MODELBASED DIAGNOSTICS, MAINTENANCE ON DEMAND AND DECISION SUPPORT ON BOILERS

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ABSTRACT

At a CFB boiler a system has been tested based on a Modelica model together with a decision support system. The model is a physical model including energy and material balances, chemical reactions like combustion and gasification reactions. For the combustion system we primarily consider equilibrium conditions while for gasification the kinetics is important and thus PLS-models built on experimental data in a pilot plant are combined with literature data and a physical model. The simulation model is first developed in Modelica, but then placed as an object in Simulink/Matlab, from which data is communicated to and from the data base through OPC-server. Measured data are collected from the process data base and inserted as initial data into the simulation model, including the boiler, separator, heat exchangers and steam system. A simulation during 300 seconds is performed and the data after this is compared to the initial data. If we have steady state conditions, the values after the simulation will be the same as the initial data, while if the data are not balanced, the difference will correspond to a balanced state between all measured data and the physical correlations in the boiler. This procedure is repeated on a regular basis and the trend of the difference between the measured and the balanced data is plotted and analyzed with respect to slope respectively variance. These data are combined with other type of information like standard deviation of sensors, which corresponds to noise; is the data value changing at all? Input of manual information like lab-data, unexpected events like noise; maintenance actions; activities like how many times a valve has been opening and closing; combination of data like Energy and Mass balances combined with conductivity in blow down from steam drum to detect possible leakages in piping or boiler systems;

All this information is introduced into a BN, Bayesian Net, which has been built from known relations, but where the quantitative data is built from experience and statistics. In this way we can then detect possible faults or probable faults coming up. This information is used by both the operators and maintenance staff. The mathematical simulation model over the CFB boiler and results from the utilization is presented in this paper.

Key words: CFB boiler, mathematical model, simulation, diagnostics, decision support

INTRODUCTION

In most process industries and power plants we always are operating under variable conditions. Steady state operations is always strived for, but seldom reached due to variations in the feed stock, fouling of heat exchanger surfaces, deterioration in sensors etc. To make it possible to both understand the process dynamics better and to make it possible to control the process in an optimal way we propose a method where a simulation model is built over the process, and this model then is used to compare the real operations with the "optimal operations". By doing this we can both get a tool to diagnose the process performance as well as the sensor status.

The models normally used for data reconciliation normally include only steady state mass balances, and not energy balances like in Sanchez et al [1] and Crow et al [2], Leibman et al[3] Romagnoli et al[4]. These applications all have been primarily focusing on chemical industry applications. For CHP plants papers have been presented by e.g. Avelin [5], Karlsson et al [6,7,8]. Concerning decision support there are many publications, but here a few are mentioned related to the methodology we are using. Genrup [9] and Bebe [10] have studied degradation in gas- and steam turbines, and the output can determine when it is time to do service. Hess [11] used physical models for the production planning and optimization of a reactor. The output from the algorithm was implemented by the operators, and as such worked as a decision support. Decision support can be structured by using e.g. Bayesian networks. These are giving relations between different input variables and different faults, including statistical probability for the different faults to be present. Jensen [12] has presented the methodology in his book "Bayesian Networks and Decision Graphs". Applications for different industry usage has been presented in e.g. Weidl´s thesis [13] "Root Cause Analysis and Decision support on Process Operation" as well as by Widarsson et al [14] specifically for a boiler application and by Bell [15] in operations decision support based on dynamic simulation and optimization in pulp and paper. A more general evaluation of the use of Bayesian networks for diagnostics has also been presented by Przytula et al [16]. Procedure for sensor diagnostics using Dynamic Characteristic Curve Estimation was presented by Latva-Käyrä et al [17].

SYSTEM DESCRIPTION

At a CFB boiler at Malarenergy, Vasteras, a system has been tested based on a Modelica model together with a decision support system. The model is a physical model including energy and material balances, chemical reactions like combustion and gasification reactions. For the combustion system we primarily consider equilibrium conditions while for gasification the kinetics is important and thus included, built on experimental data in pilot plants combined with literature data.

