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A NOVEL APPROACH FOR POWER SYSTEM LOAD FREQUENCY CONTROLLER DESIGN

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Abstract: This paper will demonstrate flexible neural networks application, as a possible solution, to automatic load frequency control problem in a deregulated electric power system environment.

We consider a typical power system in a competitive, distributed control environment with open access organizational structure. With this new structure, the conventional controllers are incapable of obtaining good dynamical performance, then, it comes the need for novel control strategies to maintain the reliability and eliminates the frequency error.

In order to achievement of all proposed design objectives, we have used flexible neural networks with dynamic neurons that have wide ranges of variation. A sample power system is used to illustrate the design method.

I. INTRODUCTION

Any power system has a fundamental control problem of matching real power generation to load plus losses, a problem called Load Frequency Control (LFC) or frequency regulation. The purpose of Load Frequency Control is tracking of load variation while maintaining system frequency and tie line power interchanges close to specified values. Reference [1], give a detailed discussion of LFC.

In this paper, we consider the system as an area that includes separate generation, transmission and distribution companies with an open access policy. In this new structure, each control area has its own generation and transmission network, and distribution company is responsible for tracking its own load and honoring tie-line power exchange contracts with its neighbors by securing as much transmission and generation capacity as needed.

Under current organizations, several notable approaches based on classical, optimal, H^{∞}, μ-synthesis, conventional neural networks and other control theorems have already been proposed [2-13]. [14], discusses several LFC scenarios and issues in power system operation after deregulation.

This paper will demonstrate Flexible Neural Networks (NNs) application to automatic LFC in a deregulated electric power system environment. The application of Artificial Neural Networks (ANNs) in control of complex system has been a subject of extensive studies in the past decade.

As we know, the ANNs are based on the biological nervous systems. Learning algorithms cause the adjustment of the weights so that the controlled system gives the desired response. 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 from of the sigmoid unit function, with a parameter that must be learned, to fulfill the above-mentioned goal.

Following this introduction, the second section gives a description of the ANNs with Flexible Sigmoid Functions (FSFs). The third section demonstrates the design of load

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frequency controller, and simulation results are presented in section 4.

II. NEURAL NETWORKS WITH FLEXIBLE STRUCTURES

A. The Flexible Sigmoid Function

The basic concepts and definitions of the introduced Flexible Sigmoid Function (FSF) were also described in [15]. We consider as a sigmoid unit function, the following hyperbolic tangent function:

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

The shape of this bipolar sigmoid function can be altered by changing the parameter **a**, as shown in Fig. 1. It also has the property

$$\lim_{a\to 0} f(x,a)=\frac{0}{0} \quad (2)$$

So, by making use of the l'Hospital rule, we have

$$\lim_{a\to 0} f(x,a)=x \quad (3)$$

Thus it is proved that the above function becomes linear when $a\to 0$, while the function becomes nonlinear for large values of **a** [16]. It should be noted here that in this study, the learning parameters are included in the update of connection weights and Sigmoid Function Parameters (SFPs).

B. Learning Algorithms

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.

The learning process of FNNs is to minimize the following performance function given by:

$$J=\frac{1}{2}\sum_{i=1}^{n}(y_{di}-y_i^M)^2 \quad (4)$$

Where y_{di} represent reference signal, y_i^M represent output units, M denote output-layer and n is the number of units in 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,

$$\Delta a_i^k=-\eta_1\frac{\partial J}{\partial a_i^k} \quad (5)$$

Where $\eta_1>0$ is a learning rate given by a small positive constant. Now, in the output-layer M, the partial derivative of J with respect to **a** is described as,

$$\frac{\partial J}{\partial a_i^M}=\frac{\partial J}{\partial y_i^M}\frac{\partial y_i^M}{\partial a_i^M} \quad (6)$$

