Multiple faults detection and isolation approach applied to a kraft recovery boiler

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ABSTRACT: Recovery boilers play a key role in chemical pulp mills. Early detection of defects, such as water leaks, in a recovery boiler is critical to the prevention of explosions, which can occur when water reaches the molten smelt bed of the boiler. Early detection is difficult to achieve because of the complexity and the multitude of recovery boiler operating parameters. Multiple faults can occur in multiple components of the boiler simultaneously, and an efficient and robust fault isolation method is needed. In this paper, we present a new fault detection and isolation scheme for multiple faults. The proposed approach is based on principal component analysis (PCA), a popular fault detection technique. For fault detection, the Mahalanobis distance with an exponentially weighted moving average filter to reduce the false alarm rate is used. This filter is used to adapt the sensitivity of the fault detection scheme versus false alarm rate. For fault isolation, the reconstruction-based contribution is used. To avoid a combinatorial excess of faulty scenarios related to multiple faults, an iterative approach is used. This new method was validated using real data from a pulp and paper mill in Canada. The results demonstrate that the proposed method can effectively detect sensor faults and water leakage.

Application: This paper represents a major step toward development of online monitoring and detection of water leaks in recovery boilers.

Principal component analysis (PCA) has been applied successfully for the monitoring of complex systems [1-3]. It enables the determination of the redundancy relationships, which are then used to detect and isolate faults. It transforms large data to a smaller set of variables, which are linear combinations of the original variables, while retaining as much information as possible. In the classical approach, the principal components correspond to the directions in which the projected observations have the largest variance. The principal components correspond to the eigenvectors of the empirical covariance matrix. From a regression point of view, PCA also constructs the optimal orthogonal linear projections (in terms of mean squared error) from the eigenvectors of the data covariance matrix. The performance of a PCA model is then based on the accurate estimation of the covariance matrix from the data, which is very sensitive to abnormal observations. In general, most of the training data set is associated with normal operating conditions. The PCA model so obtained describes normal process behavior, and unusual events are then detected by referencing the observed behavior against this model.

Our work is devoted to the problem of multiple-fault detection and isolation using reconstruction-based contribution. The variable reconstruction approach estimates a set of variables using the PCA model from the remaining variables. If the faulty variables are reconstructed, the fault effect is removed, which is useful for fault isolation. To avoid the combinatorial multiplication of faulty scenarios related to multiple faults, an iterative approach is used. A short presentation of principal component analysis and its use for fault detection and isolation is first presented. Then, its successful application to multiple fault detection and isolation of recovery boilers is explained.

FAULT DETECTION AND ISOLATION USING PCA

PCA modeling

Let us consider a data matrix $X \in \Re^{N\times m}$ with row vector x^T_i, $\in \Re^m$, $(i = 1, \ldots, N)$, which gathers N measurements collected on the m system variables. In the classic PCA case, data are supposed to be collected on a system that is in normal process operation. PCA determines an optimal linear transformation (with respect to a variance criterion) of the data matrix X:

$$t = P^T x \quad \text{and} \quad x = P\,t \tag{1}$$

where $t \in \Re^m$ is the principal component vector and $P = [p_1 \ldots p_m] \in \Re^{m\times m}$ is the matrix of the eigenvectors associated to the eigenvalues of the covariance matrix Σ of X:

$$\Sigma = P\Lambda P^T \quad \text{with} \quad PP^T = P^T P = I_m \tag{2}$$

where $\Lambda = diag(\lambda_1 \ldots \lambda_m)$ is a diagonal matrix with diagonal elements in decreasing magnitude order.

Once the component number ℓ to retain is determined, the eigenvalue and eigenvector matrices are split as follows:

$$P = \begin{pmatrix} \hat{P} & \tilde{P} \end{pmatrix} \quad \hat{P} \in \Re^{m\times\ell}, \tilde{P} \in \Re^{m\times(m-\ell)} \tag{3}$$

$$\Lambda = \begin{pmatrix} \hat{\Lambda} & 0 \\ 0 & \tilde{\Lambda} \end{pmatrix} \quad \hat{\Lambda} \in \Re^{\ell\times\ell}, \tilde{\Lambda} \in \Re^{(m-\ell)\times(m-\ell)} \tag{4}$$

From Eq. (1), the measurement vector x is decomposed into an estimated vector $\hat{x}$ and an error vector $\tilde{x}$, which are, respectively, the projections of x onto the principal and residual spaces:

$$x = \hat{x} + \tilde{x} \tag{5}$$

with

$$\hat{x} = C_\ell x \tag{6}$$

$$\tilde{x} = (I - C_\ell)x \tag{7}$$

where the matrix $C_\ell = \hat{P}\hat{P}^T$ is not equal to the identity matrix, except in the case where $\ell = m$.

Fault detection using PCA

Once the PCA is obtained, the fault detection indices *SPE*, *SWE*, T^2, Φ[5], or D (Mahalanobis distance) are generally used to detect faults [6]. *SPE* (Eq. [8]) and *SWE* (Eq. [9]) are used to detect fault in the residual space. T^2 (Eq. [10]) is used to detect fault in principal space. Finally, Φ (Eq. [11]) and D (Eq. [12]) are used to detect fault in principal and residual space. Φ is defined as the sum of *SPE* and T^2. D is defined as the sum of *SWE* and T^2.

$$SPE = x^T (I - C_\ell)x \tag{8}$$

$$SWE = x^T \tilde{P}\tilde{\Lambda}^{-1}\tilde{P}^T x \tag{9}$$

$$T^2 = x^T \hat{P}\hat{\Lambda}^{-1}\hat{P}^T x \tag{10}$$

$$\Phi = \frac{SPE}{\delta_{SPE}} + \frac{T^2}{\delta_{T^2}} \tag{11}$$

with δ_{SPE} a control limit of *SPE* and δ_{T^2} a control limit of T^2.

