Design of Stabilizing Signals for Power System Damping Using Optimal Fuzzy Wavelet Neural Network Controller

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Abstract—**This paper presents a new optimal damping controller design based on fuzzy wavelet neural network (FWNN) to damp the multi-machine power system low frequency oscillations. The error between the desired system output and the output of control object is directly utilized to tune the network parameters. 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. In this paper, Shuffled Frog Leaping Algorithm (SFLA) is proposed for learning of FWNN and to find the optimal values of the parameters of the FWNN damping controller. To illustrate the capability of the proposed approach, some numerical results are presented on a 2-area 4-machine. To show the effectiveness and robustness of the designed controller, the case studies are tested under two conditions: applying a line-to-ground fault at a bus and applying a three phase fault at a bus. Furthermore, to make a comparison, a conventional damping controller is applied. The simulation results show the superiority and capability of the proposed optimal FWNN damping controller.**

Keywords- fuzzy wavelet neural network, shuffled frog leaping algorithm, low frequency oscillations, damping controller, PSS.

I. INTRODUCTION

Low frequency electromechanical oscillations are inevitable characteristics of power systems. Due to increasing complexity of electric power systems, especially with the interconnection of these systems by weak tie-lines, spontaneous system oscillations present limitations on power transfer capability and affect operational system economics and security [1]. Power system stabilizers (PSSs) for generators are damping controllers and efficient tools for improving the stability of power systems through damping of low frequency modes. Numerous works are done and published around the world on the design of damping controller for enhancing the power system low frequency oscillations [2]-[5]. Each of these techniques has their own advantages and disadvantages.

In this paper, an alternative new damping controller design based on fuzzy wavelet neural network is proposed to damp the power system inter-area low frequency oscillations. The FWNN is used to construct a damping controller for generating a supplementary control signal to the excitation system on the base of target characteristic of the power system. In the proposed FWNN based controller, each fuzzy rule corresponds to one sub wavelet neural network (sub-WNN). 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, to avoid trial-and-error and time-consuming, a self-tuning process by applying Shuffled Frog Leaping Algorithm (SFLA) is used to find the optimal values of the controller parameters of translation, weights, and membership functions. To illustrate the effectiveness of the proposed approach, some numerical results are presented on a 2-area 4-machine. Also, the results obtained are compared with conventional damping controller designed by SFLA using the suggested approach in [5]. The main properties of the proposed approach are: this approach does not require real-time model identification; hence it can be easily implemented on a microcomputer. Also, the simulation results reveal that the proposed FWNN damping controller enhances system stability against different fault types and provides some advantages such as self-tuning of FWNN parameters and easy algorithm.

The paper is organized as follow: to make a proper background, the basic concepts of FWNN and SFLA are briefly explained in Section II. The 2-area 4-machine system which used in the simulations studies is given in section III. In Section IV, the design procedures of the proposed FWNN damping controller and its learning algorithm are described. Simulation results are provided in Section V and finally some conclusions are concluded in Section VI.

II. REVIEW OF FWNN AND SFLA

A. Fuzzy Wavelet Neural Network Structure

The basic concepts of FWNN method, originally presented by Daniel et al [6] which is briefly described in this section. The FWNN is a multi-layer network which integrates fuzzy model with wavelet neural networks. For a multi-input-single-output (MISO) with $\underline{x} = [x_1, \ldots, x_q]$ as input and y as output of the system, a typical FWNN for approximating arbitrary nonlinear function y can be described by a set of fuzzy rules as follow :

$$R_i : if\ x_1\ is\ A_1^i\ and\ x_2\ is\ A_2^i\ and\ \dots\ and\ x_q\ is\ A_q^i\ ,$$

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

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

where R_i $(1 \le i \le c)$ is the i^{th} fuzzy rule and x_j is the jth input variable of the system. $\hat{y}_i$ 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.

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

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:

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

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 follow:

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

where $\hat{\mu}_i(x) = \mu_i(x) / \sum_{i=1}^{c} \mu_i(x)$ and $\mu_i(x) = \prod_{j=1}^{q} A_j^i(x_j)$, are the firing strength of the i^{th} 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 [7]. 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 [7]. The structure of applied FWNN is shown in Fig.1.

