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Water Distribution System Condition Monitoring based on Bottleneck Neural Networks

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***Abstract*—**
The success of any diagnosis strategy critically depends on the sensors measuring process variables. This paper presents a detection and diagnosis sensor faults method based on a Bottleneck Neural Network (BNN). The BNN approach is used as a statistical process control tool for drinking water distribution systems (DWDS) to detect and isolate the sensor faults. This method is validated in simulation on a nonlinear system: a quadruple tank and an actual drinking water distribution system. Several results are presented.

I. Introduction

Currently, the meaning advances in process sensing technologies make it possible to collect enormous amounts of measured data. However, the valuable information about the state of the process is rarely used in an optimal way. A common reason for this inefficient handling of the process measurements is a difficulty of the information processing. Thus, it is urgent to develop an effective methodology to fully accommodate and utilize the automated in-process sensing devices to withdraw all quality-related diagnostic information. Modern model-based condition monitoring capitalizes on the principle of information redundancy. In fact, abnormal states can be detected by a consistency checking between an observed behavior as indicated by sensors and an expected behavior provided by mathematical models.

The models may be explicit, obtained from first principles or system identification [9], or implicit, obtained by principle component transformation [11]. For fault isolation, some structured residuals, which respond to subsets of faults [8], may be generated by algebraic transformation or by direct techniques. In the principal component framework, the direct computation involves structured partial principal component models [5]. Alternative fault isolation techniques, in the PCA framework, involve contribution charts [11], statistical measures [14] and the sensor validity index [7].

Over the last decade, the application of statistical methodology in process monitoring referred as multivariate statistical process control (MSPC) has been used as a tool in the control and improvement of manufacturing processes in a wide range of industries. MSPC aims to remove the redundancy often observed in the recorded variables by defining a reduced set of artificial variables. PCA is one of the most widely applied MSPC techniques. More precisely. Then fault detection and diagnosis (FDD) is accomplished in the low-dimensional space by monitoring the sum of prediction error (SPE) and principal component scores charts [11]. According to the principle of PCA, the loading plot can provide the relationship between the original variables, which can be utilized to identify faults because most malfunctions may destroy the relationships between process variables.

Unfortunately, if the process exhibits multiple operating regimes, the application of conventional PCA gives an excessive number of false alarms or alternatively, missed detection of processes faults, which significantly compromises the reliability of the monitoring system. Nonlinear extensions have been reported by [10] using principal curves, Kramer [12] using auto associative neural networks, Qin and McAvoy [13] using an embedded neural networks into the framework of partial least squares (PLS). Webb [15] and Wilson [16] proposed a nonlinear extension of PCA using radially symmetric kernel functions, and radial basis function (RBF) networks, respectively. Recently, the sequential data analysis methods such as dynamic time warping (DTW) and hidden Markov models (HMM) have been developed for FDD. Empirical models like neural networks and fuzzy logic have been also proposed. However, for analysing nonlinear systems, Kramer [12] suggested to use an auto-associative neural network to perform a nonlinear data reduction similar to PCA.

Global demand for water is continuously due to population growth, industrial development, and improvements of economic conditions, while accessible source keep decreasing in number and capacity, moreover, the applications involving manipulation and transport of water demand high power consumption. The optimal use of such water supply networks seems to be the best solution for the present and thus it is necessary to carefully operate water distribution transfer [1]. The objective of this research is the contribution in supervising a water distribution network systems using the Neural Network diagnosis method.

This paper is organized as follows. In section II, the Bottleneck Neural Network is developed in more details.

In section III, the quadruple tank process is described and a simulation case study using an actual water distribution network is performed. the results are discussed in section IV. Finally, some concluding remarks as well as some possible improvements are given in section V.

