INTELLIGENT CONTROLLERS FOR AUTOMATIC GENERATION CONTROL

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ABSTRACT

This paper presents a novel approach of Artificial Intelligence (AI) techniques viz., Fuzzy logic, Artificial Neural Network (ANN) and Hybrid Fuzzy Neural Network (HFNN) for the Automatic Generation Control (AGC). The limitations of the conventional controls viz., Proportional, Integral and Derivative (PID) are slow and lack of efficiency in handling system non-linearities. The primary purpose of the AGC is to balance the total system generation against system load and losses so that the desired frequency and power interchange with neighboring systems is maintained. Any mismatch between generation and demand causes the system frequency to deviate from scheduled value. Thus high frequency deviation may lead to system collapse. This necessitates an accurate and fast acting controller to maintain constant nominal frequency. The intelligent controllers, viz., Fuzzy logic, ANN and Hybrid Fuzzy Neural Network approaches are used for Automatic Generation Control for the single area system and two area interconnected power systems. The performance of the intelligent controllers has been compared with the conventional PI and PID controllers for the single area system as well as two-area interconnected power system. The results shows that Hybrid Fuzzy Neural Network (HFNN) controller has better dynamic response i.e., quick in operation, reduced error magnitude and minimized frequency transients.

KEYWORDS: Automatic Generation Control, Frequency Deviation, Fuzzy Logic, Artificial Neural Network, and Hybrid Fuzzy Neural Network.

1.0 INTRODUCTION

The growth in size and complexity of electric power systems along with increase in power demand has necessitated the use of intelligent systems that combine knowledge, techniques and methodologies from various sources for the real-time control of power systems. The intelligent systems possess human like expertise within a specific domain, adapt themselves and learn to do better in changing environments and explain how they make decisions or take actions. In the past few decades, major advances in the hardware and software technologies have transformed the power system control from a simple process control to a system of distributed processing capable of supporting several levels of application functions. The Supervisory Control And Data Acquisition / Automatic Generation Control (SCADA/AGC) system have now given to the full-fledged Energy Management Systems (EMS). This very large and complex hardware and software system is based on in utility company's load dispatch or control centers which performs extensive on-line monitoring, assessment, analysis and optimization functions to ensure economic and secure operation of power system as well as to facilitate the periodic tasks carried out by the operating personnel.

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Automatic Generation Control (AGC) is used in real-time control to match the area generation changes to area load changes in order to meet tie-line flows and keep frequency at nominal value. By processing frequency and tie line deviations, AGC can determine whether the load changed in its own area or in its neighbor's area. If the former, the generations of units under AGC is adjusted until the deviations becomes zero.

The AGC problem of interconnected system is not only to see that the generation balances the demand but also to allocate generation between various systems, so that the total system operation schedules are kept up. Thus in interconnected system either executed manually or automatically, the function of AGC is to reallocate the generation changes to pre-selected machines after an initial random accommodation of the load by governor action. It is necessary to obtain much better frequency constancy than obtained by speed governor itself. To accomplish this we must overcome speed changes in accordance with some suitable control strategy. In practice different conventional control strategies are utilized for AGC viz., Proportional and Integral (PI), Proportional, Integral and Derivative (PID) and Optimal Control. The PI controller improves steady state error simultaneously allowing a transient response with little or no overshoot. As long as error remains, the integral output will increase causing the speed changer position, attains a constant value only when the frequency error has reduced to zero. So it introduces oscillations into the system. The PID controller improves the transient response so as to reduce error amplitude with each oscillation and then output is eventually settled to a final desired value. Better margin of stability is ensured with PID controllers. The limitation of conventional PI and PID controllers are slow and lack of efficiency in handling system non-linearities [2]. The optimal control is quite often impractical for the implementation due to the following reasons [8].

(i) The optimal control is a function of all the states of the system. In practice all the states may not be available. The inaccessible states or missing states are required to be estimated.

(ii) It may not be economical to transfer all the information over long distances.

(iii) The control, which is a function of the states in turn, is dependent on the load demand. Accurate prediction of load demand may be essential for realizing optimal controller.

(iv) The optimal control is also dependent on the weighing matrices and is not unique.

Indulkar and Baldevraj [7] designed the fuzzy controller for AGC and tested for the two area interconnected power system. The draw back in this approach is that the tie-line power steady state error in not reduced when compared with integral controller. Where as the settling time of the frequencies in area-1 and area-2 are much higher and they did not compared their results with the conventional PID controller.

An attempt has been made in this paper, to apply Fuzzy logic, Artificial Neural Network (ANN) and Hybrid Fuzzy Neural Network (HFNN) controllers for the Automatic Generation Control and tested for the single area and two-area interconnected power systems. The performance of the Hybrid Fuzzy Neural Network (HFNN) controller is compared with the Fuzzy controller, ANN controller and conventional PI and PID controllers.

2.0 FUZZY LOGIC CONTROLLER (FLC) MODEL

Fuzzy modeling is the method of describing the characteristics of a system using fuzzy inference rules. The method has a distinguishing feature in that it can express linguistically complex non-linear systems. It is however, very hard to identify the rules and tune the membership functions of the fuzzy reasoning. Fuzzy controllers are normally built with the use of fuzzy rules. These fuzzy rules are obtained either from domain experts or by observing the people who are currently doing the control. The membership functions for the fuzzy sets will be derived from the information available from the domain experts and/or observed control actions. The building of such rules and membership functions require tuning. That is, performance of the controller must be measured and the membership functions and rules adjusted based upon the performance. This process will be time consuming.

The basic configuration of Fuzzy Logic Controller (FLC) consists of four main parts [3].