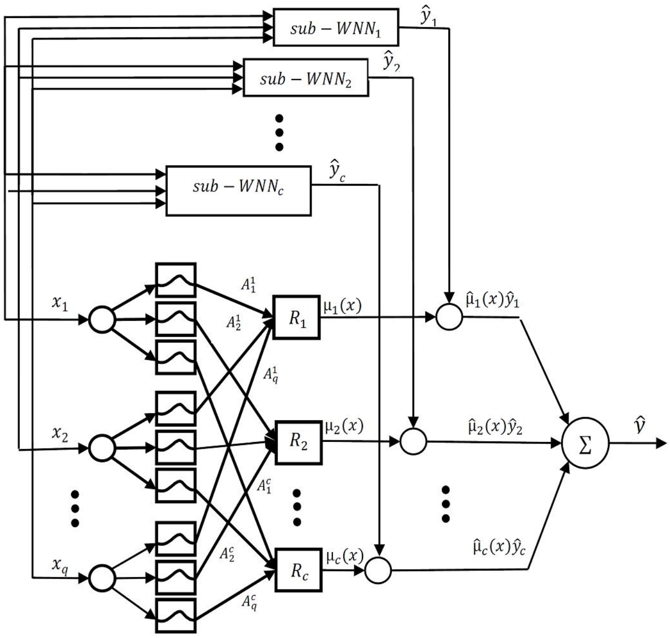

Figure 1. Structure of FWNN [6].

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 suggested by employing the SFLA to determine significant parameters of FWNN based controller such as dilation, translation, weights, and membership functions. In other words, during the learning process, these network parameters are optimized using SFLA. To make a proper background, the concept of SFLA is given in the next subsection.

B. SFLA Overview

The SFLA is a meta-heuristic cooperative stochastic optimization algorithm which is drawn from natural biological evolution and the social behavior of a group of frogs [8]. The SFLA begins with an initial population of n frogs ($P = \{X_1, X_2, ..., X_n\}$) which are created randomly within the possible search space. For the optimization problems with d variables (d-dimensional problems), the position of i^{th} frog in the search space is represented as $X_i = [x_{i1}, x_{i2}, ..., x_{id}]^T$. Afterward, to evaluate the frog's position, a fitness function is defined. Then the performance of each frog is computed based on its position. Then, frogs are sorted in a descending order regarding to their fitness. The frog with the global best fitness is introduced as X_g. The entire group can be separated into m memeplexes, each of which consisting of q frogs, which satisfy $n = m \times q$. The strategy of division is as follows: the first frog goes to the first memeplex, the second frog goes to the second memeplex, m^{th} frog goes to the m^{th} memeplex, and $(m+1)^{th}$ frog goes back to the first memeplex, etc. Within each memeplex, the frogs with the best and the worst fitness are identified as X_b and X_w, respectively. Within each memeplex, the position of the ith frog (D_i) 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 (5), where rand () is a random number in the range of [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 follow:

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

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

where $D_{\max}$ is the maximum allowed change of frog's position in a single jump. If a frog with a better fitness value is produced in this process, it replaces the worst frog, otherwise, the calculation in (5) and (6) are repeated with respect to the global best frog X_g (i.e. X_g replaces X_b). If no improvement becomes possible in this case, then a new frog is randomly generated to replace the worst frog. The evolution process will continue for a specific number of iterations.

III. Case Studie

A Single line diagram of 2-area-4-machine power system is shown in Fig. 2. The sub-transient model for the generators, and the IEEE-type DC1 and DC2 excitation systems are used for machines 1 and 4, respectively. Moreover, the IEEE-type ST3 compound source rectifier exciter model is used for machine 2 and the first-order simplified model for the excitation systems is used for machine 3. One damping controller is going to be designed for this system and placed on machines 2. Details of the system data are given in [9].

