IJST, Transactions of Electrical Engineering, Vol. 39, No. E1, pp 101-113
Printed in The Islamic Republic of Iran, 2015

IMPROVEMENT OF MODELING QUALITY THROUGH MONITORING TECHNIQUES*

M. JAFARI AND A. A. SAFAVI**

Dept. of Power and Control, School of Electrical and Computer Engineering,
Shiraz University, Shiraz, I. R. of Iran
Email: safavi@shirazu.ac.ir

Abstract– Modeling is one of the most interesting areas in various fields of science. Unfortunately data quality, which has an important role in the modeling, is not considered. In fact, most often processes encounter disturbances which results in the collection of abnormal data and may lead to a model different from the real behavior of the process. On the other hand, most of real industrial processes are time varying and developing on-line models to capture the variations of the process is very appealing. High capability of intelligent models has attracted considerable attention. Therefore, on-line intelligent models can effectively characterize both time invariant and time varying processes. Current on-line modeling techniques adapt the primarily identified process model with the new changes in time varying processes without consideration of abnormal situations. This will affect the model. To overcome this problem, this paper proposes to combine process monitoring techniques with modeling approaches. Although the proposed approach is not restricted to a specific process monitoring or modeling approach, wave-net on-line techniques and recursive principal component analysis (RPCA) methods are invoked. A double continuously stirred tank reactor (CSTR) is considered as a case study. The results show the effectiveness of the proposed approach.

Keywords– On-line model improvement, wave-net learning, process monitoring, data quality

1. INTRODUCTION

Most real processes are time varying. Therefore, changes of the process dynamics affect the parameters of the process model and the model performance. This fact leads to the need for improving the model with continuous stream of data. On-line model improvement techniques address this issue. On the other hand, it is possible that an abnormal condition occurs in the process for a short time interval and the model is consequently reformed based on abnormal data. Though several papers address the time varying nature of some processes and the need to improve the model, and some address how to detect abnormal conditions of processes [1-12], not many papers address the need to consider these techniques simultaneously and the result of ignoring this issue. The main objective of this paper is to improve process models by considering quality of the invoked data. This will be done with a focus on a special class of intelligent models.

Intelligent models have attracted a great deal of attention in recent years in various areas of science and technology. While Neural Networks (NNs) [13, 14] are one of the most well known and powerful tools to develop intelligent models, they suffer from the lack of a rigorous mathematical framework and also from major trial and error steps in the design phase. Wave-net is a mathematical framework for a class of NNs based on wavelets and multi-resolution analysis suggested by Bakhshi and Stephanopolous in 1993 [13, 15] to overcome drawbacks of NNs. Further research and improvements on wave-net

*Received by the editors May 4, 2013; Accepted April 13, 2015.
**Corresponding author

structures were performed by Safavi and Romagnoli [14]. Three wavelet learning algorithms were then discussed in [16]. Extensions to on-line wave-net learning methodologies when detecting any changes within the process are presented in [17]. Nevertheless, no discussion is made in [17] on how to deal with quality of the data for on-line model improvement.

This brings us to another line of research, the so-called statistical process control (SPC) [18] or multivariate statistical process monitoring approaches (e.g. [19]). The basic philosophy of multivariate statistical approaches is that the behavior of the process is characterized using data obtained when the process is operating well. Subsequently, future unusual events and possible abnormalities in the new data are detected by referencing the measured process behavior against the available "in control" model. Relying on the nominal historical data, standard Principal Component Analysis (PCA) is a multivariate statistical method that models the linear correlation structure of a multivariate process. A major limitation of monitoring based on standard PCA is the assumptions of normal distribution and stationary variables and observations with no auto-correlation. Besides, the standard PCA is basically a linear static model while in dynamic systems current observations of variables are dependent on the previous observations of those variables. Therefore, Dynamic PCA (DPCA) is suggested for dynamic systems [20, 21]. However, it should be noted that standard PCA and DPCA models which are built from historical data are time-invariant while most real industrial processes are time-varying. When a time-invariant model is used to monitor time varying processes, normal changes are interpreted as false alarms. Therefore, adaptive process monitoring approaches are proposed to deal with the time-varying process conditions [22]. Li *et al.*, demonstrate that their approach can deal with time varying process behavior by adapting the linear relationships between the process variables [23].

In this paper, an on-line learning method in conjunction with on-line monitoring is proposed to improve the performance of the updated model. Here, based on on-line monitoring approaches, first, normal variations of the process from its abnormal variations are distinguished, then the process model is only updated based on normal variations.

The rest of this paper is structured as follows. In Section 2, wavelets and wave-net design are briefly discussed. In Section 3, on-line wave-net algorithms are presented. Section 4 presents process monitoring with recursive principal component analysis (RPCA). The on-line learning based on on-line monitoring approach is proposed in Section 5. A case study is illustrated in Section 6 to demonstrate the performance of the proposed approach. Simulation results are presented in Section 7. Section 8 presents the concluding remarks.

