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A Monitoring Method based on Fuzzy Detection and PCA Diagnosis

Ouni KHALED, Nabli LOTFI and Hassani MESSAOUD

Abstract- **In this paper we present an approach to detecting and locating defects based on an indirect supervision using Principal Component Analysis (PCA) and Average Dynamics of Metrics (ADM). Our contribution lies in the combined use of the fuzzy logic technique for detection and the ACP for the diagnosis method. In a unity of textile spinning, we have defined some indicators of product quality. ADM permits the valuation of the product quality to different levels of the manufacturing procedure. An indication of calculated detection from the last principal components is used to detect defects. Once a defect is detected, its variable tally is located by calculating its contribution.**

Index Terms—**Indirect supervision, Principal component analysis, Fuzzy set, Average dynamic of metrics, Diagnosis, Detection of defects, and Calculation of contributions.**

NOMENCLATURE

A	proper vector matrix
b_j	factors of level-headedness
C	model projection matrix
c	row vector of matrix C
d	fault magnitude
$D_i(k)$	detecting index
$\overline{D}$	filtered detecting index
E	projection of X to $\Re^{m-\ell}$
e	projection of x to $\Re^{m-\ell}$
$\overline{e}(k)$	filtered residue
H	hairiness indication
I	identity matrix
L	length
ℓ	number of principal components
M	mass
m	number of sensors
n	number of sample measurement
N_M	metric number
P	proper value matrix
P_k	function of numeric projection
R	correlation matrix
s	function of classification
SPE	square prediction error
$\overline{SPE}$	filtered square prediction error
T^2	Hotelling statistic
$\overline{t}_i(k)$	the last filtered component
T	score matrix
T_{Tex}	the title
v	variance of reconstruction errors
X	reduced centre matrix
X	measurement matrix, or data matrix
$\hat{X}$	projection of X to $\Re^{\ell}$
x	sample vector
$\hat{x}$	projection of x to $\Re^{\ell}$
$\tilde{x}$	projection of x to $\Re^{m-\ell}$
Z	fuzzy variable
α	variation of linear mass
β	number of thin speckles
γ	residual factor
ε	number of spots
φ	percentage of short fibres
θ	number of large speckles
ξ	fault vector
σ_H	Variance of hairiness indication
η	elementary classes

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*Ouni Khaled is currently a Assistant in the Superior Institute of Applied Sciences and Technology in Kairouan (ISSATK)
(e-mail: ouni_khaled@yahoo.fr)
**Nabli Lotfi is currently a professor at the Superior Institute of Applied Sciences and Technology in Sousse (ISSATS)
(e-mail: lotfinabli@yahoo.fr)
***Hassani Messaoud is a full professor at the National School of Engineers of Monastir.
(e-mail: hassani.messaoud@enim.rnu.tn)

INTRODUCTION

Functional safety is an important factor in conducting a manufacturing process. This one can be noticed at the time of lapse appearance of a physical process. Thus, the automation has become important to ensure productivity while improving the industrial process mastery. Therefore, the enterprises are obliged to guarantee the safe functioning of their equipment. They must, then, supervise the system of production in order to reduce the lapse cost of the equipment and to ensure its maximal availability.

The supervision of a system is executed with the help of a model that regroups the different functions of the supervision in this context. Many approaches have been developed for decay detection using statistical tools like the approach of Principal Component Analysis (PCA). This approach is adapted to show the significant linear correlations among the variables of a process [4].

PCA is a method of reducing a classic linear dimension that consists in projecting the samples on the axes of maximum variance of the data [3, 4, and 6]. Recently the methods of detecting and localizing defects based on PCA have received particular attention and have been broadly used in the supervision of industrial processes [1, 4, 8, and 9].

The originality of the approach to the follow-up of quality evolution of a product resides in a definition of quality indication (QI) and in the setup of a new method based on Average Dynamics of Metrics (ADM), which permits the valuation of the product quality to different levels of the manufacturing procedure.

1. UNIT PRESENTATION OF TEXTILE SPINNING

The process that describes manufacturing the thread differs according to the technology and type of the manufactured thread. In long and short fibre spinning, one uses the same principles of spinning (preparing for carding or beating, carding, stretching, combing and spinning).

The irregularity of linear textile structures is based on the study of probable properties related to the variable length between the ideal linear textile and its proportional real structures. The mass and length yield can be expressed with ideal and real linear structures and with the help of the metric number or the title [10]. They are defined as:

$$N_M = \frac{L(m)}{M(g)} = \frac{L(Km)}{M(Kg)} \quad (1)$$

$$T_{Tex} = \frac{1000}{N_M} \quad (2)$$

The most important parameter of quality is the variation of the linear mass; therefore, the first quality indicator is the coefficient of α variation that is defined by the following equation:

$$\alpha = \frac{100}{\overline{X}} \quad \frac{1}{T}\sqrt{\int_0^T \left(X_i - \overline{X}\right)^2 dt} \quad (3)$$

X_i : instantaneous value of measurement,

$\overline{X}$: mean of X_i ,

The variation coefficient is determined by the Uster tester device. However, the imperfections of the thread can be distributed in three groups: thin speckles, large speckles and spots.