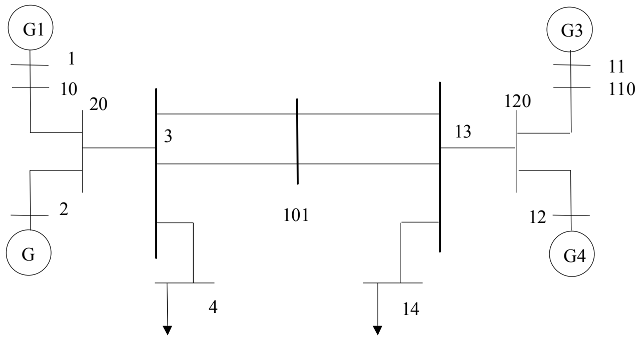

Figure 2. A 2-area power system.

IV. FWNN Damping Controller

The FWNN structure and its learning algorithm are used in designing of damping controller to damp the power system low frequency oscillations by generating a supplementary control signal to the excitation system. Following, the architecture of proposed FWNN damping controller and its optimization method based on SFLA are described.

A. Architecture of the proposed FWNN controller

The structure of control system is given in Fig. 3. As can be seen, FWNN is utilized as a controller which has one input and one output. Let $e(t)$ defined as follow:

$$e(t) = r(t) - y(t) \tag{7}$$

where $r(t)$ and $y(t)$ are desired output and the output of control system, respectively. In the proposed control strategy, neural control system synthesis is performed in the closed-loop control system and $e(t)$ is used for tuning network parameters to provide appropriate control input. By minimizing a quadratic measure of the error between desired system output and the output of control object, i.e. $e(t)$, 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 FWNN controller.

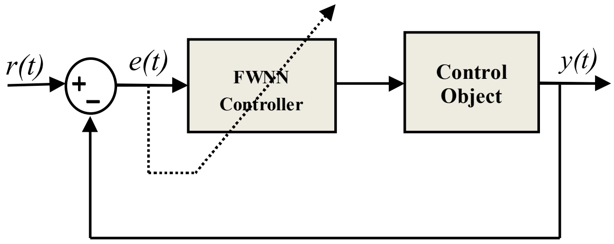

Figure 3. Structure of a control system.

By using above control strategy, the designing FWNN damping controller is equivalent to determination of the FWNN parameters. The proposed FWNN damping controller scheme is shown in Fig. 4.

In the proposed FWNN damping controller, the stabilizing signal is calculated by FWNN using the generator speed deviation $(\Delta\omega)$ and acceleration $(\Delta\dot{\omega})$ as the input signals to the network during each sampling period. However in practice, only shaft speed deviation is readily available. Thus, the acceleration signal can be computed from the speed signals measured at two successive sampling instants as follows:

$$\Delta\dot{\omega}(zT) = \frac{\Delta\omega(zT) - \Delta\omega((z-1)T)}{T} \tag{8}$$

Where T is the sampling period and z is the sampling count. In this work the sampling period is chosen as 10 *ms*. According to Fig. 4, the FWNN output which is u_d is defined so that error between V_{ref} and V_t is minimized. To calculate the desired u_d, the FWNN parameters including dilation, translation, weights, and membership functions should be set so that the error $e(t)$ is minimized. In this work, to obtain the FWNN parameters the SFL algorithm is used. In this case, finding the FWNN parameters is considered as an optimization problem and the quadratic measure of $e(t)$ is considered as the objective function. In the learning step, the FWNN controller parameters are calculated by minimizing a fitness function which is used the difference between the desired and real generator terminal voltage as follow:

$$E = \sum_{l=1}^{L} \left(V_{ref} - V_t\right)^2 \tag{9}$$

where L is number of network training data. According to Fig. 4, the generator output voltage is measured in each iteration and will be given to the SFLA optimizer after being compared to the reference voltage.