The simulation model is first developed in Modellica, but then placed as an object in Simulink/Matlab, from which data is communicated to and from the data base through OPC-server. See figure 1. Measured data are collected from the process data base and inserted as initial data into the simulation model, including the boiler, separator, heat exchangers and steam system. A simulation during 300 seconds is performed and the data after this is compared to the initial data. If we have steady state conditions, the values after the simulation will be the same as the initial data, while if the data are not balanced, the difference will correspond to a balanced state between all measured data and the physical correlations in the boiler. This procedure is repeated on a regular basis and the trend of the difference between the measured and the balanced data is plotted and analyzed with respect to slope respectively variance. In figure 2 we have a simple example with a tank, a pump and two valves. The sum of the flows do not match, but by including also information on level in the vessel, valve positions and pump motor power as well a balance can be calculated by a physical model. In figure 3 we see the measured, the calculated and the difference for the three positions for three time steps with 15 minutes in-between. Here we can see that for position 1 the difference is the same for all three time steps, while for position 3 it is increasing, indicating drift in a sensor or clogging of a valve.

These data from the model calculations are combined with other type of information like standard deviation of sensors, which corresponds to noise. Different types of deviations are considered. First of all - is the data value changing at all? If so, is there a significant trend in the deviation in one direction, or is it fluctuating but at a principally constant level? Is the fluctuation random or more like a sinus curve, indicating oscillations?

Aside of on-line data also input of manual information like lab-data are used. Unexpected events are noticed, both manually as input from operators, as well as input from maintenance staff. Maintenance actions are registered and statistics about different type of actions stored and used as input to the decision support system.

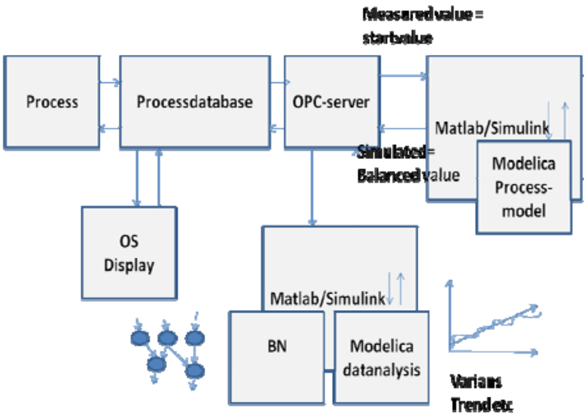

Figure 1. System layout for on-line application of the decision support system for maintenance on demand and process performance diagnostics

Activities like how many times a valve has been opening and closing can give an indication on both how well the control of the valve is tuned but also indicate the need for service.

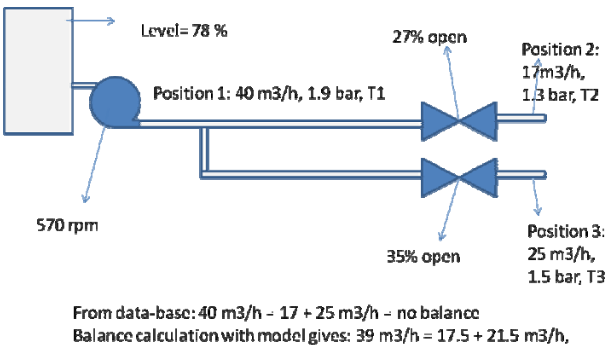

Figure 2 A simple example of a system to illustrate the procedure

Sometimes different type of information can be combined to give indications on most probable cause of a problem as well as an isolation of where a problem has occurred. Combination of data like Energy and Mass balances together with conductivity in blow down from a steam drum can give information not only about a possible leak in the boiler tubes but also where the leakage can be. If the conductivity is constant it indicates a leakage in the Economizers, while if the conductivity drops, it indicates a leakage in the actual boiler room, as the concentration of salts in the water going back to the steam drum is reduced as less water goes back.