2. THE WAVE-NET DESIGN

Wave-nets [13, 14, 16] are defined as hierarchical multiresolution neural networks with one hidden layer of nodes and localized learning, whose basis functions are drawn from a family of wavelets. The primary difference of wave-nets to other regression methods is the use of multiresolution analysis that expands hierarchically with the wavelet basis functions according to a specified norm [17]. Wavelets are usually introduced in the multiresolution framework developed by Mallat [14, 15]. In this framework any $F(x) \in L^2(R)$ can be expressed as linear combinations of orthogonal wavelets $\psi_{m,k}$ as shown below.

$$F(x) = \sum_{m=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} d_{m,k} \psi_{m,k}(x) \tag{1}$$

$$\psi_{m,k} = 2^{-m/2} \psi(2^{-m} x - k) \quad m,k \in z \tag{2}$$

Where m and k correspond respectively to the dilation and translation factors of the wavelets and $2^{-m/2}$ is an energy normalization factor. If one starts from a particular resolution, for instance $m=0$, (1) can be re-expressed as

$$F(x) = \sum_{k=-\infty}^{+\infty} a_{0,k}\phi_{0,k}(x) + \sum_{m=-\infty}^{0}\sum_{k=-\infty}^{+\infty} d_{m,k}\psi_{m,k}. \quad (3)$$

Where $\phi_{m,k}$ is the scaling function and is defined as (see [13, 17])

$$\phi_{m,k} = 2^{-m/2}\phi(2^{-m}x-k) \quad m,k \in z. \quad (4)$$

Equation (3) is the basic framework of wave-nets. In fact, by incorporating the basis functions at a particular resolution, namely resolution $m=0$ here, the first approximation of the desired function is obtained. A wave-net is presented with a set of input-output pairs as training data and then it learns the mapping between the input-output pairs at multiple resolutions [14].

$$F_0(x) = \sum_{i=-\infty}^{+\infty} a_{0,i}\phi_{0,i}(x) \quad (5)$$

Then, by including the wavelets of the same resolution, a finer approximation is provided:

$$F_{-1}(x) = F_0 + \sum_{j=-\infty}^{+\infty} a_{0,j}\psi_{0,j}(x), \quad j \in z \quad (6)$$

In general, a finer approximation of $F(x)$ is obtained by adding wavelets of a higher resolution to a current approximation:

$$F_{m-1}(x) = F_m + \sum_{j=-\infty}^{+\infty} a_{m,j}\psi_{m,j}(x) \quad (7)$$

3. CURRENT ON-LINE LEARNING APPROACHES FOR WAVE-NETS

Wave-net learning is the process of finding the network coefficient $a_{m,k}$ and $d_{m,k}$. Three learning methods (the Direct Inner Product, L_2 learning algorithm and L_∞ learning algorithm) are presented in [16]. Real processes are dynamic and time-varying. On-line wave-net learning [17] is proposed to capture the changes of the process and reflect it to the primary model. Therefore, primary model adapts itself based on the incoming data. Three methods including L_2 Learning-Algorithm with L_2 or L_∞ Error-Threshold, L_∞ Learning-Algorithm with L_∞ Error-Threshold and Lyapunov approach are proposed in [17] for on-line wave-net learning. In this paper, L_2 learning algorithm with L_2 Error-Threshold and Lyapunov approach will be discussed.

a) L_2 *Learning–algorithm with* L_2 *error-threshold*

In this approach, in the first step a process model is estimated based on L_2 learning algorithm. Second, mean square error between (MSE) model and process data is calculated and based on the nature of the process an appropriate L_2 Error-Threshold is selected. At the third step, locations of the wavelets which support the approximation error are determined. Wherever error occurred, wavelets are retrained with the new incoming data at the same resolution (wavelet coefficients are changed). If error still exists, one can either retrain one lower resolution or train one higher resolution to improve the model. In the higher resolution direction, more detail and high frequency characteristics of the process will be captured. Finally, if all of these do not lead to satisfactory results, retraining the whole model is the last choice.

b) Lyapunov approach

Regardless of the learning-algorithms used, applying the error threshold as L_2 norm or L_∞ norm requires an available set of data since these norms are defined on a set of data and not on a single point or pair of data. But, the following approach which is based on Lyapunov theory improves the model by utilizing each single point of data.

Consider a multi-input multi-state system as follows:

$$dx/dt = f(x,u)\,,\ x(0) = x_0\,,\ u \in R^r\,,\ x \in R^d \tag{8}$$

As mentioned above, $f(x,u)$ can be approximated by

$$\hat{f}(x,u) = \sum_{k \in A_{j0}} A_{j0k}\,\phi_{j0k}(x,u) + \sum_{j=j_0}^{N} \sum_{k \in B} \sum_{i=1}^{2^n-1} B_{jk}^{(i)} \psi_{jk}^{(i)}(x,u) \tag{9}$$

where $A_{j0k}, B_{jk}^{(i)} \in R^n, n = r + d$.

Equation (8) is a more general form than (3) because of using multi-dimensional wavelets [14]. It is proved [24, 25] that the coefficients should be updated as shown below

$$\frac{d\,A_{j0k}}{dt} = \alpha_{j0}\, e_x^T P\, \phi_{j0k}(x,u) \tag{10}$$

$$\frac{d\,B_{jk}^i}{dt} = \beta_j\, e_x^T P \psi_{jk}^{(i)}(x,u) \tag{11}$$

Where α_{j0} and β_j are positive constants acting as adaptive rates [24], P is a positive-definite matrix that satisfies Lyapunov equation [25]. $e_x\,(e_x = x - \hat{x})$ is the difference between the true state x and approximated state $\hat{x}$.

4. PROCESS MONITORING WITH RECURSIVE PRINCIPAL COMPONENT ANALYSIS

While standard PCA is the basic block of the most commonly used monitoring approaches, the majority of industrial processes have a naturally time varying behavior and standard PCA model wrongly interprets these behaviors as faults. Existence of a recursive process monitoring method can improve performance of fault detection techniques. On this basis, Li *et al* [22] proposed recursive principal component analysis (RPCA) to deal with this problem. Li *et al* proposed three methods, rank-one modification, lanczos tridiagonalization, and standard singular value decompositions (SVD) for RPCA calculation. In this paper, standard SVD will be used. In the RPCA, first a block $X_1^0 \in R^{n_1 \times m}$ of nominal data is used to construct a primary PCA model in the off-line monitoring phase. n_1 is the number of observations and m is the number of variables, including inputs and outputs of the process. This block is converted to X_1 with zero mean and unit variance through the following equation,