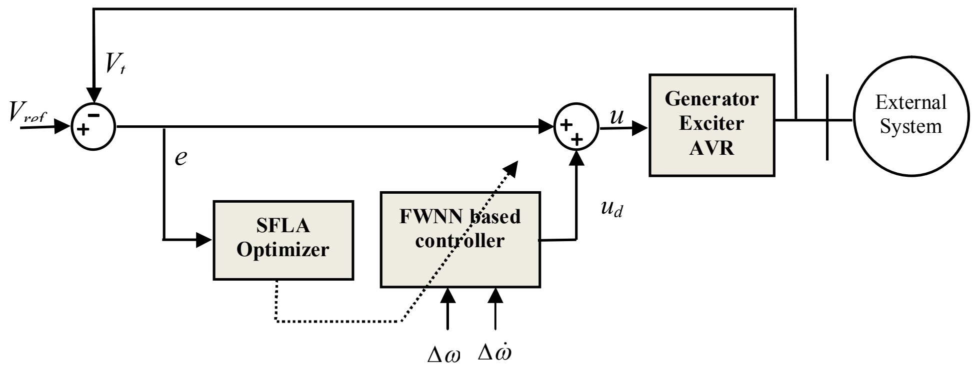

Figure 4. The proposed FWNN damping controller scheme

Then the solution vector is obtained by SFLA by minimizing the fitness function which gives the FWNN controller parameters. By using the obtained parameters, the network output (u_d) is calculated and applied to the exciter followed by calculating the new output voltage. 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.

B. The FWNN Optimization Method

Equations (2)-(4) show that the free parameters to be trained in FWNN controller are p_{j1}^{i} , p_{j2}^{i} , $\underline{t}^{k}$ and w_{M_i} where , $i = 1,...,c$, $j = 1,...,q$. Our goal is to design the FWNN basis function expansion such that the error between V_{ref} and V_t is minimized. Therefore SFLA is applied for tuning parameters of FWNN by optimizing the following objective or cost function.

$$E_f = \frac{1}{L}\sum_{l=1}^{L}\left|V_{ref} - V_t\right|^2 = \frac{1}{L}\sum_{l=1}^{L}\left|e_f(t)\right|^2 \tag{10}$$

Where E_f is the fitness of f^{th} frog. Suppose that there are N samples $(x(1), x(2), \ldots, x(s))$ for $s = 1,2,...,N$, over a time interval from 0 to t_s which is the simulation time. According to (1)-(4), the FWNN output for f^{th} frog associated with sample s, can be written as follows:

$$\hat{y}^{(f)}{}_{FWN}(\underline{x}(s)) = \frac{\sum_{i=1}^{c}\hat{y}_i^{(f)}\left[\prod_{j=1}^{q}\exp\left[-\left(\frac{(x_j(s) - p_{j1}^{i,(f)})}{p_{j2}^{i,(f)}}\right)^2\right]\right]}{\sum_{i=1}^{c}\left[\prod_{j=1}^{q}\exp\left[-\left(\frac{(x_j(s) - p_{j1}^{i,(f)})}{p_{j2}^{i,(f)}}\right)^2\right]\right]} \tag{11}$$

and

$$\hat{y}_i^{(f)} = \sum_{k=1}^{T_i} w_{M_{i},t^k}^{(f)} \prod_{j=1}^{q} 2^{\frac{M_i}{2}} \psi_j^{(f)\prime}(2^{M_i} x_j - t_j^k) \tag{12}$$

In the SFLA, each population is a solution to the problem which determines the parameters of FWNN. Therefore, the f^{th} frog is represented as:

$$frog_f = [p_{j1}^{i,(f)}, p_{j2}^{i,(f)}, \underline{t}^{k,(f)}, w_{M_i}^{(f)}]^T \tag{13}$$

In (13), the superscript T denotes the vector transpose operation. Thus, the all free design parameters that to be updated by SFLA in FWNN based controller are as follows:

$$\begin{cases} \underline{p}_{j1}^{i,(f)} = [p_{11}^{1,(f)} \ldots p_{11}^{c,(f)} \ldots p_{q1}^{1,(f)} \ldots p_{q1}^{c,(f)}] \\ \underline{p}_{j2}^{i,(f)} = [p_{12}^{1,(f)} \ldots p_{12}^{c,(f)} \ldots p_{q2}^{1,(f)} \ldots p_{q2}^{c,(f)}] \\ \underline{t}^{k,(f)} = [t_1^{1,(f)} \ldots t_1^{S,(f)} \ldots t_q^{1,(f)} \ldots t_q^{S,(f)}] \\ \underline{w}_{M_i}^{,(f)} = [w_{M_1}^{,(f)} \ldots w_{M_c}^{,(f)}] \end{cases} \tag{14}$$