II. The Concept of Bottleneck Neural Network

Bottleneck Neural Network (BNN) is used to identify and remove correlations between variables as an aid to dimensionality reduction, visualization, and exploratory data analysis. BNN uncovers both linear and nonlinear correlations, without restriction on the character of the nonlinearities present in the data. The neural network used contains five layers: input layer, mapping layer, bottleneck layer, de-mapping layer and output layer [2]. These neural networks are a special class of artificial neural networks which are able to learn the principal components without explicitly solving the eigenvalues and eigenvectors from the sample covariance matrix [3] . The objective function used to train this neural network is:

$$E = \frac{1}{n}\sum_{i=1}^{n} \|e_i\|^2 \tag{1}$$

Where e_i =x_i +$\hat{x}_i$ the reconstruction error [4].
An auto-associative neural network is a special case of a bottleneck neural network (BNN) in which the output is an estimation of the input, figure 1. Between the input layer x_i and the output layer $\hat{x}_i$ there are three layers of hidden neurons (the 1^{st}, 2^{nd} and 3^{rd} layers). The 2^{nd} layer is the bottleneck u giving the nonlinear principal component. The 1^{st} one is called the encoding layer the 3^{rd} is the decoding layer, each with m hidden neurones. The encoding layer, represented by $\mathscr{G}$, the activation function f_1 maps from the input x to the encoding layer,

$$\mathscr{G}_{\mathrm{k}}{=}f_1\left(\left(V^{(x)}X + b^{(x)}\right)_k\right) \tag{2}$$

Where $V^{(x)}$ is an $m \times n$ weight matrix, $b^{(x)}$, a column vector of length m contaning the offset parameters, and k=1,...,m. A second activation function f_2 maps from the encoding to the bottleneck layer, which represents the nonlinear principal component u,

$$\mathrm{u} = f_2\left(v^{(x)}.\mathscr{G} + \overline{b}^{(x)}\right) \tag{3}$$

The activation function f_3 maps from u to the decoding layer $\mathscr{F}$,

$$\mathscr{F}_k = f_3\left(\left(v^{(u)}u + b^{(u)}\right)_k\right) \tag{4}$$

The 4^{th} function is mapping from $\mathscr{F}$ to the output vector $\hat{x}_i$,

$$\hat{\mathrm{x}}_{\mathrm{i}}{=}f_4\left(\left(V^{(u)}\mathscr{F} + \overline{b}^{(u)}\right)_i\right) \tag{5}$$

The objective function E is minimised by finding the optimal values of $V^{(x)}$, $b^{(x)}$, $v^{(x)}$, $\overline{b}^{(x)}$, $v^{(u)}$, $b^{(u)}$, $V^{(u)}$ and $\overline{b}^{(u)}$. The BNN was implemented using the hyperbolic tangent function for f_1 and f_3, the identity function for f_2 and f_4, So

$$u = v^{(x)}.\mathscr{G}_k + \overline{b}^{(x)} \tag{6}$$

$$\hat{\mathrm{x}}_{\mathrm{i}} = \left(V^{(u)}F + \overline{b}^{(u)}\right)_i \tag{7}$$

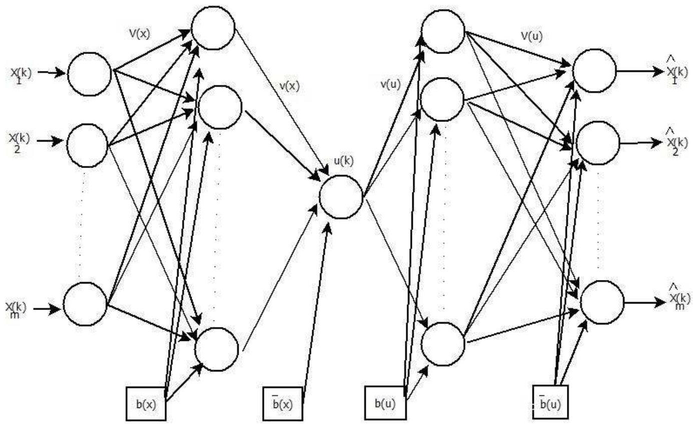

Figure 1. Nonlinear PCA neuronal architecture

A. Fault detection

Sensor fault detection using BNN is performed by monitoring the residuals. The Squared Prediction Error (SPE) is a statistic that measures the lack of fit of the BNN model. At time k, the detection index SPE is given by:

$$SPE(k) = e^T(k)e(k) = \sum_{i=1}^{m} e_i^2(k) \tag{8}$$

The SPE statistic distribution can be well approximated by

$$SPE \propto g\mathscr{X}_h^2 \tag{9}$$

Where the weight g and the degree of freedom h can be estimated by the matching moments of the mean (m) and variance (v) of the cumulants [6] :

$$g = \frac{v}{2m} \tag{10}$$

and

$$h = \frac{2m^2}{v} \tag{11}$$

The resulting upper control limit can thus be calculated as

$$\delta_\alpha = \frac{v}{2m}\mathscr{X}_{1-\alpha}^2\left(\frac{2m^2}{v}\right) \tag{12}$$

Where α is the predefined level of significance.

An abnormal situation exists when:

$$SPE(k) > \delta_\alpha^2 \tag{13}$$

Where δ_α^2 is a confidence limit for SPE estimated using the historical data.
In order to improve the detection we can apply the filter exponentially weighted moving average (EWMA), to reduce the rate of false alarms due to the noise. The general *EWMA* expression for residual is:

$$\overline{\mathbf{e}}(k) = (I-\beta)\,\overline{\mathbf{e}}(k-1) + \beta\,\mathbf{e}(k) \tag{14}$$

$$\overline{SPE}(k) = \|\overline{\mathbf{e}}(k)\|^2 \tag{15}$$

Where $\beta = \gamma I$ denotes a diagonal matrix whose diagonal elements γ are forgetting factors for the residuals.

III. Results and discussions

A. Quadruple tank benchmark

The BNN method has been carried out in simulation on a benchmark: the quadruple-tank process.
The quadruple tank laboratory process, was originally presented in [17] The process consists of four interconnected water tanks, two pumps, and associated valves; where the water from the two upper tanks flows into the two lower tanks. A pump is used to pour water into the upper left tank and the lower right tank. A valve width fixed position is used to allocate pump capacity to the upper and lower tank respectively. A second pump is used to pour water into the upper right tank and lower left tank. See figure 2.

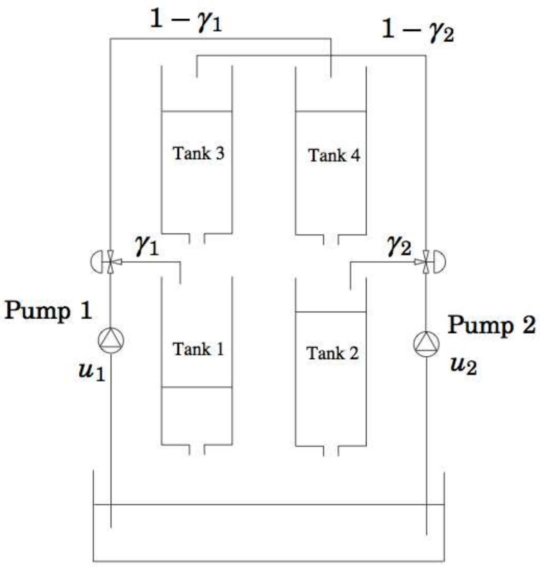

Figure 2. A schematic picture of the quadruple tank process

The control variables are the pump voltages u_1 and u_2. Let the states of the system be defined by the water levels of the tanks (expressed in cm) $x_1, x_2, x_3\, and\, x_4$ respectively. The maximum level of each tank is 20 cm. The dynamics of the system is given by:

$$\dot{x}_1 = -\frac{a_1}{A_2}\sqrt{2gx_1} + \frac{a_3}{A_1}\sqrt{2gx_3} + \frac{\gamma_1 k_1}{A_1}u_1 \tag{16}$$

$$\dot{x}_2 = -\frac{a_2}{A_2}\sqrt{2gx_2} + \frac{a_4}{A_2}1\sqrt{2gx_4} + \frac{\gamma_2 k_2}{A_2}u_2 \tag{17}$$

$$\dot{x}_3 = -\frac{a_3}{A_3}\sqrt{2gx_3} + \frac{(1-\gamma_2)}{A_3}k_2 u_2 \tag{18}$$

$$\dot{x}_4 = -\frac{a_4}{A_4}\sqrt{2gx_4} + \frac{(1-\gamma_1)}{A_4}k_1 u_1 \tag{19}$$