$$X_1 = \left(X_1^0 - 1_{n_1} b_1^T\right)\Sigma_1^{-1}$$

$$1_{n_1} = [1 \ \cdots \ 1]^T \in R^{n_1}$$

$$b_1 = \frac{1}{n_1}\left(X_1^0\right)^T l_{n_1}$$

$$\Sigma_1 = diag(\sigma_{1.1} \ \cdots \ \sigma_{1.m})$$

where b_1 is the mean of X_1^0 and Σ_1 consists of $\sigma_{1.1} \ \cdots \ \sigma_{1.m}$ which are standard deviations of m variables of X_1^0 . Correlation matrix is obtained by

$$R_1 = \frac{1}{n_1 - 1} X_1^T X_1.$$

In on-line monitoring phase, at each step $K+1$, PCA model is updated by augmenting incoming block or sample of data to the matrix of data at step K . It means that, if $X_{n\,k+1}^0$ is the block that comes at step $K+1$, this block is augmented with the block that is collected at step K (X_k^0). Augmented signal at step $K+1$ is X_{k+1}^0,

$$X_{k+1}^0 = \begin{bmatrix} X_k^0 \\ X_{n\,k+1}^0 \end{bmatrix}.$$

Then mean, variance, and correlation matrix are updated and X_{k+1}^0 is scaled to zero mean and unit variance using updated mean and variance and becomes X_{k+1}.

In the presented RPCA in [22], it is possible to update mean and variance and correlation matrix by an incoming vector (x_{k+1}^0) only, which contains one sample of each variable, instead of a block of data ($X_{n\,k+1}^0$) at each step.

The next step in RPCA is the calculation of loading vectors. By applying standard SVD on correlation matrix, eigenvectors are extracted first, and then number of significant PCs and loading vectors are obtained through current methods. For more details on these approaches see [22]. In this paper, cumulative percent variance (i.e. CPV) method is used and the number of PCs is selected so that CPV reaches 97%. T^2 and Q [26-30] are used as statistics for detecting abnormal conditions. It is clear that time varying behavior of the process leads to changes in principal components and finally updating of mentioned statistics and their thresholds.

5. THE PROPOSED METHOD

Most of the real processes are time varying and multi-input multi output. In these cases, modeling each of the variables of the process, for example $F(t)$, is not only dependent on the time t, but also is dependent on the other variables. Therefore, a time varying model, here wavenet model, cannot efficiently characterize that variable without taking the other variables into consideration.

In the proposed approach, a monitoring technique shows the condition of the operation.

Data driven monitoring techniques, here RPCA, distinguish this condition based on the collected block data. As mentioned before, this block is, for example, $X \in R^{n \times m}$ in which n is the number of observations and m is the number of variables, including inputs and outputs of the process.

It is clear that, at any time t, $X \in R^{n \times m}$ includes $F(t)$ which is one of the variables.

Therefore, if the collecting data belongs to the normal operating condition, the model update procedure will be activated to follow the behavior of $F(t)$. Otherwise no action will take place until the process returns to the normal condition.

For this purpose, a block of data which is collected in the normal condition of the process, is invoked to create a standard PCA model for monitoring purpose. A primary intelligent model of the mentioned variable is also constructed. This model is dependent on the time. All of these procedures are done in off-line phase. Then, in on-line phase, a block of data is collected from the process. This block is first projected to the constructed PCA model to distinguish its situation. It means that, if both T^2 and Q for this block is less than T^2 and Q thresholds, which are calculated in off-line phase, that block belongs to the normal condition of the process and both of the primary intelligent and primary PCA models will be updated, otherwise updating models will be stopped. This procedure will be continued for all of the incoming blocks in on-line phase.

Here, we restrict ourselves to the current on-line wave-net model to demonstrate the applicability of the proposed method. In the time varying wave-net model, the primary model of the process is improved based on new variations in the process. Therefore, even when some disturbances or abnormal conditions are occurred, on-line learning reflects those changes to the model. In fact, the model would be updated by changing wavelet coefficients, or going to higher resolutions or even retraining the whole model for good tracking of new training data. This procedure may be time consuming when abnormal conditions occur and the newly adapted model may be quite different from the real process. Again, whenever the process returns to its normal condition, approximation error is large and the model needs to go to higher resolutions or retrain the whole model for tracking new data set in a time consuming procedure.

It was mentioned in Section 3.b that L_2 learning-algorithm is defined on a set of data and not on a single point but Lyapunov approach improves the model by utilizing each single point of data. It is also considerable that in RPCA algorithm the correlation matrix would also be updated by an incoming block (block-wise) or a vector (sample-wise) of variables. Therefore, in this proposed approach sample-wise and block-wise RPCA will be applied to Lyapunov approach and L_2 learning-algorithm, respectively.

6. THE CASE STUDY

The multi-input multi-output process considered in this paper consists of two continuously stirred tank reactors (CSTRs) in series with an intermediate mixer for the introduction of the second feed. The system is time-varying as seen from $\phi_h(t)$ and $\phi_c(t)$ below. A single, irreversible, exothermic, first-order reaction $A \rightarrow B$ takes place in each reactor. The independent variables in this system are input compositions (C_F^1, C^2), two input flow rates (Q_F^1, Q^2) and input temperatures (T_F^1, T^2). The outputs of this system are reactors' compositions (C_1, C_2), reactors' temperatures (T_1, T_2) and mixer's composition and temperature (C_m, T_m). The following equations describe CSTR process. Further description about these equations can be seen in [19, 31].

