Automatic Generation Control of Multi-Area Power System Using a Fuzzy Wavelet Neural Network Load Frequency Controller Combined With Shuffled Frog Leaping Algorithm

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ABSTRACT:
In this paper, an auto tuned load frequency controller based on Fuzzy Wavelet Neural Network (FWNN) and Shuffled Frog Leaping Algorithm (SFLA) is employed to damp the deviations of frequency and tie line power due to the load disturbances in a multi-area power system. Optimal tuning of the FWNN parameters is very important to improve the design performance and achieve a satisfactory level of robustness, for a particular operation. In this work, a new systematic tuning method is developed for designing the FWNN load frequency controller. For this, the error between the desired system output and output of control object is employed to tune the FWNN parameters. Tuning rule is accomplished based on SFLA approach by minimizing a combination of control error. To show the effectiveness of the proposed method, some numerical results are presented for a two area power system considering governor saturation and the results are compared to the obtained results by a classic PI controller and a fuzzy load frequency 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: Automatic Generation Control, Fuzzy Wavelet Neural Network, SFLA.

1. INTRODUCTION

With the development of extensive power systems, especially with increasing size, changing structure and complexity of these interconnected systems, Load Frequency Control (LFC) has become one of the important criterion in electric power system design and operation and has received a great deal of attention [1].

An interconnected modern power system with commercial and industrial loads, require operating at constant frequency with stable and reliable power. The fundamental goals of the LFC in an interconnected power system are to hold reasonably uniform frequency at each area and maintain the tie-line power interchanges in a predefined tolerance in the presence of modeling uncertainties, system nonlinearities, area load disturbances and sudden changes in load demands. In the modern power system, as a power load demand changes randomly, tie-line power interchange and area frequency change too. Therefore, a load frequency controller design is necessary to keep the reliability of the electric power system and provide better conditions for electricity trading and power system's safe operation.

During the past decades, several control approaches have been proposed and applied to the LFC design problems including: optimal control, adaptive control, sliding mode control and robust control which can be found in [2-5], 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) [6-8], Artificial Neural Network (ANN) [9, 10] and Biologically Inspired (BI) algorithms [11-13] to design the load frequency controller in a power system by the researches all over the world. From among these techniques, since the fuzzy logic controllers provide an effective means to model and control a complex and ill-defined plant, many control strategies based on fuzzy logic control approach have been suggested and applied successfully regarding the load-frequency control of power systems.

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 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.

In this paper, a new Load Frequency Controller based on the FWNN called 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 Shuffled Frog Leaping Algorithm (SFLA). 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 SFLA 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 regarding governor saturation. The obtained results by proposed approach are compared to those obtained by classic PI controller and a fuzzy 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: the basic concepts of the FWNN and SFLA are briefly explained in Sections2 and 3, respectively. The used study system in the simulations is given in section 4. In section 5, the proposed FWNN-LFC scheme is described. The simulation results of the study system are presented in section 6 and some conclusions are drawn in section 7.

2. FUZZY WAVELET NEURAL NETWORK OVERVIEW

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]:

$$R_i : if\ x_1\ is\ A_1^i\ and\ x_2\ is\ A_2^i\ and\ ...\ and\ x_q\ is\ A_q^i\ ,$$
$$then\ \hat{y}_i=\sum_{k=1}^{T_i} w_{M_{i,t^k}}\psi^{(k)}_{M_{i,t^k}}(\underline{x})$$
$$M_i \in z,\ t^k \in R^q\ and\ w^{t^k}_{M_i} \in R\ ,\ x \in R^q \tag{1}$$

Where R_i $(1 \le i \le c)$ is the i th fuzzy rule and x_j is the j th 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 i th 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:

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

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:

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

By applying fuzzy inference mechanism and let $\hat{y}_i$ be the output of each sub-WNN, the total 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 of the output degree of the wavelet based model with resolution level, M_i .