As can be seen, the total number of parameters to be determined is $2q(\sum_{i=1}^{c} T_i + c)$. In SFLA, during each generation, the frogs are evaluated with the objective function defined in (10). Then the best frogs are chosen. In the current problem, the best frog is the one that has minimum fitness. After applying the SFLA, the best frog of the final iteration is the solution. Summarized the whole proposed approach for constructing FWNN damping controller is illustrated in Fig. 5.

V. Simulation Studies

To provide a reasonable dynamic performance for the considered multi-machine power systems, damping controllers are designed using the FWNN based controller. The results obtained by the proposed method are compared with conventional damping controller designed by SFLA using the suggested approach in [5]. At first, according to Fig. 5, initializing of the network is performed and the optimal number of fuzzy rules and the optimal number of wavelets in each sub-WNN is determined using OLS algorithm. For this, a performance index as (15) is considered for the OLS algorithm and some experiments are performed using the proposed FWNN damping controller.

$$J = \int \Delta\omega^2 t^2 dt \tag{15}$$

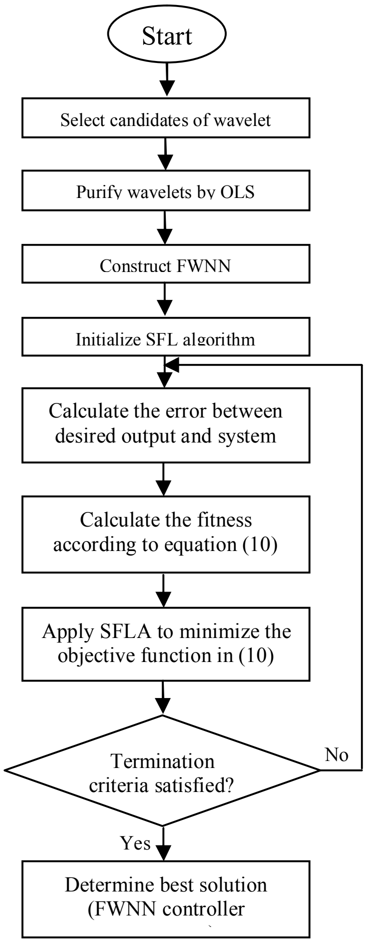

Figure 5. General principles of FWNN damping controller design

By applying OLS algorithm, three fuzzy rules with three selected wavelets are represented for constructing the FWNN controller. In the learning step, the FWNN parameters are calculated by minimizing the fitness function (10) using the difference between the desired and real generator terminal voltage.

According to Fig. 4, the generator output voltage is measured in each iteration and will be given to the SFLA optimizer after being compared to the reference voltage. The first step to implement the SFLA is generating the initial population (*N* frogs) where *N* is considered to be 300. The number of memeplex is considered to be 10 and the number of evaluation for local search is set to 20. Also D_{max} is chosen as *inf*. Then the solution vector is obtained by SFLA by minimizing the fitness function defined in (10) which gives the FWNN controller parameters defined in (14). By using the obtained parameters, the network output (u_d) is calculated and applied to the exciter followed by calculating the new output voltage. The procedure continues until a termination criterion is met. In this paper, the number of iteration is set to be 5000.

When the FWNN has been trained, it will yield the desired FWNN damping controller parameters. After applying the SFLA with 5000 iterations, the best frog corresponding to the smallest fitness value at each iteration is recorded and averaged over 10 independent runs. To have a better clarity, the convergence characteristic in finding the best values of FWNN parameters is given in Fig. 6. Also the obtained FWNN membership function parameters are shown in Table I. For brevity, other parameters of FWNN are not presented here.