$$\frac{dC}{dt} = Rate * \phi_c(t) + \frac{Q_F}{V}(C_F - C) \tag{12}$$

$$\frac{dT}{dt} = DH.Rate * \phi_c(t) + \frac{Q_F}{V}(T_F - T) + \frac{\rho_c C_{pc}}{\rho C_p V} q_c \left[1 - \exp\left(-\frac{hA}{q_c \rho C_{pc}} \phi_h(t)\right)\right] \times (T_{cf} - T) \tag{13}$$

Where,

$$DH = -\frac{\Delta H}{\rho . C_\rho}, \quad Rate = -K_0.C.e^{-E/RT}$$

$$\phi_h(t) = (1 - .01t)$$

$$\phi_c(t) = \exp(-.00067 * \frac{E}{RT} t).$$

7. SIMULATION AND RESULTS

In this paper, two different time varying variables, output temperature of the first reactor and output composition of the second reactor of a double CSTR, are considered for the implementation of the proposed approach. Our explanations and comparisons of the current and proposed approach are based on output composition of the second reactor and results of the temperature of the first reactor are presented at the end. For this purpose an early wave-net model of the mentioned CSTR is trained with L_2 learning algorithm at resolution $m = -5$ of 80 samples of normal conditions data. For this model, $\phi_c(t) = 1$ in expressions (12) and (13) and the exponential term in (13) is equal to zero. At normal conditions, inputs variations are restricted within 5% of their operating point. Meyer Wavelet [15] is used in the developed wave-net model. Figure 1 shows real output composition and it's approximation by an early wave-net model.

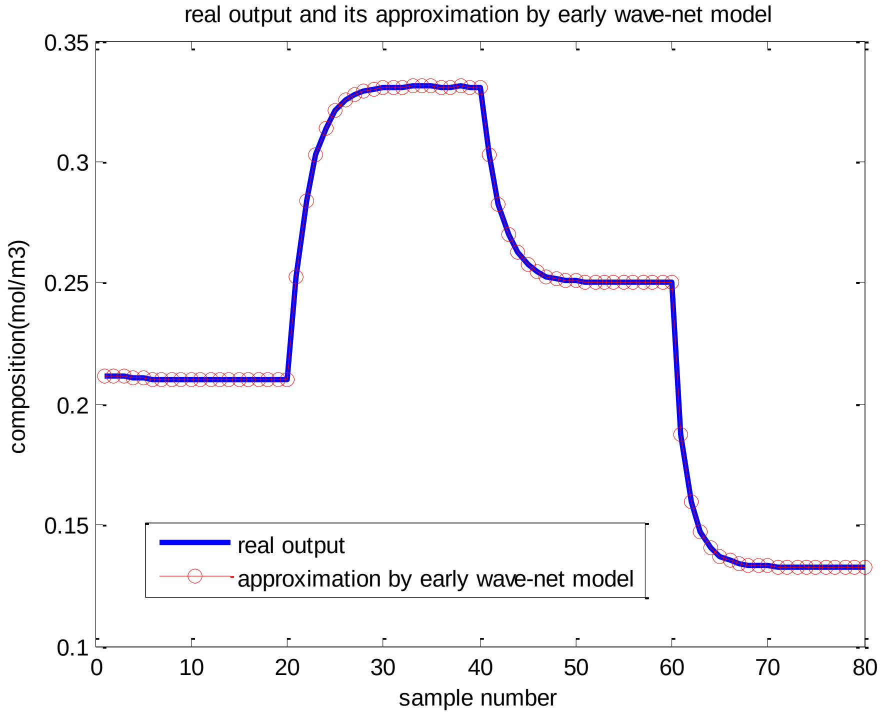

Fig. 1. Real output composition and its approximation of early wave-net model

In on-line wave-net learning, two approaches (i.e. L_2 learning-algorithm with L_2 error-threshold and Lyapunov approach) are considered here. In L_2 learning-algorithm with L_2 error-threshold, 80 samples of time-varying process data come into the model in windows of length 2. In Lyapunov approach, the 80 samples come one by one. Incoming data at the 40th to 60th samples are collected when a disturbance of 10% of operating point is applied to the input temperature of the first reactor. Other remaining data are collected at normal conditions. The following results represent the comparison of the two approaches, current on-line wave-net learning and proposed on-line learning based on on-line monitoring.

a) On-line wave-net learning approach

In the current on-line wave-net learning approach, early wave-net model is updated based on incoming data without considering the possibility of any disturbance when collecting data. In this experiment, 80 samples are used and two mentioned on-line learning methods, L_2 learning-algorithm and Lyapunov, will update the model based on these data without considering the disturbance that had occurred at the 40th to 60th samples. Therefore, the on-line learning methods will point the model toward the new data (include both disturbance and variation of the process). At the 61st sample, the disturbance has vanished but the variations in the process have continued. Therefore, the on-line learning approach again points the model toward these new data. At all these stages the model is forced to update and reach the process output. At each stage the update formula should act to push the MSE toward zero. See Figs. 2 and 3, output after occurrence of disturbance (dash-dot line) and approximated output with the current on-line wave-net learning method (dash-circle line).

b) The Proposed on-line learning based on on-line monitoring approach

1. L_2 Learning-Algorithm with L_2 Error-Threshold: In this on-line learning based on on-line monitoring approach, each block of data consists of 2 samples of variables (i.e. $X_{n_{k+1}} \in R^{2\times4}$) T^2, and Q statistics are computed on-line first. These statistics are compared with T^2 and Q thresholds which are obtained from a primary block of 80 samples of nominal variables (i.e. $X_1 \in R^{80\times4}$) (See Fig. 4 where circles are T^2 and Q statistics of the incoming blocks of data and solid lines show T^2 and Q statistic thresholds) and model is updated only if the incoming data block is in normal condition. If one of the T^2 and Q statistics is more than its threshold, it means that a disturbance has occurred. In our case, as it was mentioned before, the blocks that contain data between 40th-60th samples are not in normal condition and the model will not be updated with them. It must be noticed that at each step, only the samples of one column of $X_{n_{k+1}}$ (here samples of output composition of the second reactor) are applied to the wave-net model for adaptation.