Here, defining

$$\sigma_i^M\equiv-\frac{\partial J}{\partial y_i^M} \quad (7)$$

gives

$$\sigma_i^M=(y_{di}-y_i^M) \quad (8)$$

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

$$\frac{\partial J}{\partial a_i^k}=\frac{\partial J}{\partial y_i^k}\frac{\partial y_i^k}{\partial a_i^k}=\frac{\partial J}{\partial y_i^k}f^*(h_i^k,a_i^k) \quad (9)$$

where h, denotes outputs of hidden layer, and defining

$$a_i^k\equiv-\frac{\partial J}{\partial y_i^M} \quad (10)$$

we have

$$\frac{\partial J}{\partial y_i^k}=\sum_m\frac{\partial J}{\partial y_m^{k+1}}\frac{\partial y_m^{k+1}}{\partial y_i^k}=-\sum_m\sigma_m^{k+1}\frac{\partial y_m^{k+1}}{\partial h_m^{k+1}}\frac{\partial h_m^{k+1}}{\partial y_i^k}$$
$$=-\sum_m\sigma_m^{k+1}\frac{\partial f(h_m^{k+1},a_m^{k+1})}{\partial h_m^{k+1}}w_{i,m}^{k,k+1} \quad (11)$$

Gradually, it follows that

$$a_i^k=\sum_m\sigma_m^{k+1}\frac{\partial f(h_m^{k+1},a_m^{k+1})}{\partial h_m^{k+1}}w_{i,m}^{k,k+1} \quad (12)$$

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

$$a_i^k(t+1)=a_i^k(t)+\eta_1\sigma_i^k f^*(h_i^k,a_i^k)+\alpha_1\Delta a_i^k(t) \quad (13)$$

where $f^*(.,.)$ is defined by $\partial f(.,a_i^M)/\partial y_i^M$ in the output layer, $\partial f(.,a_i^k)/\partial y_i^k$ in the hidden-layer and α_1 is a stabilizing coefficient defined by $0<\alpha_1<1$.

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

$$w_{ij}^{k,k-1}(t+1)=w_{ij}^{k,k-1}(t)+\eta_2\delta_j^k y_j^{k-1}+\alpha_2\Delta w_{ij}^{k,k-1}(t) \quad (14)$$

where

$$\delta_j^M=(y_{dj}-y_j^M)f'(h_j^M) \quad (15)$$

and

$$\delta_j^k=f'(h_j^k)\sum_m\delta_m^{k+1}w_{ij}^{k,k+1} \quad (16)$$

where t denotes t-th update time, $f'(h_j^M) = df'(h_j^M)/dh_j^M$, $\eta_2 > 0$ is a learning rate given by a small positive constant, and α_2 is a stabilizing (or momentum) coefficient defined by $0 < \alpha_2 < 1$.

III. DESIGN METHODOLOGY

A. A Sample System, [5, 9-10]

Based on the new structure, let us consider a simple distribution company and its suppliers as shown in Fig. 2. In this example the distribution comp any (DISCO) buys firm power from one generation company (GENCO 2) and enough power from other generation company (GENCO 1) to supply its load and support the LFC task. Transmission company (TRANSCO 1) delivers power from GENCO 1. TRANSCO 1 is also contracted to deliver power associated with the LFC problem.

In the structure proposed the DISCO are to be responsible for tracking the load and hence performing the load frequency control task by securing as much transmission and generation capacity as needed. Connections of the DISCO to other companies are considered as disturbances (d1).

For simplicity assume that GENCOs 1 and 2 have one generator each. The state space realization of the distribution area as presented in [9], has the following form:

$$\dot{x} = Ax + Bu + Dw \qquad (17)$$

where,
$x^T = [\Delta f_1 \;\; \Delta P_{M1} \;\; \Delta P_{V1} \;\; \Delta\delta_1 - \Delta\delta_2 \;\; \Delta f_2 \;\; \Delta P_{M2} \;\; \Delta P_{V2}]$ a
$w^T = [\Delta P_L \;\; d_1]$; $u = \Delta P_{ref1}$
nd,

Δ : deviation from nominal value
f_0 : nominal frequency
f_i : frequency
δ_i : rotor angle
P_M : turbine (mechanical) power
d_i : disturbance (power quantity).
P_V : steam valve power
P_{refi} : reference set point (control input)