$$D = SWE + T^2 \tag{12}$$

The index *SWE* may be more powerful than the index *SPE* because taking into account the residual variances can enable the detection of faults that cannot be detected using *SPE* [7]. For this reason, the indicator D is used for fault detection in the following:

$$D = x^T M x \tag{13}$$

where

$$M = P\Lambda^{-1}P^T \tag{14}$$

A fault is detected if the observation is over a detection threshold. One drawback of this approach is the rate of false alarm. To reduce the false alarm rate and the noise influence, an exponentially weighted moving average (EWMA) filter is used. The EWMA is a statistic for monitoring the process that averages the data in a way that gives less and less weight to data as they are further removed in time. This indicator is defined as follows:

$$D_{ewma}(k) = \varepsilon D(k) + (1-\varepsilon)D_{ewma}(k-1) \tag{15}$$

where $\varepsilon \in [0\ 1]$ is a constant that determines the depth of memory of the EWMA. By the choice of this constant, the EWMA filter can be made sensitive to a small or gradual drift in the process.

A fault is detected at time k if the detection indicator (Eq. [15]) is above a threshold:

$$D_{ewma}(k) > \delta^2 \tag{16}$$

where δ^2 is the detection threshold defined by Eq. (17).

Using a theoretical threshold may cause high rates of false alarms resulting from temporary process disturbances and approximately normally distributed noise. In the proposed method, an alarm arises when the detection indicator times exceed a given level. In other words, the proposed method declares an alarm condition only in the presence of persistent faults or disturbances, but not under common disturbances and noise. Therefore, the false alarm rate is significantly reduced. This threshold has been defined by experimentation based on the following formula:

$$\delta^2 = \overline{D}_{ewma} + 3\hat{\sigma}_D + D_{\exp} \tag{17}$$

where $\overline{D}_{ewma}$ is the average value of $D_{ewma}(k)$, $\hat{\sigma}_D$ is the standard deviation of $D_{ewma}(k)$, and $D_{\exp}$ is a modification factor that depends on the real process conditions of noises and disturbance.

Fault isolation using PCA

Although the contribution plot approach is popular and has been adopted by many authors as the default method, there has been no rigorous analysis of diagnosability or guarantee of correct diagnosis reported in the literature. There are, however, reports that contribution plots involve fault "smearing" that can lead to misdiagnosis [6,8]. Yoon and MacGregor [9] reported an example in which traditional contribution plots failed to give correct diagnosis results.

In the following discussion, the reconstruction-based contribution (RBC) proposed by Alcala and Qin [10] is used. The method used to reconstruct a set of variables is presented first. Then, the generation of structured residuals from reconstructed variables is described. Finally, a hierarchical method to isolate multiple faults is proposed.

Reconstruction of a variable subset R involves estimating the vector $\hat{x}_R$ from the remaining variables using the PCA model. Let us define the matrix $\Xi_R \in \Re^{m\times r}$ of the reconstruction directions. This matrix is orthonormal and is only built with 0 and 1, where 1 indicates the reconstructed variables and 0 is used for the other variables. For example, to reconstruct variables $R = \{2 \;\; 4\}$ among five variables, matrix Ξ_R is formed as follows:

$$\Xi_R = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}^T$$

Based on minimization of D_R, the reconstruction $\hat{x}_R$ of the vector x is given by:

$$\hat{x}_R = x - \Xi_R f_R \tag{18}$$

where

$$f_R = \left(\Xi_R^T M \Xi_R\right)^{-1} \Xi_R^T M\, x \tag{19}$$

$$M = P\Lambda P^T \tag{20}$$

The RBC of variable x to the fault detection index RBC_R^D is the amount of reconstruction along the direction Ξ_R, which can be expressed as follows:

$$RBC_R^D = \left\|\Xi_R f_R\right\|_M^2 \tag{21}$$

$$RBC_R^D = \left\|\Xi_R\left(\Xi_R^T M \Xi_R\right)^{-1}\Xi_R^T M\, x\right\|_M^2 \tag{22}$$

In the presence of faults on a subset F of variables, the measurement vector is written as:

$$x = x^* + \Xi_F d \tag{23}$$

where x^* is the fault-free measurement vector, d is the vector of fault magnitude, and Ξ_F is the matrix of fault direction, which is unknown.

Then, the residual (Eq. [22]) is:

$$RBC_{R\neq F}^D = \left\|\Gamma x^* + \Gamma \Xi_F d\right\|_M^2 \tag{24}$$

$$RBC_{R=F}^D = \left\|\Gamma x^* + \Xi_R d\right\|_M^2 \tag{25}$$

where

$$\Gamma = \Xi_R\left(\Xi_R^T M \Xi_R\right)^{-1}\Xi_R^T M$$

Multiple faults are isolated when the contributions are under the detection threshold, defined as follows:

$$\delta_R^2 = g_R \chi_\alpha^2\left(h_R\right) \tag{26}$$

where

$$g_R = \frac{tr\left\{\Sigma M \Xi_R\left(\Xi_R^T M \Xi_R\right)^{-1}\Xi_R^T M\right\}^2}{tr\left\{\Sigma M \Xi_R\left(\Xi_R^T M \Xi_R\right)^{-1}\Xi_R^T M\right\}} \tag{27}$$

$$h_R = \frac{\left[tr\left\{\Sigma M \Xi_R\left(\Xi_R^T M \Xi_R\right)^{-1}\Xi_R^T M\right\}\right]^2}{tr\left\{\Sigma M \Xi_R\left(\Xi_R^T M \Xi_R\right)^{-1}\Xi_R^T M\right\}^2} \tag{28}$$

