SENSOR FAULT DETECTION AND ISOLATION OF AN AIR QUALITY MONITORING NETWORK USING NONLINEAR PRINCIPAL COMPONENT ANALYSIS

M. Faouzi Harkat[*], **Gilles Mourot**[**], **José Ragot**[**]

[*] *Université Badji Mokhtar - Annaba*
Faculté des Siences de l'Ingénieur - Département d'Electronique
BP. 12, Sidi Amar, 23000 Annaba, Algérie
mharkat@ensem.inpl-nancy.fr
[**] *Centre de Recherche en Automatique de Nancy UMR 7039*
Institut National Polytechnique de Lorraine
2, Avenue de la Forêt de Haye
54516 Vandoeuvre-lès-Nancy Cedex - France
{gmourot, jragot}@ensem.inpl-nancy.fr

Abstract: Recently, fault detection and process monitoring using principal component analysis (PCA) were studied intensively and largely applied to industrial process. PCA is the optimal linear transformation with respect to minimizing the mean squared prediction error. If the data have nonlinear dependencies, an important issue is to develop a technique which can take into account this kind of dependencies. Recognizing the shortcomings of PCA, a nonlinear extension of PCA is developed. This paper proposes an application for sensor failure detection and isolation (FDI) to an air quality monitoring network via nonlinear principal component analysis (NLPCA). The NLPCA model is obtained by using two cascade three layer RBF-Networks. For training these two networks separately, the outputs of the first network are estimated using principal curve algorithm [7] and the problem is transformed as two nonlinear regression problems.

Keywords: sensor fault detection, model-based fault diagnosis, principal curves, nonlinear PCA, RBF-network, air pollution, air monitoring network.

1. INTRODUCTION

Many human activities produce primary pollutants like nitrogen oxides (NO2 and NO), sulfur dioxide and volatile organic compounds which formed in the lower atmosphere by chemical or photochemical reactions secondary pollutants like ozone. Air quality monitoring networks have the following missions: data recording (pollutant concentration and a range of meteorological parameters related to pollution events) including the measurement network management, the diffusion of data for permanent information of population and public authorities, and surveillance in reference to norms. Therefore, the data validity of the delivered information is essential. Sensor data validation is therefore an issue of great importance for the development of reliable environmental monitoring and management systems.

In collaboration with air quality monitoring network AIRLOR, (France), the aim of this work is to develop a method to perform sensor failure detection and isolation. By way of their interaction, the different pollutants constitute a dynamic chemical system that is strongly influenced by atmospheric conditions. The physico-chemical mechanisms taking place are poorly understood, but it clearly appears that this process is multivariable and strongly nonlinear. Furthermore, most existing models take into account the atmospheric chemistry of one hundred reactions, also the emissions of primary pollutants, as well as vertical and horizontal exchanges linked to movements of the atmosphere. These models therefore combine a large number of equations with numerous parameters which are inaccessible and unknown. These models then are very complex, computationally costly and, above all, need measurements that are seldom available in air quality monitoring network.

Model-based diagnosis relies on information redundancy concepts [3]. Its principle is generally based on consistency checking between an observed behavior of the process provided by sensors and an expected behavior provided by a mathematical representation of the process. This mathematical representation may take the forms of analytical redundancy [4] which is an explicit input-output relationship, but in many situations it may be difficult to obtain (owing to complexity of the process and high process dimensionality). As an alternative, methods based on principal component analysis (PCA), that is data-driven, could be very attractive for failure detection. Because of the nice features of PCA, this method can handle high dimensional and correlated process variables. In recent years, PCA has been used in the statistical process control area such as process monitoring [10], gross error detection [15], sensor fault identification [2]. However, Principal component analysis is a linear method, and most engineering problems are nonlinear. To overcome this problem, we use a nonlinear model to generate residuals for fault detection and isolation.