The state-space model is based on equation (17), however it is augmented to include the rotor angle of GENCO 1 since one of objectives of LFC problem is to guarantee that the frequency will return to its nominal value following a step disturbance. Hence, we use the augmented system that its state vector becomes:
$x^T = [\Delta f_1 \;\; \Delta P_{M1} \;\; \Delta P_{V1} \;\; \Delta\delta_1 - \Delta\delta_2 \;\; \Delta f_2 \;\; \Delta P_{M2} \;\; \Delta P_{V2} \;\; \Delta\delta_1]$

B. FNN Based Load Frequency Controller

First, in order to problem formulation, let the output variables be given by the Distribution Company Error (DCE) and its integral. DCE is defined in this paper analogously to the traditional ACE (Area Control Error) by:

$$DCE = \Delta P_1 + \Delta P_2 + \beta_1 \Delta f_1 + \beta_2 \Delta f_2 \qquad (18)$$

where β_i is the frequency response characteristic of unit i. Therefore, the output variables are given by:

$$y = Cx + Gw \qquad (19)$$

where,
$C = [\beta_1 \;\; 0 \;\; 0 \;\; 1 \;\; \beta_2 \;\; 0 \;\; 0 \;\; 1]$; $G = [1 \;\; 0]$.

We now proceed to design a load frequency controller using the neural networks with back-propagation algorithm in supervised learning mode. In order to greatest response and fast activity, we have proposed FNN based load frequency controller with dynamic neurons that have wide ranges of variation. Reference [15], gives a detailed discussion of FNNs. The block diagram of FNN Controller and sample power system as a plant, is shown in fig. 3.

As shown in fig. 3, we have constructed one multilayer neural network, which consist of three layers. This network has nine units in the input-layer, seven units in the hidden-layer, and one unit in the output-layer. The neural 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 plant output signals y(k), y(k-1), ..., y(k-4) and control output signals u(k), u(k-1), ..., u(k-3). $y_d(k)$, is the output variable y(k), when DCE must be equal to zero. Then the input vector of neural network is:

$$I = [i_1 \; i_2 \; \dots \; i_9]' = [y_d(k) \;\; y(k-1) \; \dots \; y(k-4) \;\; u(k) \;\; u(k-1) \; \dots \; u(k-3)]'$$

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

As shown in above figure, in the learning process not only the connection weights, but als o, 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.

In the following simulations, we will show that the plant can be controlled by using only three layers for ANN. Increasing the number of layers dose not significantly improve the control performance. In fact, the number of units required is entirely dependent on the system. For the problem at hand, the FSFs (bipolar) are used in hidden and output-layers, with the form of (1).

The main idea is to modify connection weights and SFPs in the proposed controlled system to minimizing the DCE signal and improvement its performance. On the other hand, it is desirable to find a set of the parameters in the connection weights and SFPs that minimizes the DCE signal.

When the Neural Network Controller (NNC) is native, i.e. the network is with random initial weights and SFPs, an erroneous plant 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. With repetitive training, the network will learn how to response correctly to the reference signal input.

As the number of training increases, the network is becoming more and more mature, hence the power system output error wo uld be smaller and smaller.

However, back-propagation of error signal cannot be directly used to train the NNC. In order to properly adjust the weights and SFPs of the network using the back-propagation algorithm, the error in the NNC output $\in(k) = u_d(k) - u(k)$, where $u_d(k)$ is the desired driving input to the plant, should be known. Since only the system output error $e(k) = y_d(k) - y(k)$ is measurable or available, $\in(k)$ can only be determined using the following expression:

$$\in(k) = e(k)\frac{\partial y(k)}{\partial u(k)} \quad (20)$$

where the partial derivative is the Jacobean of the plant. Thus, the application of this scheme requires a through knowledge of the Jacobean of the plant. For simplicity, insist of (18), we use:

$$\in(k) = e(k)\frac{\Delta\, y(k) - \Delta\, y(k-1)}{\Delta\, u(k) - \Delta\, u(k-1)}. \quad (21)$$

The proposed load frequency controller act 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.