The Uster statistics (UST91) propose a general sight of the quality thread from all over the world by statistical studies of the following criteria:

- The irregularity of ribbon, sulphur and thread.
- The frequency of thin speckles, large speckles and spots.
- The frequency of the rare defects of the thread.

We define, therefore, three other indicators related to the monitoring of quality; namely: the number of thin speckles β , large speckles θ and the number of spots ε .

The last quality indicator is the percentage of short fibres φ .

Examining a fibre thread, we notice that certain fibres escape from the process of cohesion by coming out of the linear structure; this characterizes the phenomenon of pilosity. The indication of H pilosity (Hairiness) tallies with the total length of the emergent fibres on a sample of 1 cm length of thread. The variation of pilosity indication is quantified by calculating the standard deviation of σ_H variance (determined automatically by the Uster tests 3). The variation coefficient of the pilosity is expressed as:

$$\varphi = \frac{100 \times \sigma_H}{H} \quad (4)$$

2. STRATEGIC APPROACH OF MONITORING

To make an automated production system competitive, it must have a priority objective to diminish the number of breakdowns and stops to the minimum. Obviously, this improves productivity. Therefore, it is obligatory to foresee a uniform task of maintaining the automated production system to guarantee its functioning safety.

Modelling an indirect supervision of the automated production systems makes the different steps of monitoring, clear. These latter are followed by PCA diagnosis quality indictors, fuzzy detection, and diagnosis Fig 1.

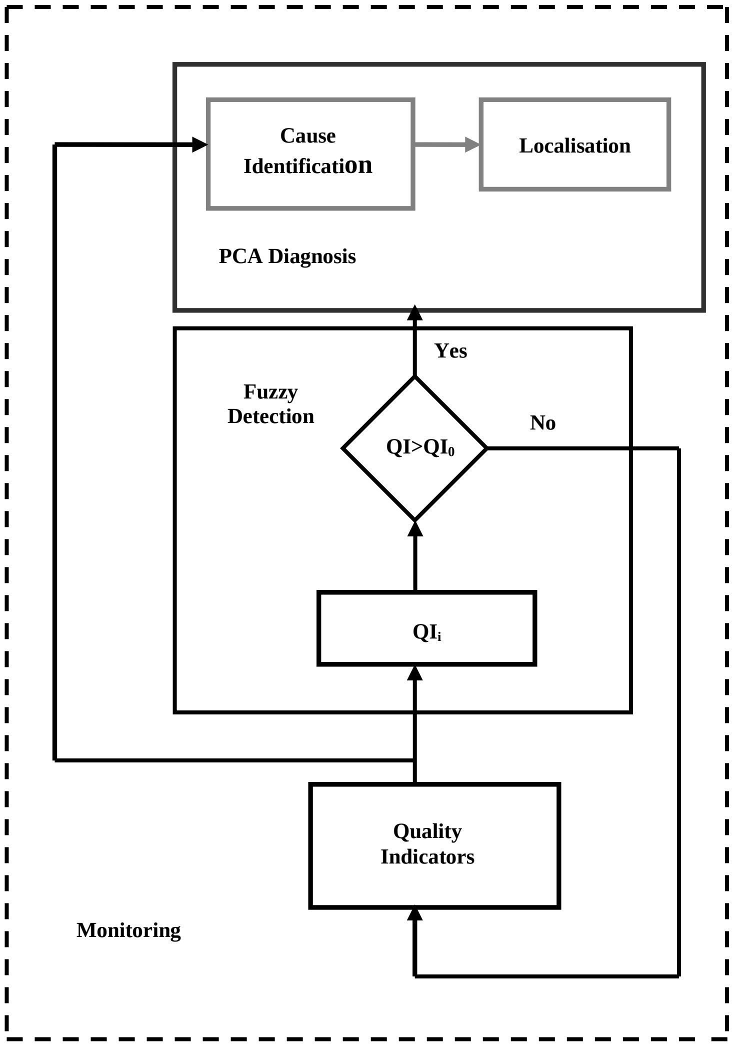


Fig.1. Model of monitoring a spinning unit

The indirect supervision is based on the quality of the descending products whose deterioration is caused by the irregularity or breakdown of one or several production resources at stake.

The connected function of evolution instantaneously allows taking the measures of the quality indicator at each stage of production, and then determining the quality indicator for its use in the detection and the identification of parameters.

After detecting a defect by the fuzzy logic method, a decision must be taken to be engaged into a process of diagnosis.

If the quality index is higher than an acceptable quality index QI_0, we pass to an operation of diagnosis by PCA. If not, we take other quality indicator measurements.

After the localization of the faltering element, it is necessary to program the actions of maintaining and minimizing the time of malfunctioning thanks to an adjustment maintaining strategy in order to guarantee the robustness of the system.

3.1 Average Dynamics of Metrics (ADM)

The ADM method [9] is based on:

- associating the membership function in every class;
- defining the weight of every variable of entry to the process of inference; and
- allowing memorization according to inference, the degree of credibility and the membership of a variable in a given class.

