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# SLIDING MODE TECHNOLOGY FOR AUTOMATIC GENERATION CONTROL OF SINGLE AREA POWER SYSTEMS

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Abstract. *Automatic generation control (AGC) is one of the most profitable ancillary services of power systems. The main goal of AGC is to maintain zero steady state errors for frequency deviation and good tracking of load demands in a power system. However, the system performance is often constrained by governor dead band nonlinearity. This paper addresses a sliding mode controller for a single area power system with governor dead band. Two RBF neural networks are employed in this presented method, where one network is designed to compensate the dead band and the other network is designed to approximate the output of the dead band. The weight update formulas of the two RBF networks are derived from Lyapunov direct method. Finally, simulation results show the feasibility of the presented method for the AGC problem of a single area power system.*
**Keywords:** Sliding mode control, Automatic generation control, Dead band nonlinearity, Neural networks

1. **Introduction.** The successful operation of power systems requires matching the total generation with the total load demand and with the associated system losses. However, the operating point of a power system changes with time, which may yield undesirable effects [1]. Automatic generation control (AGC) is one of the most important issues in electric power system design and operation for supplying sufficient and reliable electric power with good quality. The primary objectives of AGC are to adjust the power output of the electrical generator within a prescribed area in response to changes in system frequency, tie-line loading (for interconnected areas), so as to maintain the scheduled system frequency and interchange with the other areas with predetermined limits.

In the last two decades, many control methods concerning the problem of AGC have been published, e.g., optimal control [2], variable structure control [3,4], adaptive control [5], robust control [6] and intelligent control [7]. In most of the mentioned references, small signal analysis is justified for studying the systems response for small perturbations. However, implementation of an AGC strategy based on a linearized model of an essentially nonlinear system does not necessarily ensure the stability of the systems. Thus, considerable attention has been paid by researchers to consider the system nonlinearities. For the problem of AGC, the nonlinearities of governor dead band (GDB) and generation rate constraint (GRC) are usually involved. As Tripathy [8] has pointed out, the effects of these nonlinearities tend to produce continuous oscillations in the area frequency and tie line power transient response.

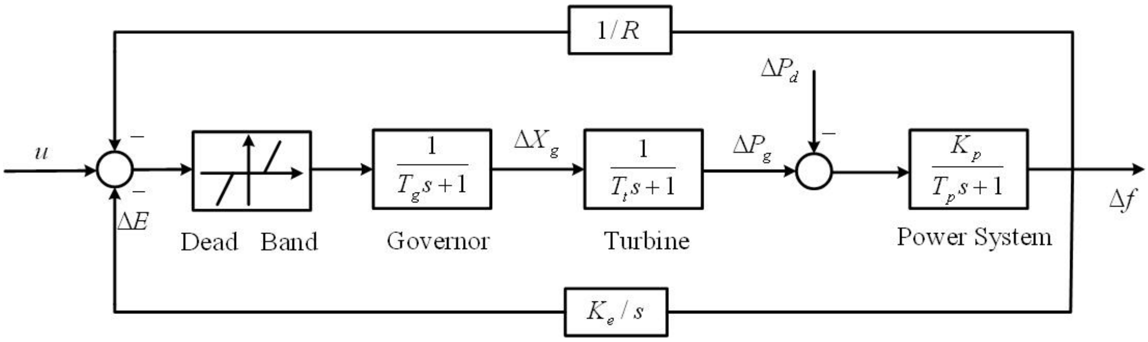


Figure 1. Diagram of a single area power system with dead band nonlinearity

It is proven that the methodology of neural networks (NNs) is a universal approximator [9]. The tool provides a good choice to deal with the nonlinearities of the AGC problem. Although the GDB problem of AGC was mentioned in [10,11], there are rare publications about employing NNs to solve the GDB problem. In this paper, a sliding mode controller is developed for the problem of AGC of a single area power system with governor dead band nonlinearity. One RBF-network-based compensator is designed to compensate the dead band nonlinearity. The other RBF-network-based approximator is designed to approximate the output of the dead band. The update formulas of the two networks are deduced from the Lyapunov direct method. Finally, simulation results show the feasibility of the presented method for the AGC problem of power systems.

