References

[1] G. Pellegrinetti, J. Benstman, "Nonlinear control oriented boiler modeling - A benchmark problem for controller design", IEEE Trans. Con. Sys. Tech., Vol. 4, No. 1, pp. 57-64, 1996.
[2] L. Ljung, "System identification: Theory for the user", Prentice-Hall, 1999.
[3] J. Sjoberg, Q. Zhang, L. Ljung, "Nonlinear black-box modeling in system identification: a unified overview", Automatica, Vol. 31, No. 12, 1995.
[4] O. Nelles, "Nonlinear System Identification: From Classical Approaches to Neural Networks and Fuzzy Models", Springer, 2000.
[5] C.J. Lin, C.C. Chin, "Prediction and identification using wavelet-based recurrent fuzzy neural networks", IEEE Trans. Sys., Man and Cyb., Vol. 34, pp. 2144-2154, 2004.
[6] C.M. Chang, T.S. Liu, "A wavelet network control method for disk drives", IEEE Trans. Con. Sys. Tech. Vol. 14, pp. 63–68, 2006.
[7] K.S. Narendra, K. Parthasarathy, "Identification and control of dynamical systems using neural networks", IEEE Trans. Neural Net.,Vol. 1, No. 1, pp. 4-27, 1990.
[8] S.A. Billings, H.B. Jamaluddin, S.Chen, "Properties of neural networks with applications to modeling nonlinear dynamical systems", Int. Jou. of Con., Vol. 55, No.1, pp. 193-224, 1992.
[9] S. Mcloone, M.D. Brown, G. Irwin, A. Lightbody, "A Hybrid Linear/Nonlinear Training Algorithm for Feed-forward Neural- Networks", IEEE Trans. Neural Net., Vol. 9, No. 4, pp. 669-684, 1998.
[10] A.B. Stephen, H.L. Wei, "A new class of wavelet networks for nonlinear system identification", IEEE Trans. Neural Net., Vol. 16, No. 4, pp. 862–874, 2005.
[11] S. Postalcioglu,Y. Becerikli, "Wavelet networks for nonlinear system modeling", Neural Com. and Appl., Vol.16, pp. 433-441, 2007.
[12] Q. Zhang, A. Benveniste," Wavelet networks", IEEE Trans. Neural Net., Vol. 3, pp. 889–898, 1992.
[13] Q. Zhang, "Using wavelet network in nonparametric estimation", IEEE Trans. Neural Net., Vol. 8, No. 2, pp. 227–236, 1997.
[14] E. Swidenbank, B.W. Hogg, "Application of system identification techniques to modeling a turbo generator", IEEE/CTA, Vol. 136, No. 3, pp. 113-121, 1989.
[15] P.K. Chawdry, B.W. Hogg, "Identification of boiler models", IEE Proc. Con. The. and Appl., Vol. 136, No. 5, pp. 261-271, 1989.
[16] M. Sugiyama, H. Sawai, A.H. Waibel, "Review of time delay neural network (TDNN) architectures for speech recognition", IEEE/CS, Vol. 1, pp. 582-585, June 1991.
[17] D. Shi, H. Zhang, L. Yang, "Time-delay neural network for the prediction of carbonation tower's temperature", IEEE Trans. Ins. and Mea., Vol. 52, pp. 1125-1128, Aug. 2003.
[18] I. Daubechies, "The wavelet transform, time-frequency localization and signal anaylsis", IEEE Trans. Inf. The., Vol. 36, pp. 961-1005, Oct. 1990.
[19] S. Haykin, "Neural Network: A comprehensive foundation", Prentice-Hall, New Jersey, 1999.
[20] B.L.R. Moor, DaISy: Database for the Identification of Systems, Department of Electrical Engineering, ESAT/SISTA, K.U. Leuven, Belgium, URL: http://homes.esat.kuleuven.be/~smc/daisy

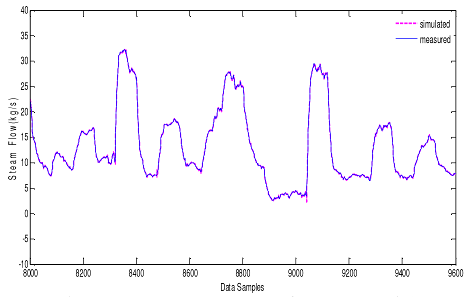

Fig. (14): Fourth output of WNN model

Also, the MSE Comparison for the TDNN and the WNN model are shown in Figs. 15-18 and the results are summarized in Table 2.