Hastie and Stuetzle [8] proposed a principal curve methodology to provide a nonlinear summary of a m-dimensional data set. However, this approach is non-parametric and can not be used for continuous mapping of new data. To overcome this parametrization problem, an auto-associative neural network has been used [1, 9, 14]. For such networks, however, the training problem becomes a complicated nonlinear optimization task, defined in a multidimensional space. For this reason, Webb [16] proposed an approach to nonlinear principal component analysis using radial basis function (RBF) networks. In this approach, the NLPCA model consists of two three layer RBF- networks where the nonlinear principal components are the outputs of the first network. The second network tries to perform the inverse transformation by reproducing the original data from the nonlinear principal components. However, the training of these two networks remains complicated.

A new training procedure of the RBF-NLPCA model is presented in [7]. In this paper we propose an application of the RBF-NLPCA model [7] for sensor fault detection and isolation of an air quality monitoring network.

The proposed paper will be organized as follows. The section 2 presents a description of RBF-NLPCA model. The proposed training procedure of this RBF-NLPCA model is given in section 3. Based on the RBF-NLPCA model, the test for detection of faulty sensor and the isolation approach based on the contribution plot are presented and successfully applied to an air quality monitoring network in Lorraine (France) in the section 4. The last section gives conclusions.

2. RBF-NLPCA MODEL

2.1 Problem settings

Nonlinear PCA is an extension of linear PCA. Whilst PCA identifies linear relationships between process variables, the objective of nonlinear PCA is to extract both linear and nonlinear relationships. This generalization is achieved by projecting the process variables down onto curves or surfaces instead of lines or planes. Fig. 1 illustrates the concept of linear PCA. The first principal component minimizes the sum of squared orthogonal deviations between the straight line and all variables. The concept of nonlinear PCA is illustrated in Fig. 2. The nonlinear approach is like linear PCA, except it represents the data by one dimensional smooth curve which is determined by the nonlinear relationship between the variables. The curve is defined to minimize the orthogonal deviations between the data and the curve. The NLPCA model can be represented by two sub-models (Mapping and Demapping model).

The mapping model gives from a data matrix X the nonlinear principal component T and the demapping model gives estimation. In this case, the nonlinear mapping has the following form

$$\mathbf{t} = \mathscr{G}(\mathbf{x}) \tag{1}$$

where $\mathbf{x}$ and $\mathbf{t}$ are rows of X and T respectively, $\mathscr{G}$ is the mapping function. The demapping model gives estimation $\hat{\mathbf{x}}$ of $\mathbf{x}$ from the nonlinear principal component $\mathbf{t}$ and has the form

$$\hat{\mathbf{x}} = \mathscr{F}(\mathbf{t}) \tag{2}$$

where $\mathscr{F}$ represents the demapping function.

Therefore a data set X including m variables can be expressed in terms of ℓ nonlinear principal components

$$X = \hat{X} + E = \mathscr{F}(T) + E \tag{3}$$

where $T = [T_1, \ldots, T_\ell]$ is the matrix of nonlinear principal components $T = \mathscr{G}(X)$, and E is the matrix of residuals. The problem is now to identify the nonlinear projection functions $\mathscr{G}$ and $\mathscr{F}$. To do this, the objective function to minimize is the sum of squared orthogonal deviations:

$$\min \sum_{i=1}^{N} \|\mathbf{x}_i - \hat{\mathbf{x}}_i\|^2 = \min \sum_{i=1}^{N} \|\mathbf{x}_i - \mathscr{F}(\mathscr{G}(\mathbf{x}_i))\|^2 \tag{4}$$

where $\mathbf{x}_i$ is the ith row of X and $\hat{\mathbf{x}}_i$ is its estimation by the RBF-NLPCA model.

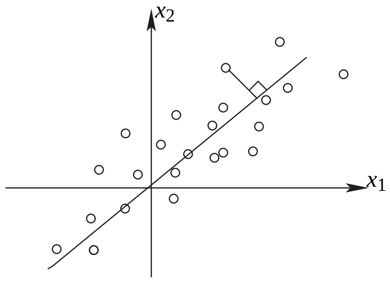

Fig. 1. The linear principal component minimizes the sum of squared orthogonal deviations using a straight line.

