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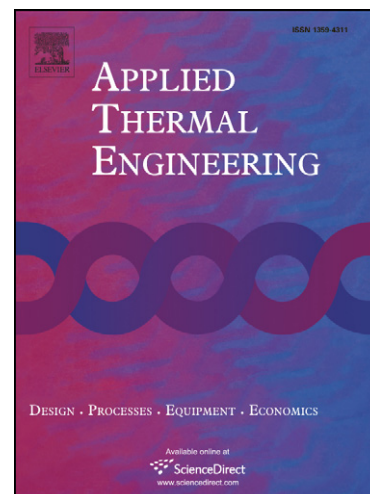
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Bayesian network based early-warning for leakage in recovery boilers

Björn Widarsson^{1*} and Erik Dotzauer²

¹*Dept. of Public Technology, Mälardalen University, P.O.Box 883, SE-721 23 Västerås, Sweden*

²*Fortum, SE-115 77 Stockholm, Sweden*

Abstract

Early-warning for leakage in a recovery boiler can help the process operator to detect faults and take action when a dangerous situation is developing. By analysing the mass-balances on both the steam and combustion side of the boiler in a Bayesian network, the probability of leakage can be determined and used as an early-warning. The method is tested with real plant data combined with leakage simulations. The results show that it is possible to detect considerably smaller leakages using this method than using the type of simple steam-side mass-balance method that is in use today. Bayesian network is an efficient tool to combine information from measurement-signals and calculations giving an early-warning system that is robust to signal faults.

Keywords: Early-warning; Bayesian networks; Recovery boiler

* Corresponding author. Tel.: +46 21 101 356; fax: +46 21 101 370.

E-mail address: bjorn.widarsson@mdh.se

1 Introduction

Operating and diagnosing complex industrial processes are usually difficult tasks. Faults that cause only minor disturbances in the production can be frequent. It is mainly the operator who detects, isolate and take action when a disturbance or fault appears. It can be very hard to distinguish between normal process operation with its minor disturbances and a developing fault.

Early-warning systems can help the process operator to detect faults at an early stage and thus prevent further fault development. Early warning systems have been developed for safety critical events, e.g. fire on ships [1], disconnections in electrical systems [2] and landslides [3]. Common for early-warning systems are that they are designed to make a person aware of that a critical situation is or might be developing.

Industrial processes normally have alarms on signal levels to pay attention to large deviations from a normal value. The alarm triggering levels are set to protect the process equipment, maintain product quality, etc. A diagnostic system can give the process operator more information than just an alarm that a signal is deviating. Fault diagnosis is commonly divided in the two steps; detection and isolation [4]. Fault detection is to determine that there is a fault and isolation is to determine where the fault is located. An early-warning system is a diagnosis system aimed to help the process operator to detect and isolate faults as early as possible.

Leakage detection in recovery boilers is important to avoid severe damages on equipment. The walls of the furnace are containing evaporating water with high pressure. Fireside corrosion and thermal stress can cause leakages, implying that water or steam comes in contact with the smelt. Water in the smelt can cause an explosion with total destruction of the boiler as result. There are a number of commercial systems for detection of leakage flows in both conventional boilers and recovery boilers [5] [6]. These systems are detecting the leakage flow or cracking with acoustic sensors.

In this work, a new method to detect boiler leakage flows by a mass balance in a Bayesian network is evaluated by study of a typical recovery boiler. Data from real process operation are combined with a process model to simulate leakage flows. Bayesian networks [7] [8] have been used for diagnostics in many different areas e.g. medicine, electronics and mechanics [9]. An advantage over other diagnostic methods is the handling of uncertainty. An alternative would be to use e.g. fuzzy logic [10]. This methodology will be investigated in future research on the current application.

2 Chemical recovery

Black-liquor is a residue from the cooking-plant in sulphate pulp mills. It consists of both organic and inorganic materials and has a dry solids content of 14-18 %. The organic material contains energy and the inorganic material gives valuable process chemicals. Before it can be combusted, the dry solid content has to be increased in an evaporation plant. Content of dry solids is 65-80 % after the evaporation plant.

2.1 *Black-liquor combustion*

The recovery boiler burns the organic material in the concentrated black-liquor and produces high pressure steam [11]. It also recycles and regenerates chemicals through reduction, mainly from potassium-sulphate to potassium-sulphide. The recovery boiler is an important component in the process because it both regenerates the cooking chemicals and produces steam to processes.