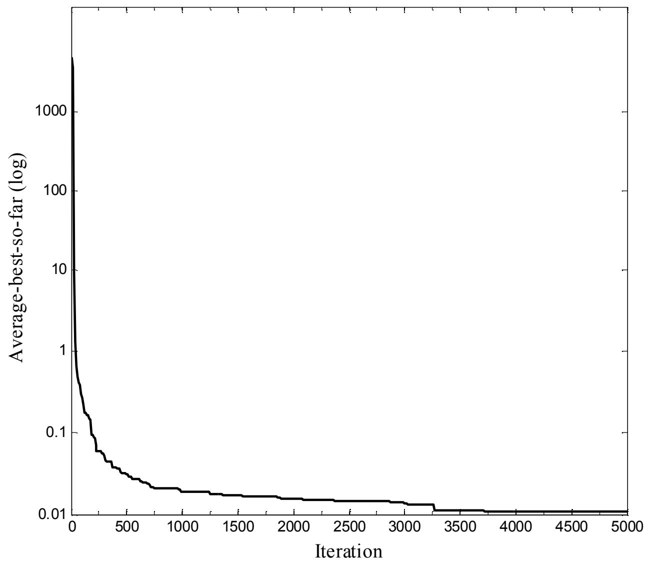

Figure 6. Convergence characteristic of SFLA in finding the best values of FWNN parameters.

TABLE I. THE FWNN MEMBERSHIP FUNCTION PARAMETERS

A_1^1	$P_{11}^1 = 0.3564,\ P_{12}^1 = 1.0875$	A_2^1	$P_{21}^1 = -0.6758,\ P_{22}^1 = 1.1208$
A_1^2	$P_{11}^2 = 1.4574,\ P_{12}^2 = -0.6710$	A_2^2	$P_{21}^2 = 0.9087,\ P_{22}^2 = 0.6574$
A_1^3	$P_{11}^3 = 0.2074,\ P_{12}^3 = 1.8656$	A_2^3	$P_{21}^3 = -0.9984,\ P_{22}^3 = 1.4922$

The designed FWNN damping controller and those obtained by SFLA are placed in the case study (Fig. 2). To indicate the effectiveness of the proposed FWNN damping controller for improving the stability of the test system, a time-domain analysis is performed and its performance is investigated under different fault type.

In first case, a line-to-ground fault is applied in one of the tie lines at bus 3. The fault cleared after 70.0 *ms*. The voltage magnitude at the faulted bus is shown in Fig. 7. Also, Figs. 8 and 9 show the machine angles, δ with respect to a particular machine (machine 1) as a function of time for the above fault. Furthermore, to show the effectiveness of the designed damping controller under more severe condition, a three phase fault is applied in one of the tie lines at bus 3. The fault cleared after 70.0 *ms*. The voltage magnitude at the faulted bus is shown in Fig. 10. Also, Figs. 11 and 12 show the machine angles, δ with respect to a particular machine (machine 1) as a function of time for the above fault. Figs 7-12 show the FWNN damping controller improve the transient response characteristics and has a better performance in terms of overshoot, settling time and rise time compared to conventional damping controller designed by SFLA.

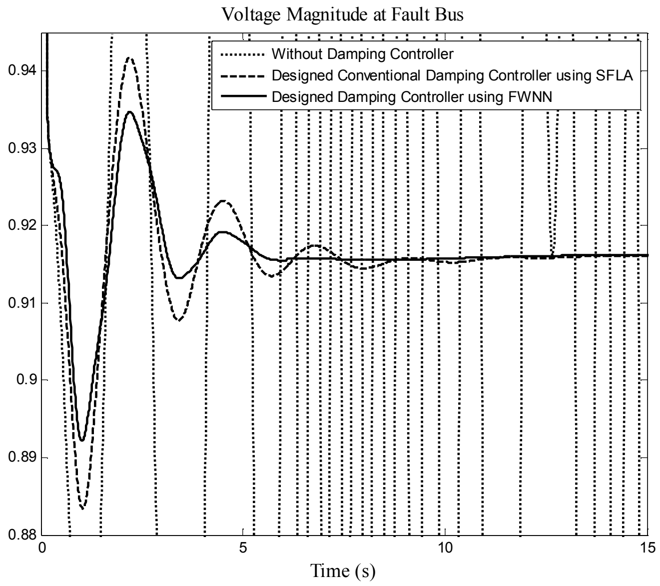

Figure 7. Voltage response of the system to a line-to-ground fault at bus 3.

