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A FUZZY WAVELET NEURAL NETWORK LOAD FREQUENCY CONTROLLER BASED ON GENETIC ALGORITHM

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Abstract- In this paper, a self tuning load frequency controller based on Fuzzy Wavelet Neural Network (FWNN) and Genetic Algorithm (GA) is developed to quench the deviations in frequency and tie line power due to load disturbances in an interconnected power system. The error between desired system output and output of control object is employed to tune the network parameters. Tuning rule is accomplished based on GA approach by minimizing a compound of control error. For the purpose of the proposed method's evaluation, the proposed method is applied to a two area power system with considerations regarding governor saturation and the results are compared to the one obtained by a classic PI controller. Moreover, the robustness of the proposed method is tested against change of parameters. The simulation studies show that the designed controller by proposed method has a very desirable dynamic performance, better operation and improved system parameters such as settling time and step response rise time even when the system parameters change.

Keywords: Fuzzy Wavelet Neural Network, Load Frequency Controller, Genetic Algorithm.

I. INTRODUCTION

Load Frequency Control (LFC) has been one of the major issues in electric power system design and operation and is becoming much more significant recently in accordance with increasing size, changing structure and complexity of modern interconnected power systems. The primary objective of the LFC in an interconnected power system is to maintain reasonably uniform frequency for dividing the load between generators of each area and to keep the tie-line power interchanges to permissible limits in the presence of modeling uncertainties, system nonlinearities and area load disturbances [1].

The conventional proportional-integral (PI) control is probably the most commonly used technique in load frequency control problem. The main disadvantage of this method is that the dynamic performance of the system is highly dependent on the selection of its gain. Moreover, due to the nonlinearity of power systems, unpredictability of load variations and errors in the modeling, the operating points of a power system may varies very remarkably and randomly during a daily cycle. As a result, a fixed controller based on classical theory may no longer be suitable in all operating conditions for LFC problem.

During the past decades, several control approaches have been proposed and applied to the LFC design problem including; optimal control, adaptive control, model predictive control, sliding mode control and robust control which can be found in [2-6], respectively. Each of these techniques has their own advantages and disadvantages. More recently, there has been a growing concern in Artificial Intelligence (AI) techniques, such as fuzzy logic control (FLC) [7], Artificial Neural Network (ANN) [8] and Biologically Inspired (BI) algorithms [9-13] to design of load frequency controller in a power system by the researches around the world.

Recently, based on the combination of feed-forward neural networks and wavelet decompositions, wavelet neural network (WNN) has received a lot of attention and has become a popular tool for function learning [14]. The main characteristic of WNN is that some kinds of wavelet function are used as the activation function in the hidden layer of neural network, so time frequency property of wavelet is incorporated into the learning ability of neural networks. However, the main problem of WNN with fixed wavelet bases is the selection of wavelet frames because the dilation and translation parameters of wavelet basis are fixed and only the weights are adjustable.

Daniel et al, [15] have proposed a FWNN based on the wavelet theory, fuzzy concepts and neural network to improve function approximation accuracy. The FWNN has multi resolution capability, simple structure, high approximation accuracy and good generalization performance. The complexity and uncertainty of the system can be also reduced and handled by the concepts of fuzzy logic. Also, the local details of non stationary signals can be analyzed in terms of the dilation and translation parameters of wavelets. Considering these specifications, there are many papers that discuss the synthesis of a fuzzy wavelet neural inference system for function approximation, identification and control of nonlinear systems [16-18].

In this paper, a new Load Frequency Controller based on fuzzy wavelet neural network (FWNN-LFC) is proposed to design load frequency controller of a multi-area power system with system parametric uncertainties. The FWNN is used to construct load frequency controllers. The architecture of the control system is presented and the parameter update rules of the system are derived. Learning rules are based on the Genetic Algorithm (GA). The orthogonal least square (OLS) algorithm is used to purify the wavelets for each rule and determine the number of fuzzy rules and network dimension. Furthermore, in order to improve the function approximation accuracy and general capability of the FWNN system, a self-tuning process that uses the GA is used to adjust the network's nonlinear and linear parameters such as translation parameter of wavelets, membership function characteristic and weights coefficients of sub-WNN.

The proposed approach is implemented to a two-area interconnected power system with considerations regarding governor saturation. The results obtained by proposed approach are compared with those obtained by classic PI controller reported in the literature. Simulation studies show that the dynamic performance of the proposed controller is considerably desirable.

The paper is organized as follows: to make a proper background, the basic concepts of the FWNN and GA are briefly explained in Section II. The study system which used in the simulations studies is given in section III. In section IV, the proposed FWNN-LFC scheme is described. Simulation results in the study system are provided in section V and some conclusions are drawn in section VI.