As for detection, to ensure the isolation of the fault, an average on a window is used to calculate the RBC fault indicator. To isolate a multiple fault, an iterative approach is used. This approach is explained in the following algorithm:

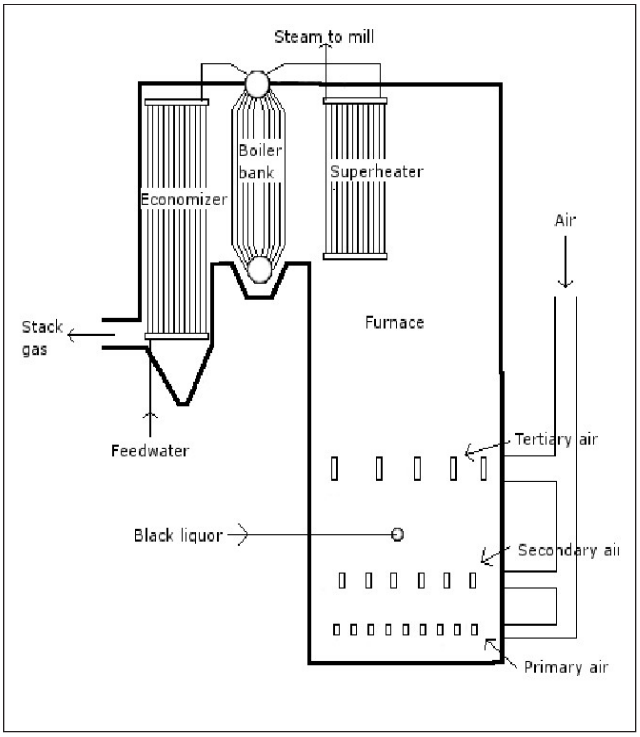
1. Compute the detection indicator $D_{ewma}(k)$
2. **if** $D_{ewma}(k) > \delta^2$ (Eq. [17]) **then**
3. Compute the contribution of each variable
4. Find the faulty variable (with the highest contribution)
5. **while** $RBC_R^D < \delta^2_R$ (Eq. [26]) **do**
6. Compute the contribution of the combination of the faulty variable and the others
7. Find the faulty variables (with the highest contribution)
8. **end while**
9. **end if**

APPLICATION

Process description

The following case study applies to a chemical recovery boiler at a kraft pulp mill in Canada. One of the goals is to produce high pressure steam for process heat needs. The fuel is the residual liquor originating from the cooking stage of wood chips. The recovery boiler has two sections: a furnace, where the combustion of the liquor and the recovery of specific inorganic compounds occur, and a convective heat transfer section, as in power boilers, co-responsible for transforming fresh water into high pressure steam. For that, this section has a series of heat exchangers (super-heater, boiler bank, and economizer), as shown in **Fig. 1**.

The recovery boiler plays a central role in chemical pulp mills. The boiler produces energy for the mill. The spent liquor from the digesting plant goes first to the evaporation plant, where the dry solids content of the liquor is increased. Then the evaporated liquor comes to the recovery boiler plant. Fly ash from electrostatic precipitators is mixed into the black liquor. After additional concentration of the black liquor in the evaporation plant, the liquor is burned in the combustion chamber of the boiler. Feed water is pumped first to the economizers, where it is preheated by flue gas. The water then enters the water circulation system of the boiler. During combustion of the black liquor, high pressure steam is generated



1. Recovery boiler layout.

in the boiler. The superheated steam flows from boiler to a turbine generator plant. The hot smelt flow of the regenerated chemicals is drained from the furnace floor to the dissolving tank. The chemicals are dissolved into weak white liquor and returned to a recausticizing plant for further processing.

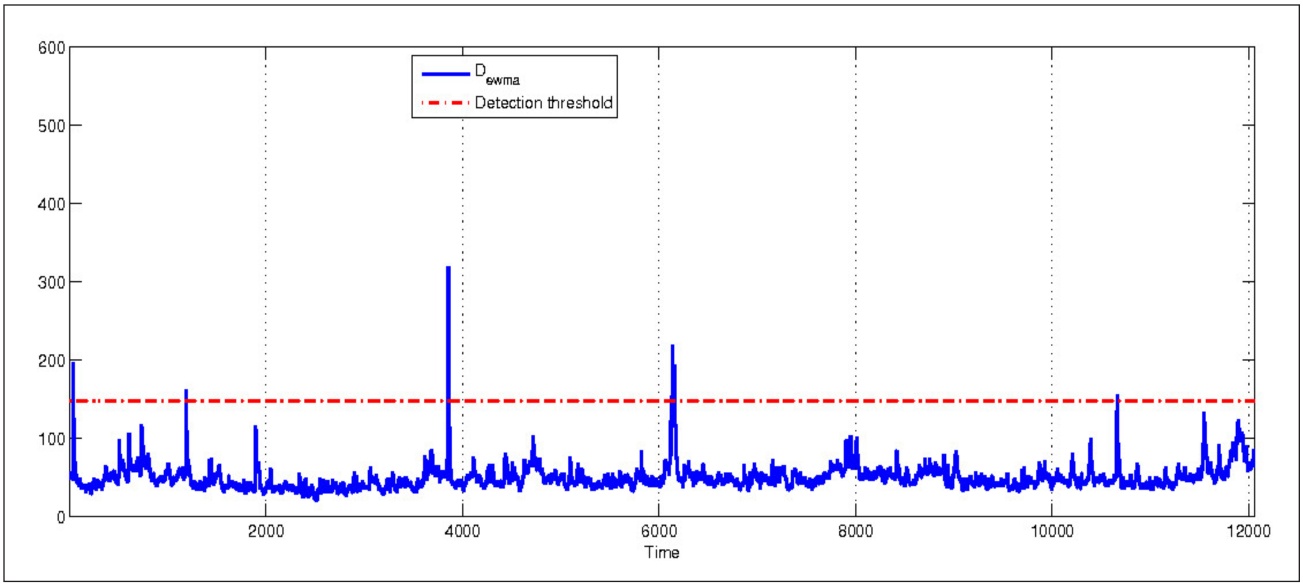
Water leaks in heat exchanger tubes during boiler operation are a great concern because of the potential for water-smelt contact. Smelt is a pool of melted sodium-based compounds over the furnace floor, with a surface temperature of about 850°C (1560°F), which is more than enough to cause an explosion in case of contact with water. These leaks mostly result from aging, thermal stress, weld failures, corrosion, fatigue, and erosion of tubes. Common mill practices are still based on operator actions in response to information obtained through patrols around the boiler and monitoring of key variables (mainly the fuel gas temperature along the heat exchange section). This deterioration invariably leads to leaks, which not only reduce the amount of steam generated, but also cause a variety of problems in the normal plant operation. Serious leakage can necessitate a boiler shutdown. Similarly, steam leaks are undesirable and may lead to a series of problems affecting normal operation. Thus, in cases of boiler water tube leakage or steam leakage, it is important to detect the problem as early as possible so that repair and shutdown, if necessary, can be scheduled [4]. Moreover, other faults (e.g., sensor faults) can affect the recovery boiler operation and control.

