

Load-frequency regulation under a bilateral LFC scheme using flexible neural networks

H Bevrani*, T Hiyama*, Y Mitani†, K Tsuji‡ and M Teshnehlab°

*Department of Electrical and Computer Engineering, Kumamoto University, Kumamoto 860-8555, Japan
Email: bevrani@st.eecs.kumamoto-u.ac.jp

†Department of Electrical Engineering, Kyushu Institute of Technology, Kitakyushu 804-8550, Japan

‡ Department of Electrical Engineering, Osaka University, 2-1 Yamada-Oka, Suita, Osaka 565-0871, Japan

° Department of Electrical Engineering, K. N. T. University of Technology, 16315-1355, Tehran, Iran

A new approach based on artificial Flexible Neural Networks (FNNs) is proposed to design of load frequency controller for a large scale power system in a deregulated environment. In this approach, the power system is considered as a collection of separate control areas under the bilateral Load Frequency Control (LFC) scheme. Each control area which is introduced by one or more distribution companies, can buy electric power from some generation companies to supply the area-load. The control area is responsible to perform its own LFC by buying enough power from pre-specified generation companies, which equipped with a FNNs based load frequency controller. The proposed control strategy is applied to a 3-control area power system. The resulting controllers are shown to minimize the effect of disturbances and achieve acceptable frequency regulation in the presence of load variations and line disturbances.

Keywords: Load frequency control, Bilateral LFC scheme, Artificial neural network, Flexible sigmoid function, Back propagation algorithm

1. INTRODUCTION

In a deregulated environment, Load Frequency Control (LFC) acquires a fundamental role to enable power exchanges and to provide better conditions for the electricity trading. LFC is treated as an ancillary service essential for maintaining the electrical system reliability at an adequate level. In an open energy market, generation companies (Gencos) may or may not participate in the LFC task, therefore the control strategies for new structure with a few number of LFC participators are not such straight than those for vertically integrated

utility structure. Technically, this problem will be more important as Independent Power Producers (IPPs) get into the electric power markets [1].

There are several schemes and organizations for the provision of LFC services in countries with a restructured electric industry, differentiated by how free the market is, who controls generator units, who has the obligation to execute LFC. Some possible LFC structures are introduced in [1-4]. Under deregulated environment, several notable solutions have already been proposed. [1], [5] and [6] have reported strategies to adapt well-tested classical LFC schemes to the changing

environment of power system operation under deregulation. The H^∞ -based method for a distribution area with two generation units is given in [7]. [8] has proposed the μ -based load frequency controller for the same example. [9-10] discuss on some general issues for solution of LFC problem for power system after deregulation. [11] has introduced the participation matrix concept to generalized the classic LFC scheme in a deregulated environment, and recently some robust control techniques are suggested to design of market-based LFC system [12-15].

In response to the coming challenge of integrating computation, communication and control into appropriate levels of system operation and control, a comprehensive scenario is proposed to perform the LFC task in a deregulated environment. In the developed scenario, the boundary of control area encloses the generation companies (Gencos) and the distribution companies (Discos) associated with the performed contracts. Therefore, the concept of physical control area is replaced by Virtual Control Area (VCA) [1].

It is assumed that in a VCA, the necessary hardware and communication facilities to enable reception of data and control signals are available and Gencos can bid up and down regulations by price and MW-volume for each predetermined time period to the regulating market. Also the control center can distribute load demand signals to available generating units on a real-time basis.

The participation factors which are actually time dependent variables, must be computed dynamically based on the received bid prices, availability, congestion problem and other related costs in case of using each applicant (Genco). Each participating unit will receive its share of the demand, according to its participation factor; through a dynamic controller which it usually includes a simple Proportional-Integral (PI) structure in real world power system. Since the PI controller parameters are usually tuned based on classical, experiences and trial-and-error approaches, they are incapable of obtaining good dynamical performance for a wide range of operating conditions and various load scenarios.

An appropriate computation method for the participation factors and desired optimization algorithms for the mentioned agents have been already reported in [16]. As a part of the mentioned overall scenario, this paper focuses on the design of dynamic controller unit using the artificial Flexible Neural Networks (FNNs). Technically, this unit has a very important role to guarantee a desired LFC performance. An optimal design ensures a smooth coordination between generator set-point signals and the scheduled operating points. This paper shows that the FNN control design provides an effective design methodology for the load-frequency controller synthesis in a new environment.

It is notable that this paper is not about how to price either energy or any other economical aspects and services. These subjects are getting much attention already. It is assumed that the necessary pricing mechanism and congestion management program are established either by free market, by specific government regulation or by

voluntary agreements, and, this paper focuses on technical solution for designing of load-frequency controllers in a bilateral based electric power market.

The artificial neural networks (ANNs) have been already used to design of load-frequency controller for power system with classical (regulated) structure [17-21]. Generally, in the all applications, the learning algorithms cause the adjustment of the connection weights so that the controlled system gives a desired response. In this work, in order to greatest response and better performance, we have proposed FNN-based load frequency controller with dynamic neurons that have wide ranges of variation [22].

The proposed control strategy is applied to a 3-control area example. The obtained results show that designed controllers guarantee the desired performance for a wide range of operating conditions. This paper is organized as follows. Section 2 describes the bilateral LFC scheme and control area modeling. The synthesis methodology is given in section 3. In section 4, the proposed strategy is applied to a 3-control area, and, finally some simulation results are given in section 5 to demonstrate the effectiveness of the proposed method.

