Journal of Theoretical and Applied Information Technology
31st August 2017. Vol.95. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

COMBINATION OF SECOND ORDER MODELING AND ACP TOOL FOR FAULT ISOLATION

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ABSTRACT

Automation has become important to meet the needs and requirements of industries especially the transportation industries. Thus, in a transport context, the aim is to increase the level of traffic flow and to develop monitoring techniques by monitoring the evolution of the performance indicators of a system; The detection of a defect and its diagnosis are of great interest and the prognosis is currently the subject of several in-depth studies.

This paper suggests a detection approach in the flow problem regarding the road traffic the rough principal component analysis (PCA). This control technique is considered very effective in the field of surveillance. The PCA is considered an indispensable tool applied by industries with the objective of avoiding or reducing any anomaly that may intervene in the field of operation of the system. . It is applied to a road section of Lille-France with 829 measurements with four variables: traffic density, flow rate, average speed and occupancy rates following the application of a modeling tool of the second order in the Pre-processing phase of the data. The PCA is used to detect defects by statistical predictive square error SPE and method Hotteling T^2. Thus before the isolation, the segmentation has become a necessary step to ensure the visualization of classes (in faults and without defects). The calculations of contributions allow isolating faults and identifying faulty variables. In our example, the defectives variables are both the flow rate and the average speed.

Keywords: *Modeling of second order, Linear PCA, Fault detection, segmentation, Fault isolation*

1. INTRODUCTION

Currently, transport systems have played a fundamental role in the development of different countries. Nevertheless, it was only from the end of the last century that they became problematic [1]. Normally, these problems are mainly related to rapid changes in the number of vehicles, which generally lead to a slowdown in traffic, traffic delays, congestion, an increased risk of catastrophic accidents, increased emissions of gases. They can influence the quality of life of citizens.

Indeed, these various difficulties cited above constitute a major problem for society. Hence the need to develop solutions to reduce or minimize the negative consequences that may appear [2].

In this framework, several investigations are used to detect and isolate the various problems of traffic flow, among the approaches that seek to achieve the previous object are: Algebraic approach [1], Classical Kalman filter [2], Luenberger observers [3], and the main components analysis PCA [18, 20].

The PCA is taken into account in this work, it is considered a statistical tool to monitor system operation, it is very efficient to reduce their dimensionality.

This approach is simple, through the graphs it provides, the PCA makes it possible to understand a large part of its results at a glance and to construct a complete view of the relations existing between the quantitative variables of a Study population [8, 9, 10].

The PCA statistical tool allows the detection of defects by the SPE or T^2method while ensuring detection by the contribution calculation.

In this work, we are interested on the one hand to ensure a detailed analysis of model of second order METANET in order to have a simulation close to the reality.

Journal of Theoretical and Applied Information Technology
31st August 2017. Vol.95. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

On the other hand, a detailed explanation and application of the multi-variable PCA statistical method on real measurements of a motorway section of Lille Nord of France to ensure detection and identification of defect direction by visualization of the different Class and isolation of abnormal situations.
Finally, we end with a part that is the subject of a conclusion and perspectives.

2. SECOND ORDER MODELING TOOL

Concerning the macroscopic model of the second-order ability, we aim at predicting a complex phenomenon that occurs and can not be identified and captured via the first order model, and of the most powerful model in several METANET studies [11].

As for the macroscopic model capability it produces higher-order complex phenomena that occur and can't be identified and captured by the first order model. Added to that, the most powerful model in several METANET studies [11].

Thus, the use of this model has recently been known to model, and to simulate a phenomenon [4, 5, 6].

Our process that is used here, it is modeled by the macroscopic model of second order and is based on the model of Payne that is discretized in space and time [6, 11].

This modeling system targets modeling the network by a directed graph composed of links and nodes:

• Regarding the links, they represent the segments from the model discretization in space;

• Nodes represent the points of convergence or divergence that may be at the network level.

This type of second order macroscopic model is classified as deterministic models. Iit considered that all segments have uniform characteristics (the same number of channels).

Like all macroscopic models, our tool describes the evolution of:

• The output segment of each stream that is given by the following relationship:

$$q_{m,i}(t) = \lambda_m \rho_{m,i}(t) v_{m,i}(t) \tag{1}$$

λ_m, $\rho_{m,i}$, $v_{m,i}$ are respectively the number of channels in the same segment, the segment density and average speed.

• The density ρ is a segment that is based on the discretization of the differential equation by taking into consideration the speed of an input or / and output ramp is:

$$\rho_{m,i}(t+1) = \rho_{m,i}(t) + \frac{T}{L\lambda_m}\left(q_{m,i-1}(t) - q_{m,i}(t)\right) \tag{2}$$

With $\rho_{m,i}(t)$, $q_{m,i-1}(t)$ and $q_{m,i}(t)$ are respectively the previous density, the flow of the upstream segment and the segment of the stream itself.