Data selection and retrieval

The number of variables measured on-line in a pulp and paper mill is substantial. For the recovery boiler in this study, 100 tags were selected, with a sampling interval of 10 min.

One of the problems associated with the detection of faults in industrial systems is that plant data recorded on-site is always polluted by noise and disturbances. When measurement noise and disturbances exist in an industrial process, false alarms may be produced when a PCA-based fault detection technique is used. Thus, a suitable data pre-processing scheme is necessary to improve the fault detection performance. For the pre-processing in this study, an in-house software (EXPLORE) was used to remove the abnormal data (e.g., from the startup and shutdown periods).

All data observations relative to the boiler are taken into



2. Detection indicator** D_{ewma} **on identification data.

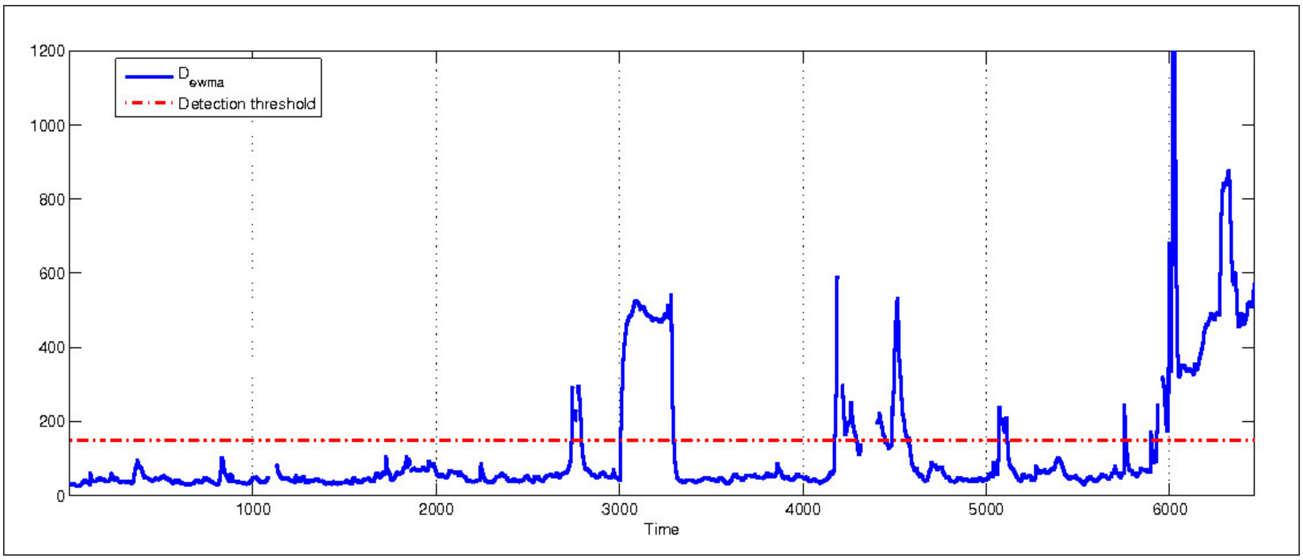
account to construct a PCA model (i.e., black liquor flow, density, pressure, air flow, and temperature). The first step to construct the PCA model is to select data associated with normal operating conditions. In this case, 106 variables were used, and 7000 observations, with a sampling time of 10 min. **Figure 2** shows the value of the detection indicator D_{ewma}. Data were used to determine the detection threshold empirically (Eq. [17]). The parameter D_{exp} was selected experimentally by trading off how long the system can continue to operate if a fault occurs versus an increased false alarm rate caused by persistent disturbances.