A good initialization of wavelet neural networks leads to fast convergence. Several methods are implemented for initializing wavelets such as: Orthogonal Least Square (OLS) procedure and clustering method [16]. In this paper the OLS algorithm is used to select important wavelets and determine the number of fuzzy rules and network dimension. More details about the construction of FWNN and network parameter initialization can be found in [16].

Furthermore, it is important to adjust the required network parameters in the dynamic systems design. In order to avoid trial-and-error, a self-tuning process is used by employing the SFLA 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 SFLA. To make a proper background, the concept of SFLA will be defined in the next section.

3. SFL ALGORITHM OVERVIEW

Shuffled Frog Leaping (SFL) algorithm is one of the biologically-based inspirations that its formulation is derived from two other search techniques: the local search of the "particle swarm optimization" technique and the competitive mixing of information of the "shuffled complex evolution" technique. That attempts to balance between a wide scan and also a deep search of promising locations for a global optimum. The SFLA is derived from a virtual population of frogs in which individual frogs represent a set of possible solution. Each frog is distributed to a different subset of the whole population referred to as Memeplex. The different memeplexes are considered as different culture of frogs that are located at different places in the solution space (i.e. global search). Each culture of frogs performs simultaneously an independent deep local search using a particle swarm optimization like method. Within each memeplex, the individual frogs hold ideas, that can be influenced by the ideas of other frogs within their memeplexand evolve through a change process of information among frogs from different memeplexes [18], [19].

To ensure global exploration, after a defined number of memeplex evolution steps (i.e. local search iterations), information is passed between memeplexes in a shuffling process. Shuffling improves frog ideas quality after being infected by the frogs from different memeplexes; ensure that the cultural evolution towards any particular interest is free from bias [20]. In addition to the improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions. After this stage, local search and shuffling processes (global relocation) will continue until defined convergence criteria are satisfied. The flowchart of the SFLA is illustrated in Fig. 1.

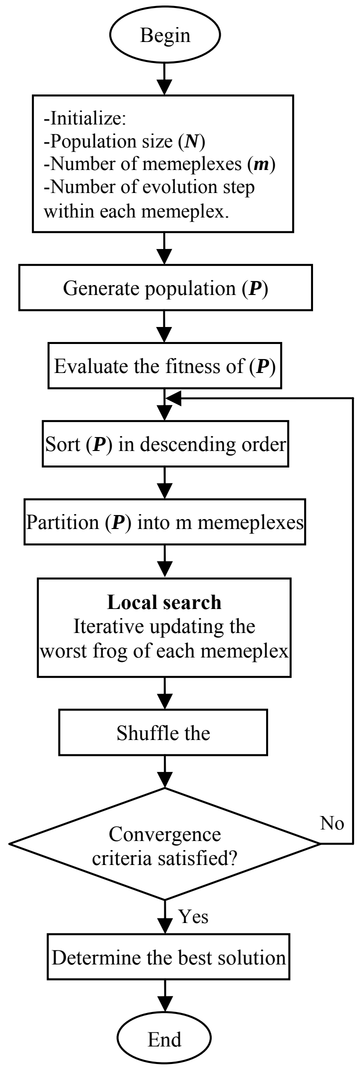

Fig. 1. General principle of the SFLA [20]

The SFLA begins with an initial population of "N" frogs, $P=\{X_1,X_2, \ldots,X_N\}$ created randomly within the feasible space Ω. For *S*-dimensional problems (S variables), the position of the "*i*th" frog is represented as $X_i= (x_{i1},x_{i2},...,x_{iS})$. A fitness function is defined to evaluate the frog's position.

Afterward the performance of each frog is computed based on its position. The frogs are sorted in a descending order according to their fitness. Then, the entire population is divided into *m* memeplexes, each of which consisting of *n* frogs (i.e. $N=m\times n$). In this process, the first frog goes to the first memeplex, the second frog goes to the second memeplex, frog *m* goes to the *m* thmemeplex, and frog *m+1* back to the first memeplex, and so on.

