Performance Analysis of Adaptive Neural Network Frequency Controller for Thermal Power Systems

OGNJEN KULJACA, SEJID TESNJAK*, VLADIMIR KOROMAN+
Systems Research Institute, Department of Advanced Technologies
Alcorn State University
1000 ASU Drive #360, Alcorn State, MS 39096
USA

*Department of Power Systems, Faculty of Electrical Engineering and Computing
University of Zagreb
Unska 3, 10000 Zagreb
CROATIA

+Control Engineering Department
Brodarski Institute
Av. V. Holjevca 20, 10020 Zagreb
CROATIA

Abstract: - An adaptive neural network control scheme for thermal power system is described. No off-line training is required for the proposed neural network controller. The online tuning algorithm and neural network architecture are described. The performance of the controller is illustrated via simulation for different changes in process parameters. Performance of neural network controller is compared with conventional proportional-integral control scheme for frequency control in thermal power systems.

Key-Words: -power system, neural network, adaptive control, frequency control

1 Introduction

This paper deals with the neural network (NN) frequency controller for isolated thermo power system. Frequency control becomes more and more important as power systems enter the era of deregulation. It is becoming very hard, if not impossible to schedule loads precisely. Emerging market of ancillary services means that primary controllers and turbines that are used in secondary control change constantly. These changes pose a problem when conventional control schemes are used.

The literature about frequency and load – frequency control is numerous ([1], [2], [3], [4], [5], [6], [7] and many others). Many non-adaptive schemes are given in [1], [2], [3], [4], [5] and [6]. A self-tuning adaptive controller is given in [7]. However, the modern power systems in deregulated environment are subject to often parameters changes that may diminish the quality of control when nonadaptive controllers are used. NN load-frequency control is described in [8], [9] and [10]. The results obtained by using NN controllers are good. However, the described controllers require training. There are many well-developed training algorithms for NNs, but in the case of power system the training has to be done using models and ther4e is always a danger of not having NN properly trained. We provide here a performance analysis of adaptive NN controller that does not require training. The neural network is capable of on-line learning. Stability proofs for this control scheme can be found in [30].

The paper is organized as follows. In Section 2 are given some mathematical preliminaries. Model of isolated thermo power system is given in Section 3. Neural network control scheme is described in Section 4. In Section 5 the simulation results are given and the conclusion is given in Section 6.

2 Mathematical Preliminaries

Let R denote the real numbers, R^n the real n-vectors, R^{mxn} the real mxn matrices. Let S be a compact simply connected set of R^n., With map $f: S \to R^m$. let us define $C^m(S)$ the space such that f is continuous. Let $\|\bullet\|$ be any suitable vector norm. The supremum norm of $f(x)$ over S is defined as:

$$\sup\|f(x)\|,\ f: S \to R^m,\ \forall x \in S \qquad (1)$$

Given $x \in R^{N_1}$, a two-layer NN (Fig. 1) has a net output given by

$$y = W^T \sigma(V^T x) \qquad (2)$$

where $x = [1 \quad x_1 \quad \cdots \quad x_{N_1}]^T$, $y = [y_1 \quad y_2 \quad \cdots \quad y_{N_3}]^T$ and $\sigma(\bullet)$ the activation function. If $z = [z_1 \quad z_2 \quad \cdots]^T$, we define $\sigma(z) = [\sigma(z_1) \quad \sigma(z_2) \quad \cdots]^T$. Including "1" as a first term in $\sigma(V^T x)$ allows one to incorporate the tresholds as the first column of W^T. Then any tuning of NN weights includes tuning of thresholds as well.

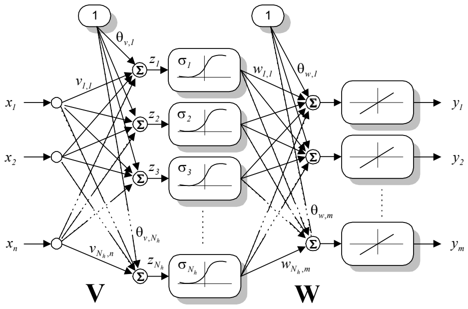

Fig.1. Two layer neural network

The main property of NN we are concerned with for control and estimation purposes is the function approximation property ([16], [20]). Let $f(x)$ be a smooth function from $R^n \to R^m$. Then it can be shown that if the activation functions are suitably selected, as long as x is restricted to a compact set $S \in R^n$, then for some sufficiently large number of hidden-layer neurons L, there exist weights and thresholds such one has

$$f(x) = W^T \sigma(V^T x) + \varepsilon(x). \qquad (3)$$

The value of $\varepsilon(x)$ is called the neural network functional approximation error. In fact, for any choice of a positive number ε_N, one can find a neural network such that $\varepsilon(x) \le \varepsilon_N$ for all $x \in S$.