Fault detection and isolation

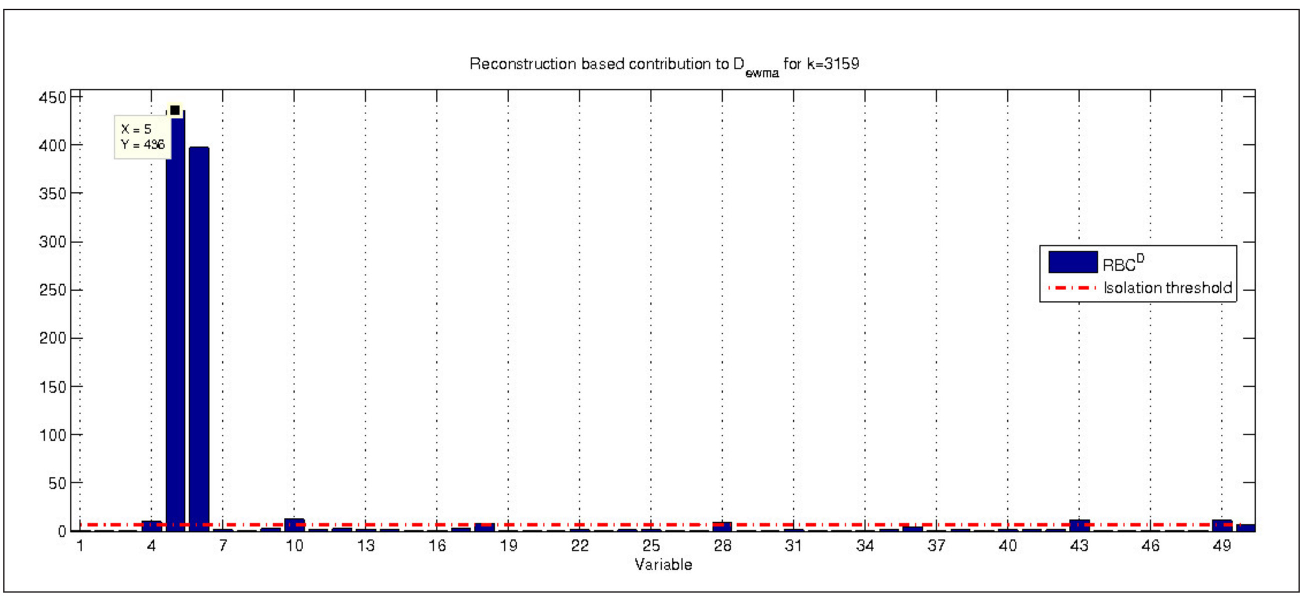
New data were collected from the recovery boiler. **Figure 3** shows the detection indicator. On this graphic, the horizontal line represents the detection threshold. If the indicator is above this line, a fault is detected. Once a fault is detected, it is possible to isolate it.

To illustrate our approach to isolate multiple faults, two different cases are considered. The first, at time k = 3159, the second, at k = 6079. In each case, the procedure presented in the algorithm is applied.

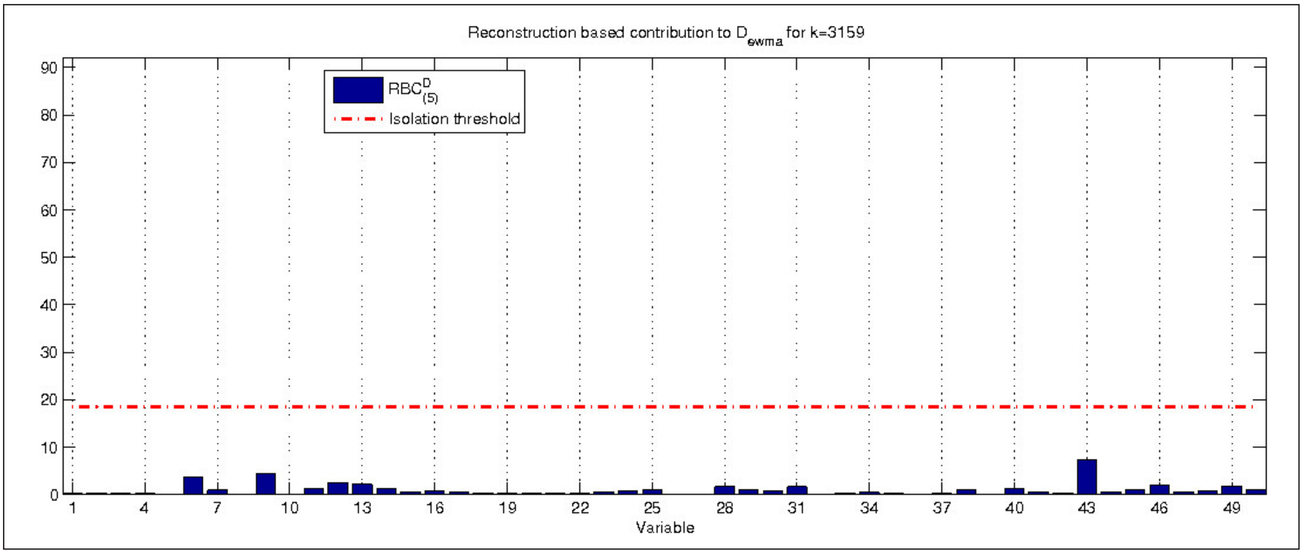
1) Case 1: k = 3159. For the first case, the contribution values were calculated (**Fig. 4**). Variable 5 has the highest contribution. We then calculated the contribution of the combination of this variable (variable 5) with the others, but all the contributions are under the detection threshold (**Fig. 5**). In this case, there is only one faulty variable (variable 5). **Figure 6** shows the value of this variable. At this time, variable 5 is faulty (sensor fault).



