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CONTROL SCHEME OF A BOILER-TURBINE USING ADAPTIVE WAVELET NEURAL NETWORK

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In power plant control system, the capability to achieve an optimal tracking property of the nonlinear multi-input multi-output (MIMO) units has been an important task. This paper proposes a direct adaptive wavelet neural network controller of boiler-turbine system for improving the performance and efficiently achieving the good tracking property to meet the load demands under load changes, large disturbances and change of system operating points. This paper describes the application of a multi-loop direct adaptive wavelet neural network for a drum boiler; three important outputs were controlled using a direct adaptive controller. WNNs are rapidly trained with adaptive learning rates (ALRs) which have been derived from the discrete Lyapunov stability theorem and used to guarantee the convergence of the WNN controllers. Simulation results show that the robustness and the good performance of the proposed control system to satisfy stable tracking of the boiler-turbine system.

***KEYWORDS**: Boiler-turbine control system, Wavelet transforms, Neural networks, Direct adaptive control.*

1. INTRODUCTION

In recent years, great efforts have been made on control of steam boiler- turbine system which is the crucial part in power plant, where the control of power plant system has a central role of plant performance. Steam boiler- turbine system is a nonlinear, time varying multi-input multi-output (MIMO) and uncertain industrial process whose states generally vary with operating conditions. The main control problem in nonlinear industrial processes is the tracking problem, so the outputs must be able to follow the desired references even with the presence of load changes and large disturbances. The central task of the boiler- turbine system control is to adjust the output power to meet the electrical load demand, while maintaining the steam pressure and water level in the drum within acceptable tolerance.

Several different types of controllers have been designed for this system. In [1-3] a linear control is presented based on a linear nominal model for designing a linear control around nominal operating points of the nonlinear plant and the robustness of the controller was achieved. Nonlinear control system is designed that use an accurate plant model [4-6]. In [7, 8] a generalized predictive control (GPC) is designed for controlling the system with large range of varying operation conditions. In [9, 10] intelligent methods are used. Model Predictive Control (MRAC) was designed in [11]. A decentralized controller was designed in [12].

Due to the highly nonlinear dynamic characteristics of boiler- turbine unit, the designed controller should be strongly enough in order to guarantee the best tracking of the desired system demand. There is, therefore, a strong motivation for considering adaptive control system such as wavelet neural network controller for this unit. Wavelets which provide a very simple and efficient analysis have been widely used in various areas. By dilations and translations, wavelet transform can extract the detail information of signals with multiresolution capability. Combining the wavelet analysis theory with artificial neural network theory results wavelet neural network (WNN). In 1992, Zhang and Benveniste proposed the concept and algorithm of wavelet neural network [13]. The main feature of the WNN is that some kind of wavelet functions are used as activation functions of the hidden layer of the WNN instead of sigmoid functions used in multi-layer Perceptron (MLP) or the radial basis function used in RBF networks. Incorporating the time-frequency localization properties of the wavelet transform and the learning abilities of neural network shows the advantages of the WNN over NNs for various applications. WNN have been widely used for modeling of nonlinear systems [14, 15], and control of nonlinear dynamical systems [16-20].

In this paper a direct adaptive wavelet neural network controller is proposed. The presented control system is a decentralized control where we use three separated local controllers (multi-loop scheme) each one is composed of wavelet neural network to give a control input (control signal) to the plant to be controlled. The structure of WNN consists of three layer network with wavelet function as activation function in the hidden layer. In order to improve the system performance the backpropagation (BP) algorithm is used for training the parameters of the wavelet neural network (WNN). But since the BP method has a problem that the optimal learning rates cannot easily be found, the adaptive learning rates (ALRs), which can adapt rapidly the changes of the plant, have usually been derived from the discrete Lyapunov stability theorem [21,22] and used to guarantee the convergence of the WNN controllers in the proposed control systems.

The rest part of the paper is organized as follows. Section 2 formulates the nonlinear MIMO boiler-turbine unit. In section 3, the architecture and training algorithm of the direct adaptive control using wavelet neural network are described. The convergence and stability analysis of the WNNC is explained in section 4. Section 5 gives simulation results of boiler-turbine control system. Finally, Conclusion of this paper is summarized in section 6.