2. BILATERAL LFC SCHEME AND MODELING

2.1 Bilateral LFC scheme

Depending on the electrical system structure, there are different control methods and LFC schemes, but the common objective is restoring the frequency and the net interchanges to their desired values, in each control area. In this paper we will focus on LFC design in a given control area under bilateral structure. The bilateral LFC scheme can be considered similar to the decentralized pluralistic LFC which is defined by Union for the Coordination of Transmission of Electricity (UCTE) in Europe [3].

In the bilateral LFC scheme the power system is considered as a collection of distribution control areas interconnected through high voltage transmission lines or tie-lines. Each control area has its own load frequency controller and is responsible for tracking its own load and honoring tie-line power exchange contracts with its neighbors. Similar to [1], the general theme in our paper is that the loads (the Discos) are responsible for purchasing the services they require.

In a bilateral LFC structure, each distribution area must purchase LFC from one or more Gencos. Control is highly decentralized. Each load matching contract requires a separate control process, yet this control processes must cooperatively interact to maintain system frequency and minimize time error. In this structure, a separate control process exists for each control area. Such a configuration is conceptually shown in Figure 1 for a 3-control area power system. Each control area is interconnected to others either through

Transco or Gencos.

The control areas regulate their frequency by their own controllers. If some control areas perform a control block, in this case a separate controller/operator (block coordinator) coordinates the whole block towards its neighbor blocks/control area by means of its own controller and regulating capacity. The control algorithm for each control area is executed at the Genco end (which here is equipped with a FNN controller), since ultimately the Genco must adjust the governor set-point(s) of its generator(s) for LFC.

In vertically integrated power system structure, it is assumed that each bulk generator unit is equipped with secondary control and frequency regulation requirements, but in an open energy market, generation companies may or may not participate in the LFC problem. Therefore, in a control area including numerous distributed generators with an open access policy and a few LFC participators, comes the need for novel control strategies to maintain the reliability and eliminates the frequency error.

2.2 Control area modeling

Consider a general distribution control area includes N Generator companies that supply the area-load and assume the k th Genco G_k can be able to generate enough power to satisfy necessary participation factor for tracking the load and performing the LFC task, and other Gencos are the main supplier for area-load. The connections of each control area to the rest of power system are considered as disturbances.

Power systems are inherently non-linear. There are different complicated and nonlinear models for power systems. For LFC, however, a simplified and linearized model is usually used. In advanced control strategies (such as the one considered in this paper), the error caused by the simplification and linearization can be considered in respect to their adaptive property. For simplicity, assume that each Genco has one generator. The linearized dynamics of the individual generators are given by:

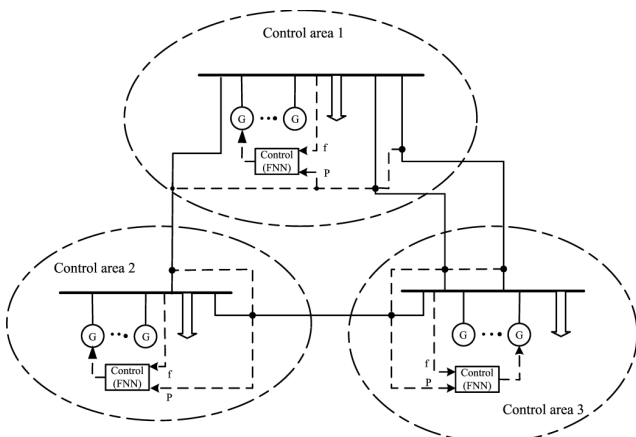


Figure 1 Three control areas

$$\frac{2H_i}{f_0} \frac{d\Delta f_i}{dt} = \Delta P_{Mi} - \Delta P_i - d_i - D_i \Delta f_i; \quad (1)$$

$$\frac{d\Delta \delta_i}{dt} = 2\pi \Delta f_i \quad i = 1, 2, \dots, N$$

where

Δ : Deviation from nominal value,
 H_i : Constant of inertia,
 D_i : Damping constant,
 δ_i : Rotor angle,
 f_0 : Nominal frequency,
 P_{Mi} : Turbine (mechanical) power,
 f_i : Frequency,
 d_i : Disturbance (power quantity).

The generators are equipped with a speed governor. The linear models of speed governors and turbines associated with generators are given by differential equations:

$$\frac{d\Delta P_{Vi}}{dt} = \frac{1}{T_{Hi}} - \Delta P_{Vi} + \frac{K_{Hi}}{T_{Hi}} (\Delta P_{refi} - \frac{1}{R_i} \Delta f_i); \quad i=1, \dots, N \quad (2)$$

$$\frac{d\Delta P_{Mi}}{dt} = \frac{1}{T_{Mi}} \Delta P_{Mi} + \frac{K_{Mi}}{T_{Mi}} \Delta P_{Vi}$$

where

P_{Vi} : Steam valve power,
 R_i : Droop characteristic,
 T_M, T_H : Time constants of turbine and governor,
 K_M, K_H : Gains of turbine and governor,
 P_{refi} : Reference set-point (control input).