IV. SIMULATION RESULTS

As an example, consider a distribution company as depicted in figure 1. Parameters of selected sample power system and other required data is given in table 1, according to [5,9-10]. It is assumed that the control sampling period is T=5 ms.

The following figures show the simulation results following a 10% load increase in the distribution system by using the conditions given in table 2, and, initial weights and initial Uniform Random Number (URN) of sigmoid function unit parameters that are shown as W1o and W2o.

Fig. 4 shows the distribution control error (or ACE) signal and fig. 5 and 6 compare the closed-loop and open-loop frequency deviations at both GENCOs. At steady state the frequency is back to its nominal value. These figures demonstrate the effectiveness of the proposed design. The simulation results using different input vector, learning rates and momentum terms are given in [16].

$$W1_0 = 10^{-3}\times \begin{bmatrix} 0.7 & 9.7 & -7.8 & 1.8 & 6.4 & -9.1 & 5.7 & 9.5 & -3 \\ -8.8 & -3.8 & 5.3 & -6.8 & 6.9 & -5 & -4.3 & -4.2 & 7 \\ 0.9 & -7.4 & 3.9 & 4.6 & -1.4 & -1.1 & 7.4 & -8.8 & -3.6 \\ -5.2 & -2.6 & 3 & 1.7 & -6 & -7.8 & 8.2 & 5.2 & 2.3 \\ -5.4 & -4.7 & -0.3 & -0.7 & 9.3 & -2.5 & 4.5 & 6.4 & 2.2 \\ -6.6 & -4.5 & -1.8 & 0.6 & -0.7 & -6.8 & 9.9 & 3.6 & 0 \\ 7.5 & -10 & -6.9 & 4.3 & 0 & 6.8 & 1.7 & -7.7 & 7 \end{bmatrix}$$

$$W2_0 = 10^{-3}\times\begin{bmatrix}-1.7 & -6.9 & -1.8 & -9.1 & -1.1 & 7 & -9.7\end{bmatrix},$$

Initial as=URN[0,1].

Table 1: Data for the simulation

Quantity	*GENCO1*	*GENCO2*
Rating (MW)	1000	800
Constant of Inertia: H(sec)	5	5
Damping: D(puMW/Hz)	0.02	0.015
Droop characteristic: R(%)	4	5
Generator's: $T_P = 2H / f_0$	0.2	0.2
Turbine's Time Constant: T_M	0.5	0.5
Governor's Time Constant: T_H	0.2	0.1
Gains: K_M, K_H	1	1
Synchronizing coefficients: T_i	0.2	0.1

Table 2: Learning rates and momentum terms for proposed FNN

Learning rates	η_1=0.0005 η_2=0.0010
Momentum terms	α_1=0.050 α_2=0.070

In 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 compare to traditional ANNs, [12].

Totally, 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. But the proposed algorithm causes to reduce the sensitivity of ANN to the parameters such as connection weights while increasing the sensitivity of ANN to the SFPs.

Simulation results show that Changes in power coming to the distribution company from GENCO 1 and GENCO 2, shows that power is initially coming from both units to respond to the load increase, which will result in a frequency drop that is sensed by the speed governors of both machines. But at steady state the additional power is coming from GENCO 1 only and GENCO 2 does not contribute to the LFC problem solution.

V. CONCLUSION

An approach to load frequency controller for electric power system for a possible structure in a deregulated environment is proposed using the flexible neural networks. The system is modeled as a collection of independent distribution companies supplied by generation companies either directly or trough transmission companies. The distribution companies are responsible for tracking the load and hence they are in charge of the LFC problem. Connections between distribution companies and the rest of the system are taken as disturbances. The methodology presented here can be extended to larger size systems.

A simple test system is given to demonstrate the effectiveness and validity of the proposed approach. It has been shown that the suggested ANN structure of the FNN load frequency controller gives a better ACE minimization and a quick convergence to the desired trajectory in comparison with one based on the traditional ANNs. 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.

Based on extensive simulation results, it is verified that all proposed design objectives are met.

