FUZZY NEURAL NETWORK CONTROLLER ON LOAD FREQUENCY CONTROL CONSIDERING GOVERNOR DEADBAND AND GENERATION RATE CONSTRAINTS

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***Abstract*— A neural network based fuzzy controller of load frequency control is proposed in this paper. In this approach, a fuzzy controller is designed at first to adaptively decide the PI like controller gains according to the area control errors and their changes. Case studies justify that the limitations of PI controller can be overcome by including Fuzzy concept and thereby the response of frequency and tie line power can be improved substantially following a load change in any area. Unfortunately, it is difficult for systems designers to obtain optimal fuzzy rules because these are most likely to be influenced by the intuitiveness of the operators and the system designers. Neural network implementation to fuzzy systems is proposed as a possible approach for overcoming the limitations of generating fuzzy rules in fuzzy controller. The approach is to realize the process of fuzzy reasoning by the structure of a neural network and to express the parameters of fuzzy reasoning by the connection weights to the neural network. The resulting Fuzzy neural network (FNN) can automatically identify the fuzzy rules and tune membership functions by modifying the connection weights of the network using Widro-Hoff learning algorithm. The proposed controller has been tested for a two area single reheat system with considering the practical aspect of the problem such as Deadband and Generation Rate Constraint (GRC).**

Keywords-**:** ***Load Frequency Control, PI like Fuzzy Logic Control, Fuzzy Neural Network, Widro-Hoff Algorithm***

I. INTRODUCTION

Large-scale power systems are normally composed of control areas or regions representing coherent groups of generators. The various areas are interconnected through tie lines. Successful operation of a power system is the process of properly maintaining several sets of balances. Two of these balances are between load and generation and scheduled tie line flows and actual tie line flows. These two balances are predominant factors to keep frequency constant. Both of these balances are maintained by adjusting generation keeping load demand in view. A number of control strategies have been employed in the design of load frequency controllers in order to achieve better dynamic performance. The most widely employed controller is the conventional proportional integral (PI) controller. The advantages of PI controller is that it can reduce the steady state error to zero but generally gives large frequency deviations[1-5]. The optimal control is quite often impractical for the implementation because it is a function of all the states of the system but in practice, all the states may not be available [6-7]. In variable structure or sliding mode control system [8-10], the structure of the control law may change (e.g. jump of controller parameter values, change of the form of the function) during the course of action in accordance with the state, output or error measurement. The major difficulties of such work are the selection of switching vector and the uncertainty of hitting switching hyper plane. The choice of switching hyper plane makes very difficulty for practical implementation. In recent years-modern intelligent methods such as Artificial Neural Networks (ANN) and Fuzzy Logic (FL) have been successfully applied to the load frequency control problem with promising results [11-14]. The salient feature of these techniques is that they provide a model-free description of control systems and do not require any model identification. But the main drawbacks of ANN include large number of neurons in the hidden layers for complex function approximation, and very large training time required. The shortcoming in Fuzzy logic is the lacking of any systemic procedure for the design of fuzzy systems. It is difficult for systems designers to obtain optimal fuzzy rules because these are most likely to be influenced by the intuitiveness of the operators and the system designers. Some information will be lost when human operators express their experience by linguistic rules. This results in a set of less than optimal linguistic rules. It is therefore important to establish a mechanism for adjusting the fuzzy rules automatically in order to make the controller perform robustly. Here comes the necessity of the learning capability of neural networks.

In this paper, a technique of neural network implementation in Fuzzy system design is developed in order to identify fuzzy rules and the memberships for the corrective signal to the governor following a load change. In practice, there exist different types of physical constraints such as GRC and Governor Deadband. This work also incorporates the above constraints to get the effect in the system dynamic response. The superiority of the proposed controller over commonly used integral controller and Variable Structure System (VSS) are verified .