The individual generator models are coupled to each other via the control area system. Mathematically, the local state space of each individual generator must be extended to include the system coupling variable, which allows the dynamics at one point on the system transmitted to all other points. The state space model of control area can be obtained as follows [12]:

$$\dot{x} = Ax + Bu + Fw \quad (3)$$

$$y = Cx + Ew \quad (4)$$

where

$$x^T = [X_1 X_2 \dots X_N X_{N+1}], \quad w^T = [\Delta P_L d], \quad u = \Delta P_{refK}$$

$$X_i = [\Delta f_i \Delta P_{Mi} \Delta P_{Vi}]; \quad i = 1, 2, \dots, N$$

$$X_{N+1} = [\Delta \delta_{k1} \Delta \delta_{k2} \dots \Delta \delta_{k(k-1)} \Delta \delta_{k(k+1)} \dots \Delta \delta_{kN} \Delta \delta_k]_{1 \times N}$$

$$C = [C_1 C_2 \dots C_N C_{N+1}], \quad E = [I \theta]$$

$$C_i = [\beta_i \ 0 \ 0], \quad C_{N+1} = [1]_{1 \times N}; \quad i = 1, 2, \dots, N$$

The ΔP_L is the area load demand and d shows the input disturbance vector. The θ is a zero vector with the same size of d .

3. DESIGN METHODOLOGY

3.1 Control strategy

The objective is to formulate the LFC problem in each control area and propose an effective controller based on ANNs. There is a strong relationship between the training of ANNs and adaptive control. Therefore, increasing the flexibility of structure induces a more efficient learning ability in the system, which in turn causes less iteration and better error minimization. To obtain the improved flexibility, teaching signals and other parameters of ANNs (such as connection weights) should be related to each other.

In this paper we use a sigmoid unit function, as a mimic of the prototype unit, to give a flexible structure to the neural network. For this purpose, we introduce a hyperbolic tangential form of the sigmoid unit function, with a parameter that must be learned [22], to fulfill the above-mentioned goal. The overall scheme of the proposed control system for a given control area is shown in Figure 2.

In fact this figure shows the main framework and synthesis strategy for obtaining desired controller. The FNN uses back-propagation algorithm in supervised learning mode. The accuracy and speed of back propagation method is improved using the dynamic neurons. The main idea is to modify connection weights and Sigmoid Functions Parameters (SFPs) in the proposed FNNs-based controller (FNNC) to minimizing the output error (e) signal and improvement system performance. On the other hand, it is desirable to find a set of parameters in the connection weights and SFPs that minimizes the output error signal.

The designed FNNC acts to maintain area frequency and total exchange power close to the scheduled value by sending a corrective signal to the assigned Gencos ($\Delta P_{Ci} = u$). This secondary regulating power signal, weighted by the generator participation factor C_{ij} , is used to modify the set-points of generators. I is an input vector which includes a properly set of output (y), reference (y_d) and control signal (u) in current and previous iteration steps.

The proposed control scheme, shown in Figure 3, uses the demand and frequency changes as input signals. The β_i and λP_i are properly setup coefficient of the secondary regulator. The proposed controller acts to

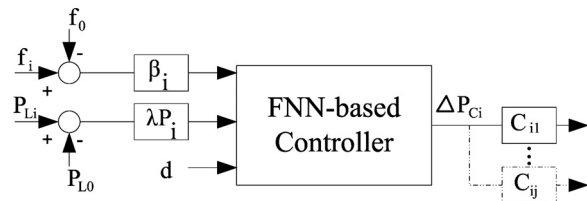


Figure 3 The proposed control scheme

maintain area frequency and total exchange power close to the scheduled value by sending a corrective signal to the assigned Gencos. This signal, weighted by the generator participation factor C_{ij} , is used to modify the set-points of generators. As there are many Gencos in each area, the control signal has to be distributed among them in proportion to their participation in the LFC. Hence, the generator participation factor shows the sharing rate of each participant generator unit in the LFC task. Note that for a given control area i with N Gencos we can write,

$$\sum_{j=1}^N C_{ij} = 1$$

The general structure of FNN-based controller is shown in Figure 4. In this figure, unit functions in the hidden and output layers are flexible functions. The number of hidden layers and units in each layer is entirely dependent on the area control system, and there is no mathematical approach to obtain the optimum number of hidden layers [23], since such selection is generally fall into the application oriented category.

However the number of hidden layers can be chosen based on the training of the network using various configurations. The FNN configuration gives the fewer number of hidden layers and nodes than traditional ANN, which still yield the minimum root-mean-squares (RMS) error quickly and efficiently. Experiences and simulation results showed that using a single hidden layer is sufficient to solve of LFC problem for many control area with different structures.

The equivalent discrete time domain state space of continues models (3) and (4) can be obtained as following forms, respectively:

$$x(k + 1) = Ax(k) + Bu(k) + Fw(k) \tag{5}$$

$$y(k) = Cx(k) + Ew(k) \tag{6}$$

When the FNNC is native, i.e. the network is with random initial weights and SFPs, an erroneous system input $u(k)$ may be produced erroneous output $y(k)$. This output will then be compared with the reference signal $y_d(k)$. The resulting error signal $e(k)$ is used to train the weights and SFPs in the network using the back-propagation algorithm. In fact, the basic concept of the back propagation method of learning is to combine a nonlinear perceptron-like system capable of making decisions with the objective error function and

