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Adaptive Load Frequency Control of Nigerian Hydrothermal System Using Unsupervised and Supervised Learning Neural Networks

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Abstract--**This paper presents a novel load frequency control design approach for a two-area power system that relies on unsupervised and supervised learning neural network structure. Central to this approach is the prediction of the load disturbance of each area at every minute interval that is uniquely assigned to a cluster via unsupervised learning process. The controller feedback gains corresponding to each cluster center are determined using modal control technique. Thereafter, supervised learning neural network (SLNN) is employed to learn the mapping between each cluster center and its feedback gains. A real time load disturbance in either or both areas activates the appropriate SLNN to generate the corresponding feedback gains. The effectiveness of the control framework is evaluated on the Nigerian hydrothermal system. Several far-reaching simulation results obtained from the test system are presented and discussed to highlight the advantages of the proposed approach.**

Index Terms: **Load Frequency Control, Neural Network, Unsupervised Learning, Supervised Learning**

I. INTRODUCTION

T HE load demand on a present-day power system is characterized by continual unknown variations that can adversely impact its dynamical process. For this singular reason, it is desirable to balance generated power with time varying demand whilst allowing system real power losses. For the purpose of management and control, a large power system comprises a number of control areas, which are interconnected by tie lines. The generating units in each control area tend to swing in unionism in respect to a change in the demand on the system and therefore can be represented by a single equivalent generator. The input and output of the equivalent generator is equal to the sum of the inputs and outputs respectively of the constituent generators in the area and its frequency is equal to the frequency on the common bus bar in the area.

Whenever an interconnected power system experiences a change in the demand imposed on it, the frequency of the bus voltages and currents and the inter-area tie line power flow among interconnected areas deviate from their specified values. The share of the total power demand on the whole system carried by the individual generators deviate from their optimum values. The deviations in frequency and inter-area tie line flow are traditionally restored to their scheduled value by a load frequency control (LFC) strategy. In the last the last two decades, LFC has been analyzed using classical linear and optimal control approaches.

In recent years, however, LFC design has gradually shifted to the use of artificial intelligence systems that admit fuzzy control and neural networks [1-6]. What has been clearly established is the fact that the satisfactory dynamic behavior of a power system can no longer be guaranteed by fixed gain controllers over wide operating conditions. In order to ensure well-damped system dynamics over a wide range of operating conditions, it is pertinent to adjust controller gains recursively in accord with on-line information [4].

In view of this, an adaptive neural network based load frequency control scheme is revisited in this paper. It is essentially an improvement on the earlier work by Djoukanovic et al [5]. The parameters monitored on-line in ref. [5] which include power system time constant, synchronizing power coefficient and the frequency bias setting are replaced in this present work by direct monitoring of the area load changes. Relying on the monitored load changes of each area, an adaptive LFC is then constructed via unsupervised and supervised neural networks. The effectiveness of the proposed control approach is reasonably well evaluated via computer simulation of a Nigerian grid system comprising a thermal area interconnected with a hydro area. The simulation results obtained for realistic system parameters and over wide operating conditions are set forth and discussed.

II. SYSTEM MODEL AND STATE EQUATIONS

The Nigerian electric system used as test system is essentially an interconnection of thermal area and hydro area. The two-area system model shown in Fig. 1 therefore, results with the derived equivalent parameters from available base data for each area given in the appendix.

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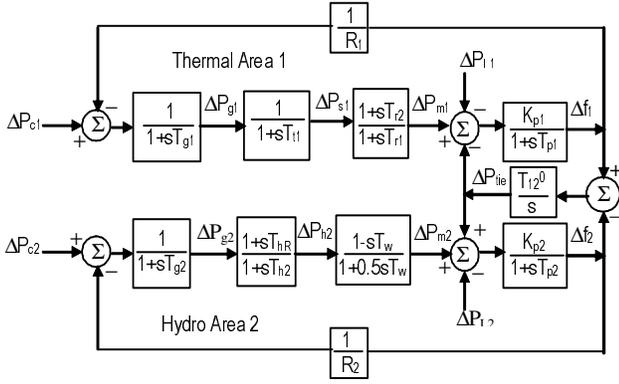
Fig. 1. Nigerian two-area hydrothermal system.