II. AN OVERVIEW OF FWNN AND GA

A. Fuzzy Wavelet Neural Network Structure

The FWNN is a multi-layer network which integrates fuzzy model with wavelet neural networks. For a multi-input-single-output (MISO) with $\underline{x}=[x_1,...,x_q]$ as input and y as output of the system, a typical fuzzy wavelet neural network for approximating arbitrary nonlinear function y can be described by a set of fuzzy rules as follow [15]:

R_i : if x_1 is A_1^i and x_2 is A_2^i and ... and x_q is A_q^i ,

$$\text{then } \hat{y}_i=\sum_{k=1}^{T_i} w_{M_{i,t^k}} \psi^{(k)}_{M_{i,t^k}}(\underline{x}) \tag{1}$$

$M_i \in z$, $t^k \in R^q$ and $w^{t^k}_{M_i} \in R$, $x \in R^q$

where R_i $(1 \le i \le c)$ is the ith fuzzy rule and x_j is the jth input variable of $\underline{x}$. Also $\hat{y}_i$ calculates the output of local model for rule R_i. M_i and T_i determine the dilation parameters and total number of wavelets for the ith rule, respectively. $\underline{t}^k=[t_1^k,t_2^k,...,t_q^k]$, where t_j^k denotes the translation value of corresponding wavelet k. Finally, A_i^j is the fuzzy set characterized by the following Gaussian type membership function and $A_j^i(x_j)$ is the grade of membership of x_j in A_j^i, where:

$$A_j^i(x_j)=\mathrm{e}^{-(\frac{(x_j-p_{j1}^i)}{p_{j2}^i})^2} \quad , \quad p_{j1}^i, p_{j2}^i \in R \tag{2}$$

where p_{j1}^i represents the center of membership function and p_{j2}^i determine the width and the shape of membership function, respectively. Moreover, wavelets $\psi^{(k)}_{M_i,t}(\underline{x})$ are expressed by the tensor product of 1-D wavelet functions:

$$\begin{aligned}\psi^{(k)}_{M_i,t}(\underline{x}) &= 2^{\frac{M_i}{2}} \psi^{(k)}(2^{M_i}\underline{x}-\underline{t}^k)= \\ &=\prod_{j=1}^{q} 2^{\frac{M_i}{2}} \psi^{(k)}(2^{M_i}x_j-t_j^k)\end{aligned} \tag{3}$$

By applying fuzzy inference mechanism and let $\hat{y}_i$ be the output of each sub-WNN, the whole output of FWNN for function $y(x)$ is as follows:

$$\hat{y}_{FWN}(\underline{x})=\sum_{i=1}^{c}\hat{\mu}_i(\underline{x})\hat{y}_i \tag{4}$$

where $\hat{\mu}_i(x)=\dfrac{\mu_i(x)}{\sum_{i=1}^{c}\mu_i(x)}$ and $\mu_i(x)=\prod_{j=1}^{q}A_j^i(x_j)$ are the firing strength of the ith rule for current input and satisfies $0 \le \hat{\mu}_i \le 1$, $\sum_{i=1}^{c}\hat{\mu}_i=1$. Also, $\hat{\mu}_i$ determines the contribution degree of the output of the wavelet based model with resolution level, M_i.

A good initialization of wavelet neural networks leads to fast convergence. Numbers of methods are implemented for initializing wavelets, such as Orthogonal Least Square (OLS) procedure and clustering method [19]. In this paper the OLS algorithm is used to select important wavelets and to determine the number of fuzzy rules and network dimension. More details about construction of FWNN and network parameter initialization can be found in [19]. The structure of applied FWNN is shown in Figure 1.

Furthermore, it is important to adjust the required network parameters in the design of dynamic systems. In order to avoid trial-and-error, a self-tuning process is used by employing the GA to determine significant parameters such as dilation, translation, weights, and membership functions. On the other word, during the learning process, these network parameters are optimized using GA. To make a proper background, the concept of GA is given in the next subsection.

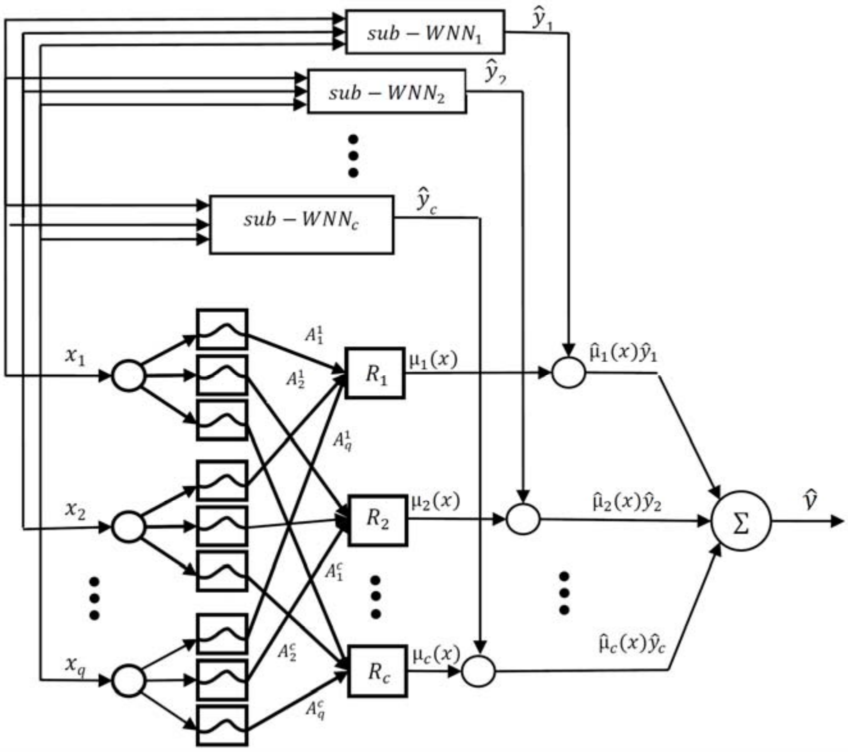

Figure 1. Structure of FWNN [15]

B. Genetic Algorithm

A genetic algorithm is a probabilistic and population search technique that computationally simulates the process of biological evolution. The GA starts with a randomly selected initial population of feasible solutions, and then recombines them in a way to guide their search to only the most promising areas of the state space. The changes to the population occur through the processes of selection based on fitness, and alteration using crossover and mutation. The application of selection and alteration leads to a population with a higher proportion of better solutions. The evolutionary cycle continues until an acceptable solution is found in the current generation of population, or some control parameter such as the number of generations is exceeded.

