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CPS Compliant Fuzzy Neural Network Load Frequency Control

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Abstract—**Power systems are characterized by non-linearity and uncertainty. A neural network predictive fuzzy control is proposed for load frequency control. Recurrent neural network is employed to forecast controller and system's future output, based on the current Area Control Error (ACE) and the predicted change-of-ACE. The Control Performance Standard (CPS) criterion is introduced into the fuzzy controller design, thus improves the dynamic quality of system. Simulations on a two-area power system that takes into account load disturbance demonstrate the effectiveness of the proposed methodologies.**

I. Introduction

MODERN power systems are normally composed of interconnected subsystems or control areas. The constant change of load in a given power system can affect the system frequency. Controlling of the power system frequency within a certain scope is realized through maintaining the total power input of the parallel operation unit equal to the effective power consumption of the system load. The process is known as the power grid load frequency control(LFC).

The tie-line bias control of power system has been achieved using conventional PI control considering Area Control Error (ACE). As the frequency and tie-power deviate from the scheduled values, accumulations of time error and inadvertent interchange may occur.

Paper [1] deals with discrete-time automatic generation control(AGC) of an interconnected reheat thermal system considering a new area control error (ACEN) based on tie-power deviation, frequency deviation, time error and inadvertent interchange. This controller can effectively regulate time error ξ and inadvertent interchange accumulations I. However, it did not consider the generation rate constraint (GRC) and the nonlinear effect of dead zone.

The inherent non-linearity in system components and synchronous machines has led researchers to consider artificial neural network(ANN) and fuzzy logic techniques to build a non-linear controller with high efficiency. In [2], a feed forward neural network has been trained by back propagation-through-time algorithm to control the steam turbine admission valve. The ANN based controller on a four area interconnected system which consists of reheat turbines and generation constraints has been studied in [3]. The inputs of the proposed ANN controller are system state variables and disturbance vector. Back propagation-through-time algorithm has been used to cope with the continuous time dynamics as the learning rule.

In using neural networks for dynamic power system control, since it contains large number of parallel input vector, the total system may be too complicated. Paper [4] initially designed a fuzzy logic controller for automatic generation control. The results show advantages over classical integral controller. Paper [5] presented fuzzy gain scheduling PI controllers. This scheme has been designed for a four area interconnected power system with control dead zone and generation rate constraints. Paper [6] developed a combined fuzzy logic, GA and ANN based controller for LFC. A multi layered feed-forward neural network with inputs from GA based fuzzy controller trained by back propagation has been used to develop the proposed controller.

Control Performance Criteria (CPC) has been formerly used to evaluate AGC performance. This has been difficult to meet the requirements of today's high power quality control. The Control Performance Standard (CPS) is specifically designed to comply with the performance standards imposed by the North American Electric Reliability Council (NERC) for equitable operation of an interconnected system. Fuzzy logic system is usually designed to assure that the control performance is in compliance with NERC's control performance standards [7].

Considering the power system load frequency control, this paper establishes a recurrent neural network model to predict the future frequency of the target object, thus forecasting the ACE and the CPS standard index. Based on this prediction, the optimized controller is designed, which follows the CPS performance standards through the fuzzy logic. Simulation results show the effectiveness of the proposed method.

II. Interconnected Electrical Power Systems

Interconnected power systems consist of many control areas connected by tie-lines. The block scheme of a two-area power system is shown in Fig. 1. T_g , T_t and T_p represents the time constant of the governor, the time constant of the turbine and the time constant of the power system respectively. R_i (hereinafter area i = 1, i = 2) is the governor speed regulation parameter; β_i is the frequency bias; K_p is

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the power system gain; ΔP_{gi} is the incremental generation change; ΔX_{ei} is the incremental change for the position of the governor valve; ΔP_{ci} is the incremental change of the governor; U_i is the output value of the controller; dPL_i is the local demand; df_i is the frequency deviation from nominal value; dP_{tie} is the error in schedule tie flow; T12 is the synchronizing coefficient between 1st and 2nd Area.