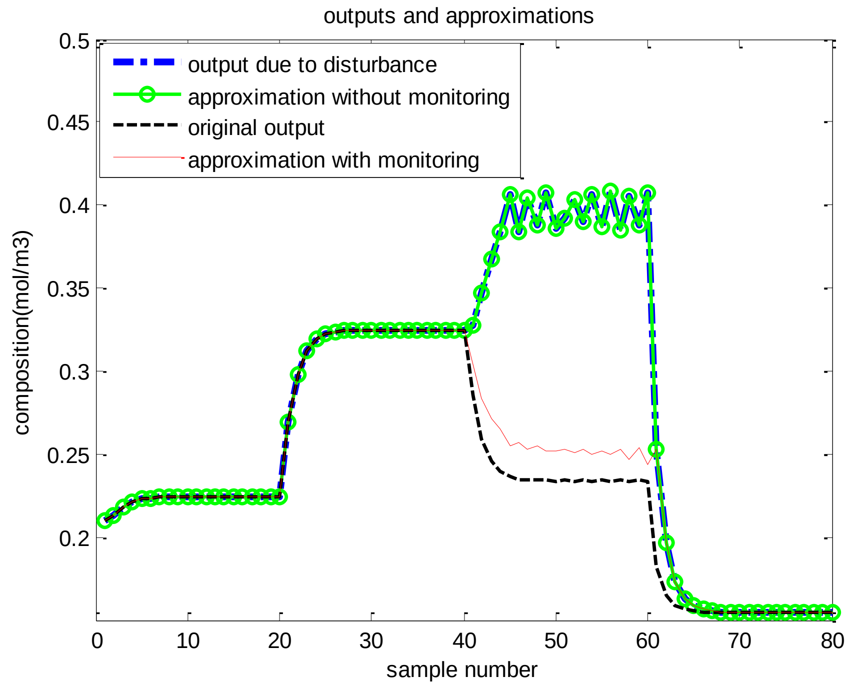

Fig. 2. Output composition approximation based on block-wise adaptation

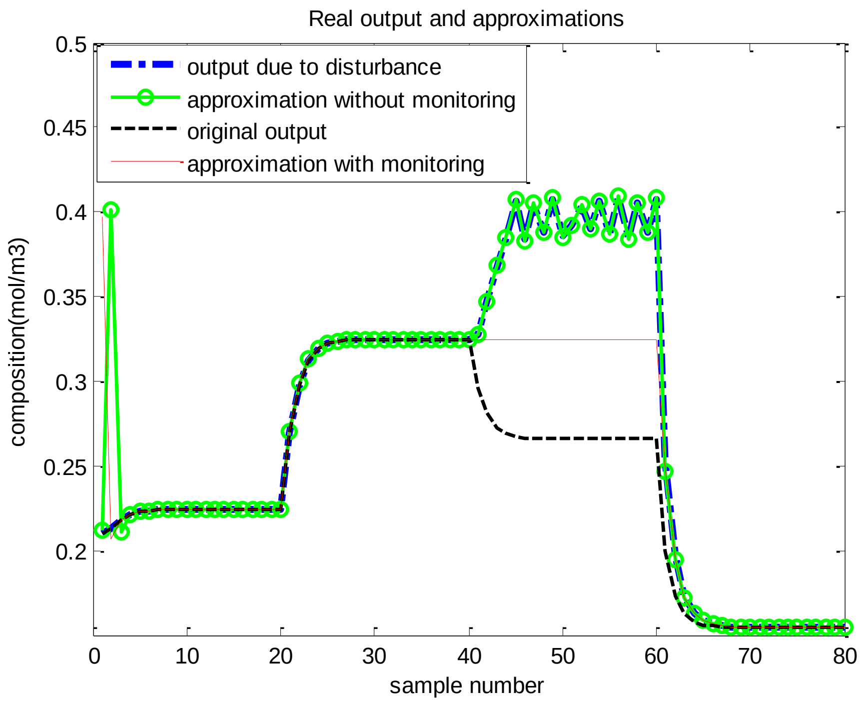

Fig. 3. Output composition approximation based on sample-wise adaptation

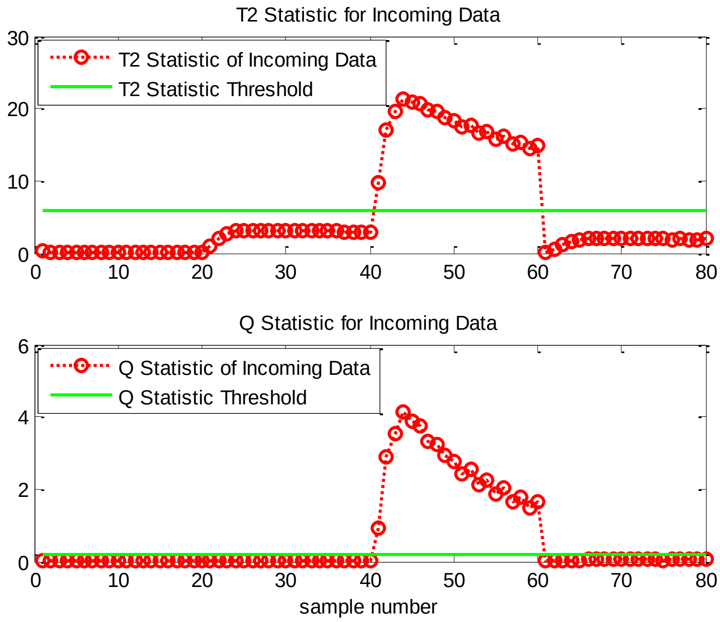

Fig. 4. T^2 and Q statistics plot for block-wise RPCA

Disturbance occuring in the inputs of a process makes the output of the process different from the real output. Therefore, the updated model based on uncorrect data may be different from real process behavior. In fact, we should avoid the change of the wave-net model based on the abnormal data available as this model may be used by a controller or elsewhere. Figure 2 shows the output of the process when no disturbance has occurred (dash-dash line), output after disturbance has occurred (dash-dot line), approximated output with the current on-line wave-net learning method (dash-circle line), and approximated output with L_2 learning-algorithm based on on-line monitoring (solid line). As explained before, the first approach (current L_2 learning-algorithm) updates the model even for data in abnormal conditions, but the second approach (L_2 learning-algorithm based on on-line monitoring) updates the model only for data in normal conditions. Thus, for the 40th-60th samples, before updating the model, as the on-line monitoring approach detects the disturbance and abnormal condition, the model is not updated. This new approach leads to more efficient models that are near to real system with fewer computation loads.

The whole precedure for final update of the current and the proposed approach takes 19.69 seconds and 17.55 seconds, respectively. A Sony laptop, SR Series (JAB), with RAM 4G is used to run the current and all of the following simulations in MATLAB2009a. This shows the accuracy and effectiveness of the proposed approach.