(i) Fuzzification
(ii) Knowledge base
(iii) Decision-making logic and
(iv) Defuzzification

The functions of the above modules are described below.

(i) The Fuzzification:

(a) Measure the values of input variables.
(b) Performs a scale mapping that transforms the range of values of input variables into corresponding universe of discourse.
(c) Performs the function of fuzzification that converts input into suitable linguistic values, which may be, viewed labels of fuzzy sets. Triangular fuzzy membership functions are shown in Fig-1.

(ii) The Knowledge Base:

It consists of data base and linguistic control rule base.

(a) The database provides necessary definitions, which are used to define linguistic control rules and fuzzy data, manipulation in an FLC.
(b) The rule base characterizes the control goals and control policy of the domain experts by means of set of linguistic control rules.

(iii) **The Decision Making Logic:**

It is the kernel of an FLC, it has the capability of simulating human decision making based on fuzzy concepts and of inferring fuzzy control actions employing fuzzy implication and the rules of inference in fuzzy logic.

(iv) The Defuzzification:

(a) A scale mapping which converts the range of values of input variables into corresponding universe of discourse.

(b) Defuzzification, which yields a non-fuzzy, control action from an inferred fuzzy control action.

3.0 ARTIFICIAL NEURAL NETWORK (ANN) MODEL

Artificial Neural Networks are commonly referred as connectionist networks or simply neural networks, have been motivated from the recognition that the brain performs certain tasks much more efficiently in an entirely different way than the conventional digital computers. The neurons are the structural constituents of the brain, which are highly complex non-linear and parallel processing systems. ANNs are massively parallel-interconnected networks of simple elements known as artificial neurons and their connectivity is intended to interact with the objects of the real world, in a similar manner as the biological nerves systems do. Neural networks have emerged as a powerful technique for pattern recognition, control, functional mapping and generalization.

Neural networks are divided into classes based on network topology, computational element characteristic and training or learning rules. The basis features of neural networks are

(i) High computational rates due to the massive parallelism.

(ii) Fault tolerance (damage to a few nodes does not significantly implies over all performance)

(iii) Learning or training (the network adopts itself, based on the information received from the environment).

(iv) Goal-seeking (the performance to achieve the goal is measured and used to self organize the system, programmed rules are not necessary).

(v) Primitive computational elements (each element resembles one simple logical neuron and cannot do much).

In this paper the ANN paradigm namely Radial Basis Function (RBF) network is used for the AGC. The RBF network topology and operation are described below.

3.1 Radial Basis Function (RBF) Network

The radial basis function is similar to the Gaussian density function which is defined by a center (u_I) and a width parameter (σ_I). The Gaussian function gives the highest output when the incoming variables are closest to the center position and decreases monotonically as the distance from the center increases. The width gives the rapidly decreasing function and a large value gives a slowly decreasing function. The topology of the RBF network is shown in Fig-2 and the neuron response function is shown in Fig-3.

3.2 Radial Basis Function Network Operation

The network has two operating modes, named, training and testing. During training the adjustable parameters of the network (u_I , σ_I and the output layer matrix w) are set as to minimize the average error between the network output and the desired output over the vectors in a training set. During the testing phase, input vectors are applied and the network produces output vectors.

Training itself has two stages. First the center (u) and width parameter (σ) of each hidden layer neuron must be assigned values, next, the weight matrix (w) must be trained. These weights are adjusted by supervised training method, therefore a training set is required. The set is composed of input vector and target vector pairs, where the input vector will be referred to as X and the target vector as T.

3.3 Training of RBF Parameters

3.3.1 Computation of RBF unit centers (u_I)

(i) Initialize the center of each cluster to a different randomly selected training pattern.

(ii) Assign each training pattern to the nearest cluster. This can be accomplished by calculating the Euclidean distances between the training patterns and the cluster centers.

(iii) When all training patterns are assigned, calculate the average position for each cluster center. They become new cluster centers.

(iv) Repeat steps (ii) and (iii) until the cluster centers do not change during the subsequent iterations.

3.3.2 Computation of RBF unit widths (σ_I)

When the RBF centers have been established, the width of each RBF unit can be calculated. The width of any RBF unit selected as root mean square distance to the nearest design parameter (p) of the RBF network. For the unit I, it is given by

$$\sigma_I = [\ 1/p \sum^{p}_{j=1} \sum^{r}_{k=1} (X_{ki} - X_{kj})^2]^{1/2}$$

Where X_{ki} and X_{kj} are the kth entries of the centers of the ith and jth hidden units.

3.3.3 Computation of Activation

The activation level O_j of the hidden unit j is

$$O_j = \exp[\ - (x - u_j)^T . (x - u_j) / 2\sigma^2_j\ ]$$

The activation level O_k of an output unit is determined by

$$O_k = W_{ji} . O_I$$

3.3.3 Weight Learning

(a) Adjust weights in the hidden layer by clustering algorithm. In the output layer adjust weights by

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji}$$

Where, W_{ji} (t) is the weight from the unit I to j at time t (where the t is the iteration count) and ΔW_{ji} is the weight adjustment.

(b) The weight change is calculated by

$$\Delta W_{ji} = \eta \delta_j O_I$$

Where, η is learning rate and δ_j is the error at unit j.

$$\delta_j = T_j - O_j$$

Where, T_j is the desired (or target) output activation and O_j is the actual output activation at the output unit j.

(c) Repeat iterations until convergence is obtained.

4.0 HYBRID FUZZY NEURAL NETWORK (HFNN) MODEL

In recent years, hybrid fuzzy neural networks have attracted considerable attention for their useful applications in such fields as control, pattern recognition, image processing, forecasting etc. In all these applications, there are different fuzzy neural network architectures proposed for different purposes and fields.

