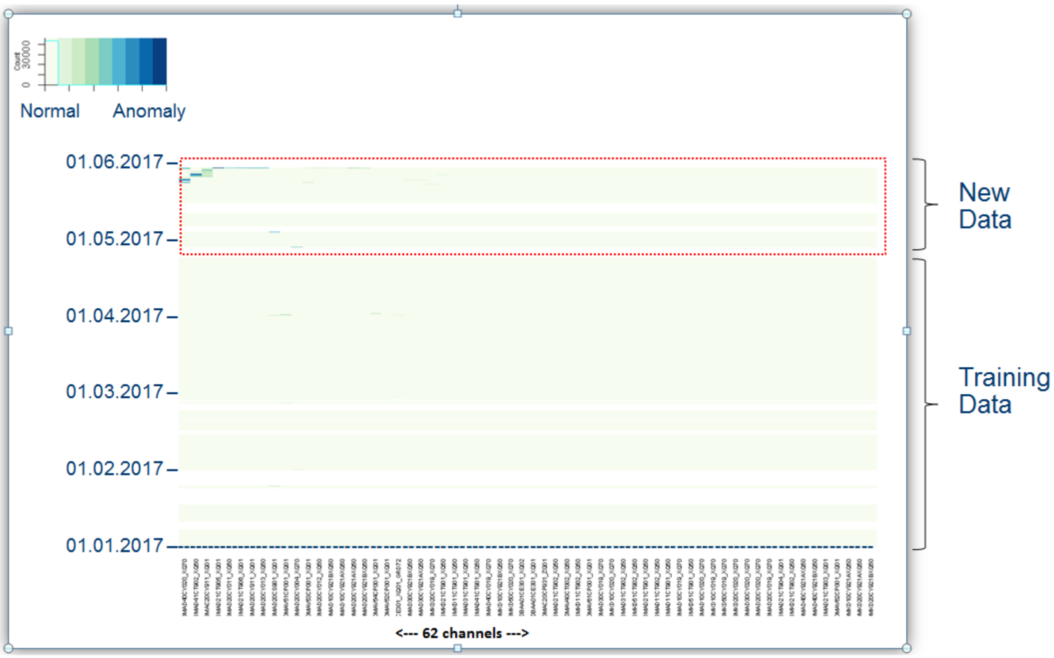

Figure 4: Heat Map for 800 MW unit with smart data approach

THE FUTURE OF PREDICTIVE MAINTENANCE

These recent developments will boost the potential of predictive analytics solutions for predictive maintenance and performance monitoring. Now two options are available to set up a system for an early detection of change in a plant.

One option is the well-established approach that combines pattern recognition methods with domain expertise to define key performance indicators that are informative for expected faults. The approach gives any required degree of freedom to tailor the KPIs to the plant and thus ensures highest possibly sensitivity to the expected fault. However, gathering the expert knowledge and tuning the KPI may require some engineering efforts.

The new option described above uses machine learning technologies and the “Big Data” approach of the Internet of Things. It will reduce the engineering efforts to set up a system because the system implementation can be done to a great extent automatically. It has the potential to autonomously monitor each and every measurement that is available in the DCS and will thus reduce the risk that some fault is not detected early enough because there is no corresponding KPI.

Future software solutions which support maintenance and performance optimization with predictive analytics have to combine both approaches. Data based KPIs resembling domain expertize will ensure highest sensitivity to ensure highest possible reliability for the detection of critical faults. An additional anomaly detection using “Big Data” technologies will cover a majority of the measurements which are available in the DCS and thus ensure that any anomaly in the plant behavior is uncovered in an early stage allowing engineering analysis and rectification if needed.

These solutions which combine expert domain knowledge and the power of some most recently developed “BigData” methods will help the plant staff to reduce fuel consumption and improve availability with highly efficient employment of human resources because they will focus the manpower on assets, which do show indications of damages or degradation and they will allow to use planned outages to fix the faults. The smart data approach presented in the paper is one relevant step in this direction.