Within each memeplex, the position of frog *i* th (D_j) is adjusted according to the difference between the frog with the worst fitness (X_w) and the frog with the best fitness (X_b) as shown in equation (1), where *rand()* is a random number in the range [0,1]. During memeplex evolution, the worst frog X_w leaps toward the best frog X_b. According to the original frog leaping rule, the position of the worst frog is updated as follows:

$$\text{Position change}\,(\mathrm{D_i}) = rand() \times (X_b - X_w) \tag{5}$$

$$X_w(new) = X_w + D, (\|D\| < D_{\max}) \tag{6}$$

Where D_{max} is the maximum allowed change of frog's position in one jump. If this repositioning process produces a frog with better fitness, it replaces the worst frog, otherwise, the calculation in equations (5) and (6) are repeated with respect to the global best frog (X_g), (i.e. X_g replaces X_b.). If no improvement is possible in this case, then a new frog is randomly generated to replace the worst frog. The evolution process is continued for a specific number of iterations [17], [20].

4. 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 makes the exact forecast of real power demand unassured. 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 restore the system frequency and the net interchanges to their desired values for each control area.

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:

$$\begin{aligned} ACE_i &= P^{act}_{tie_i} - P^{s}_{tie_i} - 10B_i(f^{act}_i - f^s_i) \\ &= \Delta P_{tie_i} - 10B_i\Delta f_i \end{aligned} \tag{7}$$

Where $P^{act}_{tie_i}$ and $P^{s}_{tie_i}$ are the actual and scheduled (manually set) interchange of *i* th area with neighboring areas, respectively. Also, f^{act}_i and f^s_i 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:

$$ACE_i = \Delta P_{tiei} + \beta_i \Delta f_i \tag{8}$$

$$\beta_i = \frac{1}{R_i} + D_i \tag{9}$$

In which D_i is the damping ratio or the frequency sensitivity of the *i* tharea's load and R_i is the regulation due to governor action in the *i* th area, or droop characteristic. Also, β_i is the frequency bias constant and should be high enough such that each area adequately contributes to the frequency control [5].

A two-area interconnected power system with considering governor limiters is investigated in this study. Each area consists of three major components including turbine, governor and generator. The detailed transfer function block diagram of uncontrolled two-area system is shown in Fig. 2.

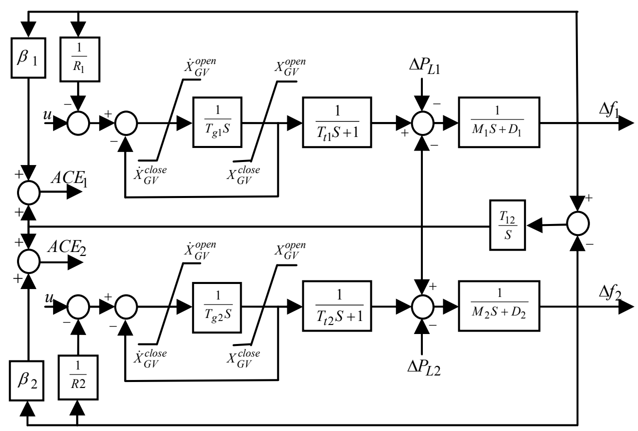

Fig. 2. Two-area interconnected power system

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 per unit (p.u). The main objective of control system is to damp these variations to zero as fast and smooth as possible and following a change in

the load demand values.
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 of the system parameters and governor limiters for the nominal operation condition are presented in Table 1.

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

5. DESIGN OF FWNN LOAD FREQUENCY CONTROLLER USING SFL ALGORITHM

The detailed block diagram of the proposed FWNN load frequency controller is given in Fig.3. 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 its change rate. 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 its change rate.

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 SFLA formulation. On the other hand, the SFLA is used to correct the network parameters for adjusting of the FWNN load frequency controller. By using above control strategy, the designing FWNN load frequency controller is equivalent to determination of the FWNN parameters.