• Average speed v

$$\begin{aligned} v_{m,i}(t+1) &= v_{m,i}(t) + \frac{T}{\tau}\left(v_e\left(\rho_{m,i}(t)\right) - v_{m,i}(t)\right) \\ &+ \frac{T}{L} v_{m,i}(t)\left(v_{m,i-1}(t) - v_{m,i}(t)\right) \\ &- \frac{\nu T}{\tau L}\left(\frac{\left(\rho_{m,i+1}(t) - \rho_{m,i}(t)\right)}{\rho_{m,i}(t) + \kappa}\right) \end{aligned} \tag{3}$$

With $v_{m,i}(t), \frac{T}{\tau}\left(v_e\left(\rho_{m,i}(t)\right) - v_{m,i}(t)\right) + \frac{T}{L},$ $\frac{T}{L} v_{m,i}(t)\left(v_{m,i-1}(t) - v_{m,i}(t)\right) - \frac{\nu T}{\tau L}$ and $\frac{\nu T}{\tau L}\left(\frac{\left(\rho_{m,i+1}(t)-\rho_{m,i}(t)\right)}{\rho_{m,i}(t)+\kappa}\right)$ are respectively the average speed at the moment t, the term relaxation that expresses the intention of the driver to reach the desired speed $v_e(\rho)$.this convection term shows the increasing or decreasing speed and anticipation term that expresses the evolution of the speed (ascending or descending) according to changes in density.

τ, ν and κ are respectively the temporal constant, and constant anticipation. Different parameters are considered constant for all links (m : the length of each channel) network.

Furthermore, we must point out that this modeling tool uses the fundamental diagram of May [12], the desired speed is given by the following equation:

$$v\left(\rho_{m,i}(t)\right) = v_{l,m} \exp\left[-\frac{1}{\alpha_m}\left(\frac{\rho_{m,i}(t)}{\rho_{c,i}}\right)^{\alpha_m}\right] \tag{4}$$

v_l is the free speed is the critical density and α_m fundamental diagram parameter link m.

To account for the phenomenon of falling speed and capacity of a fall in the equation for the average speed, following the narrowing or ramp input and / or output, respectively, which will be mentioned as following:

$$-\phi \frac{T_s \Delta\lambda_m \rho(t) v_m^2(t)}{L_m \lambda_m \rho_c} \quad \text{and} \quad -\gamma \frac{T_s q_{ri}(t) v_i(t)}{L_i \lambda_i \rho_i(t) + \kappa} \tag{5}$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

With ϕ, γ are the constant parameters models. T_s is the time step of the simulation. $q_{ri}(t)$ is the segment of the ingress-rates i at no time t . $v_i(t)$ is the average speed of segment i at no time t and $\Delta\lambda$ corresponds to the reduced number of channels.

3. LINEAR PRINCIPAL COMPONENT ANALYSIS

The diagram below summarizes our working approach.

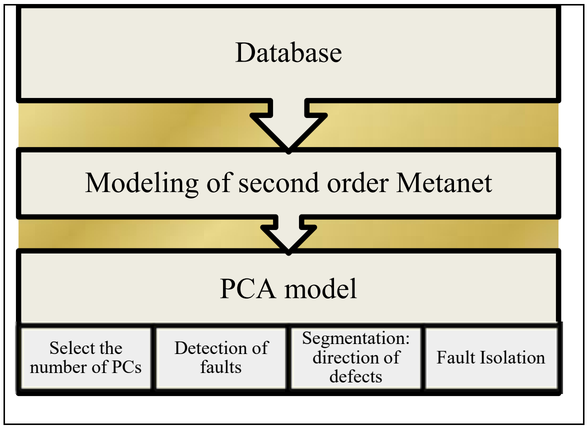

Figure 1: Detection and isolation of faulty settings LPCA

In addition, ACP is used as a process status monitoring tool. Whatever system should monitor the functioning of the system to detect abnormalities in the situations stumbles to take good decisions for the operation system in general [7].

This tool seeks to project information from a wide space to a lower dimensional space under transforming variable correlated uncorrelated variables which are called the principal components [13]. Otherwise, the CPA is to find a set of factors or components that can properly describe the main trends [13]. Thus, the CPA model objective is the realization of a diagnosis which helps to guide the choice of number of CP to remember to detect and isolate a fault or points. Understanding the principle of ACP, we can summarize the operation of the ACP by the decomposition of a matrix linear transformation as follows:

$$T_{N\times m} = X_{N\times m} P_{m\times n} \text{ et } X_{N\times m} = T_{N\times m} P^T_{m\times n} \quad (6)$$

With

$X \in \mathbb{R}^n$: matrix N observation and m variables.

$P \in \mathbb{R}^{m\times n}$: Eigenvector matrix

T : Score matrix (matrix of principal components).