2. Lyapunov Approach: In this approach, for each vector of data $x_{k+1} \in R^{1\times 4}$, T^2 and Q statistics are computed on-line. These statistics are compared with T^2 and Q thresholds which are obtained from an initial block of 80 samples of nominal variables, i.e. $X_1 \in R^{80\times 4}$. These results are shown in Fig. 5 where red circles are T^2 and Q statistics of the incoming vectors and solid lines show T^2 and Q statistic thresholds. In on-line learning phase, updating of wave-net model parameters according to the (10) and (11) occurs only if the variables of incoming vector are in normal condition. Changes in the threshold of nominal condition are due to the variation in the number of significant eigenvalues of correlation matrix that is updated sample-wise. If one of the T^2 and Q statistics is more than its threshold, it means that a disturbance has occurred and adaptation of parameters in (10) and (11) must stop. Notice that, in this Lyapunov approach in contrast to the L_2 learning-algorithm only one variable of vector x_{k+1}, that is the measure of output composition of the second reactor, is applied for the wave-net model adaptation at each step.

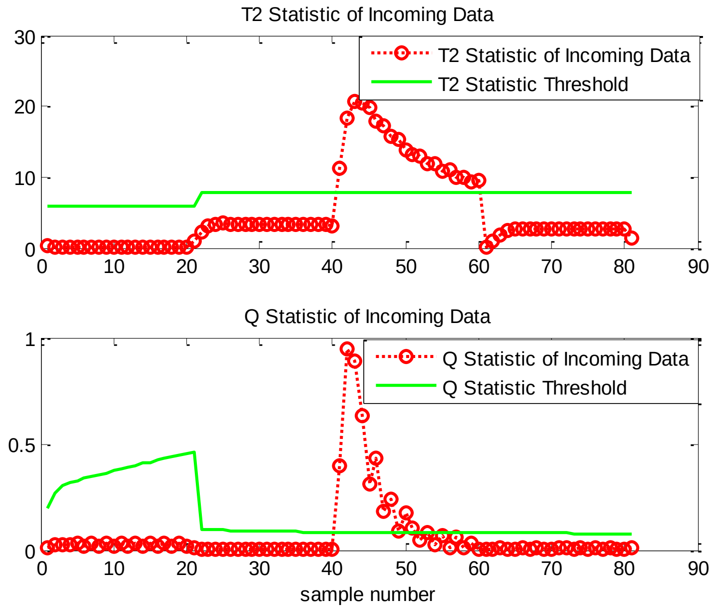

Fig. 5. T^2 and Q statistics plot for sample-wise RPCA

In Fig. 3 the output of the process when no disturbance has occurred (dash-dash line), output after disturbance has occurred (dash-dot line), approximated output with the current Lyapunov approach (dash-circle line), and approximated output that updates the parameters of (10) and (11) based on sample-wised RPCA (solid line), are illustrated. RPCA avoids the adaptation of wave-net model for the 40th -60th samples and results in a fixed model in this interval. The whole precedure for final update of the current and the proposed approach takes 11.33 seconds and 10.73 seconds, respectively. Comparison of the results that are illustrated in Figs. 2 and 4 confirms the effectiveness of our approach.

In the following figures, results of the output temperature of the first reactor are also considered. Figure 6 shows real output temperature and it's approximation by the early wave-net model with the features that were previously described.