Also, it has been shown that, if the first-layer weights V are suitably fixed, then the approximation property can be satisfied by selecting only the output weights W for good approximation. For this to occur $\varphi(x) = \sigma(V^T x)$ must be a basis [16].

If one selects the activation functions suitably, e.g. as sigmoids, then it was shown by Igelnik and Pao [19] that $\sigma(V^T x)$ is a basis if V is selected randomly. Only the output weights W are tuned.

3 Isolated Thermopower System

The model of isolated thermo power system is shown in Fig. 2.

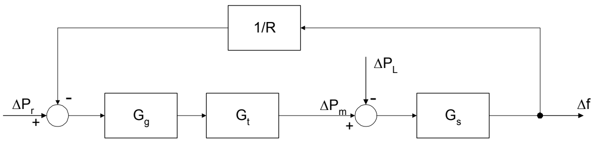

Fig. 2: The model of isolated thermo power system

The transfer functions in the model are:

$$G_g = \frac{1}{1 + s \cdot T_g}, \qquad (4)$$

$$G_t = \frac{1}{1 + s \cdot T_t}, \qquad (5)$$

$$G_s = \frac{K_s}{1 + s \cdot T_s}, \qquad (6)$$

where G_g, G_t and G_s are representing turbine governors, control turbines and the power system respectively. Such models are described in more details in [1], [2], [3], [4], [5], [6], [7] and many others. It is also shown that the system in Fig. 2 is always asymptotically stable if R is positive number. The system is linear and the need for adaptive control or use of the function approximation property of the neural network is not obvious since there are no nonlinearities in the controlled plant.

However, all the parameters can and do change during the operation. Thus, it is conceivable that adaptive control scheme would perform better than nonadaptive. It can be said that in our design NN tries to approximate the whole controlled system and to generate the appropriate control action.

The most usual way of control is to use linear PI controllers. The controller in that case takes the change of frequency Δf as the input and produces the control output ΔP_r as output. That signal is fed to turbine governors in order to counter the changes caused by the change in the load ΔP_L. The turbine output is the mechanical power ΔP_m.

The system shown in Fig. 2 can be represented in state space as

$$\dot{x} = \begin{bmatrix} -\frac{1}{T_g} & 0 & -\frac{1}{RT_g} \\ \frac{1}{T_t} & -\frac{1}{T_t} & 0 \\ 0 & \frac{K_s}{T_s} & -\frac{1}{T_s} \end{bmatrix} x + \begin{bmatrix} -\frac{1}{T_g} & 0 \\ 0 & 0 \\ 0 & -\frac{K_s}{T_s} \end{bmatrix} \begin{bmatrix} \Delta P_r \\ \Delta P_L \end{bmatrix} \qquad (7)$$
$$= Ax + Bu,$$
$$\Delta f = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} x.$$

The state vector x is

$$x = \begin{bmatrix} y_g \\ \Delta P_m \\ \Delta f \end{bmatrix}, \qquad (8)$$

where y_g is output of the turbine controllers. These states are physically available, so this representation will allow for the NN control scheme design.

4 Adaptive Neural Network Control

The neural network control scheme is shown in Fig. 3.

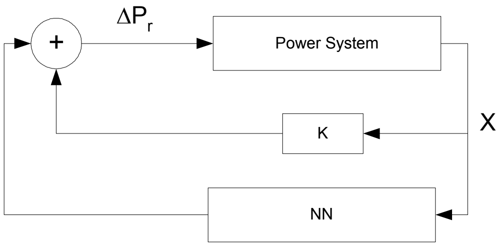

Fig. 3: NN control scheme

The neural network is built as shown in Section 2. The first layer weights are initialized randomly and then fixed to form basis *φ(x)*. The NN output is

$$y = W^T \varphi(x). \qquad (9)$$

The proportional gain K is given as

$$K = \begin{bmatrix} 0 & 0 & k \end{bmatrix}. \qquad (10)$$

This architecture is an adapted form of the tracking NN controller described in [24], [25], [26], [27], [28] and numerous other papers. However, there are some differences. Namely, here the problem is control, not tracking. Also, there is no special robustifyng term and instead of PD controller parallel to the network only proportional controller K is used. Since there are significant time constants present in the controlled plant, derivative part will not have an effect. At last, unlike in papers mentioned above, we don't use filtered error approach. In our scheme the neural network is positioned in such way that it tries to approximate the controlled plant.