$P = [P_1, P_2, \dots, P_m]$: The set of vectors in $\mathbb{R}^{m\times n}$.

Mathematically, the linear PCA of a die $Z = [Z_1, Z_2, \dots, Z_m] \in \mathbb{R}^{N\times m}$ is defined by the following equation:

$$z = TP^T + E = \sum_{i=1}^{\ell} t_i P_i + E \quad (7)$$

With $T = [t, t_2, \dots, t_m]$ is the matrix of the main components, $P = [P_1, P_2, \dots, P_m]$ is the eigenvector matrix, and E is the residue matrix.

The generalization of the ACP is effected by keeping the maximum amount of information by minimizing the following cost function:

$$E = \{\|z - \hat{z}\|^2\} \quad (8)$$

In order to detect the defects, more indicators can be used to know SPE (prediction error) or as well T^2 which tests last main components:

• Statistics square predictive error SPE

$$SPE = \|\tilde{x}\|^2 = x^T \tilde{P}\tilde{P}^T x = x^T \tilde{C} x = e^T e$$
$$= (x - \hat{x})^T (x - \hat{x}) \quad (10)$$

T^2 testing the last main components

$$T^2 = (x - \alpha) S^{-1} (x - \alpha)^T \quad (11)$$

With $e = (I - \tilde{P}\tilde{P}^T)x$ this residues of vector, the detection limit for SPE was expressed by Jackson and Mudholkar [14] as shown by the following relationship:

$$\delta_\alpha^2 = \theta_1 \left[\frac{1 - \theta_2 h_0 (1 - h_0)}{\theta_1^2} + z_\alpha \frac{(2\theta_2 h_0^2)^{1/2}}{\theta_1} \right]^{1/h_0} \quad (12)$$

With

$$\theta_1 = \sum_{i=1}^{m} \lambda_i, \theta_2 = \sum_{i=1}^{m} \lambda_i^2, \theta_3 = \sum_{i=1}^{m} \lambda_i^3, \quad (13)$$

$$h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^2} \quad (14)$$

For the calculation of contributions, it is a fault localization approach which to based on the quantification of the contribution of each variable to the detection statistic.

Concerning the SPE method, the contribution calculation for one variable is presented considering the large square residue associated with a single variable:

$$SPE_i = \tilde{x}_i^2 \quad (15)$$

Concerning the SPE, the latter is presented based on the large square residue associated with a single variable [15]:

$$c_i^{SPE} = \left(\xi_i^T \tilde{C}^{1/2} x \right)^2 = \tilde{x}_i^2 \quad (16)$$

4. SEGMENTATION

The realization of a diagnostic by introducing a classification method requires the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

passage through two stages: learning and recognition.

Training phase: this phase is carried out by the application of the ACPL

Recognition Phase: Once the estimated outputs are determined using the ACPL, using a fault detection tool and performing a classification technique to prevent the different classes to be executed: with faults and without defaults

The k-means classification was developed by MacQueen in the sixties. [26] With this type of classification that allows the object to change its class from one iteration to another that is not possible for other classification methods.

The method of dynamic clouds or k-means method is a repetitive method that seeks to converge towards a solution. This method repeats the calculation k times until obtaining an optimal optimal solution according to the criterion chosen at the beginning (numbers of class k will be fixed at the beginning). Indeed, at the level of the first iteration we set a starting point which consists in uniting the center of the k classes with k observations (objects). The distance between the k centers and the objects is then determined. Later, these last observations are assigned to the center of the closest classes. Then, from these already affected objects, the centers are redefined and the objects are reassigned to the new centers according to their distance. These operations are repeated until the convergence is achieved and relevant [27].

Dynamic cluster classification allows data to be more relevant because they are calculated in the reduced center-space from the PCA tool [26], [27].

To explain this method of classification, we will cite a very simple example below [28]:

- In a first one, we fix the number of groups to be built from the beginning: K
- **A** and **B** are initially designated as the center of group respectively $\mathbf{C_1}$ and $\mathbf{C_2}$

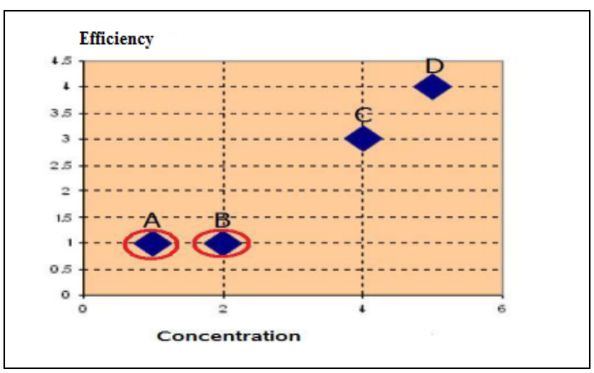

Figure 2: The first step of the K-means grouping method

- Starting with the calculation of the distance between points C and D at centers A and B