Each feasible solution is encoded as a chromosome (string) also called a genotype, and each chromosome is given a measure of fitness via a fitness (evaluation or objective) function. During each generation, the structures in the current population are rated for their effectiveness as domain solutions, and on the basis of these evaluations, a new population of candidate solutions is formed using specific genetic operators such as reproduction, crossover, and mutation

Crossover may be regarded as artificial mating in which chromosomes from two individuals are combined to create the chromosome for the next generation. This is done by splicing two chromosomes from two different solutions at a crossover point and swapping the spliced parts. The idea is that some genes with good characteristics from one chromosome may as a result combine with some good genes in the other chromosome to create a better solution represented by the new chromosome.

Mutation is a random adjustment in the genetic composition. It is useful for introducing new characteristics in a population something not achieved through crossover alone. The mutation operator changes the current value of a gene to a different one. For bit string chromosome this change amounts to flipping a 0 bit to a 1 or vice versa. The steps in the typical genetic algorithm for finding a solution to a problem are listed:

1. Create an initial solution population of a certain size randomly
2. Evaluate each solution in the current generation and assign it a fitness value.
3. Select "good" solutions based on fitness value and discard the rest.
4. If acceptable solution(s) found in the current generation or maximum numbers of generations is exceeded then stop.
5. Alter the solution population using crossover and mutation to create a new generation o solutions.
6. Go to step 2.

III. POWER SYSTEM MODEL

In actual power system operations, the load is varying randomly and continuously throughout the day. As a result, both frequencies in all areas and tie-line power flow between the areas are affected by these load changes at operating point. These changes create a mismatch between generations and demand that result in exact forecast of real power demand cannot be assured. Therefore, for good and stable power system operation, both the frequency and tie-line power flow should be kept constant against the sudden area load perturbations, system parameter uncertainties and unknown external disturbances. Therefore, to ensure the quality of power supply, a load frequency controller is needed to restoring the system frequency and the net interchanges to their desired values for each control area, still remain.

The area frequency deviation (Δf) and tie-line power deviation (ΔP_{tie}) are two important parameters of interest. The linear combinations of them are known as area control error (*ACE*). The measurements of all the generation and all load in the system for computation of the mismatch between the generation and obligation in one area is so hard. The mismatch is measured at the area control center by using *ACE*. The *ACE* for the *i*th area is defined as:

$$ACE_i = P_{tie_i}^{act} - P_{tie_i}^{s} - 10B_i(f_i^{act} - f_i^{s}) = \\ = \Delta P_{tie_i} - 10B_i\Delta f_i \quad (5)$$

where $P_{tie_i}^{act}$ and $P_{tie_i}^{s}$ are the actual and scheduled (manually set) interchange of *i*th area with neighboring areas, respectively. Also, f_i^{act} and f_i^{s} are the area's actual and scheduled frequency, in *i*th area, and *B* is the frequency bias coefficient of *i*th area that is a negative number measured in MW per 0.1Hz. However, the *ACE* signal often is calculated using the area frequency response characteristic β instead of *B* as follows:

$$ACE_i = \Delta P_{tiei} + \beta_i \Delta f_i \quad (6)$$

$$\beta_i = \frac{1}{R_i} + D_i \quad (7)$$

In which D_i is the damping ratio or the frequency sensitivity of the *i*th area's load and R_i is the regulation due to governor action in the *i*th area, or droop characteristic. Also, β_i is frequency bias constant and should be high enough such that each area adequately contributes to frequency control [20].

The frequency and interchanged power are kept at their desired values by means of feedback of area control error containing deviation in frequency and error in tie-line power, and controlling the prime movers of generators. The main objective of control system is to damp these variations to zero as fast and smooth as possible and following a change in load demand values.

A two-area interconnected power system with considering governor limiters is investigated in this study. Each area consists of three major components, which are turbine, governor, and generator. The detailed transfer function block diagram of uncontrolled two-area system is shown in Figure 2 where Δf_1 and Δf_2 are the frequency deviations in area 1 and area 2 respectively in Hz. Also ΔP_{L1} and ΔP_{L2} are the load demand changes in areas 1 and 2 respectively in per unit (p.u.). Moreover, T_{gi}, T_{ti} and M_i are speed governor time constant (s), turbine time constant (s), and power system time constant (s) of *i*th area, respectively. The detailed transfer function models of the speed governors and turbines are discussed in [1]. Typical data for the system parameters and governor limiters, for nominal operation condition, are presented in Table 1.