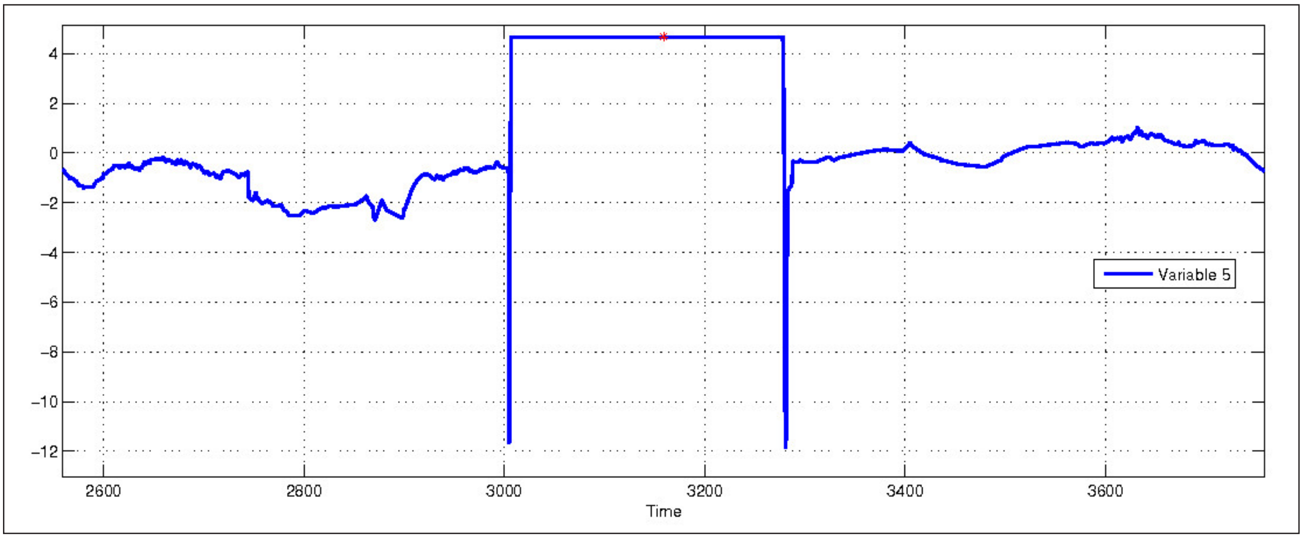
3. Detection indicator **D_{ewma}** ***on validation data.***