Fuzzy control is following what a person says by language (fuzzy sets) on the other hand, ANN control is explained as following what a person does by data. To construct non-linear and intelligent controllers, fuzzy control and ANN control should be combined.

Hybrid fuzzy neural network (HFNN) results from fusion of neural networks and fuzzy logic. Thus HFNN is a massively parallel and layered feed forward structure.

The fuzzy reasoning method (FRM) has been widely studied and used successfully in a number of control problems [9]. The FRM controllers can be alleviated by incorporating neural network learning mechanism into the fuzzy controller. A system of this type is referred to as fuzzy neural network.

In FRM, the fuzzy relation matrix plays an important role. However, the process of selecting an adaptive fuzzy relation matrix is subjective and most time consuming, generally completed by trial and error. Furthermore, it is often impractical to obtain the fuzzy relation matrix from the process operator, particularly if the system is complex and/or if the fuzzy conditional statements have more than two variables. Since the process operator usually has only a general idea of the fuzzy relation matrix in a given region, the process of making that general idea precise is the most difficult task in the design of a finely tuned fuzzy controller.

It is therefore important to establish a mechanism for adjusting the fuzzy relation matrix automatically in order to make the controller perform robustly. To this end we take advantage of the learning capability of the neural networks.

4.1 Hybrid Fuzzy Neural Network (HFNN) Algorithm

Each fuzzy degree element in the fuzzy relation matrix (FRM) is identified with interconnection weights in the neural network component and input and output are associated with input and output nodes respectively. These classes give rise to a mapping of the fuzzy inference component of the FRM on to a single layer linear feed forward neural network which constitutes the neural network component of the Hybrid Fuzzy Neural Network (HFNN) as shown in Fig.-4. The activation functions in this case are the identity function. The HFNN base single area system and two-area systems are shown in Fig. 5 and Fig.6 .

The HFNN consists of two phases: a *Learning Phase* and *Testing Phase.* For training the HFNN Widro-Hoff algorithm is used. After training, the HFNN adjusts the fuzzy relation matrix. The HFNN algorithm is given below:

1.0 Present the real-valued input X=x to HFNN. By means of the membership functions of each of the linguistic descriptions for X, obtain the input pattern $x = [x_1, x_2, \ldots, x_n]$ corresponding to a given real value of X, where each x_i is a certain membership degree of x in the ith linguistic description for X.

2.0 Compute HFNN output pattern $y = [y_1, y_2, \ldots, y_m]$ using $y_j = \sum_i x_I \cdot W_{ij}$. The pattern y is a fuzzy set of all linguistic descriptions of the object Y and W_{ij} is the fuzzy relation degree between ith linguistic description for X and jth linguistic description for Y.

3.0 Compute the training error.

3.1 Compute a real output value by means of the moment method.

$$Y = \sum_j (f_j \cdot y_j) / \sum_j y_j$$

Where, f_j's are the central values of membership functions of the linguistic descriptions for Y.

3.2 Given a desired scalar output value d, find a desired output vector $y^d = [y^d_1, y^d_2, \ldots, y^d_m]$ by means of fuzzy membership functions for Y.

3.3 Compare y^d and y:

$$\varepsilon_j = y^d_j - y_j = y^d_j - \sum_I x_i W_{ij}$$

3.4 Compute the total learning squared error (LSE):

$$LSE = 0.5 * \sum_j \varepsilon^2_j$$

4.0 If LSE is (0.001) go to step 7.

5.0 Apply the Widro-Hoff algorithm to modify the weights:

$$W_{ij}(n+1) = W_{ij}(n) + \Delta W_{ij}(n+1)$$

Where, $$\Delta W_{ij}(n+1) = \eta * \varepsilon_j * x_I + \alpha * \Delta W_{ij}(n)$$

The coefficients η and α are the learning coefficient and the momentum coefficient, respectively.

6.0 Return to step 1.0

7.0 Stop

5.0 SIMULATION AND RESULTS

5.1 Design of Fuzzy Controller

The design of fuzzy controller for single area system the frequency error (Δf) and the change in frequency error (Δf) are taken as inputs and the output is the controlled variable (ΔP_c). Where as in case of two-area interconnected power system, the area control error of area-1 (ACE-1) is ($\Delta P_{tie,1}+ B_1 \Delta f_1$) and the area control error of area-2 (ACE-2) is ($\Delta P_{tie,2} + B_2 \Delta f_2$) are considered as errors and change of errors of ACE-1 and ACE-2 are taken as the inputs and the outputs are ΔP_{c1} and ΔP_{c2}. The step load change of 10% (0.01 p.u.) disturbance is considered for the single area and two-area interconnected power systems. The fuzzy rules for the single area and the two area interconnected power systems are shown in Table-1 and Table-2 respectively.

In this simulation, error is considered every 0.05 seconds and fed to a subroutine, which computes ΔP_c . In this subroutine the error and change in error are fuzzified and fed to a rule base (inference engine). The rules, which are fired, are in fuzzy form. The fuzzy fired rules are converted into crisp value using Defuzzification. The error after introducing control input is taken and procedure is repeated. For each time step corresponding value of ΔP_c is obtained and the equations are solved iteratively using Runge-Kutta fourth order method.

The performance of Fuzzy controller and conventional PI and PID controllers for the single area system is shown in Fig-7 and Fig-8 for the frequency deviations. And the performance of Fuzzy controller based two-area interconnected power system frequency deviations of area-1, area-2 and tie-line power deviations are shown in Fig. 9 , Fig. 10 and Fig. 11 respectively in comparison with PID controller.