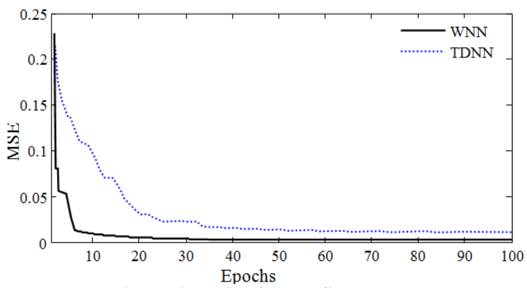

Fig. (15): MSE for the first output

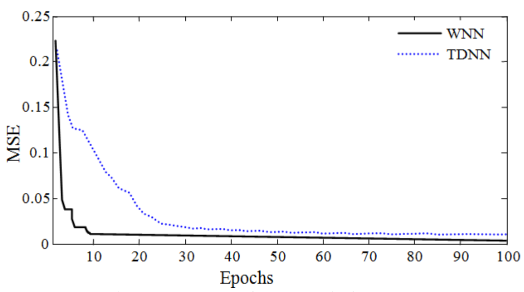

Fig. (17): MSE for the third output

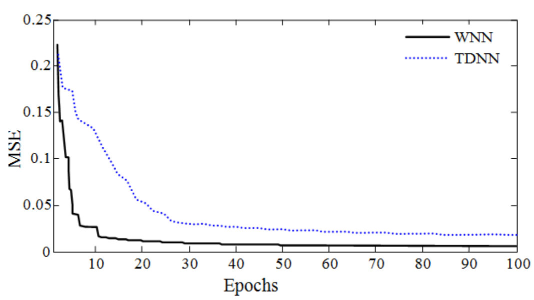

Fig. (16): MSE for the second output

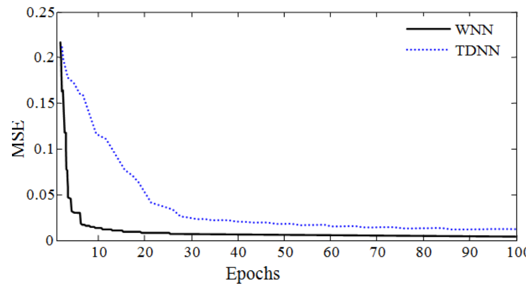

Fig. (18): MSE for the fourth output

Table (2): MSE comparison

	TDNN	WNN
Output 1	1.9980e-02	4.0218e-03
Output 2	2.8653e-02	5.0163e-03
Output 3	2.2862e-02	4.3359e-03
Output 4	2.1473e-02	4.1305e-03

Simulation results show that WNN model has a higher accuracy than TDNN model in identification of the steam generator. It is because of some intrinsic characteristics of wavelet functions such as localization in both time and frequency domains, having compact support and oscillating behavior and also the multi-resolution analysis in which wavelets with coarse resolution capture the global behavior while the wavelets with fine resolution capture the local behavior of the function accurately. These characteristics lead to the high accuracy of the WNN model.

7. Conclusion

In this paper, identification of the industrial steam generator was carried out using a TDNN model and a WNN model. First we preprocessed data using DWT and then fed them as inputs to the models. The TDNN was trained with LMBP algorithm and compared the results with results of WNN trained with BPM algorithm. Combined advantages of wavelets and abilities of NNs have effectively estimated system dynamics and plant nonlinearities using data from the plant which contained disturbances and noise. Simulation results show remarkable consistence between estimated and actual measured outputs, and we concluded that the WNN model can more accurately capture the local nonlinear system dynamics and is more precise to estimate the plant outputs than the TDNN model due to wavelet functions characteristics.