II. DYNAMIC MATHEMATIC MODEL

Electric power systems are complex, nonlinear dynamic system. The load frequency controller controls the control valves associated with High Pressure (HP) turbine at very small load variations [15,16]. Here it is assumed that small variations of load permit the linearization of system equations. The system under investigation has tandem-compound single reheat type thermal system. Each element (Governor, turbine and power system) of the system is represented by first order transfer function at small load variations in according to the IEEE committee report [16]. Two system nonlinearities likely Governor Deadband and Generation Rate Constraint (GRC) are considered here for getting the realistic response. Figure 1 shows the transfer function block diagram of a two area interconnected network .The parameters of two area model is defined in Appendix. The governor deadband is represented by the nonlinear backlash block and the GRC is taken into account by adding a limiter to the turbine to prevent the excessive control action as shown in the Figure 1.

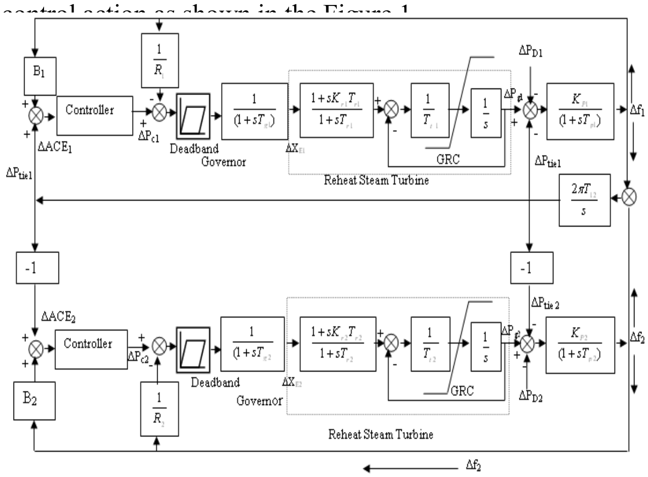

Figure 1. Transfer function model of a two area reheat thermal system

III. APPLICATION OF PI LIKE FUZZY LOGIC CONTROLLER FOR LOAD FREQUENCY CONTROL

The selection of the control variables (controller input and controller outputs) depends on the nature of the controlled system and the desired output. In this work we have designed PI- like Fuzzy Knowledge Based Controller. The basic structure of the conventional PI controller is

$$u = \kappa_P e + \kappa_I \int edt \qquad ...(1)$$

where κ_p and κ_I are the proportional and integral gains respectively and e is the error signal(i.e. e=process set point – process output variable). Taking the derivative with respect to time, the above expression 1 is transformed into equivalent expression

$$\dot{u} = \kappa_p \dot{e} + \kappa_I e . \qquad ...(2)$$

The inputs to the Fuzzy controller for i[th] area at a particular instant 't' are $ACE_i(t)$ and $\Delta ACE_i(t)$, where $ACE_i(t)=\Delta P_{tiei}+B_i \Delta f_i$ and $\Delta ACE_i(t) = ACE_i(t)- ACE_i(t-1)$ and output of the fuzzy controller is Δu .This is in accordance with the eqn. (2) for PI like controller. The inputs and output are transformed to seven linguistic variables NB, NM, NS, Z, PS, PM and PB which stand for Negative Big , Negative Medium, Negative small, Zero, Positive Small, Positive Medium and Positive Big respectively is shown in Figure 2. Symmetrical triangular (expect of the two outermost ones which have a trapezoidal shape) membership function is considered here for all the three variables of ACE, ΔACE and Δu.

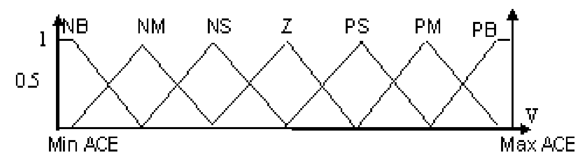

Figure 2. Membership functions for the fuzzy variables of ACE

The control policy is established in the rule base and Table-1 shows the 49 rules that are generated through the knowledge of the system.

