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Title: **Improvement of an Adaptive Threshold Technique for Fault Detection in a Cement Rotary Kiln**

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Improvement of an Adaptive Threshold Technique for Fault Detection in a Cement Rotary Kiln

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Abstract: In this paper, we suggest to use a two-dimensional plot characterizing the statistical variability of a large-sized multivariate data. This graphical representation is based on the mean and variance values. The two statistical parameters plot is used to assess fault detection performances in a cement rotary kiln system. The adaptive threshold technique is shown to result in more accurate and reliable detection. The threshold is established through several repeated experiments under the healthy mode with the same operating conditions. An adequate statistical test is used to examine the validity of the adaptive threshold estimation approach. At each mean's subinterval for all experiments, a confidence interval closely linked to the distribution frequencies of the variance as a random variable is obtained. In addition, several significance levels are considered to show the performances of the proposed adaptive thresholding technique compared to the limitations of the fixed threshold through the rate of false alarms. Two different experimental faults are considered to demonstrate the effectiveness and accuracy of the adaptive threshold in terms of no false alarms and negligibly small missed alarms in comparison to the fixed threshold technique.

Keywords: Fault detection, adaptive threshold, large sized multivariate data, mean, variance, cement rotary kiln.

1. INTRODUCTION

During the last two decades, substantial research has been conducted in developing enhanced techniques for fault detection and diagnosis in industrial processes in general, and cement production in particular. The objective being to predict fault occurrences and identify their causes against which appropriate decisions are taken [1-3]. In the cement manufacturing process, the rotary kiln is crucial and any fault that occurs in it will have immediate adverse economical and ecological impact in addition to medium to long-term public health issues.
Among many data analysis approaches, the Principal Component Analysis (PCA) [4] and Artificial Intelligence have been proposed for a cement process monitoring and fault diagnosis [5-6]. PCA based methods consist of extracting the underlying information from sample data and defining an acceptable operating region delimited by the so-called confidence limits. Accurate mathematical process models are usually difficult to establish due to process complexity, making model-based techniques to industrial processes greatly restricted [7-8]. Their principle consists in developing an approximate model for which the information generated from comparison of its output with the output of the real system is used to discriminate the healthy process behaviour from the faulty one [9-11]. Compared with PCA based technique, the model-based approach relies more on the degree of agreement between the PCA model-based output and real system output. It remains, however, that both PCA and model-based approaches perform poorly when applied to industrial processes. They may lead to inaccurate estimation of the fault detection index due to various correlations and interactions among variables. A possible solution would be to obtain a representative model with fewer variables or subsystems that can adequately describe the process [12]. This task remains difficult. Neglecting non-nonlinear effects and high order dynamics will make an adaptive threshold technique inaccurate, increasing, therefore, the number of false alarms and undetected faults.
For the above reasons, there is a need for a new systematic approach that will help identify process parameters variations reliably. Such a new approach proposed in this paper should be able to robustly cater for measurement device inaccuracies, measurement noise and system parameter uncertainties. It is a statistical-based method that uses a two-dimensional plot with two significant statistical quantitative parameters based on the mean and variance values of the

available database. A qualitative statistical analysis using the mean and variance quantities plot has been proposed by Kouadri et al. [1]. It uses squared radii, which represent the sum of these statistical parameters under healthy process operation. If any point from the two-dimensional plot moves outside the confidence limit given by a circle of a given radius, it indicates an abnormal change or the occurrence of a process fault. The fault detection technique performance is evaluated on two faults in a cement rotary kiln system.
The paper is organized as follows: Section 2 briefly describes the cement rotary kiln process. The problem is formulated in section 3. The proposed solution is described in section 4 where the complete methodology for employing two consecutive projections based on the mean and variance values of a large-sized multivariate data for cement rotary kiln fault detection is expanded. In section 5, a comparative study is performed between the developed adaptive threshold technique and the fixed one with respect to their estimation schemes, extracted statistical knowledge types, domain partitioning, and performances in terms of the rate of false and missed (non detected) alarms due to various types of faults that take place in a cement rotary kiln system. Findings of the present study are given in the conclusion in section 6.