After data decomposition, the approximated denoised signals are normalized and divided into three parts: 60% for training dataset, 20% for validation dataset and 20% for test dataset. The training dataset is used during the supervised training process to adjust the network parameters to minimize the error between the network's outputs and the plant outputs. The validation dataset is used to periodically check the generalization ability of the network and avoid from over-fitting. The test dataset is used as a final measure to see how the network performs on unseen data. The number of inputs and outputs of the networks are determined by the problem, and as stated before the plant has 4 inputs and 4 outputs. We used a try and error based procedure to determine the number of hidden nodes, as it is dependent on the complexity of the relationships in the dataset. The networks parameters are initialized to small random values and we started to train the networks with one hidden node and gradually increased the number of hidden nodes, periodically stopping the training process to observe the training and validation errors, until increasing the number of hidden nodes result in decreasing error in training data set while validation error remained relatively constant. Finally the optimum number of hidden nodes to minimize the MSE criterion for the TDNN and WNN was found 14 and 8 respectively. The TDNN model has a 4-14-4 structure which is trained with LMBP learning algorithm. The WNN model has a 4-8-4 structure which is trained with BPM learning algorithm. In order to compare the ability of these two models, estimated outputs in comparison with actual outputs for TDNN model and WNN model are shown in Figs. 7-10 and Figs. 11-14 respectively. The dashed lines show estimated outputs and solid lines show actual outputs of the plant.