## 2. System Model.

The power system for the AGC problem under consideration is expressed only to relatively small changes so that it can be adequately represented by the linear models of governor, turbine and power system in Figure 1. Figure 1 represents the block diagram of a single area power system with governor dead band nonlinearity. Note that the generating unit in Figure 1 means all units in the prescribed area are lumped together. The symbols in Figure 1 are explained as Laplace operator $s$, speed regulation due to governor action $R$ (Hz/p.u.MW), governor time constant $T_g$ (s), turbine time constant $T_t$ (s), electric system time constant $T_p$ (s), electric system gain $K_p$, incremental frequency deviation $\Delta f(t)$ (Hz), incremental change in generator output $\Delta P_g((t)$ (p.u.MW), load disturbance $\Delta P_d(t)$ (p.u.MW), incremental change in governor valve position $\Delta X_g(t)$, control input produced by the designed AGC controller $u(t)$. In state space, to force the steady state of $\Delta f(t)$ to tend to zero, the integral of $\Delta f(t)$ is used as an additional state, defined as

$$\mathscr{L}[\Delta E(t)] = \frac{K_e}{s}\mathscr{L}\left[\Delta f(t)\right] \tag{1}$$

where $K_e$ is gain of the additional state, $\mathscr{L}[\cdot]$ means Laplace transform. It is obvious that the system consists of three parts:

- Turbine with dynamics $G_t(s) = \frac{1}{T_t s+1}$.
- Generator with dynamics $G_g(s) = \frac{1}{T_g s+1}$.
- Electric power system with dynamics $G_p(s) = \frac{K_p}{T_p s+1}$.

## 3. Control Design.

### 3.1. Design of sliding mode controller.

Sliding mode control is a kind of state feedback control method, its total control law usually is made up of two parts, equivalent control and switching control [12]. The closed-loop system in Figure 1 involves four state variables, i.e., $\Delta P_g$, $\Delta X_g$, $\Delta f$ and $\Delta E$, if there is no dead band nonlinearity. The state space expression of the system with no nonlinearity can be depicted as:

$$\dot{\mathbf{x}}(t) = A\mathbf{x}(t) + Bu(t) + Fd(t) \tag{2}$$

where $\mathbf{x} = [\Delta f\ \Delta P_g\ \Delta X_g\ \Delta E]^T$ is state vector, $A$ is a $4 \times 4$ system matrix, $B$ is a $4 \times 1$ input matrix, $F$ is a $4 \times 1$ disturbance matrix.

$$A = \begin{bmatrix} -\frac{1}{T_p} & \frac{K_p}{T_p} & 0 & 0 \\ 0 & -\frac{1}{T_t} & \frac{1}{T_t} & 0 \\ -\frac{1}{RT_g} & 0 & -\frac{1}{T_g} & -\frac{1}{T_g} \\ K_e & 0 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T_g} \\ 0 \end{bmatrix} \quad F = \begin{bmatrix} \frac{K_p}{T_p} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Since the control objective in the AGC problem is to keep the change in frequency $\Delta f$ as close to 0 as possible when the system is subjected to a load disturbance $d$ by manipulating the input $u$, we employ the sliding mode control law to achieve this goal. At first, a sliding surface is defined as:

$$S = c^T\mathbf{x} \tag{3}$$

Adopting the methodology of equivalent control [12], we differentiate $S$ with respect to time $t$ and let $\dot{S} = 0$. The equivalent control law $u_{eq}$ can be gotten as:

$$u_{eq} = -\left(c^T B\right)^{-1} c^T A\mathbf{x} \tag{4}$$

Further, substituting (4) to (2), we can have $c$ by placing the system poles. Define a Lyapunov function $V = \frac{S^2}{2}$, define the total control law $u$ as $u_{eq} + u_{sw}$ where $u_{sw}$ is the switching control law, differentiate $V$ with respect to time $t$, substitute (2) – (4) into $\dot{V}$, then we are able to obtain $u_{sw}$ from $\dot{V} < 0$ as:

$$u_{sw} = -(c^T B)^{-1}[KS + \eta sgn(S)] \tag{5}$$

where $K$ and $\eta$ are positive constants, $sgn(\cdot)$ means sign function. On the aspect of system stability, we choose $\eta > c^T F\bar{d}$, here $\bar{d} = \sup d(t)$. Then, the final control law $u$ can be obtained by $u_{eq}$ plus $u_{sw}$.

3.2. **Design of RBF neural networks.** Due to RBF networks owning the ability to approximate complex nonlinear mapping directly from input-output data with a simple topological structure [13], we will adopt such the kind of neural networks to achieve our purpose. In Figure 2, RBF NN1 is employed to approximate the output of the dead band nonlinearity. Its output $\Delta\hat{\tau}$ is used as the estimated value of the output of the nonlinear component $\Delta\tau$, and its inputs are $\Delta\hat{u}^*$ and $\Delta\tau^*$. The other network with the input $u^*$ and the output $\Delta u^*$, RBF NN2, is utilized to compensate the dead band of the system. Here, $u^*$ and $\Delta\tau^*$ are defined as $u - \Delta E - \frac{\Delta f}{R}$ and $u^* + \Delta\hat{u}^*$, respectively.

Define a nonlinear function $D(\cdot)$ as $\Delta\tau = D(\Delta\tau^*)$ to depict the dead band nonlinearity in Figure 2, then, the inverse of the dead band nonlinearity $D^{-1}$ is able to be obtained as

$$D^{-1}(u^*) = u^* + \Delta u^* \tag{6}$$

here $\Delta u^*$ is the desired output of the neural networks. From (6), $\Delta u^*$ can be obtained as $\Delta u^* = D^{-1}(u^*) - u^*$. These cases inspire us to approximate $D$ and $\Delta u^*$ by utilizing the properties of neural networks. In Figure 2, it is obvious that $\Delta\hat{u}^*$ and $\Delta\hat{\tau}$ are the estimated value of $\Delta u^*$ and $D$, respectively. Thus, the NN1 and NN2 outputs are determined as:

$$\Delta\hat{\tau} = \mathbf{w}_a{}^T\Phi_a(\Delta\tau^*) \quad \Delta\hat{u}^* = \mathbf{w}_c{}^T\Phi_c(u^*) \tag{7}$$

here, $\mathbf{w}_a \subseteq R^{n_a\times 1}$ and $\mathbf{w}_c \subseteq R^{n_c\times 1}$ are the weight vectors of the RBF NN1 and NN2 networks, where $n_a$ and $n_c$ are the number of their hidden neurons, $\Phi_a(\Delta\tau^*) = [\phi_{a1}(\Delta\tau^*),$

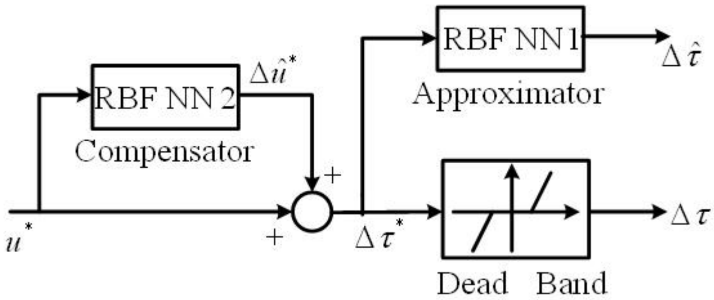


FIGURE 2. Diagram of RBF-network-based compensator and approximator for dead band nonlinearity