2.2 RBF-NLPCA model

The proposed nonlinear principal component analysis model can be obtained by using two RBF-Networks for mapping and demapping data. Firstly, a three layer RBF-network is used (Fig. 3), the hidden layer was composed of radial basis neurons performing a nonlinear mapping of the input space onto a lower dimension space, such that the nonlinear features are captured. The aim is to use this network to define a transformation $\mathscr{G} : \Re^m \to \Re^\ell$.

$$\mathscr{G}(\mathbf{x}) = \sum_{i=1}^{r} w_i \phi_i(\mathbf{x}) \tag{5}$$

where $\{\phi_i,\ i = 1,\ldots,r\}$ are radial basis functions of $\mathbf{x} \in \Re^m$, r is the number of kernels and $\{w_i,\ i = 1,...,r\}$ denotes a set of weight parameters of the output layer to be determined. The gaussian basis functions ϕ_i are gaussian and defined as:

$$\phi_i(\mathbf{x}) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{c}_i\|^2}{2\sigma_i^2}\right) \tag{6}$$

where $\mathbf{c}_i$ and σ_i respectively denote center and dispersion. In the first step, the centers $\mathbf{c}_i$ are initialized with K-means clustering and the dispersions σ_i^2 are determined as the distance between $\mathbf{c}_i$ and the closest $\mathbf{c}_j$ $(j \neq i,\ j \in \{1,...,r\})$.

By preserving the original dimension of the data, the second network tries to perform the inverse transformation from the reduced data (Fig. 4). We define the inverse transformation $\mathscr{F} : \Re^\ell \to \Re^m$:

$$\hat{\mathbf{x}} = \mathscr{F}(\mathbf{t}) = \sum_{j=1}^{k} v_j \psi_j(\mathbf{t}) + v_0 \tag{7}$$

for some kernels ψ_j, $(j = 1,...,k)$, weights $V = (v_0,...,v_k)$, where k is the number of kernels and $v_i \in \Re^\ell$, $(i = 0,\ldots,k)$.

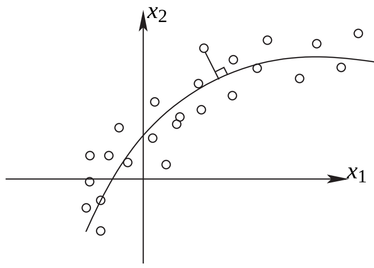

Fig. 2. The nonlinear principal component minimizes the sum of squared orthogonal deviations using a smooth curve.

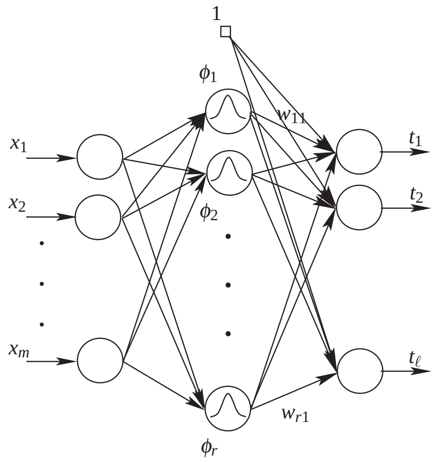

Fig. 3. RBF-Network for mapping from $\Re^m \to \Re^\ell$.

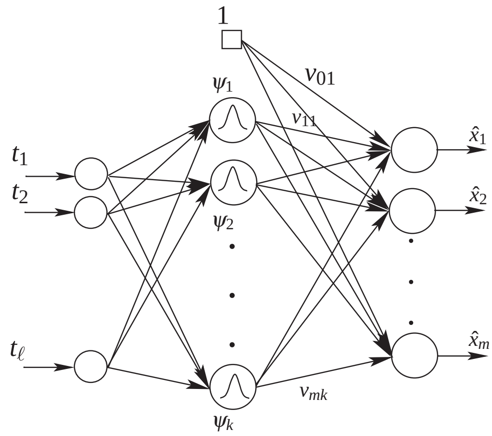

Fig. 4. RBF-Network for mapping from $\Re^\ell \to \Re^m$

To identify the RBF-NLPCA model, we have to determinate the parameters of radial basis functions (centers and dispersions) and the weight parameters for the two RBF-networks. The number of principal component analysis to retain in the NLPCA model can be determined by the reconstruction approach [6]. It should be noted that the nonlinear principal component matrix T being unknown, the training of the two RBF-networks separately is then impossible.