Time	Pos	measured	calculated	difference
08:00	1	40	39	1
	2	17	17.5	0.5
	3	25	21.5	3.5
08:15	1	40.5	39.5	1
	2	17.5	18	0.5
	3	26	21.5	4.5
08:30	1	39	39	1
	2	18	18	0
	3	27	21	6

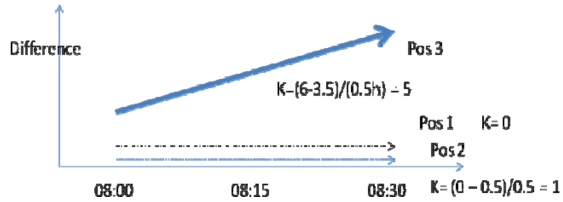

Figure 3. Measured data for each position respectively calculated data for the same positions using the simulation model, for three times

Other type of information can be information about local diagnosis, like noise in sensors due to poor electrical contact or similar.

All this information is introduced into a belief tree, e.g. a BN, Bayesian Net, which has been built from known relations between cause and effects principally. The quantitative data is gathered from specific experience from operators and maintenance staff as well as from statistics on different measurements etc described earlier. In this way we can detect probable faults coming up. An example of this using the previous example is shown in figure 4.

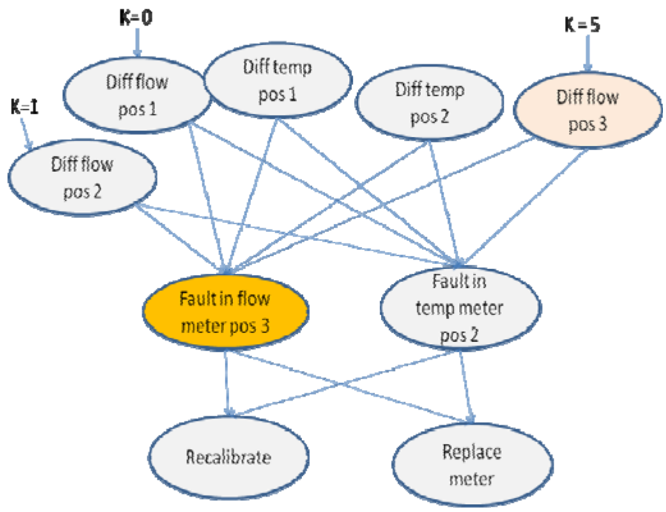

Figure 4. Decision support on possible faults from the previous example

This information can be used by both the operators and maintenance staff. What information that should be used by different categories will have to be defined, but principally immediate actions should be taken by the operators, while more planned service should be performed by the maintenance staff.

The procedure can be summarized as a set of calculations using the physical model combined with data from the process data base.

1. The data base is filtered with different filters as a “moving window” : filtered value of variable x1 (t+1) = v* old value variable x1 (t) + (1-v)*new value variable x1 (t+1) where $0 < v < 1.0$. For a high damping v is close to 1.0. Different values of v are used in parallel during the development phase, but later the value is fixed for a specific variable.
2. The filtered data are sent to the simulation model as “initial values”. The simulator runs for a specific predefined time period. 300 seconds gave a stable situation.
3. The final data from the simulation were sent back to the database and stored
4. The data set for each variable with both simulation and measured data were sent to the calculation of the deviation trends as well as a variance analysis of the time series for different time horizons
5. The data then are sent to the BN tree as input data.On a frequent basis the weighting factors in the BN tree are calculated

EXAMPLE FOR A CFB BOILER

The method has been tested of line at Malarenergy but will be implemented on-line later this year. The simulation model contains the following elements [18]:

The mass in the bed inventory by time is given from:

$$\partial m_{inventory} / \partial t = \sum m_{i,in} - \sum m_{i,out} \quad (1)$$

where $m_{i,in}$ is the mass in-flow of each single component *i* (C,H,O,N,CO_2,H_2O,NO_2,ash) and $m_{i,out}$ is the corresponding out-flow. The change in concentration of each component *i* is given by c_i in the bed inventory:

$$\partial c_i / \partial t = \left(\sum c_i * m_{j,in} - \sum c_i * m_{k,out}\right) / m_{inventory} \quad (2)$$

where *j* are all incoming flows and *k* all flows out of the inventories. Except the bed inventory we also have one inventory for the Intrex and one for the steam system. The steam system has only water and steam components, while the Intrex has the same components as the bed. The temperature $T_{inventory}$ in the inventory is calculated from the energy balance:

$$\partial T_{inventory} / \partial t = = \left(\sum T_j * Cp_i * c_i * m_{j,in} - \sum T_k * Cp_i * c_i * m_{k,out}\right) + \Delta H - U*A*(T_{inventory} - T_{outside})) / (m_{inventory} * (\sum c_i * Cp_i)) \quad (3)$$

Here ΔH is the energy released during combustion and U is the heat transfer number, A the area of the heat exchanger area and $T_{outside}$ the temperature at the other side of the heat exchanger surface – steam temperature vs exhaust gas temperature. Cp_i is the heat capacity for component *i*. These equations are the most important. Aside of them we also need correlations describing the change in each single component. Carbon, C, in the biomass is combusted to CO_2, and the hydrogen is forming H_2O. Oxygen in the fuel is used for the combustion aside of the oxygen in the air.

The boiler is seen in figure 5. It is a 170 MW CFB boiler operating on biomass. As seen in the figure the steam system is quite complex where two steam lines are in parallel but not symmetric. In the model we have run a simplified configuration with the Modelica model while a complete model was used using APROS, to see the impact of detailed modeling for the diagnostic purpose, where the exhaust gas train heat exchangers were not in focus, but the bed and the Intrex. The model was used together with input data from the database.

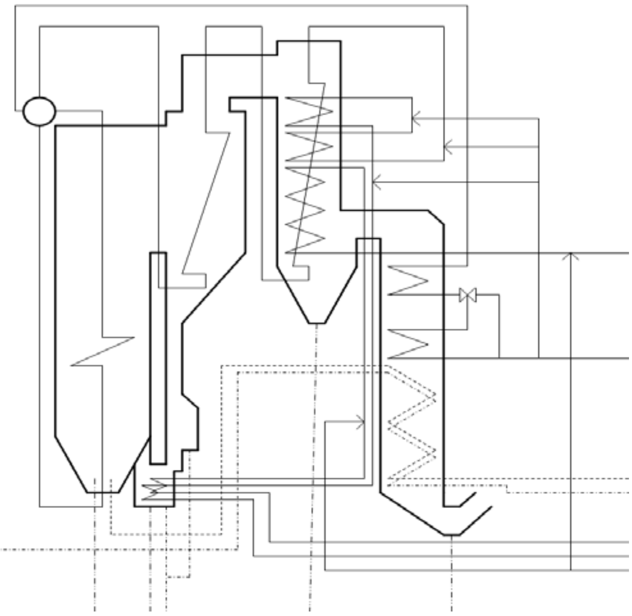

Figure 5. The boiler 5 at Malarenergy

In figure 6 we see the development of the deviation between the simulation calculation and the measured values for the temperature in the separator (“cyclone”) over a 14 day period to the left and the steam temperature in the Intrex super heater to the right.