3.1.1. Fuzzification stage

Every variable of entry or exit Z is associated with a function of membership μ. The fuzzification stage consists in converting this variable into vague subsets modelling the human expertise.

To prepare the stage of numeric inference, we associate to every variable Z a function of classification s , allowing classifying every measure of the variable in one of the vague subsets defined by the fuzzification. Formally we define s in the following way:

$$s : D \rightarrow [1..m(Z)]$$
$$X_j \rightarrow b_j(X_j)$$

where

D = [Z_{min}... Z_{max}] is the domain of definition of the variable Z, m(Z) is the vague number of set defined for the variable Z, and a value of Z and w is the number of the classes to which the value belongs.

The function of classification s is defined so as to model from the point of view of an expert the nature of the evolution of variable Z. Hence, if a variable has a monotonous evolution, the function of classification is going to classify the vague subsets in a monotonous way, to see an example you can refer to section V.

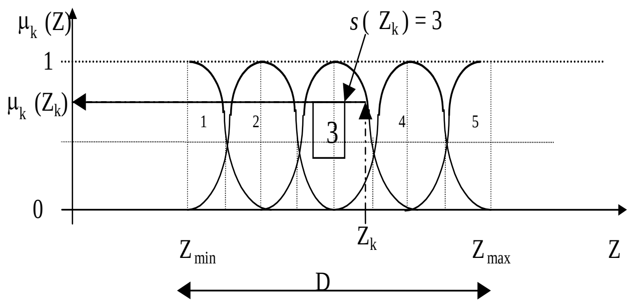


Fig.2. Variable Z fuzzification and classification

3.1.2. Weight of entry variables and inference mechanism

The classic approaches are characterized by the definition of a certain number of rules of inferences allowing coding the human expertise under a vague shape. Generally, the coding is not exhaustive and an expert retains a number of rules which seem to model the problem. These rules contribute to the calculation of the exits according to the reserved inference mechanism.

The framework of ADM consists in realizing a projection of the space of entry variables to the space of the exit variables. To realize this projection we have introduced the factor notion of level-headedness b_j associated to an entry variable X_j :

$$b_j : D_j \rightarrow \Re$$
$$X_j \rightarrow b_j(X_j)$$

These factors of level-headedness have a double meaning. On the one hand, they serve for quantifying the influence of a variable of entry to the determination of the value of an exit variable. On the other hand, they allow characterizing the representation space of the exit variables considering the classification realized on the vague subsets of every variable. Indeed, we have to take into account the fact that the number of classes associated to every exit variable is not necessarily the same as that of the entry variables. According to our needs, the factors of level-headedness will dilate or reduce the space of an exit variable in terms of number of classes defined by s .

We have formalized the knowledge by a function of numeric projection P_k, defined for every exit variable Y_k. The P_k function allows determining the membership class of the value of an exit variable Y_k knowing the membership classes of the values of the entry variables Xj.

$$P_K : D_{Y_K} \rightarrow [1..m(Y_K)]$$
$$Y_K \rightarrow P_K(Y_K)$$

with

$$P_K(Y_K) = E(0.5 + \sum_{j=1}^{n} b_j^k X_j \times s_j(X_j))$$

with

D_{Y_k} as the domain of definition of the variable of exit Y_k,

$m(Y_k)$ as the number of fuzzy subsets associated with variable Y_k, $b_j^k(X_j)$ as the factor of level-headedness of X_j related to the determination of Y_k, and $s_j\ (X_j)$ as the value of the class associated to the current value of the variable X_j.

The sum of products $b_j^k(X_j) \times s_j(X_j)$ allows determining a value approaching the class associated to Y_k. The addition of the coefficient 0.5 and the rounded off by the calculation of the whole value allow us to determine the closest integer for the exit class. The coefficients $b_j^k(X_j)$ are defined in a way that the definite value is included between 1 and m(Y_k) considering the current value of every entry variable X_j.

3.1.3. Defuzzification stage

Within the framework of the ADM, defuzzification consists in calculating the numerical value associated to an exit variable. This calculation is elaborated from the knowledge of its membership class defined by the numeric inference and from the values of the membership functions in relation to the entry variables. To formalize this calculation, we have associated to every variable Y_k a metrics defined by the function below:

$$f_K : X^n \times D_{Y_K} \rightarrow [0,1]$$
$$(X, Y_K) \rightarrow \mu_K(Y_K)$$

with

$$\mu_K(Y_K) = f_K\left(\mu_n(X_n)...\mu_j(X_j)...\mu_1(X_1), b_n^k(X_n)...b_j^k(X_n)...b_1^k(X_1)\right) \quad (5)$$

with

$X = [X_1, ..., X_j, ..., X_n]^T$ as a vector entry defined on X_n,

μ_k (Y_k) as the degree of membership of the current exit value Y_k,

$\mu_j(X_j)$ as the degree of membership of the current entry value X_j,

$b_j^k(X_j)$ as the factor of level-headedness of variable X_j related to the determination of Y_k.