To overcoming this problem we suggest to estimate this nonlinear component matrix T by using the principal curve algorithm [8]. When the matrix T is estimated, each RBF network can be trained separately. So, the training problem is transformed into two classical nonlinear regression problems.

3. RBF-NLPCA TRAINING

The proposed training procedure involves three steps :

(1) Find principal curves by successively applying the principal curve algorithm [8] to observed data and residuals. Then in the first step T_1 denotes the first nonlinear principal component, so: $X = \mathscr{F}_1(T_1) + E_1$, where E_1 is the residual. When more than one nonlinear principal component is needed we do the same calculation from the residual data [11].
(2) Train an RBF network that maps the original data onto the nonlinear principal components (obtained by the principal curves algorithm).
(3) Train the second RBF network that maps the nonlinear principal components onto the original data.

The training of the two RBF-Networks (mapping and demapping network) is presented in detail in [7].

4. APPLICATION FOR FDI OF AIR QUALITY MONITORING NETWORK

4.1 Description of air quality monitoring network

The air quality monitoring network AIRLOR working in Lorraine, (France), will be described. The monitoring network consist of twenty stations placed in rural, peri-urban and urban sites. Each monitoring station consists of a set of sensors, dedicated to the acquisition of the following pollutants: carbon monoxide CO, nitrogen oxides NO and NO_2, sulfur dioxide SO_2 and ozone O_3. Moreover, seven stations are dedicated to the recording of additional meteorological parameters. The measures are averages calculated over fifteen minutes in order to limit spatial and temporal sampling problems. In this work, only six stations are considered.

The purpose is to to detect sensor failures mainly those which record ozone concentration (O_3) and primary pollutants like nitrogen oxides (NO and NO_2).

The matrix X contains 18 variables, v_1 to v_{18}, corresponding, respectively, with ozone O_3 and nitrogen dioxide (NO_2 and NO) of each station. Data set is chosen to have different concentration levels to show the performance of the proposed method.

4.2 Sensor Fault detection and isolation

Abnormal situations that occur due to sensor drifts induce changes in sensor measurements. Nonlinear Principal components analysis is used to model normal process behavior and faults are then detected by checking the observed behavior against this model.

Our approach for PCA process monitoring involves a Squared Prediction Error (SPE) chart. The *SPE* is given by

$$SPE_k = \sum_{j=1}^{m} (x_j(k) - \hat{x}_j(k))^2 \tag{8}$$

with x_j is a process variable and $\hat{x}_j$ is the estimation of x_j from the NLPCA model. Analysis of SPE_k provides a way to detect abnormalities in data [2,12]. To reduce false alarms, exponentially weighted moving average (EWMA) filter can be applied to the residuals but it introduce a delay in detecting faults. The general EWMA expression for residual is [2]:

$$\bar{\mathbf{e}}_k = (I - \Lambda)\bar{\mathbf{e}}_{k-1} + \Lambda \mathbf{e}_k \tag{9}$$

$$\overline{SPE}_k = \|\bar{\mathbf{e}}_k\|^2 \tag{10}$$

where $\bar{\mathbf{e}}_k$ and $\overline{SPE}_k$ are the filtered residuals and *SPE* respectively. $\Lambda = \gamma I$ denotes a diagonal matrix whose diagonal elements are forgetting factors for the residuals.

If $\overline{SPE}$ is above the confidence limits, a new event is found in the data, which is not described by the process model. In this case, to identify faulty sensor, contributions of each process variable to $\overline{SPE}$ should be examined [13]. The contribution of the jth variable to $\overline{SPE}$ is given by

$$Cont_j^{(\overline{SPE})}(k) = (\bar{x}_j(k) - \hat{\bar{x}}_j(k))^2,\ (j = 1, ..., m) \tag{11}$$

where $\bar{x}_j$ is the filtered variable x_j and $\hat{\bar{x}}_j$ is its estimate.

The sensor having the biggest contribution to $\overline{SPE}$ is considered as the faulty sensor.

