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False Alarms Rate Reduction Using Filtered Monitoring Indices

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Abstract: False alarms are the major problem in fault detection when using multivariate statistical process monitoring such as principal component analysis (PCA), they affect the detection accuracy and lead to make wrong decisions about the process operation status. In this work, filtering the monitoring indices is proposed to enhance the detection by reducing the number of false alarms. The filters that were used are: Standard Median Filter (SMF), Improved Median Filter (IMF) and fuzzy logic based filter. Signal to Noise Ratio (SNR), False Alarms Rate (FAR) and the detection time of the fault were used as criteria to compare their performance and their filtering action influence on monitoring. The algorithms were applied to cement rotary kiln data; real data, to remove spikes and outliers on the monitoring indices of PCA, and then, the filtered signals were used to supervise the system. The results, in which the fuzzy logic based filter showed a satisfactory performance, are presented and discussed.

Keywords: False Alarms Rate, Fault Detection and Diagnosis, Fuzzy Logic Based Filter, Median Filter, Principal Component Analysis (PCA).

7. INTRODUCTION

Fault is defined as an unpermitted deviation of at least one characteristic property (feature) of the system from the acceptable, usual, standard condition [1]; so, fault may occur at any time when the process is operating, it will be dangerous unless it is detected. The task of determining whether a fault has occurred is called fault detection [2]. Fault detection is necessary because faults might cause fatal accidents, economic losses and environmental damages. To avoid these undesirable consequences, process monitoring can be used to indicate the existence of any malfunction; furthermore, it helps to know the operation status of the system.

Various fault detection and diagnosis methods had been proposed in literature, they can be classified into three major categories: quantitative model-based, qualitative model-based and data based methods [3]. Fault detection using quantitative model-based needs a mathematical description of the process that expresses the relationships between the inputs and the outputs of the system. In contrast, these relationships, in qualitative model-based, are expressed in terms of qualitative functions centered around different units in the process [4]. However, in data based methods, known also as process history or data driven methods, a mathematical model of the system is not needed, only the availability of large amount of historical process data is required [5].

Generally, industrial systems are very sophisticated processes for which a mathematical model is not always available; hence, data driven methods are suitable to monitor such systems. Multivariate statistical process control (MSPC) such as principal component analysis (PCA) is appropriate technique to supervise high dimensional data processes; it has a reputation for its usefulness in multivariate statistical techniques for reducing the dimensionality of the process data [6], this dimensionality reduction is achieved by projecting the data into a lower-dimensional space that accurately characterizes the state of the process [7].

PCA model is obtained by using measured data that may be corrupted by noise or affected by the sensors' errors. The PCA model constructed by this data will not be accurate, as a result, the efficiency of monitoring will be decreased because of the existence of outliers in the monitoring indices which are seen as false alarms when the system is operating in free fault mode; no fault occurred. There are many filters that have been developed to remove noise in signals but they are rarely applied with PCA since they may lead to loose its sensitivity. The mean and the standard median filter (SMF) are the simplest ones; the problem with the use of the mean filter is the poor robustness of its performance which can been seen clearly with intermittent and abrupt faults for which the fault recovering time requires to be equal to the window size used; however, with SMF, there is not such problem.

The objective of this work is to apply three chosen filters: Standard median filter (SMF), improved median Filter (IMF) and fuzzy based filter in the purpose of reducing the false alarms rate without influencing too much the sensitivity; The IMF and the fuzzy based filter are based on SMF. The monitoring indices were filtered using these filters to remove outliers; moreover, they have been compared according to their filtering process, the reduction of the false alarms rate and the detection time of a fault.