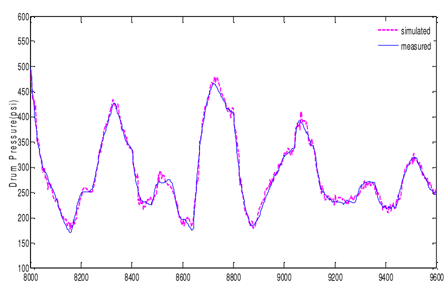

Fig. (7):First output of TDNN model

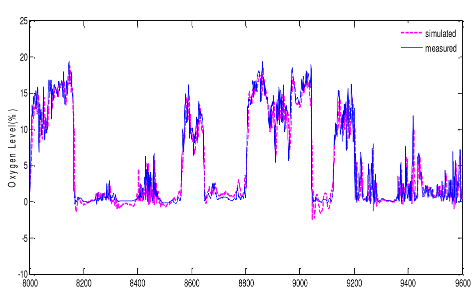

Fig. (8): Second output of TDNN model

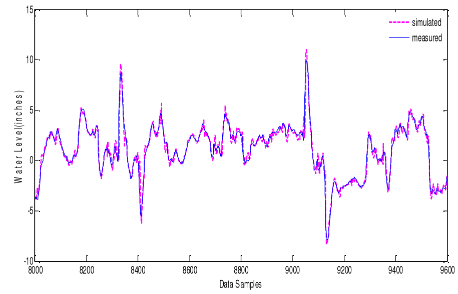

Fig. (9): Third output of TDNN model

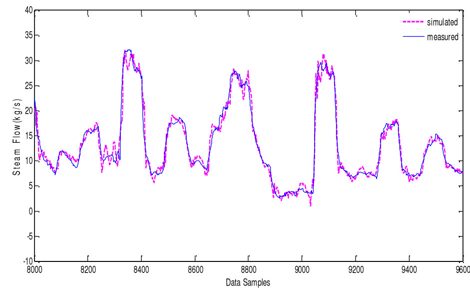

Fig. (10): Fourth output of TDNN model

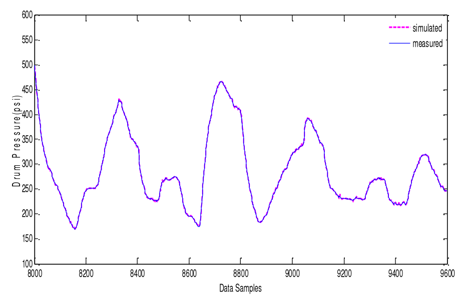

Fig. (11): First output of WNN model

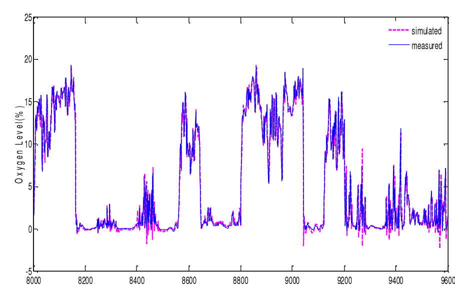

Fig. (12): Second output of WNN model

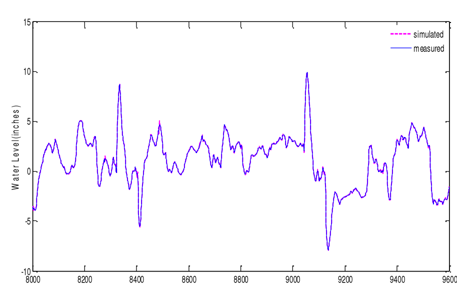

Fig. (13): Third output of WNN model

for j=1,…,m; k=1,…, n

$$w_{kj}(t+1) = w_{kj}(t) - \eta \frac{\partial E}{\partial w_{kj}} + \mu\left(w_{kj}(t) - w_{kj}(t-1)\right) \quad (15)$$

$$a_j(t+1) = a_j(t) - \eta \frac{\partial E}{\partial a_j} + \mu(a_j(t) - a_j(t-1)) \quad (16)$$

$$b_j(t+1) = b_j(t) - \eta \frac{\partial E}{\partial b_j} + \mu(b_j(t) - b_j(t-1)) \quad (17)$$

Where η and μ denote the learning rate and momentum factor respectively and n is the number of outputs. Adding momentum improves the convergence speed and helps network from being trapped in a local minimum.

5. Proposed Method for Steam Generator Identification

In order to identify the steam generator described in section (2), the input-output data set was taken from DaISy Database [20]. Since the data set is recorded from a real industrial steam generator and it contains noise, it is important to have data preprocessing. First the DWT of the signals is taken using symlet wavelets of order 4 (sym4) at level 5. Then we normalize the approximated denoised signals and feed them as inputs to the NN models. The TDNN model has a 4-14-4 structure which uses hyperbolic tangent and linear activation functions in the hidden and output layer respectively and is trained with LMBP learning algorithm. The WNN model has a 4-8-4 structure which uses Morlet wavelet and linear activation functions in the hidden and output layer respectively and is trained with BPM learning algorithm. These two models are used to identify the plant. The block diagram of the proposed method is shown in Fig. 5 and more details are described in the next section.

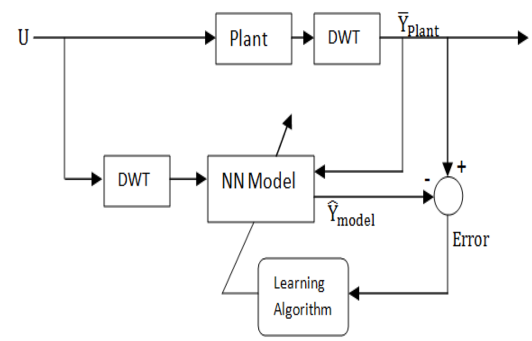

Fig. (5): Block diagram of the proposed method

6. Simulation Results and Discussion

As described earlier the steam generator has 4 inputs and 4 outputs and the real industrial input-output data is taken from DaISy Database. We use DWT to remove the noise of the signals. Different decomposition level and different wavelet function were used, we have the best results in denoising with symlets of order 4 (sym4) at level 5, as shown in Fig. 6. The wavelet transform is a multi-resolution approximation technique in which the original signal is decomposed into two types of components, approximation and details of the signal. The DWT uses a series of high-pass and low-pass filters, low-pass filters are used to analyze the low frequencies and are capable of providing coarser approximation of the signal and high-pass filters are used to analyze the high frequencies and are capable of providing finer approximation of the signal. The outputs of the low-pass filters are the approximation coefficients $\{a_1, a_2, \ldots, a_5\}$ which contain approximate information about low frequency components and retain the main features of the original signal. The outputs of the high-pass filters are detail coefficients $\{d_1, d_2, \ldots, d_5\}$ which retain detail information about the high frequency components such as noise.