TABLE I FUZZY RULES FOR TWO-AREA SYSTEM

ACE \ ΔACE	NB	NM	NS	Z	PS	PM	PB
NB	PB	PB	PM	PM	PS	PS	Z
NM	PB	PM	PM	PS	PS	Z	Z
NS	PM	PS	PS	PS	Z	Z	Z
Z	Z	Z	Z	Z	Z	Z	Z
PS	Z	Z	Z	NS	Z	NS	NS
PM	Z	Z	NS	NS	NM	NM	NB
PB	Z	NS	NS	NM	NM	NB	NB

The control output Δu is determined using the center of gravity by the following expression,

$$\Delta u = \frac{\sum(\text{membership of input} \times \text{output corresponding to be membership of input})}{\sum(\text{membership of input})}$$

$$\Delta u = \frac{\sum_{j=1}^{49} \mu_j u_j}{\sum_{j=1}^{49} \mu_j} \qquad ...(3)$$

Where, μ_j is the membership value of the linguistic variable recommending the fuzzy controller action, and u_j is the precise numerical value corresponding to that fuzzy controller action. This Δu is added with the existing previous signal will be the actually output signal u which goes to the governor.

IV. DRAWBACKS OF FUZZY LOGIC CONTROLLER

There is no such systemic procedure for the design of fuzzy systems. Usually the linguistic rules are generated by converting the human operator's experience into linguistic from directly or by summarizing the sampled input-output pairs of the systems to be dealt with. Unfortunately, it is difficult for systems designers to obtain optimal fuzzy rules because these are most likely to be influenced by the intuitiveness of the operators and the system designers. Moreover, some information will be lost when human operators express their experience by linguistic rules. This results in a set of less than optimal linguistic rules. Therefore, fuzzy systems capable of developing and improving the linguistic rules and structures automatically are highly desired.

V. DESIGN OF FNN CONTROLLER

To overcome the basic limitation of a fuzzy controller i.e inability to learn and adapt in a changing environment, an amalgamation of fuzzy logic and neural network (FNN) is proposed. The proposed FNN method has been developed based on type-I method among the proposed three methods for identifying the structure of fuzzy model of a nonlinear system by Harikawa et al. [19]. The resulting Fuzzy neural network (FNN) can automatically identify the fuzzy rules and tune membership functions by modifying the connection weights of the network using Widro-Hoff learning algorithm [18]. The FNN model will consist of the same three stages i.e. fuzzification, Database (Knowledge base and rule base) and Defuzzification of a conventional fuzzy controller, but the if-then rules in the rule base are adjusted by iterative learning algorithms similar to neural network learning.

A. Fuzzification

In this design, Area Control Error (ACE) and Governor signal ΔP_c has been taken as input and output respectively. Area control error is taken as only input to FNN controller but both area control error and rate of change of area control error (ΔACE) are considered as inputs while designing fuzzy logic controller. ACE is considering as only input in FNN since the control signal is more dependent on the value ACE than ΔACE. By considering ACE as input to FNN controller we have obtained the same performance as Fuzzy Logic controller though both the variables can also be considered in the computational process of FNN. In the present work the entire possible input and output values are converted into seven triangular membership functions with each membership representing different linguistic variables which are Negative Big(NB), Negative Medium(NM), Negative small(NS), Zero(ZE), Positive Small(PS), Positive Medium (PM) and Positive Big(PB) as shown in the Figure 3 . The membership function would perform a mapping from the crisp value to a fuzzified value. As shown in Figure 3, one particular crisp input ACE is converted to fuzzified value i.e. $\frac{\overline{.8}}{NS} + \frac{\overline{.2}}{NM}$,where 0.8 and 0.2 are membership grades corresponding to the linguistic variable NS and NM in FNN system. The membership grades are zero for all other linguistic values except NS and NM. The crisp value input to the system in this way will be converted to a fuzzified value consisting of several membership grades corresponding to each linguistic variable. As input is fuzzified by seven linguistic variables so the neural network consists of seven nodes in the input layer as shown in Figure 4. Each node represents a particular input linguistic variable.