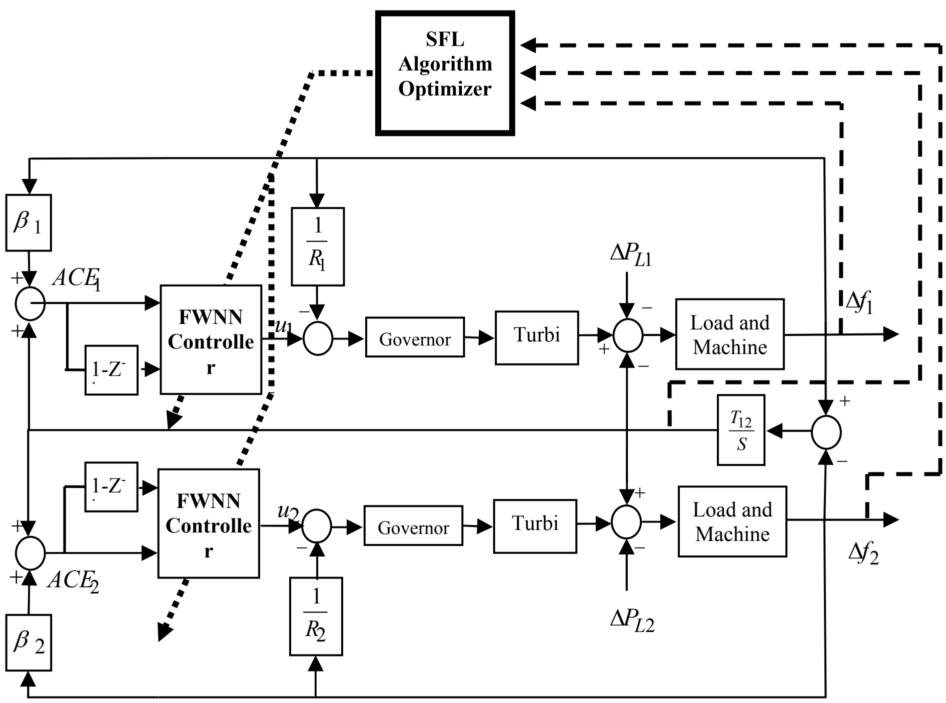

Fig. 3. Fuzzy Wavelet Neural Network load frequency controller scheme

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

$$Fitness = \sum_{l=1}^{L}\left(ACE_1^2 + ACE_2^2\right) \quad (10)$$

Where L is the number of network training data. According to Fig. 3, the *ACE* of each area is measured in eachiterationand will be given to the SFLA optimizer. Then the solution vector is obtained by SFLA 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 are $p_{j1}^{i}, p_{j2}^{i}, \underline{t}^{k}$ and w_{M_i} where , $i=1,...,c$, $j=1,...,q$. Our task is to design the FWNN basis function expansion such that the objective function (10) is minimized. Therefore SFLA is applied for tuning parameters of FWNN by optimizing the following objective or cost function.

$$F_k = \sum_{l=1}^{L}\left(ACE_{1,k}^2 + ACE_{2,k}^2\right) \quad (11)$$

Where F_k is the fitness of K^{th} frog. In the SFLA, 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} frog is represented as:

$$F_k = [p_{j1}^{ik}, p_{j2}^{ik}, \underline{t}^{kk}, w_{M_i}^{k}]^T \quad (12)$$