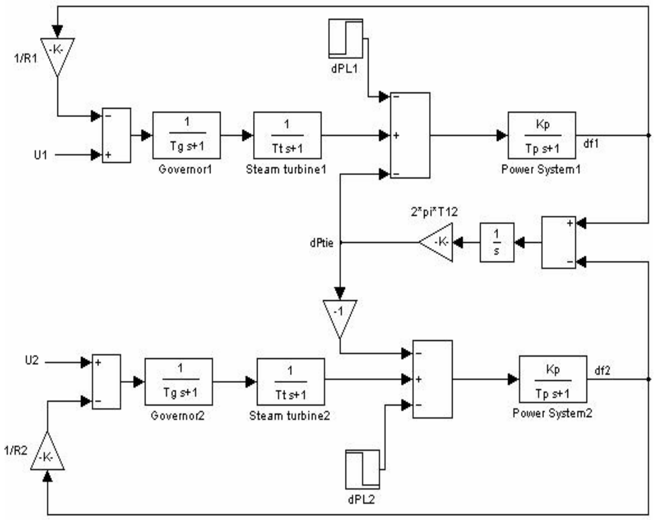

Fig. 1.The block scheme of a two-area power system

The overall system can be modeled as a multi-variable system in the following form:

$$\dot{X} = AX + BU + F\Delta P_d \quad X(0) = 0 \qquad (1)$$

where A is the system matrix, B and F are input and disturbance distribution matrices, x(t), u(t) and d(t) are state, control and load changes disturbance vectors, respectively. $X=[X_1, X_2]^T$, $U=[U_1, U_2]^T$, $\Delta P_d=[\Delta P_{d1}, \Delta P_{d2}]^T$; X_i, U_i and ΔP_{di} represent state variable vector, control variable vector and disturbance load vector of the 1st or 2nd subsystem respectively.

$$X_i=[\Delta f_i, \Delta P_{gi}, \Delta P_{ci}, \Delta X_{ei}, \Delta P_{tiei}, \int ACE_i dt, \int ACEN_i dt, ACEN_i]^T$$

The output of the system is based on ACEN:

$$Y=\begin{bmatrix} Y1 \\ Y2 \end{bmatrix}=\begin{bmatrix} ACEN_1 \\ ACEN_2 \end{bmatrix}=CX \qquad (2)$$

in which $ACEN_i=ACE_i+\gamma_i \int ACE_i dt$, $ACE_i=\Delta P_{tie}+\beta_i \Delta f_i$.

In the existing literature, since a normally operated power system is only exposed to small change in the vicinity of the load demand, the above linearised model is usually used to express the dynamic behavior of the system around the operating point. However, when a sudden large change in the load demand occurs by deregulated operations, frequent on–off controls of large capacity load units may cause large amount of overshoot or long-lasting oscillation on the valve position of the governor [4].The nonlinearity of the systematical model mainly exists in:

1) The impact of the generator rate constraints on LFC. This constraint is to avoid damage to the equipment as a result of excessive changes of the variables such as temperature and pressure.

2) The influence of the governor dead zone on LFC.

III. THE NEURAL NETWORK FUZZY CONTROL

In the control scheme, neural network is chosen to create the real-time dynamic model of the power system. In accordance with the current controller output u(r), the tie-line power deviation dPtie(r) and the frequency deviation df(r), the neural network is used to predict the next moment's frequency deviation df (r+1), thus calculate the ACE, the ACEN as well as CPS. The predicted CPS1 and CPS2 are used as input variables to the fuzzy controller that offers optimal PI parameters.

A. The recurrent neural network LFC model

Elman network is a typical dynamic recurrent neural network. Its feedback consists of a group of connected modules and is used to record the implicit memory. Meanwhile, the feedback, along with the network input, acts as the import to hidden units in the next moment. This nature renders recurrent neural network with dynamic memory and thus the capacity to predict future output, which is quite fitful to power system load frequency control.