The load frequency control problem at hand is that of maintaining zero steady state deviations of the frequency and tie line flows when either or both areas are subjected to time dependent load changes. For the problem formulation, the state equations for the two-area system are expressed in compact form as follows:

$$\dot{x}(t) = Ax(t) + Bu(t) + Lw(t) \qquad (1)$$

$$y = Cx(t) + v(t)$$

Where

$x(t) = [\Delta f_1, \Delta P_{m1}, \Delta P_{s1}, \Delta P_{v1}, \Delta P_{tie12}, \Delta f_2, \Delta P_{m2}, \Delta P_{h2}, \Delta P_{v2}]^T$

$u(t) = [u_1, u_2]^T = [\Delta P_{c1}, \Delta P_{c2}]^T$

$w(t) = [\Delta P_{L1}, \Delta P_{L2}]^T$

The matrices A, B, C and L are real and appropriately dimensioned whilst w(t) and v(t) are the load disturbance and the measurement/modeling errors, respectively. Pertinent to obtaining solution of the problem is the well-known area control error (ACE) given by:

$$y_i = \Delta P_{tie}(t) + b_i \Delta f_i(t) = ACE_i \qquad i = 1,2 \qquad (2)$$

The discrete form of the state equations is as follows:

$$x(k+1) = Fx(k) + Gu(k) + Dw(k)$$
$$y(k) = Hx(k) + v(k) \qquad (3)$$

Where F, G, and D are derived from A, B and L respectively in the usual manner and H = C.

Computation of LFC Feedback Gains

In reality, the disturbances on a power system are complex and stochastic in nature. Step load disturbances occur only very occasionally as a result of switching on or off of very large loads and sudden loss of a generating unit. The proportional control alone cannot reduce the deviation in the frequency and tie line flow to zero because of the finite disturbance. The disturbance rejection proportional plus integral control strategy can be employed to minimize the effect of the step disturbances. However, the generation of training examples is by the modal control technique (pole

placement) rather than optimal control technique. It has been observed [7] and supported here that optimal control is unsuitable for LFC design because of the selection of one performance index from the many indices required by AGC.

The modal control theory is to ensure that the eigenvalues $\{\lambda_I : i=1,2,3\ldots\ldots n\}$ of the system are placed well in the left half plane by choosing the elements of the feedback gain K. Of course, the poles should be located close to the origin in discrete equations to achieve near dead-beat response. The computational procedure of the feedback gain, well documented in [8-10], has been suppressed to accommodate new information.

III. THE NEURAL NETWORK BASED CONTROL SCHEME

In most control schemes with neural network [11-12], the nonlinear mapping function, g_{net}, is established between the historic input and output, u and y, respectively thus:

$$H(u(t)) = \hat{g}_{net}(H(u(t(t - n \Delta t), y(t - m \Delta t)))$$

$$n = 1, 2, 3, \ldots, N \ \& \ m=0, 1, 2, \ldots, M \qquad (4)$$

The controller is then estimated during the consultation phase via this relation:

$$\hat{u} = \hat{g}_{net}(u, t) \qquad (5)$$

Here, the mapping between area i load change ΔP_{Li} and the elements of the controller feedback gain matrix, K is established thus:

$$H(K) = \hat{g}_{net}(H(\Delta P_{Li})) \qquad (6)$$

Also, the elements of the controller gain matrix are determined as follows.

$$\hat{K} = \hat{g}_{net}(\Delta P_{Li}) \qquad (7)$$

Here, ΔP_{Li} i=1, 2, …, m, are the cluster centers at the end of an unsupervised clustering of the predicted area load demand changes.

A. Neural Network and Supervised Learning Concepts

Artificial neural networks (ANNs) are composed of nonlinear computational elements called neurons operating in parallel. The neurons are interconnected through weights that are obtained by training the ANN so as to produce any desired association between the input space and output space. ANNs are capable of learning complex nonlinear relationship between the input space and the output space. ANN technology is described in detail in several literatures such as [13-14].