In (12), the superscript T denotes the vector transpose operation. Thus, all free design parameters that to be updated by SFLA in FWNN load frequency controller are as follows:

$$\begin{cases} \underline{p}_{j1}^{ik} = [p_{11}^{1k} \cdots p_{11}^{ck} \cdots p_{q1}^{1k} \cdots p_{q1}^{ck}] \\ \underline{p}_{j2}^{ik} = [p_{12}^{1k} \cdots p_{12}^{ck} \cdots p_{q2}^{1k} \cdots p_{q2}^{ck}] \\ \underline{t}^{kk} = [t_1^{1k} \ldots t_1^{Sk} \ldots t_q^{1k} \ldots t_q^{Sk}] \\ \underline{w}_{M_i}^{k} = [w_{M_1}^{k} \ldots w_{M_c}^{k}] \end{cases} \quad (13)$$

By applying the SFLA, the best frog (solution) corresponding to the smallest fitness value can be obtained. In SFLA, during each generation, the frogs are evaluated with some measure of fitness, which is calculated from the objective function defined in (11). Then the best solutions are chosen. In the current problem, the best solution is the one that has minimum fitness.

6. SIMULATION STUDIES

In this section, a two-control area power system, shown in Fig.3 is considered as a test system. The typical data for the system parameters and governor limiters for nominal operation condition are presented in 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 those using the conventional proportional integral (PI) [1] and fuzzy controller [7] are performed, and the results are discussed.

At first, the network was initialized and each FWNN-LFC was trained using a set of 500 input-output. By applying OLS algorithm, three fuzzy rules with four selected wavelets are represented for constructing the FWNN based controller. Three fuzzy rules are used in FWNN structure and consequently 36 parameters have to be updated. The initial values of the parameters of FWNNs are generated randomly in the interval [–5, 5] and a SFLA based approach is used to reach the optimal values. The training of FWNN system is performed for 500 data points. The fitness value is calculated as (11).To impediment the SFL algorithm, the number of frogs in the population is set to be 400. Also, the number of memeplex is considered to be 10 and the number of evaluation for local search is set to 10. Also, $D_{\max}$ ischosen as $in\ f$ and the number of iterations is considered to be 200.

In order to show the ability and efficiency of the proposed method, a conventional PI controller by using adopted approach 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. Moreover a fuzzy load frequency controller is designed based on the proposed approach in [7] and applied for comparison.

The designed FWNN load frequency controller and those obtained by PI controller and fuzzy controller are placed in the case study (Fig. 3). To show the effeciency 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 per unit (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 Figs. 4, 5 and 6 respectively.

The comparison between curves indicates that by using the proposed method, the frequency deviation and tie-line power variation of the two areas follow the load changes and are quickly driven back to zero. It should be mentioned that although the overshoot of frequency response of fuzzy controller shown in Fig. 5 is better than the proposed approach, but the time settling of the latter is better than the former. Generally, by looking at Figs. 4-6 it can be concluded that the proposed method gives a better performance than the classic LFC.

To show the robustness of the proposed approach and to investigate the effect of the changing parameters on the 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 20 s. Figs 7-12 show response system for upper and lower bound of parameters condition including frequency deviation of areas 1 and 2, and also, tie-line power deviation.