$$d(D, \mathbf{C_1}) = \sqrt{(x_D - x_A)^2 + (y_D - y_A)^2} = 5 \quad (18)$$

$$d(D, \mathbf{C_2}) = \sqrt{(x_D - x_A)^2 + (y_D - y_A)^2} = 4.25 \quad (19)$$

- We keep the class $\mathbf{C_1}$of center A and we pass to calculate the coordinates of new center of class $\mathbf{C_2}$

$$C_2\left(\frac{x_B + x_C + x_D}{3}, \frac{y_B + y_C + y_D}{3}\right) \quad (20)$$

$$\boldsymbol{C_2}(3.7, 2.5)$$

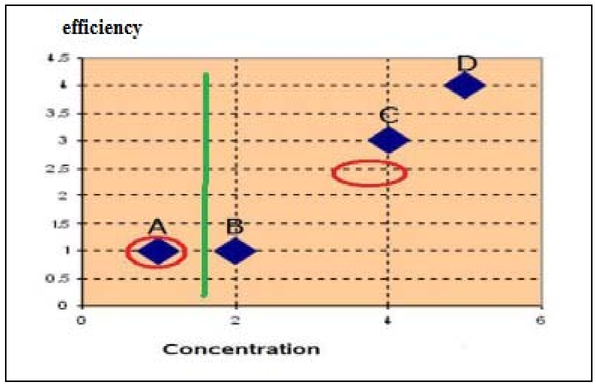

Figure 3: The second step of the K-means grouping method

Then the coordinates of two classes are:

$$C_1(1, 1)$$

$$C_2(3.7, 2.5)$$

- We return to the initial step and start the iteration 2 and recalculate the distance that separates each observation to the new class centers.
- Moving to the second step
- And we repeat its iterations until the convergence towards the expected solution is realized. Indeed, since the class number is known beforehand, one calculates their class centers for their new member.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

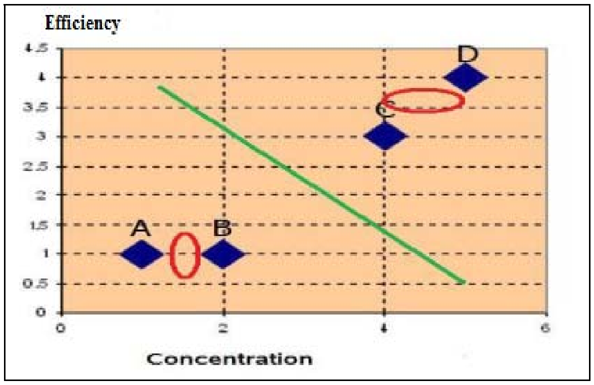

Figure 4: The third step of the K-means grouping method

$$C_1\left(\frac{x_A+x_B}{2},\frac{y_B+y_A}{2}\right) \quad (21)$$

$$C_1(1.5, 1)$$

$$C_2\left(\frac{x_C+x_D}{2},\frac{y_D+y_C}{2}\right) \quad (22)$$

$$C_2(4.5, 3.5)$$

So the group **C1** regroups the observations **A** and **B** so the group **C2** regroups the observations **D** and **B**.

5. EXPERIMENTAL RESULT

We apply the proposed approach on the data of a road traffic process motorway section based on the following criteria:

• Flow rate (D) measures the distribution of the vehicle over time and expressed as v / h;

• Occupancy rate (TO) (in%). This variable is translated to the simulation needs in terms of density;

• The average speed (V) of the vehicle is expressed as (Km / h);

• The density (d) (veh / km / lane): This index traffic is the number of vehicles present at the same moment on a given length of the road section.

The data matrix is based on a package of the mentioned criteria, a matrix of 4 variables and 829 steps. In the following, we set the CPA approach to the detection and fault isolation of the studied process.

(1). We start by modeling the motorway network to study based on a model of second METANET order.

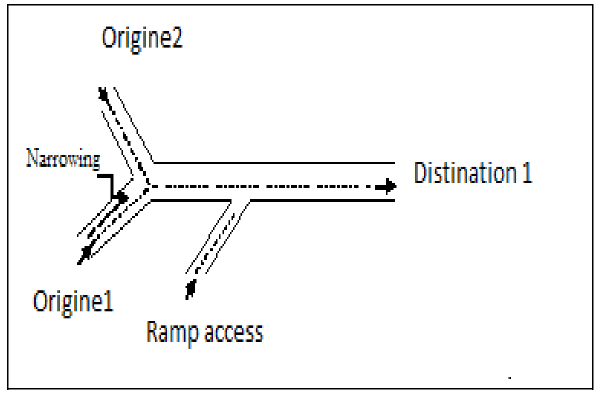

Figure 5: A Motorway Section

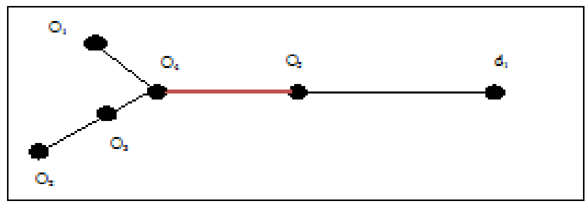

Figure 6: A Motorway Section In The Form Of Directed Graph Using The Modeling Tool METANET