Thus the input crisp value of ACE is converted to fuzzify value as $[x_1, x_2, x_3, x_4, x_5, x_6, x_7]$ .Where, $[x_1, x_2, x_3, x_4, x_5, x_6, x_7]$ are seven nodes representing NB, NM, NS, Z, PS, PM, PB respectively as shown in Figure 4. Like the input layer, the nodes in the output layer corresponds to all the linguistic concepts i.e. seven in the present case, of the output variable. So y_1 in the output layer represents membership grade for the linguistic variable NB. Thus output fuzzy set can also be

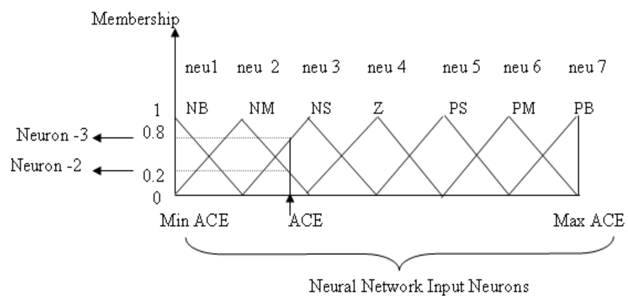

Figure 3. Membership Functions for the fuzzification mappings

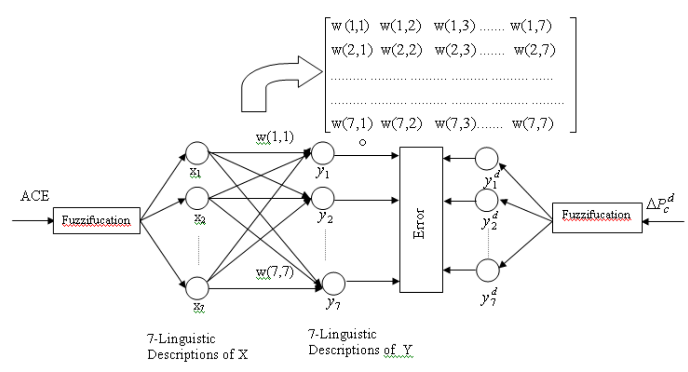

Figure 4. Fuzzy Neural Network (FNN) model

B. Formation of rule base

Each synaptic weight between the input and output layer represents the strength of the relation between the corresponding linguistic concepts e.g. w_{ij} =0.7 means that for the i^{th} neuron i.e. input linguistic concept in the input layer, the j^{th} neuron i.e. output linguistic concept in the output layer would be activated to an extent of 70%. The resulting weight matrix is called as Fuzzy Relation matrix (FRM). The seven membership grades coming out of the seven neurons from the input layer are multiplied with the concerned synaptic weight to arrive at seven output values. The fuzzified value for each node in the output layer is calculated as follows.

$$y_1 = x_1 \times w(1,1) + x_2 \times w(2,1) + x_3 \times w(3,1) + x_4 \times w(4,1) + x_5 \times w(5,1) + x_6 \times w(6,1) + x_7 \times w(7,1)$$

$$y_2 = x_1 \times w(1,2) + x_2 \times w(2,2) + x_3 \times w(3,2) + x_4 \times w(4,2) + x_5 \times w(5,2) + x_6 \times w(6,2) + x_7 \times w(7,2)$$

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$$y_7 = x_1 \times w(1,7) + x_2 \times w(2,7) + x_3 \times w(3,7) + x_4 \times w(4,7) + x_5 \times w(5,7) + x_6 \times w(6,7) + x_7 \times w(7,7)$$

Thus, $y_j = \sum_{j=1}^{7} \sum_{i=1}^{7} x_i W_{ij}$ .The seven y_j values thus obtained correspond to seven linguistic outputs at seven output neurons.

These seven linguistic values as obtained would be compared with the fuzzified desired output. The desired output ΔP_c^d is fuzzified by seven linguistic values, y_j^d , j=1 to 7, as shown in the Figure 4 , in a manner similar to the fuzzification of the input crisp ACE value. The error ε_j between each linguistic value of y_j^d and y_j as shown in Figure 4.The Least Squared Error ($LSE = 0.5 \times \sum_{j=1}^{7} \varepsilon_j^2$) is calculated using errors. If the LSE falls outside the tolerance limit, the weights are updated through Widro-Hoff algorithm as follows,

$$W_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n+1) \qquad \ldots(4)$$

Where,

$$\Delta w_{ij}(n+1) = \eta * \varepsilon_j * x_j + \alpha * w_{ij}(n) \qquad \ldots(5)$$

$w_{ij}(n)$ = the current weight

$w_{ij}(n+1)$ = the updated weight

$\Delta w_{ij}(n+1)$ = the change in weight (initially it is taken as Zero).