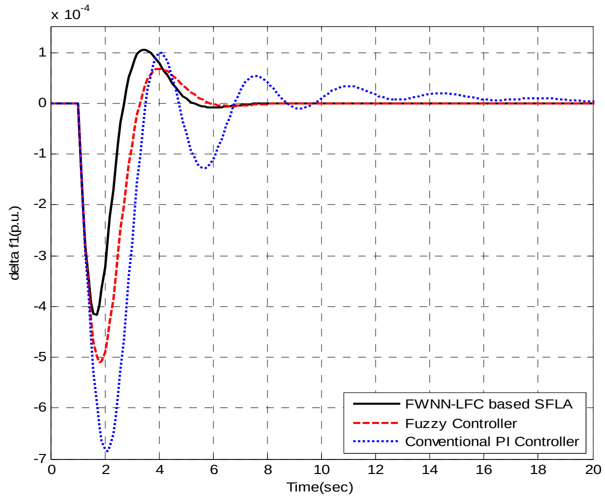

Fig. 4. Frequency deviation of area 1

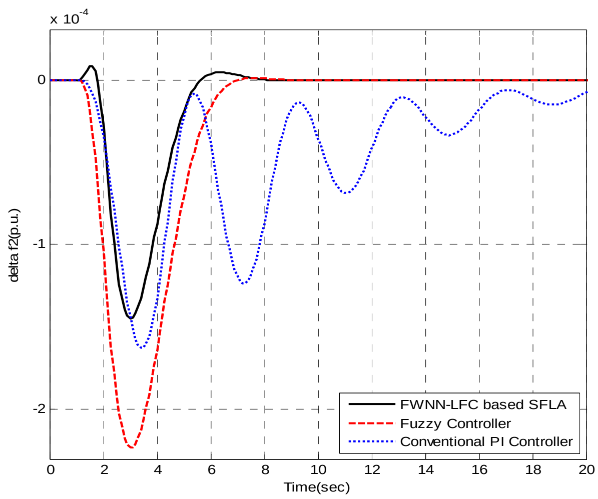

Fig. 5. Frequency deviation of area 2

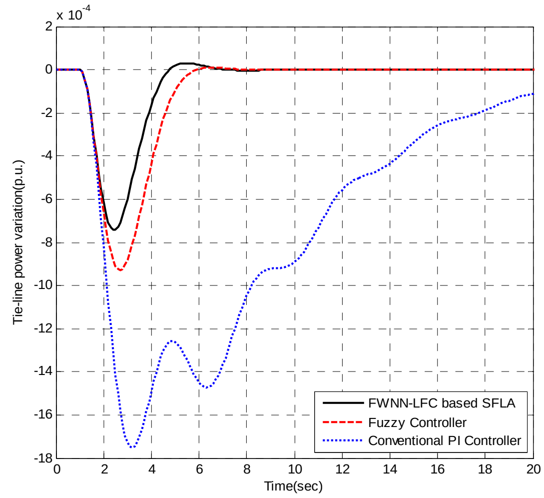

Fig. 6. Tie-line power deviation

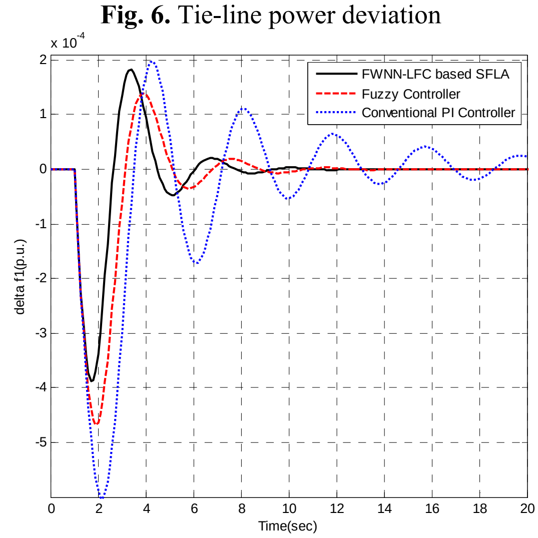

Fig. 7. Frequency deviation of area 1 for upper bound of parameters

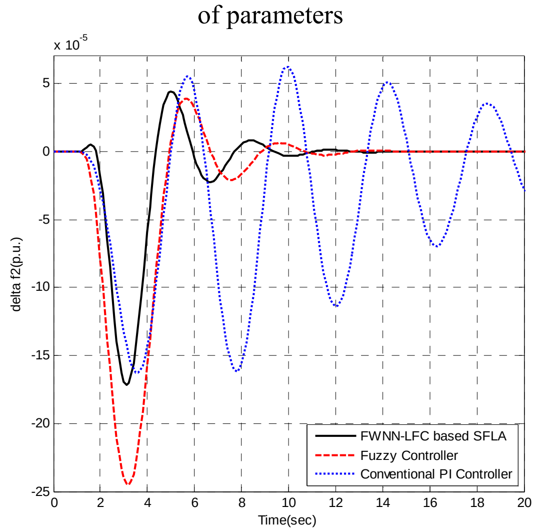

Fig. 8. Frequency deviation of area 2 for upper bound of parameters

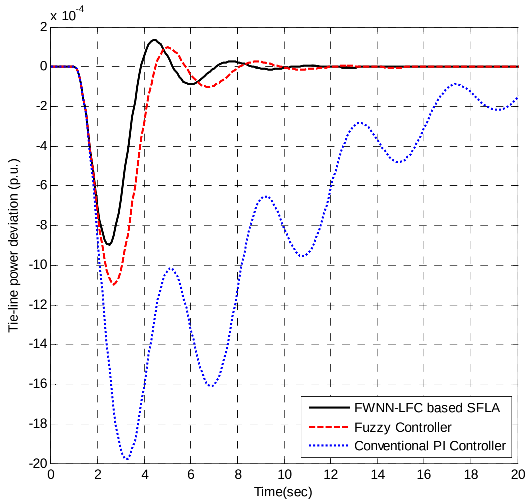

Fig. 9. Tie-line power deviation for upper bound of parameters

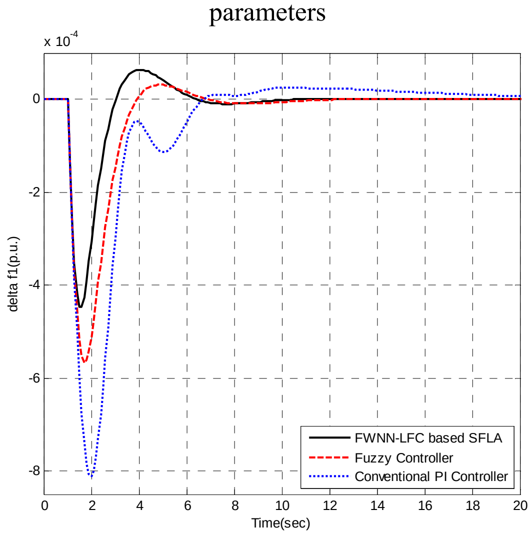