2. BRIEF DESCRIPTION OF A CEMENT ROTARY KILN

The heart of a cement plant is the rotary kiln which is used to produce the clinker, a dense heavy stony black material which is then mixed with some additives to make cement. The clinker is obtained through a slightly inclined 80 m long and 5 m diameter rotary kiln (Fig. 1). Two 250 kW squirrel cage induction motors spin the kiln at a low variable speed around 2 r.p.m. The material feeds the kiln after being preheated at 900 °C in the preheating tower. It consists of four floors of cyclones which are mounted in two parallel vertical positions. Each of them is separately fed by a dry craw material feeder which has a capacity of 150 tons/hour. The raw material itself is milled apart using a three element mixture, limestone, marl and iron with adequate proportions. Two natural gas burners are used to heat up the process. The main burner is fixed at the end of the rotary kiln whereas the second one is mounted on the first floor of the preheating tower. The kiln output material is fed to a post-kiln called the cooler. It consists of many fans that blow the stream of material moving on a mobile grid in order to cool it to less than 100 °C and get the clinker ready for next use.

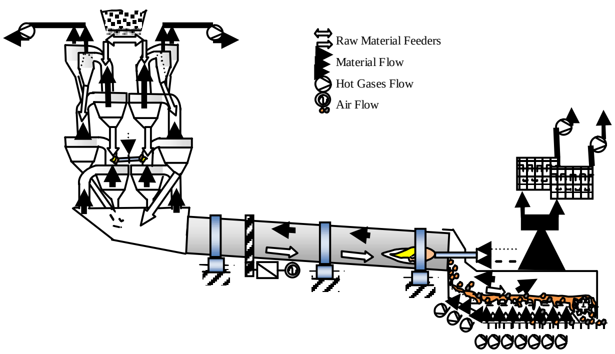

Fig. 1: Schematic diagram of a cement rotary kiln

3. PROBLEM STATEMENT

Model-based or model-free methods can be used for fault detection and diagnosis in system actuators or sensors (Kouadri, & Zelmat, 2010, Kouadri, Namoune, Zelamt, & Aitouche, 2013, Marseguerra & Zio, 2009, Cui, Shi & Wang, 2015). Some improved diagnostic methods can also estimate the amplitude of the fault and its time of appearance (Kouadri, Aitouche, & Zelmat, 2012). However, this relies on the assumption that the process is operating under ideal conditions (Lee, Qin, & Lee, 2006). Unfortunately, such ideal conditions in engineering systems do not exist. Generally speaking, the plant is nonlinear, time variant and has complex dynamic characteristics, rendering very difficult the accurate knowledge of the system structure parameters, and the noise statistical properties. Furthermore, techniques based on only one experiment in selecting fault detection threshold suffer from the difficulty of extracting the statistical properties of the analyzed signals of a given industrial process. Furthermore, it is difficult to define accurately the best random phenomena associated with these signals. Therefore, fixed threshold based-techniques increase false faults and non detected faults making them impractical. To overcome the drawbacks of these methods, a data-based method uses repeated measurements to formulate an adaptive threshold able to better describe the process under healthy mode operation. This method reduces a large-sized multivariate data to two statistical dimensions based on the mean and variance values. Contrary to the fixed threshold technique where alarm indicator status may be wrongly determined, the adaptive thresholding technique should be able to correctly identify the status of the alarm indicator; a no-fault status is read as an actual fault by the fixed threshold technique (false alarm) whereas it is not read so by the adaptive threshold technique. The other possible case, upon a fault occurrence, an alarm is not activated by the fixed threshold technique (non detected or missed alarm), whereas the adaptive threshold technique correctly detects this fault by activating an alarm.