It is assumed that the load disturbance ΔP_L is bounded so that

$$\Delta P_L \le P_M. \qquad (11)$$

This assumption is always true as long as we deal with the power system in the normal mode of operation. If the load disturbance is too big there cannot be any control action since in that case the system just doesn't have enough power generation capability available. The protection functions take over in that case and some loads have to be disconnected.

Let the control signal be given by

$$\Delta P_r = Kx + y = Kx + W^T \varphi(x) \qquad (12)$$

and the weight updates are provided by

$$\dot{W} = F\varphi(x)\Delta f - k_w \|x\| FW. \qquad (13)$$

with F any symmetric and positive definite matrix and k_w positive design parameter. Then, the system states x and neural network weight W are ultimately uniformly bounded (UUB) and the system is stable in Lyapunov sense as long as.

$$\|x\| > \frac{d_M \sigma(P)_{\max} + \frac{D^2}{4k_w^2}}{\frac{1}{2}\sigma(Q)_{\min}}, \qquad (14)$$

$$\|W\| = \frac{D}{2k_W} + \sqrt{\frac{D^2}{4k_W^2} + \frac{d_M \sigma(P)_{\max}}{k_W}}. \qquad (15)$$

Thus, the Lyapunov derivative is negative as long x and W are outside a compact set, meaning that x and W are UUB and the system is stable. The detailed proof can be found in [30].

5 Simulation Results

The simulations were performed for the following srt of parameters: $T_q = 0.08$ s, $T_t = 0.3$ s, $K_s = 120$ pu/s, R = 2.4 Hz/pu. Parameter k was k = 0.08. The neural network had 20 nodes in the hidden layer; initial network values were initialized to small random values. The network used sigmoid activation function. The responses of the system with NN control is compared with the usual PI controlled system with proportional gain of the controller $k_p = 0.08$ and integral gain $k_i = 0.1$.

The simulation results for changes in the grid parameters are shown in Figs 4 – 6. It can be seen that NN control scheme out performs conventional PI controller in the case of the process parameters for which PI design was performed, as well as when the parameters change. NN control scheme reacts much faster.

The control signals of the proportional controller and NN for the original simulation case with the NN controller are shown in Fig. 7. It can be seen that NN takes over the complete control effort, which illustrates the ability of NN to approximate the whole controlled plant in this case.

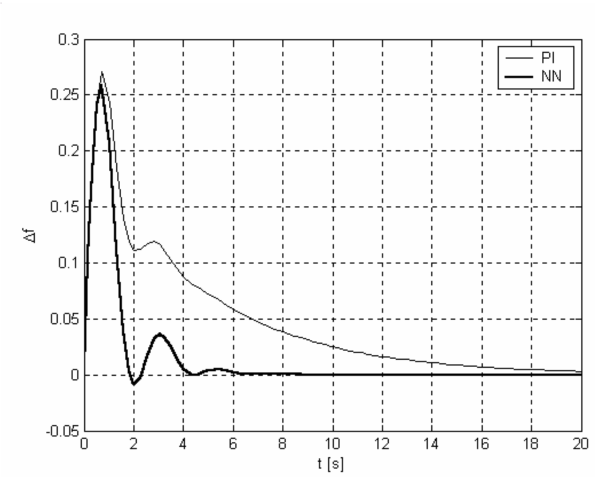

Fig. 4: The response for the step change in load of 0.1 pu

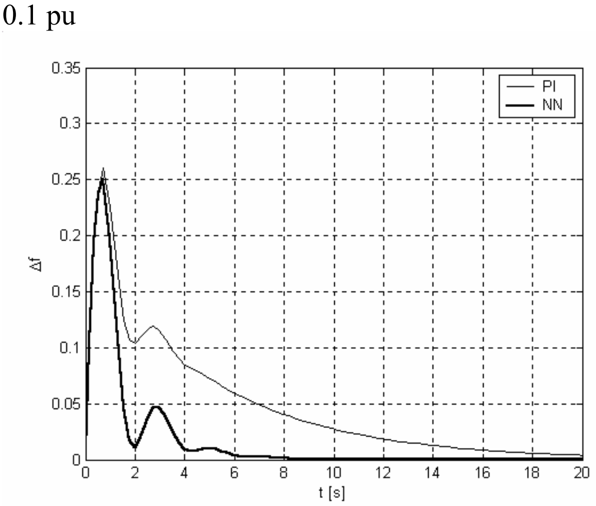

Fig. 5: The response for the step change in load of 0.1 pu with R, $T_{s,}$ and K_s increased 10%