Fig. 10. Frequency deviation of area 1 for lower bound of parameters

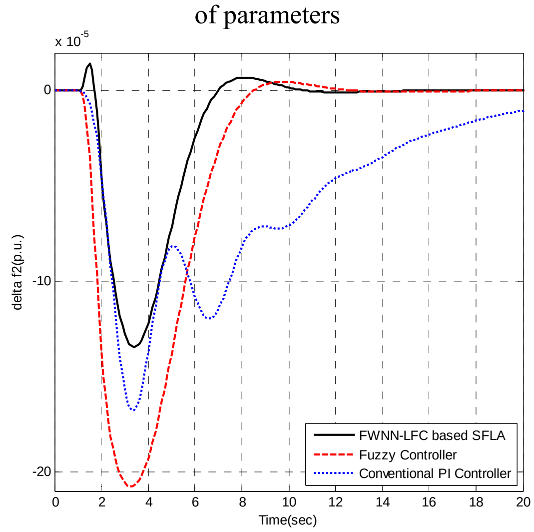

Fig. 11. Frequency deviation of area 2 for lower bound of parameters

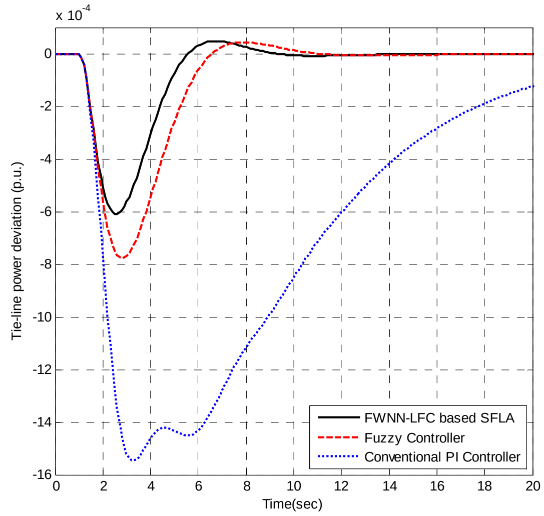

Fig. 12. Tie-line power deviation for lower bound of parameters

Figs 8-13 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 obvious in damping the system frequency oscillations very fast. Also, there is less undershoot for area number one and area number two, and the damping of the tie line power oscillations is very fast with the proposed FWNN controller.