Once the exit class and membership degree of the exit are known, it is necessary to apply a method of defuzzification adapted to the monotonous nature of the classification function related to the exit variable. There exist in literature numerous methods of defuzzification such as the gravity centre. We have named the function of partial membership as the function defining the curve wraps with a given class. If the function of partial membership defines the exit class in a monotonous evolution, a method of defuzzification consists in throwing (planning) on the X axis the point of the curve defining the class with the right-hand side stemming from the orderly k (Y_{kc}) (Fig 3).

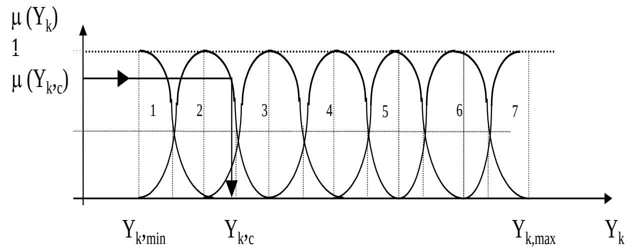


Fig.3. Projection defuzzification onto an Y_K axis

3.2 Principal Component Analysis (PCA)

The methods for detecting defects and localizing parameters based on PCA have received a particular attention and been broadly used to the supervision of industrial processes [2, 11, 12, and 13]. The principle of this approach is using the analysis in principal components to establish a model for the comportment of a normal working process, and thus detecting the defects while comparing the observed comportment to the given one.

In principal components, a characteristic vector $t \in \Re^{\ell}$ is associated to each vector of data so that it can optimize the representation to the sense of minimizing the error of estimation of X or maximizing the variance of the score matrix T. The vector t and the x letter are bound by a linear transformation t = P^Tx, where the matrix of transformation $P \in \Re^{m \times l}$ meets the condition $P^T P = I$.

Using PCA, an $n \times m$ normalized data matrix can be decomposed as follows:

$$X = \hat{X} + E \quad (6)$$

In this way, the columns of X are normalized to zero mean and unit variance. The matrices $\hat{X}$ and E represent the modeled and unmodeled variations of X respectively;

$$\hat{X} = TP^T \quad (7)$$

$$E = \tilde{T}\tilde{P} \quad (8)$$

X is composed in a way that the composed matrix $[P\tilde{P}]$ is orthonormal, and $[T\tilde{T}]$ is orthogonal. After the PCA model is built, a new sample vector X $\in \Re^m$ can be decomposed in two parts;

$$x = \tilde{x} + e \quad (9)$$

where $\tilde{x} = PP^T x \equiv Cx \in \Re^{\ell}$ is the projection of the sample vector to the principal component subspace (PCS), $\Re^{\ell}$, and $e = (I - C)x \equiv \tilde{C}x \in \Re^{m-\ell}$ is the projection of the sample vector to the residual subspace (RS), $\Re^{m-\ell}$.

The prediction $\hat{x}_i$ is used as a recovery of x_i, which can be expressed as in (10).

$$\hat{x}_i = xc_i = [x_1 x_2 .... x_i ..... x_m][c_{1i} c_{2i} ..... c_{ii} ..... c_{mi}]^T \quad (10)$$
$$= [c_{-i}^T \, 0 c_{+i}^T]x + c_{ii} x_i$$

where $C = PP^T = [c_1 c_2 ...... c_m]$ (11)

In the approach to PCA-based detection, two statistics T^2 and SPE are used for surveillance.

For the instant k we have:

$$T^2(k) = \sum_{i=1}^{\ell} \frac{t_i^2(k)}{\lambda_i}$$

(12)

$$SPE(k) = \sum_{j=1}^{m} (e_j(k))^2$$

(13)

where $e_j(k)$ is the j[th] residue which is given by :

$$e_j(k) = x_j(k) - \hat{x}_j(k) \tag{14}$$

where $x_j(k)$ is the j^{th} element of measuring vector, x(k) is the i^{th} principal component and t_i is the i^{th} proper value of the correlation matrix Σ, which represents the variance of t_i. m is the number of quality indictors and ℓ is the number of components, with $\ell \prec$ m which is the estimation of x by the PCA model given by:

$$\hat{x} = Cx \tag{15}$$

where $C = P_\ell P_\ell^T$. P_ℓ is the matrix formed by the ℓ first proper vectors of the matrix Σ. The process will be considered functioning abnormally (presence of a default) if one of these following inequalities at least is true:

$$SPE \prec \delta_\alpha^2 \tag{16}$$

$$T^2 \prec \chi_\alpha^2(\ell) \tag{17}$$

where δ_α^2 and $\chi_\alpha^2(\ell)$ are respectively the thresholds of T^2 and SPE [4]. To reduce the false alarms, the EWMA (exponentially weighted moving average) filter can be applied to residues [9]. The general expression of filtered residues is given by:

$$\overline{e}(k) = (I - \tau)\overline{e}(k-1) + \tau e(k) \tag{18}$$

where $\tau = \gamma I$ ($0 \prec \gamma \prec 1$). I is a diagonal matrix whose diagonal elements are the emission factors of the residues.