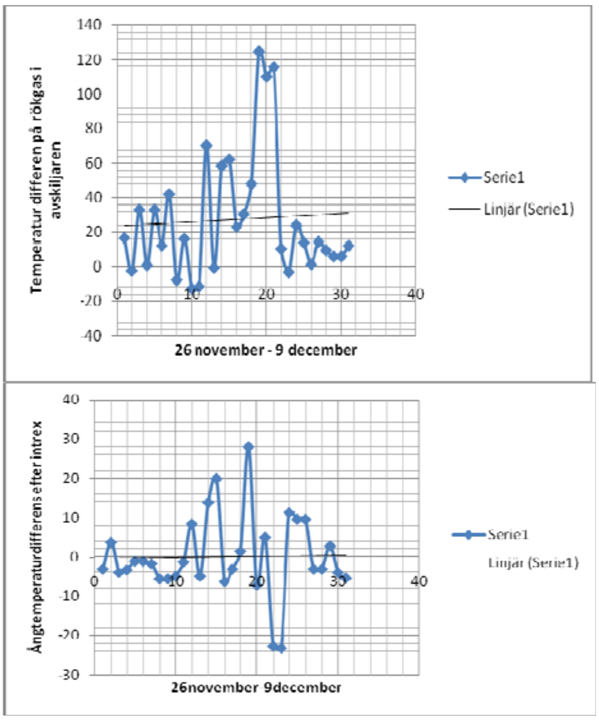

Figure 6. The deviation between calculated and measured temperature in the separator (”cyclone”) to the left and in the Intrex Super Heater steam temperature during a two week period to the right.

What we can see is that first the deviation is oscillating around an average for five days, but then it moves away almost 100 oC for several days, until it goes back again at the end of the period. This indicates that we had combustion high up in the separator instead of in the bed, at least to some extent, during several days. For the steam temperature in the super heater we can see that deviation first is very small, but then starts to oscillate. When the temperature is high in the separator, it goes down in the Intrex steam compared to what it should have been from a balance point of view, indicating that the solids going down to the Intrex is affecting also the Intrex performance. In figure 7 we have made a cause tree for the Intrex steam temperature, showing possible relations. This tree can then be used to identify possible problems and the probable cause of these. By tuning the tree formulated as a BN we can also determine the probability for different causes in relation to each other. We have not had time to do that tuning yet, but it will be implemented later this year.

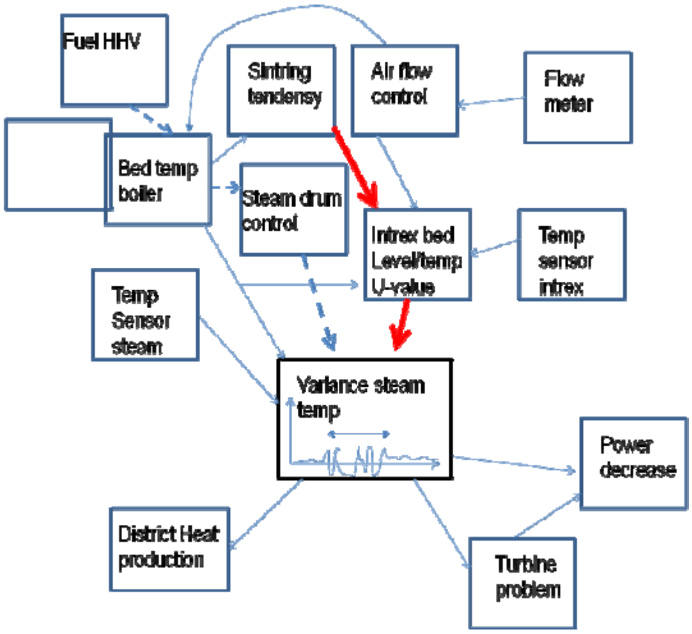

Figure 7. A tree structure showing the possible root causes of the increased variation in the steam temperature in the super heater inside the Intrex

DISCUSSION AND CONCLUSIONS

From the example we can see that it may be interesting to use simulation models to correlate different variable to each other through physical relations. By calculating the probable balance as a function of time development of different type of faults can be detected at an early stage. This includes both process problems and sensor problems. By structuring the information we can achieve a decision support system that can be used both for the daily operations as well as for maintenance on demand. By feeding back information on true causes of different problems we can tune e.g. a BN to get the quantitative information about the relative probability of different possible faults in relation to each other. By then checking more in detail the status of each possible problem, the operators and maintenance people can identify the true fault and the model can be upgraded on a continuous basis.

By doing this more advanced control will make sense, to optimize the performance of the process, in this case the power boiler.

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