Control is basically the determination of inputs that will result in a desired output. The use of neural network involves

the generation of the control action from knowledge of the past input-output pairs and the desired output by learning the relation:

$$u(n) = f\{y_d(n), y(n-1), y(n-2).....y(n-m),$$
$$u(n-1), u(n-2,.....u(n-m)\} \tag{8}$$

A generalized neural network controller with inputs and outputs is shown in Fig. 2.

B. Unsupervised Learning Scheme

The unsupervised learning or self-organization in neural network [15] can be used to discover similarities in data and place similar data into cluster. The first pattern is selected as the center of the first cluster. The next pattern is clustered with the first pattern if its Euclidean distance is less than a threshold called the vigilance parameter. Otherwise it forms the center of another cluster. This process is reiterated until the all input patterns are classified. This algorithm is implemented here on the platform of the modified 'follow the leader' approach of Djoukanovic et al., [15]. This constitutes the learning phase of the neural network LFC to be described further later.
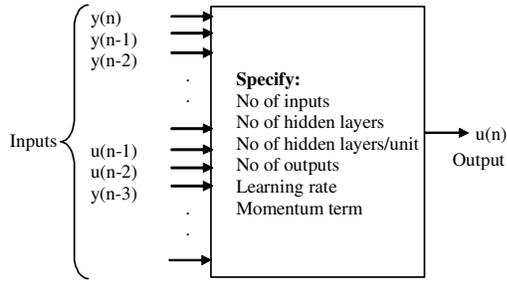

Fig. 2. Generalized neural network controller with inputs and outputs.

IV. DESCRIPTION OF THE PROPOSED CONTROL SCHEME

The proposed control scheme can be considered as comprising the training phase and the consulting phase. The salient steps of the unsupervised learning phase are shown in Fig. 3. In here, predicted load changes in each interconnected power areas are reduced dimensionally by putting them into few clusters using the unsupervised learning process previously highlighted. At the end of clustering process, a supervised learning neural network (SLNN) learns the relationship between each cluster center and the corresponding feedback gains.

The main thrust of consulting phase of the proposed control scheme shown in Fig. 4 is essentially an adaptation of the indirect mode concept of Miodrag et al [16]. This concept is not only suitable for on-line implementation but also the problem of getting new controller for changes in the plant parameters that do not give significant changes in the output is avoided. An unsupervised learning neural network places the monitored input into clusters and, depending on the number, activates one of supervised learning neural networks SLNN that generates the elements of the feedback matrix.

The elements of the controller feedback matrix are determined at different cluster centers corresponding to the different operating conditions using the technique outlined above. SLNN learn the mappings between feedback gains and the monitored input each cluster center.
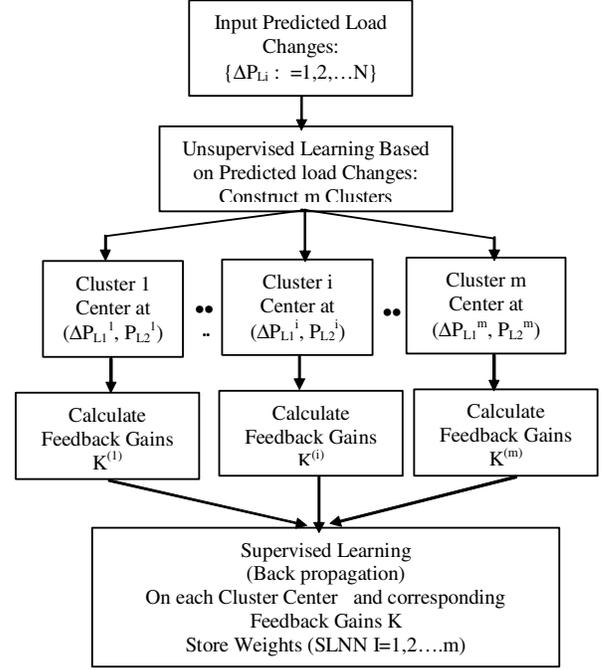