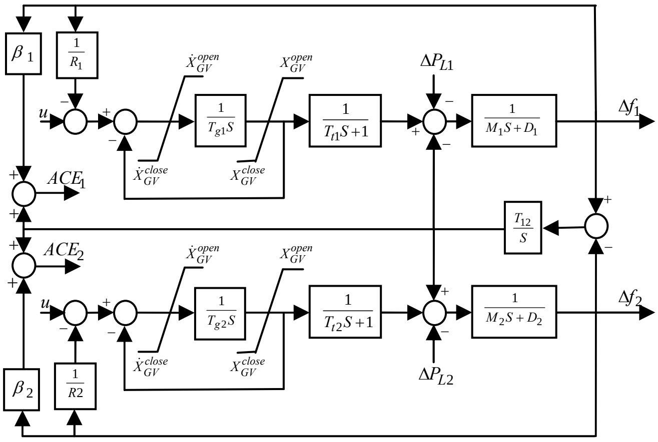

Figure 2. Two-area interconnected power system

Table 1. Two Area Interconnected Power System Parameters

Area	Parameters
Area 1	M=10, D_1=0.8, T_g=0.2, T_t=0.5, R_1=0.05, $\dot{X}_{GV}^{open}=0.4$, $\dot{X}_{GV}^{close}=1.5$, $X_{GV}^{open}=1.2$ $X_{GV}^{close}=0.4$, T_{12}=2
Area 2	M=8, D_2=0.9, T_g=0.3, T_t=0.6, R_2=0.0625, $\dot{X}_{GV}^{open}=0.4$, $\dot{X}_{GV}^{close}=1.5$, $X_{GV}^{open}=1.2$, $X_{GV}^{close}=0.4$, T_{12}=2

IV. DESIGN OF FUZZY WAVELET NEURAL NETWORK LOAD FREQUENCY CONTROLLER USING GENETIC ALGORITHM

The detailed block diagram for the proposed FWNN load frequency controller is given in Figure 3. According to this figure, the proposed FWNN-LFC implements two input signals for each area. The two signals used for area number one is the area control error (*ACE*) for area number one and it's rate of change. The two input signals used for the FWNN load frequency controller of area number two is the area control error (*ACE*) for the area number two, and it is rate of change.

The objective of the control problem is to track the frequency deviation to zero in the case of a load disturbance. To achieve this control means, the neural control system synthesis is performed in the closed-loop control system and the linear combinations of frequency deviation and tie-line power deviation, i.e. area control error (*ACE*) is taken as tracking error for tuning FWNN load frequency controller parameters to provide appropriate control input.

By minimizing a quadratic measure of the tracking error, the design problem can be characterized by the GA formulation. On the other hand, the GA is used to correct the network parameters for adjusting of FWNN load frequency controller. By using above control strategy, the designing FWNN load frequency controller is equivalent to determination of the FWNN parameters.

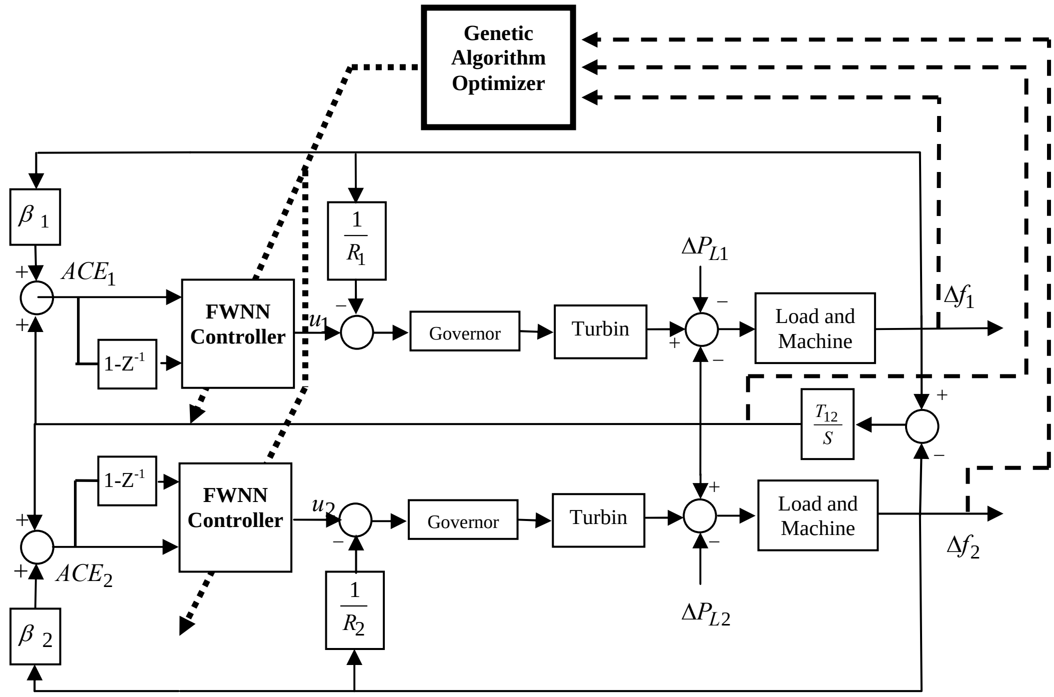

Figure 3. Fuzzy wavelet neural network load frequency controller scheme

The outputs of two FWNN-LFCs, U_1 and U_2, are defined so that tracking error is minimized. To calculate the desired control signals, the FWNN parameters including dilation, translation, weights, and membership functions should be set so that the *ACE* is minimized. In this work, to obtain the FWNN parameters the GA is used. In this case, finding the FWNN parameters is considered as an optimization problem and the quadratic measure of *ACE* is considered as the objective function.