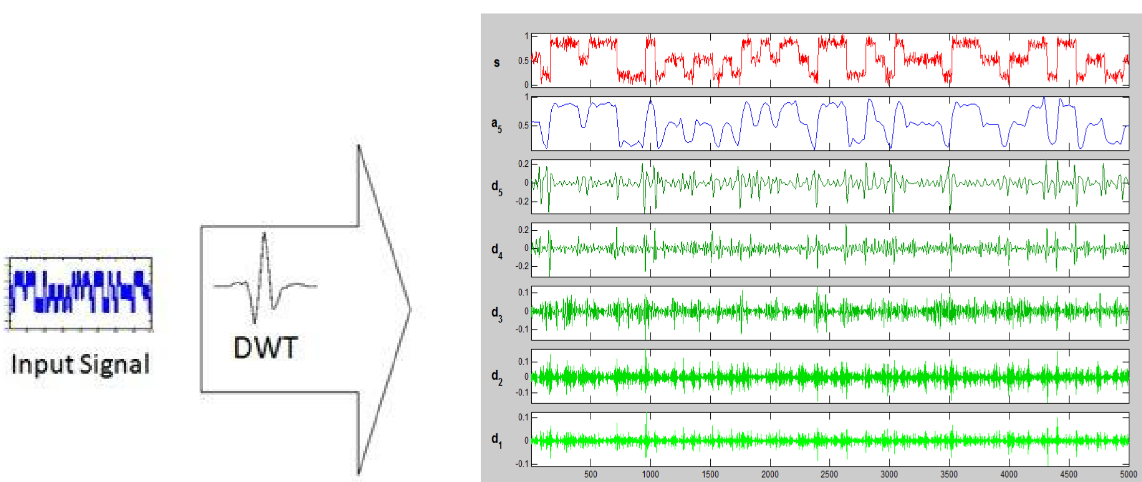

Fig. (6):Data decomposition for first input using DWT

In this work, Levenberg–Marquart back propagation (LMBP) algorithm is used to train the TDNN which weight update rule is defined as:

$$W(k+1)=W(k)-(J^TJ+\mu I)^{-1}J^Te \quad (6)$$

Where J is the Jacobian matrix, μ is the learning rate, I is the identity matrix and e describes the error vector. The error is defined between the output of the network and the desired output. The advantage of using this algorithm is the rapid execution of the trained network. During training, the estimated output is compared with the desired output, and the mean square error (MSE) which is defined in equation (7), is calculated.

$$\mathrm{MSE} = \frac{1}{P}\sum_{i=1}^{P}(y_k^d - \hat{y}_k)^2 \quad (7)$$

y_k^d is kth desired output and $\hat{y}_k$ is kth estimated output and P is the number of elements of the training set. If the MSE is more than a prescribed limiting value, it is back propagated from output to input, and weights are further modified till the error or number of iterations is within a prescribed limit.

4. Wavelet Theory

4.1. Wavelet Transform

Wavelet transform is a time-scale representation of a signal associated with building a model for signals using a family of wavelets, which are scaled and shifted versions of the mother wavelet [18]. The wavelet family is defined by scale and shift parameters (a,b) as in equation (8).