4. PROPOSED METHODOLOGY

The data are collected from a given process, a cement rotary kiln, and specified for each data set by a n x p matrix $\boldsymbol{A}$ which represents a series of n observations obtained by sampling from p different measurement devices. These data are recorded under the same system operating conditions. Initially, for each data set, the two consecutive projections based on the mean and variance values are evaluated respectively by

$$m_i = \frac{1}{p}\sum_{j=1}^{p} A_{i,j} \tag{1}$$

and

$$\sigma_i^2 = \frac{1}{p}\sum_{j=1}^{p}\left(A_{i,j} - m_i\right)^2 \tag{2}$$

where i varying from 1 to n.

Based on the range of each measurement signal for which no fault takes place in the system, the interval of the mean value is divided into an appropriate number of subintervals along the mean's range. Moreover, minimum and maximum values of the variance for each subinterval and for an experiment t are regrouped respectively in

$$\Omega_{k,t} = \left\{\max\left(\left[\sigma_{i,t}^2\right]\right) / \, m(\sigma_{i,t}^2) \in \left[m_{k-1} \;\; m_k\right]\right\} \tag{3}$$

and

$$\omega_{k,t} = \left\{\min\left(\left[\sigma_{i,t}^2\right]\right) / \, m(\sigma_{i,t}^2) \in \left[m_{k-1} \;\; m_k\right]\right\} \tag{4}$$

The sequences vectors $\boldsymbol{\Omega}_{k,.}$ and $\boldsymbol{\omega}_{k,.}$ of the k-th subinterval can be considered as random variables where they are subjected to changes from one experiment to another under the same system operating conditions; noise parameters and uncertainties are unknown and no fault takes place in the system. For these sequences, a confidence interval can be established at a given typical significant level α (Shin, Gu, Lennox, & Ball 2005). Any sampled confidence interval is to be closely related to the probability density function estimation. *Shapiro-Wilk* hypothesis testing is performed and employed to confirm the obtained probability distribution law for the random variable (Shapiro, & Wilk, 1965).This statistical test is defined as the squared weighting mean divided by the variance of a given sampled random variable times the total number of observations. The sampled confidence interval limits for sequences vectors $\boldsymbol{\Omega}$ and $\boldsymbol{\omega}$ are given as follows

$$CI_{\boldsymbol{\Omega}_k}^{\alpha} = m_{\boldsymbol{\Omega}_{k,.}} \pm F^{-1}(\alpha)\sqrt{\sigma_{\boldsymbol{\Omega}_{k,.}}^2} \tag{5}$$

and

$$CI_{\boldsymbol{\omega}_k}^{\alpha} = m_{\boldsymbol{\omega}_{k,.}} \pm F^{-1}(\alpha)\sqrt{\sigma_{\boldsymbol{\omega}_{k,.}}^2} \tag{6}$$

where $F^{-1}(\alpha)$ denotes the inverse normal distribution function with zero-mean and unit-variance. $m_{\boldsymbol{X}}$ and $\sigma_{\boldsymbol{X}}^2$ represent the mean and variance values of the sequence vector ***X***, respectively.

If the system fault takes place, the sampled mean and/or the corresponding sampled variance of equations 1 and 2 would change dramatically. i.e.,

$$\begin{cases} m_i \prec m_0 \\ \text{or} \\ m_i \succ m_K \end{cases} \tag{7}$$

and/or

$$\begin{cases} \sigma_i^2 \succ max\left(CI_{\Omega_k}^{\alpha}, CI_{\omega_k}^{\alpha}\right) \\ \text{or} \\ \sigma_i^2 \prec min\left(CI_{\Omega_k}^{\alpha}, CI_{\omega_k}^{\alpha}\right) \end{cases} \tag{8}$$

m_0 and m_K denote the left and right endpoints of the interval of the mean's range, respectively.