η = the Learning rate Coefficient.

α = Momentum factor.

The weight updating procedure is carried out till a certain termination criterion (tolerance limit) is fulfilled.

C. *Defuzzification in FNN:*

After offline training the final FRM establishes the accurate relation between the input and output nodes. In real time operation, the linguistic values coming out from the 7 neurons of the input layer when multiplied with the final FRM will give 7 linguistic outputs at 7 output neurons as shown in the Figure 5. Defuzzification is required to convert these seven linguistic outputs into a real value. Moment method [18] is used here for defuzzification where the output value of j^{th} node ($y_j = \sum_{j=1}^{7} \sum_{i=1}^{7} x_i W_{ij}$) multiplied with the centre value (f_j) of the corresponding triangular membership function gives the real value corresponding to the related variable. The summation of such real values of all nodes divided by the sum of output values at output node gives the final defuzzified value i.e

$$\Delta P_c = \frac{\sum_{j=1}^{7} f_j y_j}{\sum_{j=1}^{7} y_j} \qquad \ldots(6)$$

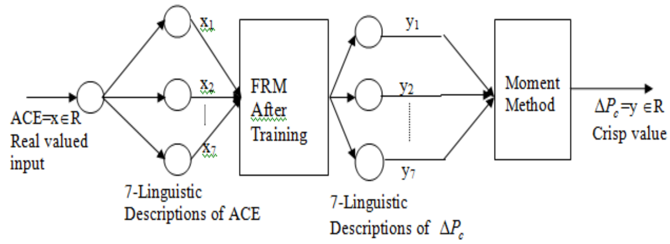

Figure 5. Fuzzy Neural Network (FNN) structure in real time operation

VI. SIMULATION AND RESULTS

The proposed Fuzzy Neural Network Controller has been applied to a two area reheat thermal system and simulation has been conducted with Simulink in MATLAB 6.1. The input data used here is shown in Table II.

TABI ... ERS

$D_1 = D_2 = 8.33 \times 10^{-3}$ p.u Mw/Hz
$H_1 = H_2 = 5$ sec ;
P_r=2000 Mw (area rated capacity);
P_{tiemax}=200 Mw (tie line capacity);
$T_{12} = 2\Pi(\frac{P_{tie\max}}{P_r}\cos 30^{\circ})$;
$R_1 = R_2 = 2.4$ Hz/p.u Mw
$T_{g1} = T_{g2} = 0.08$ sec; $T_{t1} = T_{t2} = 0.3$ sec;
$T_{r1} = T_{r2} = 10.0$ sec ; $K_{r1} = K_{r2} = 0.5$ sec;
$B_1 = B_2 = 0.425$;
K_P=120 Hz/ p.u M W
T_P = 20 sec

The limiting value of deadband is specified as 0.06% and a specific value of generation rate limitation is 0.1 p.u. per minute [4] i.e. $\left|\frac{d\Delta P_{gi}}{dt}\right| \leq$0.1pu/min=.0017pu/sec. The continuous output from the conventional integral controller at 0.005 p.u. load change is sampled at a rate of 0.05 sec. The outputs at corresponding inputs generates four hundred input and output patterns. Out of which, 300 patterns are used for training the FRM and remaining patterns are utilized for testing the robustness of FNN. Learning rate, momentum constant and error convergence criterion are considered as 0.1, 0.01,10^{-7} respectively The Fuzzy Relation Matrix (FRM) is shown in Table III are used as the initial FRM. The initial values of FRM may be chosen randomly but the more or less accurate initialization will reduce the number of iterations performed to train the FRM. The final Fuzzy relation matrix has been generated from the initial FRM after training the FNN, which represents the new rule base as given in Table IV. The results of FNN based controller is compared with the conventional fixed gain integral controller [4] and Variable structure system (VSS) [8] .