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \quad (8)$$

The operation of the dilation and translation parameters causes the wavelet superior location performance in both time and frequency. The wavelet transform is called continuous if the scaling and translation parameters, a and b are continuous. The continuous wavelet transform has two drawbacks, redundancy and impracticality. These problems are solved by discretizing the transform parameters (a, b) as expressed:

$$a = a_0^j \quad b = kb_0a_0^j \quad (9)$$

The discrete wavelet transform (DWT) is defined as:

$$X(j,k) = \sum_{n\in\mathbb{Z}} x(n)\,\psi_{j,k}(n) \quad (10)$$

where

$$\psi_{j,k}(n) = a_0^{-j/2}\,\psi(a_0^{-j}n - kb_0) \quad j,k \in \mathbb{Z}, a_0 \quad (11)$$

One of the simplest choice is $a_0 = 2$ and $b_0 = 1$. So the scale and translation parameter are expressed as powers of 2. This type of DWT is called as dyadic DWT.

4.2. Wavelet Neural Network

WNN inspired by both FFNN and wavelet analysis have received considerable attention and become a popular tool for function approximation and system identification [11],[13].WNNs are FFNNs using wavelets as activation function. They have been used in classification and identification problems with more accuracy caused by combining of the time-frequency localization properties of wavelets and the global learning abilities of neural network. In this paper, the WNN is designed as a three-layer structure consisting of an input layer, a hidden layer and an output layer as shown in Fig. 3. The activation functions of the wavelet nodes in the hidden layer are derived from a mother wavelet, $\psi(x) \in L^2(\mathbb{R})$, which $L^2(\mathbb{R})$ implies the space of all square integrable functions on $\mathbb{R}$, that has limited duration and zero mean value and satisfying the admissibility condition:

$$\int_{-\infty}^{+\infty}\frac{|\hat{\Psi}(\omega)|^2}{\omega}d\omega < \infty \quad (12)$$

Where $\hat{\Psi}(\omega)$ indicates the Fourier transform of $\psi(x)$. Then, the function of $\psi(x)$ can become the mother wavelet with a dilation(a) and a translation (b). In this study Morlet wavelet function is adopted as the activation function of the wavelet nodes in hidden layer which is shown in Fig. 4 and is expressed in equation (13).

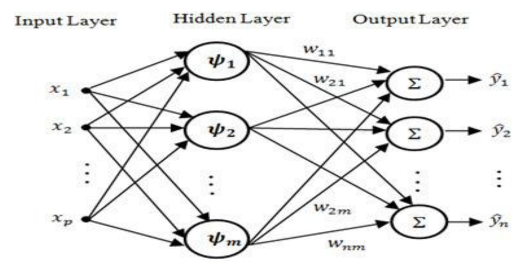

Fig. (3): Structure of WNN

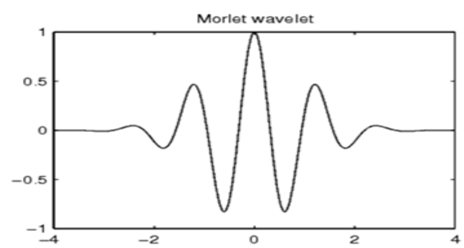

Fig. (4): Morlet wavelet function

$$\psi_j(x) = \cos\left(5\times\frac{x-b_j}{a_i}\right)\exp\left(-\frac{(x-b_j)^2}{2a_i^2}\right) \quad (13)$$

The output layer activation function is linear and the kth output of the WNN is calculated as:

$$\hat{y}_k = \sum w_{kj}\psi_j(x) \quad (14)$$

Where w_{kj} denote the weights connecting the hidden layer and output layer and m is the number of hidden neurons. The task of WNN training involves estimating the parameters of the network by minimizing a cost function. Here we used MSE as the cost function which was defined in equation (7). As described earlier, the wavelet family can be constructed by translating and dilating the mother wavelet. Therefore, the weights between layers, the translation and dilation parameters need to be computed. The basic steps of the standard BP algorithm have been described in [19]. Adjusting each parameter of the network using BP with momentum (BPM) learning algorithm can be defined by equations (15-17).