Where the parameters γ_i determine the positions of the valves which control the flow rate to upper and lower tanks respectively. The parameters A_i and the a_i represent the cross section area of the tanks and the holes respectively. The control signals are given by the u_i. The objective is to control the levels of the two lower tanks,i.e.x_1 and x_2 . Numerical values of the parameters are given in Table I. The control of the quadruple-tank process is studied at an operating point. The parameter values are given in Table II.

Parameters	*Values*	*Unit*
A_1,A_2	28	cm^2
A_3,A_4	232	cm^2
a_1, a_2	0.071	cm^2
a_3 , a_4	0.057	cm^2
k_1,k_2	3.33,3.35	cm^3/Vs
k_c	0.50	V/cm
g	981	cm/s^2

Table I
PARAMETER VALUES OF THE QUADRUPLE-TANK

Parameters	*Values*	*Unit*
x_1^0,x_2^0	12.4,12.7	cm
x_3^0,x_4^0	1.8,1.4	cm
u_1^0,u_2^0	3.00,3.00	v
γ_1,γ_2	0.70,0.60	

Table II
OPERATING POINTS PARAMETERS

B. The drinking water distribution system

To illustrate the BNN method on an actual water distribution network, the network in figure 3 is used as a case study. This network is constituted of stations of pumping, a dam in cascade and three tanks. In principal, the pressure, the debit and the velocity provided by each of the tanks are supervised.

Let: $P_1(t), P_2(t), P_3(t)$: The pressure of water coming out of every tank.

$q_1(t), q_2(t), q_3(t)$: The flow of water provided by tanks.

$V_1(t), V_2(t), V_3(t)$: The velocity of each of the reservoires to supervise.

Therfore, the input data are: $\mathrm{X} = [\mathrm{P}_1\ \mathrm{q}_1\ \mathrm{V}_1\ \mathrm{P}_2\ \mathrm{q}_2\ \mathrm{V}_2\ \mathrm{P}_3\ \mathrm{q}_3\ \mathrm{V}_3]$

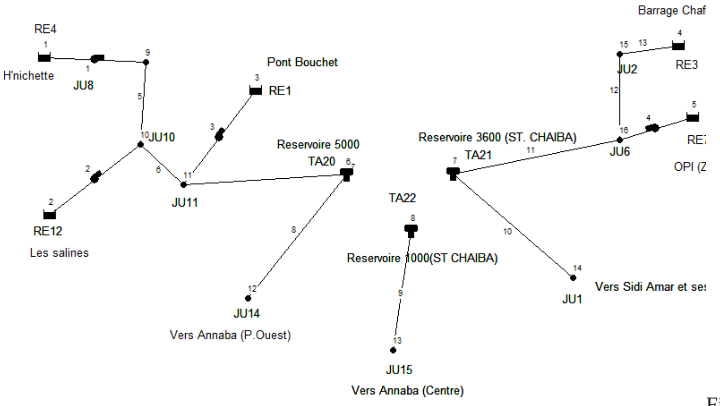

Figure 3. The water distibution network under study

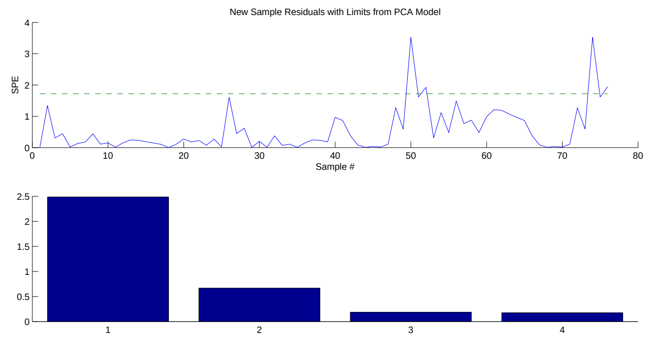

Figure 5. (a)The statistical SPE of the global PCA for the abnormal state. (b)The contribution of the variables