Here we used a fitness function that using the *ACE* of each area, as follow:

$$Fitness = \sum_{l=1}^{L}\left(ACE_1^2 + ACE_2^2\right) \tag{8}$$

where L is number of network training data. According to Figure 3, the *ACE* of each area is measured in each iteration and will be given to the GA optimizer. Then the solution vector is obtained by GA by minimizing the fitness function which gives the FWNN-LFC parameters. By using the obtained parameters, the network's outputs are calculated and applied to the system followed by calculating the new *ACEs*. The procedure continues until a termination criterion is met. The termination criterion could be the number of iterations, or when a solution of minimal fitness is found.

Equations (2)-(4) show that the free parameters to be trained in FWNN *b* are p_{j1}^i, p_{j2}^i, $\underline{t}^k$ and ω_{M_i} where , $i = 1,...,c$, $j = 1,...,q$. Our task is to design the FWNN basis function expansion such that the objective function (8) minimized. Therefore GA is applied for tuning parameters of FWNN by optimizing the following objective or cost function.

$$F_k = \sum_{l=1}^{L}\left(ACE_{1,k}^2 + ACE_{2,k}^2\right) \tag{9}$$

where F_k is the fitness of *k*th chromosome. In the GA, each population is a solution to the problem which determines the parameters of FWNN, i.e. $[p_{j1}^{iN}, \; p_{j2}^{iN}, \underline{t}^{kN}, \; w_{M_i}^N]$. So *k*th chromosome is represented as:

$$C_k = [p_{j1}^{ik}, \; p_{j2}^{ik}, \underline{t}^{kk}, \; w_{M_i}^k]^T \tag{10}$$

In Equation (10), the superscript T denotes the vector transpose operation. Thus, all free design parameters that to be updated by GA in FWNN load frequency controller are as follows:

$$\begin{cases} \underline{p}_{j1}^{ik} = [p_{11}^{1k}...p_{11}^{ck}...p_{q1}^{1k}....p_{q1}^{ck}] \\ \underline{p}_{j2}^{ik} = [p_{12}^{1k}...p_{12}^{ck}...p_{q2}^{1k}....p_{q2}^{ck}] \\ \underline{t}^{kk} = [t_1^{1k}...t_1^{Sk}....t_q^{1k}...t_q^{Sk}] \\ \underline{w}_{M_i}^k = [w_{M_1}^k....w_{M_c}^k] \end{cases} \tag{11}$$

By applying the GA, the best chromosome (solution) corresponding to the smallest fitness value can be obtained. In GA, during each generation, the chromosomes are evaluated with some measure of fitness, which is calculated from the objective function defined in (9). Then the best solution is chosen. In the current problem, the best solution is the one that has minimum fitness.

V. SIMULATION RESULTS

In this section, a two-control area power system, shown in Figure 2 is considered as a test system. The typical data for the system parameters and governor limiters for nominal operation condition can be given as Table 1. To indicate the effectiveness of the proposed FWNN load frequency controller for the studied two area power system that is subjected to two different load disturbances, the studied power system frequency deviations and tie line power are obtained. Comparisons between the power system response using the proposed wavelet neural network controller, and that using the conventional proportional plus integral (PI) controller are performed, and the results are discussed

At first, initializing of the network is performed and each FWNN-LFC was trained using a set of 300 input-output. By applying OLS algorithm, three fuzzy rules with three selected wavelets are represented for constructing the FWNN based controller. Three fuzzy rules are used in FWNN structure and consequently 27 parameters have to be updated. The initial values of the parameters of FWNNs are generated randomly in the interval [–10, 10] and a GA based approach is used to reach the optimal values. The training of FWNN system is performed for 300 data points. The fitness value is calculated as (9).

The number of chromosomes in the population is set to be 200. One point crossover is applied with the crossover probability $p_c = 0.9$ and the mutation probability is selected to be $p_m = 0.01$. Also, the number of iterations is considered to be 500.

In order to show the ability and effectiveness of the proposed method, a conventional PI controller by using the approach adopted from [1] is applied for comparison, too. It was found that $K_{I1} = K_{I2} = 0.3$ were the best selections for having the best performance.

The designed FWNN load frequency controller and those obtained by PI controller are placed in the case study (Figure 3). To show the effectiveness of the designed controllers, a time domain analysis is performed for the case study. To test the proposed method, a sudden small load perturbation which continuously disturbs the normal operation of the power system is applied to the system. Here we use a step load change of 0.01 p.u., (i.e. $\Delta P_{L1} = \Delta P_{L2} = 0.01$). The frequency deviation of both areas and tie-line power variation in nominal condition of the closed loop system are obtained and shown in Figures.4, 5 and 6, respectively.