$\phi_{a2}(\Delta\tau^*)\,,\ \cdots\,,\ \phi_{an_a}(\Delta\tau^*)]^T$ and $\Phi_c(u^*) = [\phi_{c1}(u^*)\,,\ \phi_{c2}(u^*)\,,\ \cdots\,,\ \phi_{cn_c}(u^*)]^T$ are radial basis function vectors, where the $k$-th RBF function of the NN1 and NN2 networks is determined as:

$$\phi_{ak}(\Delta\tau^*) = \exp\left(-\frac{||\Delta\tau^* - \gamma_{ak}||^2}{\delta_{ak}^2}\right) \quad \phi_{ck}(u^*) = \exp\left(-\frac{||u^* - \gamma_{ck}||^2}{\delta_{ck}^2}\right) \tag{8}$$

here, $\gamma_{ak}$ & $\delta_{ak}$ and $\gamma_{ck}$ & $\delta_{ck}$ depict the center and width of the $k$-th hidden neuron of the NN1 and NN2 networks, respectively. To deduce the update formulas, we make the following assumption [14].

- A1: There exist optimal weight vectors $\mathbf{w}_{ao}$ and $\mathbf{w}_{co}$ so that the outputs of the NN1 and NN2 networks satisfy $|\mathbf{w}_{ao}{}^T\Phi(\Delta\tau^*) - \mathbf{w}_a{}^T\Phi(\Delta\tau^*)| < \epsilon_a$ and $|\mathbf{w}_{co}{}^T\Phi(u^*) - \mathbf{w}_c{}^T\Phi(u^*)| < \epsilon_c$, respectively, where $\epsilon_a$ and $\epsilon_c$ are positive constants.

Define $\tilde{\mathbf{w}}_a = \mathbf{w}_{ao} - \mathbf{w}_a$ and $\tilde{\mathbf{w}}_c = \mathbf{w}_{co} - \mathbf{w}_c$ as the weight error of the two networks, so that we have $\dot{\tilde{\mathbf{w}}}_a = -\dot{\mathbf{w}}_a$ and $\dot{\tilde{\mathbf{w}}}_c = -\dot{\mathbf{w}}_c$. Then, we re-define another Lyapunov function (9) to deduce the update formulas of the two networks.

$$V_n = \frac{S^2}{2} + \frac{\alpha^{-1}\tilde{\mathbf{w}}_a^T\tilde{\mathbf{w}}_a}{2} + \frac{\beta^{-1}\tilde{\mathbf{w}}_c^T\tilde{\mathbf{w}}_c}{2} \tag{9}$$

Here, $\alpha$ and $\beta$ are positive constants. Differentiating $V_n$ with respect to time $t$ yields

$$\dot{V}_n = S\dot{S} + \alpha^{-1}\tilde{\mathbf{w}}_a^T\dot{\tilde{\mathbf{w}}}_a + \beta^{-1}\tilde{\mathbf{w}}_c^T\dot{\tilde{\mathbf{w}}}_c = S\dot{S} - \alpha^{-1}\tilde{\mathbf{w}}_a^T\dot{\mathbf{w}}_a - \beta^{-1}\tilde{\mathbf{w}}_c^T\dot{\mathbf{w}}_c \tag{10}$$

Substituting (2) – (5) into (10), we have

$$\begin{aligned}\dot{V}_n &= S\left[-KS - \eta sgn(S) + c^TFd(t)\right] - \alpha^{-1}\left(\mathbf{w}_{ao}^T - \mathbf{w}_a^T\right)\dot{\mathbf{w}}_a - \beta^{-1}\left(\mathbf{w}_{co}^T - \mathbf{w}_c^T\right)\dot{\mathbf{w}}_c \\ &= -KS^2 - \eta|S| + c^TFd(t)S - \alpha^{-1}\left(\mathbf{w}_{ao}^T - \mathbf{w}_a^T\right)\dot{\mathbf{w}}_a - \beta^{-1}\left(\mathbf{w}_{co}^T - \mathbf{w}_c^T\right)\dot{\mathbf{w}}_c\end{aligned} \tag{11}$$