The network is represented by a directed graph, where we exclude all geographical changes (to enter ramp, output ramp, shrinkage ...). Once it appears a node n as introduced in the graph. Our motorway network consists of two origins $o_1 o_2$ and three nodes o_3 ; o_4; o_5 the link length L_1; L_2 ; L_3; L_4 ; L_5 and a single destination d_1 which has a flow limit as displayed in figure 2.

(2) Our study will focus on the section between o_4; o_5. We turn to determine the number of principal components (CP) to remember. In the literature, there are several methods for determining the number of CP. For this, we present a certain technique that helps finding the CP that is:

• PVC method (cumulative percentage of the total variance) [16], [17] see that PVC is a percentage measure of variance captured by ℓ first principal components.

$$PVC(\ell) = 100\frac{\sum_{j=1}^{\ell}\lambda_j}{\sum_{j=1}^{m}\lambda_j} \quad (23)$$

j: indique la $j^{éme}$ colonne

With m, ℓ, λ_j are respectively the number as variables, the first principal components and $j^{éme}$ eigenvalue of the covariance matrix $\sum$ (or the correlation matrix R).

• Kaiser Approach Method

Journal of Theoretical and Applied Information Technology
31st August 2017. Vol.95. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

This method does not take into account the component having a lower variance than 1, will not keep because they contain less information than the main variables.

• Method of reconstruction errors of the variances [18], [19]

Authors Qin and Dounia suggest to determine the number of CP VER VER The following equation represents VER the ith component X(k):

$$\mathrm{ver}_i = \frac{\tilde{\xi}_i^T R \tilde{\xi}_i}{(\tilde{\xi}_i^T \tilde{\xi}_i)^2} \qquad (24)$$

With : $\tilde{\xi} = (I - C)\xi$ et $\xi_i = [0 \quad \dots \quad 1 \quad \dots \quad 0]$, one being the scalar 1 being the i th position otherwise ξ_i is the i th column of the identity matrix.

$X_i(k)$: The measurement vector $x(k)$ whose i th component that was built;

The method is reconstructed as follows:

$$X_i(k) = \frac{[C_{-i}^T \quad 0 \quad C_{+i}^T]}{1 - C_{ii}} \qquad (25)$$

Or

$$C_i^T = [C_{1i} \quad C_{2i} \quad \dots \quad C_{mi}] = [C_{-i}^T \quad C_{ii} \quad C_{+i}^T] \qquad (26)$$

C_i : is the i ème column C ;

$-i$; $+i$: these indicators respectively denote vectors forms by $i-1$ first and last elements $m - i$ vector C_i .

In addition, the number of principal components ℓ to remember is obtained by minimizing the following criterion [23] :

$$\mathrm{VER} = \sum_{i=1}^{m} \frac{\mathrm{ver}_i}{\xi_i^T R \xi_i} \qquad (27)$$

• Average Method of eigenvalues

This method eliminates the reconstruction of values that are lower than the arithmetic mean and retains only the higher values.

According to a comparative study between the different number of main components of the selection criteria, the method of VER [20] is considered more effective life in their behavior and principle and those interested can refer to [21, 24,25,22].

So Table 1 established a comparison between the number CP retained for certain criterion.

Table1. Number of CP ℓ for the four criteria outlined above

PVC	Kaiser	VER	MVP
1	2	2	2

We notice from the table that the number of retained main components varies from one test to another, but most of the methods gives a result $\ell = 2$. The model has two components that have been identified, where it is said that we have a number of linear principal component equal to 2, $\ell = 2$.

(3) For this step,it aims at detecting the defects, its for our case, as the default will be the congestion which is considered a massive problem especially in the field of road traffic.

In the figure below, each has the flaw detection results by adapting the methods T² and SPE. The first figure shows that our measurement contains defects while the second shows no defect. Therefore, we note that the SPE method is more reliable by comparing these results with the traffic database.