$$\overline{SPE}(k) = \left\|\overline{e}(k)\right\|^2 \tag{19}$$

The threshold of detection for $\overline{SPE}$ [9] is given by:

$$\overline{\delta}_\alpha^2 = \frac{\gamma}{2-\gamma}\delta_\alpha^2$$

(20)

Using the statistic T^2 implies a multivariable normal distribution of observations. Now that this condition is rarely verified, using T^2 in this context generates an efficiency loss of this test. Haraket and al [9] showed that the SPE is very sensitive to modelling errors and proposed a new method of detecting and locating faults which uses the test of the square sum of the last principal components. In the case of this detecting index, the last filtered components are given in the following equation:

$$\overline{t_i}(k) = (1-\gamma)\overline{t_i}(k-1) + \gamma t_i(k) \tag{21}$$

where $\overline{t_i}(k)$ is the j^{th} filtered principal component at the instant k. The detecting index based on the last components is defined by:

$$D_i(k) = \sum_{j=m}^{m-i+1} \overline{t}_j^2(k) \qquad \text{i=1,2,.....,(m-}\ell\text{-1)} \tag{22}$$

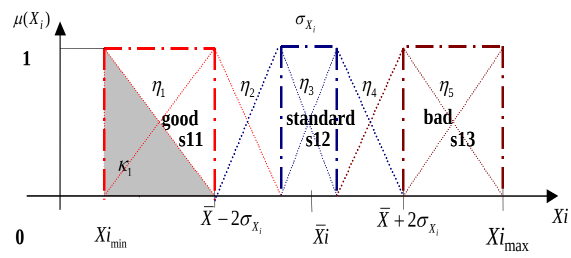
3. Application to Textile Spinning Unit

3.1 Fuzzy Logic Detection

As part of our study, we admit that valuation has allowed us to associate three fuzzy classes to each input and output variable. Let n=5, which is the number of input variables ($\beta, \theta, \alpha, \varepsilon$, and φ), and $m(X_i)$ be the number of classes where $m(X_i) = 3$.

To increase the number of fuzzy classes, we define elementary classes from initial fuzzy subsets. Thus, we define an elementary class corresponding to the part of each fuzzy subset where the membership function of the variable is equivalent to 1.

As an example, we consider the case of noted classes η_1 , η_3 and η_5 in Fig 4. In other respects, we associate an elementary class by a space field where a measurement can be equally associated with either of the fuzzy subsets; for instance, we take the case of elementary classes η_2 and η_4 in Fig 4. So, the number q of the elementary classes is equal to $2 \times m(X_i) - 1$. Then, we divide each η_i into elementary subsets delimited by the diagonals of rectangles defining the elementary classes. We note these elementary subclasses κ_i . The number r of elementary



The membership function $\mu(X_i)$, represented in Fig 4, consists of 3 classes, 5 elementary classes (q=5) and 10 elementary subclasses κ_i in Fig 5 (r=10).

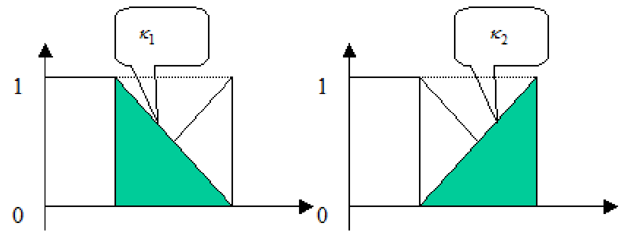


Fig.5. Elementary subclasses associated with an elementary class

The Quality Indication QI representing the variations of five quality parameters is quantified by the exploitation of the ADM method. This method is applied from the same membership functions allowing the linguistic qualification of the partial quality indicators (α, β , and θ). For the inference, we have used the level-headedness defined in Table 1 to determine static weights for every partial quality indicator considered in the entry. For example, the weight of α in the resolution is fixed to 0.4. Peaks noted on these figures correspond to phases of degradation of the material resources followed by phases of maintenance.

Table 1: Logic of level-headedness

Components	α	ε	θ	β	φ
Moderation	40%	26%	20%	7%	7%

In order to put in evidence the effect of the number of vague classes on the precision of the estimation of the quality of the product used in the manufacturing process, we present the experimental measurement, realized over a period of 2 months for the Acrylique 100. They allow making the quality control of products and the follow-up of evolution of the production system.

The ADM, however, allows a continuous follow-up of the evolution of the quality indication as shown in Fig 6. This evolution allows us to fix thresholds of detection within a membership class of the quality indication. Thus, this one allows us to discover more damages.