Concentrated black-liquor is fed in a furnace where volatile organic material is combusted. The remaining material falls down to the bottom and forms a smelt. Reducing conditions in the lower part of the boiler reduces the sulphates to sulphide with some of the energy generated in the combustion. The smelt is also containing a number of other components, mainly sodium carbonate, which are not active in the process. Smelt spouts bleeds the smelt out of the furnace to be solved in weak-liquor.

2.2 *Steam generation*

Water is fed from a feed-water deaerator thorough the economiser. The economiser is located as the last component in the flue gas path and utilises the reminding heat in the flue gas to preheat the feed water before it enters the steam drum. Furnace walls and a convection section in the flue gas path are cooled by evaporating water. From the steam drum, the furnace walls and the convection section are connected in a natural circulation system, see Figure 1.

Steam is separated in the upper part of the steam drum and lead to the super-heaters. Super-heaters are located first in the flue gas path, close to the furnace. To protect the

super-heater closest to the furnace from radiation, water or steam cooled screen-tubes can be located in front of the super-heater. Steam cooling to control the outgoing steam temperature of each super-heater section is done with injection of water or by a surface-cooler. Injection water can be feed-water or, to prevent salts and other contaminations in the steam, water produced by condensing steam from the drum thorough cooling with feed-water [11].

2.3 Leakage

Corrosion, erosion and thermal stress can cause holes and cracks resulting in a flow of water or steam into the combustion side of the boiler. The leak can be located in either the water or steam tubes, but a leak in the furnace wall-tube is the most severe due to the risk of water to come in contact with the smelt. A leak in the economiser results mainly in a water flow, with some flashing steam, while a leak in the super-heaters results in a pure steam-flow.

A smaller leak from a corrosion hole can cause erosion on tubes close to the leaking tube. The erosion can then lead to a larger tube rupture with an extensive leakage flow as result. The magnitude of a leakage can be varying. Leakages have in other models been simulated with flows from 0.2 kg/s [12] [13].

3 Early-warning

Leakage detection by analysing the mass balance on the steam side of the boiler is only possible when a large leakage flow is present. This due to the relatively low measurement precision on feed-water and steam-flow in comparison to a leakage flow.

A leakage can also be detected on the combustion side by indirect calculations of mass flows, but the precision is lower with this method compared to the method exploiting the mass balance on the steam side. By combining the two balances, indications on a leakage can be considered from both the steam side and the combustion side. This is exploited here to generate an early-warning to the process operator.

3.1 Bayesian networks

In this paper, we use a Bayesian network for diagnostics. A Bayesian network is defined from [7];

- a set of nodes representing variables,
- directed arcs between the nodes, and
- a probability table for each node.

If there is an arc from node A to node B, B is a child of A and A is a parent to B. The nodes are originally discrete, but handling of continuous variables is possible if they are not parents to discrete nodes. Discrete nodes have two or more states. A conditional probability table (CPT) describes the probability for the states given all possible combinations of the parent states. This means that a combination of many parent nodes with a lot of states gives a large CPT. An example of a CPT is shown in Figure 2, which is describing the conditional probabilities for node B depending on the states of node A and C. Continuous nodes have instead of discrete states a Gaussian distribution with a mean and standard deviation. Analogous to the CPT for a discrete node, the mean and standard deviation of the continuous node are computed as functions of its parents.

The nodes in a Bayesian network for diagnostics can be classified as fault nodes, intermediate nodes and symptom nodes, see the illustrating example in Figure 3. Input data are inserted as evidences of a node state in the symptom nodes. The network is then propagated, which means that the probabilities are computed for all nodes. After the propagation, the probabilities of the fault nodes form the output.

3.2 Calculation of mass flows

The mass-balance on the combustion side is defined as

$$\dot{m}_{fuel} + \dot{m}_{air} + \dot{m}_{soot-blow} = \dot{m}_{flue-gas} + \dot{m}_{smelt} , \quad (1)$$

where the sum of fuel flow (\dot{m}_{fuel}), air flow (\dot{m}_{air}) and soot-blow steam-flow ($\dot{m}_{soot-blow}$) equals to the sum of flue-gas flow ($\dot{m}_{flue-gas}$) and smelt flow (\dot{m}_{smelt}). On the steam-side, the mass balance is

$$\dot{m}_{feed-water} = \dot{m}_{hp-steam} + \dot{m}_{soot-blow} + \dot{m}_{blow-down} . \quad (2)$$

The feed-water flow ($\dot{m}_{feed-water}$) leaves the boiler as high pressure steam-flow ($\dot{m}_{hp-steam}$), soot-blow steam flow ($\dot{m}_{soot-blow}$) and blow-down flow ($\dot{m}_{blow-down}$).