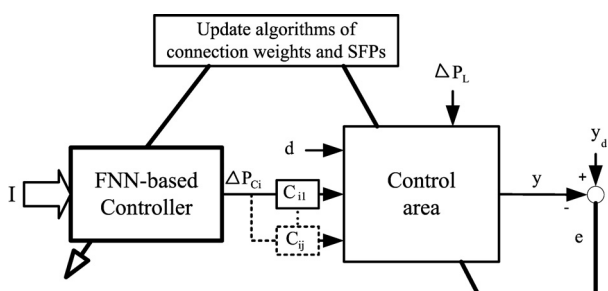


Figure 2 The area controller synthesis framework

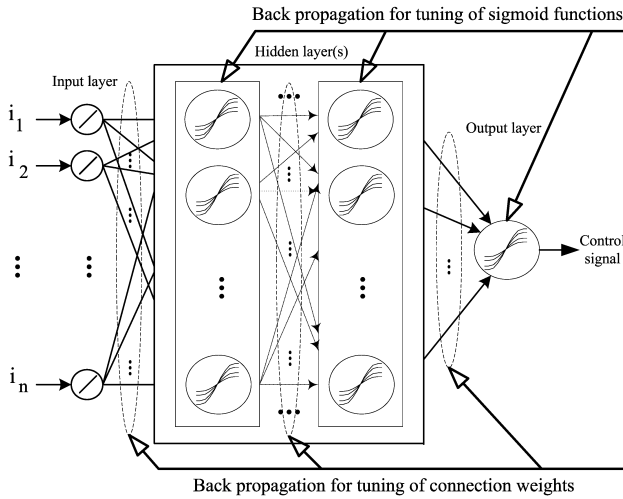


Figure 4 General structure of FNN-based controller

gradient descent method. With repetitive training, the network will learn how to respond correctly to the reference signal input.

As the number of training increases, the network is becoming more and more mature; hence the area control error would be smaller and smaller. However, as it is seen from Figure 4, the back-propagation of error signal cannot be directly used to train the FNNC. In order to properly adjust the weights and SFPs of the network using the back-propagation algorithm, the error in the FNNC output, i.e.

$$\varepsilon(k) = u_d(k) - u(k) \quad (7)$$

where $u_d(k)$ is the desired driving input to the control area, should be known. Since only the system output error

$$e(k) = y_d(k) - y(k) \quad (8)$$

is measurable or available, $\varepsilon(k)$ can only be determined using the following expression,

$$\varepsilon(k) = e(k) \frac{\partial y(k)}{\partial u(k)} \quad (9)$$

where the partial derivative is the Jacobean of the power system. Thus, the application of this scheme requires a thorough knowledge of the Jacobean of the system. For simplicity, instead of (7), we can use the following term:

$$\varepsilon(k) = e(k) \frac{\Delta y(k) - \Delta y(k-1)}{\Delta u(k) - \Delta u(k-1)} \quad (10)$$

This approximation avoids the introduction and training of a neural network emulator, which brings a substantial saving in development time.

The proposed load frequency controller acts as a self-tuning controller, that, it can learn from experience, in the sense that connection weights and SFPs are adjusted

on-line; in other words this controller should produce ever-decreasing tracking errors from sampling by using FNN.

3.2 Neural networks with flexible structure

The FNNC uses the Flexible Sigmoid Function (FSF). Basic concepts and definitions of the introduced FSF were described in [22]. The following hyperbolic tangent function as a sigmoid unit function is considered in hidden and output layers:

$$f(x, a) = \frac{1 - e^{-2xa}}{a(1 + e^{-2xa})} \quad (11)$$

The shape of this bipolar sigmoid function can be altered by changing the parameter α , as shown in Figure 5. It also has the property

$$\lim_{a \rightarrow 0} f(x, a) = x \quad (12)$$

Thus it is proved that the above function becomes linear when $a \rightarrow 0$, while the function becomes nonlinear for large values of a [22]. It should be noted that in this study, the learning parameters are included in the update of connection weights and SFPs.

Generally, the main idea is to present an input pattern, allow the network to compute the output, and compare this to the desired signals representing provided by the supervisor or reference signal. Then, the error is utilized to modify connection weights and SFPs in the network to improve its performance with minimizing the error.

3.2.1 Learning algorithms

The learning process of FNNs for control area i is to minimize the performance function given by:

$$J = \frac{1}{2} (y_{di} - y_i^M)^2 \quad (13)$$

where y_{di} represents the reference signal, y_i^M represents

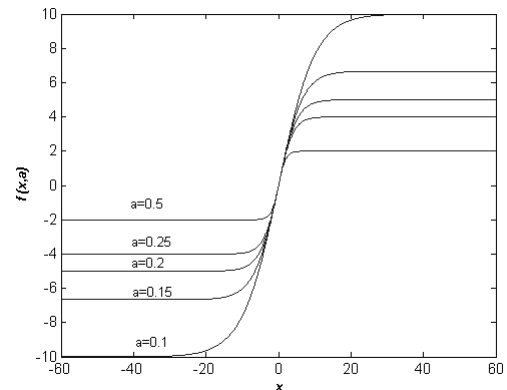


Figure 5 Sigmoid function with changeable shape

the output unit and M denotes the output-layer. It is desirable to find a set of the parameters in the connection weights and SFPs that minimizes the J , considering the same input-output relation between the k th layer and the $(k+1)$ th layer. It is useful to consider how the error varies as a function of any given connection weights and SFPs in the system.

The error function procedure finds the values of all of the connection weights and SFPs that minimize the error function using a gradient descent method. That is, after each pattern has been presented, the error gradient moves toward its minimum for that pattern provided a suitable learning rate.