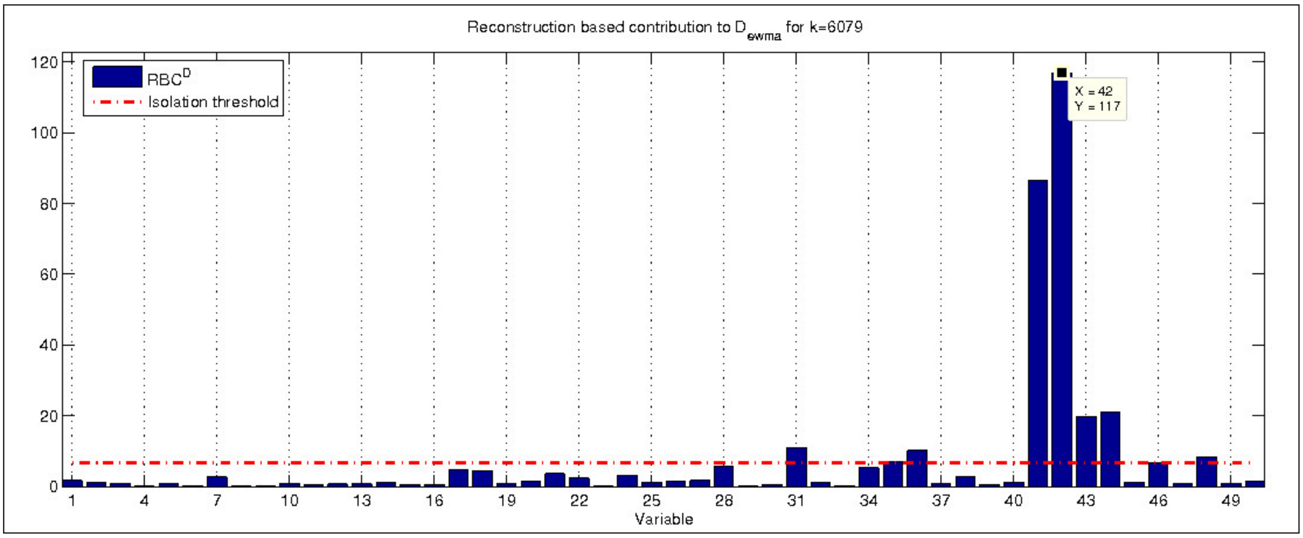
4. **RBC^D** ***at k = 3159.***



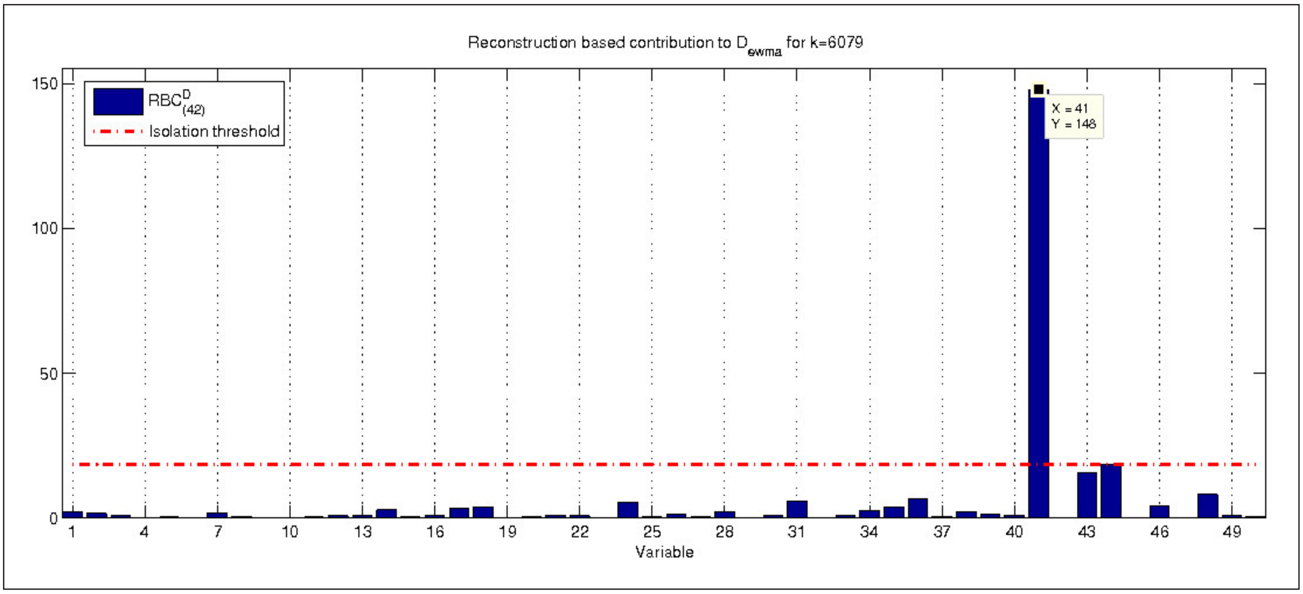
5. $RBC^D_{(5)}$ *at k = 3159.*



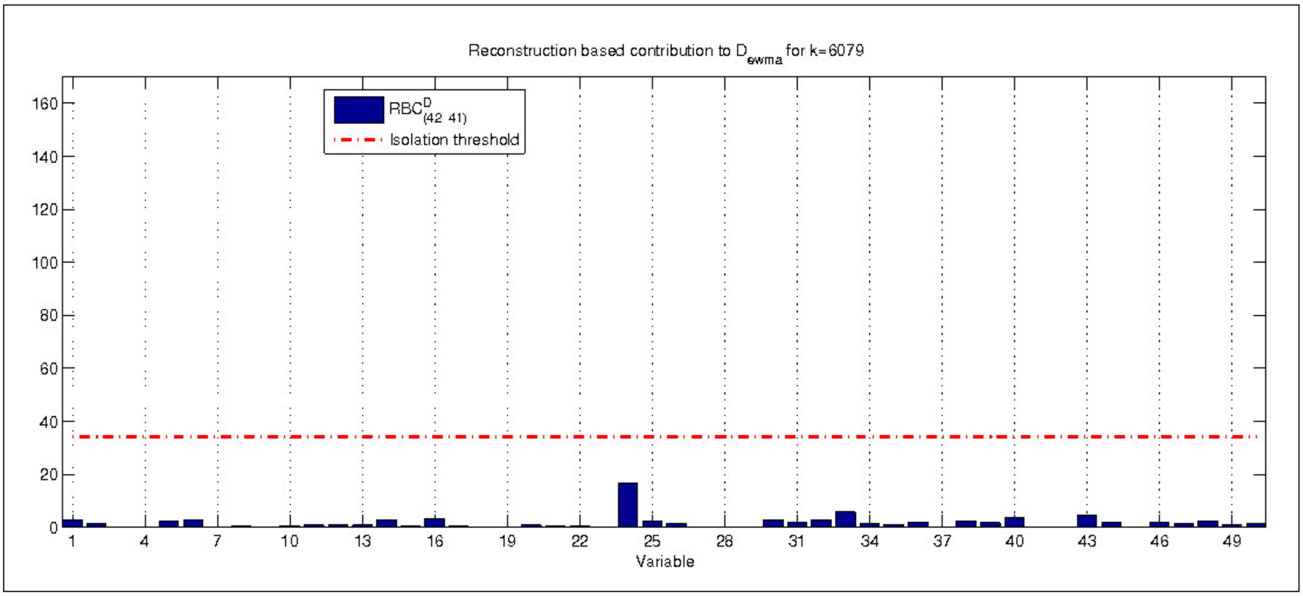
6. Faulty variable 5 at k = 3159.



7. RBC^D *at k = 6079.*



8. **$RBC^{D}_{(42)}$** ***at k = 6079.***



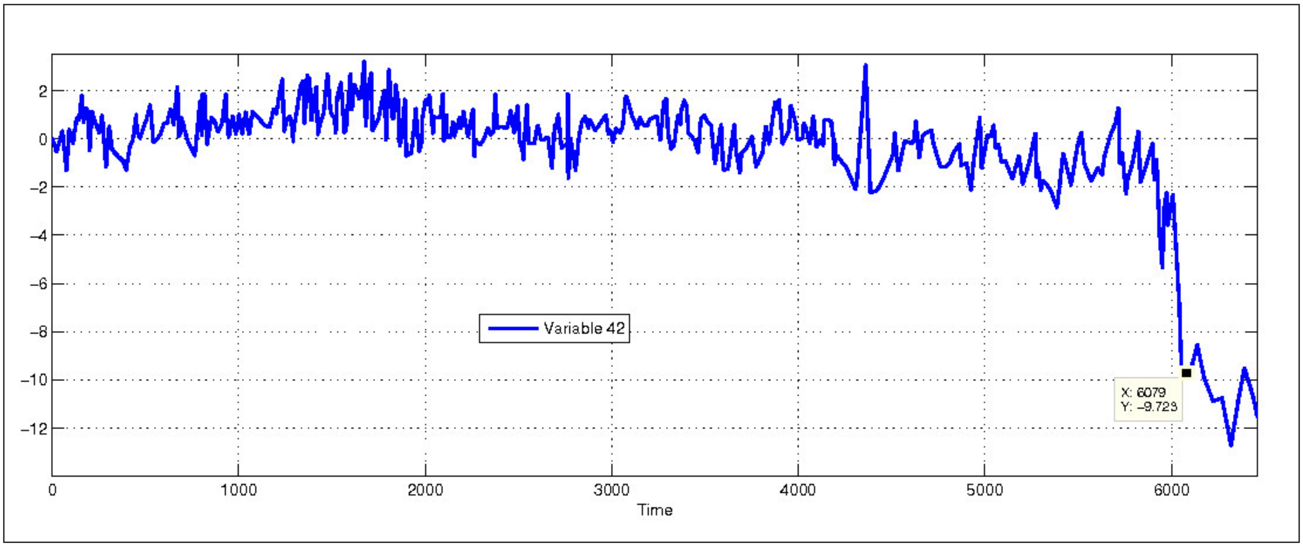
9. **$RBC^{D}_{(42,41)}$** ***at k = 6079.***