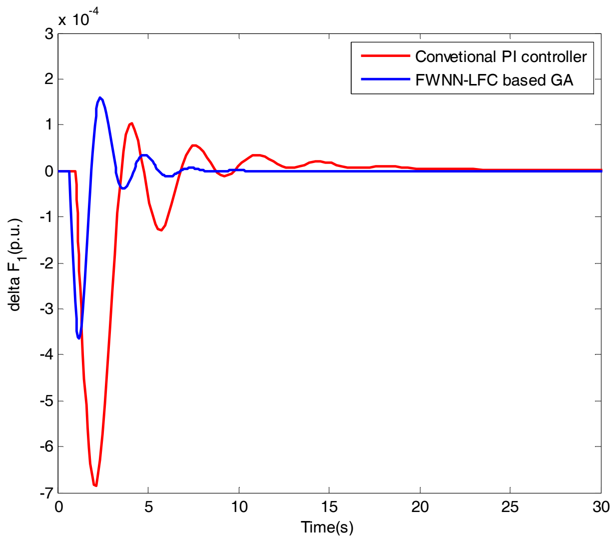

Figure 4. Frequency deviation of area 1

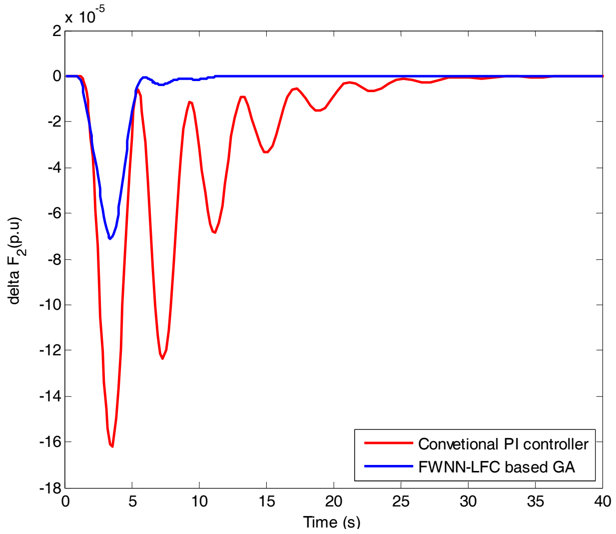

Figure 5. Frequency deviation of area 2

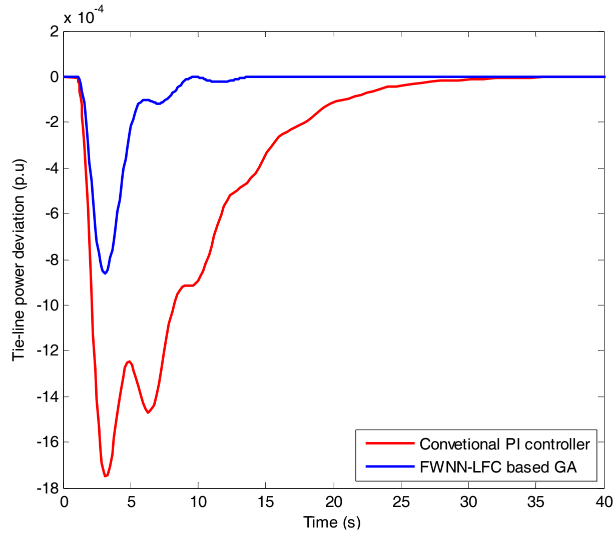

Figure 6. Tie-line power deviation

From the comparing curves it can be seen, using the proposed method, the frequency deviation and tie-line power variation of two areas following the load changes and are quickly driven back to zero. It should be mentioned that although the overshoot of frequency response of classical PI controller shown in Figure 4 is better than the proposed approach, but the settling time of the latter is better than the former. Generally, by looking at Figures 4-6 it can be concluded that the proposed method gives a better performance than the classical LFC.

To show the robustness of the proposed approach and to investigate the effect of changing the system parameters on system performance, two system parameters are considered as 20% increase for all system parameters (upper bound) and 20% decrease for all system parameters (lower bound). The dynamic behavior of the system was evaluated for 30 s. Figures 7-12 show response system for upper bound and lower bound of parameters condition including frequency deviation of areas 1 and 2, and also, tie-line power deviation.