For this application, the linear PCA model has been firstly used [5] and the *SPE* index is calculated. In addition to the measurement noise, the *SPE* index is affected by modeling errors. When no fault is present, many false alarms can occur. To overcome this problem a nonlinear PCA model is used.

By applying the principal curve algorithm we can calculate the nonlinear principal components **t**. Table 1 presents the variance explained by each principal component. Then, the two RBF networks are trained separately and the RBF-NLPCA model is identified.

The three following figures present, respectively, measurements and estimation of O_3, NO_2 and NO levels. The estimations are given by the RBF-NLPCA model (7). For our application, six components was retained in the model which explain 95% of the variance of data.

By taking into account the nature of the modeled process, the results obtained are very satisfactory, with the RBF-NLPCA model obtained, even the peaks of NO, O_3 and NO_2 are well estimated (Figure 5 to 7) which are essential for the alarm procedures. In the case of the nitrogen oxides that are more localized pollutants, and more difficult to model, the estimation of these two variables remains correct for weak values as well as for high values.

Based on the obtained NLPCA model, the indices for detecting sensor faults and isolating faulty sensor can

Table 1. Percent Variance Captured by linear and nonlinear PCA

PC	Linear PC	Total	Nonlinear PC	Total
1	40.52	40.52	58.46	58.46
2	18.35	58.88	15.29	73.76
3	10.09	68.97	10.00	83.76
4	7.02	76.00	6.18	89.94
5	6.75	82.75	3.77	93.72
6	5.17	87.93	2.09	95.81
7	3.56	91.50	1.50	97.32
8	2.59	94.09	0.84	98.16
9	1.47	95.57	0.61	98.77
10	1.25	96.82	0.43	99.21
11	0.96	97.78	0.31	99.52
12	0.90	98.69	0.22	99.74
13	0.46	99.16	0.10	99.85
14	0.37	99.54	0.06	99.92
15	0.17	99.71	0.03	99.96
16	0.16	99.87	0.02	99.98
17	0.09	99.97	0.01	99.99
18	0.02	100.00	0.00	100.00

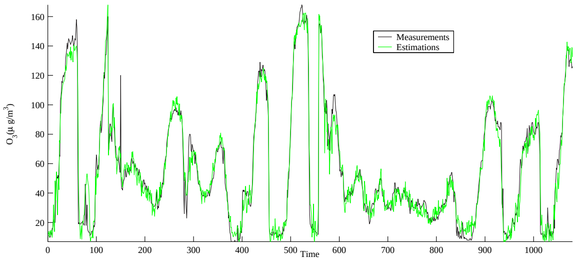

Fig. 5. Measurements and estimations of the Ozone concentrations

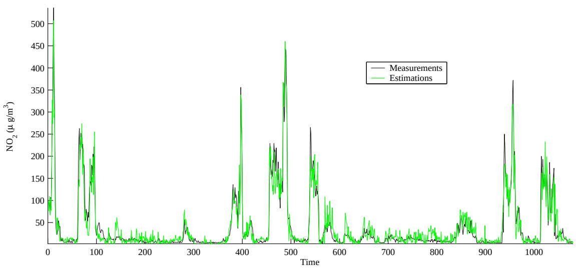

Fig. 6. Measurements and estimations of the NO_2 concentrations

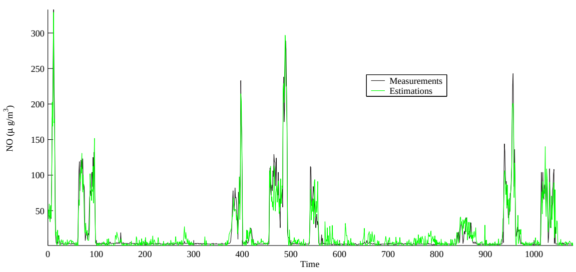

Fig. 7. Measurements and estimations of the NO concentrations

be calculated on line. To apply the sensor validation method, a bias fault is introduced for the sensor 1 between sample 800 and 1080 (O_3). The magnitude of the fault amounts to 20% of the range of variation of variable v_1. $\overline{SPE}$ in Fig. 8 almost immediately allows to detecting the fault. To identify the faulty sensor is faulty, contribution of all sensors to the $\overline{SPE}$ is examined and Fig. 9 shows that the sensor 1 has the largest contribution which indicates that sensor 1 is the faulty one.