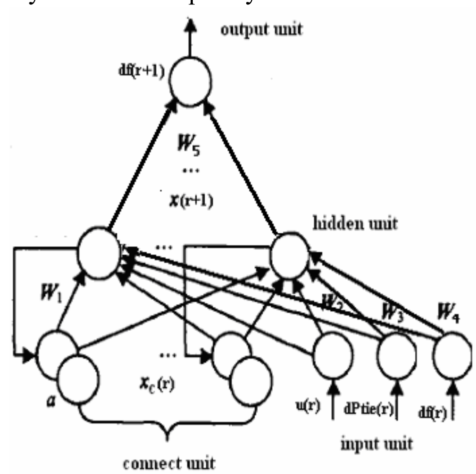

Fig. 2.The Elman neural network structure in the load frequent control

The network structure is shown in Fig. 2. $\alpha(0\leq\alpha\leq1)$ is the feedback link gain. The external inputs to the network are the fuzzy controller output $u(r)\in\mathbf{R}$, the tie-line power deviation $dPtie(r)\in\mathbf{R}$ and frequency deviation $df(r)\in\mathbf{R}$. The network output is the predicted frequency deviation for the next moment $df(r+1)\in\mathbf{R}$, in which r is the sampling instant. Let the hidden layer output be $x(r+1)\in\mathbf{R}^5$, then:

$$x(r+1)=f(W_1 x_c(r)+W_2 u(r)+W_3 dPtie(r)+W_4 df(r))$$
$$x_c(r)=x(r)+\alpha x_c(r-1) \quad (3)$$
$$df(r+1)=g(W_5 x(r+1))$$

where W1, W2, W3, W4 and W5 are the weight matrix of connected units to the hidden units, input units to hidden units and hidden units to the output unit respectively. f (•) and g (•) are the non-linear vector function of the activation function of the hidden layer neural cell and output layer neural cell; $x_c(r+1)$ represents the state at r+1 moment. Here, x(r+1) is the total state of the power system dynamic. Genetic algorithm is used to train the feed-forward and the feedback connection weights.

In this way, the connection weights will be in a binary encoded string form. Assume that the connection weights have the right to pre-define the scope of the changes. The relationship between the network connection weights and the actual weights could be expressed as:

$$w_t(i,j,m,k)=w_{min}(i,j,m,k)+\frac{(w_t(i,j,m,k))_2}{2^1-1}\bullet [w_{max}(i,j,m,k)-w_{min}(i,j,m,k)] \quad (4)$$

where t represents sampling time; k represents the number of learning times; $[w_{max}(i,j,m,k),w_{min}(i,j,m,k)]$ is the changing scope of these connection weights; $w_t(i,j,m,k)$ represents the connection weight between the ith neuron of the (m-1)th layer to the jth neuron of the (m)th layer at that sampling time t; $(w_t(i,j,m,k))_2$ represents the corresponding binary strings of $w_t(i,j,m,k)$.

The optimizing genetic algorithm can be summarized as:

(1) Generate a set of randomly binary strings, each string represents a collection of all network collection weights.

(2) Translate the binary strings into network connection weights according to (4), and evaluate the performance by running the network. Make the individual choice of the network according to the following probability expression:

$$P_s=\frac{f_{il}}{\sum_{i=1}^{N} f_{il}} \quad (5)$$

where P_s is the selection probability; f_{il} represents adapter value of using one bit of binary code in individual i. Here the adapter value is the countdown of the quadratic square of the difference between the network output and the actual output. Obviously, the greater the adapter value is, the greater the genetic probability is. For the selected network, make crossover and mutation under pre-determined value of the probability P_c and P_m to generate the next network.

Repeat equation (4) and (5) until the difference between the network output and the desired value reaches the required condition. At this time, decode the optimal individuals in the finalized group to find out the network connection properties.

B. Fuzzy logic design based on CPS optimization

1) CPS performance standard

For equitable operation of the interconnected system, control areas have to comply with the North American Electric Reliability Council control performance standards CPS1 and CPS2, which were adopted in February 1997. CPS1 assesses the impact of ACE on frequency over a certain period window or horizon and it is defined as follows: over a sliding period, the average of the “clock-minute averages” of a control area’s ACE divided by “10 times its area frequency bias” times the corresponding “clock-minute averages of the interconnection frequency error” shall be less than the square of a given constant, ε_1, representing a target frequency bound. This is expressed by:

$$AVG_{period}\left\| \frac{ACE_i}{-10\beta_i} \right|_1 \times \Delta f_1| = \varepsilon_1^2 \qquad \Delta f=f_a-f_s \quad (6)$$

where Δf_1 is the interconnection frequency error, β_i the frequency bias of the ith control area, ε_1 the targeted frequency bound for CPS1 and $\left| \; \right|_1$ is the clock-1-min average.