Sensors measure all flows in and out from the boiler on the steam side, while only fuel is measured on the combustion side. This means that $\dot{m}_{flue-gas}$, \dot{m}_{air} and \dot{m}_{smelt} has to be computed by an indirect method.

By a combustion and smelt reduction calculation on the combustion side, it is possible to determine flue-gas (g), combustion-air (a) and smelt quantity (s) per mass unit of fuel. The calculation is based on the ultimate analysis of the fuel, reduction rate (R), fraction of sulphur-oxide, $[SO_2]_{flue-gas}$, in flue-gas and fraction of oxygen, $[O_2]_{flue-gas}$, in flue-gas [11].

Solid fuel fired boilers utilise an indirect combustion calculation to determine flow of fuel, flue-gas, air and slag. This method is also applicable on boilers where the fuel flow is measured, to get a calculated fuel mass-flow. With a measured thermal power (P_{th}), a known lower heating value (LHV) of the fuel and the boiler efficiency (η_{boiler}), the fuel mass-flow is calculated as

$$\dot{m}_{fuel} = \frac{P_{th}}{LHV \cdot \eta_{boiler}} \quad (3)$$

The boiler efficiency is calculated by determining the relative losses in the flue gas ($l_{flue-gas}$), unburnt in flue gas (l_{CO}) and heat in the slag (l_{slag}). Heat losses to the surroundings ($P_{radiation}$) are constant heat flows determined by the size and type of boiler. Nominal boiler power ($P_{nominal}$) is used to get the relative loss. The boiler efficiency is then given as

$$\eta_{boiler} = \frac{1 - l_{flue-gas} - l_{CO} - l_{slag}}{\frac{P_{radiation}}{P_{nominal}}}. \quad (4)$$

Recovery boilers are similar to conventional boilers in the sense that the smelt is equivalent to the slag. Slag losses are often negligible in conventional boilers since the ash content in the fuel is low. The flow of smelt in a recovery boiler is considerably higher and it leaves the boiler at a high temperature. Instead of an effective heating value, a net heat value (NHV) is used for recovery boilers in (3). The net heat value is the lower heating value for the black-liquor corrected with the energy to the reduction process [11],

$$NHV = LHV - \frac{78}{32} \cdot Dh_R \cdot C_S \cdot R, \quad (5)$$

where the heat for reduction (Dh_R) is 13.1 MJ/kg_{Na₂S} and C_S is the sulphur content. The efficiency of reduction (R) is expressed as [11],

$$R = \frac{Na_2S}{Na_2S + Na_2SO_4}. \quad (6)$$

Mass-flow of combustion-air (\dot{m}_{air}) are then calculated using the fuel mass-flow and air quantity from the combustion calculation,

$$\dot{m}_{air} = a \cdot \dot{m}_{fuel}. \quad (7)$$

In a similar way, the mass-flow of smelt (\dot{m}_{smelt}) is computed from smelt quantity and fuel mass-flow,

$$\dot{m}_{smelt} = s \cdot \dot{m}_{fuel} \cdot \quad (8)$$

In the current application, the combustion-air ratio (a) is about 4.1 kg air per kg fuel and the smelt ratio (s) is about 0.26 kg smelt per kg fuel.

The flue-gas flow is calculated using an energy balance over the economisers. Heat transferred ($P_{economiser}$) is determined on the feed-water side. Specific heat capacity ($c_{p, flue-gas}$) and temperature difference of the flue gas ($t_{flue-gas, in} - t_{flue-gas, out}$) gives the flue-gas mass-flow as

$$\dot{m}_{flue-gas} = \frac{P_{economiser}}{c_{p, flue-gas} \cdot (t_{flue-gas, in} - t_{flue-gas, out})} \cdot \quad (9)$$

The specific heat capacity is determined from flue gas temperature and composition.