The rest of this paper is organized as follows: In section 2, principal component analysis is introduced and described how it can be used in monitoring, then, in section 3, standard median filter (SMF) is presented. Next, improved median filter algorithm is explained in section 4, after that, section 5 is about the fuzzy based filter, afterward, an application of these filters, results and discussion are shown in section 6, finally, some conclusions and future works are exposed at the end of this paper;

8. PRINCIPAL COMPONENT ANALYSIS

Definition and Concepts

Principal component analysis (PCA) is a linear dimensionality reduction technique, optimal in terms of capturing the variability in the data [7]. PCA is defined a linear transformation of the original correlated variable into a new set of variables that are uncorrelated with each other [8].
In general, given an *n* by *m* data matrix *X* where *n* is the number of observations and *m* is the number of variables:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{1}$$

Assuming that columns of X have been normalized to zero mean and unity variance, the covariance matrix is defined as [9]:

$$cov(X) = \frac{X^T X}{n-1} \tag{2}$$

By means of singular value decomposition, the covariance matrix can be rewritten as:

$$cov(X) = P^T \Delta P \tag{3}$$

In which P is m by m matrix consists of eigenvectors of the covariance matrix satisfying:

$$P^T P = I \tag{4}$$

Δ is m by m diagonal matrix containing the eigenvalues of the covariance matrix sorted in descending order. $\lambda_1^2 \geq \lambda_2^2 \geq \cdots . \geq \lambda_m^2)$

Once the number of principal components a is selected, P and Δ matrices can be decomposed into:

$$\Delta = \begin{pmatrix} \Delta_{PC} & 0 \\ 0 & \Delta_{res} \end{pmatrix} \tag{5}$$

$$\Delta_{PC} = \mathrm{diag}(\lambda_1^2, \lambda_2^2 \dots . \lambda_a^2) \in R^{axa} \tag{6}$$

$$\Delta_{res} = \mathrm{diag}(\lambda_{a+1}^2, \lambda_{a+2}^2 \dots . \lambda_m^2) \in R^{(m-a)x(m-a)} \tag{7}$$

$$P = (P_{PC} \quad P_{res}) \tag{8}$$

Where $P_{PC} \in R^{mxa}$, $P_{res} \in R^{mx(m-a)}$ and λ_i^2 is the i^{th} eigenvalue of the covariance matrix.

The original data matrix can be then expressed as:

$$X = \hat{X} + E = \hat{T}P_{PC} + \tilde{T}P_{res} \tag{9}$$

T is called the principal component matrix whereas *P* is called loading matrix [10].

Finding the Number of Principal Components

The criterion that is used in this work to select the number of principal components is the cumulative percent variance (CPV), which is a measure of the percent variance, captured by the first *a* principal components. It is defined as [11]:

$$CPV(a) = \frac{\sum_{j=1}^{a} \lambda_j}{\sum_{j=1}^{m} \lambda_j} 100\% \tag{10}$$

λ_j is the j^{th} nonzero element of the matrix Δ ; j^{th} eigenvalue . In general, the value of CPV is chosen between (90% and 95%).

Fault Detection Using Principal Component Analysis

PCA based fault detection consists of defining two different thresholds, one for the Hotelling T^2 and the other for the sum of square predicted error SPE know also as Q statistic. The T^2 statistic is a measure of the variations captured by the principal components at different time samples, while the Q statistic is a measure of the amount of variations in the residuals, which are not captured by the PCA model [10].

T^2 and Q can be computed by [9]:

$$T^2 = x^T P_{PC} \Delta_{PC}^{-1} P_{PC}^T x \tag{11}$$

$$Q = \|(I - P_{PC}P_{PC}^T)x\|^2 = x^T (I - P_{PC}P_{PC}^T)^2 x \tag{12}$$

The T^2 threshold is provided by [7]:

$$T_\delta^2 = \frac{a(n-1)(n+1)}{n(n-a)} F_\delta(a, n-a) \tag{13}$$

Such that *n* is the number of observations and *a* is the number of retained principal components. $F_\delta(a, n-a)$ is an F-distribution of *a, n-a* degree of freedom evaluated at given confidence level δ.

The Q threshold is given by [12]:

$$Q_\delta = \theta_1 \left(\frac{C_\delta \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right)^{\frac{1}{h_0}} \quad (14)$$

Where: $\theta_i = \sum_{j=a+1}^{m} \lambda_j^i$, i = 1,2,3

$$h_0 = 1 - \frac{2\theta_1\theta_2}{3\theta_2^2} \quad (15)$$

And C_δ is the normal deviate corresponding to $(1-\delta)$ percentile.