To calculate CPS1 (K_{CPS1}), a compliance factor (K_{CF}) is defined as:

$$K_{CF}=\frac{\sum \left\| \frac{ACE_i}{-10\beta_i} \right|_1 \times \Delta f_1|}{n\varepsilon_1^2} \quad (7)$$

CPS1 is then obtained from the following equation:

$$K_{CPS1}=(2-K_{CF})\times 100\% \quad (8)$$

Thus,

1) When $K_{CPS1} \geq 200\%$, which means $K_{CF} \leq 0$, there is $\sum(ACE_1 \times \Delta f_1) \leq 0$. Under this condition, ACE facilitates the frequency quality.

2) When $100\% \leq K_{CPS1} < 200\%$, which means $0 < K_{CF} \leq 1$, there is $0 \leq \sum \left\| \frac{ACE_i}{-10\beta_i} \right|_1 \times \Delta f_1| \leq n\varepsilon_1^2$. The CPS1 standard is satisfied.

3) When $K_{CPS1} < 100\%$, which means $K_{CF} > 1$, there is $\sum \left\| \frac{ACE_i}{-10\beta_i} \right|_1 \times \Delta f_1| > n\varepsilon_1^2$. ACE has exceeded the permitted range so that it has a bad effect on the frequency and quality of power grid.

The second performance standard, CPS2 (K_{CPS2}), limits the magnitude of short-term ACE values. It requires the 10-min averages of a control area’s ACE be less than a given constant (L_{10}), as in the equation below:

$$AVG_{10min}(ACE_i) \le L_{10} \tag{9}$$

Where, $L_{10}=1.65\varepsilon_{10}\sqrt{(-10\beta_i)(-10\beta_s)}$. Note that β_s is the summation of the frequency bias settings of all control areas in the considered interconnection, and ε_{10} is the target frequency bound for CPS2. To comply with this standard, each control area must have its compliance no less than 90%. A compliance percentage is calculated from the following equation:

$$K_{CPS2}=\frac{AVG_{10min}(ACE_i)}{L_{10}} \tag{10}$$

In order to meet the requirements of the power grid frequency quality, the average ACE value during 10 min in each control region should be in the normal distribution as:

$$\sigma=\varepsilon_{10}\sqrt{(-10\beta_i)(-10\beta_s)}\ . \tag{11}$$

2) Optimization rules based on CPS standards

Suppose $CPS1 \ge 100\%$ and $CPS2 \ge 90\%$ to be the goal of the AGC control strategy. Table 1 shows AGC optimization rules based on CPS

TABLE I AGC OPTIMIZATION RULES BASED ON CPS

condition		The state of AGC units
$CPS1 \ge 100\%$ and $CPS2 \ge 90\%$		No optimization adjusting
$CPS1 < 100\%$ and $CPS2 \ge 90\%$	$ACE \times \Delta f > 0$	optimization adjusting
	$ACE \times \Delta f < 0$	No optimization adjusting
$CPS1 \ge 100\%$ and $CPS2 < 90\%$		optimization adjusting
$CPS1 < 100\%$ $CPS2 < 90\%$		optimization adjusting

3) Fuzzy PI controller based on CPS

Fuzzy logic rules are designed to manipulate the conventional PI-type load frequency control. The proposed control structure is shown in Fig.3. The controller uses information that reflects compliance with CPS1 and CPS2 as the inputs to the fuzzy logic rules. Parameters Kp and Ki are fuzzy rule outputs.