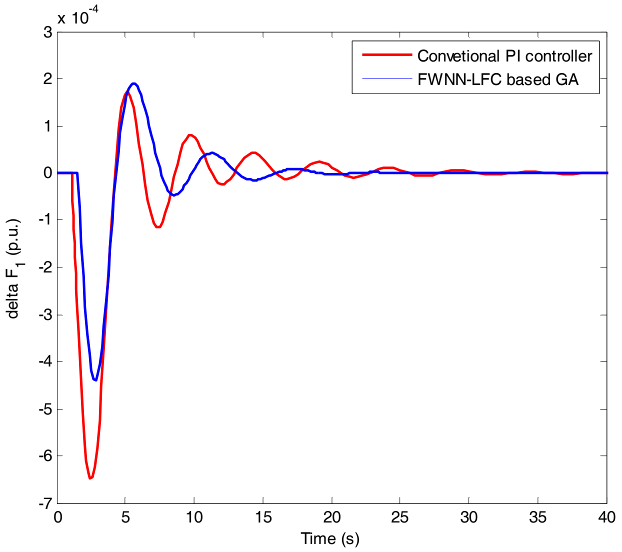

Figure 7. Frequency deviation of area 1 for upper bound of parameters

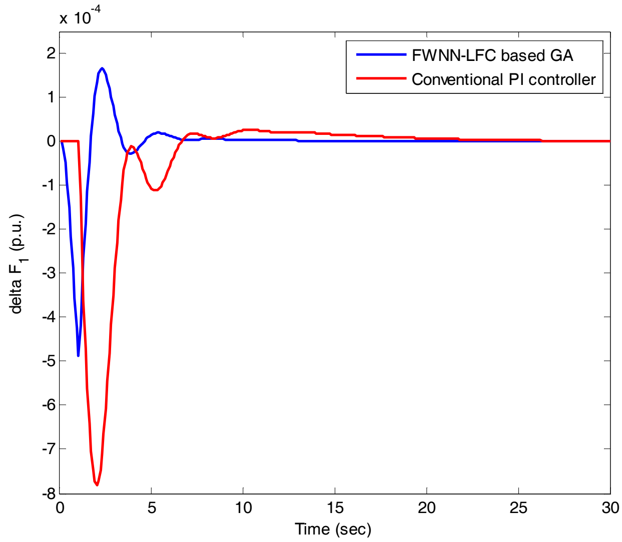

Figure 10. Frequency deviation of area 1 for lower bound of parameters

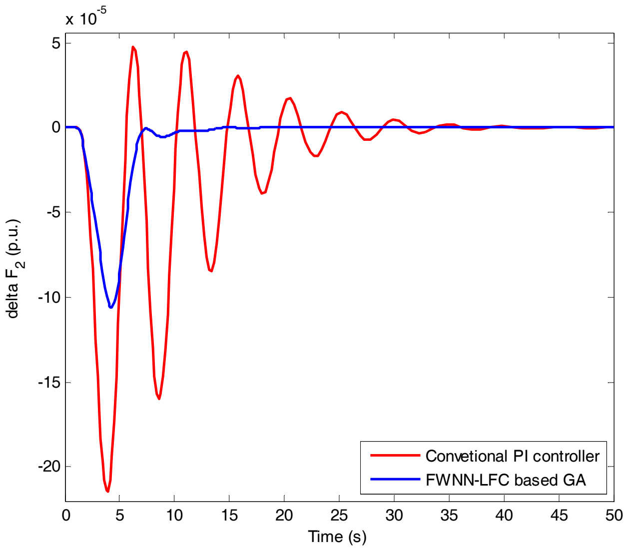

Figure 8. Frequency deviation of area 2 for upper bound of parameters

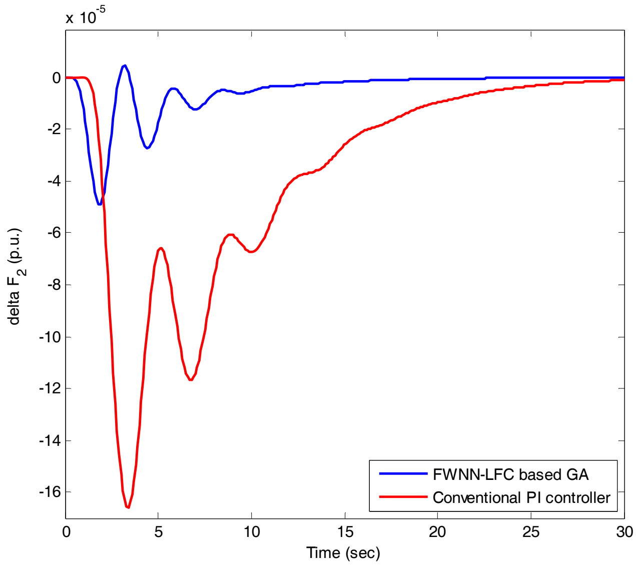

Figure 11. Frequency deviation of area 2 for lower bound of parameters

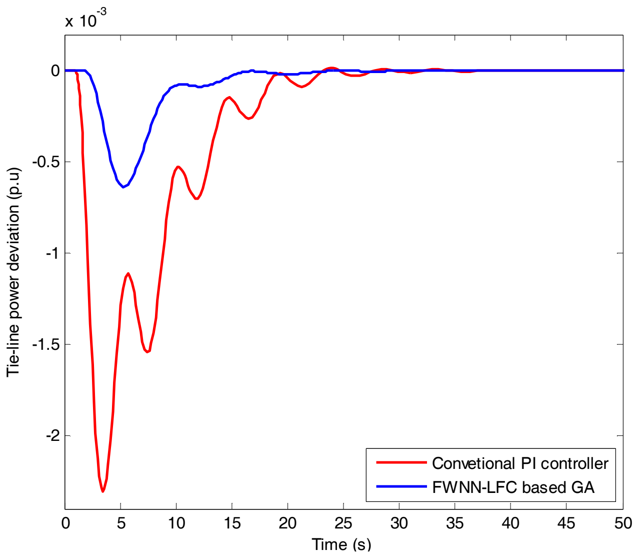

Figure 9. Tie-line power deviation for upper bound of parameters

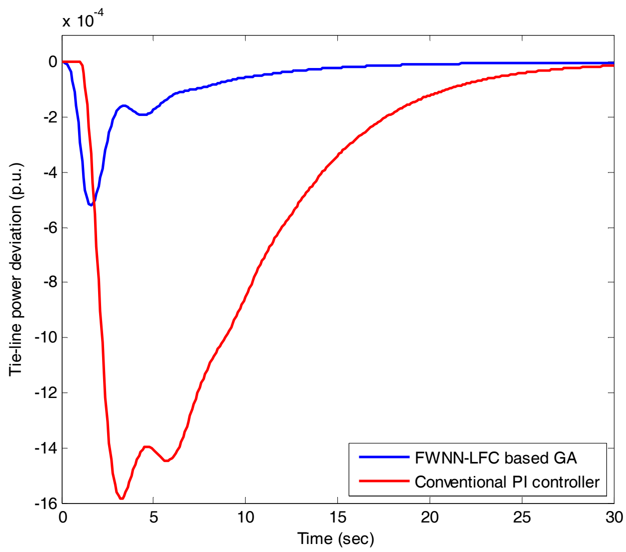

Figure 12. Tie-line power deviation for lower bound of parameters

Figures 7-12 show the dynamic performance of the studied two area power system with the conventional PI controller and with the proposed fuzzy wavelet neural network controller. The superiority of the proposed FWNN controller over the conventional PI controller is evident in damping the system frequency oscillations very fast. Also, there is less undershoot for area number one and area number two, and the damping o the tie line power oscillations is very fast with the proposed FWNN controller.