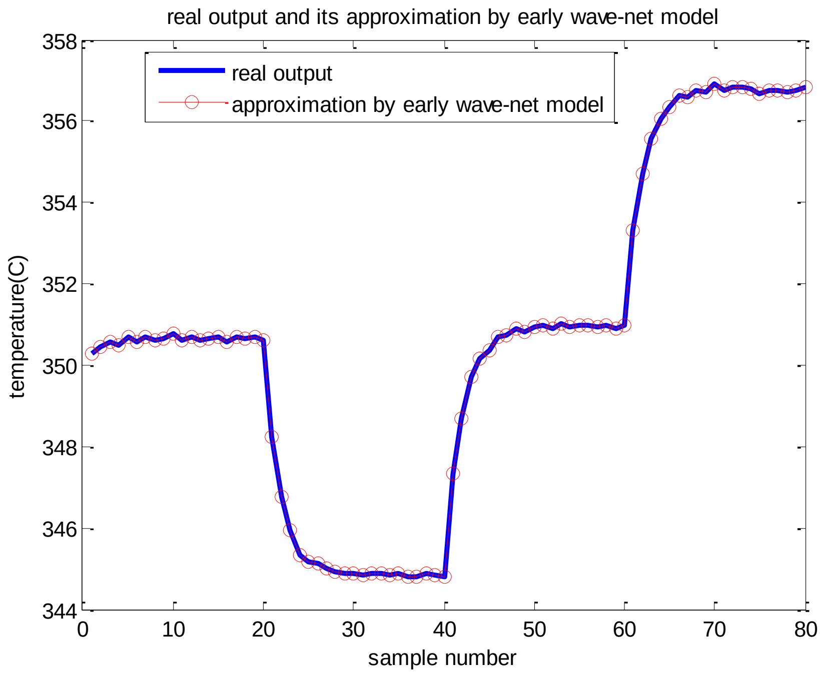

Fig. 6. Real output temperature and its approximation of early wave-net model

In Fig. 7 the output temperature when no disturbance has occurred (dash-dash line) and output after disturbance has occurred (dash-dot line) are presented. In this figure, dash-circle line and solid line represent approximated output temperature with the current on-line wave-net learning method, and approximated output with L_2 learning-algorithm based on on-line monitoring in the block-wised phase, respectively. The whole precedure for final update of the current and the proposed approach takes 20.60 seconds and 18.25 seconds, respectively.

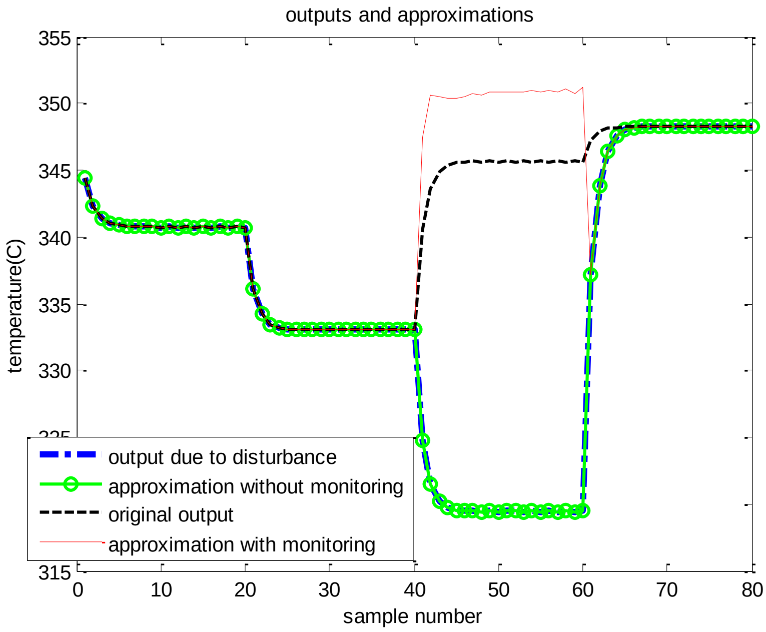

Fig. 7. Output temperature approximation based on blocked-wised adaptation

In Fig. 8 the output temperature when no disturbance has occurred (dash-dash line) and output after disturbance has occurred (dash-dot line) are presented. In this figure, dash-circle line and solid line represent approximated output temperature with the current on-line wave-net learning method, and approximated output with Lyapunov approach based on on-line monitoring in the sample-wised phase, respectively. The whole precedure for final update of the current and the proposed approach takes 11.64 seconds and 11.20 seconds, respectively.

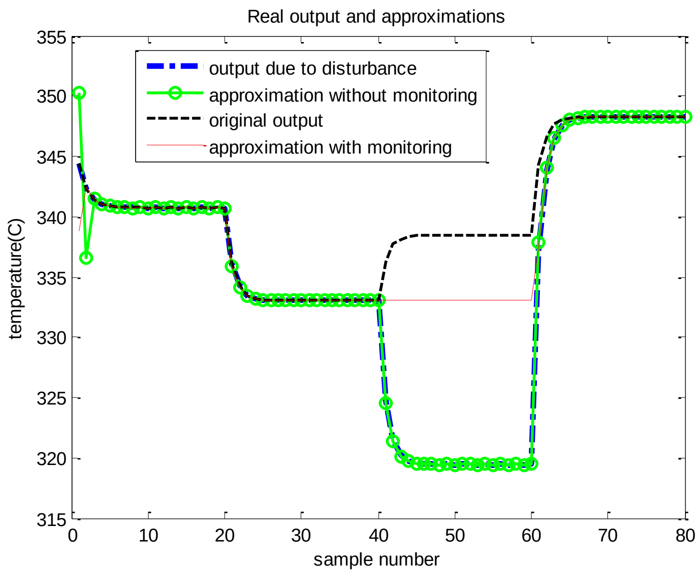

Fig. 8. Output temperature approximation based on sample-wised adaptation

8. CONCLUSION

As most real industrial processes are time varying, developing on-line intelligent models to capture such variations are very appealing. Current on-line modeling techniques adapts the primary identified process model with the new changes in time varying processes without taking into consideration abnormal situations in the process operation. To overcome this problem, this paper proposed combining process monitoring techniques with on-line learning methods. For this purpose, wave-net on-line techniques and recursive principal component analysis (RPCA) methods were invoked to show the effectiveness of this proposition. A double continuously stirred tank reactor (CSTR) was considered as a case study.