λ_j is the j^{th} element of the matrix Δ.

A fault is detected whenever one or both monitoring indices exceed its corresponding threshold. Since T^2 and Q measure variations in different spaces, they may detect different faults, it means that an abnormal behaviour can be detected by one or by both monitoring indices; therefore, it is preferable to use both of them in the monitoring.

9. STANDARD MEDIAN FILTER

Standard median filter is one of the most popular and robust nonlinear filter [13]. It is simple to be implemented. If one wishes to filter the vector of data *Z* which is *1* by *n* vector:

$$Z = [z_1 \quad z_2 \quad \cdots \quad z_n] \quad (16)$$

The necessary steps to filter the vector are:

1. Define a window (W_i) of size *k; k* is chosen to be 5 in all the three filters, for the i^{th} iteration that will slide over the vector *Z.*

$$W_i = [z_{1+(i-1)} \quad z_{2+(i-1)} \quad \cdots \quad z_{k+(i-1)}] \quad (17)$$

Where *i* is the number of iterations *(i=1,2….n-k+1).*

2. Compute the output of the filter at the i^{th} iteration which is just the median value of the window

$$m_i = median(W_i) \quad (18)$$

3. Exclude the first element in the window and include the next element. Then repeat from 2.

The 3rd step is repeated until the last element in the vector *Z* is reached.

4. IMPROVED MEDIAN FILTER

The standard median filter filters all the samples, in other words, even the uncorrupted samples are filtered. The objective of the improved median filter is to restrict the filtrating action only to those samples which are classified as outliers or corrupted by noise. The authors in [13] proposed this filter to remove noise in images in an adaptive way. By simple modifications, this filter can be used to filter a vector of data.

Fig. 2 represents the schematic diagram of the modified switching filters.

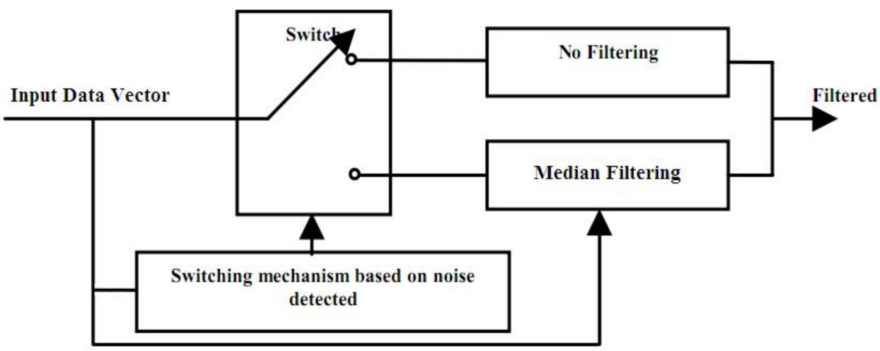

Fig. 1 Block Diagram of modified IMF

The output of the switching mechanism based on noise detection is a binary value that indicates whether a sample is affected by noise or not. Using the same vector of data defined by equation (16), the algorithm can be summarized in the following steps:

1. Initiation a window of size k that will slide over the vector, same as the one in equation (17). Initiate the binary flag f_r^i to Zero where r is the sample number in the window; $r=1, 2\ldots k$.

2. Find the median m_i value in the window W_i.

3. Compute the absolute difference between z_r and m_i, then assign:

$$f_r^i = \begin{cases} 0 & if\ |z_r - m_i| < T \\ 1 & otherwise \end{cases} \tag{19}$$

   Where T is a predefined threshold.

4. If the r^{th} sample in the window is detected to be an outlier or a noise, the sample z_r will be modified as :

$$z_r = \begin{cases} m_i & if\ f_r^i = 1 \\ z_r & f_r^i = 0 \end{cases} \tag{20}$$

5. FUZZY LOGIC BASED FILTER

Fuzzy logic is a branch of fuzzy set theory that attempts to human reasoning with simple fuzzy IF-THEN rules [14]. Fuzzy set theory was first proposed by Zadeh in 1965, and was first used in control by Mamdani [15].