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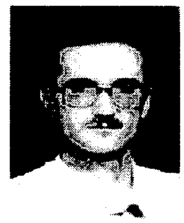
VII. BIOGRAPHY



Hassan Bevrani was born in Iran, on Sept. 1967. He received the B. S. degree in electronic engineering in 1991 and the M. S. degree in control engineering (Hons I) from the K. N. Toosi University of technology (Tehran, Iran) in 1997. His special fields of interest included power electric and power electronic systems analysis, modeling and control. He is the author of more than 15 published technical papers.

He has taught undergraduate courses on circuits, automatic control and power electronic systems. From 1997 to 1999 he was the Research Office manager of West Regional Electric Company and the chairman of West Iranian Association of Electrical & Electronics Engineers. Since 1999, he has been with Kurdistan University (Sanandaj, Iran) as an academic member.

VIII. APPENDIX: FIGURES

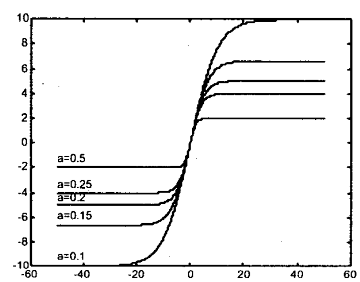


Fig. 1. Sigmoid function with changeable shape

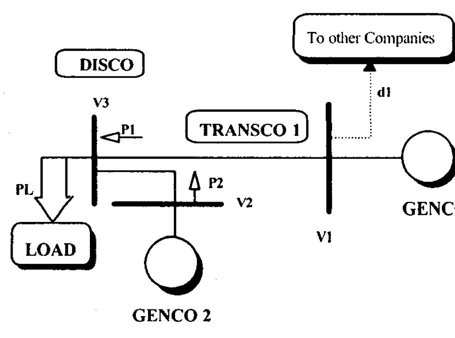


Fig. 2. A distribution company and its suppliers

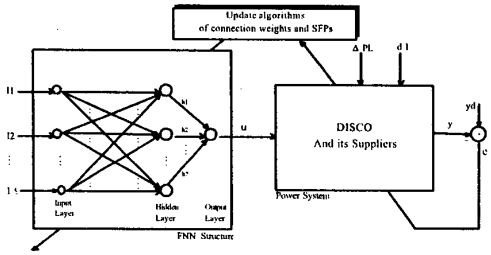


Fig. 3 : The proposed LFC based on FNN

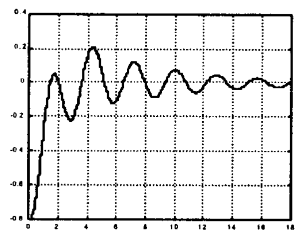
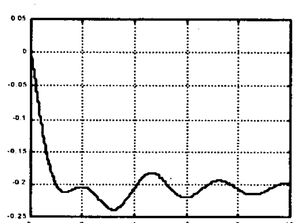
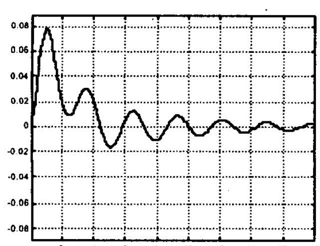


Fig. 4. The area control error (ACE) signal

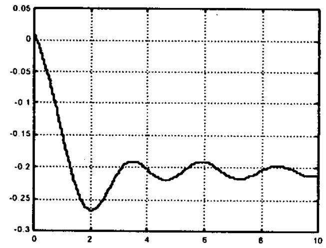


(a)

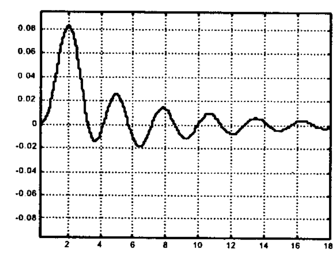


(b)

Fig. 5. Frequency deviation at GENCO 1 following a 10% load increase, (a) Open-loop system; (b) Closed-loop system



(a)



(b)

Fig. 6. Frequency deviation at GENCO 2 following a 10% load increase, (a) Open-loop system; (b) Closed-loop system