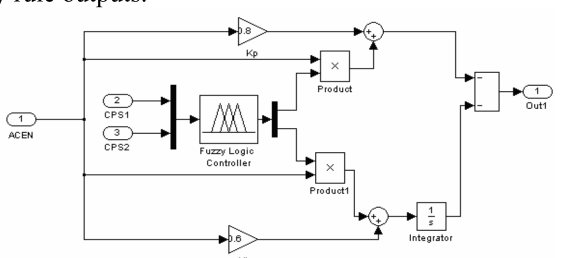

Fig. 3.Fuzzy PI controller for CPS

According to the optimized rules from the Table 1, the membership functions of CPS1, CPS2, Kp, and Ki could be defined as Fig. 4 and Fig. 5. Fuzzy rules are summarized in Table 2.

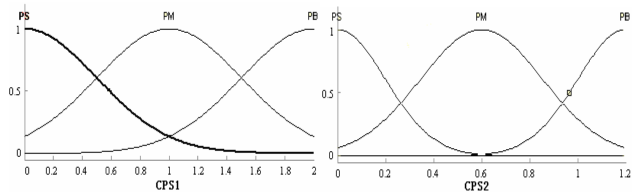

Fig. 4.Membership function for the input variables（CPS1, CPS2）

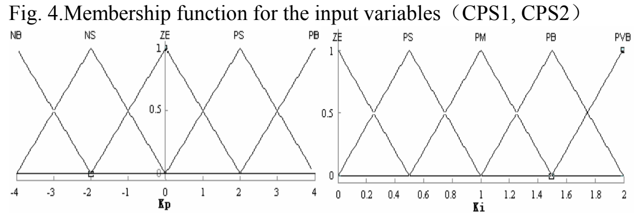

Fig. 5.Membership function for the controller outputs (Kp, Ki)

TABLE II FUZZY LOGIC RULES

CPS2 \ CPS1	PS	PM	PB
PS	Kp=PB Ki=ZE	Kp=ZE Ki=ZE	Kp=NS Ki=PS
PM	Kp=PB Ki=PS	Ki=ZE Ki=PM	Ki=NS Ki=PM
PB	Kp=PS Ki=PB	Kp=ZE Ki=PB	Kp=NB Ki=PVB

C. The control algorithm

The proposed algorithm based on fuzzy neural network predictive method can be summarized as follows:

(1) Set the initial values of the desired frequency deviation df(r), desired ACE(r) and desired ACEN(r) to 0;

(2) Forecast the frequency deviation $\overline{df(r+1)}$ at the (r+1) moment using recurrent neural network as shown in Fig. 2, resulting the forecasting of $\overline{ACE(r+1)}$;

(3) Forecast $\overline{CPS1(r+1)}$ and $\overline{CPS2(r+1)}$ at the (r+1) moment based on $\overline{ACE(r+1)}$ and the CPS;

(4) Get control outputs $\overline{Kp(r+1)}$ and $\overline{Ki(r+1)}$ at the (r+1) moment by $\overline{CPS1(r+1)}$ and $\overline{CPS2(r+1)}$ from fuzzy rules in Table 1, return to (2).

Here, the superscrip $^{-}$ represents the predicted value.

IV. CASE STUDY

Simulation is conducted on the two regional load frequency model shown in Fig. 1. The system parameters are chosen as: T_{gi} = 0.08s; T_{ti} =0.3s; T_{pi} =20s; R_i =2.4; β_i =0.425; K_{pi} =120Hz/pu; T_{ij} =0.086; a_{ij} =-1; ε_{1i} =5.40mHz; ε_{10i} =0.56mHz, ($i = 1,2; j = 1, 2$, where $i \neq j$). Kp=0.8, Ki=0.6, γ= 0.5. Correlation coefficients of frequency

ε_{1i} , ε_{10i} have a direct impact on CPS1 and CPS2 indicators. Here ε_{1i} =5.40mHz, ε_{10i} =0.56mHz. Consider turbine GRC to be $\Delta \dot{P}_{gi} \le \lambda$=0.03MW/s , the dead zone of governor to be 0.002. Add random source with magnitude of 0.003 and frequency of 0.5 to simulate the uncertainty of parameters. Genetic algorithms are used to train the Elman neural network that models the plant. After a series of trial and error, the ANN architecture is chosen to be 3 × 6 × 1. The activation function of the networks neurons is hyperbolic tangent,

$$f(s)=\frac{1-\exp(-0.8s)}{1+\exp(-0.8s)},\ g(s)=\frac{1-\exp(-0.6s)}{1+\exp(-0.6s)}$$

Feedback gain α = 0.65, sampling period T = 0.01s.