Learning of SFPs by employing the gradient descent method, the increment of a_i^k denoted by Δa_i^k , can be obtained as,

$$\Delta a_i^k = -\eta_1 \frac{\partial J}{\partial a_i^k} \quad (14)$$

where $\eta_1 > 0$ is a learning rate given by a small positive constant. In the output-layer M , the partial derivative of J with respect to a is described as follows:

$$\frac{\partial J}{\partial a_i^M} = \frac{\partial J}{\partial y_i^M} \frac{\partial y_i^M}{\partial a_i^M} \quad (15)$$

Here, defining

$$\sigma_i^M = -\frac{\partial J}{\partial y_i^M} \quad (16)$$

gives

$$\sigma_i^M = (y_{di} - y_i^M) \quad (17)$$

The next step is to calculate α in the hidden-layer k :

$$\frac{\partial J}{\partial a_i^k} = \frac{\partial J}{\partial y_i^k} \frac{\partial y_i^k}{\partial a_i^k} = \frac{\partial J}{\partial y_i^k} f^*(h_i^k, a_i^k) \quad (18)$$

where h denotes the outputs of the hidden layer, by defining

$$a_i^k = -\frac{\partial J}{\partial y_i^k} \quad (19)$$

we have

$$\begin{aligned} \frac{\partial J}{\partial y_i^k} &= \sum_m \frac{\partial J}{\partial y_m^{k+1}} \frac{\partial y_m^{k+1}}{\partial y_i^k} = -\sum_m \sigma_m^{k+1} \frac{\partial y_m^{k+1}}{\partial h_m^{k+1}} \frac{\partial h_m^{k+1}}{\partial y_i^k} \\ &= -\sum_m \sigma_m^{k+1} \frac{\partial f(h_m^{k+1}, a_m^{k+1})}{\partial h_m^{k+1}} w_{i,m}^{k,k+1} \end{aligned} \quad (20)$$

where

$$a_i^k = \sum_m \sigma_m^{k+1} \frac{\partial f(h_m^{k+1}, a_m^{k+1})}{\partial h_m^{k+1}} w_{i,m}^{k,k+1} \quad (21)$$

Therefore, the learning update equation for a in the output and hidden-layers neurons is obtained, respectively, by

$$a_i^k(t+1) = a_i^k(t) + \eta_1 \sigma_i^k + f^*(h_i^k, a_i^k) + \alpha_1 \Delta a_i^k(t) \quad (22)$$

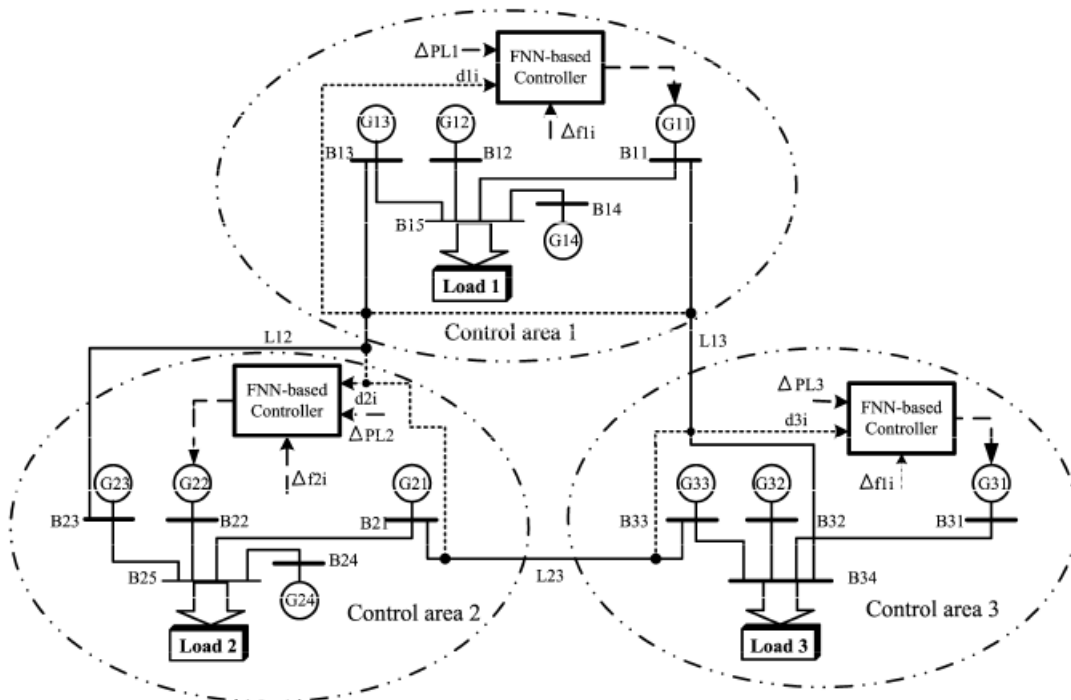


Figure 6 Three control area power system

where $f^*(\dots)$ is defined by $\partial f(\dots, a_i^M) / \partial y_i^M$ in the output layer, $\partial f(\dots, \alpha_i^k) / \partial y_i^k$ in the hidden-layer and α_i is a stabilizing coefficient defined by $0 < \alpha_1 < 1$. For deeper insights in to the subject, the interested reader is referred to [22].