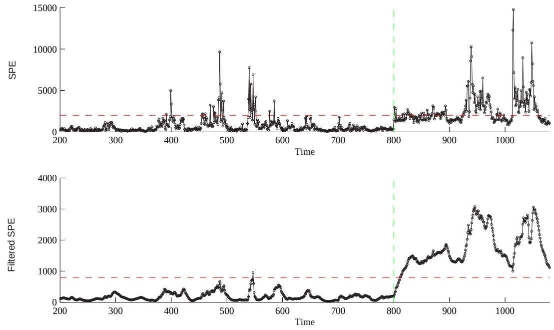

Fig. 8. Squared prediction error with a fault on v_1

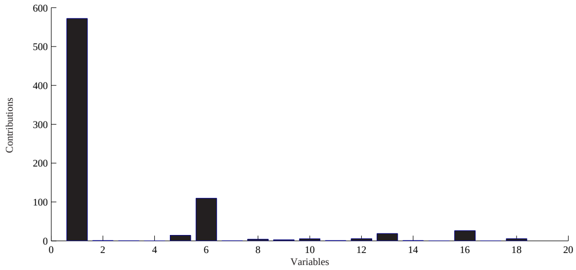

Fig. 9. Contribution plot with a fault on v_1

Another fault is simulated on the sensor 2 (NO_2) between sample 800 and 1080. The fault is detected on the $\overline{SPE}$ (Fig. 10). Contribution plot for the $\overline{SPE}$ (Fig. 11) shows that the sensor 2 is the faulty one. Fig. 12 shows $\overline{SPE}$ with a fault on variable v_3 (NO). Contribution plot is depicted in Fig. 13, the biggest contribution indicates that the variable v_3 is the faulty one.

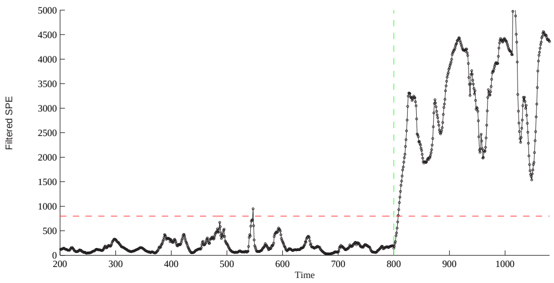

Fig. 10. Squared prediction error with a fault on v_2

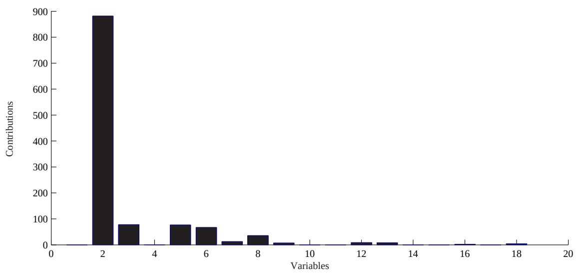

Fig. 11. Contribution plot with a fault on v_2

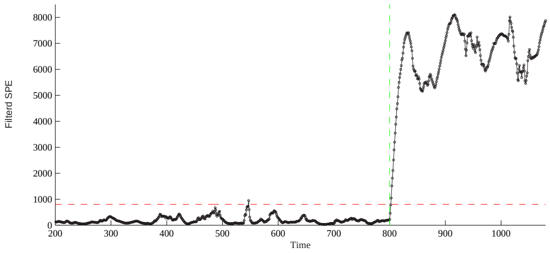

Fig. 12. Squared prediction error with a fault on v_3

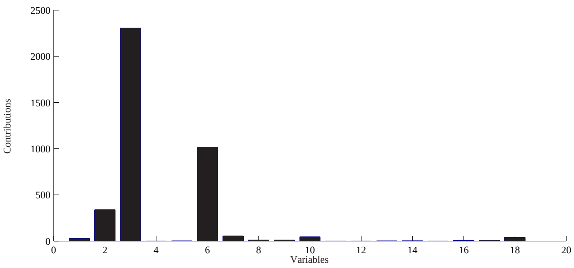

Fig. 13. Contribution plot with a fault on v_3

In this paper, only three sensor fault detection and isolation cases are represented. Faults on other variables are also detected and successfully isolated.