VI. CONCLUSIONS

In this paper a new load frequency controller based on fuzzy wavelet neural network and genetic algorithm (FWNN-LFC) is developed to quench the deviations in frequency and tie line power due to load disturbances in an interconnected power system. The FWNN is trained to tune the parameters of FWNN-LFC based on real-time measurements of area control error in each area.

Also, an efficient genetic algorithm is proposed for the learning of FWNN and to find optimal values of the parameters of FWNN-LFC. The performance of designed FWNN-LFC is tested on a two area interconnected power system with considering governor limiters and the results obtained are compared with the classical PI controller.

The robustness and effectiveness of the proposed FWNN-LFC is verified under different disturbances. Simulation results show that the superiority of the proposed FWNN controller over the conventional PI controller is evident in damping the system frequency oscillations very fast. Also, there is less undershoot for area number one and area number two, and the damping o the tie line power oscillations is very fast with the proposed FWNN load frequency controller.

REFERENCES

[1] P. Kundur, "Power System Stability and Control", New York, Mc Graw Hill, 1994.

[2] N.N. Bengiamin, W.C. Chan, "Variable Structure Control of Electric Power Generation", IEEE Trans. Power App. Syst., Vol. PAS-101, pp. 376-380, 1982.

[3] C.T. Pan, C.M. Liaw, "An Adaptive Controller for Power System Load-Frequency Control", IEEE Trans. Power Syst., Vol. 4, pp. 122-128, February 1989.

[4] A.M. Kassem, "Neural Predictive Controller of a Two-Area Load Frequency Control for Interconnected Power System", Ain Shams Engineering Journal, Vol. 1, pp. 49-58, 2010.

[5] K. Vrdoljak, N. Peric, I. Petrovic, "Sliding Mode Based Load-Frequency Control in Power Systems", Electric Power Systems Research, Vol. 80, pp. 514-527, 2010.

[6] H. Shayeghi, "A Robust Decentralized Power System Load Frequency Control", Journal of Electrical Engineering, Vol. 59, pp. 281-293, 2008.

[7] H. Mohamed, L. Hassan, M. Moghavvemi, S. Yang, "Load Frequency Controller Design for Iraqi National Super Grid System Using Fuzzy Logic Controller", SICE Annual Conference, pp. 227-232, August 2008.

[8] D.K. Chaturvedi, P.S. Satsangi, P.K. Kalra, "Load Frequency Control: A Generalized Neural Network Approach", International Journal of Electrical Power and Energy Systems, Vol. 21, pp. 405-415, 1999.

[9] H. Shayeghi, A. Jalili, H.A. Shayanfar, "Robust Modified GA Based Multi-Stage Fuzzy LFC", Energy Conversion and Management, Vol. 48, pp. 1656-1670, 2007.

[10] Y.L. Abdel-Magid, M.M. Dawoud, "Genetic Algorithms Applications in Load Frequency Control", Genetic Algorithms in Eng. Sys. Innovations and Applications, Vol. 1, September 1995.

[11] E Bijami, R. Abshari, J. Askari, S.M. Saghaiannejad, "Load Frequency Control of Interconnected Power System Using Brain Emotional Learning Based Intelligent Controller", Proc. 19th Iranian Conference in Electrical Engineering, 2011.

[12] H. Shayeghi, H.A. Shayanfar, "Application of PSO for Fuzzy Load Frequency Design with Considering Superconducting Magnetic Energy Storage", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 2, Vol. 2, No. 1, pp. 24-33, 2010.

[13] H.A. Shayanfar, M. Ghazal, M. Karami, "Load Frequency Control Using Multivariable Characteristic Loci Method in Power Systems", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 1, Vol. 1, No. 1, pp. 5-11, 2009.

[14] Q. Zhang, A. Benveniste, "Wavelet Networks", IEEE Transactions on Neural Networks, Vol. 3, pp. 889-898, 1992.

[15] D.W. C. Ho, P.A. Zhang, J. Xu, "Fuzzy Wavelet Networks for Function Learning", IEEE Trans. Fuzzy Systems, Vol. 9, No. 1, pp. 200-211, 2001.

[16] S.T. Tzeng, "Design of Fuzzy Wavelet Neural Networks Using the GA Approach for Function Approximation and System Identification", Fuzzy Sets and Systems, Vol. 161, pp. 2585-2596, 2010.

[17] R.H. Abiyev, O. Kaynak, "Fuzzy Wavelet Neural Networks for Identification and Control of Dynamic Plants - A Novel Structure and a Comparative Study", IEEE Transactions on Industrial Electronics, Vol. 55, pp. 3133-3140, 2008.

[18] M. Shahriari Kahkeshi, E. Bijami, F. Sheikholeslam, M. Zekri, M.M. Farsangi, "Power System Stabilizer Design for Damping Power System Low Frequency Oscillation Based on Fuzzy Wavelet Neural Network", Intelligence Systems in Electrical Engineering, Vol. 1, No. 1, pp. 1-22, 2011.

[19] T. Kugarajah, Q. Zhang, "Multidimensional Wavelet Frames", IEEE Transaction on Neural Networks, Vol. 6, pp. 1552-1556, 1995.

[20] A. Khodabakhshian, M. Edrisi, "A New Robust PID Load Frequency Controller", Control Engineering Practice, Vol. 16, pp. 1069-1080, 2008.

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