3.3 Signal diagnostics

Uncertainty in process signals and calculated values are represented in the Bayesian network as a signal or calculation node. The node is connected as a child to the node representing the real value together with a node representing the signal or calculation status [14], see Figure 4.

The signal status node has the states "normal" and "faulty". If the state of the signal status node is "normal", the process signal node is Gaussian distributed with a mean of the real value and a standard deviation representing the measurement precision. When the signal status is "faulty", the standard deviation in the signal node is changed to a significant larger value, covering the entire signal range. For the current process signals it was found suitable to increase the standard deviation with a factor of ten.

3.4 Mass balance in Bayesian network

The mass balances on both the combustion side (1) and the steam side (2) of the boiler are defined in a Bayesian network. All mass flows are represented with continuous nodes and forms a structure of intermediate nodes.

A discrete node with the states "none" and "leakage" connects the two mass balances, see Figure 5. The upper part is representing the steam-side balance and the lower part the combustion side balance. The soot-blow flow is also connecting the two mass balances. When the state of leakage is "none", the node has no impact on flue-gas and high-pressure steam. When the state is "leakage", a flow is added to the mean value of the flue-gas and subtracted from the mean value of high-pressure steam.

In particular (see Figure 5), equation (1) is modelled in the node $\dot{m}_{flue-gas}$ and equation (2) is modelled in the node $\dot{m}_{hp-steam}$. Equations (3) - (9) are parts of the nodes representing calculated values. For all nodes representing signals and calculated values, the status handling described in Section 3.3 is applied.

All mass-flow nodes are defined as intermediate nodes, see Figure 3. The signals and calculated values are interpreted as symptoms. Leakage and status nodes are defined as fault nodes. If the signal and calculated values are added into the network, and the network is propagated, the probabilities of leakage and signal status are obtained. The leakage probability is then used to assess if there is a possible leakage or not.

If available, other observations such as acoustic, blow-down analysing or image leak detection can be inserted as nodes connected to the leakage node. The studied recovery boiler has none of these leak detection systems installed.

4 Results

The Bayesian network defined in Section 3.4 is applied to process history data from a recovery boiler at Vallviks Bruk, Sweden. The data is from operation at varying load conditions during a time period of three months.

Three different cases have been evaluated;

- normal operation,
- test with simulated leakage, and
- test with fault in signals.

Since data from operation with a leaking boiler is not available, a simulation model has been developed. The software Prosim [15] is used to build a model with possibility to simulate leakage in four components; furnace wall, super-heater, convection section and economiser. Prosim is a thermal power plant simulator. The software includes

general modules for conventional thermal power plants and specific modules for recovery burning.

4.1 Normal operation

A test with data from normal process operation is verifying the indirect calculation of liquor flow, etc. The results are shown in Figure 6. Case number 1-29 are from normal load operation and case number 30-34 are from low load operation.

The leakage probability is below 7 % during normal load conditions. In the low load cases, the probability is between 13 and 18 %. This indicates that the indirect fuel mass flow calculation is not enough accurate under low load conditions.

4.2 Simulated leakage

Real plant operation data are used as input to the model and a leakage is simulated. Output from the model is used to determine the probabilities of leakage for a leakage flow of 0.25, 0.5 and 1 kg/s, respectively. Figure 7 depicts the results.

A calculation without leakage gives a leakage probability of about 5 %. Simulation with 0.25 kg/s leakage results in a significant leakage probability for all components (above 20 %). The probabilities increase when the leakage flow increases to 0.5 kg/s. If a leakage of 1 kg/s is simulated in the economiser or convection section, the leakage probabilities are continuing to increase. A simulated leakage of 1 kg/s in the furnace or super-heater is resulting in a decreasing leakage probability. The reason for this may be

that the network finds it more probable that a signal is faulty when the leakage is in the furnace or super-heater.

4.3 *Fault in signals*

A bias is added to the process signals one at the time to simulate a fault in the signal, see the results in Figure 8.

The feed-water flow and black-liquor dry substance is the most important signals. A fault in one of these signals can make the early-warning system indicating leakage probabilities over 15 % and thereby generating false warnings. Faults in the other signals result in a leakage probability below 10 %.

The performance of the system is shown in Table 1, where the average leakage probability of normal operation is compared to cases with 0.25 kg/s leakage flow and cases with signal faults of ± 2 %. In the table, we see that the leakage probability is below 15 % during normal operation for both normal and low load. A leakage of 0.25 kg/s results in a leakage probability of about 25-30 %. A signal fault may cause a high leakage probability when the current sensor is measuring feed-water flow or black-liquor dry substance.

