NEURAL NETWORK BASED CONTROLLER FOR NONLINEAR AUTOMATIC GENERATION CONTROL

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Abstract: This paper presents an Artificial Neural Network (ANN) based controller design for nonlinear multivariable systems. The proposed method uses a novel algorithm for using and training a radial basis function (RBF) neural network based controller. The training algorithm makes sure that it does not violate any constraints on the inputs or outputs. Trajectory tracking results are presented for the challenging problem of nonlinear single area Automatic Generation Control (AGC) power system. Both linear and nonlinear cases are considered and robustness of the controller is tested as well.

1 INTRODUCTION

Artificial neural networks (ANN) have been used for pattern recognition, function approximation, time-series prediction and classification problems for quite some time (Haykin, S., 1999). Owing to their learning capability, the use of ANN for applications requiring intelligence, is of no surprise. Hence, like all fields, researchers working in the field of system theory and control systems have been attracted to the use and development of ANN to solve complex, nonlinear, and often time varying real life processes. Controlling a real life process is a task of imminent industrial significance and requires effective controller design, that can steer the process from one operating point to another, keeping in mind all the deterministic as well as stochastic constraints and limitations on various inputs and outputs. The learning properties of neural networks make them ideal for this purpose.

The use of neural network for controller design can be found in the literature with different designs and training techniques. Smith and Boning (Smith, T. H., Boning, D. S., 1997) proposed a self-tuning EWMA adaptive controller which, according to the authors was able to replace an experienced engineer needed to tune the controller. Thapa, Jones, and Zhu proposed a scheme for combining back propagation trained neural network with self tuning regulator techniques (Thapa, B. K., Jones, B., Zhu, Q. M., 2000). Other efforts to solve control problems using ANN include, but are not limited to those of (Shukla, D., Dawson, D. M., Paul, F. W., 1999; Lu, J., Yahagi, T., 2000; Hayakawa, T., Haddad, W., Hovakimyan, N., 2000; Yang, Y., Wang, X., 2007; Hayakawa, T., Haddad, W., Volyanskyy, K. Y., 2008; Zayed, A. S., Hussain, A., Abdullah, R. A., 2006; Petre, E., Selisteanu, D., Sendrescu, D., 2008; Cong, S., Liang, Y., 2009), and (Al-Duwaish, H. N., Rizvi, S. Z., 2010).

Power systems play a vital role in our lives, ensuring proper generation, distribution, conservation, recycling and regeneration of power for domestic as well as commercial life. Power systems can safely be regarded as the backbone of every industry. Hence, proper control of power systems is an extremely important task and calls for accelerated efforts from researchers all over the world (Shijie, Y., Xu, W., 2009). This paper presents a new neural network based controller design for nonlinear multivariable systems. The design uses radial basis function (RBF) neural network as controller. Output layer synaptic weight are updated and weight update equations using classical least mean square (LMS) principle is derived for the RBF network. Because of remarkable adaptation properties of neural networks, the derived

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controller is robust to accommodate parameter variations, if any, as well. The developed controller is tested by employing it to control frequency deviation caused by changes in loading in a power generator. This problem is known as Load Frequency Control (LFC) or Automatic Generation Control (AGC), and has been an important control problem for power engineers owing to its significance in daily life.

Notations in this paper are used in the following manner. Variables in lower case represent scalar quantities. Lower case bold variables represent vector quantities. Upper case bold variables represent matrices. The only exceptions to this convention is in the choice of a more conventional J for the cost function, and where notations are defined otherwise, as in the AGC model. The paper is arranged as follows. Section 2 takes a detailed look at the development and training algorithm of the proposed controller. Section 3 takes a look at the power system model and defines the AGC control problem in detail. Simulation results for the AGC problem are presented in section 4. Finally, conclusions are drawn and recommendations for future work are provided in section 5.