The Filter scheme proposed in [14] was used to remove spike noise from 2 dimensional electrical resistivity data. Again, by simple modifications to this filter, it will be useful to remove spikes from a vector of data. Assuming that one wish to filter the vector of data define by equation (16).

1 by 5 window will slide over this vector:

$$W_i = [z_{1+(i-1)} \quad z_{2+(i-1)} \quad z_{3+(i-1)} \quad z_{4+(i-1)} \quad z_{5+(i-1)}] \tag{21}$$

Always the central value $z_{3+(i-1)}$ in the window is filtered. The filtering methodology is the same as the one proposed in [14], the following absolute differences will be fuzzified (i.e., transformed to linguistic values):

$$\Delta_{FL=}|z_{3+(i-1)} - z_{1+(i-1)}| \tag{22}$$

$$\Delta_{NL=}|z_{3+(i-1)} - z_{2+(i-1)}| \tag{23}$$

$$\Delta_{NR=}|z_{3+(i-1)} - z_{4+(i-1)}| \tag{24}$$

$$\Delta_{FR=}|z_{3+(i-1)} - z_{5+(i-1)}| \tag{25}$$

FL stands for far left, NL for near left, *NR* for near right and *FR* for far right.

Reference [14] contains more details about the filter description, the membership functions and the rules used.

6. APPLICATION

Rotary Kiln Description

Rotary kilns are usually considered to be most important part of any cement manufacturing plant. They are used by industry to heat the solid material to the point where chemical reactions can take place. Fig. 2 shows schematic diagram of cement plant in which rotary kiln is the rotating sloped cylinder. The size of rotary kiln depends on the type of process and production rate. The data used in this work are obtained from rotary kiln which has 80 m as length and 5 m in its diameter, it is being rotated at a speed of 2 r.pm using two 250 kW squirrel cage induction motors. Cement production goes through several phases: first, raw materials are fed at the upper end of the kiln after they were preheated to 900 C°. The rotation makes the mixture moving gradually to the other end. After that, with some additives and at 1450C°, the chemical reactions take place to produce cement. As last phase, the kiln output material is fed to a post-kiln called the cooler. It consists of many fans that below the stream of matter moving on a mobile grid so as to cool it down to less than 100C°.