2. Nonlinear Multivariable Steam Generator

A boiler or steam generator is an industrial unit, which is used for generating steam and hot water for industrial process and electrical energy generation. Boiler operation is a complex operation in which hot water must be delivered to a turbine at constant rate, pressure and temperature in order to ascertain reliable operation. An efficient boiler should generate maximum amount of steam at a required pressure and temperature and quality with minimum fuel consumption and should be able to cope with fluctuating demands of steam supply [14], [15]. In this work we consider an industrial benchmark, the steam generator in operation at Abbott Power Plant generation unit located in Champaign, IL, USA. It is a dual fuel (oil/gas) fired unit used for heating and generating electric power. The plant has 4 inputs and 4 outputs which are described in Table-1. The plant is rated at 22.096 kg/s of steam at 22.4 MPa (325psi) of pressure. The plant has dynamics of high order, as well as nonlinearities, instabilities, and time delays. Fig. 1 shows the structure of the plant [1].

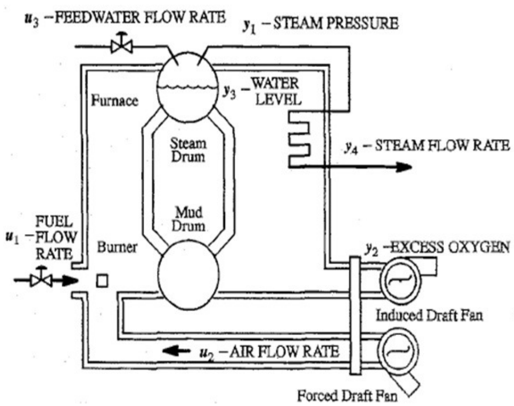

Fig. (1): Architecture of the steam generator [1]

3. Time-Delay Neural Network

TDNN is a feed-forward neural network (FFNN) capable of using a fixed number of previous system inputs to predict the following outputs of the system. TDNN is a variant of the multi-layer perceptron (MLP) which uses time-delayed inputs to the hidden layer. In the input layer each neuron is presented a total number of D delayed values in addition to the current value, for each input to the network [16], [17]. The input vector $X_i(t)$ and the weight vector $W_{ji}(t)$ are defined as follows:

$$X_i(t) = [x_i(t), x_i(t-1), \ldots, x_i(t-D)]^T \quad (1)$$

$$W_{ji}(t) = [w_{ji}(0), w_{ji}(1), \ldots, w_{ji}(D)] \quad (2)$$

Table (1):Inputs and outputs of the steam generator

Inputs	Outputs
u_1: Fuel flow rate	y_1: Steam pressure
u_2: Air flow rate	y_2: Excess oxygen in exhaust gases
u_3: Feed water flow rate	y_3: Drum water level
u_4: Changes in steam demand	y_4: Steam flow rate

The output is a weighted sum of past-delayed values of the input, expressed as:

$$s_j(t) = \sum_{i=1}^{R} \sum_{l=0}^{D} W_{ji}(l) X_i(t-l) + b_j \quad (3)$$

Where W_{ji} denotes the weights connecting the inputs and hidden layer and b_j is the bias and R is the number of inputs. When the neurons in the hidden layer use the hyperbolic tangent activation function, the output of each neuron j is calculated as follows:

$$o_j(t) = \frac{1-\exp(-2s_j(t))}{1+\exp(-2s_j(t))} \quad (4)$$

When the output layer neurons use a linear activation function kth output of the network is calculated as:

$$\hat{y}_k(t) = \sum_{j=1}^{m} v_{kj} o_j(t) + b_k \quad (5)$$

Where v_{kj} denotes the weights connecting the hidden layer and output layer and b_k is the bias vector for the output layer and m is the number of hidden neurons. A TDNN with one hidden layer is shown in Fig. (2), where z^{-1} is delay operator.