Fig. 6 shows the output of the Elman neural network. It can be seen that the proposed ANN could effectively predict the power output.

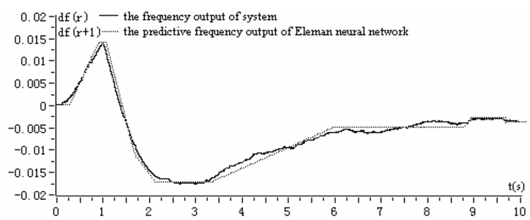

Fig. 6.The predictive output of the Elman neural network

Simulation is made under the condition that the two regions are added different load disturbance, with 0.005 p.u.MW to the first region and 0.013 p.u.MW to the second region. From Fig. 7 and Fig. 8, the proposed method offers a much better frequency response to both areas than that of the tradition fuzzy control with the settling time of 15 s in area1 and 13s in area2. The maximum frequency overshoots are -0.025 and -0.02 respectively. Due to the impact of a random source, the frequency output based on the traditional fuzzy control oscillates constantly with the maximum overshoots being -0.024 and -0.023 respectively. From Fig. 9 and Fig. 10, the power output under the ANN prediction fuzzy control is more stable than that of traditional fuzzy control in both areas. From Fig. 11 and Fig. 12, the control effort under the ANN predictive fuzzy control is much less than that of traditional fuzzy control, which means wear and tear of generating unit's equipments are quite reduced. From Fig.13 and Fig. 14, the ACEN is quickly driven to zero and have smaller overshoots using the proposed method. From Fig.15-Fig.18, the ANN prediction fuzzy control can better meet the CPS performance standards.