5.2 Design of ANN Controller

The input to the Artificial Neural Network (Radial Basis Function Network) for the single area system are ΔF, ΔX_v, ΔP_g and ΔP_D and output is the command signal ΔP_c. For the single area system the number of input nodes are 4 and output node is one. Whereas the number of nodes in the hidden layer is 12, selected by trial and error. In case of two-area interconnected power system the inputs to the ANN are ΔF_1, ΔF_2, ΔX_{v1}, ΔX_{v2}, ΔP_{G1}, ΔP_{G2}, ΔP_{D1}, $\Delta P_{tie,1}$ and the output of the network are ΔP_{c1} and ΔP_{c2}. Where the subscripts 1 and 2 indicates the parameters of area-1 and area-2 respectively. The number of input nodes is 8 and the output nodes are two. Whereas the number of nodes in the hidden layer are 25 selected by trial and error. Using conventional algorithms of uncontrolled case of AGC, 400 patterns are generated. Out of these 400 patterns, 350 patterns are used for the training, remaining 50 patterns are used for the testing. The learning rate (η) is considered as 0.05 and convergence criteria is 0.0001 p.u. The performance of single area system ANN controller and conventional PI and PID controllers are shown in Fig. 12 and Fig. 13 for the frequency deviations.

5.3 Design of Hybrid Fuzzy Neural Network (HFNN)

The fuzzy neural network consists seven neurons in the input layer and seven neurons in the output layer corresponding to the seven fuzzy linguistic descriptions of the input/output variables. The fuzzy reasoning models shown in Table-3 and Table-4 are used for the single area system and two area system (area-1) respectively, used as the initial fuzzy relation matrix and assigned the values 0.1 and 0.01 to the learning rate (η) and momentum coefficient (α) respectively used for weight adjustments to train the HFNN.

For training the HFNN a convergence criterion of 0.001 and maximum number of iterations of 210 were used for the single area and two area systems. 150 patterns are generated using conventional AGC algorithm. Out of these, 125 patterns are used for training and remaining 25 patterns are utilized for testing the robustness of HFNN. The new fuzzy relation matrix is generated after the training of HFNN. The results of HFNN based single area and two area systems are compared with the conventional PI and PID controllers. The comparison of HFNN based single area system frequency deviations with conventional PI and PID controllers are shown in Fig. 14 and Fig. 15 respectively. The comparison of HFNN based two area interconnected system frequency deviations in area-1 and area-2 and tie-line power deviation with PID controller is shown in Figs. 16, 17 and 18 respectively.

6.0 CONCLUSIONS

In this paper Fuzzy, Artificial Neural Network and Hybrid Fuzzy Neural Network controllers are utilized for the Automatic Generation Control of single area and Two-area interconnected power systems and compared the results with the conventional PI and PID controllers. From the results of the three Artificial Intelligent techniques following conclusions can be made.

(1) In case of Fuzzy controller, the frequency error of single area system was reduced from -0.0187 Hz to -0.004701 Hz in comparison with the PID controller and settling time is also reduced drastically from 6.0 seconds to 2.05 seconds. Similarly in case of two-area interconnected power system using fuzzy controllers, frequency error in area-1 is reduced from -0.025 Hz to -0.00207 Hz and settling time is reduced from 8.3 seconds to 1.95 seconds and in area-2 frequency error reduced from -0.015 Hz to +0.00075 Hz and settling time is reduced from 8.5 seconds to 2.25 seconds. In case of tie-line power deviation, settling time is reduced from 8.5 seconds to 2.5 seconds.

(2) The Artificial Neural Network (Radial Basis Function Network) controller, for the single area system, the steady state error is reduced from 0.0002 Hz to 0.000 Hz and the time taken to reach steady state is reduced from 20 seconds to 4.5 seconds and the error magnitude is reduced from 0.02 Hz to 0.012 Hz. In case of Two-area interconnected power system, the error magnitude is reduced from 0.01 Hz to 0.005 Hz for area -1, 0.018 Hz to 0.00355 Hz for the area - 2 and the tie -line power deviation is reduced from 0.0045 p.u. to 0.0035 p.u. And the time taken to reach steady state is reduced from 8.0 seconds to 3.0 seconds for area-1 and from 8.0 seconds to 2.0 seconds for area - 2, compared to the Proportional and Integral (PI) controller . The error magnitude is reduced from 0.0162 Hz to 0.0050 Hz and the time taken to reach steady state is reduced from 6.5 seconds to 3.0 seconds as compared to PID controller.

(3) The Hybrid Fuzzy Neural Network (HFNN) controller, for the single area system, the magnitude of the error is drastically from -0.025 Hz to -0.0047 Hz and settling time is also reduced from 10.0 sec to 2.05 sec. Whereas for the two-area interconnected power system, the settling time of the frequency in area-1 is reduced from 11.0 sec to 2.50 sec and in area - 2 the settling time of the frequency is reduced from 10.5 sec to 2.50 sec. And the tie-line power settling time is reduced from 11.0 sec to 2.0 sec. The error magnitudes are also reduced in both the areas considerably. In area -1 and area - 2 error

magnitudes are reduced from -0.025 Hz to -0.0015 Hz and -0.0010 Hz to -0.00025 Hz respectively. Whereas tie-line power deviation is reduced from -0.001 p.u. to -0.0005 p.u.

The results of the Hybrid Fuzzy Neural Network (HFNN) controller, compared to the Fuzzy controller and Artificial Neural Network controller, following conclusions can be made:

(i) The advantage of the hybrid fuzzy neural network controller is simple, fast, accurate and robust.
(ii) Using neural network as a structure for the fuzzy controller significantly reduces the design time of conventional fuzzy controller model.
(iii) Compared to the Artificial Neural Network, the training time is drastically reduced.
(iv) The magnitudes of error deviations and settling times are reduced considerably.