5. CONCLUSION

This paper proposes the application of a fault detection and isolation (FDI) based NLPCA method to an air quality monitoring network. An algorithm for determining the NLPCA model is proposed. The first step of this algorithm consists of using the principal curve algorithm [8] to find nonlinear principal components. Then, two cascade RBF-networks are trained with a three phase procedure. A NLPCA model is built, using data obtained when the process is under normal condition. The proposed approach for fault detection and isolation is presented and successfully applied to air monitoring networks in Lorraine, (France). Future work will include using the reconstruction approach [6] for the determination of the number of nonlinear principal components to keep in the NLPCA model and also to give replacement values of faulty measurements.

REFERENCES

[1] Dong D. and McAvoy T. J., Nonlinear principal component analysis - based on principal curves and neural networks. Proceedings of the American Control Conference, Baltimore, Maryland, pp. 1284-1288, June 1994.

[2] Dunia R., Qin S. J. and Edgar T. F., Identification of faulty sensors using principal component analysis. AIChE Journal, vol. 42, N. 10, pp. 2797-2812, October 1996.

[3] Frank, P.M., Analytical and qualitative model-based fault diagnosis: a survey and some new results. Eur. J. Cont., vol. 2, pp. 6-28, 1996.

[4] Gertler J. and McAvoy T., Principal component analysis and parity relations - A strong duality. IFAC Conference SAFEPROCESS, Hull, UK, pp. 837-842, 1997.

[5] Harkat M. F., Mourot G., Ragot J., Sensor fault detection of an air quality monitoing network. IFAC Symposium on Fault Detection, Supervision and Safety for Technical Process, SAFEPROCESS’2000, Budapest, Hungary, 2000.

[6] Harkat M. F., Mourot G., Ragot J., Variable reconstruction using RBF-NLPCA for process monitoring. IFAC Symposium on Fault Detection, Supervision and Safety for Technical Process, SAFEPROCESS’2003, Washington, USA, 2003.

[7] Harkat M. F., Mourot G., Ragot J., Nonlinear PCA Combining Principal Curves and RBF-Networks for Process Monitoring. 42nd IEEE Conference on Decision and Control, Hyatt Regency Maui, Hawaii, USA, 2003.

[8] Hastie T. and Stuetzle W., Principal curves. Journal of the American Statistical Association, vol. 84, N. 406, pp. 502-516, 1989.

[9] Kramer M. A., Nonlinear principal component analysis using auto-associative neural networks. AIChE Journal, vol. 37, N. 2, pp. 233-243, February 1991.

[10] Kresta J. V., MacGregor J. F. and Marlin T. E., Multivariate statistical monitoring of process operating performance. Canadian J. Chem. Eng., vol. 69, N. 1, pp. 35-47, 1991.

[11] LeBlanc M. and Tibshirani R., Adaptive principal surfaces. Journal of American Statistical Association, vol. 89, N. 425, pp. 53-64, 1994.

[12] MacGregor J. F., Kourti T. and Nomikos P., Anlysis, monitoring and fault diagnosis of industrial processes using multivariate statistical projection methods. IFAC, 13th Triennial Word Congress, San Francisco, USA, pp. 145-150, 1996.

[13] Miller P., Swanson R. E., and Heckler C. E., Contribution plots: A missing link in multivariate quality control. Applied Mathematics and Computer Science, vol. 8, N. 4, pp. 775-792, 1998.

[14] Tan S. and Mavrovouniotis M. L., Reduction data dimensionality through optimizing neural network inputs. AIChE Journal, vol. 41, N. 6, pp. 1471-1480, June 1995.

[15] Tong H. and Crowe C. M., Detection of Gross errors in data reconciliation by Principal Component Analysis. Process systems engineering, vol. 41, N. 7, July 1995.

[16] Webb A. R., An approach to nonlinear principal component analysis using radially symmetric kernel functions. Statist. Comput., vol. 6, pp. 159-168, 1996.