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Multi-Machine Power System Stability Improvement Using a New Fuzzy Wavelet Neural Network Damping Controller

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Abstract

This paper presents a new 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 and a 5-area-16-machine power system. 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, the proposed approach is compared with a classical based method and a FWNN based genetic algorithm approach, which is adopted from literature, through eigenvalue analysis, time- domain simulation and some performance indices. The simulation results show the superiority and capability of the proposed FWNN damping controller.

Keywords: *Fuzzy Wavelet Neural Network, Shuffled Frog Leaping Algorithm, Low Frequency Oscillations, Damping Controller*

1. Introduction

Power systems stability is one of the most important aspects in electric system operation. Due to the development complexity of modern large-scale electric power systems, particularly with the interconnection of these systems by weak tie-lines, heavy loading and highly variable generation patterns, the spontaneous wide-area electromechanical oscillations present limitations on power transfer capability and threaten the operational system economics and security [1].

The power system damping controllers, designed to address low-frequency oscillations, are mostly based on a linearized model of power system, realized through Power System Stabilizers (PSSs) and FACTS devices [2]. However, the nonlinearity and large-scale power systems structure is an important issue for designing damping controllers [3]. Until now, many control strategies applying various techniques based on optimal control, robust control and adaptive control have been proposed and developed by the researchers around the world over the last three decades [4]-[6].

More recently, the concepts of Artificial Intelligence (AI) techniques, such as Heuristic Algorithms [7]-[10], fuzzy logic control (FLC) [11]-[14], Artificial Neural Network (ANN) [15]-[17] are applied to design of damping controllers in nonlinear power system stabilization problem.

An indirect adaptive fuzzy damping controller is presented in [11] to damp inter-area modes of oscillation in power systems. It consists of a variable structure identifier to on-line identification of nominal model of the power system and a feedback linearization-based control law. Also, a type-2 fuzzy logic power system stabilizer with differential evolution algorithm is proposed in [12] in which, the corresponding parameters and rule base of type-2 fuzzy logic power system stabilizer are optimally tuned by using differential evolution algorithm for multi-machine power system.

The authors in [13] present an adaptive fuzzy control combining a proportional integral controller with a sliding mode controller for damping local and inter-area modes of oscillations for multi-machine power systems. Furthermore, an adaptive fuzzy power system stabilizer is developed in [14] based on robust synergetic control theory and terminal attractor techniques. Although fuzzy logic controller based methods have an efficient capability for dealing with ill-defined and nonlinear system, but their design in general is based on a trial-and error method.

In [16], the authors present a neural network based adaptive sliding mode damping controller. The Neural network is used for online prediction of the optimal SMC gains when the operating point changes. Also, an online trained fuzzy neural network controller (OTFNNC) is introduced in [17], in which adaptive learning rates derived by the Lyapunov stability are employed to guarantee the convergence of the proposed controller. The main disadvantage of neural network based approaches is they require a large number of neurons to deal with the complex problems and result in slow convergence and convergence to local optimum.

On the other hand, the fuzzy wavelet neural network (FWNN) methodology, which is based on the wavelet theory, fuzzy concepts and neural network, improved the function approximation accuracy and received a lot of attention and has been successfully used for nonlinear power system stabilization [18]-[21]. However, the learning of FWNN and adjust the required network parameters, such as translation, weights, and membership functions, is an important issues in the design of dynamic systems.