5 **Conclusions**

Early-warning for fault detection in a recovery boiler was considered. A methodology based on mass balances in a Bayesian network was developed. The early-warning

system was tested on real plant data from normal operation combined with simulations to derive leakage cases.

The results show that normal load operation gives a leakage probability below 10 %. A simulated leakage of 0.25 kg/s gives a leakage probability of about 25 %. This means, during normal operation, that an early-warning can be generated when the leakage probability exceeds 10 % without generating false alarms. A fault in measurement signals can cause a leakage probability of more than 10 %, but only when the relative fault in the signal is large. The detection level and reliability are depending on the measurements on feed-water flow and black-liquor dry substance.

A limit for early-warning when the leakage probability exceeds 20 % can help the operator to be aware of that something is wrong, possibly a leak in the boiler. Further investigations can then be done to assess if it is a leakage or not. The ability to combine the mass-flow balance with other leakage detection methods in the Bayesian network is a possible way to further improve the warning sensitivity and reliability.

The method with mass balances formulated in a Bayesian network is an efficient tool to analyse the balances and warn the process operator if the leakage probability becomes too high. Integrating signal diagnosis in the network structure makes the system robust to minor signal faults. Early-warning for a recovery boiler is one application in which the method is applicable, but it can also be generalized to other applications, e.g. screen clogging, hang-ups or sintering.

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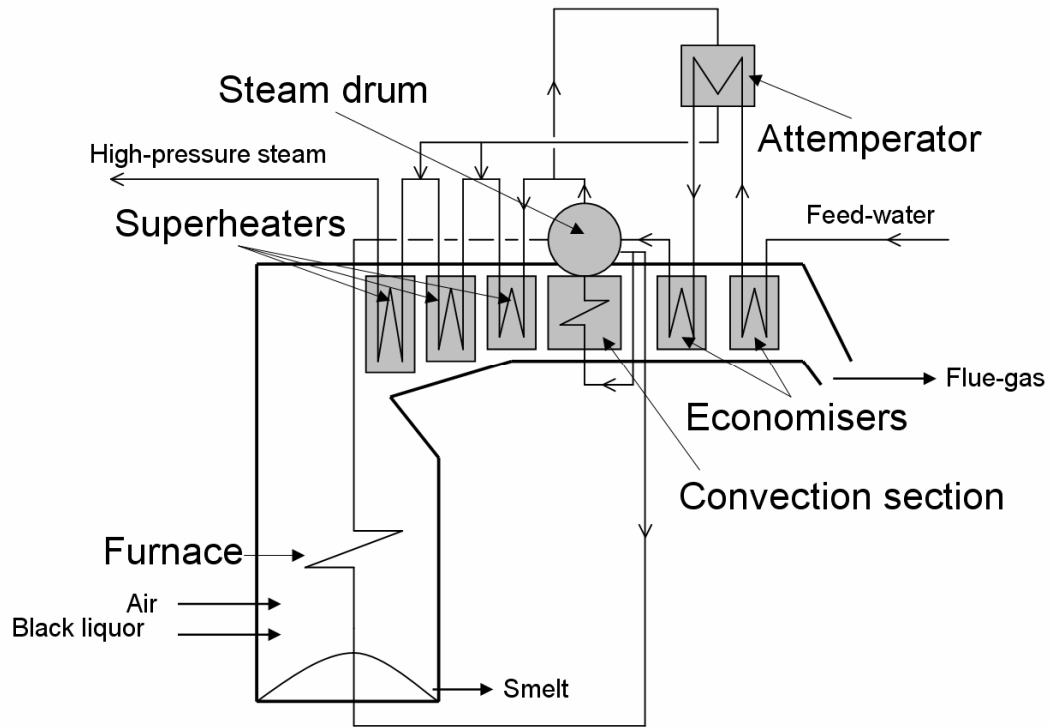


Figure 1. Recovery boiler.