Generally, the learning algorithm of connection weights has been studied with different authors. Here, we simply summarize it as follows:

$$W_{ij}^{k,k-1}(t+1) = W_{ij}^{k,k-1}(t) + \eta_2 \delta_j^k y_j^{k-1} + \alpha_2 \Delta w_{ij}^{k,k-1}(t) \quad (23)$$

where t denotes the t th update time, $\eta_2 > 0$ is a learning rate given by a small positive constant, α_2 is a stabilizing (or momentum) coefficient defined by $0 < \alpha_2 < 1$ and,

$$\delta_j^M = (y_{dj} - y_j^M) f'(h_j^M) \quad (24)$$

$$\delta_j^k = f'(h_j^k) \sum_m \delta_m^{k+1} W_{ij}^{k,k-1} \quad (25)$$

$$f'(h_j^M) = df'(h_j^M) / dh_j^M \quad (26)$$

4. APPLICATION TO A 3-CONTROL AREA

A power system with three control areas under bilateral LFC scheme is shown in Figure 6. Each control area has some Gencos with different parameters and it is assumed that one generator unit with enough capacity is responsible to area load frequency regulation, for example in areas 1 and 3 we have,

$$\begin{aligned} C_{i1} &= 1, \\ C_{ij} &= 0, \quad j \neq 1 \end{aligned} ; \quad i = 1, 2 \quad (27)$$

The control area 1 delivers enough power from G_{11} and firm power from other Gencos to supply its load and support the LFC task. In case of a load disturbance, G_{11} must adjust its output accordingly to track the load changes and maintain the energy balance.

A control area may have a contract with a Genco in other control area. For example, control area 3 buys power from G11 in control area 1 to supply its load. The control areas are connected to neighbor's areas through $L12$, $L13$ and $L23$ interconnection lines. It is assumed that each Genco has one generator unit. The power system parameters are given in [12].

A discrete time domain state space model for each control area can be obtained as given in (5) and (6). Here, the sampling time is chosen in 1 ms. To achieve the LFC objectives the proposed control strategy is applied to each control area as shown in Figure 7.

As can be seen from the block diagram, a multilayer neural network including three layers is constructed. This network has nine units in the input-layer, seven units in the hidden-layer, and one unit in the output-layer. The neural

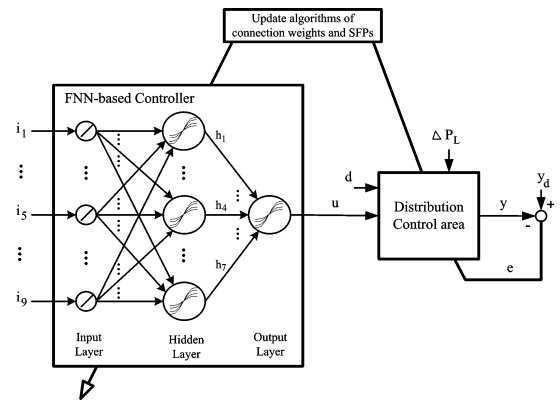


Figure 7 The proposed FNNC for the given control area

network acts as a feed forward controller to supply the plant a correct driving input $u(k)$, which is based on the reference input signal $y_d(k)$, previous system output signals $y(k-1), \dots, y(k-4)$ and control output signals $u(k-1), \dots, u(k-4)$. $y_d(k)$, is the output variable $y(k)$, when the error signal must be equal to zero. Then the input vector of neural network is:

$$I^T(k) = [y_d(k) \quad y(k-1) \quad \dots \quad y(k-4) \quad u(k-1) \quad \dots \quad u(k-4)] \quad (28)$$

h_1, \dots, h_7 are outputs of the hidden-layer, $u(k)$ is the output of the output-layer.

As shown in Figure 7, in the learning process not only the connection weights, but also, the SFPs are adjusted. Adjusting the SFPs causes a change in the shapes of sigmoid functions in turn. The proposed learning algorithm considerably reduces the number of training steps, resulting in a much faster training in comparison to traditional ANNs [22].

For the problem at hand, simulations show that three layers are enough for the proposed FNNC to obtaining desired performance. Increasing the number of layers dose not significantly improve the control performance. In the proposed controller, the input layer uses the linear neurons, while the hidden and output-layers use the bipolar FSFs (11).

5. SIMULATION RESULTS

In order to demonstrate the effectiveness of the proposed strategy, some simulations were carried out. In these simulations, the proposed load frequency controllers were applied to the 3-control area power system described in Figure 6.

In order to project physical constraints during simulation, the linear model of a nonreheating turbine (2) is replaced by a nonlinear model shown in Figure 8. This is to take into account the generating constraint (GRC), i.e. the practical constraint on the response speed of a turbine.

The initial connection weights and initial uniform random number (URN) of sigmoid function unit parameters for each control area are properly chosen. For

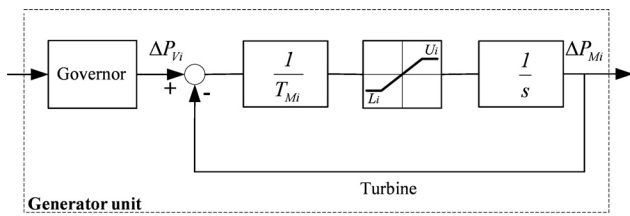


Figure 8 Model of nonlinear generator unit

Table 1 Learning rates and momentum terms for proposed FNN

Learning rates	Momentum terms
$\eta_1 = 0.005$	$\alpha_1 = 0.07$
$\eta_2 = 0.002$	$\alpha_2 = 0.09$

example, a set of suitable learning rates and momentum terms for area 1 are given in Table 1.

Figure 9 demonstrates the closed-loop frequency deviation at Gencos of 3-control area, following a 0.1 pu step load increase in the each control area. The closed-loop system is equipped with traditional neural network (NN) controllers, means their sigmoid unit functions' parameter α_i (18) have been fixed at $\alpha_i = 1$ (non flexible unit functions). It can be seen that at steady-state the frequency at each Genco is back to its nominal value.