Fig.6. Representation of the quality indication calculated by the ADM

4.2 Identifying Defects and Localizing Parameters

We have a corresponding database to accomplish measurement for 4-month duration with a sampling period of 5 days. In our application, we have chosen a first sample for 2-month duration. Measuring the variables of the process and representing all the normal working way of the latter are collected in a matrix $X \in \Re^{n\times m}$. That is, m is the variable number ($\beta,\theta,\alpha,\varepsilon$, and φ) and n is the number of observances of each variable.
All the data is then centred and reduced. The new matrix of the normalized data is obtained.

$$X = \begin{pmatrix} -1.1597 & -1.5181 & -1.2622 & -1.2086 & -1.4057 \\ -0.8078 & 0.1667 & -0.1685 & 0.5005 & -0.4939 \\ -0.1039 & 1.1145 & -0.1685 & 1.7214 & 1.7857 \\ 0.2655 & -0.5177 & 1.4718 & -0.5249 & -0.0379 \\ -1.1597 & -1.5181 & -0.6607 & -1.2086 & -1.4057 \\ -0.8078 & 0.1667 & -1.2622 & 0.5005 & -0.4932 \\ -0.1039 & 1.1145 & 1.4718 & 1.7214 & 1.7857 \\ 0.2655 & -0.5177 & -0.6607 & -0.5249 & -0.0379 \\ 0.2655 & -0.5177 & -0.6607 & -0.5249 & -0.0379 \\ 0.3183 & -0.3597 & -0.1139 & -0.7203 & -0.0379 \\ 0.4942 & 1.3777 & 0.8156 & -0.2319 & -0.0379 \\ 2.5354 & 1.0091 & 1.1984 & 0.5005 & 0.4179 \end{pmatrix}$$

The matrix of correlation of data is noted:

$$R = \begin{pmatrix} 1.0002 & 0.5212 & 0.6087 & 0.1949 & 0.4259 \\ 0.5212 & 0.9999 & 0.5845 & 0.8121 & 0.7751 \\ 0.6087 & 0.5845 & 0.9999 & 0.3877 & 0.5641 \\ 0.1949 & 0.8121 & 0.3877 & 0.9999 & 0.8506 \\ 0.4259 & 0.7751 & 0.5641 & 0.8506 & 0.9999 \end{pmatrix}$$

The matrix of the proper vectors is given by:

$$P = \begin{pmatrix} -0.2460 & 0.1655 & 0.5773 & -0.6760 & 0.3490 \\ 0.4459 & -0.6932 & 0.2265 & 0.1219 & 0.5045 \\ -0.0988 & -0.0970 & -0.7833 & -0.4436 & 0.4130 \\ -0.7201 & -0.0282 & 0.0381 & 0.5222 & 0.4544 \\ 0.4609 & 0.6942 & -0.0194 & 0.2422 & 0.4967 \end{pmatrix}$$

The matrix of the proper values is given by:

$$A = \begin{pmatrix} 0.0724 & 0 & 0 & 0 & 0 \\ 0 & 0.2141 & 0 & 0 & 0 \\ 0 & 0 & 0.3774 & 0 & 0 \\ 0 & 0 & 0 & 1.0024 & 0 \\ 0 & 0 & 0 & 0 & 3.3335 \end{pmatrix}$$

4.2.1. Determining the number of principal components

An URV, the variance of the reconstruction error, is proposed to determine the number of principal components.

We are also interested in determining the component count to be kept. We have used a criterion based on the minimisation of the variance of the reconstruction error [13]. The URV in the direction ξ_i is denoted by v_i , and represents the variance of the projection of $x - x_i^*$ to the indicator fault direction ξ_i .

$$v_i = \frac{\xi_i^T (I-C)R(I-C)\xi_i}{(\xi_i^T (I-C)\xi_i)^2} \tag{23}$$

Variances of reconstruction errors of the different indicators are given in Table 2.

Table 1: Variance of reconstruction errors of different indicators

v_α	v_β	v_θ	v_ε	v_φ
$\ell=1$	$\ell=2$	$\ell=3$	$\ell=4$	$\ell=5$
1.86	4.79	23.98	5.69	6.55

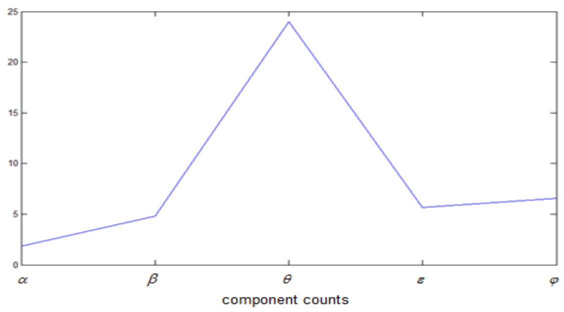


Fig.7. Evolution of component selection criterion.

Fig 7 presents the evolution of the criterion according to the component count. The minimum of this criterion tallies to $\ell = 1$. Therefore, a model with a component is kept.

4.2.2. Identifying the drifts to γ near zero (abrupt changes)

In Fig 8 we present the simulation of a defect of d=4.46 amplitude affecting the quality indicator φ from k=30/01/09, where the defect is detected only by $\bar{D}3$ and $\bar{D}4$ indications.