TABLE III. ... FRM ... TRAINING.

ACE \ ΔP_C	PB	PM	PS	Z	NS	NM	NB
NB	0.9	0.8	0.7	0	0	0	0
NM	0.8	0.5	0.4	0	0	0	0
NS	0.4	0.2	0.1	0	0	0	0
Z	0	0	0	0	0	0	0
PS	0	0	0	0	0.1	0.15	0.3
PM	0	0	0	0	0.2	0.5	0.7
PB	0	0	0	0	0.6	0.8	0.9

TABLE IV.

ACE \ ΔP_C	PB	PM	PS	Z	NS	NM	NB
NB	1.0845	0.9845	0.8845	0	0	0	0
NM	0.7845	0.5845	0.3845	0	0	0	0
NS	0.3767	0.1579	0.1139	0.1053	0.0031	0.0042	0.0080
Z	0.0002	0.0001	0.0000	1.0569	0.0001	0.0001	0.0009
PS	0.0240	0.0087	0.0048	0.0490	0.0682	0.0704	0.0000
PM	0.2813	0.0000	0.0000	0.1968	0.0380	0.0389	0.0433
PB	0.0000	0.0001	0.0000	0.0391	0.2060	0.2458	0.2858

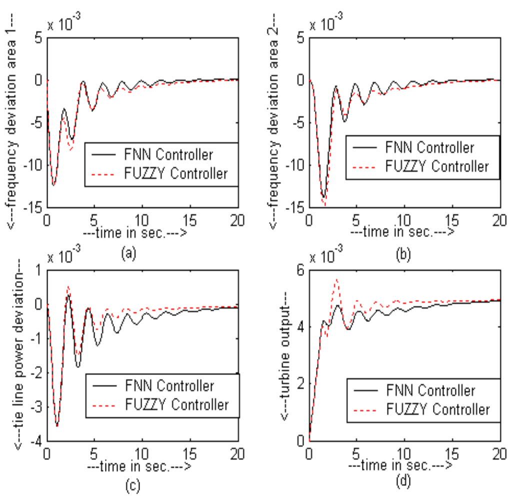

Figure 6. System response with GRC and Governor Deadband (a) Frequency deviation in area 1(Δf_1) (b) Frequency deviation in area 2(Δf_2) (c) Tie-line power deviation (ΔP_{tie})(d) Deviations in generated power in area 1(ΔP_{g1})

Figure 6 shows the comparison between Fuzzy and FNN controller for the same load change of 0.005 p.u. in area 1 with considering GRC and Governor Deadband. From this, it is clear that the performances of FNN controller and Fuzzy Logic Controller are of similar nature. The proposed FNN controller is thus able to create the rule base automatically and is not user defined as like Fuzzy controller. For fuzzy logic controller, substantial time and efforts are necessary to create rules by trail and error, which is no longer, require in FNN controller.

Chun-Feng Lu et al. [4] have developed fixed-gain integral controller for load frequency in same two area reheat thermal system considered in this study. The gain setting (K_I) of integral controller is optimized by least square error criterion and reported as 0.48 for 0.005 p.u. step load change of area 1 [4] . Figure 7 shows the deviations of system variables in response to the 0.005 p.u. load change by fixed-gain integral control and FNN. It is observed turbine power output ΔP_{g1} and ΔP_{g2} in integral controller reaches lower and upper bound which leads the system oscillations sustain for a long period in integral controller as shown in Figure 7. Whereas result designed by the proposed FNN approach achieves better performance because of the generation of proper FRM, according to which the gain changes for every incoming error signal.