Figure 10 shows the same simulation results, using the FNN based controllers. $\Delta f_{ij}, \dots, \Delta f_{ij}$ display the frequency deviation at G_{ij}, \dots, G_{ij} , respectively. At steady-state the frequency in each control area reaches to its nominal value. Simulation results for the control action signals show following a load change, the power is initially coming from all Gencos to respond to the load increase which will result in a frequency drop that is sensed by the speed governors of all machines. But after a few seconds and at steady-state the additional power is coming from participated unit(s) in LFC only and other Gencos do not contribute to the LFC task. Comparing Figures 9 and 10 illustrates the effectiveness and ability of the proposed control design against the traditional NN-based LFC design.

Figure 11 demonstrates the disturbance rejection property of the closed loop system. This figure shows the frequency deviation at Gencos in all control areas, following a step disturbance of 0.1 pu on areas interconnection lines L12, L13 and L23 at $t=15s$.

Finally, the system response is tested in the presence of a random demand load signal. A random load pattern, shown in Figure 12, representing expected area demand load fluctuations, is applied to the control area 1. The frequency deviations at Gencos are shown in the same figure. Figure 12 shows the proposed controller tracks the load fluctuations effectively.

Simultaneous learning of the connection weights and the sigmoid unit function parameters in the proposed method causes an increase in the number of adjustable parameters in comparison with the traditional method, and, the proposed algorithm causes to reduce the sensitivity of

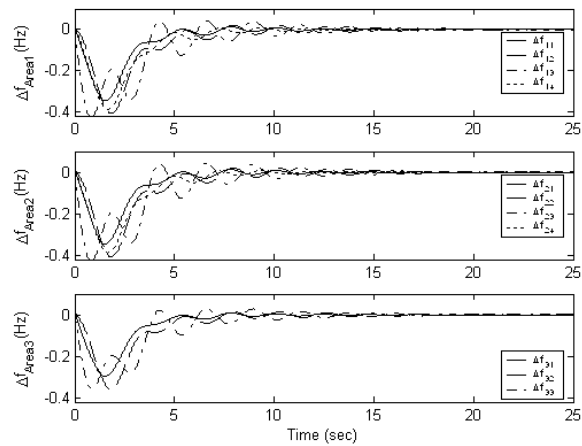


Figure 9 Frequency deviations at Gencos following a 0.1 pu step load increase, using traditional NN-based controllers

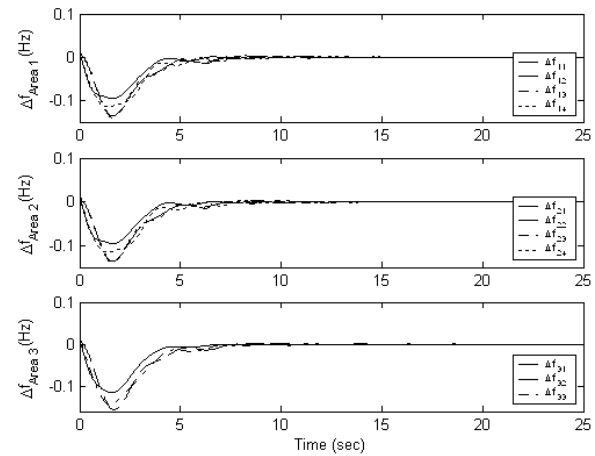


Figure 10 Frequency deviations at Gencos following a 0.1 pu step load, using proposed controllers

artificial neural network (ANN) to the parameters such as connection weights while increasing the sensitivity of ANN to the SFPs. However in the proposed structure, the training of SFPs causes change in the shape of individual sigmoid functions according to input space and reference signal and achieves betterment convergence and performance compare to traditional ANNs.

In summary, it can be recognized from these simulations that the learning parameters of connection weights and SFPs increase the load of learning algorithms with keeping high capability in the training process.

6. CONCLUSION

In this paper a new method for load frequency controller design using flexible neural networks in a restructured power system has been proposed. Design strategy includes enough flexibility to set a desired level of performance.

The proposed control methodology was applied to a 3-control area power system under a bilateral LFC scheme. Simulation results demonstrated the effectiveness of methodology. It has been shown that the suggested FNN load frequency controllers give better ACE minimization

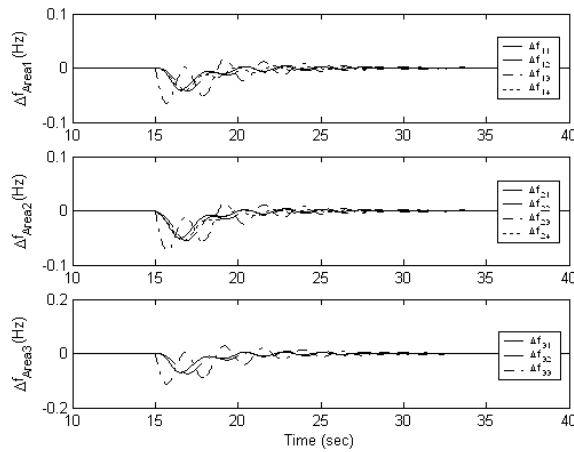


Figure 11 Frequency deviation at Gencos, following a 0.1 pu step disturbance on interconnection lines at $t=15s$