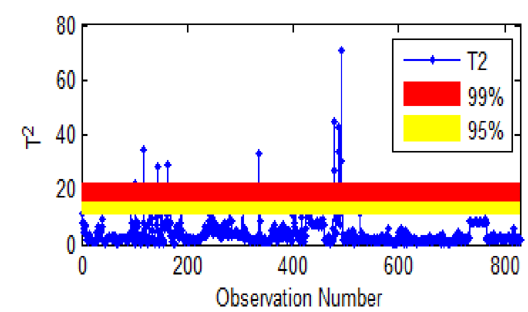

Figure 7: Statistical Evolution T²

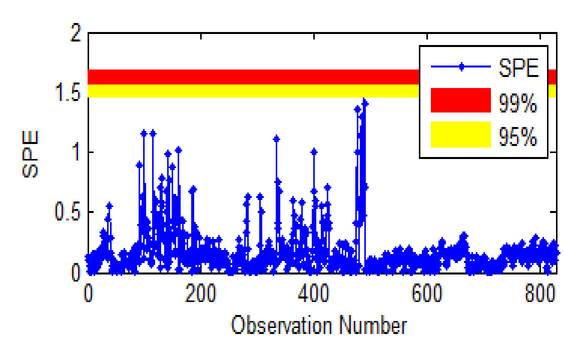

Figure 8: Statistical Evolution SPE

For further the verification the reliability of the SPE detection method, we stimulate a default by modifying the data matrix for measurement =

Journal of Theoretical and Applied Information Technology
31st August 2017. Vol.95. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

100. Indeed, we create a sudden jump rate variation range; then we apply again the SPE statistic and T^2 for the detection of defects in figures.7 and 8 .

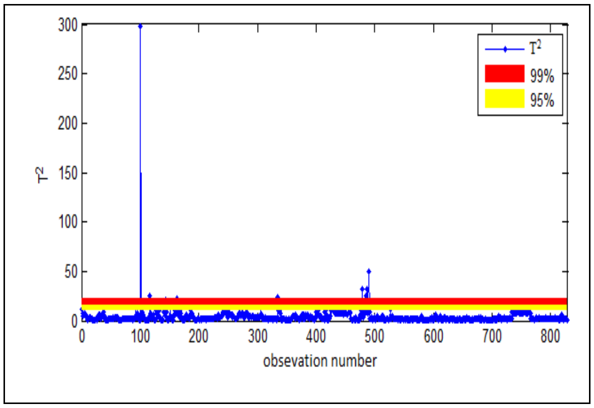

Figure 9: Evolution of T2 with a defect affecting the flow variable for observation = 100

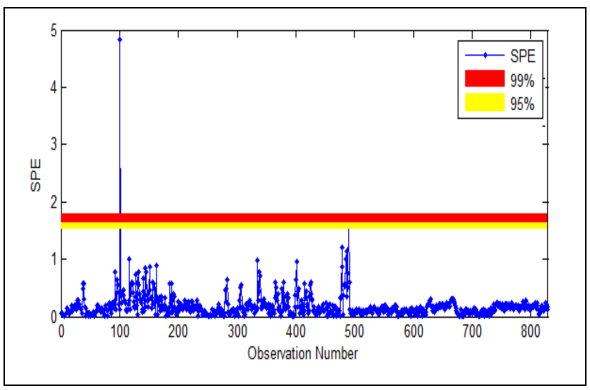

Figure 10: Evolution of SPE with a defect affecting the flow variable for observation = 100

(4) According to the evolution of SPE FIG.10, we distinguish two regions where A is a fault region and B is a faultless region.

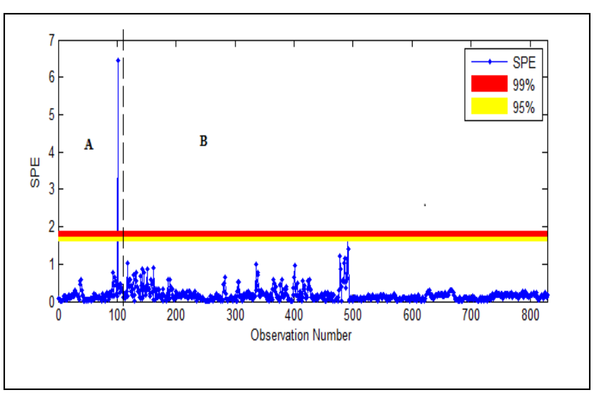

Figure 11: The different regions in default

After extraction of the transient points, FIG.11 below represents the various classes **A** and **B**. Meanwhile, class A designates a faulted region while class B is without defects.

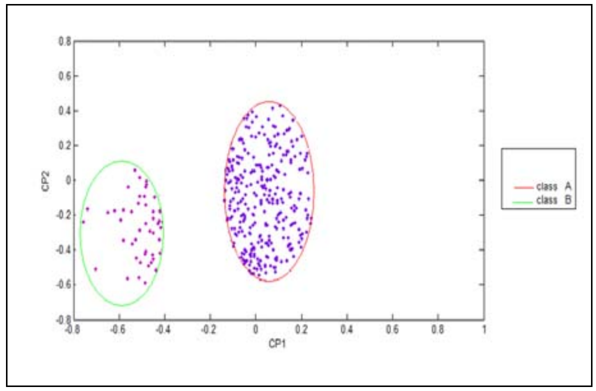

Figure 12: Evolution of different classes by K-means

(5)Using the K-means classification tool, the data are divided into two classes with and without defects. This counterpart, the insulation of defects is ensured by the different contribution calculation region.