Let

$$\dot{\mathbf{w}}_a = \alpha S^2\Phi_a(\Delta\tau^*) \quad \dot{\mathbf{w}}_c = \beta S^2\Phi_c(u^*) \tag{12}$$

Substituting (12) into (11), we can obtain

$$\dot{V}_n = -KS^2 - \eta|S| + c^TFd(t)S - S^2\left(\mathbf{w}_{ao}^T - \mathbf{w}_a^T\right)\Phi_a(\Delta\tau^*) - S^2\left(\mathbf{w}_{co}^T - \mathbf{w}_c^T\right)\Phi_c(u^*) \tag{13}$$

Further, there exists the following inequation in light of our Assumption A1.

$$\begin{aligned}\dot{V}_n &< -KS^2 - \eta|S| - \epsilon_aS^2 - \epsilon_cS^2 + c^TFd(t)|S| \\ &< -KS^2 - \epsilon_aS^2 - \epsilon_cS^2 - \left(\eta - c^TF\bar{d}\right)|S|\end{aligned} \tag{14}$$

In the sense of Lyapunov stability scheme, (14) indicates $\dot{V}_n < 0$ so that both the update formulas in (12) of the two RBF NNs are able to ensure the asymptotic stability of the control system with dead band nonlinearity by employing the sliding mode control law.

4. **Simulation Results.** In this section, the presented control method will be applied on automatic generation control of a single-area power system with governor dead band constraint, shown in Figure 1. Typical values of the system parameters of the single area power system [15] are determined as $K_p = 120$, $T_p = 20$, $T_t = 0.3$, $T_g = 0.08$, $R = 2.4$ and $K_e = 0.1$. Typical dead band constrait of AGC problem [8] is 0.06%. The parameters of the sliding surface $S$ are gotten as $c = [0.04\ 0.50\ \ -0.15\ 1.88]^T$ from Acker command of MATLAB by placing the pole of Ackermann's formula in the specified vector $[-1\ \ -2+2i\ \ -2-2i\ \ -9]^T$. The switching control parameters are picked up as $K = 7$, $\eta = 0.10$ after trial and error. Both $\gamma_{ak}$ and $\gamma_{ck}$, the center of the $k$-th hidden neuron of the two RBF networks, are set as random number in the interval [0, 1]. Both $\delta_{ak}$ and $\delta_{ak}$, the width of the $k$-th hidden neuron of the two RBF networks, are set as 10. Other parameters $\alpha$, $\beta$, $n_a$ and $n_c$ are set as 10, $10^{-1}$, 10 and 10, respectively. Both the initial weights of the two networks are set as random number in the interval $[0\ 10^{-4}]$. Load disturbance $d(t)$ is set as 1%.

Simulation results in Figure 3 and Figure 4 illustrate the feasibility of the presented control method, where the black solid depicts the results with RBF NNs compensating the dead band constraint and the blue solid illustrates the results with no RBF NNs compensator. Both the simulation results are executed by the same sliding mode controller and load disturbance. The solitary difference between the two simulations is that one is with compensator and approximator and the other is without any compensator or approximator.