This paper proposed an alternative robust fuzzy wavelet neural network damping controller scheme, called FWNN-SFLA, to design the stabilizing controls to damp the multi-machine interconnected nonlinear power system low frequency oscillations. On the other words, the FWNN is suggested 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 approach, first of all, the Orthogonal Least Square (OLS) algorithm is employed to purify the wavelets for each rule and determine the number of fuzzy rules and network dimension. Then, to avoid trial-and-error and time-consuming, a self-tuning process based on Shuffled Frog Leaping (SFL) optimization algorithm is proposed to find the optimal values of the controller parameters of translation, weights, and membership functions. In order to demonstrate the capability and effectiveness of the proposed approach in designing the damping controller, two nonlinear uncertain power systems with interconnected areas are considered. The effectiveness and robustness of the designed damping controller is illustrated by considering various operation conditions. Also, the results obtained are compared with conventional damping controller designed by SFLA using the suggested approach in [22] and the FWNN based genetic approach which is proposed in [19]. 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 2. The multi-machine systems which used in the simulations studies are given in section 3. In Section 4, the design procedures of the proposed FWNN damping controller and its learning algorithm are described. Section 5 presents the application of SFLA method for the conventional damping controller optimal tuning. Simulation results are provided in Section 6 and finally some conclusions are drawn in Section 7.

2. A Review of FWNN and SFLA

2.1 Fuzzy Wavelet Neural Network Structure

The FWNN is a multi-layer network which integrates the fuzzy model with wavelet neural networks, which each fuzzy rule corresponds to one sub wavelet neural network (sub-WNN). 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 FWNN for approximating arbitrary nonlinear function y can be described by a set of fuzzy rules as follow [23]:

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

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

Where $R_i\ (1 \le i \le c)$ is the i^{th} fuzzy rule and x_j is the j^{th} input variable of the system. Also, $\hat{y}_i$ calculates the output of local model for rule R_i. Parameters M_i and T_i determine the dilation parameters and total number of wavelets for the i^{th} rule, respectively. Moreover, $\underline{t}^k = [t_1^k, t_2^k, ..., t_q^k]$, where t_j^k denotes the translation value of corresponding wavelet k. Finally, A_i^j denote 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.

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

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

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

By applying the 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:

$$\hat{y}_{FWN}(\underline{x}) = \sum_{i=1}^{c} \hat{\mu}_i(\underline{x})\hat{y}_i,$$
$$\hat{\mu}_i(x) = \mu_i(x) / \sum_{i=1}^{c} \mu_i(x), \quad \mu_i(x) = \prod_{j=1}^{q} A_j^i(x_j) \tag{4}$$

Where $\hat{\mu}_i(x)$ and $\mu_i(x)$, are the firing strength of the i^{th} rule for current input and satisfies $0 \le \hat{\mu}_i \le 1$ and $\sum_{i=1}^{c} \hat{\mu}_i = 1$. 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 applied for initializing wavelets, such as Orthogonal Least Square (OLS) procedure and clustering method [24]. In this paper the OLS algorithm is employed to select the 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 [24]. 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. As mentioned before, in order to avoid trial-and-error, a self-tuning process is used 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 briefly given in the next subsection.