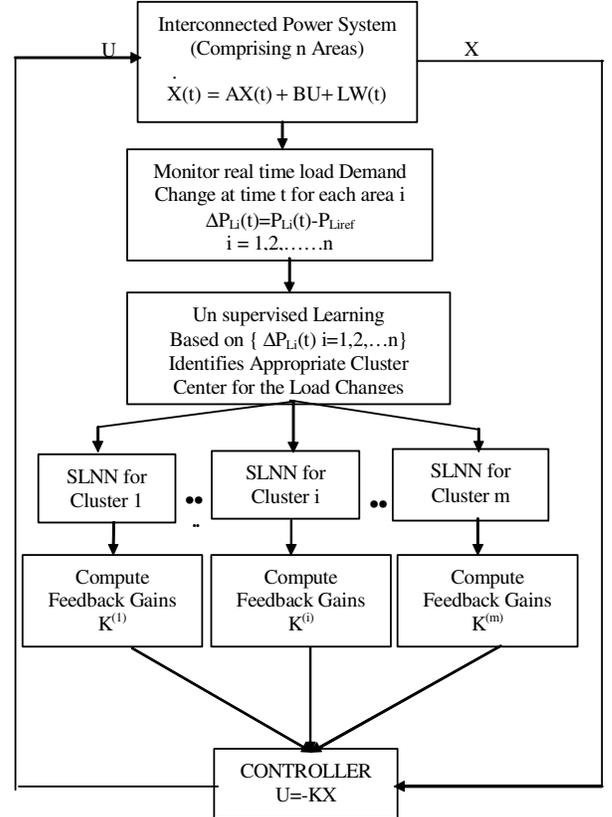Fig. 3. Neural network learning phase algorithmic procedure.

Fig. 4. Block diagram of adaptive neural network load frequency controller.

Characterization of Power System Variable Parameters

As earlier observed, power system is continuously subjected to load changes thus resulting in wide operating points. In load frequency control studies, time constants, bias, tie-line synchronizing coefficients and damping coefficients are subject to changes due load variations. Most existing work on neural networks and fuzzy controllers [3-6, 17] considered the aforementioned parameters. The significant departure of this work lies in the use of the predicted load demand changes to capture the effects of the changing system parameters.

The following linear relation reasonably approximates [10] the stiffness of an ith power system area.

$$D_i = \alpha P_{Ti} - \beta P_{Li}$$
(10)

Where P_{Ti} is the area turbine capacity and P_{Li} is the load of the area; α and β are constants to be determined from the knowledge of the area's load behavior. The system parameters that change with respect to the operating points are as follows:

$$M_i = \frac{G_i H_i}{120f}; \qquad K_{pi} = \frac{1}{D_i}; \qquad T_{pi} = \frac{M_i}{D_i} \&$$

$$T_{tie}^0 = \frac{2\pi V_i V_j}{x_{ij}} \cos(\delta_i^0 - \delta_j^0)$$
(11)

The parameters defined in (11) can easily be computed from the knowledge of the power system operating state as well as the coefficients of the system equations that depend on them.

V. Test System And Case Study

The test system used in this work is a two-area system comprising a hydro area and thermal area. This is representative of the aggregate thermal and hydro generations of the Nigerian power system. The base case system parameters used in the simulations are given in Table I. The load disturbances of each area are predicted at one-minute interval for about 50 minutes. The predicted load changes are depicted in Fig. 5. An unsupervised learning process with vigilance parameter of 0.3 partitions the predicted loads into six clusters. The six cluster centers are shown in Table II.

Using the parameters of Table 1, the coefficients of the system matrices are calculated for each of the cluster centers. A set of controller feedback gain is calculated for the load condition in each cluster center. A supervised learning neural network learns the relation between the cluster centers and their respective feedback gains. A supervised learning neural network with 2-input nodes, 20-hidden nodes and 10-output nodes learn the relation between each cluster center and its K. These feedback gains are generated whenever the conditions on the power system are such as to be classified into that cluster.