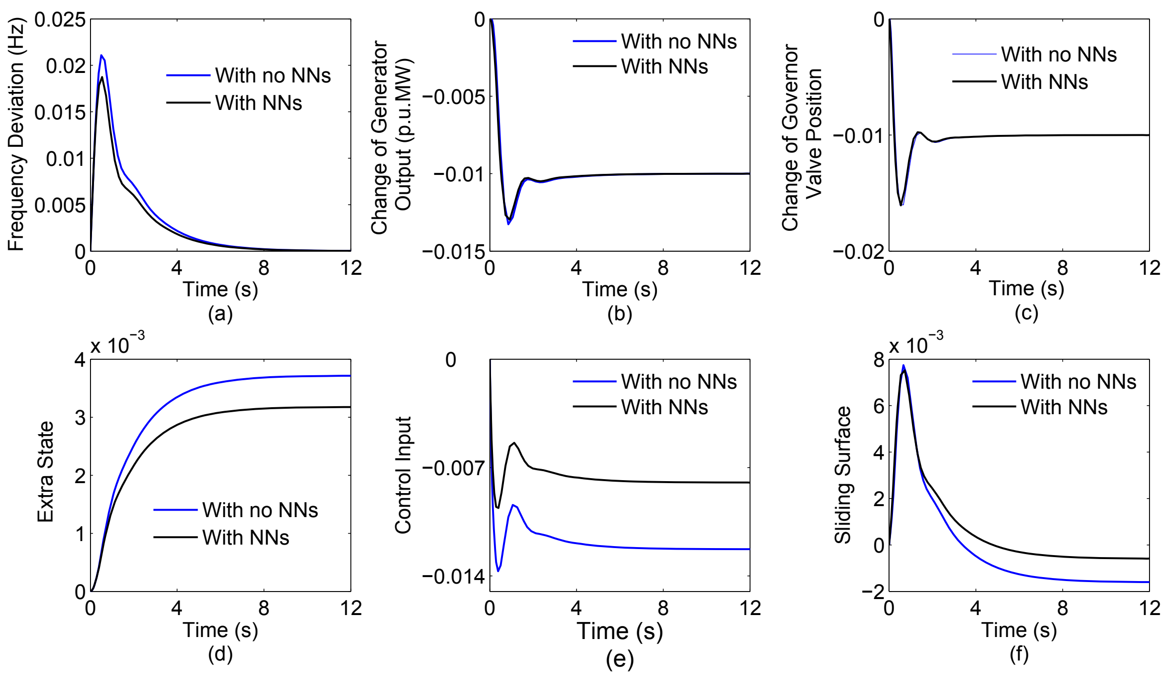


FIGURE 3. Simulation results: (a) frequency deviation $\Delta f$, (b) change of generator output $\Delta P$, (c) change of governer valve position $\Delta X$, (d) extra state, (e) control input $u$, (f) sliding surface $S$

As displayed in Figure 3 and Figure 4, the presented approach with the RBF NNs compensator and approximator updateing the network weights as (12) is able to ensure

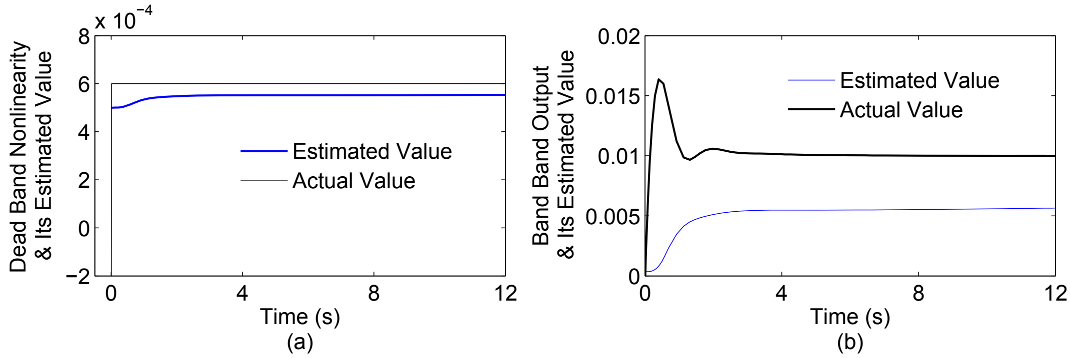


FIGURE 4. Outputs of the two RBF neural networks

the asymptotic stability of the control system in the sense of Lyapunov. In Figure 3(b) and Figure 3(c), the curves of change of governor output $\Delta P$ and change of governor valve position $\Delta X$ almost make no difference. However, the curve of frequency deviation $\Delta f$ in Figure 3(a) demonstrates the superiority of the presented method on the aspect of decreasing overshoot. In Figure 4, the blue solid indicates the outputs of the two RBF NNs and the black solid means the actual value during the simulations. From Figure 4, the designed compensator and approximator are able to partly compensate and approximate the dead band nonlinearity of power systems.