2. BOILER-TURBINE SIMULATION

The boiler-turbine simulation model employed in this study is the Bell and Astrom model as considered in [23, 24]. The model is a third order non-linear dynamical model. The feature of the model is the non-linear equations utilized in the predictions of the three outputs, drum steam pressure, output power and drum water level, these outputs being functions of the three inputs, fuel flow, control valve position and feed water flow. The simulation contains the major inputs and outputs which are needed for the overall plant control and essential non-linearityes, so that regulation about normal operating conditions may be investigated. The model parameters have been estimated from a 160 MW oil-fired unit on the Swedish grid system. The three inputs, three outputs nonlinear model is given by the following equations:

$$\begin{aligned} \dot{x}_1 &= -0.0018u_2 x_1^{9/8} + 0.9u_1 - 0.15u_3 \\ \dot{x}_2 &= \left(-0.073u_2 - 0.016\right)x_1^{9/8} - 0.1x_2 \\ \dot{x}_3 &= \left(141u_3 - \left(1.1u_2 - 0.19\right)x_1\right)/85 \end{aligned} \tag{1}$$

Where the state variables x_1, x_2 and x_3 are the drum steam pressure, the electrical output, and the density of fluid in the system respectively. The control inputs u_1, u_2 and u_3 denote the fuel actuator position, the governor valve position, and the feed water actuator position. The variables to be regulated are the drum pressure y_1, the electrical output y_2, and the drum water lever y_3:

$$\begin{cases} y_1 = x_1 \\ y_2 = x_2 \\ y_3 = 0.05\left(0.13073x_3 + 100\alpha_{cs} + \left(q_e/9 - 67.975\right)\right) \end{cases} \tag{2}$$

Where α_{cs} is the quality factor of steam, and q_e is the evaporation mass flow rate. They can be expressed by:

$$\alpha_{cs} = \frac{\left(1 - 0.001538x_3\right)\left(0.8x_1 - 25.6\right)}{x_3\left(1.0394 - 0.0012304x_1\right)} \tag{3}$$

$$q_e = \left(0.854u_2 - 0.147\right)x_1 + 45.59u_1 - 2.514u_3 - 2.096 \tag{4}$$

Due to actuator limitations, the control inputs are subject to the following constraints:

$$\begin{aligned} &0 \le u_i \le 1 \qquad i = 1,2,3 \\ &-0.007 \le \dot{u}_1 \le 0.007, \\ &-2 \le \dot{u}_2 \le 0.02, \\ &-0.05 \le \dot{u}_3 \le 0.05. \end{aligned} \tag{5}$$

The normal operating point of Bell and Astrom model (1) with initial conditions and corresponding system set-points are shown in Table 1 [24].

Table 1: Normal operating point of Bell and Astrom model

x_1^0	x_2^0	x_3^0	u_1^0	u_2^0	u_3^0	y_3^0	y_1	y_2	y_3
108	66.65	428	0.34	0.69	0.433	0	108	66.65	0

3. CONTROL STRATEGY

The block diagram of the direct adaptive wavelet neural network controller (WNNC) is shown in Fig.1. As shown, there is a multi-loop wavelet neural network control system that provides control signals to the plant.

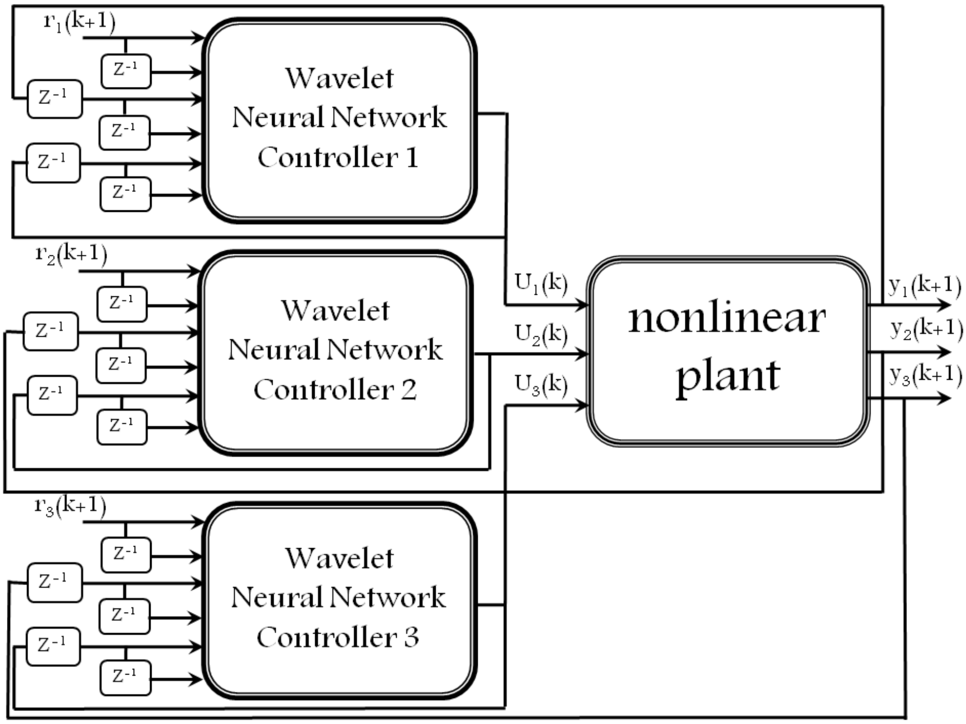


Fig.1.The architecture of the direct adaptive control

3.1. Wavelet Neural Network Controller (WNNC)

The control problem in MIMO control system is to generate control signals such that the plant output tracks the desired references. The structure of every sub-controller is shown in Fig. 2. The WNN structure consists of three layers:

***Layer 1*:** is an input layer with N_i inputs that accepts the input variables and transmits the weighted inputs to the next layer. The input vector to the WNN is the desired reference, previous values of the plant control input and the plant output.

$$X = [r(k),...,r(k-p), y(k-1),..., y(k-q), u(k-1),...,u(k-m)]^T \tag{6}$$

Where, r is the desired output, y is the actual output of MIMO plant and u is the output of WNNC (control signal). p, q, and m are the number of previous desired output, actual output and control signal respectively.

Layer 2: is a hidden layer that uses a wavelet function as an activation function in each node. In this paper, the second derivative of Gaussian (Mexican Hat), $\psi(t) = (1-t^2)\exp(\frac{-t^2}{2})$ is selected as a mother wavelet function. The output of the j^{th} node in the hidden layer is:

$$\psi_{aj,bj}(net_j) = \frac{1}{\sqrt{a_j}}\psi(\frac{net_j - b_j}{a_j}) \text{ , with } net_j = \sum_{i=1}^{N_i} w_{ji} X - \theta_j \tag{7}$$

Where w is the connection weight matrix between input nodes and hidden nodes, θ is the bias input, a and b are the dilation and translation parameters of the wavelets in the WNNC.

Layer 3: is the output layer that accepts a linear combination of the outputs from layer 2 and provides the control input (control signal) to the plant to be controlled. The output of this layer is:

$$u(k)=\sum_{j=1}^{N_h} v_j \psi_{aj,bj}(net_j) \tag{8}$$

Where v is the connection weight vector from hidden nodes to output node in the WNNC.

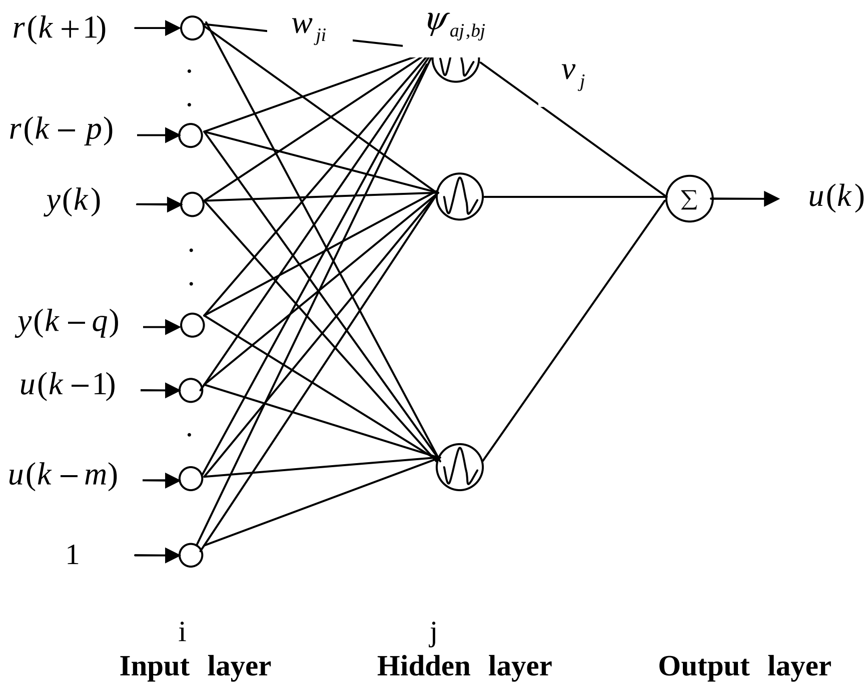


Fig. 2.The structure of a wavelet neural network controller

3.2. Training of the WNNC

The goal of the training is to obtain optimal control signal $u(k)$ from each controller to minimize the following cost function:

$$E=\frac{1}{2}e^2(k) \tag{9}$$

Where, $e(k)=r(k+1)-y(k+1)$ is the control error; the difference between the reference $r(k+1)$ and the actual output of the plant $y(k+1)$.

The weights and the wavelet parameters of each controller are adjusted by propagating the calculated error signal using the gradient-descent (GD) method as follows:

$$v_j(k+1) = v_j(k) + \Delta v_j(k) = v_j(k) + \eta_v(-\frac{\partial E}{\partial v_j}) \tag{10}$$

$$w_{ji}(k+1) = w_{ji}(k) + \Delta w_{ji}(k) = w_{ji}(k) + \eta_w(-\frac{\partial E}{\partial w_{ji}}) \tag{11}$$

$$a_j(k+1) = a_j(k) + \Delta a_j(k) = a_j(k) + \eta_a(-\frac{\partial E}{\partial a_j}) \tag{12}$$

$$b_j(k+1) = b_j(k) + \Delta b_j(k) = b_j(k) + \eta_b(-\frac{\partial E}{\partial b_j}) \tag{13}$$

Where, $\eta_v, \eta_w, \eta_a, \eta_b$ are the learning rates for the weights and wavelet parameters of WNNC.