For the purpose of easy description, the steps in developing an adaptive threshold are summarized in the following algorithm

Step 0. Parameter setting

Sample rate: *l*
Measurement time: T_m
Samples per measurement time: $n = l.T_m$
Number of the experiments: *N*
Number of mean's subinterval: *K*
Level of significance: α

Step 1. Healthy mode

for $k \leftarrow 1$ **to** *p* **do**
for $j \leftarrow 1$ **to** *n* **do**
$A_{j,k} \leftarrow$ get data from the process for each experiment
end
end

Step 1.1. Different instantaneous statistical parameters for each experiment

for $k \leftarrow 1$ **to** *p* **do**
for $i \leftarrow 1$ **to** *n* **do**
Compute the mean at each sample time

$$m_{ik} \leftarrow \frac{1}{p}\sum_{k=1}^{p} A_{ik}$$

Compute the variance at each sample time

$$\sigma_i^2 \leftarrow \frac{1}{p}\sum_{i=1}^{p} (A_{ik} - m_{ik})^2$$

end
end

Step 1.2 Compute maximum and minimum values for each experience at each subinterval

for $k = 1$ to *p* **do**
for $i = 1$ **to** *K* **do**

$$\Omega_{ki} \leftarrow \max(\sigma^2)$$

$$\omega_{ki} \leftarrow \min(\sigma^2)$$

end
end

Step 1.3 Compute the limits of the confidence interval at each subinterval

for $i = 1$ **to** *K* **do**
Compute the upper and lower limits

$$CI_{\Omega_k}^{\alpha} \leftarrow m_{\Omega_{k,-}} \pm F^{-1}(\alpha)\sqrt{\sigma^2_{\Omega_{k,-}}}$$

$$CI_{\omega_k}^{\alpha} \leftarrow m_{\omega_{k,-}} \pm F^{-1}(\alpha)\sqrt{\sigma^2_{\omega_{k,-}}}$$

end

Step 2. Fault detection test

for j←1 **to** n **do**

for k←1 **to** p **do**

$A_{j,k}$← get data from the process

end

$$m_j \leftarrow \frac{1}{p}\sum_{k=1}^{p} A_{jk}$$

$$\sigma_j^2 \leftarrow \frac{1}{p}\sum_{k=1}^{p}(A_{jk}-m_j)^2$$

for i=1 **to** K **do**

if $\sigma_j^2 \succ \max\left(CI_{\Omega_k}^{\alpha}, CI_{\omega_k}^{\alpha}\right)$ **or** $\sigma_j^2 \prec \min\left(CI_{\Omega_k}^{\alpha}, CI_{\omega_k}^{\alpha}\right)$ **or** $m_j \prec m_0$ **or** $m_j \succ m_K$ **then**

Detection of fault

endif

end

end

5. RESULTS AND DISCUSSION

The proposed algorithm is applied to a cement rotary kiln process at Ain El Kabira Cement Plant (Algeria). The two consecutive projections based on the mean and variance values are calculated from N=29 independent runs of the rotary kiln system which operates under the same operating conditions in healthy mode. Each run consists of n=600 samples of eighteen different measurement signals. The 600 samples cover a time window of duration 600 seconds. It is fixed for any statistical analysis.

The two limits of the first projection of the mean value are obtained, for all the experiments, and divided into K=23 subintervals. For each experiment and at each subinterval, the maximum and minimum values with respect to the second projection in the variance value are obtained. The QQ-plots of these values which are taken from four different subintervals in m-axis are shown in figure 2.