Once the disturbance occurs. It must be isolated by the contribution calculation for each variable: the parameter (s) with the highest contributions in relation to the others are considered as faults. According to the results cited in FIG.13, the defects are isolated: at the level of the flow rate and speed parameters, which is explained by the existing problem of traffic fluidity which can be aggravated as a function of time in the The absence of intervention

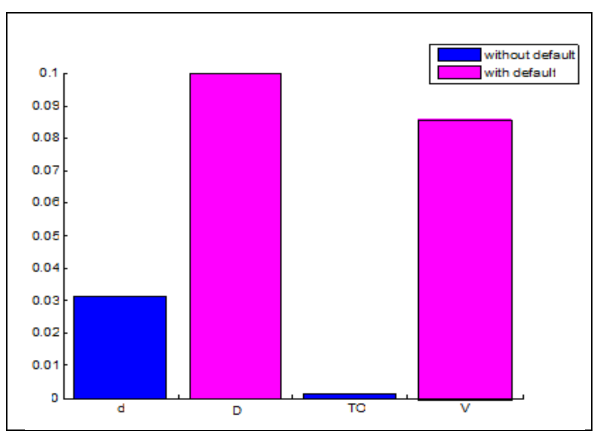

Figure 13: Fault isolation using variables contributions

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

6. CONCLUSION

In this paper, we contribute exploit by the new approach of a model of second order METANET as a modeling tool for pretreatment steps. The latter are used as a base data to the linear PCA tool for detection and fault isolation that describe a traffic flow problem. Our approach is applied to a highway traffic process by 4 variables matrix and 829 steps.

The number of principal components is determined the upstream of this step based on different methods of which the majority donne l = 2, then the number of CP to remember is 2.

Thereafter the SPE statistic is introduced for detecting defects. A defect is discovered by exceeding the threshold limits of this method. Normally, when congestion occurs, an indicator correlated change appears. The contribution is calculated for each variable for insulation fault: the variables with the most significant contributions compared to others are considered defective. In our case, the defects are isolated in terms of flow and speed settings which can be explained by the existing problem of fluidity in the road traffic system.

In a nutshell approach has the advantage of timeliness with concrete results. In addition, with this approach we can introduce a large number of variables and measures of keeping the same reliability.

This is true the classic ACPL tool is characterized by its ability to handle large size data base by reducing space but despite this this type of algorithm has several disadvantages that are presented below. Indeed, the ACP is considered a tool for analyzing the correlations between several variables. Through this tool, we obtain new uncorrelated variables with high variance and therefore strong information power.

Given the ability of CPRA to capture the relationships between the parameters of a given system, this tool is applicable to the stationary state of a process. However, industrial domains exhibit nonstationary characters, which renders classical PCA ineffective in treating this type of nonlinear relationships. Then, with ACPL, the nonlinearity of the parameters can not be emphasized [29].

To this end, we need an efficient tool to fully exploit the nonlinearity of the variables and to estimate the situation of road traffic flow.

REFRENCES:

[1] Y. Tian. Estimation d'état pour des systèmes linéaires : approche algébrique. Manuscrit auteur, publié dans JDMACS, 2009.

[2] X. Sun, L. Muñoz, and R. Horowitz. " Mixture kalman filter based highway congestion mode and vehicle density estimator and its application". In Proceeding of the American Control Conference, Boston, Massachusetts, June 30 - July 2, 2004.

[3] D. G. Luenberger. An introduction to observers. IEEE Transactions on Automatic Control, Vol. AC-16, No.6 :596–602, 1971.

[4] M. Papageorgiou, J. M. Blosseville, and H. Hadj-Salem. Modelling and real-time control of traffic flow on the southern part of boulevard périphérique in Paris : Part I : Modelling. Transportation Research Part A, Vol. 24A, No. 5 :345–359, 1990.

[5] B. KAMEL, A. BENASSER, D. JOLLY, "Limitation Dynamique de la vitesse en cas de rétrécissements", 8éme conférence internationale de modélisation et simulation-MOSIM'10 - 10 au 12 mai 2010 - Hammamet - Tunisie.

[6] A. Messemer and M. Papageorgiou. Metanet : a macroscopic simulation program for motorway networks. Traffic Engineering and Control, Vol. 31, No. 9 :446–470, 1990.

[7] L. Nabli. "Surveillance Préventive Conditionnelle Prévisionnelle Indirecte d'une Unité de Filature Textile : Approche par la Qualité", Thèse de Doctorat, Université des Sciences et Technologies de Lille, Avril 2000.