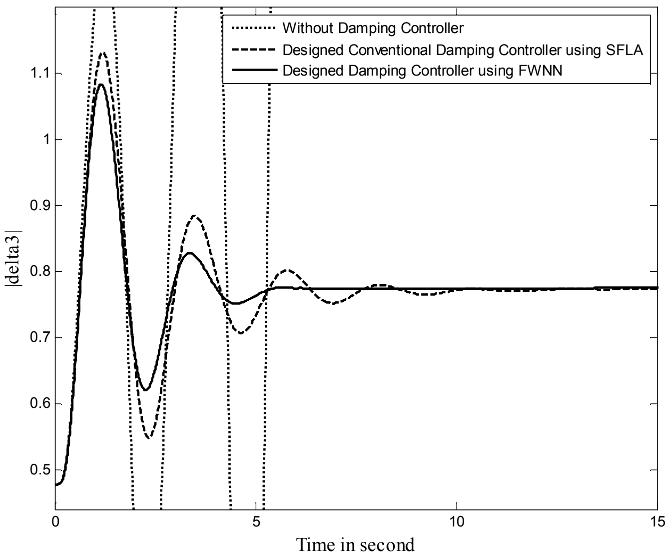

Figure 8. The response of generator 3 to a line-to-ground fault.

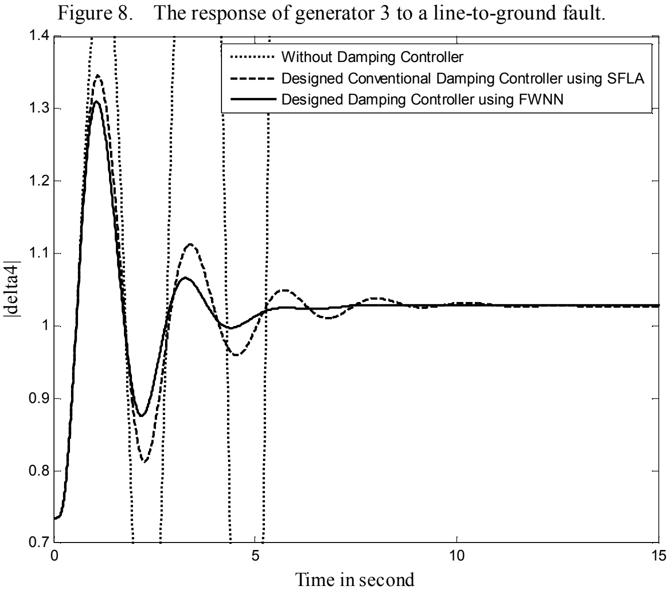

Figure 9. The response of generator 4 to a line-to-ground fault.

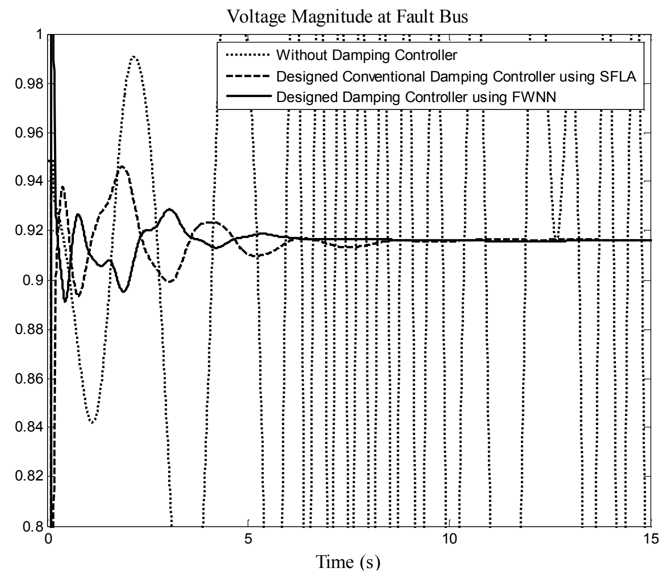

Figure 10. The response of the system to a three-phase fault at bus 3.