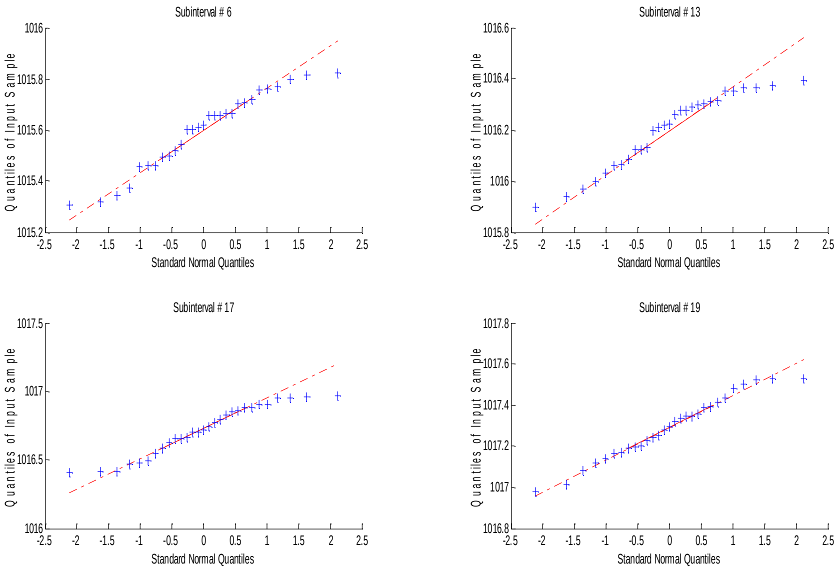

Fig. 2: QQ-plot of maximum variance values for four different subintervals

The *QQ*-plot constitutes a graphical test for the normal distribution law. It uses the cumulative frequency of a given random variable versus its corresponding standard normal distribution law with the same mean and variance (Dudoit, Yang, Callow, & Speed, 2002). Their co-linearity means that the considered random variable is normally distributed. It can be seen from *QQ*-plots that the cumulative appearance frequency of the maximum and minimum values in σ^2-axis show a linear correlation with the obtained frequency by the standard normal law with the same mean and variance of the minimum and maximum values. Therefore, these values are normally distributed. Furthermore, the *Shapiro-Wilk* test confirms the normal distribution law, at a typical risk error of 5%, with acceptable *p*-values. The obtained *p*-values of the chosen minimum and maximum variance values are very close to unity. This *p*-value represents the probability of observing a given minimum/maximum sample in the experimental system under the assumption that these values are normally distributed. It can be easily seen from table I, for the maximum variance taken randomly from four different subintervals that this probability is close to one. The chosen risk error level is related to the degree of certainty in rejecting that the minimum and maximum variance values follow a normal law. This is true if the probability of observing a sampled result is greater than the risk error level. Therefore, the minimum and maximum values of the datasets of variance values at each mean's subinterval satisfy the normal distribution law with fairly acceptable probability.

Similarly, the fixed threshold is evaluated based on one experiment chosen randomly. This threshold is computed with respect to two consecutive statistical projections. The *QQ*-plot for these two statistical projections mean and variance values are shown in figure 3. Their distribution normality is revealed by the strong linearity between their cumulative appearance frequencies and their corresponding frequencies obtained by the standard normal distribution law with the same statistical mean and variance values. Figure 4 depicts the adaptive and fixed thresholds. The fixed threshold is illustrated with dashed lines in m-σ^2 plane. The obtained adaptive threshold limits appear to have a stepwise function behavior.

Table 1 p-value for different subinterval values

Subinterval number	#6	#13	#17	#19
p-value	0.875 4	0.719 4	0.942 8	0.900 2

Figure 5 shows the rate mean of the false alarms with the fixed and adaptive thresholding techniques at different significant levels. The rate mean of false alarms represents the quotient of false alarms in all considered experiments at each sample time. It can be seen that the fixed threshold is irrelevant and is more affected by uncertainties in the measurement database. On the contrary, the adaptive threshold is adjusted to the observations and the rate of false alarms remains constant at the different small elapsed time and during the whole process and at the significant level 95% and 98%. Consequently, the adaptive thresholding technique quite eliminates the false alarms at the significant level 99%. Thus, it fully satisfies the condition of reliable faults and increases the fault detection sensitivity and accuracy.