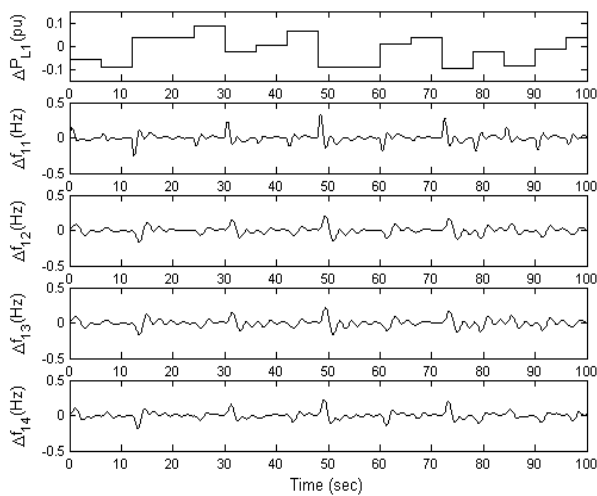


Figure 12 System response to a random demand load; Load pattern and frequency deviations in area 1

and a quick convergence to the desired trajectory in comparison with one based on the traditional ANNs.

ACKNOWLEDGMENT

This work is supported by Japan Society for the Promotion of Science (JSPS) under grant P04346. The preliminary step was supported in part by the West Regional Electric Co. (Iran).

REFERENCES

- 1 Chritie RD, Bose A. Load frequency control issues in power system operation after deregulation. *IEEE Transactions on Power Systems* 1996; 11(3): 1191–1200.
- 2 Meliopoulos APS, Cokkinides GJ, Bakirtzis AG. Load-frequency control service in a deregulated environment. *Decision Support Systems* 1999; 24: 243–250.
- 3 UCPTC Doc. UCPTC rules for the co-ordination of the accounting and the organization of the Load-frequency Con-

trol 1999.

- 4 Roffel B, deBoer WW. Analysis of power and frequency control requirements in view of increased decentralized production and market liberalization. *Control Engineering Practice* 2002; Article in press.
- 5 Kumar J, Hoe NGK, Sheble GB. AGC simulator for price-based operation Part 1: A model. *IEEE Transactions on Power Systems* 1997; 2(12): 527–532.
- 6 Delfino B, Fornari F, Massucco S. Load-frequency control and inadvertent interchange evaluation in restructured power systems. *IEE Proc Gener Transm Distrib* 2002; 149(5): 607–614.
- 7 Feliachi A. Reduced load frequency controller in a deregulated electric power system environment. *Proc of the Conference on Decision & Control* 1997; USA: 3100–3101.
- 8 Bevrani H. Robust load frequency controller in a deregulated environment: A μ -synthesis approach. *Proc of IEEE Int Conf on Control applications* 1999; USA: 616–621.
- 9 Bakken BH, Grande OS. Automatic generation control in a deregulated power system. *IEEE Trans on Power Systems* 1998; 13(4): 1401–1406.
- 10 Bevrani H, Rezaazadeh A, Teshnehlab M. Comparison of existing LFC approaches in deregulated environment. *Proc of 5th IEE Int Conf on Power System Management and Control* 2002; UK: 238–243.
- 11 Donde V, Pai MA, Hiskens IA. Simulation and optimization in a AGC system after deregulation. *IEEE Trans on Power Systems* 2001; 16(3): 481–489.
- 12 Bevrani H, Mitani Y, Tsuji K. On robust load-frequency regulation in a restructured power system. *IEEJ Trans on Power and Energy* 2004; 124(2): 190–198.
- 13 Yu X, Tomsovic K. Application of linear matrix inequalities for load frequency control with communication delays. *IEEE Trans on Power Systems* 2004; 19(3): 1508–1515.
- 14 Bevrani H, Mitani Y, Tsuji K. Robust decentralized load-frequency control using an iterative linear matrix inequalities. *IEE Proc-Gen Transm Distrib* 2004; 151(3): 347–354.
- 15 Feliachi A. On the control of re-structured electric power systems. *Int Journal of Control Automation and Systems* 2005; 3(2): 363–375.
- 16 Bevrani H, Hiyama T. A scenario on market based automatic generation control. *Proc of IEEJ Annual Conf on Power and Energy* 2005; Osaka Japan.
- 17 Zeynelgil HL, Demiroren A, Sengor NS. The application of ANN technique to automatic generation control for multi-area power system. *Electrical Power and Energy Systems* 2002; 24: 345–354.
- 18 Beaufays F, Abdel-Magid Y, Widrow B. Application of neural networks to load-frequency control in power systems. *Neural Networks* 1994; 7(1): 183–194.
- 19 Chaturvedi DK, Satsangi PS, Kalra PK. Load frequency control – a generalized neural network approach. *Electrical Power and Energy Systems* 1999; 21: 405–415.
- 20 Karnavas YL, Papadopoulos DP. AGC for autonomous power system using combined intelligent techniques. *Electric Power Systems Research* 2002; 62: 225–239.
- 21 Djukanovic M, Novicevic M, Sobajic DJ, Pao YP. Conceptual development of optimal load-frequency control using artificial neural networks and fuzzy set theory. *Engineering Intelligent Systems for Electrical Engineering & Communication* 1995; 2: 95–108.
- 22 Teshnehlab M, Watanabe K. *Intelligent control based on flexible neural networks*. Kluwer publishers: 1999.
- 23 Zilouchian A, Jamshidi M. *Intelligent control systems using soft computing methodologies*. CRC Press: 2001.