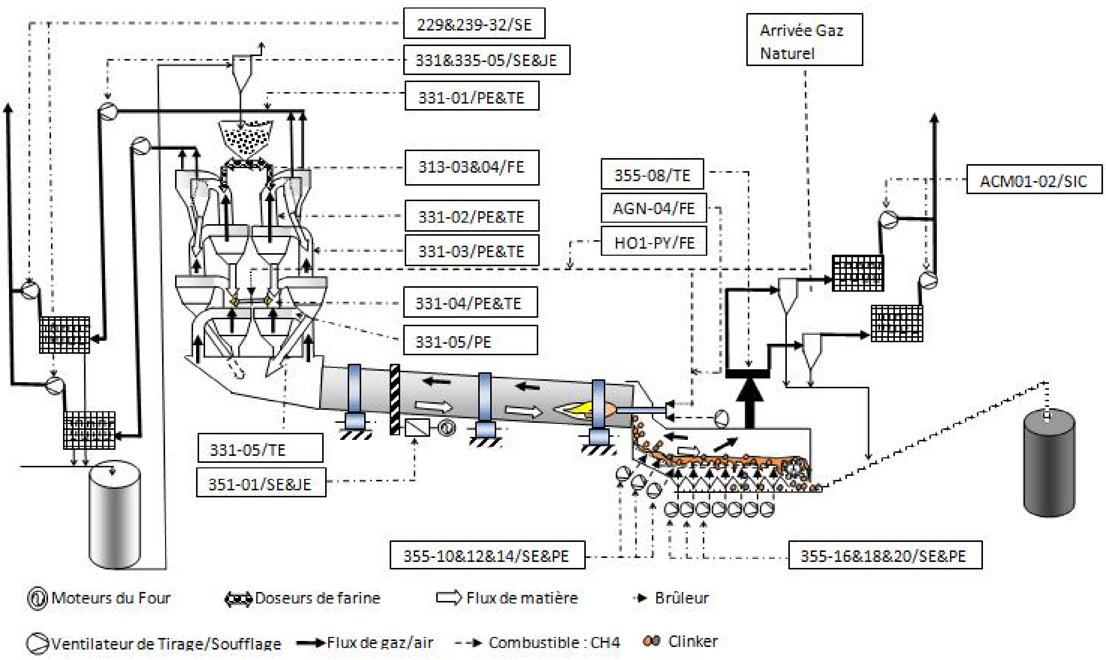

Fig. 2 Schematic Diagram of cement plant

For monitoring purpose, 51 measured signals are used to monitor the rotary kiln by static PCA with fixed threshold. The signals were measured in different locations on the rotary kiln, they include power, temperature and pressure, 15344 observations were collected when the process is in the normal operation (no fault) with sampling time of one second. Data pre-processing has been done to remove outliers and corrupted observations, because it is necessary to construct PCA model using clean data. After pre-processing, a total of 14730 samples are used to construct the PCA model. For each sample, the motoring indices T^2 and Q, are evaluated then they are passed through the filters, after that they are compared to the predefined thresholds T_δ^2 and Q_δ.

Application of the Algorithms

The unfiltered monitoring indices (i.e.; Q and T^2) and the filtered ones by different filters are shown in the following figures:

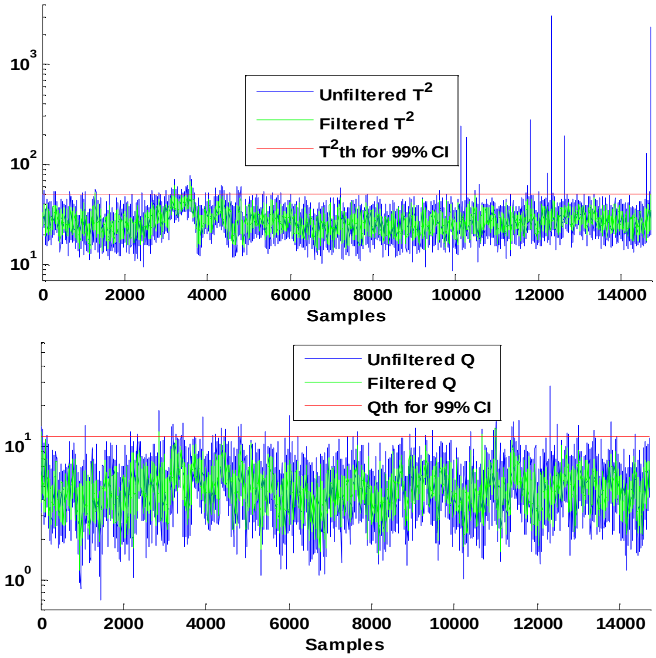

Fig. 3: Thresholds, Unfiltered and Filtered Signals Using SMF

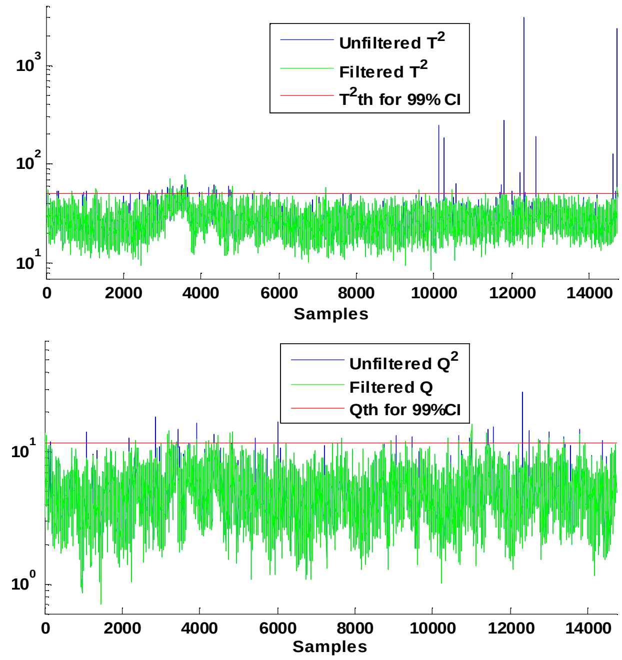

Fig. 4: Thresholds, Unfiltered and Filtered Signals

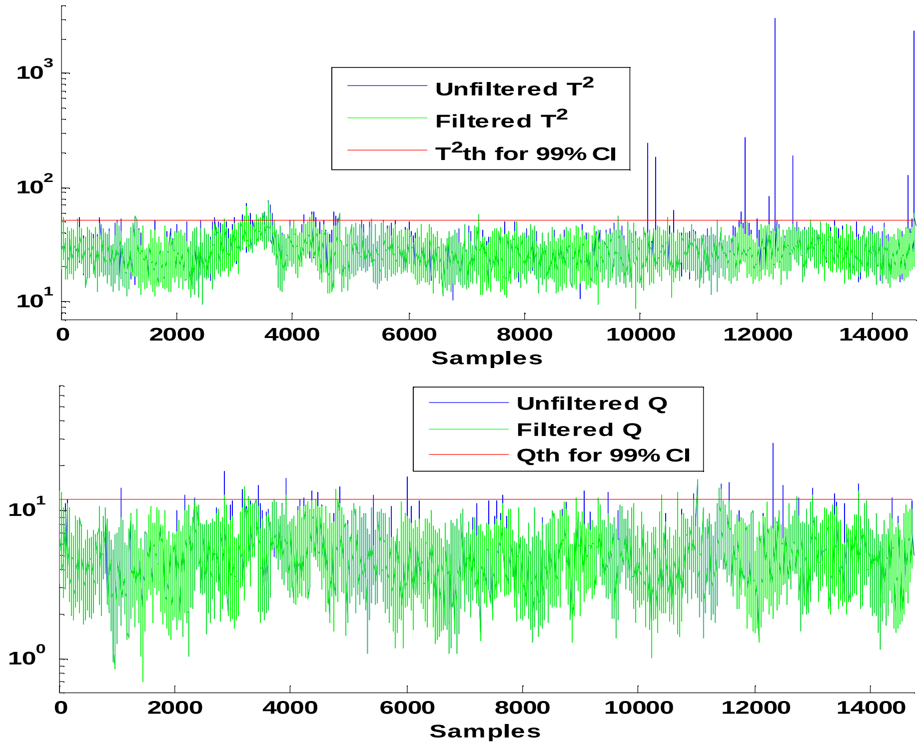

Fig. 5: Thresholds, Unfiltered and Filtered Signals Using Fuzzy Based Filter

Fig. 4 shows the unfiltered and the filtered monitoring indices of PCA with standard median filter, in which it can be seen clearly that not only the outliers have been filtered, but even those uncontaminated samples have been modified, this seems to be good; however, it leads to the signal distortion and also to decrease the sensitivity.
Fig. 5 and Fig 6 represent the unfiltered and the filtered monitoring indices of PCA with standard improved median filter and fuzzy based filter respectively, for which, the problem of uncontaminated samples filtering has been resolved, in these cases, only the outliers were concerned in the filtering action.

To compare the performance of the filters, signal to noise ratio (SNR) and the false alarms rate (FAR) were used. SNR is computed using the equation below [14]:

$$\mathrm{SNR(dB)} = 10\log_{10}\left(\frac{\left(\sum_{i=1}^{n} s_i\right)^2}{n\sum_{i=1}^{n} s_i^2-\left(\sum_{i=1}^{n} s_i\right)^2}\right) \quad (26)$$

The higher value of SNR indicates a better filtering action and smaller FAR will increase the accuracy of fault detection.

The FAR is defined as in equation 26:

$$FAR = \frac{Number\ of\ sample\ above\ the\ limits}{Total\ samples} \quad (27)$$

Too small FAR is undesirable because the sensitivity will be affected very much, in other hand, high FAR is also undesired because it decreases the fault detection accuracy.