4. CONVERGENCE AND STABILITY ANALYSIS

For training the WNNC effectively, adaptive learning rates, which guarantee the convergence of WNNC based on the analyses of a discrete-type Lyapunov function, are derived. In this section, we develop some convergence theorems to derive appropriate learning rates adaptively for the wavelet neural network parameters to ensure the stability of the proposed controller of boiler- turbine system.
A discrete-type Lyapunov function can be defined as:

$$V(k) = \frac{1}{2}e^2(k) \tag{14}$$

Where $e(k)$ is the control error. The change in the Lyapunov function is obtained by:

$$\Delta V(k) = V(k+1) - V(k) = \frac{1}{2}\left[e^2(k+1) - e^2(k)\right] \tag{15}$$

The error difference of WNNC can be represented by [19, 20]:

$$e(k+1) = e(k) + \Delta e(k) = e(k) + \left[\frac{\partial e(k)}{\partial W}\right]^T \Delta W \tag{16}$$

Where W is arbitrary weight of the WNNC weighting vector and ΔW represent the corresponding change of this weight. In WNNC, the weight change is obtained from the update rules of Eqs. (10– 13) as:

$$\Delta W(k) = -\eta^W e(k)\frac{\partial e_{cl}(k)}{\partial W_{cl}} \approx \eta^W e_{cl}(k)\frac{\partial u(k)}{\partial W} \tag{17}$$

where η^W is the arbitrary learning rate of corresponding weight component in the WNNC .

Theorem1: Let $\eta^W = \lfloor \eta^v \quad \eta^b \quad \eta^a \quad \eta^w \rfloor$ be the learning rates of the WNNC and define $S^W_{\max}$ as $S^W_{\max} = \max k\left\|S^W(k)\right\|$, where $S^W(k) = \partial u(k)/\partial W$, and $\|.\|$ is the

Euclidean norm. Then, the asymptotic convergence of WNNC is guaranteed if η^W are chosen to satisfy:

$$0 < \eta^W < \frac{2}{\left(S^W_{\max}\right)^2} \tag{18}$$

in which W is the weights and wavelet parameters v, a, b, w.

Proof: From Eqs. (19) – (21), the change in the Lyapunov function is

$$\Delta V(k) = \Delta e(k)\left[e(k) + \frac{1}{2}\Delta e(k)\right]$$

$$= \left[\frac{\partial e(k)}{\partial W}\right]^T \eta^W e(k) \frac{\partial u}{\partial W} . \left\{ e(k) + \frac{1}{2}\left[\frac{\partial e(k)}{\partial W}\right]^T \eta^W e(k) \frac{\partial u}{\partial W} \right\} \tag{19}$$

Since for WNNC $\partial e(k)/\partial W = -\partial u/\partial W$, and let $S^W(k) = \partial u(k)/\partial W$,

$S^W_{\max} = \max k\left\|S^W(k)\right\|$, we obtain

$$\Delta V(k) = -\frac{1}{2}e^2(k)\left\|S^W(k)\right\|^2 \eta^W \left(2 - \eta^W \left\|S^W(k)\right\|^2\right) \equiv -\lambda e^2(k)\,. \tag{20}$$

Where $\lambda = \frac{1}{2}\left\|S^W(k)\right\|^2 \eta^W \left(2 - \eta^W \left\|S^W(k)\right\|^2\right)$ (21)

If $\lambda > 0$, then $\Delta V(k) < 0$ is satisfied. Thus the asymptotic convergence of the proposed control system is guaranteed, and from (21) we obtain (18).This completes the proof.

Corollary 1: The maximum learning rates which guarantee the convergence are:

$$\eta^W = \frac{1}{\left(S^W_{\max}\right)^2} \tag{22}$$

Proof: From theorem 1,

$$\lambda = \frac{1}{2}\left\|S^W(k)\right\|^2 \eta^W \left(2 - \eta^W \left\|S^W(k)\right\|^2\right) = -\frac{1}{2}(S^W_{\max})^4\left[\eta^2 - \frac{2\eta}{(S^W_{\max})^2}\right]$$

$$\lambda = -\frac{1}{2}(S^W_{\max})^4\left[\eta - \frac{1}{(S^W_{\max})^2}\right]^2 + \frac{1}{2} \tag{23}$$

For the condition of the asymptotic convergence $\lambda > 0$, the maximum learning rates which guarantee the convergence were obtained as (22). This completes the proof.