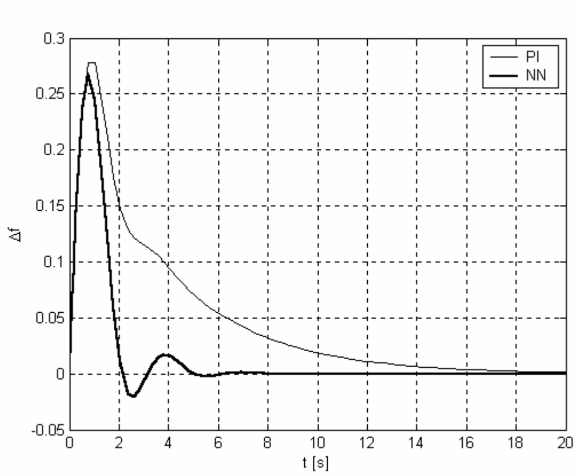

Fig. 6: The response for the step change in load of 0.1 pu with R, $T_{s,}$ and K decreased 10%

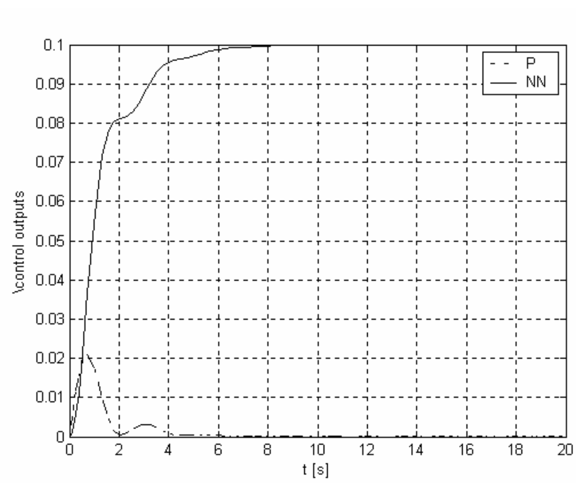

Fig. 7: The control output signals of the proportional controller and NN, nominal case

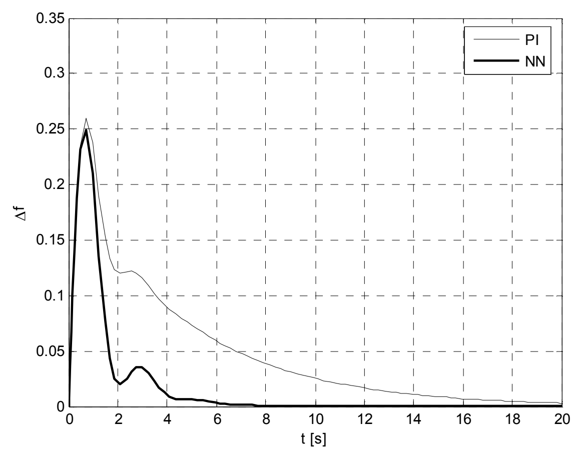

Fig. 8: The response for the step change in load of 0.1 pu and time constants T_g and T_t decreased 10%

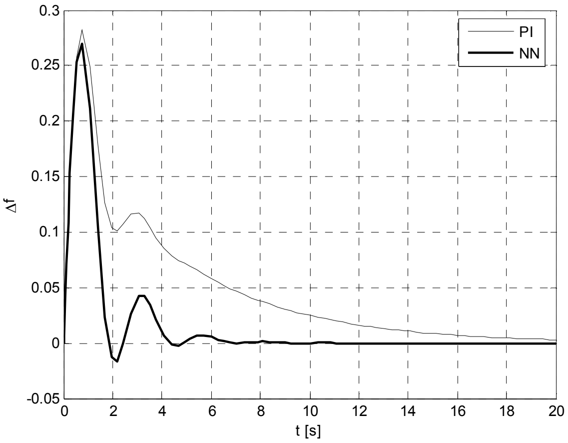

Fig. 9: The response for the step change in load of 0.1 pu and time constants T_g and T_t increased 10%