REFERENCES

1. Gertler, J. (1998). Fault detection and diagnosis in engineering systems. New York, Marcel Dekker.
2. Chiang, L. H., Russell, E. L. & Braatz, R. D. (2001). *Fault detection and diagnosis in industrial systems*. London, UK: Springer-Verlag.
3. Venkatsubramanian, V., Rengaswamy, R., Yin, K. & Kavuri, S. N. (2003). A review of process fault detection and diagnosis Part I: Quantitative model-based methods. *Computers & Chemical Engineering journal*, Vol. 27, No. 3, pp. 293-311.
4. Choi, S. W., Lee, C., Lee, J. M., Park, J. H. & Lee, I. B. (2005). Fault detection and identification of nonlinear processes based on kernel PCA. *Chemometrics and Intelligent Laboratory Systems*, Vol. 75, No. 1, pp. 55-67.
5. Kano, M., Tanaka, S., Hasebe, S. & Hashimoto, I. (2003). Monitoring independent components for fault detection. *AICHE Journal*, Vol. 49, No. 4, pp. 969-976.
6. Lee, J. M., Yoo, C. K. & Lee, I. B. (2004). Statistical process monitoring with independent component analysis. *Journal of Process Control*, Vol. 14, pp. 467–485.
7. Lee, J. M. & Joe Qin, S. (2006). Fault detection and diagnosis based on modified independent component analysis. *AICHE Journal*, Vol. 52, No. 10, pp. 3501-3514.
8. Ge, Z. & Song, Z. (2007). Process monitoring based on independent component analysis—principal component analysis (ICA-PCA) and similarity factors. *Industrial and Engineering Chemistry Research*, Vol. 46, pp. 2054–2063.
9. Hsu, C. C., Chen, M. C. & Chen, L. S. (2010). A novel process monitoring approach with dynamic independent component analysis. *Control Engineering Practice*, Vol. 18, pp. 242-253.
10. Zhang, Y. & Zhang, Y. (2010). Fault detection of non-Gaussian processes based on modified independent component analysis. *Chemical Engineering Science*, Vol. 65, pp. 4630-4639.
11. Wang, J., Zhang, Y., Cao, H. & Zhu, W. (2012). Dimension reduction method of independent component analysis for process monitoring based on minimum mean square error. *Journal of Process Control.*, Vol. 22, pp. 477-487.
12. Qin, S. J. (2012). Survey on data-driven industrial process monitoring and diagnosis. *Annual Reviews in Control.*, Vol. 36, pp. 220-234.
13. Bakshi, B. R. & Stephanopoulos, G. (1993). Wave-net: a multiresolution, hierarchical neural network with localised learning. *AICHE Journal*, Vol. 39, No. 1, pp. 57-81.
14. Safavi, A. A. & Romagnoli, J. A. (1997). Application of wavelet-based neural networks to modelling and optimisation of an experimental distillation column. *(IFAC Journal of) Engineering Applications of Artificial Intelligence*, Vol. 10, No. 3, pp. 301–313.
15. Daubechies, I. (1992). *Ten lectures on wavelets*. Philadelphia, PA: SIAM. Feedback Instruments Ltd. Manual: 326 Edc 0792.
16. Safavi, A. A. & Romagnoli, J. A. (1997). On the learning algorithm for wave-nets. In Fifth Iranian conference on electrical engineering. Tehran, Iran, Computer volume, 3-40–3-48.

17. Zakeri, V., Naghavi, V. & Safavi, A. A. (2009). Developing real-time wave-net models for non-linear time-varying experimental processes. *Computers and Chemical Engineering*, Vol. 33, pp. 1379–1385.
18. Riaz, M. (2014). Approximation effects on control charts for process monitoring. *Iranian Journal of Science and Technology (IJSTS)*, Vol. 38, No. A3, pp. 289-294.
19. Safavi, A. A., Chen, J. & Romagnoli, J. A. (1997). Wavelet based density estimation and application to process monitoring. *AICHE Journal*, Vol. 43, No. 5, pp. 1227–1241.
20. Ku, W., Storer, R. H. & Georgakis, Ch. (1995). Disturbance detection and isolation by dynamic principal component analysis. *Chemometrics and Intelligent Laboratory Systems*, Vol. 30, No. 1, pp. 179-196.
21. Chen, J. & Liu, K. C. (2002). On-line batch process monitoring using dynamic PCA and dynamic PLS models. *Chemical Engineering Science*, Vol. 57, pp. 63–75.
22. Li, W., Henry Yue, H., Valle-Cervantes, S. & Joe Qin, S. (2000). Recursive PCA for adaptive process monitoring. *Journal of Process Control*, Vol. 10, pp. 471-486.
23. Wang, X., Kruger, U. & Lennox, B. (2003). Recursive partial least squares algorithms for monitoring complex Industrial processes. *Control Engineering Practice*, Vol. 11, pp. 613–632.
24. Liu, G. P., Billings, S. A. & Kadirkamanathan, V. (2000). Indentification of nonlinear dynamical systems using wavelet networks. *International Journal of Systems Science*, Vol. 31, No. 12.
25. Khalil, H. K. (1996). *Non-linear systems*. Prentice-Hall, 1996.
26. Wise, B. M. & Gallagher, N. B. (1996). The process chemometrics approach to process monitoring and fault detection. *Journal of Process Control.*, Vol. 6, pp. 329–348.
27. Russell, E., Chiang, L. H. & Braatz, R. D. (2000). *Data driven methods for fault detection and diagnosis in chemical processes*. Springer.
28. Venkatasubramanian, V., Rengaswamy, R., Kavuri, S. N. & Yin, K. (2003). A review of process fault detection and diagnosis Part III: Process history based methods. *Computers and Chemical Engineering*, Vol. 27, pp. 327-346.
29. Jackson, J. E. (1991). *A user guide to principal components*. John Wiley & Sons, New York.
30. Hennin, S. K. (1991). Structural decisions in on-line optimization. First Quarterly Rep., Imperial College London.
31. Salahshour, K. & Jafari, M. R. (2007). On-Line identification of nonlinear systems using adaptive RBF-Based neural networks. *International Journal of Information Science and Technology*, Vol. 5, No. 2.