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Implementation of Automatic Generation Control of Hydrothermal System Employing Hybrid Genetic-Neural Approach

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ABSTRACT

This paper presents the design of controller based on the combined principle of Genetic Algorithm and Neural networks. The concept of artificial intelligent techniques greatly helps in overcoming the disadvantages posed by the conventional controllers. A hierarchical architecture of three layer feed forward neural network (NN) is proposed for controller design based on back propagation algorithm (BPA). Area Control Error (ACE) is considered as input to the neural network controller and the output of the controller is provided to the governor in each area. The main advantage of neural network is that it can adapt itself from the training data. In order to reduce the complexity of having more training data, Genetic Algorithm (GA) has been incorporated into the neural network in order to obtain optimal values of weights and bias. The proposed controller is tested for a two area hydrothermal system. Simulation results show that the limitations of conventional controller can be overcome by including Hybrid Genetic-Neural concept and thereby the dynamic response of the system with respect to peak time, overshoot and settling time can be improved drastically.

***Keywords* - Automatic Generation Control, Genetic Algorithm, Neural Networks, Hydrothermal system**.

I. INTRODUCTION

Large scale power systems are normally composed of control areas or regions representing coherent groups of generators. In a practically interconnected power system, the generation normally comprises of a mix of thermal, hydro, nuclear and gas power generation. However, owing to their high efficiency, nuclear plants are usually kept at base load close to their maximum output with no participation in the system Automatic generation control (ACE). Gas power generation is ideal for meeting the varying load demand. Gas plants are used to meet peak demands only. Thus the natural choice for AGC falls on either thermal or hydro units.

Literature survey shows that most of earlier works in the area of AGC pertain to interconnected thermal systems and relatively lesser attention has been devoted to the AGC of interconnected hydro-thermal system involving thermal and hydro subsystem of widely different characteristics. Concordia and Kirchmayer [1] have studied the AGC of a hydro-thermal system considering non-reheat type thermal system neglecting generation rate constraints. Kothari, Kaul, Nanda [2] have investigated the AGC problem of a hydro-thermal system provided with integral type supplementary controllers. The model uses continuous mode strategy, where both system and controllers are assumed to work in the continuous mode. Perhaps Nanda, Kothari and Satsangi [3] are the first to present comprehensive analysis of AGC of an interconnected hydrothermal system in continuous-discrete mode with classical controllers. It is known that load-frequency control systems include an integral controller as secondary controller in conventional control configurations. The integrator gain is set to a level that compromise between fast transient recovery and low overshoot in dynamic response of the system. Unfortunately, this type of controller is considerably slow. Because of this, the recovery of transients in the power system against to the load perturbations spends very long time.

In recent years intelligent methods such as Fuzzy logic (FL) have been applied to the load frequency control problem [4-7]. The salient feature of these soft computing techniques are 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 is required. Since artificial neural network configuration will be used to control the system, back propagation algorithm is used as a learning rule to cope with the continuous time dynamics.

GA is a search and optimization method developed by mimicking the evolutionary principles and chromosomal processing in natural genetics. Especially GA is efficient to solve nonlinear multiple-extrema problems [8-9] and is usually applied to optimize controlled parameters and constrained functions. In this study, a step load change in each area is considered. For comparison, the considered power system is controlled by using both conventional integral controller and Hybrid Genetic Algorithm-Neural Network (HGANN) controller for the case mentioned above. The results obtained show that the HGANN configuration using back propagation algorithm applied for AGC of power system gives good dynamic response with respect to conventional controller.

II. DYNAMIC MATHEMATICAL 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 [10]. The system under investigation

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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 [10]. Two system nonlinearities likely Governor Deadband and Generation Rate Constraint (GRC) are considered here for getting the realistic response. Governor Deadband is defined as the total magnitude of the sustained speed change within which there is no change in the valve position. It is required to avoid excessive operation of the governor. GRC is considered in real power systems because there exits a maximum limit on the rate of change in the generating power. Figure 1 shows the transfer function block diagram of a two area interconnected network .The parameters of two area model are defined in Appendix.