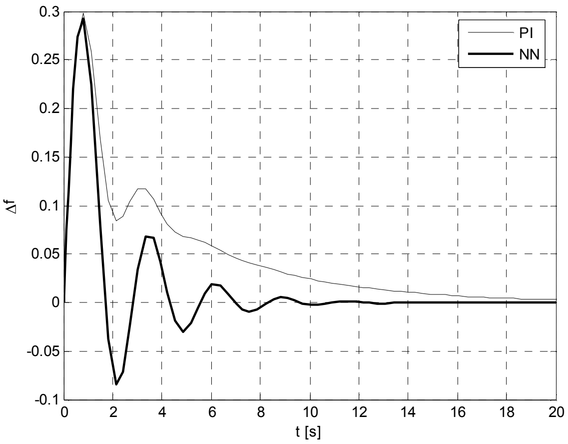

Fig. 10: The response for the step change in load of 0.1 pu and time constants T_g and T_t increased 25%

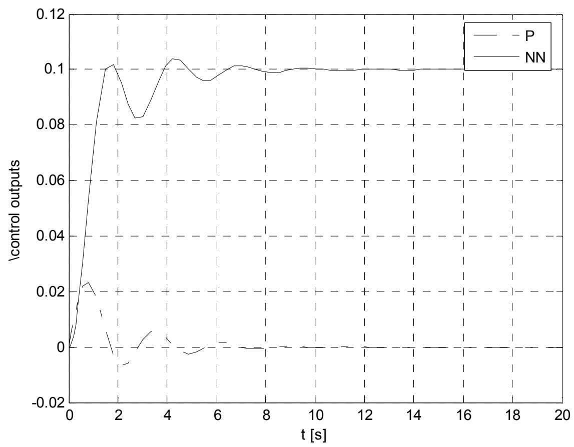

Fig. 11: The control output signals of the proportional controller and NN, time constants T_g and T_t increased 25%

Responses for changes of turbine governor and turbine parameters are shown in Figs 8. – 10. Again, neural network control scheme outperforms the conventional controller. Fig. 11 illustrates the fact that neural network takes over the control effort in this case too.

6 Conclusion

The results of an initial research in neural network control of power systems are shown. The simulation results show that controller performs well and adapts to changing parameters. The controller does not require off-line training phase. By defining the neural network differently, having output layer weights W defined as a matrix this scheme can be adjusted to deal with the multivariable systems. The performance analysis here shows that it would be worth to continue with the research effort toward neural network controllers for interconnected systems as well as for the systems with generation rate constraint.

References:

[1] Elgerd, O.I. "Control of Electric Power Systems", IEEE Proceedings, pp. 4-15, 1981

[2] Elgerd, O.I., Fosha, C.E., "Optimum Megawatt-Frequency Control of Multiarea electric Energy Systems" IEEE Transactions Power Apparatus and Systems, PAS-80, No. 4, pp. 556-562, 1970

[3] Fellachi, A., "Optimum Decentralized Load Frequency Control" IEEE Transactions on Power Systems, Vol. PWRS-2, No. 2, pp. 379-384, 1987

[4] Fosha, C.E., Elgerd, O.I., "The Megawatt-Frequency Control Problem: A New Approach Via Optimal control Theory" IEEE Transactions Power Apparatus and Systems, PAS-80, No. 4, pp. 563-577, 1970

[5] Hamza, M.H., Agathoklis, P., Chan, W.C., "A Combined Selftuning and Integral controller for Load Frequency Control of Interconnected Power systems "Regelungstechnik 30. Jahrgang Heft 7 pp. 226-232, 1982

[6] Kundur, P., Power System Stability and Control. McGraw-Hill, Inc.,1993

[7] Liaw, C.M., "Design of a Reduced-Order Adaptive Load-Frequency Controller for an Interconnected Hydrothermal Power System "International Journal of Control, Vol. 60, No. 6, pp. 1051-1063, 1994

[8] Demiroren, A., Zeyneigly, H.I., Sengor, N.S., "The application of ANN technique to load-

frequency control for three-area power system", 2001 IEEE Porto Power Tech Conference, Porto, Portugal

[9] Bevrani, H. "A novel approach for power system load frequency controller design", Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. IEEE/PES , Volume: 1 , 6-10 Oct. 2002

[10]Birch, A.P., Sapeluk, A.T., Ozveren, C.T., "An enhanced neural network load frequency control technique", International Conference on Control, 1994. Control '94. Volume 1, 21-24 Mar 1994

[11]R. Barron, "Universal approximation bounds for superpositions of a sigmoidal function," IEEE Trans. Info. Theory, vol. 39, no. 3, pp. 930-945, May 1993.