5. **Conclusions.** This paper has presented an approach for automatic generation control of power systems. In the approach, a controller based on sliding mode methodology is developed and two RBF neural networks are employed to deal with governor dead band nonlinearity, where one network is utilized to compensate the dead band nonlinearity and the other is utilized to approximate the output of the dead zone. The update formulas of the two RBF neural networks are deduced from Lyapunov direct method to ensure the asymptotic stability of the control system. Simulation results show the validity of the presented method through a single area power system. The main contribution of this presented approach is to be able to solve automatic generation control problem with governor dead band nonlinearity of power systems.

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## REFERENCES

[1] D. P. Kothari and I. J. Nagrath, *Modern Power System Analysis*, 3rd Edition, McGraw-Hill, Singapore, 2003.
[2] S. Mariano, J. Pombo, M. Calado and L. Ferreira, Optimal output control: Load frequency control of a large power system, *Proc. of International Conference on Power Engineering, Energy and Electrical Drives*, vol.2, pp.369-374, 2009.
[3] Z. M. Al-Hamouz and H. N. Al-Duwaish, A new load frequency variable structure controller using genetic algorithms, *Electric Power Systems Research*, vol.55, pp.1-6, 2000.
[4] K. Vrdoljak, N. Perić and I. Petrović, Sliding mode based load-frequency control in power systems, *Electric Power Systems Research*, vol.80, no.5, pp.514-527, 2010.
[5] R. R. Shoults and J. A. J. Ibarra, Multi-area adaptive LFC developed for a comprehensive AGC simulator, *IEEE Trans. on Power Systems*, vol.8, pp.541-547, 1993.
[6] X. F. Yu and K. Tomsovic, Application of linear matrix inequalities for load frequency control with communication delays, *IEEE Trans. on Power Systems*, vol.19, pp.1508-1515, 2004.
[7] E. Çam, Application of fuzzy logic for load frequency control of hydroelectrical power plants, *Energy Conversion and Management*, vol.48, no.4, pp.1281-1288, 2007.

[8] S. C. Tripathy, T. S. Bhatti, C. S. Jha, O. P. Malik and G. S. Hope, Sampled data automatic generation control analysis with reheat steam turbines and governor dead band effects, *IEEE Trans. on Power Apply Systems*, vol.103, no.5, pp.1045-1051, 1984.

[9] H. White, Connectionist nonparametric regression: Multilayer feedforward networks can learn arbitrary mappings, *Neural Networks*, vol.3, no.1, pp.535-549, 1990.

[10] C. F. Lu and C. C. Liu, Effect of battery energy storage system on load frequency control considering governor dead-band and generation rate constraint, *IEEE Trans. on Energy Conversin*, vol.10, no.3, pp.555-561, 1995.

[11] S. C. Tripathy, R. Balasubramanian and P. S. C. Nair, Effect of superconducting magnetic energy storage on automatic generation control considering governor dead-band and boiler dynamics, *IEEE Trans. on Power Systems*, vol.7, no.3, pp.1266-1273, 1992.

[12] V. I. Utkin, *Sliding Modes in Control and Optimization*, Springer-Verlag, New York, 1992.

[13] G. B. Huang, P. Saratchandran and N. Sundararajan, A generalized growing and pruning RBF (GGAP-RBF) neural network for function approximation, *IEEE Trans. on Neural Networks*, vol.16, no.1, pp.57-67, 2005.

[14] Z. Man, H. R. Wu and M. Palaniswami, An adaptive tracking controller using neural networks for a class of nonlinear systems, *IEEE Trans. on Neural Networks*, vol.9, no.5, pp.947-955, 1998.

[15] W. Tan and Z. Xu, Robust analysis and design of load frequency controller for power systems, *Electric Power Systems Research*, vol.79, no.5, pp.846-853, 2009.