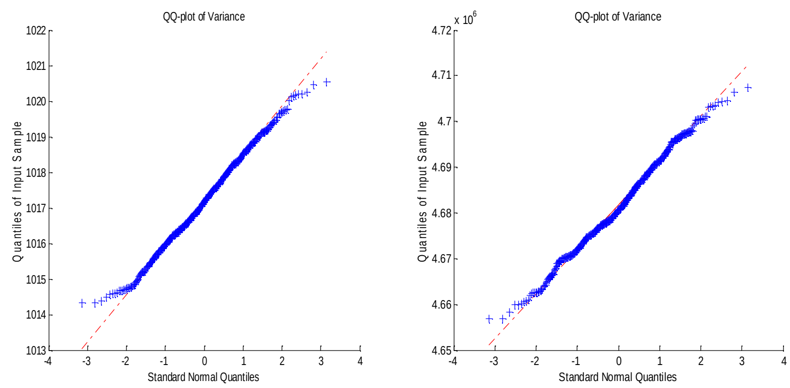

Fig. 3: *QQ*-plot of the mean and variance values

To show the performance of the proposed thresholding strategy, two kinds of faults that may occur in the cement rotary kiln are considered: (1) supper chilled kiln, (2) over-heated kiln. The abnormal mode is declared if any sampled mean and/or variance do not belong to the relevant confidence interval.

A. ***Super-chilled kiln:*** this case of a fault is accompanied by a decrease in the inside kiln temperature, this situation generally can be detected by the Central Control Room (CCR) operators through behavioural changes of some signals that should be carefully viewed permanently during the production process. Some signals are of great importance for the CCR operators. For example, the secondary air temperature and the kiln motor's power determine what should be done and how.

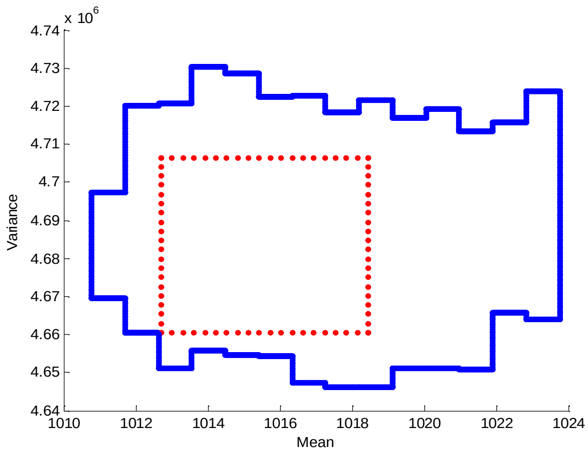

Fig. 4: Confidence regions in m-σ^2 plane using adaptive thresholding technique: (dashed line) fixed threshold, (solid line) adaptive threshold.

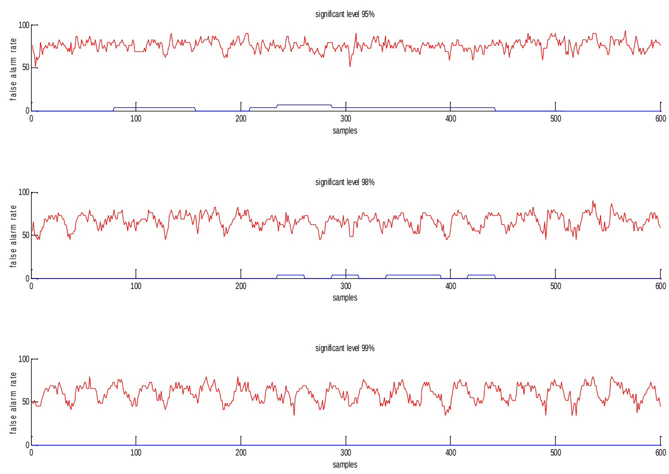

Fig. 5: Average rate of false alarms at different significant levels: (red dashed line) fixed threshold, (blue solid line) adaptive threshold.

In general, if the power is decreasing the kiln is going to cool down, whereas, if it is increasing the kiln is going to overheat; hence, the CCR operators should decrease the material feed flow rate or increase it, respectively. The secondary air temperature can also provide short prior information about this type of fault and warn the operator that the fault may occur or is being started.

Figure 6 shows the mean and the variance plot under the occurrence of the aforementioned fault. It can be seen clearly that some points are outside the developed adaptive threshold and confirm that the rotary kiln is in faulty status. However, the fixed thresholding technique masks earlier the detection. Therefore, too much false alarms are manifested before the actual process malfunction by which inaccurate intervention decisions can be taken.