2 CONTROLLER DESIGN

Consider a multi-input multi-output nonlinear process having p inputs and m outputs shown in Figure 1. It is required that the process outputs follow a desired set of reference points $\mathbf{r}(t) = [r_1(t) \cdots r_m(t)]$. The process is approximated using a linear time-invariant (LTI) model. This can be achieved in terms of offline system identification. The linearized approximation can be expressed as

$$\begin{aligned} \mathbf{x}(t+1) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t), \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t). \end{aligned} \tag{1}$$

The controller consists of an RBF nerual network. The j^{th} output of the RBF network is given by

$$v_j(t) = \mathbf{w}_j \phi^T(t), \tag{2}$$

where $\mathbf{w}_j$ is the vector for weights of j^{th} RBF output, given by

$$\mathbf{w}_j = [w_{1j} \cdots w_{qj}], \tag{3}$$

and $\phi(t)$ is the basis function vector which is given by

$$\phi(t) = [\phi(\|\mathbf{r}(t) - \mathbf{c}_1\|) \cdots \phi(\|\mathbf{r}(t) - \mathbf{c}_q\|)]. \tag{4}$$

In the above equations, q denotes the number of neurons in the hidden layer, $\mathbf{c}_i$ is the center vector for the i^{th} neuron of that layer, ϕ is the radial basis function, and $\|.\|$ denotes norm. RBF networks enjoy several advantages over multi-layer perceptrons (MLP)s in that RBF networks consist of only one hidden layer as opposed to multiple layers in MLPs. Hence, the learning time of RBF networks is much less as compared to MLPs. RBF networks are also called universal approximators (Haykin, S., 1999), and hence can approximate any continuous nonlinear function. It is this property of RBF neural networks that has motivated the authors to choose it for controller design. RBF network can compensate for the nonlinearity in the process, and hence can control the process using linearized model for updating its weights.

For $j = 1, 2, \cdots p$, the constraints on any control signal $u_j(t)$ are given by

$$u_{min} \leq u_j(t) \leq u_{max}.$$

To meet this constraint, the output of the RBF network is transformed by a tangent-sigmoid activation function forming the constrained control signal

$$\begin{aligned} u_j(t) &= \alpha \frac{e^{kv_j(t)} - 1}{e^{kv_j(t)} + 1} \\ &= \alpha \frac{e^{k\mathbf{w}_j\phi(t)} - 1}{e^{k\mathbf{w}_j\phi(t)} + 1}, \end{aligned}$$

where $\alpha = |u_{min}| = |u_{max}|$ denotes the upper and lower limits of the constraints and k is used to adjust the slope of the linear part of tangent-sigmoid function.

The difference between the reference point $\mathbf{r}(t)$ and the process output $\hat{\mathbf{y}}(t)$ gives the error $\mathbf{e}(t) = [e_1(t) \cdots e_m(t)]^T$. In order to update the controller, a cost function J is sought to be minimized.

$$J = \mathbf{e}^T(t)\mathbf{e}(t). \tag{5}$$

The RBF output layer weights are updated in the negative direction of the gradient of J. This approach, known as the classical Least Mean Square principle is a 'sensible' choice for training RBF networks according to (Haykin, S., 1999). Hence, the weight update equation for j^{th} control signal $u_j(t)$ is given in equation (6) as

$$\mathbf{w}_j(k+1) = \mathbf{w}_j(k) - \eta \frac{\partial J}{\partial \mathbf{w}_j}. \tag{6}$$

Now finding the partial derivative of J w.r.t $\mathbf{w}_j$

$$\begin{aligned} \frac{\partial J}{\partial \mathbf{w}_j} &= 2\mathbf{e}^T(t)\frac{\partial}{\partial \mathbf{w}_j}\mathbf{e}(t) \\ &= 2\mathbf{e}^T(t)\frac{\partial}{\partial \mathbf{w}_j}(\mathbf{r}(t) - \hat{\mathbf{y}}(t)) \\ &= -2\mathbf{e}^T(t)\frac{\partial}{\partial \mathbf{w}_j}\hat{\mathbf{y}}(t) \\ &= -2\mathbf{e}^T(t)\frac{\partial}{\partial \mathbf{w}_j}(\mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t)), \end{aligned}$$