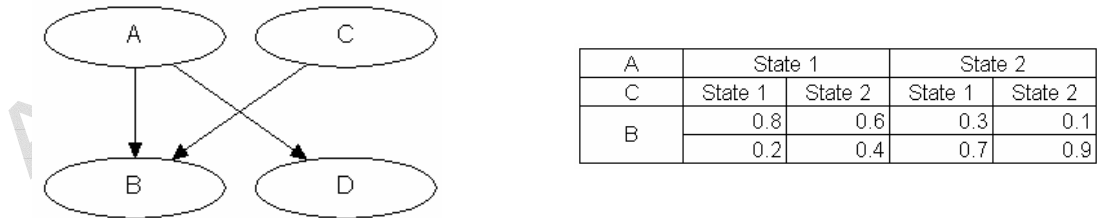


Figure 2. Bayesian network and the conditional probability table for node B.

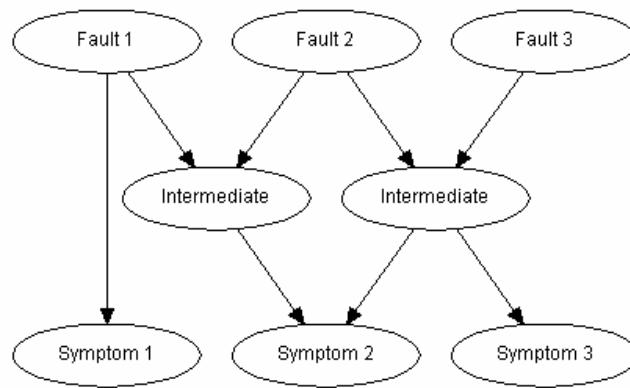


Figure 3. Principal construction of Bayesian network for diagnostics.

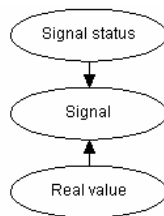


Figure 4. Real value node and signal status node connected to process signal node.

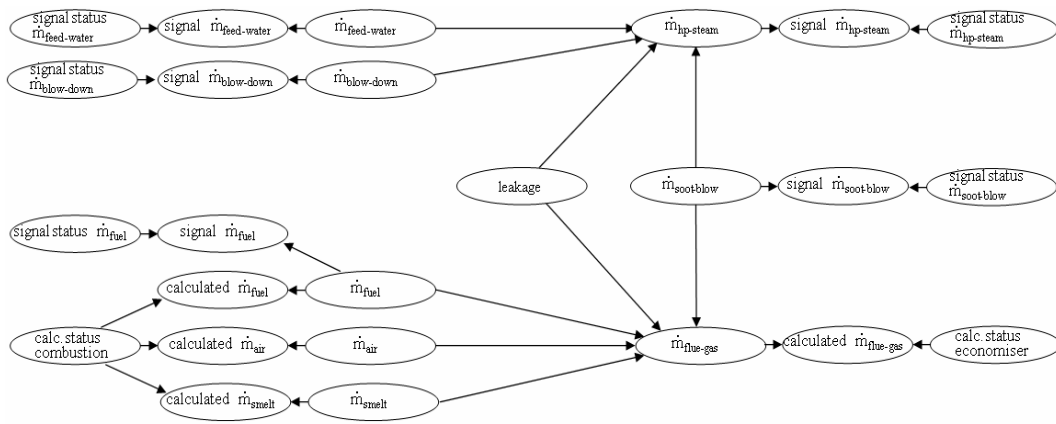


Figure 5. Bayesian network for diagnosis of a recovery boiler.

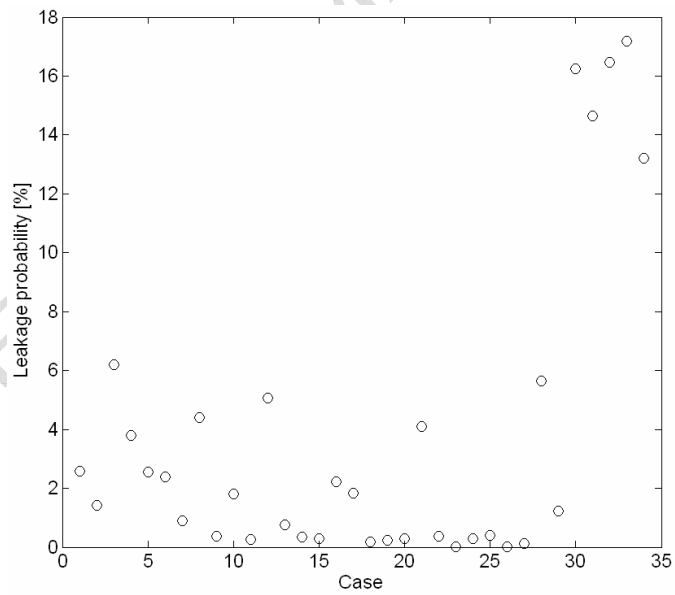


Figure 6. Test with data from real cases.