TABLE I
PARAMETERS OF THE TEST SYSTEM

Areas	Parameters – Base 3000 MVA
Thermal (1)	T_{g1}=0.59s; T_{t1}=0.4s; T_{R1}=8s; T_{R2}=3.2s; R_1=2.6Hz/pu MW K_{p1}=130Hz/pu MW; H_1=6.5s & T_{tie}^0 = 0.245 B_1=.425
Hydro (2)	T_{g2}=0.51s; T_{hR}=10 s; T_{h2}=50s; T_w=1.7s;R_2=2.24Hz/pu MW; K_{p2}=112Hz/pu MW & H_2=8s; B_2=.425

TABLE II
PARAMETERS OF THE TEST SYSTEM CLUSTER CENTERS AND THEIR FEEDBACK GAINS

| Cluster No.	Cluster Center		Feedback Gains K
	ΔP_{L1}	ΔP_{L1}	
1	0.09	0.04	.12,.34,.22,.35,-.56,.01,.25,.01,.15 .11, .28,.24,.25,-.46,.02,.34,.02,.18
2	0.06	0.03	.12,.31,.22,.32,-.54,.01,.24,.01,.16 .11, .27,.22,.26,-.48,.01,.32,.02,.17
3	0.10	0.01	.11,.34,.22,.35,-.56,.01,.25,.01,.15 .11, .28,.24,.25,-.46,.02,.34,.02,.18
4	0.06	-0.01	.12,.32,.21,.32,-.59,.07,.22,.01,.14 .11, .28,.24,.22,-.42,.02,.32,.02,.16
5	-0.03	-0.07	.12,.34,.22,.32,-.56,.04,.25,.05,.17 .11, .23,.24,.21,-.46,.02,.32,.02,.19
6	0.02	-0.03	.12,.32,.22,.35,-.56,.01,.25,.01,.151 .11, .23,.27,.22,-.44,.05,.32,.02,.17
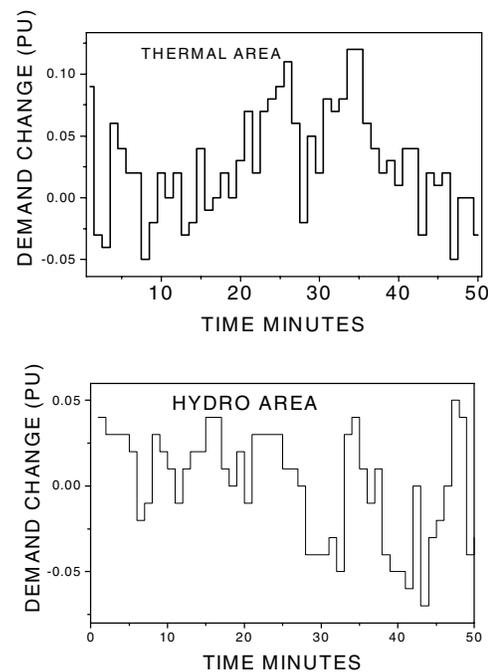
Fig. 5. Predicted load changes in the two areas.

VI. Simulation Results

The frequency error, tie line power error and area control error of the two areas for an uncontrolled system is shown in Figs. 6, 7 and 8 respectively. The effectiveness of the (P+I) control in reducing the errors to zero is shown in Figs. 9, 10 and 11 for a load change of 0.1 p.u in area 1. The

performance of the neural network based LFC has been evaluated by considering simultaneous load changes of simultaneous actual load changes of $\Delta P_{L1} = 0.05$ and $\Delta P_{12} = 0.04$ which falls in the second cluster with cluster center $\Delta P_{L1} = 0.06$ and $\Delta P_{12} = 0.03$. The response curves obtained with neural network based LFC are shown in Figs. 12, 13 and 14. Several other simulation studies were carried out for all the cluster centers and the results obtained are summarized in Table III for an optimal controller, fixed proportional plus integral controller and the proposed neural based LFC with a common performance index used to facilitate comparison.
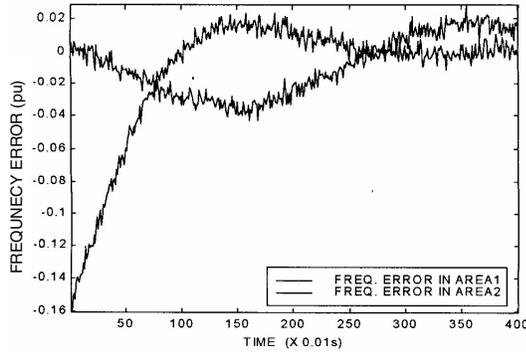