B. ***Over-heated kiln:*** this seems to be an opposite phenomenon of the chilled kiln, it is accompanied by the inside kiln temperature rise that produces a burnt clinker which does not satisfy quality requirements, Figure 7 illustrates this case. The process will produce clinker with lower density. The back temperatures (in the preheating tower) are maintained to be near the normal values in contrast to the first faulty case described before where the back temperatures increase due to the accumulation and burning of the fuel gas in the back cyclones. As it is known through the thermodynamics laws, the gases temperatures and pressures are closely related, and we can observe in some faulty situations insufficiencies and saturation on the induced draft fans because of the huge gases dilation.

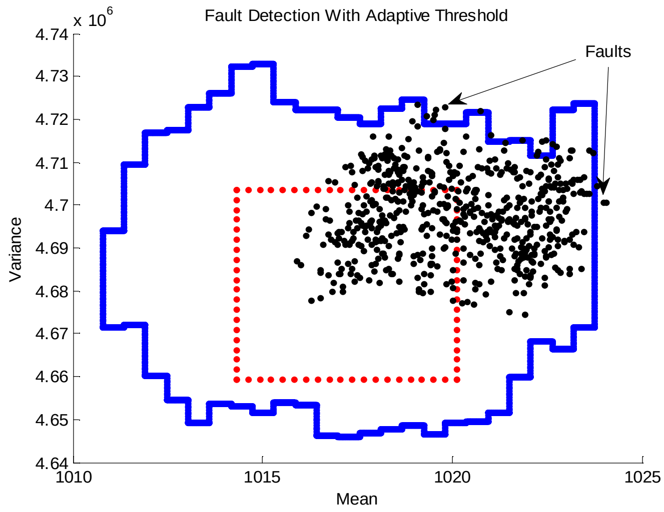

Fig. 6: m-σ^2 plot before and after fault occurrence (case 1)

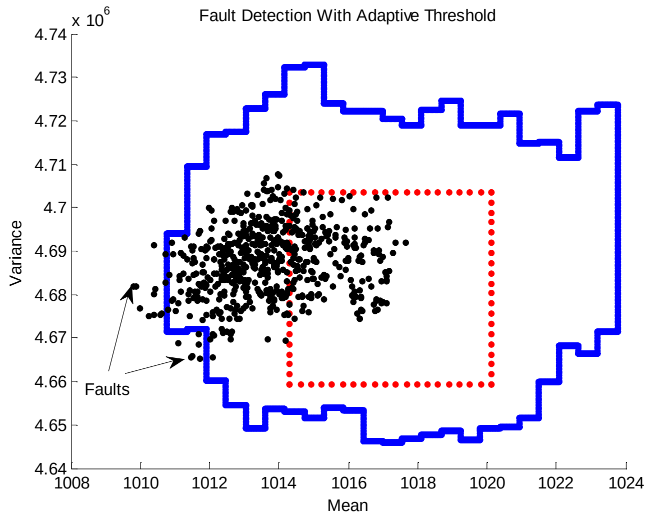

Fig. 7: m-σ^2 plot before and after fault occurrence (case 2)

6. CONCLUSION

In this paper, an efficient diagnostic technique has been presented, based on two consecutive projections of a large-sized multivariate which tracks several malfunctions occurring in a cement rotary kiln system. First of all, a statistical investigation of how large sized multivariate data sets are reduced and how they are presented in two-dimensional plot through the mean and variance values is presented. Then, an accurate adaptive thresholding technique has been developed through several repeated experiments under the same operating conditions. The efficiency of the developed thresholding technique depends on the confidence region obtained through an appropriate statistical test to estimate the probability density function of the sampled variance. By dividing the range of the mean into a chosen number of subintervals, the maximum and minimum variance values at each subinterval are considered as random variables. It has been proven experimentally that the obtained confidence intervals are sufficient to constitute a powerful tool that helps overcome the difficulties of parametric uncertainties quantification and devices measurement inaccuracies which increase false alarms and hide real faults. The experimental results have also shown both the speed and high sensitivity of proposed fault detection technique in detecting faults.

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