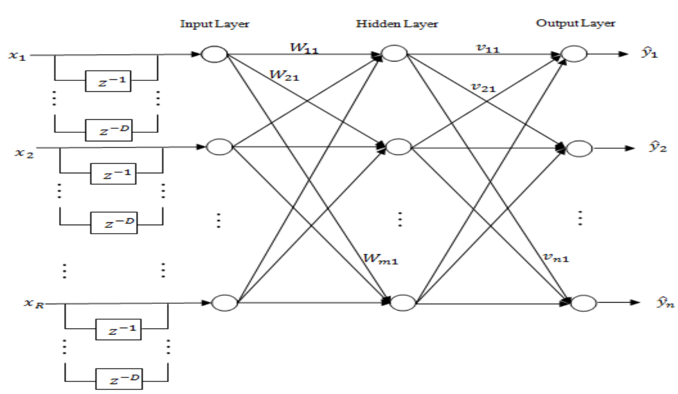

Fig. (2):TDNN structure with one hidden layer

System Identification of a Nonlinear Multivariable Steam Generator Power Plant Using Time Delay and Wavelet Neural Networks

Leila Khalilzadeh Ganjali-khani (1) - Farid Sheikholeslam(2) – Homayoun Mahdavi-Nasab(3)
(1) Ms.c - Department of Electrical Engineering, Najafabad Branch, Islamic Azad University
(2) Associate Prof. - Department of Electrical and Computer Engineering, Isfahan University of Technology
(3) Assistant Prof. - Department of Electrical Engineering, Najafabad Branch, Islamic Azad University

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Abstract
One of the most effective strategies for steam generator efficiency enhancement is to improve the control system. For such an improvement, it is essential to have an accurate model for the steam generator of power plant. In this paper, an industrial steam generator is considered as a nonlinear multivariable system for identification. An important step in nonlinear system identification is the development of a nonlinear model. In recent years, artificial neural networks have been successfully used for identification of nonlinear systems in many researches. Wavelet neural networks (WNNs) also are used as a powerful tool for nonlinear system identification. In this paper we present a time delay neural network model and a WNN model in order to identify an industrial steam generator. Simulation results show the effectiveness of the proposed models in the system identification and demonstrate that the WNN model is more precise to estimate the plant outputs.

Index Terms: System identification, time delay neural network, discrete wavelet transform, wavelet neural network.

1. Introduction

In heat generation process at a power unit, performance improvement is a critical factor and one of the most effective strategies for steam generator efficiency enhancement is to improve the control system. To achieve this objective it is essential to have a valid model of the steam generator of power plant [1]. The model of a system can be represented by a mathematical model based on the physics laws that govern the problem, or by using the experimental data measured in the system which is called system identification. In the first case, the model is defined from well known physical principles, which allow a well defined mathematical model. In the case of identification, the methods do not need previous knowledge of the system, so they are known as black-box process identifi–cation [2]. The modeling based on experimental data is an important issue in the area of identification and control. The problem of identification consists of choosing an identification model and adjusting the parameters such that the response of the model approximates the response of the real system to the same input [3]. Nowadays, soft computing techniques such as artificial neural networks and wavelet neural networks (WNNs) have become very effective tools for identification of nonlinear plants [4-6]. Neural network (NN) models have proven to be successful nonlinear black-box model structures in many applications. NNs offer a framework for nonlinear modeling and control, based on their ability to learn complex nonlinear functional mappings [7]. The characte–ristics of NN consists of distributed parallel processing, nonlinear mapping and self-adaptive learning which cause increasingly successful applications in system identifi–cation, handling large amounts of dynamic, noisy and non-linear data [8], [9]. Recently WNN has been used as a powerful tool for identification of unknown plants [10], [11]. A wavelet neural network has a nonlinear regression structure that uses localized basis functions in the hidden layer to achieve the desired input-output mapping. The integration of the localization properties of wavelets and the learning abilities of NN cause the superiority of WNN over NN for complex nonlinear system modeling [12], [13]. In this paper we present a time delay neural network (TDNN) model and a WNN model in order to identify an industrial steam generator. Simulation results show remarkable consistence between estimated and actual outputs of the plant, and it is shown that the WNN model can more accurately capture the local nonlinear system dynamics and is more precise to estimate the plant outputs than the TDNN model.