Fig. 6. Frequency error in area 1 and area 2 for an uncontrolled system.
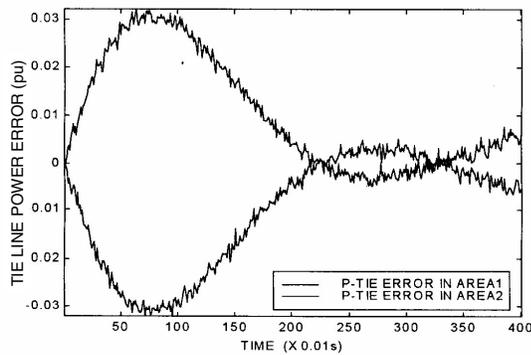

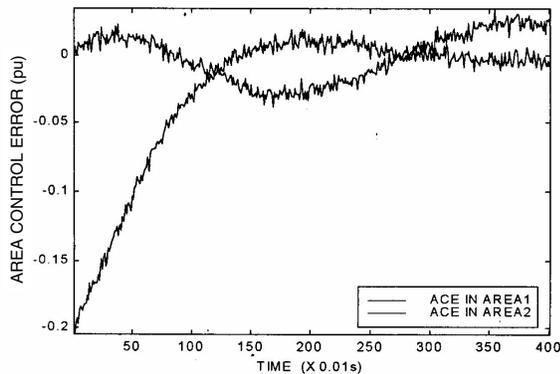Fig. 7. Tie line power error in area 1 and area 2 for an uncontrolled system.

Fig. 8. Area control error in area 1 and area 2 for an uncontrolled system.

It is clear that whenever the load disturbance on a power system changes, entire system matrices change. Therefore fixed controllers are not ideal for power system control. The ideal thing is to have a set of controller gains for each load disturbance, which is practically realizable.
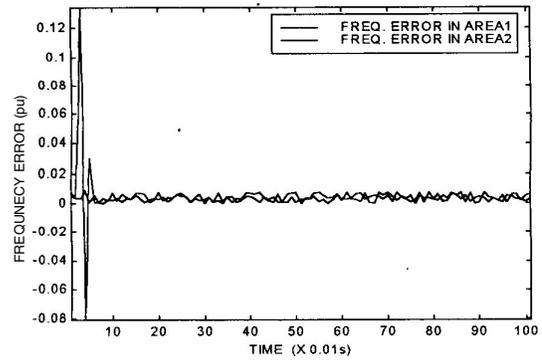

Fig. 9. Frequency error in area 1 and area 2 for a PI controlled system with 0.1 pu load change in area 1 only.
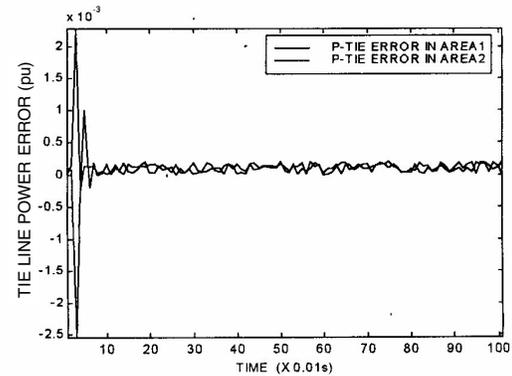

Fig. 10. Tie line power error in area 1 and area 2 for a PI controlled system with 0.1 pu load change in area 1 only.
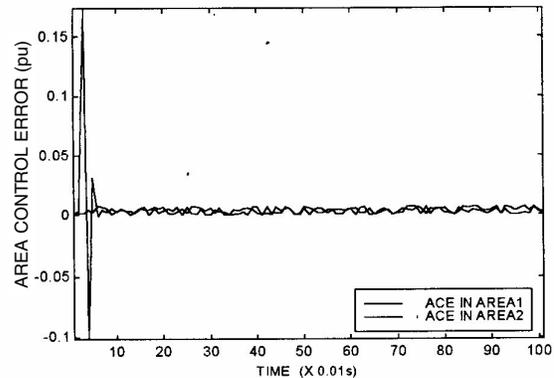