[8] V. Venkatasubramanian, R. Vaidyanathan, et Y. Yamamoto. "Process fault detection and diagnosis using neural networks: Steady state processes", Computers and Chemical Engineering, Vol. 14, N° 7, pp. 699-712, 1990.

[9] J. F. Mac Gregor et T. Kourti. "Statistical process control of multivariate processes", Control Engineering Practice, Vol. 3, N° 3, pp. 403-414, 1995.

[10] B. M. Wise et N. B. Gallagher. "The process chemometrics approach to process monitoring and fault detection", Journal of Process Control, Vol 6, N° 6, pp. 329-348, 1996.

[11] H. J. Payne. Freflo: "A macroscopic simulation model of freeway traffic". Transportation Research Records, Vol. 772 :68–75, 1979.

[12] A. D. May. Traffic Flow Fundamentals. Prentice Hall, Englewood Cliffs, NJ, 1990.J.E.Jackson et G.S. Mudeholkar.

" Control procedure for residuals associated with principal component analysis ", Technometrics, vol.40, N°20, pp. 457-469,1998.
[13] Abla .Bouguerra "diagnostic automatique des défauts de moteurs asynchrone ", mémoire de mastère en génie électrique,2009
[14] M.Vermasvuori. " Methodology for utilizing prior knowledge in constructing data-based process monitoring systems with an application to a dearmatisation process", Thèse de doctorat à Helsinki University of technology, 2008.
[15] P. Miller, R. E. Swanson, et C. F. Heckler. "Contribution plots: the missing link in multivariate quality control ", Multivariate Statistical Process Control and Plant Performance Monitoring Industrial Representatives Meeting, 1995
[16] B.Camille, "Détection de défauts sur des capteurs en ligne, validation des mesures ", Université Henry Poincaré Nancy France, Centre de Recherche Public Henri Tudor : Laboratoire de Technologie Industrielles, 2002.
[17] D. Zumoffen et M. Basualdo. "From large chemical plant data to fault diagnosis integrated to decentralized fault tolerant control: pulp mill process application ", Industrial and Engineering Chemistry Research, Vol. 47, pp. 1201-1220, 2007.
[18] K.Ouni, L. Nabli et H.Messaoud, "A Monitoring Method Based on Fuzzy Detection and PCA Diagnosis" International Journal of Intelligent Control and Systems, vol.16, N°1, pp.19-27, 2011.
[19] THESE Doctorat de l'Institut National Polytechnique de Lorraine Spécialité Automatique et Traitement du signal par « Yvon THARRAULT »Ingénieur ESSTIN en 2008.
[20] THESE Baligh MNASSRI, "Analyse des données multivariées et surveillance des processus industriels par analyse en composantes principales", présenté et soutenue publiquement le 12 octobre 2012 pour l'obtention du Doctorat de l'Université d'Aix-Marseille Spécialité Automatique.
[21] R. Dunia et S. J. Qin. "A subspace approach to multidimensional fault identification and reconstruction", AIChE Journal, Vol. 44, pp. 1813-1831, 1998.
[22] Qin, S.J. et Dunia, R. "Determining the number of principal components for best reconstruction". Journal of Process Control, (2000). 10(2), 245-250.
[23] M.F. HARAKAT, G MOUROT, J. RAGOT "Différentes méthodes de localisation de défauts basées sur les dernières composantes principales", Centre de Recherche en Automatique de Nancy, 2002.
[24] K. Ouni, H. Dhouibi et L. Nabli. "A New Fault Diagnosis Method Using Fault Directions in Partial Least Square", International Journal of Computer Science Engineering and Technology, Vol. 1, N°4, pp. 150-157, 2011.
[25] L. Nabli, K. Ouni, and H. Messaoud., " Méthode de surveillance indirecte d'un système de production par l'analyse en composantes principales", La 5ème conférence internationale JTEA 2008, Journées Tunisiennes de l'Electrotechnique et de l'Automatique, 2-4 Mai.
[26] J. McQueen. Some methods for classification and analysis of multivariate observations. In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 1:281-297, 1967.
[27] NATHALIE PESSEL , JEAN-FRANÇOIS BALMAT , NACER KOUIDER M'SIRDI. Analyse discriminante pour le diagnostic Application à une serre agricole expérimentale, 2006.
[28] Fabien Chevalier. Jérôme Le Bellac. La classification. Université de RENNE. Faculté de science économie. 2012-2013.
[29] L. Nabli, K. Ouni, and H.Haj. Salem., " Approche Multi agents pour la surveillance indirecte d'un système de production par l'analyse en composantes principales", la Conférence Internationale Francophone d'Automatique CIFA 2008, pp. 128-136, 3-5 Septembre.