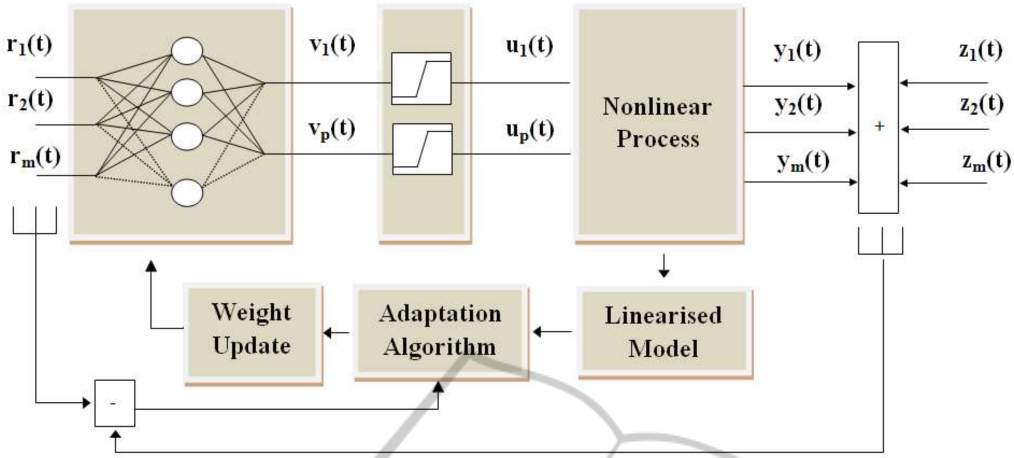

Figure 1: Neural network based controller for nonlinear MIMO systems. Parameters $z_i(t)$ indicate output additive noise at the $i^{th} output$.

which can be written as[1]

$$\frac{\partial J}{\partial \mathbf{w}_j} = -2\mathbf{e}^T(t)\frac{\partial}{\partial \mathbf{w}_j}(\mathbf{C}\{\mathbf{A}\mathbf{x}(t-1)+\mathbf{B}\mathbf{u}(t-1)\} + \mathbf{D}\mathbf{u}(t)).$$

The terms independent of $\mathbf{w}_j$ would vanish,

$$\frac{\partial J}{\partial \mathbf{w}_j} = -2\mathbf{e}^T(t)\left(\frac{\partial \mathbf{C}\mathbf{B}\mathbf{u}(t-1)}{\partial \mathbf{w}_j} + \frac{\partial \mathbf{D}\mathbf{u}(t)}{\partial \mathbf{w}_j}\right). \quad (7)$$

Finding the derivative of tangent-sigmoid function

$$\frac{\partial u_j(t)}{\partial \mathbf{w}_j} = \alpha \frac{\partial}{\partial \mathbf{w}_j}\frac{e^{k\mathbf{w}_j\phi(t)}-1}{e^{k\mathbf{w}_j\phi(t)}+1}$$
$$= \alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}. \quad (8)$$

Equation 7 can now be written as

$$\frac{\partial J}{\partial \mathbf{w}_j} = -2\mathbf{e}^T(t)\left(\frac{\mathbf{C}\mathbf{B}\partial\mathbf{u}(t-1)}{\partial \mathbf{w}_j} + \frac{\mathbf{D}\partial\mathbf{u}(t)}{\partial \mathbf{w}_j}\right) \quad (9)$$

$$= -2\mathbf{e}^T(t)\left(\begin{bmatrix}\psi_{11}\cdots\psi_{1p}\\ \vdots \ \ddots \ \vdots\\ \psi_{m1}\cdots\psi_{mp}\end{bmatrix}\begin{bmatrix}\frac{\partial}{\partial \mathbf{w}_j}u_1(t-1)\\ \vdots\\ \frac{\partial}{\partial \mathbf{w}_j}u_p(t-1)\end{bmatrix} + \begin{bmatrix}d_{11}\cdots d_{1p}\\ \vdots \ \ddots \ \vdots\\ d_{m1}\cdots d_{mp}\end{bmatrix}\begin{bmatrix}\frac{\partial}{\partial \mathbf{w}_j}u_1(t)\\ \vdots\\ \frac{\partial}{\partial \mathbf{w}_j}u_p(t)\end{bmatrix}\right), \quad (10)$$

[1]Since $\mathbf{x}(t-1)$ depends on $u(t-2)$ which in turn is a function of $\mathbf{w}$, the dependence of state vector $\mathbf{x}(t-1)$ on the weights $\mathbf{w}$ of the neural network is acknowledged. However the term for derivative of $\mathbf{CAx}(t-1)$ w.r.t $\mathbf{w}$ is deliberately neglected since expansion of $\mathbf{x}(t)$ into past state terms $\mathbf{Ax}(t-n)+\mathbf{Bv}(t-n)$ for $n \geq 2$ does not yield significant improvement on controller result.