Hence, the Hybrid Fuzzy Neural Network (HFNN) controller can be utilized for the Automatic Generation Control (AGC) for real-time operation of power systems.

7.0 ACKNOWLEDGEMENT

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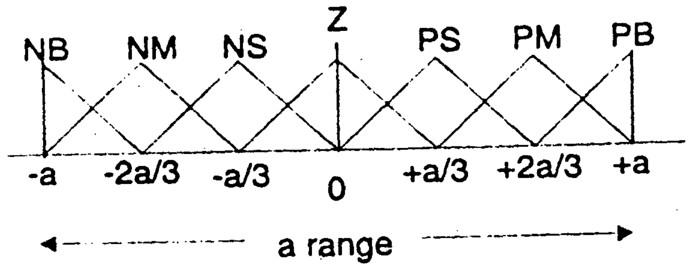

Fig.1: Membership Functions of Seven Linguistic Variables

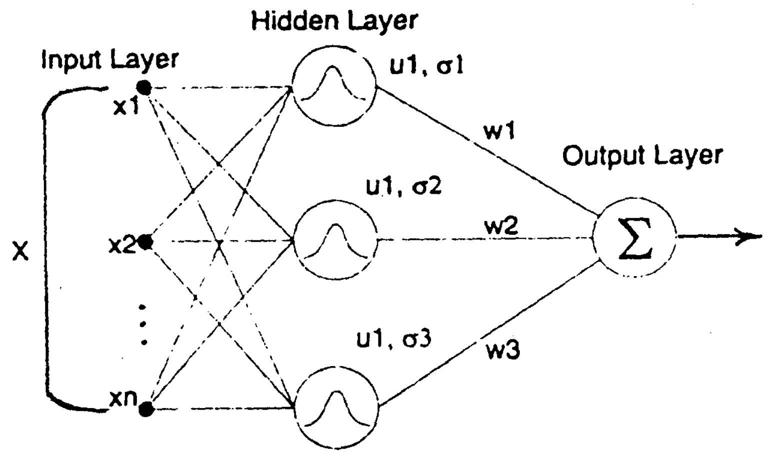

Fig.2: Radial Basis Function Network

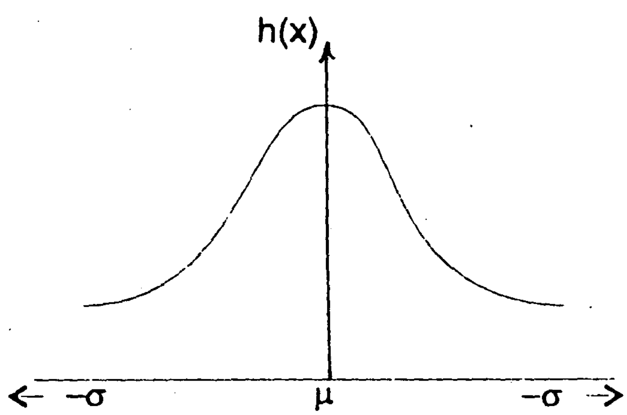

Fig.3: Neuron Response Function