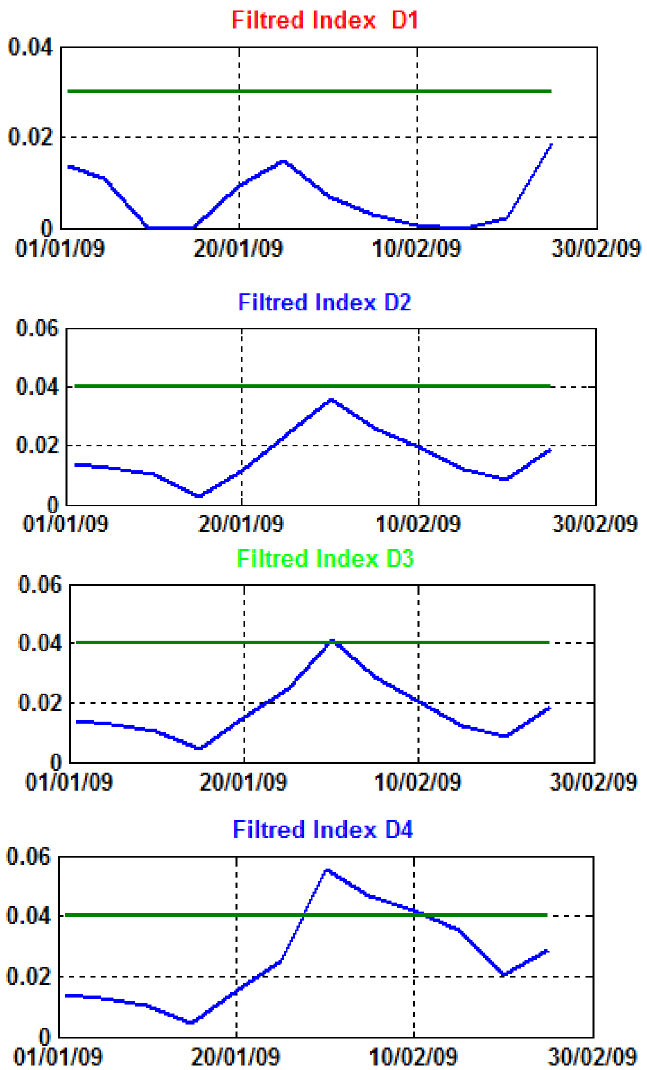


Fig.8. Evolution of indications $\bar{D}1$, $\bar{D}2$, $\bar{D}3$ and $\bar{D}4$ with a defect affecting φ indicator to a k=30/01/09 instant

4.2.3. Identifying the drifts to γ close to one (slow changes)

Also, we present the simulation of a defect of d=6.86 amplitude affecting quality indicator φ at k=10/01/09 instant, where the defect is detected by $\bar{D}1$, $\bar{D}2$, $\bar{D}3$ and $\bar{D}4$ indications shown in Fig 9.

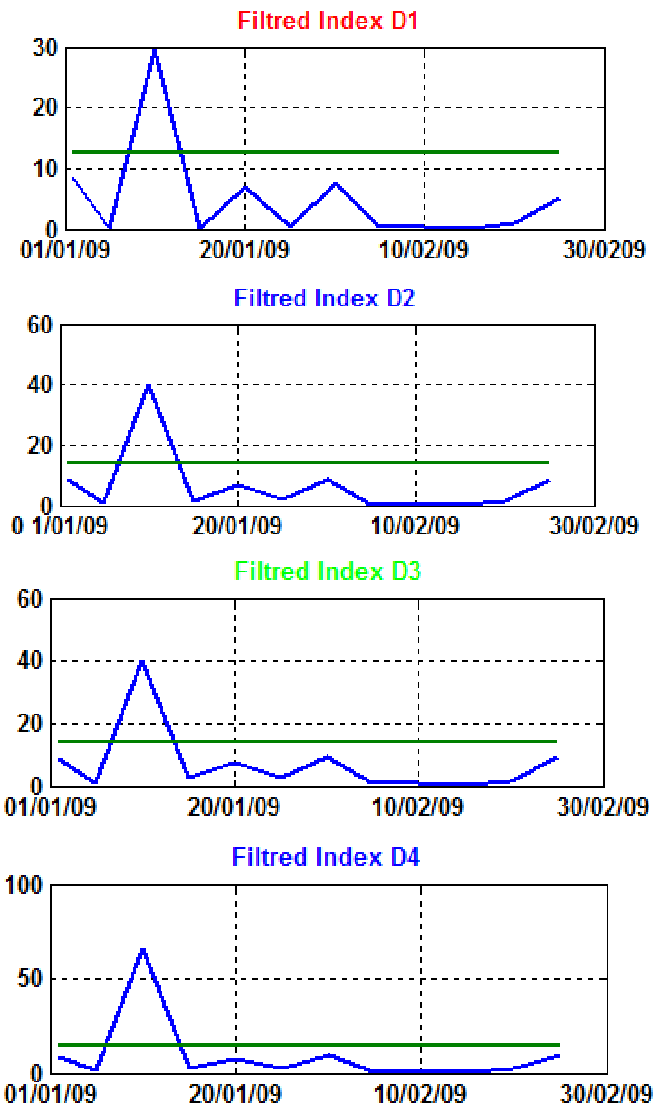


Fig.9. Evolution of indication $\bar{D}1$, $\bar{D}2$, $\bar{D}3$ and $\bar{D}4$ with a defect affecting φ indicator to a k=10/01/09 instant

4.2.4. Evaluating the drifts to γ near zero (abrupt changes)

The result of applying the analysis of the contributions to indication $\bar{D}1$ where the defect is affecting indicator φ is illustrated in Fig 10.