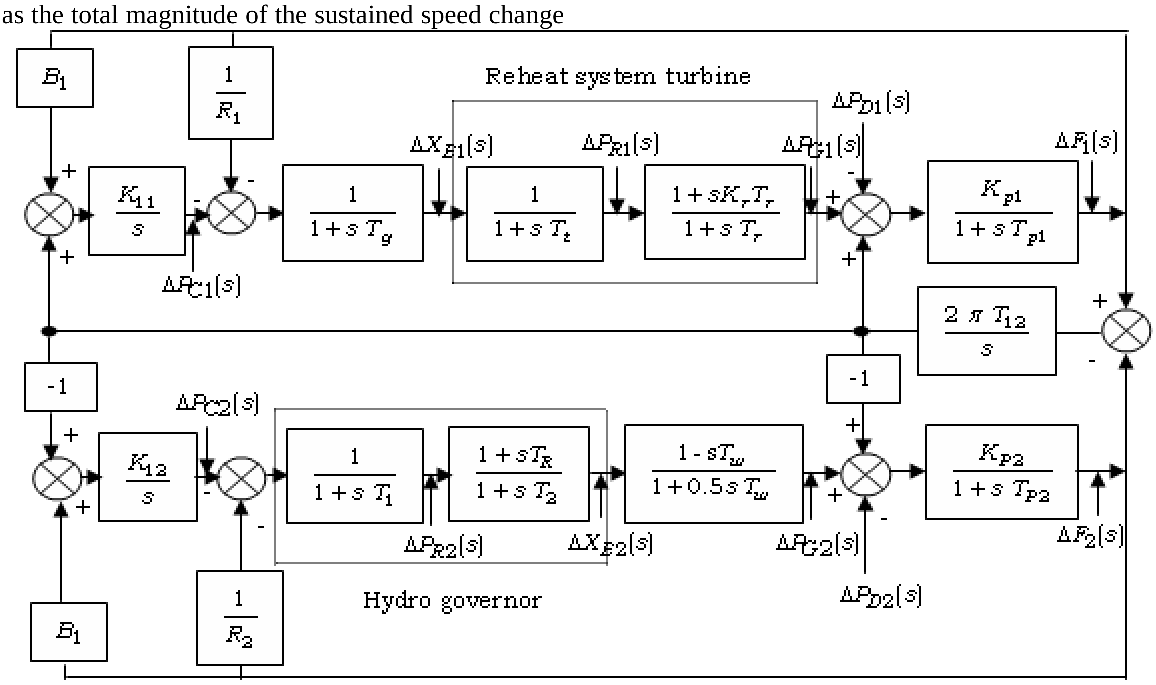


Figure. 1 Two Area Hydrothermal System

III. BACK PROPAGATION ALGORITHM

In the field of electrical engineering, one of the most exciting and potentially profitable recent developments is the increasing use of artificial intelligence techniques like neural networks in the design of various controllers. Artificial neural networks have been applied to many problems, and have demonstrated their superiority over classical methods when dealing with noisy or incomplete data. Neural networks are well suited to this method, as they have the ability to pre-process input patterns to produce simpler patterns with fewer components. A fascinating feature of the brain is that its physical organization reflects the organization of the external stimuli that are presented to it. In view of this back propagation algorithm has been used to design controller. In this back propagation algorithm the weights from input layer-hidden layer-output layer are updated iteratively during the learning phase. The updation of weights in back-propagation algorithm is done as follows: The error signal at the output of neuron j at iteration n is given by $e_j(n) = d_j(n) - y_j(n)$ (1)

The instantaneous value of error for neuron j is $\frac{1}{2}e_j^2(n)$.

This instantaneous value $\varepsilon(n)$ of total error is obtained by summing $\frac{1}{2}e_j^2(n)$ of all neurons in output layer

$$\varepsilon(n) = \frac{1}{2}\sum_{j\in c} e_j^2(n) \qquad (2)$$

where c includes all neurons in the output layer. Average squared error is given by

$$\varepsilon_{avg} = \frac{1}{N}\sum_{n=1}^{N}\varepsilon(n) \qquad (3)$$

where N is total number of patterns in training set. So minimization of ε_{avg} is required. So back propagation algorithm is used to update the weights. Induced local field $v_j(n)$ produced at input of activation function is given by