where $\Psi \ \varepsilon \ \Re^{m\times p}$ is the product of $\mathbf{C} \ \varepsilon \ \Re^{m\times n}$ and $\mathbf{B} \ \varepsilon \ \Re^{n\times p}$. The derivative of all terms except $u_j(t-1)$ and $u_j(t)$ would vanish. Substituting $\frac{\partial u_j(t)}{\partial \mathbf{w}_j}$ from the derivative equation 8,

$$\frac{\partial J}{\partial \mathbf{w}_j} = -2\mathbf{e}^T(t)\left(\begin{bmatrix}\psi_{1j}\frac{\partial}{\partial \mathbf{w}_j}u_j(t-1)\\ \vdots\\ \psi_{mj}\frac{\partial}{\partial \mathbf{w}_j}u_j(t-1)\end{bmatrix} + \begin{bmatrix}d_{1j}\frac{\partial}{\partial \mathbf{w}_j}u_j(t)\\ \vdots\\ d_{mj}\frac{\partial}{\partial \mathbf{w}_j}u_j(t)\end{bmatrix}\right) \quad (11)$$

$$= -2\mathbf{e}^T(t)\left(\begin{bmatrix}\psi_{1j}\alpha\frac{2k\phi(t-1)e^{k\mathbf{w}_j\phi(t-1)}}{(e^{k\mathbf{w}_j\phi(t-1)}+1)^2}\\ \vdots\\ \psi_{mj}\alpha\frac{2k\phi(t-1)e^{k\mathbf{w}_j\phi(t-1)}}{(e^{k\mathbf{w}_j\phi(t-1)}+1)^2}\end{bmatrix} + \begin{bmatrix}d_{1j}\alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}\\ \vdots\\ d_{mj}\alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}\end{bmatrix}\right) \quad (12)$$

$$\frac{\partial J}{\partial \mathbf{w}_j} = -2[e_1(t)\cdots e_m(t)] \quad (13)$$
$$\begin{bmatrix}\psi_{1j}\alpha\frac{2k\phi(t-1)e^{k\mathbf{w}_j\phi(t-1)}}{(e^{k\mathbf{w}_j\phi(t-1)}+1)^2}+d_{1j}\alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}\\ \vdots\\ \psi_{mj}\alpha\frac{2k\phi(t-1)e^{k\mathbf{w}_j\phi(t-1)}}{(e^{k\mathbf{w}_j\phi(t-1)}+1)^2}+d_{mj}\alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}\end{bmatrix}$$

$$\begin{aligned} &= 2e_1(t) \\ &\left(\psi_{1j}\alpha\frac{2k\phi(t-1)e^{k\mathbf{w}_j\phi(t-1)}}{(e^{k\mathbf{w}_j\phi(t-1)}+1)^2}+d_{1j}\alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}\right) \\ &\cdots-2e_m(t) \\ &\left(\psi_{mj}\alpha\frac{2k\phi(t-1)e^{k\mathbf{w}_j\phi(t-1)}}{(e^{k\mathbf{w}_j\phi(t-1)}+1)^2}+d_{mj}\alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}\right). \end{aligned} \tag{14}$$

Finally, the weight update equation for j^{th} control signal $u_j(t)$ becomes

$$\begin{aligned} \mathbf{w}_j(k+1) &= \mathbf{w}_j(k)+2\eta\sum_{l=1}^{m}e_l(t) \\ &\left(\psi_{lj}\alpha\frac{2k\phi(t-1)e^{k\mathbf{w}_j\phi(t-1)}}{(e^{k\mathbf{w}_j\phi(t-1)}+1)^2}+d_{lj}\alpha\frac{2k\phi(t)e^{k\mathbf{w}_j\phi(t)}}{(e^{k\mathbf{w}_j\phi(t)}+1)^2}\right). \end{aligned} \tag{15}$$

where $e_l(t)$ corresponds to error at the l^{th} output, ψ_{lj} is the element at the l^{th} row and j^{th} column of the matrix Ψ, η is the learning rate of the RBF neural network, $\mathbf{w}_j$ is the vector for the weights of j^{th} RBF output, m is the number of outputs of the process, and $\phi(t)$ is the basis function vector.