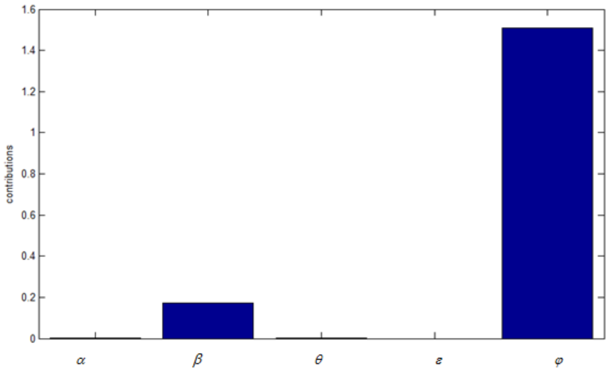


Fig.10. Contributions of different variables to an indication to a k=10/01/09 instant

The indicator φ , having the strongest contribution in relation to the other variables, is considered as the variable in fault.

4.2.5. Evaluating the drifts to γ close to one (slow changes)

The result of applying the analysis of the contributions to indication $\bar{D}1$ where the defect is affecting indicator β is illustrated in Fig 11.

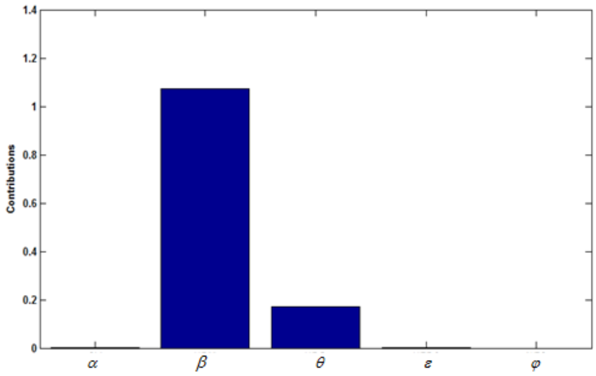


Fig.11. Contributions of different variables to an indication to a k=10/02/09instant

In Fig 9, the indicator φ , having the strongest contribution in relation with the other variables, is considered the variable in fault.

4. Conclusions

We have presented in this paper a case study by using the Average Dynamics of Metrics for detecting and Principal Component Analysis (PCA) for identifying and localizing defects.

In this work, the PCA is used like a technique of modelling the relations among the various variables of the process. However, for determining the structure of the model, it is necessary to determine the component number to be retained in this model.

In the case of installing an approach of indirectly monitoring a unit of a spinning mill, data is often vague and sometimes qualitative. So, we have used fuzzy logic to represent the vague data. Thus, our objective is to identify the amplitude of degradation related to the qualitative or quantitative variation of the intrinsic aptitudes of the process. For the detection function, we have used the ADM method resulting from the technique of fuzzy logic to determine the total quality indicator QI integrating the contributions of the indicators of wire quality ($\beta, \theta, \alpha, \varepsilon$, and φ).

A comparison test between the QI and an acceptable quality index QI_0 makes it possible to evaluate the total product quality. In the case of an acceptable degradation QI< QI_0, new measurements are made for detection until QI> QI_0 or the function of diagnosis based on the ACP state is used to identify and locate the indicators at fault.

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[1]**Ouni Khaled** received his License of Automatically Industrial Data Processing from ESST-Tunis. In 2007, he obtained his Mastery in Safety and Security of the Industrial Systems from ISSAT- Sousse.
He is currently Assistant in the Superior Institute of Applied Sciences and Technology in Kairouan (ISSATK). His research interests include Modelling, Control, Monitoring and Command Manufactory Systems.

[2]**Nabli Lotfi** received his Mastery of Sciences and DEA from ENSET- Tunis - Tunisia in 1989 and 1991 respectively. In 2000, he obtained his doctorate degree in Industrial Automation: Automatic and Industrial Computing from the University of Sciences and Technologies of Lille France. He is currently professor of Electrical Engineering professor at the Superior Institute of Applied Sciences and Technology in Sousse (ISSATS) - Tunisia. His research interests include Modeling, Control, Automatic computer, Monitoring and Command Manufactory Systems.

[3]**Hassani Messaoud** has received his Bachelor's degree in Electrical Engineering in 1983 and his Master of Science in Control Engineering 1985 from the High Normal School of Technical Education (ENSET) in Tunis – Tunisia. His PhD in Control Engineering was prepared at the University of Nice – Sophia Antipolis / France in 1993 and his Habilitation Diploma was defended at the School of Engineers (ENIT) in Tunis –Tunisia. He is presently a Professor at the School of Engineers of Monastir – Tunisia (ENIM). His main interest is robustness in identification and control of non linear systems with application to diagnosis and equalization of numerical communication channels.