7. CONCLUSION

In this paper a new load frequency controller based on fuzzy wavelet neural network and shuffled frog leaping 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 SFL algorithm is proposed to learn the FWNN and find optimal values of the parameters of FWNN-LFC. The performance of designed FWNN-LFC is examined on a two area interconnected power system with considering governor limiters and the results obtained are compared with a classic PI controller and a fuzzy 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 PI and fuzzy controllers is obvious in damping the system frequency oscillations very fast. Also, there is less undershoot for area number one and area number two, and the damping 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, McGraw-Hill, 1994.

[2] N. N. Bengiamin, W. C. Chan, **"Variable structure control of electric power generation"**, *IEEE Trans. Power App. Syst*., Vol. PAS-101, 1982, pp. 376-380.

[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, Feb. 1989.

[4] 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.

[5] A. Khodabakhshian, M. Edrisi, **"A new robust PID load frequency controller"**, *Control Engineering Practice*, Vol. 16, pp. 1069-1080, 2008.

[6] T. Hiyama, S. Koga, and Y. Yoshimuta, **"Fuzzy Logic Based Multi-Functional Load Frequency Control"**, *IEEE Power Engineering Society 2000 Winter Meeting*, Vol. 2, pp. 921–926, Jan. 2000.

[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, Aug. 2008.

[8] S. Pothiya, I. Ngamroo, **"Optimal fuzzy logic-based PID controller for load–frequency control including superconducting magnetic energy storage units"**, *Energy Conversion and Management*, Vol. 49, pp. 2833-2838, 2008.

[9] Q. H. Wu, B. W. Hogg, G. W. Irwin, **"A Neural network regulator for turbo generator"**, *IEEE Trans. Neural Networks*, Vol. 3, pp. 95- 100, 1992.

[10] H. Shayeghi, H. A. Shyanfar, **"Application of ANN technique based on μ-synthesis to load frequency control of interconnected power system"**, *Electrical Power and Energy Systems.,* Vol. 28, pp. 503-511, 2006.

[11] E Bijami, R. Abshari, J. Askari, S. M. Saghaiannejad, **"Load Frequency Control of Interconnected Power System Using Brain Emotional Learning Based Intelligent Controller"**, *in 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),* 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),* 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] T. Kugarajah, Q. Zhang, **"Multidimensional wavelet frames"**, *IEEE Transaction on Neural Networks*, Vol. 6, pp. 1552-1556, 1995.

[17] M.M. Eusuff, K.E. Lansey, F. Pasha, **"Shuffled Frog Leaping Algorithm: a Memetic Meta-heuristic for Discrete Optimization"**, *Engineering Optimization,* Vol. 38, No. 2, pp. 129-154, 2006.

[18] E. Elbeltagi, **"A Modified Shuffled Frog Leaping Algorithm for Optimizing Bridge-desk Repairs"**, *international conference on bridge management systems*, 2006.

[19] E. Elbeltagi, **"Evolutionary Algorithms for Large Scale Optimization In Construction Management"**, *The Future Trends in the Project Management,* 7-11 April, 2007, Riyadh.

[20] T. H. Huynh, **"A Modified Shuffled Frog Leaping Algorithm for Optimal Tuning of Multivariable PID Controllers"**, *Fifth IEEE International Conference on Industrial Technology, ~IEEE-ICIT'08~,* April 21-24, 2008, Chengdu, China.