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n)X_i(n) \qquad (4)$$

where m is the number of inputs applied to neuron j. So the output can be written as

$$y_j(n) = \phi_j(v_j(n)) \qquad (5)$$

The back propagation algorithm applies a correction $\Delta w_{ji}(n)$ to synaptic weights $w_{ji}(n)$ which is proportional to partial derivative $\frac{\partial\varepsilon(n)}{\partial w_{ji}(n)}$, which can be written as

$$\frac{\partial\varepsilon(n)}{\partial w_{ji}(n)} = \frac{\partial\varepsilon(n)}{\partial e_j(n)}\cdot\frac{\partial e_j(n)}{\partial y_j(n)}\cdot\frac{\partial y_j(n)}{\partial v_j(n)}\cdot\frac{\partial v_j(n)}{\partial w_{ji}(n)} \qquad (6)$$

Differentiating the equation (2) with respect to $e_j(n)$

$$\frac{\partial \varepsilon(n)}{\partial e_j(n)} = e_j(n) \quad (7)$$

Differentiating equation (1) with respect to $y_j(n)$

$$\frac{\partial e_j(n)}{\partial y_j(n)} = -1 \quad (8)$$

Differentiating equation (5) we get

$$\frac{\partial y_j(n)}{\partial v_j(n)} = \phi_j'(v_j(n)) \quad (9)$$

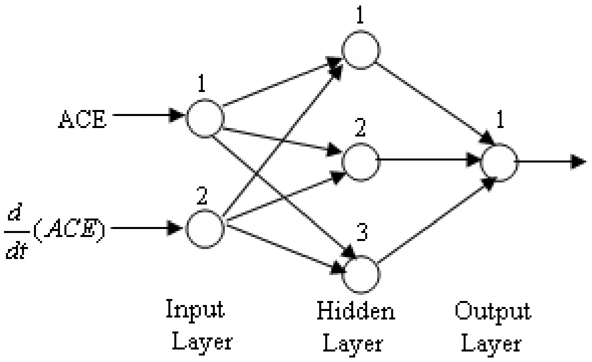


Figure. 2 Architecture of Neural Network Considered

Differentiating equation (4) with respect to $w_{ji}(n)$

$$\frac{\partial v_j(n)}{\partial w_{ji}(n)} = X_i(n) \quad (10)$$

So using equations (7-10) in equation (6) we get

$$\frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} = -e_j(n)\phi_j'(v_j(n))X_i(n) \quad (11)$$

The correction $\Delta w_{ji}(n)$ applied to $w_{ji}(n)$ is defined by

$$\Delta w_{ji}(n) = -\eta \frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} \quad (12)$$

where η is learning rate parameter. Figure 2 shows the architecture of neural network considered for this work. It can be seen that the Area Control Error (ACE) and rate of change of ACE are considered as inputs in the input layer and ΔP_c is considered as output in the output layer.

IV. GENETIC ALGORITHM

Genetic algorithms are procedures based on the principles of natural selection and natural genetics that have proved to be very efficient in searching for approximations to global optima in large and complex spaces in relatively short time. The basic components of GA are:

- Representation of problem to be solved
- Genetic operators (selection, crossover, mutation);
- Fitness function;
- Initialization procedure.

GA starts by using the initialization procedure to generate the first population. The members of the population are usually strings of symbols (chromosomes) that represent possible solutions to the problem to be solved. Each of the members of the population for the given generation is evaluated and according to its fitness value, it is assigned a probability to be selected for reproduction. Using this probability distribution, the genetic operators select some of the individuals. By applying the operators to them, new individuals are obtained. The mating operator selects two members of the population and combines their respective chromosomes to create offspring. The mutation operator selects a member of the population and changes part of the chromosome

V. HYBRID GENETIC-NEURAL NETWORK

The performance of neural network generally depends upon the values of weights and bias obtained after training. Since there is no clear methodology for determining the number of training data required for proper training of the neural network, hence the weights obtained cannot be seen as the optimum values. So in order to obtain the optimal values of weights and bias, a new hybrid technique involving both GA and NN has been proposed in this paper which uses an evolutionary technique to determine the weights instead of the steepest descent method used in traditional NN.