3 THE AUTOMATIC GENERATION CONTROL PROBLEM

Automatic Generation Control (AGC) has been an important subject for power engineers for quite some time. It is also known as Load Frequency Control (LFC) and has been under study for decades. The problem arises from the fact that loading in power systems is never constant, and changes in load induce changes in system frequency. This is because imbalance between real generated power and loading causes the generator shaft speed to change, resulting in the variation of system frequency.

Hence, a controller is needed to keep the frequency of the output electrical power at the nominal value. The input mechanical power to the generator is used to control the load frequency. The main quality risk involved during control is that control area frequencies can undergo prolonged fluctuations due to a sudden change of loading in an interconnected power system as described in (Chan, W. C., Hsu, Y. Y., 1981). These prolonged fluctuations are mainly the result of system nonlinearities. The purpose of AGC is to track load variations and reduce these fluctuations. In this way, the system frequency is maintained, transient errors are minimized and steady state error is avoided.

Linear and nonlinear control of AGC systems has been studied by several researchers as in (Pan, C. T., Liaw, C. M., 1989; Wang, Y., Zhou, R., Wen, C., 1993). AGC systems are modeled with nonlinearities, one of the main type of which is the Generation Rate Constraint (GRC) (Velusami, S., Chidambaram, I. A., 2007). This is the constraint on the power generation rate of the turbine and due to it the disturbance in one area affects the output frequency in other interconnected areas. Variable Structure Control (VSC) based techniques, (Al-Hamouz, Z. M., Al-Duwaish, H. N., 2000), (Wang, Y., Zhou, R., Wen, C., 1993) and Model Predictive Control (MPC) based techniques (Yousuf, M. S., Al-Duwaish, H. N., Al-Hamouz, Z. M., 2010), (Kong, L., Xiao, L., 2007) have been applied to AGC and an excellent literature survey is given in (Shayeghi, H., Shayanfar, H. A., Jalili, A., 2009).

3.1 AGC System Model

The block diagram of an AGC system is given in Figure 2 and the states of the system are:

$$\dot{X} = \left[\ \Delta\dot{f}_i(t)\Delta\dot{P}_{g_i}(t)\Delta\dot{X}_{g_i}(t)\Delta\dot{P}_{c_i}(t)\Delta\dot{P}_{t_i}(t)\ \right]^T. \tag{16}$$

The definitions of the symbols used in the model are as follows:

f_i : area frequency in ith area (Hz).

P_{gi} : generator output for ith area (p.u. MW).

X_{gi} : governor valve position for ith area (p.u. MW).

P_{ci} : integral control value for ith area (p.u. MW).

P_{ti} : tie line power output for ith area (p.u. MW).

P_{ti} : load disturbance for ith area (p.u. MW).

T_{gi} : governor time constant for ith area (s).

T_{pi} : plant model time constant for ith area (s).

T_{ti} : turbine time constant for ith area (s).

K_{pi} : plant transfer function gain for i^th area.

R_i : speed regulation due to governor action for ith area (Hz p.u. MW^{-1}).

B_i : frequency bias constant for ith area (p.u. MW Hz^{-1}).

a_{ij} : ratio between the base values of areas i and j.

The model can be generally represented by the following equations:

$$\dot{X}_i(t) = A_i x_i(t) + B_i u_i(t) + \sum_{j=1,\ j\neq i}^{n} E_{ij}x_j(t) + F_i d_i(t), \tag{17}$$