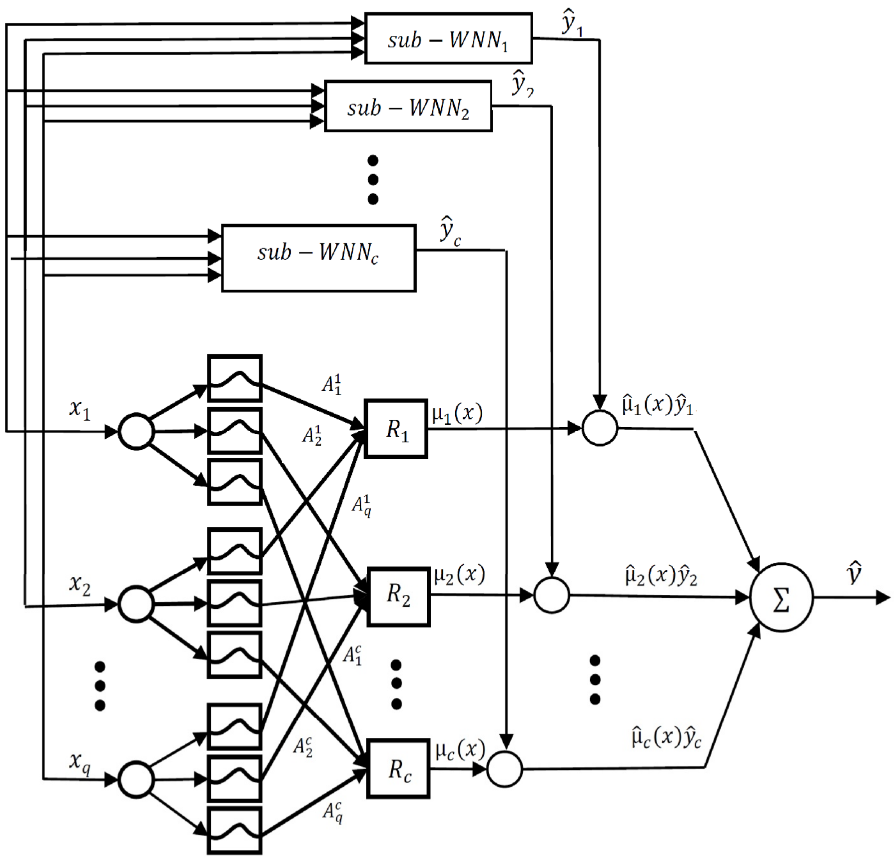

Figure 1. Structure of applied FWNN.

2.2 SFLA Overview

Shuffled Frog Leaping algorithm (SFLA) is an optimization memetic meta-heuristic technique inspired by virtual population of frogs when search for food. Unlike many search algorithms, which perform a local, greedy search, SFLA is a stochastic general search approach, capable of effectively exploring large search spaces [24]. As a first step of SFLA, an initial population of " N "individuals $P=\{X_1, X_2, \cdots, X_N\}$ are created heuristically or randomly within the feasible search space *Ω*. The individuals in the genetic search space are so-called frogs. For *S*-dimensional problems (*S* variables), the position of the i^{th} frog is represented as $X_i=[x_{i1}, x_{i2}, \cdots, x_{is}]^T$ .To evaluate the frog's position in each generation, a fitness function is defined. Next, the performance of each frog is computed based on its position. Then the frogs are sorted in a descending order regarding to their fitness. So the entire population is divided into m memeplexes, each of which consisting of n frogs (i.e. $N=n\times m$). The division is done by distributing the frogs one by one and in order between the m existing memeplexes.

Within each memeplex, the position of the i^{th} 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]. Within 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:

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

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

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 generated in this process, it substitutes the worst frog, otherwise, the calculation in (5) and (6) are renewal 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 produced to replace the worst frog. The evolution process will continue for a specific number of iterations. More details can be found in [25].

3. Case Studies

3.1 Two-area-Four machine

A Single line diagram of 2-area-4-machine power system which is considered for simulation studies is depicted in Figure 2. The sub-transient model for the machines, and the IEEE-type DC1 and DC2 excitation systems are considered for generators 1 and 4, respectively. Also, the IEEE-type ST3 compound source rectifier exciter model is employed for 2 and generator 3 uses the first-order simplified model for the excitation systems. One damping controller must be designed for this system and placed on generator 2. Details of the system data are described in [26].

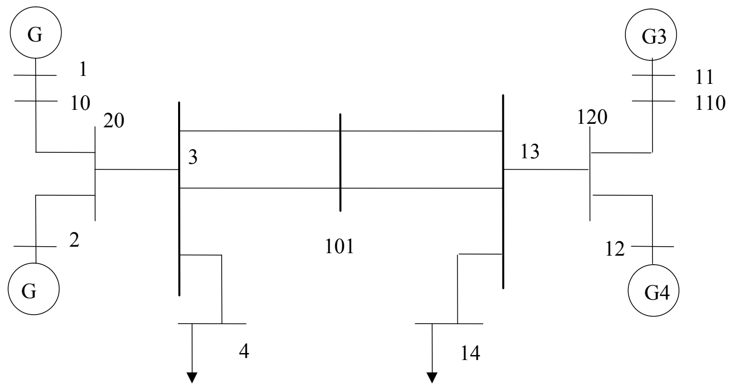

Figure 2. A 2-area power system.