Theorem 2: Let η^v be the learning rate for the weight v of the WNNC. The asymptotic convergence is guaranteed if the learning rate satisfies:

$$0 < \eta^v < 2/N_h \tag{24}$$

Where N_h is the number of neurons in the WNNC hidden layer.

Proof:

$$S^v(k) = \frac{\partial u(k)}{\partial v} = \psi$$

Where $\psi = \lfloor \psi_1 \quad \psi_2 \quad \dots \quad \psi_{N_h} \rfloor^T$ is the output vector of the hidden layer of WNNC. Since in neural networks, we have $\psi_j \leq 1$ for all j, $\left\| S^v(k) \right\| \leq \sqrt{N_h}$. Accordingly, from theorem 1, we find that

$$0 < \eta^v < 2/N_h .$$

<u>Theorem 3:</u> Let η^a be the learning rate for the dilation a of the WNNC. The asymptotic convergence is guaranteed if the learning rate satisfies:

$$0 < \eta^a < \frac{2}{N_h N_i} \cdot \left[\frac{\left| a^{3/2} \right|_{\min}}{\left| v \right|_{\max} 2e^{3/2}} \right]^2 \tag{25}$$

Where N_i is the number of inputs of the WNNC.

Proof: See the Appendix A.

<u>Theorem 4:</u> Let η^b be the learning rate for the translation b of the WNNC. The asymptotic convergence is guaranteed if the learning rate satisfies:

$$0 < \eta^b < \frac{2}{N_h N_i} \cdot \left[\frac{\left| a^{3/2} \right|_{\min}}{\left| v \right|_{\max} 2e^{3/2}} \right]^2 \tag{26}$$

Proof: See the Appendix B.

<u>Theorem 5:</u> Let η^w be the learning rate for the weight w of the WNNC. The asymptotic convergence is guaranteed if the learning rate satisfies:

$$0 < \eta^w < \frac{2}{N_h N_i} \cdot \left[\frac{\left| a^{3/2} \right|_{\min}}{\left| v \right|_{\max} 2e^{3/2} \left| X \right|_{\max}} \right]^2 \tag{27}$$

Where X is the input vector of the WNNC.

Proof: See the Appendix C.

5. SIMULATION RESULTS

In order to evaluate the performance of the proposed direct AWWNN control system, simulations under various conditions are performed. Each wavelet neural network controller consist of 9 inputs in the input layer with $p = 2$, $q = 3$ and $m = 2$. The wavelet neural network structure contains 5 wavelet nodes in the hidden layer for the drum steam pressure WNNC and 7 wavelet nodes in the hidden layer for both the electrical power and drum water level WNNC. The weights and the wavelet parameters of each controller are randomly initialized. The learning rates are chosen based on the convergence ranges.

In the following results, the system is balanced at the normal operating point shown in Table 1. The performance of the proposed multi–loop control scheme under the effect of disturbance and the variation of operation conditions was simulated.

Figure 3 shows the system response for a step output disturbance of 5% on the drum steam pressure and electrical output power at $k = 150$. It can be seen that, the boiler-turbine control system can overcome load disturbance effect on steam pressure and electrical output power as all the outputs follow their set-point values. The results also show that the constraints of actuators are satisfied although the presence of disturbance effect.

Figure 4 shows the system response for a step output disturbance of 5% and a 15% increase in the drum steam pressure set-point at $k = 150$, and $k = 300$, respectively. Simulation results show that the drum steam pressure, the electrical output power and the drum water level responses can overcome load change and disturbance effect on steam pressure as all the outputs follow their set-point values. The results also show that the constraints of actuators are satisfied.