Normally the GA starts by randomly generating a population of strings. Each string is evaluated and the weights for hidden layer and output layer along with bias are found out as shown in Figure. 3. The above process is carried out for all the other strings in the population and new offspring's are created using the genetic operators like reproduction, crossover and mutation. This process is carried out for a number of iterations and the winner string is selected based on minimum value of MSE. The final values of input and output weights along with bias are calculated as shown in Fig. 3. The various weights for both input layer and output layer along with the bias are calculated for the winner string and network is built with the help of obtained weights and bias.

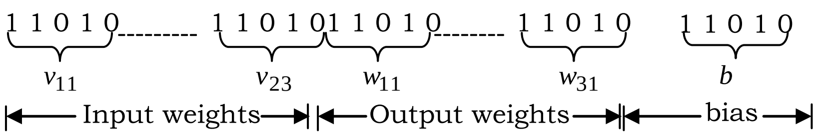


Figure. 3 Allocation of input and output weights of NN using GA

VI. RESULTS AND DISCUSSIONS

The proposed system in modeled in MATLAB/SIMULINK environment and the results have been presented. A load change of 0.04 p.u M.W in each area has been considered to study the comparison between HGANN network controller and integral controller. A value of 0.5 has been considered as the gain of integral controller. A performance index has been considered in this work to compare the performance of proposed methods is given by $J = \int_0^t \left(\alpha \cdot \Delta f_1^2 + \beta \cdot \Delta f_2^2 + \Delta P_{tie12}^2 \right)$.

Table 1. Weights between input and hidden nodes.

	Node 1	Node 2	Node 3
Node 1	520.26	1743.7	2678.4
Node 2	509.58	462.64	-381.8

Table 2. Bias Values at hidden nodes.

Node 1	0.6004
Node 2	-0.9900
Node 3	13.648

Table 3. Weights between hidden and output nodes.

	Node 1
Node 1	-2.3068
Node 2	1.9983
Node 3	-8.977

Table 4. Bias Value at output node.

Node 1	2.125

The ISE criterion is used because it weighs large errors heavily and small errors lightly. Even though Δf_1 and Δf_2 have very close resemblance, separate weighing factors i.e., α and β are considered for each of them respectively so as to obtain better performance. The parameters α and β are weighing factors which determine the relative penalty attached to the tie-line power error and frequency error. A value of 0.65 has been considered in this work as the value for both α and β. Table 1-4 shows the values of the weights and bias obtained from the winner string of genetic algorithm.

Table 5 shows the performance of the controllers in both the areas. It can be seen that the performance of the system is greatly improved in the presence of HGANN controller rather than an integral controller.

Table 5. Comparison of performance of controllers .

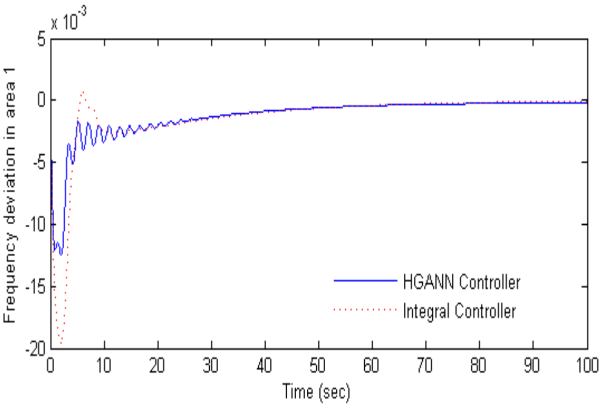
	Thermal Area			Hydro Area		
	Peak Time	Overshoot	Settling Time	Peak Time	Overshoot	Settling Time
With HGANN Controller	1.985	0.012506	21.75	1.185	0.017814	20.54
With Integral Controller	2.055	0.019635	22.745	1.565	0.023684	21.71
% Improvement	3.40	36.30	4.37	24.28	24.78	5.38

Where % improvement = $\left(\dfrac{\left(|With\ \ Integral\ controller| - |with\ \ HGANN\ \ controller| \right)}{|With\ \ Integral\ controller|} \right) \times 100$

Table 6 shows the comparison of performance index of the system in the presence of both controllers. It can be observed from the table that the system with HGANN controller has less performance index than that of the system with integral controller which demonstrates the superiority of the HGANN controller.