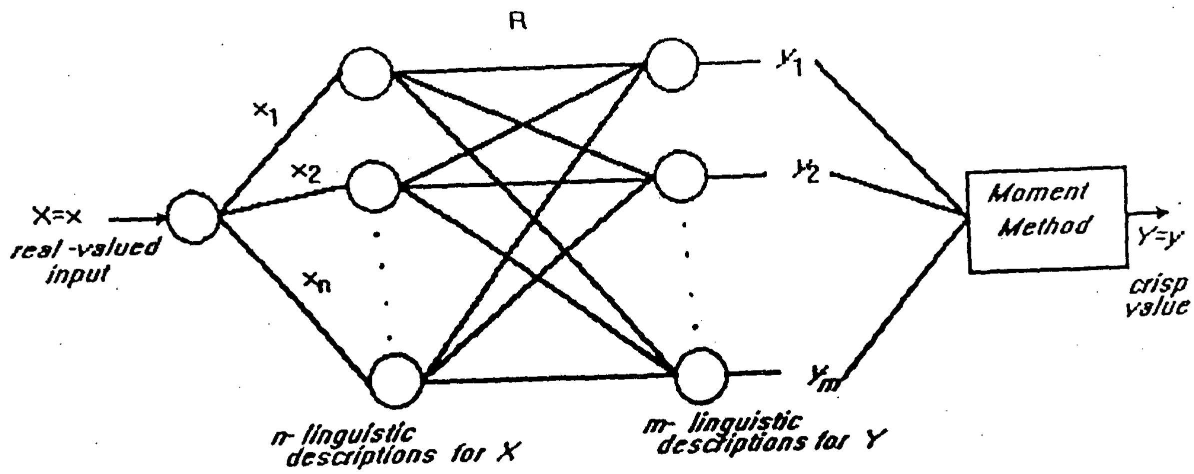

Fig.4: Hybrid Fuzzy Neural Network (HFNN) Model

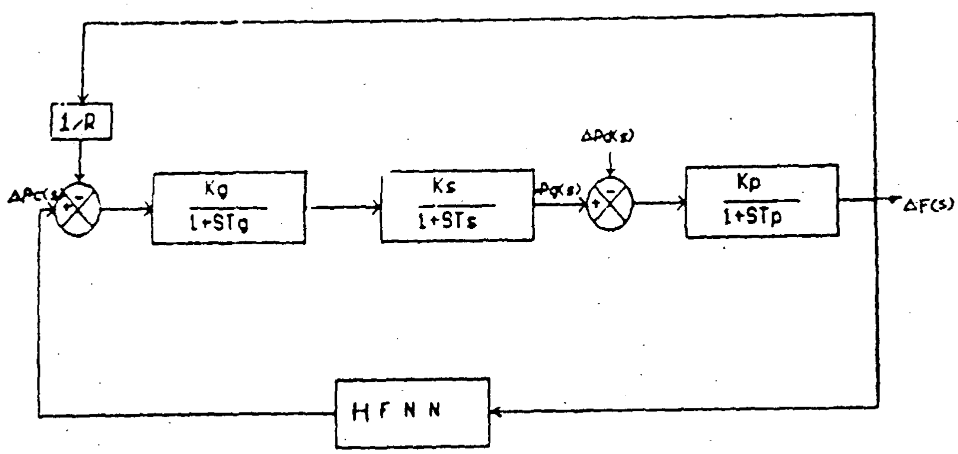

Fig.5: HFNN based Single Area System

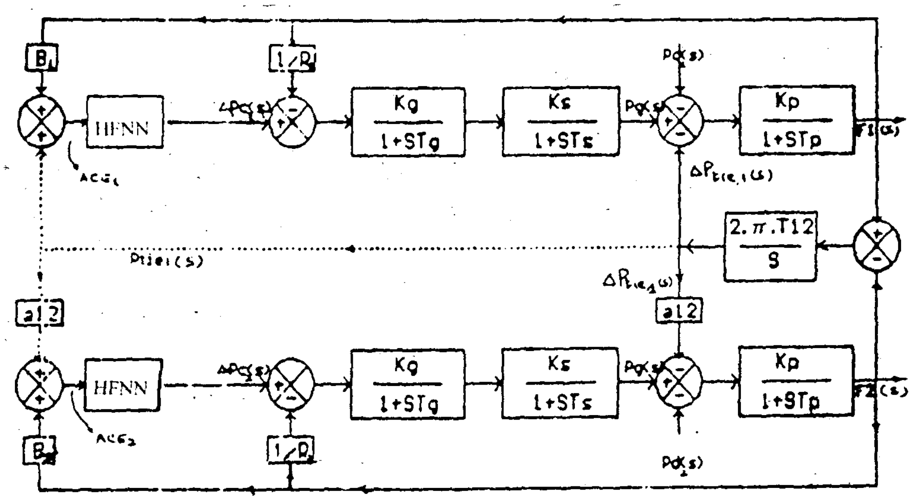

Fig.6: HFNN based Two-Area System

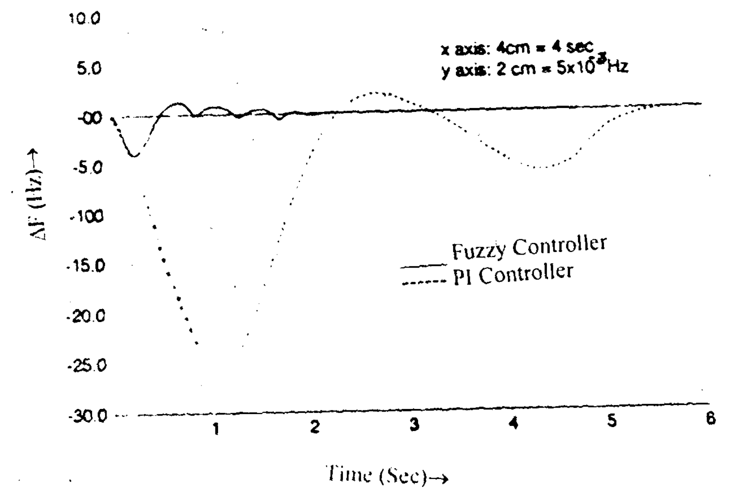

Fig.7: Comparison of PI and Fuzzy Controller (Single Area System)

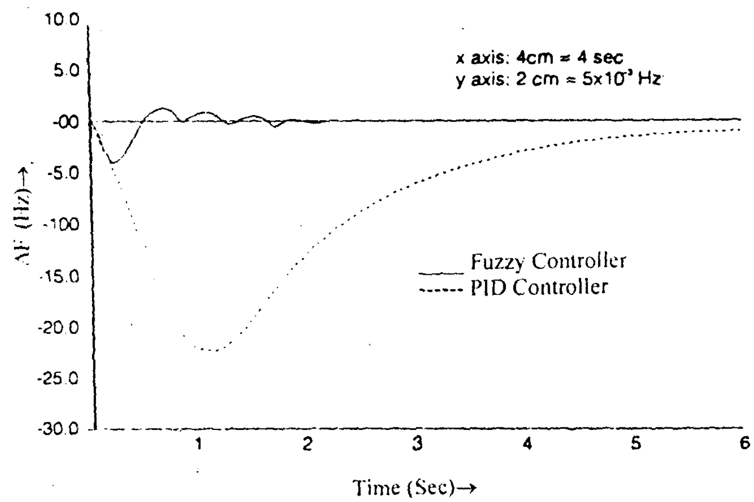

Fig.8: Comparison of PID and Fuzzy Controller (Single Area System)