2) Case 2: k = 6079. For the second case, the contribution values were calculated (**Fig. 7**). Variable 42 has the highest contribution. We then calculated the contribution of the combination of this variable (variable 42) with the others. **Figure 8** shows the results, which indicate that variable 41 is also faulty. Then the contribution values of the combination of these variables (variables 41 and 42) and the others were calculated, but all the contributions were under the detection threshold (**Fig. 9**). In this case, there are only two faulty variables (variables 41 and 42), as shown in **Figs. 10** and **11**. These variables indicate the temperature of the water in the economizer tubes. In fact, one of the effects of a leak is a diminution of the water temperature in the tube. At this time, a leak in the boiler's economizer occurs. This leak was confirmed by the operators of the boiler.

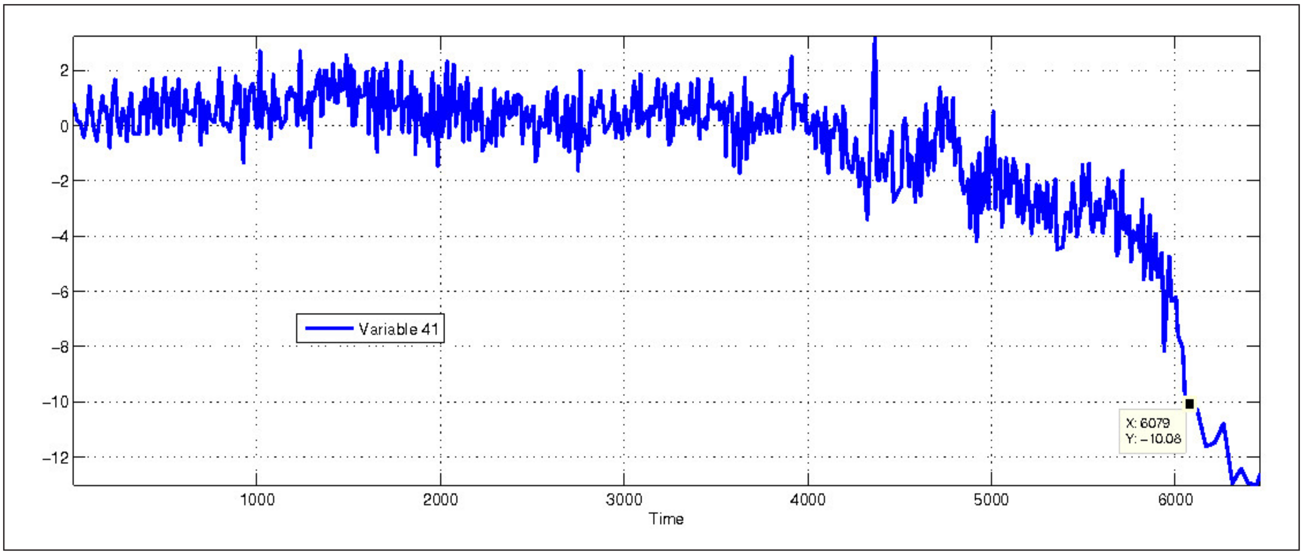
CONCLUSION

The proposed fault detection and isolation approach based on PCA successfully isolated multiple faults in an industrial recovery boiler. Fault detection indices using the Mahalanobis distance with an EWMA filter also proved efficient to reduce the false alarm rate. For fault isolation, reconstruction-based contribution allows the avoidance of the combinatorial excess of faulty scenarios related to multiple faults using an iterative approach.

This approach represents a major step toward develop-



10. Faulty variable 42 at k = 6079.



10. Faulty variable 43 at k = 6079.

ment of online monitoring for recovery boilers. The next step is to build a fault database in which all possible faults and root causes will be populated and used for the development of a more comprehensive fault isolation system. **TJ**

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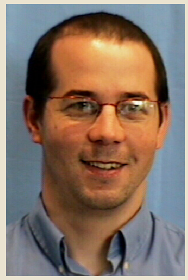

Tharrault

Amazouz

We chose this topic to research to fulfill a need of one of our industrial partners. Our organization worked on knowledge extraction from data to support process operators in their daily work. The extracted knowledge is used to inform operators on the state of the process and to flag abnormal situations, aka faults. The next step was to help operators identify variables responsible for faults.

The most difficult aspect of this work was the fault isolation when multiple faults occur at the same time. This difficulty was resolved by using the reconstruction-based contribution (RBC) of faults. This research allowed us to demonstrate that a simple method (principal component analysis) is able to correctly isolate faults.

This approach can allow mills to get value from their already existing historical data and to better operate and manage abnormal situations in recovery boilers or any other type of equipment and processes.

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