Table 6. Comparison of Performance Index Values.

	Performance Index Value
With HGANN Controller	0.0001295
With Integral Controller	0.0002114



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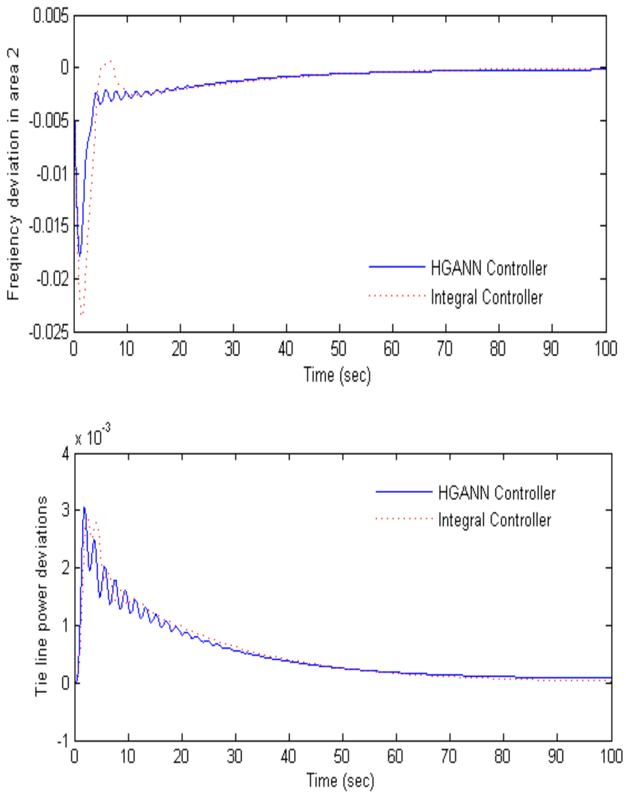

Figure. 4 Frequency and tie line power error deviations in both the areas

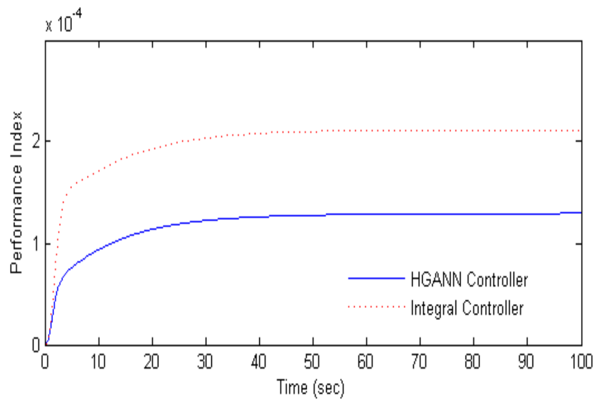

Figure. 5 Comparison of Performance index of system with both controllers

Figure 4 shows the various frequency deviations and tie line power deviations in both the areas during a load change of 0.04p.u MW. It can be observed that HGANN controller is far superior than the integral controller in terms of peak time, overshoot and settling time in both the areas. Figure 5 shows the comparison between both the controllers in terms of performance index.

VII. CONCLUSION

The performance of integral controller and HGANN controller for a two area hydrothermal system has been investigated. It has been observed that the integral is capable of bringing better dynamic response of the system to some extent. But the conventional design approach requires a deep understanding of the system, exact mathematical models and precise numerical values. The basic feature of neural concept is that the process can be controlled with slight knowledge of its underlying dynamics. But the neural network suffers from lack of optimal values of weights. In order to overcome this, an evolutionary technique like GA has been used to obtain the optimal value of weights. The simulation results show the superior performance of the system using HGANN controller.

APPENDIX

R =2.4 Hz/p.u.MW; $D = 8.33\times10^{-3}$ p.u. MW/Hz; K_g =1; T_g =0.08 sec; K_t =1; T_t =0.3 sec; K_r =0.5; T_r =10 sec; T_1, T_2, T_R =41.6, 0.513, 5 sec; T_w =1 sec; K_p =120 Hz/p.u. MW ; T_p =:20 sec; B =0.425 p.u. MW/Hz

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