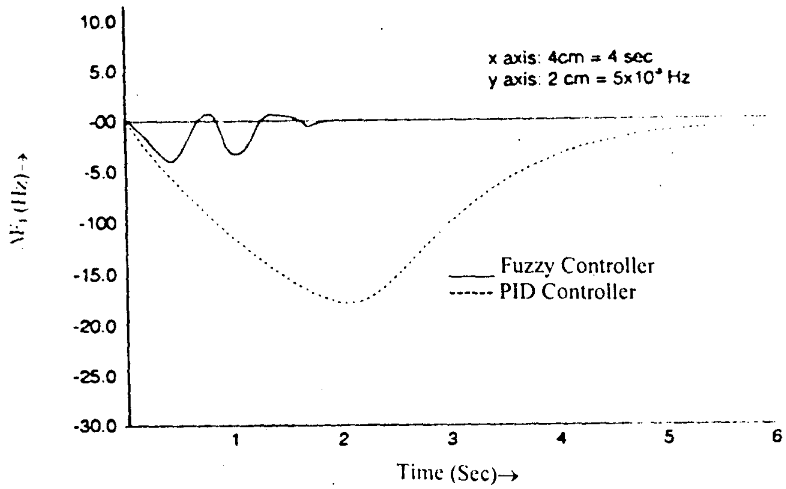

Fig.9: Frequency Deviation of Area-1

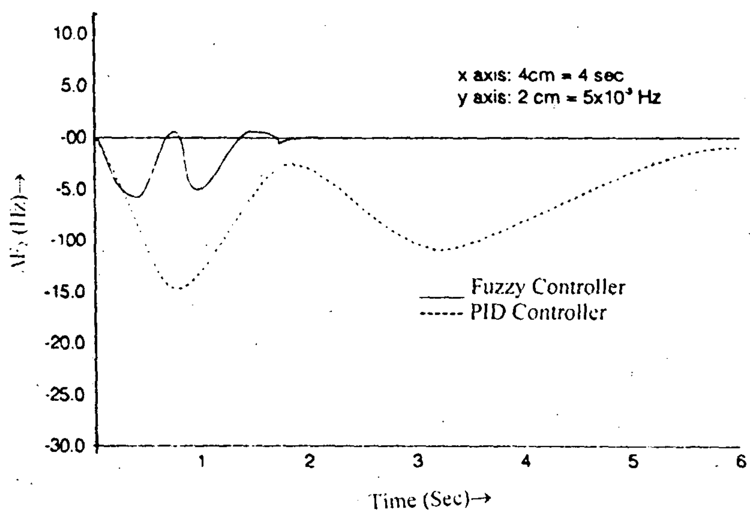

Fig.10: Frequency Deviation of Area-2

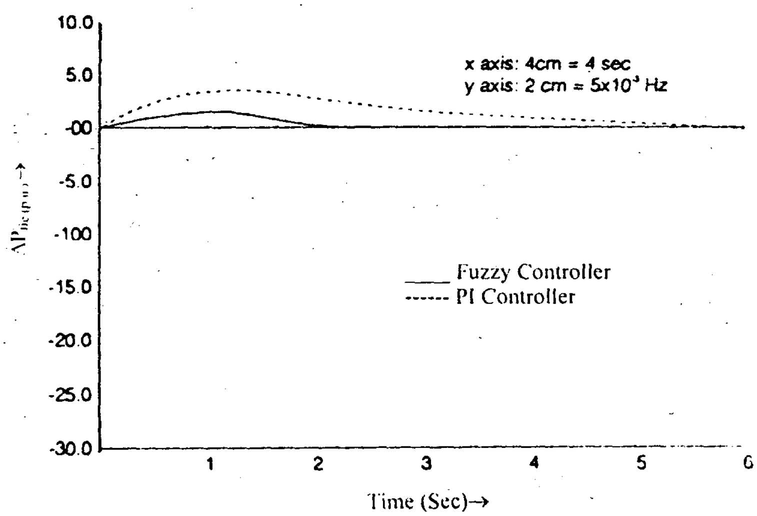

Fig.11: Tie-line Power Deviation

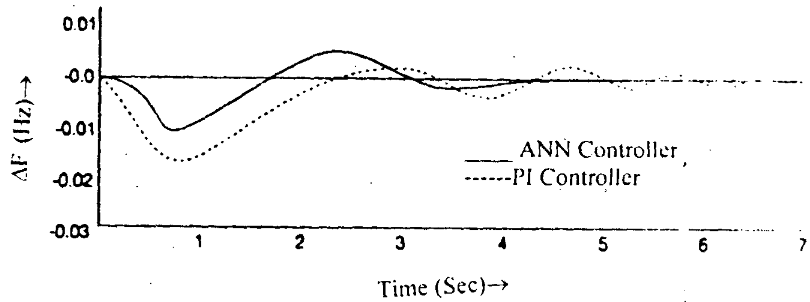

Fig.12: Comparison of PI and ANN Controller

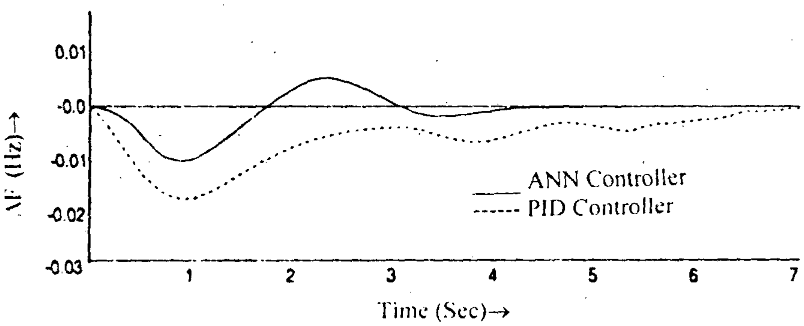

Fig.13: Comparison of PID and ANN Controller

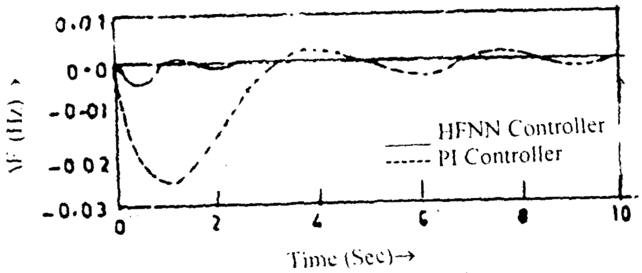

Fig.14: Frequency Deviation of PI and HFNN Controller (Single Area System)