Fig. 11. Area control error in area 1 and area 2 for a PI controlled system with 0.1 pu load change in area 1 only.
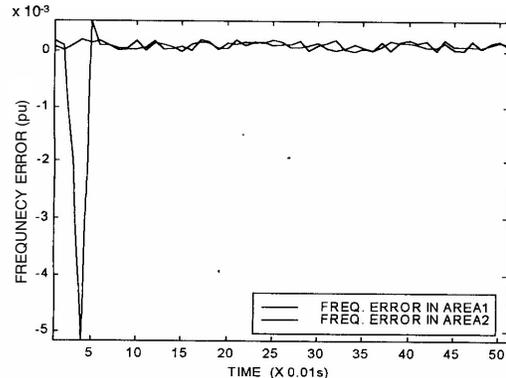

Fig. 12. Frequency error in area 1 and area 2 for neuro-controlled system with 0.05 pu load change in area 1 and 0.04 pu load change in area 2.
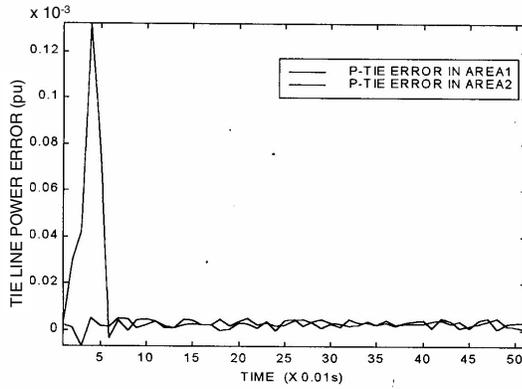
Fig. 13. Tie line power error in area 1 and area 2 for neuro-controlled system with 0.05 pu load change in area 1 and 0.04 pu load change in area 2.
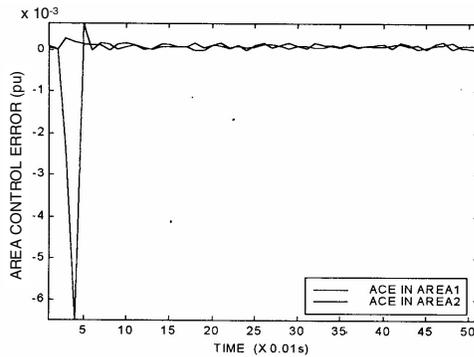

Fig. 14. Area control error (ACE) in area 1 and area 2 for neuro-controlled system with 0.05 pu load change in area 1 and 0.04 pu load change in area 2.

TABLE III
COMPARISON OF PERFORMANCE INDEX FOR THREE DESIGN TECHNIQUES

Cluster Centers	Optimal Controller $x10^2$	P+I Controller $x10^2$	Neural Based Controller $x10^2$
1	1.34	1.64	1.32
2	1.43	1.76	1.37
3	1.56	1.86	1.42
4	1.24	1.36	1.24
5	1.28	1.38	1.28
6	1.26	1.45	1.32

VII. CONCLUSION

In this paper, an adaptive neural network based load frequency control system design has been presented in which load disturbance with great similarities are represented by one load disturbance using an unsupervised neural network. Controller gains are obtained for this representative disturbance. In all, the technique presented here in which an unsupervised learning process partitions the stochastic load disturbances into several cluster and different sets of feedback gains generated for each cluster center performed better than fixed feedback gain controllers.

VIII. APPENDIX

Definitions of symbols used in the paper are given below.

i = Subscript referring to area i
Δf_i = Frequency deviation of area i;
ΔP_{ci} = Change in speed changer setting of area i;
H_i = Inertia constant of area i;
R_i = Aggregate speed regulation of area i;
D_i = Load frequency characteristics of area i ($K_{pi}=1/D_i$, $T_{pi}=2H_i/f D_i$);
T_{gi} = Governor time constant of area i;
T_w = Water time constant of hydro area;
T_{12}^0 = Synchronizing power coefficient (pu) ($T_{12}^0 = 2\pi V_1 V_2 \cos(\delta_1^0 - \delta_2^0)/X_{12}$)
T_{t1} = Thermal area turbine time constant
T_{r1} = Thermal area Reheat time constant
T_{hR} and T_{h2} = Hydro area time constants
δ_i^0 = Operating voltage of area i
V_i = nominal voltage of area I
X_{12} = Tie-line equivalent reactance (pu) between areas 1 & 2

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