The computed SNR and FAR values for the filtered signals are tabulated in the following table:

Table 1 SNR and FAR Values

Type of Filter	**FAR(%) of Q**	**FAR(%) of T^2**	**SNR (dB) of Q**	**SNR(dB) of T^2**
Unfiltered signals	0.46	0.79	8.1208	-1.2923
SMF	0.11	0.19	10.2521	13.0327
IMF	0.27	0.52	8.3584	11.2086
Fuzzy logic based filter	0.22	0.48	8.4294	11.3496

Table 1 represents the SNR and the FAR values obtained using different filters: SMF, IMF and fuzzy logic based filter, in which it can be seen clearly that the SNR values of the SMF are greater than those of IMF and fuzzy logic based filter, in addition, the FAR of Q and T^2 values are smaller compared to those ones obtained with the others; this is due to the filtering process. These results does not mean that the SMF performance is better that the performance of the two other filters, because it is mentioned before that too small FAR is undesirable when taking the sensitivity of the monitoring indices into consideration. From this table, one can conclude that the performance of the fuzzy logic based filter is better than the one of the IMF because its SNR values are greater whereas; its FAR values are little bit smaller, which indicates that the filtering action is good, the FAR is reduced and the sensitivity is not too much affected..

New measured data were collected and concontunated with the previouse ones. The filtered signals are used to to monitor the process with fixed threholds, further comparision between the filters is done to see their effect on the detection time of the fault.

The figures below represent the monitoring results of the filtered signals:

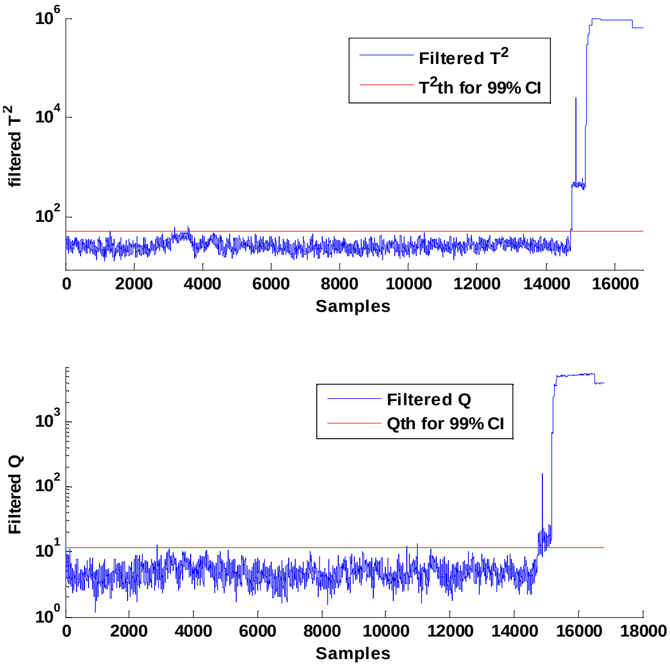

Fig. 6 fault detection using filtered monitoring indices with SMF

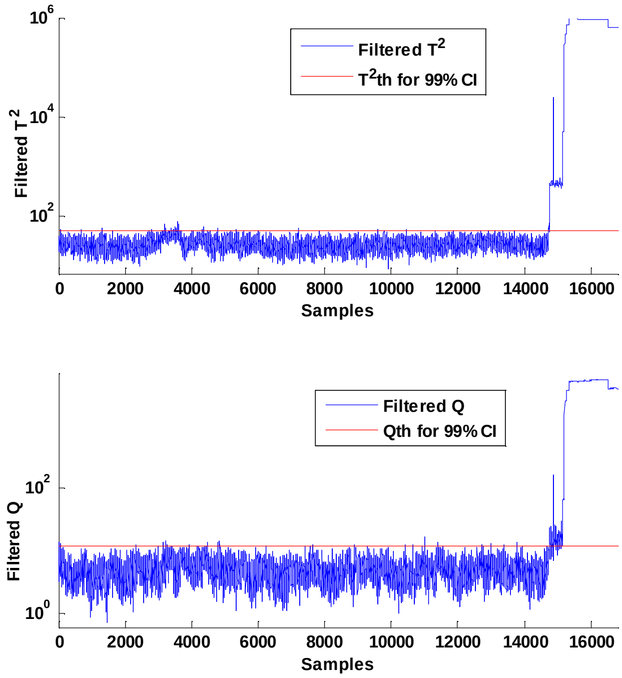

Fig. 7: fault detection using filtered monitoring indices with IMF

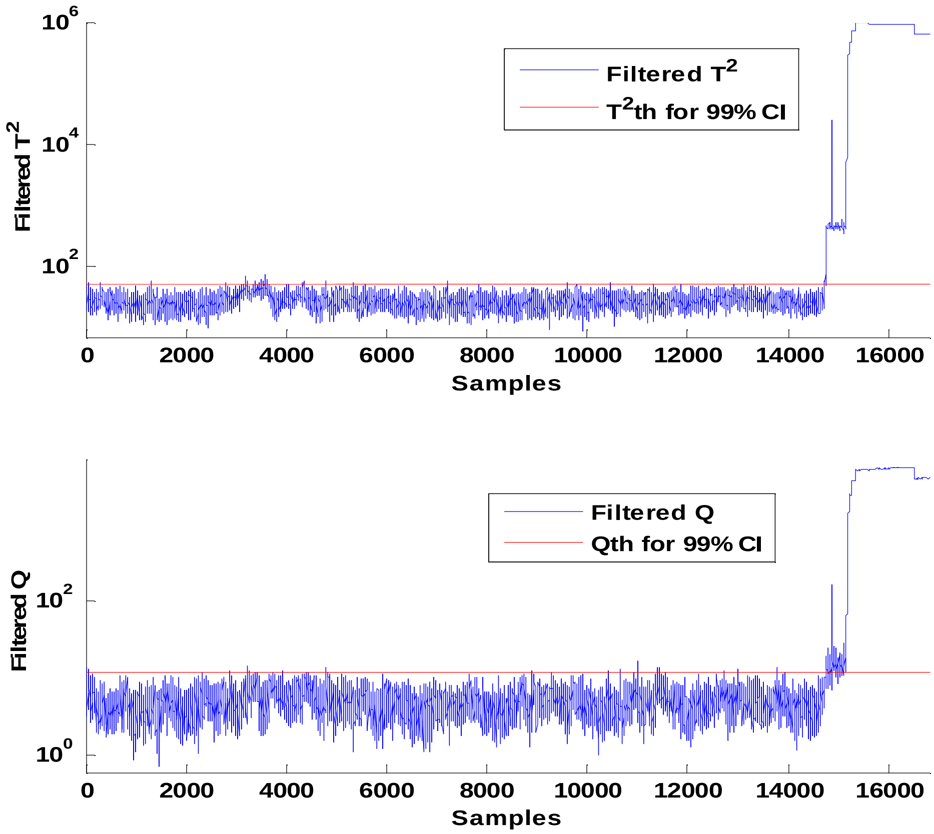

Fig. 8: fault detection using filtered monitoring indexes with fuzzy logic based filter

The filtering of the monitoring indices does not affect the fault detection; in other words, the fault can be detected even when using filters. Form Fig. 6, it can be seen that the sensitivity has been decreased.

The detection time of the fault based on fault decision rule is shown in table 2:

Table 2 Detection Time of the Fault

Signals	Detection time of the fault
Unfiltered signals	14737
Filtered signals using SMF	14738
Filtered signals using IMF	14737
Filtered signals using fuzzy based filter	14737

This table shows that the detection time based on fault decision rule for the unfiltered signals, the filtered signals using IMF and fuzzy based filter is the same as the detection time using the unfiltered signal, which ensures that filters do not introduce a delay; whereas, for the filtered signals using SMF the fault has been detected after one samples delay; delay of 1 seconds.

7. CONLUSION

The filtering action does not affect fault detection, but it enhances it by reducing the false alarms rate. The SMF filters all samples regardless if they are outliers or not, this affects the sensitivity of the monitoring indices; however, with IMF or fuzzy logic based filter only outliers are removed.

The fuzzy logic based filter gives good results in terms of the false alarms rate reduction, the sensitivity of PCA and the detection time of faults. The performance of this filter will be much better if an adjusting parameter is introduced to control the filtering action, because, sometimes, a sample may need only to be scaled rather than totally modified.

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