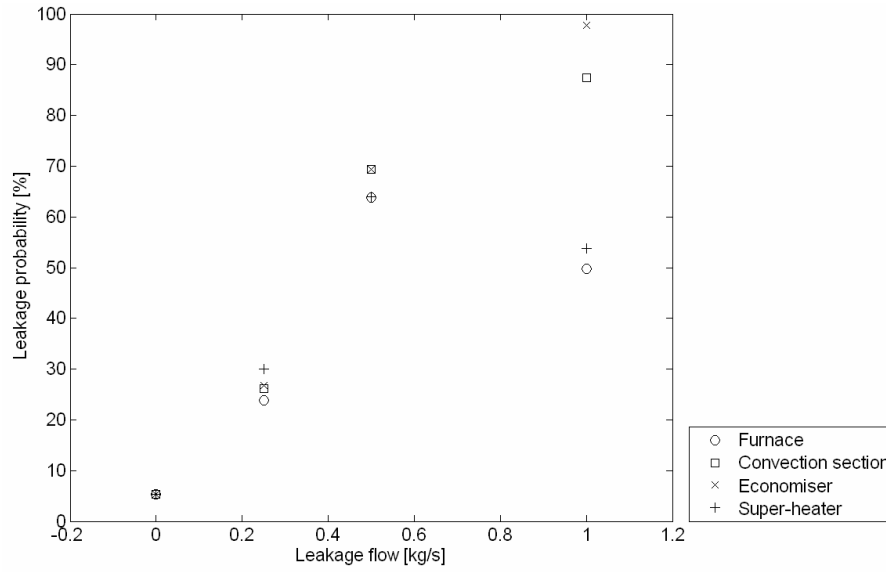


Figure 7. Test with simulated leakage flows in four positions.

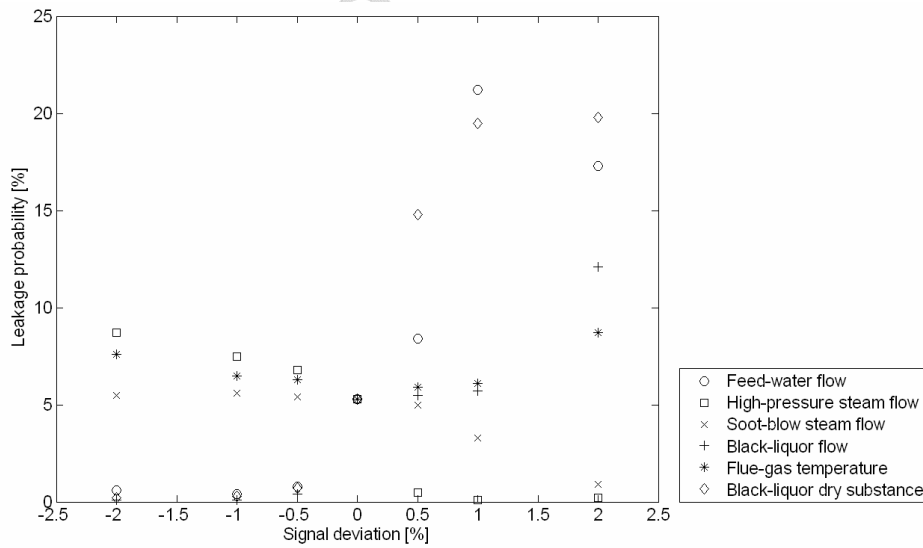


Figure 8. Test with simulated fault in signals.

Tested case	Case status	Leakage probability [%]
Normal operation	Normal load	1.61
	Low load	12.1
Leakage	Furnace	23.8
	Convection section	26.2
	Economiser	26.7
	Super-heater	30.1
Signal fault	Feed-water flow	21.2
	High-pressure steam flow	8.71
	Soot-blow steam flow	5.63
	Flue-gas temperature	12.1
	Black-liquor flow	8.69
	Black-liquor dry substance	19.8

Table 1. Comparison of results.