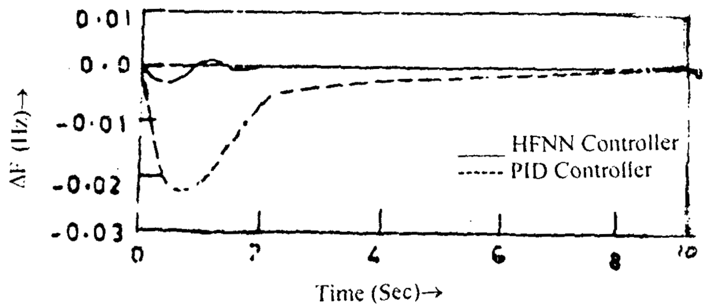

Fig.15: Frequency Deviation of PID and HFNN Controller (Single Area System)

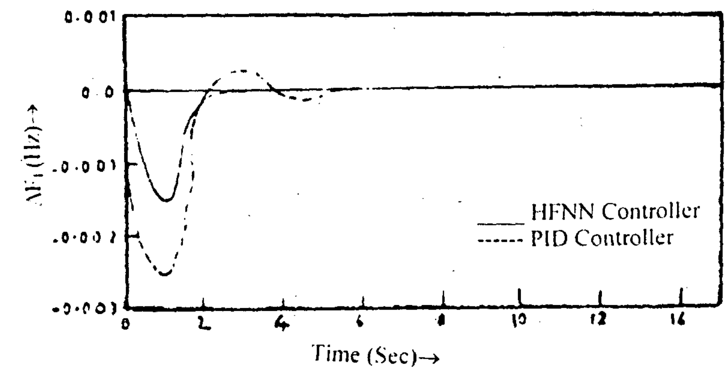

Fig.16: Frequency Deviation of Area-1 (HFNN Controller)

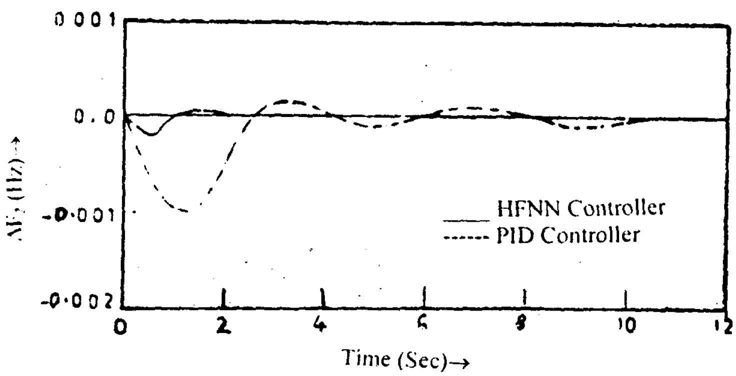

Fig.17: Frequency Deviation of Area-2 (HFNN Controller)

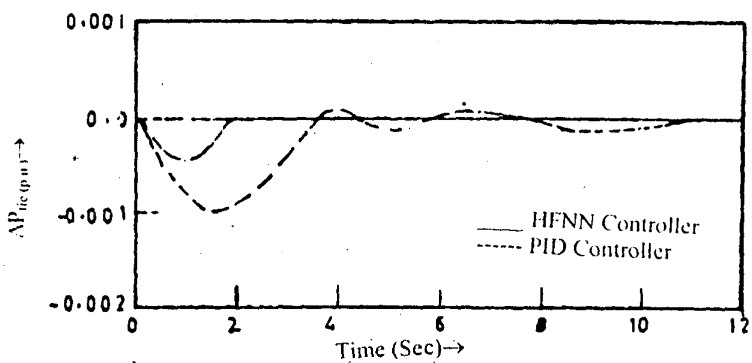

Fig.18: Tie-line Power Deviation (HFNN Controller)

$\dot{E}$ \ E	NB	NM	NS	Z	PS	PM	PB
NB	PB	PB	PM	Z	PS	Z	Z
NM	PB	PB	PM	Z	Z	NM	NM
NS	PB	PB	PM	Z	Z	NM	NM
Z	PB	PB	PM	Z	NM	NB	NB
PS	PM	PM	Z	Z	NM	NB	NB
PM	PM	PS	NS	Z	NM	NB	NB
PM	PM	PS	NS	Z	NM	NB	NB

Table-1: Fuzzy Rules for Single Area System

$\dot{E}$ \ E	NB	NM	NS	Z	PS	PM	PB
NB	PB	PB	PM	Z	Z	Z	Z
NM	PB	PM	PS	Z	Z	Z	NS
NS	PM	PM	PS	Z	Z	NS	NS
Z	PM	PS	PS	Z	NS	NS	NM
PS	PS	PS	Z	Z	Z	NM	NM
PM	PS	Z	Z	Z	NS	NM	NB
PB	Z	Z	Z	Z	NS	NB	NB

Table-2: Fuzzy Rules for Two Area System

E \ Pc	PB	PM	PS	Z	NS	NM	NB
NB	1.0	0.9	0.8	0	0	0	0
NM	0.8	0.6	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-3: Fuzzy Reasoning Model (FRM)
(Single Area System)

E \ Pc	PB	PM	PS	Z	NS	NM	NB
NB	1.0	0.9	0.8	0	0	0	0
NM	0.7	0.5	0.3	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	0.2
PM	0	0	0	0	0.2	0.3	0.4
PB	0	0	0	0	0.4	0.6	0.8

Table-4: Fuzzy Reasoning Model (FRM)
(Two Area System)