$$y_i(t) = C_i(t)x_i(t), \tag{18}$$

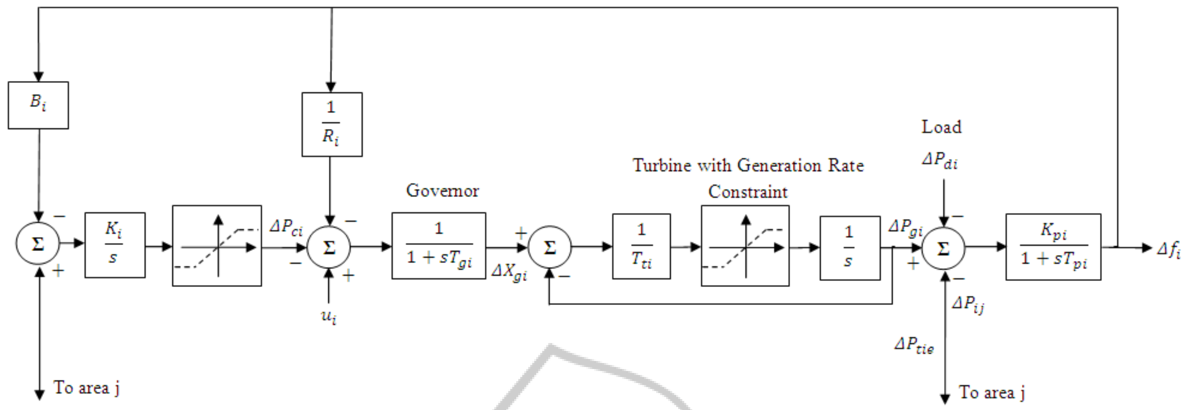

Figure 2: Block diagram of n^{th} area AGC with GRC nonlinearities.

where

$$A_i = \begin{bmatrix} \frac{-1}{T_{p_i}} & \frac{K_{p_i}}{T_{p_i}} & 00 & \frac{-K_{p_i}}{T_{p_i}} & \\ 0 & \frac{-1}{T_{t_i}} & \frac{1}{T_{t_i}} & 0 & 0 \\ \frac{-1}{R_i T_{G_i}} & 0 & \frac{-1}{T_{G_i}} & \frac{-1}{T_{G_i}} & 0 \\ K_{E_i} & 0 & 0 & 0 & K_{E_i} \\ \sum_j T_{ij} & 0 & 0 & 0 & 0 \end{bmatrix} \quad (19)$$

where K_{E_i} is zero for single area machine.

$$B_i^T = \begin{bmatrix} 0 & 0 & 1/T_{G_i} & 0 & 0 \end{bmatrix}, \quad (20)$$

$$E_{ij} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -T_{ij} & 0 & 0 & 0 & 0 \end{bmatrix}, \quad (21)$$

$$F_i^T = \begin{bmatrix} -K_{p_i}/T_{p_i} & 0 & 0 & 0 & 0 \end{bmatrix}, \quad (22)$$

$$d_i(t) = P_{d_i}(t). \quad (23)$$

The numerical values of these parameters are given in Section 4. The control objective of AGC is to keep the change in frequency, $\Delta f_i(t) = x_1(t)$ as close to 0 as possible in the presence of load disturbance, $d_i(t)$ by the manipulation of the input, $u_i(t)$. The detailed model of the system along with the values of state matrices can be found in (Yang T. C., Cimen, H., Zhu, Q. M., 1998).

3.2 Control Objective

Given a linear or nonlinear AGC system, the controller objective is to construct the ANN based controller such that it minimizes the error in the minimum time using minimum effort in the presence of disturbances and constraints.

The disturbance is applied as a p.u. load demand. Practically, this translates to a step load demand of a certain percentage from the AGC system. Naturally, this demand will cause the system to adjust its load by the same amount to fulfil the quality of service. This will change the load frequency. The proposed controller is required to minimize this frequency deviation and bring it to zero in minimum time while obeying the constraints on system states and control signal.

4 SIMULATION RESULTS

Linear as well as the nonlinear control for a single area AGC system is simulated. The system is simulated as a single-input single-output (SISO) system, with one control signal being the input and frequency deviation being the output. The cost function is given by

$$\begin{aligned} J &= \mathbf{e}^T(t)\mathbf{e}(t) \\ &= \|\mathbf{r}(t) - \hat{\mathbf{y}}(t)\|^2, \end{aligned}$$

where $\mathbf{r}(t)$ denotes reference values for frequency deviation, which is zero for the given control objective. The vector $\hat{\mathbf{y}}(t)$ denotes the actual AGC output values of these parameters. The AGC parameters are computed using the following values:

T_p = 20s, K_p = 120 Hz p.u. MW^{-1}, T_t = 0.3s, T_g = 0.08s, R = 2.4 Hz p.u. MW^{-1}, T_s = 0.05s, where T_s refers to discretization sampling time. The corresponding values of A, B & F are:

$$A = \begin{bmatrix} -0.05 & 6 & 0 & 0 \\ 0 & -3.33 & 3.33 & 0 \\ -5.208 & 0 & -12.5 & -12.5 \\ 0.6 & 0 & 0 & 0 \end{bmatrix}, \quad (24)$$

$$B = \begin{bmatrix} 0 & 0 & 12.5 & 0 \end{bmatrix}^T, \quad (25)$$

$$F = \begin{bmatrix} -6 & 0 & 0 & 0 \end{bmatrix}^T. \quad (26)$$

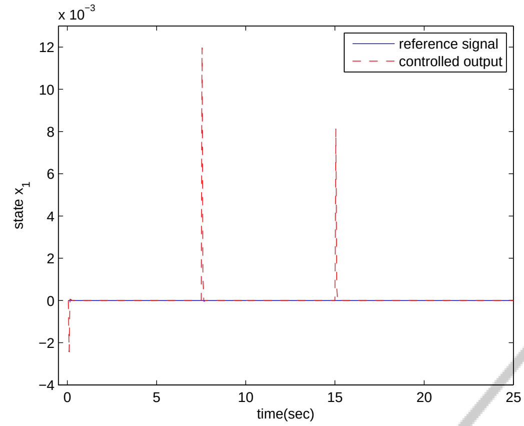

Figure 3: Frequency deviation for linear AGC.

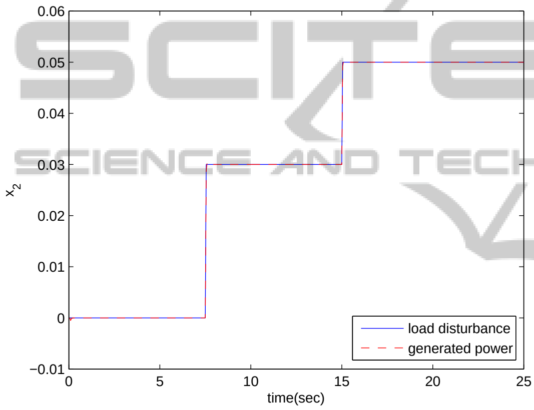

Figure 4: Change in generated power for linear AGC.

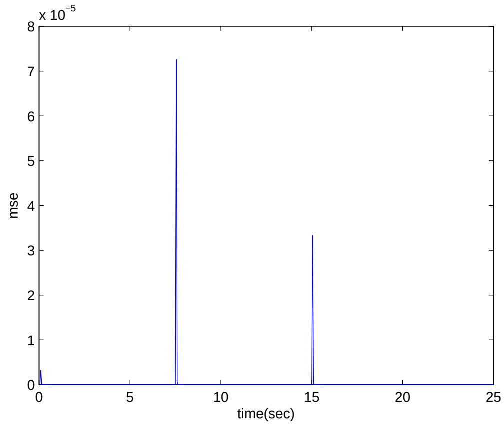

Figure 5: Convergence of error function for linear AGC.

While designing a controller, a suitable number of neurons can be chosen based on experience. Repeated simulations can then be run to test the controller with increased number of neurons each time until no appreciable increase in performance is noted. To begin with, a network of just two RBF neurons is used for

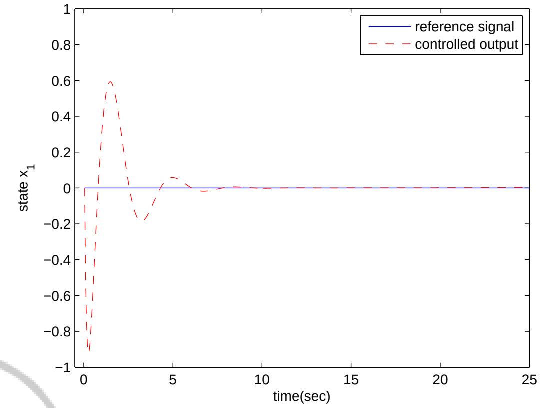

Figure 6: Frequency deviation for AGC with GRC nonlinearity.