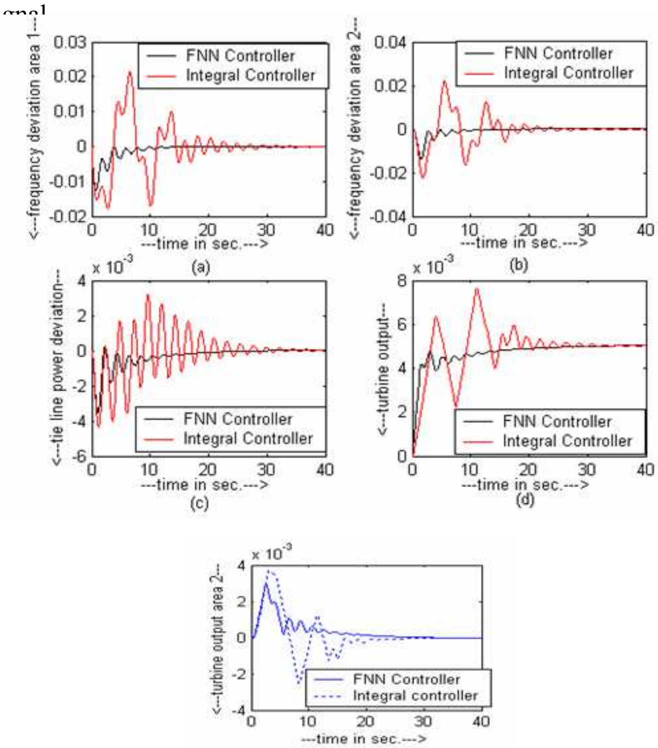

Figure 7. Responses of power system by fixed Integral gain (dotted curve) and FNN (solid curve) with load change ΔP_{D1}=0.005 p.u. MW and ΔP_{D2}=0 in area 1 and area 2. a) Frequency deviation in area 1(Δf_1) (b) Frequency eviation in area 2(Δf_2) (c) Tie-line power deviation (ΔP_{tie})(d) Deviations in generated power in area 1(ΔP_{g1}) e) Deviations in generated power in area 2(ΔP_{g2})

TABLE V. COMPARISON OF PERFORMANCE FOR THE CASE OF

	Δf_1		Δf_2	
	Settling time (sec.)	Max. deviation (Hz)	Settling Time, (sec.)	Max. deviation, (Hz)
Variable structure Scheme	16	-0.014 +0.008	14.5	-0.019 +0.006
FNN Controller	12	-0.0124162	11	-0.013766

The results obtained from the proposed FNN controller are compared with VSS controller reported in reference [8] and presented in Table V. It can be observed that great improvements in system performance have been obtained by using the proposed FNN control scheme. VSS controller is quite often impractical for the implementation in real time because this technique is a function of all the states of the system [8]. In practice all the states may not be available. The inaccessible states or missing states are required to be estimated [10]. Again, this control technique which is a function of the states in turn is dependent on the load demand.

VII. CONCLUSIONS

Fuzzy Neural Network based proposed structure has been successfully applied to a load frequency control system. The fuzzy logic based neural network has been trained at first using known input-output sets, in which the knowledge of rules is explicitly expressed in weights of the neural network and inferences are executed efficiently at a high rate on off-line. The trained FRM only needs to be placed at real time operation between input and output layer. Thus, using neural network as a structure for the fuzzy controller is significantly reducing the designing effort and time of conventional fuzzy controller model and does not depend only on the experience and intuitiveness of the system designer. The computer simulation has been conducted for the two-area reheat system with GRC and Governor Deadband. The simulation results justified that the proposed FNN controller yields more improved control performance than the fixed integral controller and VSS.

APPENDIX

ΔP_{gi} = incremental generation change,

ΔX_{Ei} = incremental governor valve position change

ΔP_{Di} = incremental load demand change

Δf_i = incremental frequency deviation

ΔP_{tiei} = incremental change in tie-line power

ΔP_{Ci} = incremental change in speed changer position

f = nominal system frequency

H_i = inertia constant

D_i = load frequency constant ($K_{Pi}=\frac{1}{D_i}$, $T_{pi}=\frac{2H_i}{fD_i}$)

T_{ij}^0 = synchronizing coefficient

R_i = speed regulation parameter

T_{gi} = governor time-constant

T_{ti} = turbine time constant

K_{ri} ,T_{ri} = reheat coefficient and reheat time constant

T_{pi} = Power System time constant

The area control error (ACE) for the i^{th} area is defined as

$ACE_i = \Delta P_{tie\ i} + B_i \Delta f_i$, Where B_i is the frequency bias constant.

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