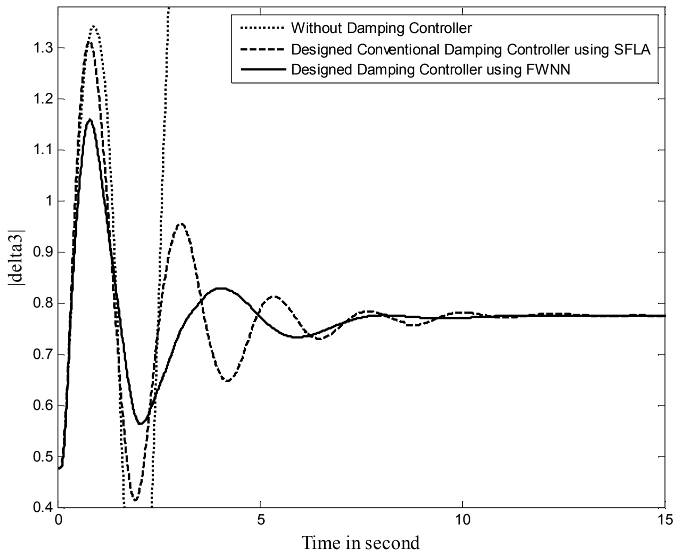

Figure 11. The response of generator 3 to a three-phase fault

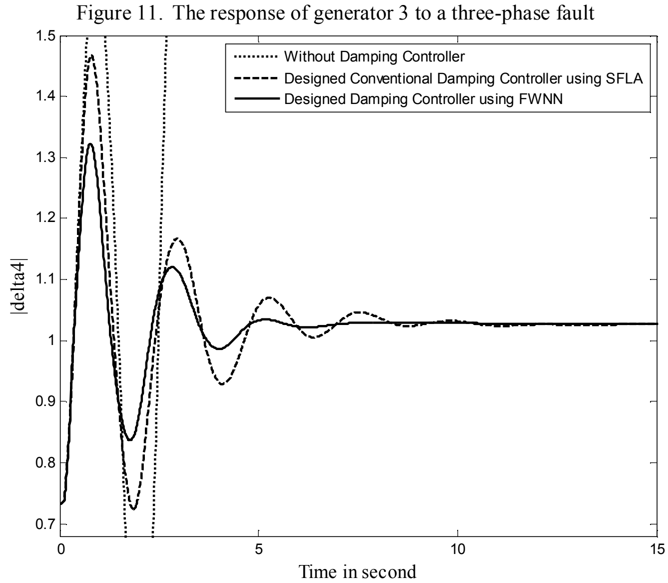

Figure 12. The response of generator 4 to a three-phase fault.

VI. CONCLUSION

In this paper a new control system incorporating the FWNN based controller is developed for damping multi-machine power system low frequency oscillations. The FWNN is used to construct a damping controller for generating a supplementary control signal to the excitation system on the base of target characteristic of the power system. Also, an efficient Shuffled Frog Leaping Algorithm (SFLA) is proposed for the learning of FWNN and to find optimal values of the parameters of FWNN based controller. The performance of designed controllers is tested on a 2-area 4-machine power system. The robustness and effectiveness of the proposed FWNN damping controllers are verified under different disturbances. It is shown that the FWNN damping controller damps satisfactorily low frequency oscillations of system. Also, conventional damping controllers are designed for comparison. The simulation results show the superiority and capability of FWNN damping controllers in comparison with the designed conventional by SFLA, in improving the stability of the system.

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