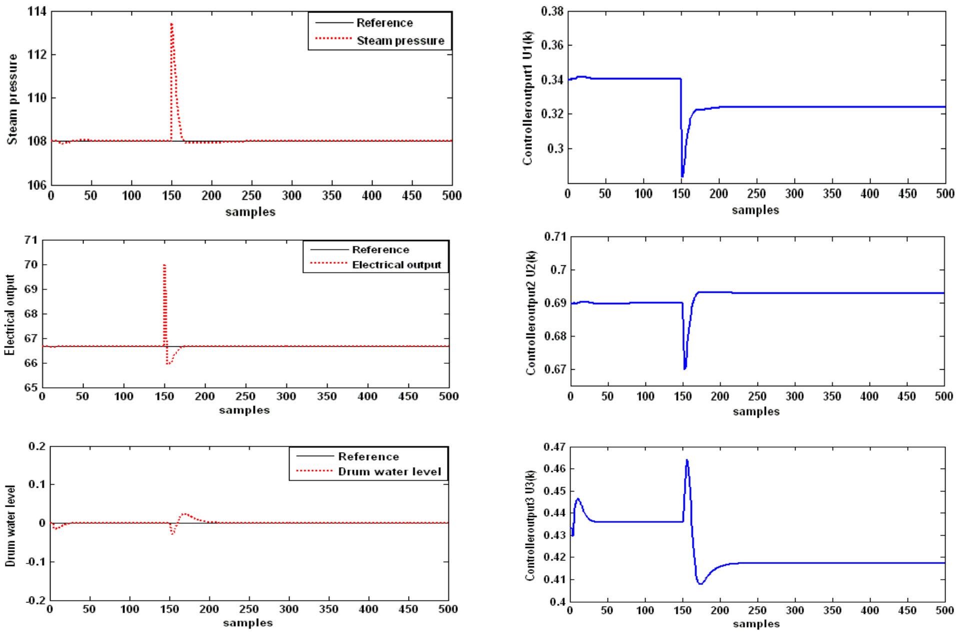
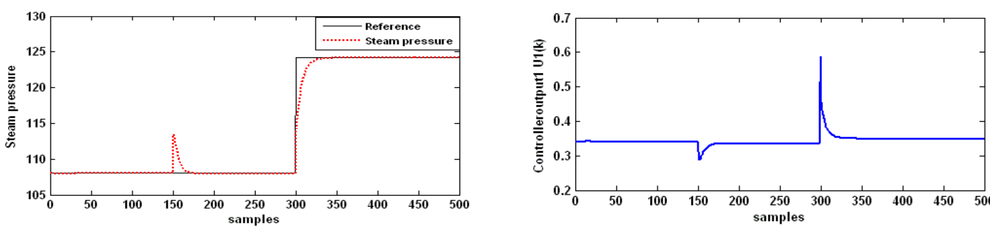


Fig.3. System responses to 5 % disturbance in steam pressure and electrical output power set points.



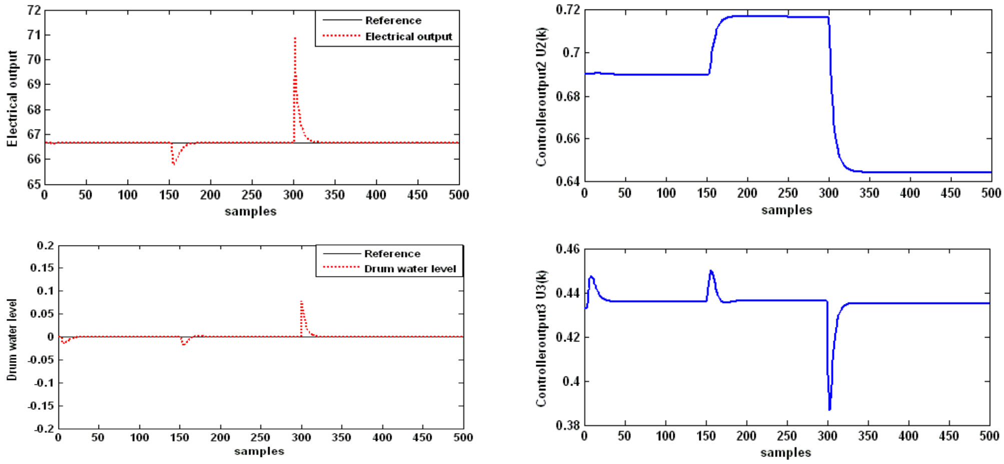


Fig.4. System responses to 5% disturbance and a 15% increase in steam pressure set-point.

Figure 5 shows the system response for changes in the boiler operating point with 30% increase in the drum steam pressure set-point and 35% increase in the electrical output power set-point at $k = 100$. Results show that the proposed control algorithm improves the performance of the nonlinear MIMO boiler-turbine system and efficiently achieving a stable tracking to the system demands under load changes from operating point to another. There are some oscillations of water drum level response at the change of pressure and power set- points but the controller can overcome it and follow the desired output. It can be seen that there is no saturation of actuators and the constraints are satisfied although the wide range of operating points.