IV. Results

We strictly concentrated on sensor faults. The BNN approach is based on an auto-associative Neural Network model with five layers. The detection of the fault sensor in the quadruple tank is carried out using the Squared Prediction Error (SPE), the figure 4 allows to detect the presence of a variation of SPE from the beginning to the end of the simulation. The evolution plot of the SPE in figure 5 (a) shows two operating regions, the second one which begins from the 50^{th} sample to the end of the simulation presents a fault. The localization of the faulty variable is depicted in the figure 5 (b) where the contribution plots of the first variable (which represents the water level of the the first lower tank) is higher than the other contributions.

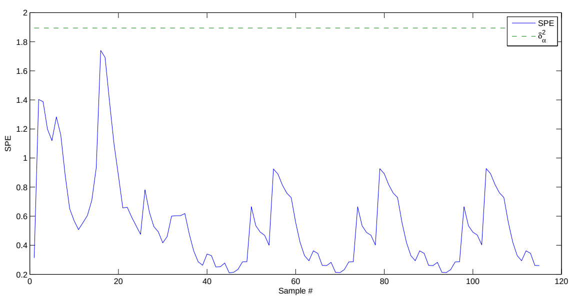

Figure 4. SPE normal case

Now, To illustrate the BNN method on an actual water distribution network, we use the network in figure 3 as a case study. This network is constituted of stations of pumping, a dam in cascade and three tanks. In principal, the pressure, the flow and the velocity provided by each of the tanks are supervised. After elaborating the hydraulic model and during the simulation, we inject a fault from the 30^{th} sample to the end of the simulation, figure 7 (a) shows the SPE statistical behavior of the process variables with an offset from the 30^{th} sample to the end of the simulation. To determine the root cause of the fault, we check out the contribution of each variables see figure 7 (b), so we can say that the water's debit sensor presents a default from the 30th until the end of the simulation.

The simulation's results show how the BNN approach is used for the detection of flows, according to the statistical SPE and while localization using the contribution plots.

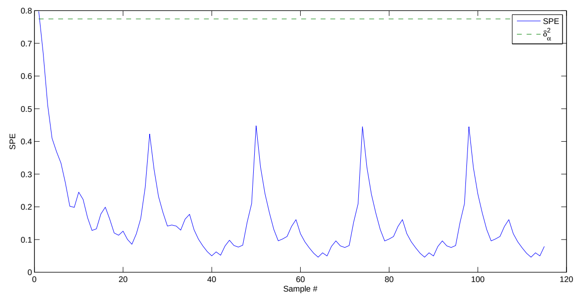

Figure 6. SPE normal case

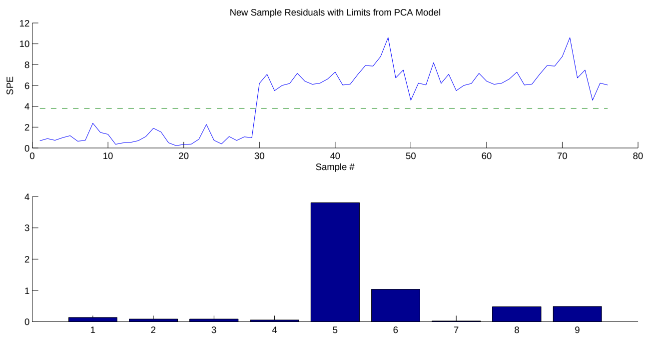

Figure 7. (a)The statistical SPE of the global PCA for the abnormal state. (b)The contribution of the variables

V. Conclusion

This paper presents a detection method for systems with a nonlinear behavior. We propose in this study a contribution, to replace the linear PCA model with a Bottleneck Neural Network (BNN) in order to adapt this diagnostic method to the nonlinear systems. The results are satisfactory. To through the application of a quadruple tank process, we show the possibility of detecting a default of the sensor and the possibility of the method's application on an actual water distribution system.

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