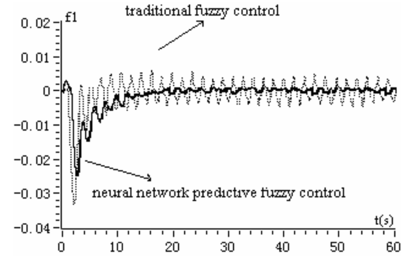

Fig. 7.Frequent deviation in area 1

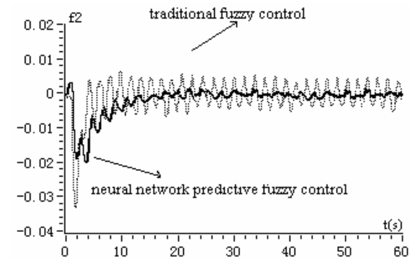

Fig. 8.Frequent deviation in area 2

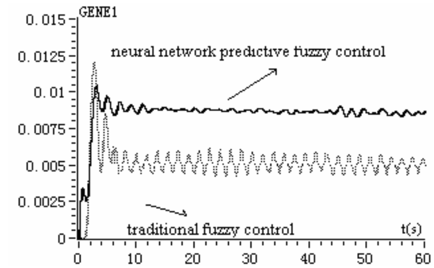

Fig. 9.Power generation output in area 1

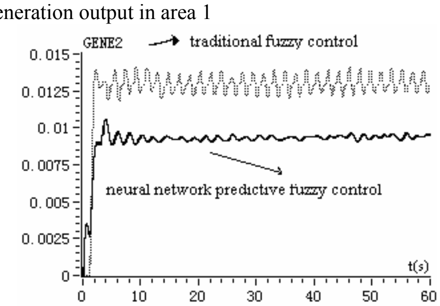

Fig. 10.Power generation output in area 2

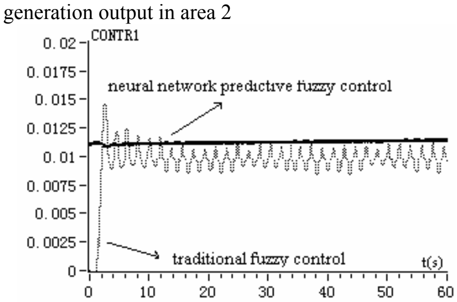

Fig. 11.Control effort in area 1

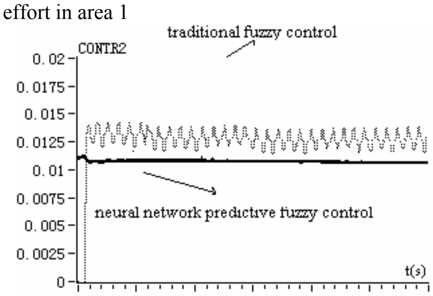

Fig. 12.Control effort in area 2

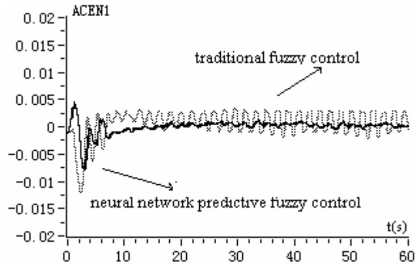

Fig. 13.ACEN in area 1

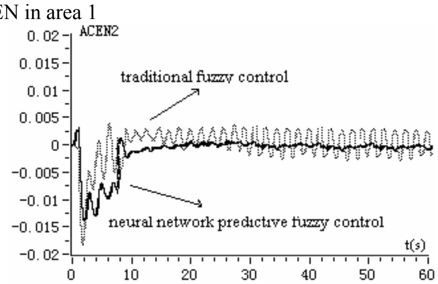

Fig. 14.ACEN in area 2

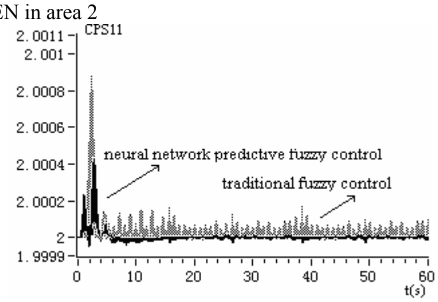

Fig. 15.Output of CPS1 in area 1

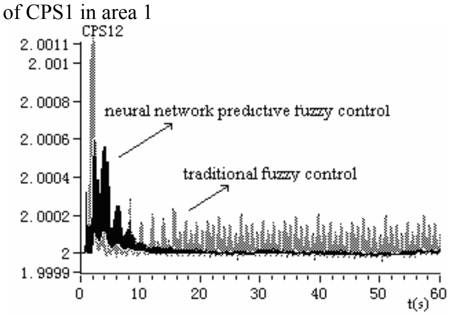

Fig. 16.Output of CPS1 in area 2

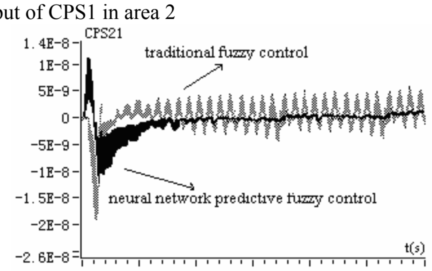

Fig. 17.Output of CPS2 in area 1

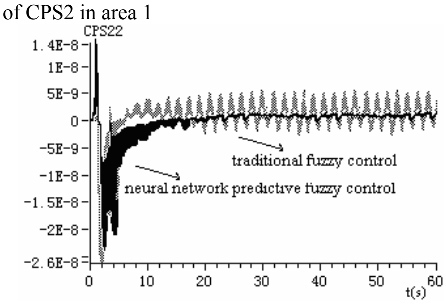

Fig. 18 .Output of CPS2 in area 2

V. Conclusions

In this paper, Elman network is proposed to model the load frequency control of a two-area power system. Fuzzy control strategy was chosen to comply with the North American Electric Reliability Council's control performance standards, CPS1 and CPS2. To demonstrate the effectiveness of the proposed method, the control strategy is tested under load perturbation. The simulation results show that the proposed ANN controller has better control performance compared to the conventional fuzzy controllers even in the presence of GRC. In addition, it is effective and can ensure the stability of the overall system for all admissible uncertainties and load changes. The simulation results obtained also show that the performance of ANN controller is better than conventional fuzzy controller against the load perturbation at any area. Especially it can reduce wear and tear of generating unit's equipments, and thus offer a feasible control structure for AGC.

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