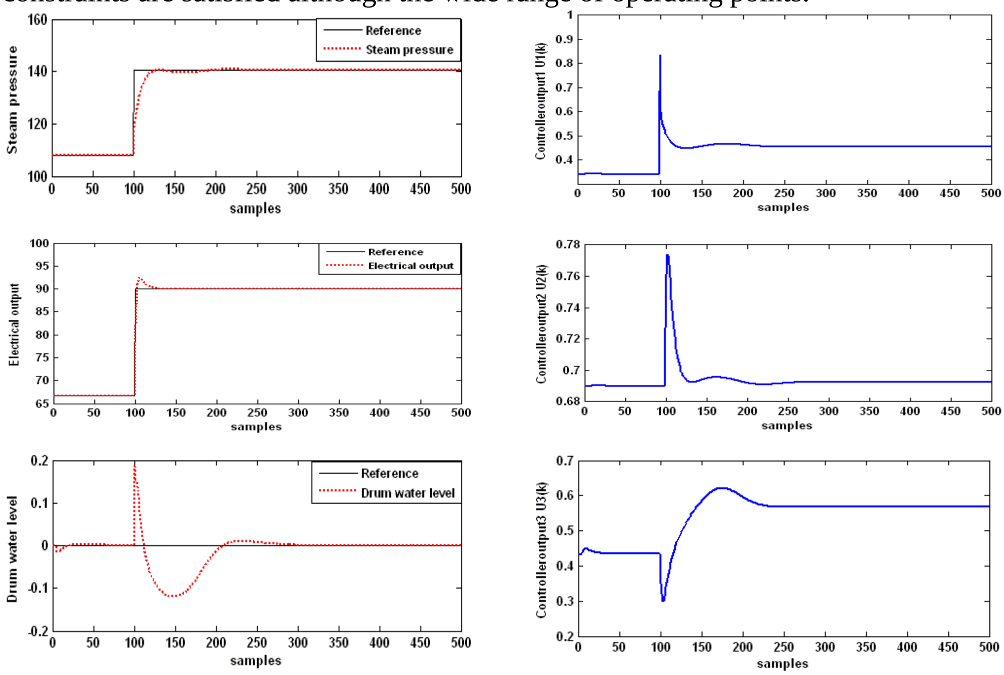


Fig.5. System response for 30% increase in the drum steam pressure and 35% increase in the electrical output power set-points.

6. CONCLUSION

In this paper, a direct adaptive wavelet neural network controller for the nonlinear MIMO boiler-turbine system has been designed. The convergence and stability of the proposed control system is guaranteed through the adaptive training of wavelet neural networks using adaptive learning rates (ALRs) derived from the discrete Lyapunov stability theorem.

The system performance has been evaluated and results show good performance over a wide range of operating conditions. The direct adaptive wavelet neural network controller can also applied to other MIMO complex processes.

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APPENDIX

A. The proof of Theorem 3

In order to proof Theorem 3, the following lemmas are used.

Lemma 1: Let $f(r) = r\exp(-r^2)$. Then $\left|f(r)\right| < 1, \forall f \in \Re$.

Lemma 2: Let $g(r) = r^2\exp(-r^2)$. Then $\left|g(r)\right| < 1, \forall g \in \Re$.

Since

$$S^a(k)=\frac{\partial u}{\partial a}=v(\frac{\partial \psi_j(net)}{\partial net}\cdot\frac{\partial net}{\partial a})$$
$$\le |v|\left\{\max\left[\left|\frac{\partial \psi(net)}{\partial net}\cdot\frac{\partial net}{\partial a}\right|\right]\right\}$$
$$\le |v|\left\{\max\left[\left|\frac{1}{\sqrt{a}}(net^3-3net)\exp(-net^2/2)\cdot\frac{-net}{a}\right|\right]\right\}$$
$$\le |v|\left\{\max\left[\left|\frac{1}{a\sqrt{a}}(3-net^2)\exp(net^2/2)\cdot net^2\exp(-net^2)\right|\right]\right\}$$

$$\le |v|\left\{\max\left[\left|\frac{2e^{3/2}}{a^{3/2}}\right|\left|\left(\frac{3}{2}-\frac{net^2}{2}\right)\exp\left(-\left(\frac{3}{2}-\frac{net^2}{2}\right)\right)\right|\left|net^2\exp(-net^2)\right|\right]\right\} \tag{28}$$

According to Lemma 2,

$\left|\left(\frac{3}{2}-\frac{net^2}{2}\right)\exp\left(-\left(\frac{3}{2}-\frac{net^2}{2}\right)\right)\right|<1$, and $\left|net^2\exp\left(-net^2\right)\right|<1$, then

$$S^a(k)\le |v|\left\{\max\left[\left|\frac{2e^{3/2}}{a^{3/2}}\right|\right]\right\}=|v|\left(2e^{3/2}/\left|a^{3/2}\right|_{\min}\right) \tag{29}$$

Thus

$$\left\|S^a(k)\right\|<\sqrt{N_h}\sqrt{N_i}|v|_{\max}\left(2e^{3/2}/\left|a^{3/2}\right|_{\min}\right)$$