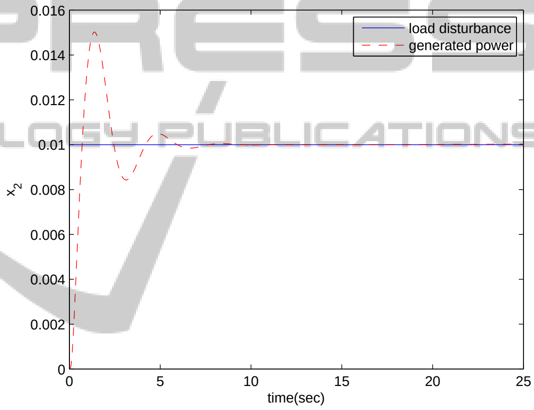

Figure 7: Change in generated power for AGC with GRC nonlinearity.

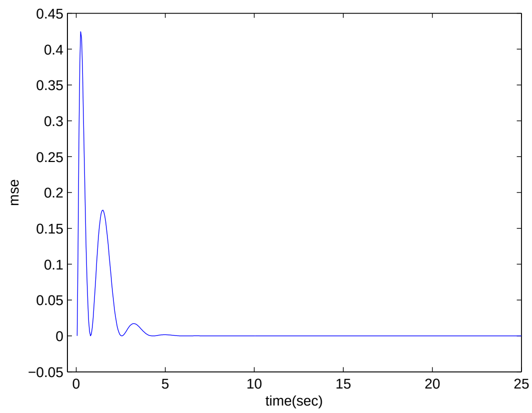

Figure 8: Convergence of error Function for AGC with GRC nonlinearity.

controller design. The input to the neural network is the reference signal for frequency deviation. A neuron center for each neuron is chosen around the desired set-point on the reference trajectory. Spread of the gaussian basis function σ is chosen such that the RBF functions are neither too peaked nor too flat. Methods to find proper basis function spread exist in (Haykin, S., 1999). A nominal spread of 0.04 is chosen. The learning rate η has to be chosen with care as well. Small value of learning rate can cause slow convergence of error while too large a value can make the controller unstable.

The constraint $\alpha = |u_{min}| = |u_{max}|$ on the control signal is given by

$$-0.5 \leq \alpha \leq 0.5.$$

Single area linear and nonlinear AGC is simulated with zero initial conditions and the neural network controller shows satisfactory control results for both cases.

4.1 Single Area AGC excluding Nonlinearities

First, the nonlinearity is excluded and the performance of the proposed controller is tested for the linear system.

To study the robustness of the proposed controller, a condition of varying load disturbance is considered. The load is simulated to vary from a disturbance of 0 p.u. to 0.03 p.u. after 7.5 seconds, and then going up to 0.05 p.u. after 15 seconds. This directly affects the load frequency as seen in Figure 3. It is seen that the load frequency varies most when the disturbance varies most, but the neural network controller quickly pushes it back zero. The corresponding behavior of the change in generated power is seen in the Figure 4. It is seen that the change in generated power follows the load disturbance as well, meaning that the system can supply the load its power demand. The power generated changes most when the disturbance is largest. The error convergence is given in Figure 5.

4.2 Single Area AGC including GRC Nonlinearities

Now the case of nonlinear AGC system is considered. The nonlinearities in the system appear in the form of saturation on change of states x_2 and x_4 as illustrated in Figure 2. Mathematically, the nonlinearity can be described as

$$x_i(t-1) - GRC \leq \Delta x_i(t) \leq x_i(t-1) + GRC, \quad for \quad i = 2,4$$

The system is tested for a practical GRC value of 0.6 p.u. $MW\ min^{-1}$ = 0.01 p.u. $MW\ sec^{-1}$, as done in previous work of (Wang, Y., Zhou, R., Wen, C., 1993). This means that the generated power output of the system cannot vary by more than 0.01 p.u. MW in 1 second. A disturbance of 1% p.u. is present in the system. The proposed controller is applied to the system with this nonlinearity and the results can be seen in Figures 6, 7, and 8. The NN controller successfully keeps the frequency deviation to zero while the Generated power follows the step change in load demand disturbance.

5 CONCLUSIONS

A new and efficient ANN based control scheme is designed. Weight update algorithm is worked out and the controller is shown to be viably applicable to practical power systems. The dynamical behavior of the single nonlinear AGC system with proposed controller is examined. The proposed controller performs well for linear as well as nonlinear case. With just two neurons, the performance of the controller is well acceptable under rapid load variations. Encouraging results are a sound motivation for possible future application of proposed controller to multiple area linear and nonlinear AGC problem.

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