[12]A.G. Barto, "Reinforcement learning and adaptive critic methods," Handbook of Intelligent Control, pp. 469-492, Van Nostrand Reinhold, New York, 1992.

[13]J. Campos and F.L. Lewis, "Adaptive critic neural network for feedforward compensation," Proc. American Control Conf., vol. 4, pp. 2813 – 2818, San Diego, 1999

[14]F.-C. Chen, and H. K. Khalil, "Adaptive control of nonlinear systems using neural networks," Int. J. Contr., vol. 55, no. 6, pp. 1299-1317, 1992.

[15]M. J. Corless and G. Leitmann, "Continuous state feedback guaranteeing uniform ultimate boundedness for uncertain dynamic systems," IEEE Trans. Automat. Contr., vol. 26, no. 5, pp. 850-861, 1982.

[16]G. Cybenko, "Approximation by superpositions of a sigmoidal function," Math. Contr. Signals, Syst., vol. 2, no. 4, pp. 303-314, 1989.

[17]C. A. Desoer and S. M. Shahruz, "Stability of dithered nonlinear systems with backlash or hysteresis," Int. J. Contr., vol. 43, no. 4, pp. 1045-1060, 1986.

[18]B. Friedland, Advanced Control System design, Prentice-Hall, New Jersey, 1996.

[19]B. Igelnik and Y. H. Pao, "Stochastic Choice of Basis Functions in Adaptive Function Approximation and the Functional-Link Net," IEEE Trans. Neural Networks, vol. 6, no. 6, pp. 1320-1329, Nov. 1995.

[20]K. Hornik, M. Stinchombe, and H. White, "Multilayer feedforward networks are universal approximators," Neural Networks, vol. 2, pp. 359-366, 1989.

[21]B.S. Kim and A.J. Calise, "Nonlinear flight control using neural networks," AIAA J. Guidance, Control, Dynamics, vol. 20, no. 1, pp 26-33, 1997.

[22]J.-H. Kim, J.-H. Park, S.-W. Lee, and E. K. P. Chong, "Fuzzy precompensation of PD controllers for systems with deadzones," J. Int. Fuzzy Syst., vol. 1, pp. 125-133, 1993.

[23] S.-W. Lee and J.-H. Kim, "Control of systems with deadzones using neural-network based learning control," Proc. IEEE Int. Conf. Neural Networks, June 1994, pp. 2535-2538.

[24] F. L. Lewis, C. T. Abdallah, and D. M. Dawson, Control of Robot Manipulators, Macmillan, New York, 1993.

[25] F. L. Lewis, A. Yesildirek, and K. Liu, "Multilayer neural-net robot controller with guaranteed tracking performance," IEEE Trans. Neural Networks, vol. 7, no. 2, pp. 1-11, Mar. 1996.

[26] F. L. Lewis, K. Liu, and A. Yesilidrek, "Neural net robot controller with guaranteed tracking performance," IEEE Trans. Neural Networks, vol. 6, no. 3, pp. 703-715, 1995.

[27] F. L. Lewis, K. Liu, R. R. Selmic, and Li-Xin Wang, "Adaptive fuzzy logic compensation of actuator deadzones," J. Robot. Sys., vol. 14, no. 6, pp. 501-511, 1997.

[28] F.L. Lewis, S. Jagannathan, and A. Yesildirek, Neural Network Control of Robot Manipulators and Nonlinear Systems, Taylor and Francis, Lindon, 1998.

[29] N. Sadegh, "A perceptron network for functional identification and control of nonlinear systems," IEEE Trans. Neural Networks, vol. 4, no. 6, pp. 982-988, Nov. 1993.

[30] Kuljaca, O., Lewis, F. Tesnjak, S., "Neural Network Frequency Control for Thermal Power Systems", IEEE Control and Decision Conference, 2004