B. The proof of Theorem 4

Since

$$S^b(k)=\frac{\partial u}{\partial b}=v(\frac{\partial \psi(net)}{\partial net}\cdot\frac{\partial net}{\partial b})$$

$$\le |v|\left\{\max\left[\left|\frac{\partial \psi(net)}{\partial net}\cdot\frac{\partial net}{\partial b}\right|\right]\right\}$$
$$\le |v|\left\{\max\left[\left|\frac{1}{\sqrt{a}}(net^3-3net)\exp(-net^2/2)\cdot\frac{-1}{a}\right|\right]\right\}$$
$$\le |v|\left\{\max\left[\left|\frac{1}{a\sqrt{a}}(3-net^2)\exp(net^2/2)\cdot net\exp(-net^2)\right|\right]\right\}$$

$$\leq |v| \left\{ \max \left[\left| \frac{2e^{3/2}}{a^{3/2}} \right| \left| \left(\frac{3}{2} - \frac{net^2}{2} \right) \exp\left(-\left(\frac{3}{2} - \frac{net^2}{2} \right) \right) \right| \left| net \exp(-net^2) \right| \right] \right\} \quad (30)$$

According to Lemma 1 and Lemma 2,

$\left| net \exp(-net^2) \right| < 1$, and $\left| \left(\frac{3}{2} - \frac{net^2}{2} \right) \exp\left(-\left(\frac{3}{2} - \frac{net^2}{2} \right) \right) \right| < 1$. Then

$$S^b(k) \leq |v| \left\{ \max \left[\left| \frac{2e^{3/2}}{a^{3/2}} \right| \right] \right\} = |v| \left(2e^{3/2} / \left| a^{3/2} \right|_{\min} \right) \quad (31)$$

Thus

$$\left\| S^b(k) \right\| < \sqrt{N_h} \sqrt{N_i} |v|_{\max} \left(2e^{3/2} / \left| a^{3/2} \right|_{\min} \right)$$

C. The proof of Theorem 5

Since

$$S^w(k) = \frac{\partial u}{\partial w} = v\left(\frac{\partial \psi(net)}{\partial net} \cdot \frac{\partial net}{\partial w} \right)$$

$$\leq |v| \left\{ \max \left[\left| \frac{\partial \psi(net)}{\partial net} \cdot \frac{\partial net}{\partial w} \right| \right] \right\}$$

$$\leq |v| \left\{ \max \left[\left| \frac{1}{\sqrt{a}} (net^3 - 3net) \exp(-net^2/2) \cdot \frac{X}{a} \right| \right] \right\}$$

$$\leq |v| \left\{ \max \left[\left| \frac{X}{a\sqrt{a}} (3 - net^2) \exp(net^2/2) \cdot net \exp(-net^2) \right| \right] \right\}$$

$$\leq |v| \left\{ \max \left[\left| \frac{2e^{3/2} X}{a^{3/2}} \right| \left| \left(\frac{3}{2} - \frac{net^2}{2} \right) \exp\left(-\left(\frac{3}{2} - \frac{net^2}{2} \right) \right) \right| \left| net \exp(-net^2) \right| \right] \right\} \quad (32)$$

According to Lemma 1 and Lemma 2,

$\left| net \exp(-net^2) \right| < 1$, and $\left| \left(\frac{3}{2} - \frac{net^2}{2} \right) \exp\left(-\left(\frac{3}{2} - \frac{net^2}{2} \right) \right) \right| < 1$. Then

$$S^w(k) \leq |v| \left\{ \max \left[\left| \frac{2e^{3/2} X}{a^{3/2}} \right| \right] \right\} = |v| \left(2e^{3/2} |X| / \left| a^{3/2} \right|_{\min} \right) \quad (33)$$

Thus

$$\left\| S^w(k) \right\| < \sqrt{N_h} \sqrt{N_i} |v|_{\max} \left(2e^{3/2} |X|_{\max} / \left| a^{3/2} \right|_{\min} \right)$$

مخطط لمتحكم مباشر فى الغلاية والتوربينات عن طريق الشبكات العصبية المويجية المتكيفة

من المهم فى نظم القدرة الكهربية مقدرة نظام التحكم على تحقيق خاصية التتبع الأمثل للوحدات اللاخطية والتى تكون عديدة المداخل والمخارج. يقدم هذا البحث نظام تحكم فى وحدة الغلاية والتوربينات فى محطات توليد الطاقة 160 ميجا وات باستخدام متحكم متوائم مباشر يعتمد على الشبكات العصبية المخصبة بدوال المويجة حيث أنه يتم التحكم فى ثلاثة مخارج للنظام وهى ضغط البخار و القدرة الكهربية وكذلك منسوب المياه داخل اسطوانة الغلاية. يقوم نظام التحكم المقترح فى هذا البحث بتحسين الأداء وتحقيق خاصية تتبع جيده لتحقيق متطلبات الأحمال تحت تأثير تغير الأحمال، وجود إضطرابات عاليه على المخارج وكذلك تغير نقاط التشغيل للنظام .

يتم تعليم الشبكات المويجية المستخدمة فى نظام التحكم باستخدام معدلات التعلم المتكيفه المستمدة من نظرية lyapunov لضمان استقرار المتحكم المستخدم لكل خرج من النظام.