3.2 Five-area-Sixteen machine

A Single line diagram of 5-area-16-machine power system is shown in Figure 3, is made up of 16 generators and 68 buses with 5 interconnected areas [26]. The first nine machines (G1 to G9) and the second four machines (G10-G13) organize the simple representation of area 1 and 2, respectively. Also, there are other three machines (G14-G16) used as the dynamic equivalents of the three large neighboring areas interconnected to area 2. The sub transient reactance model for the machines, the first-order simplified model for the excitation systems, and the linear models for the loads and AC network are employed. One damping controller to be placed in G9 is going to be designed for this system.

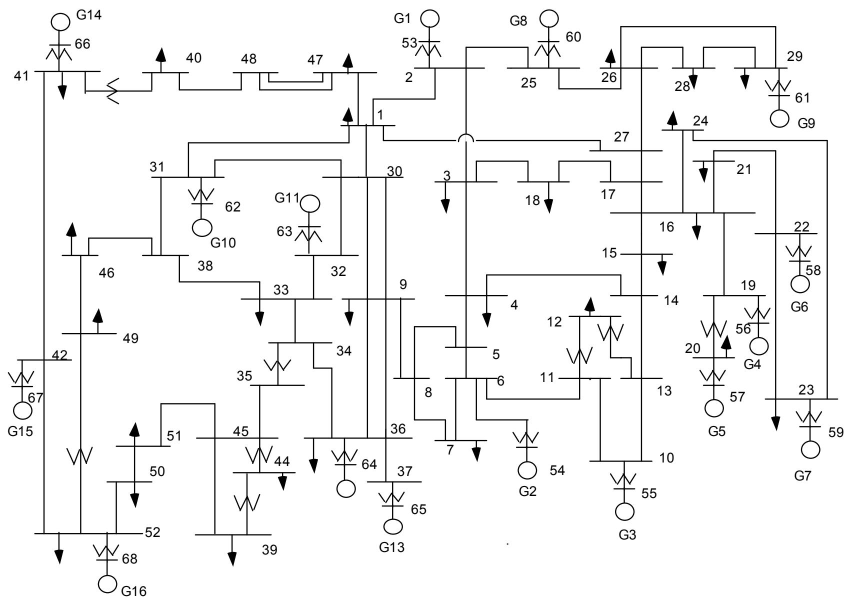

Figure 3. A 5-area power system.

4. 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.

4.1 Architecture of the proposed FWNN damping controller

The structure of control system is drawn in Figure 4. 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 SFL optimization algorithm formulation. On the other hand, the SFLA is used to correct the network parameters for adjusting of FWNN controller.

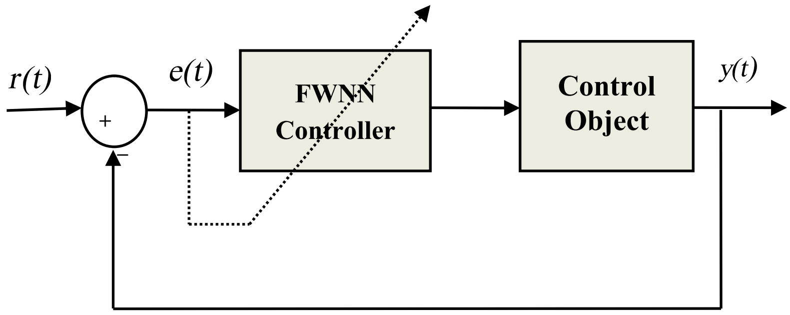

Figure 4. Structure of a control system.

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 Figure 5.

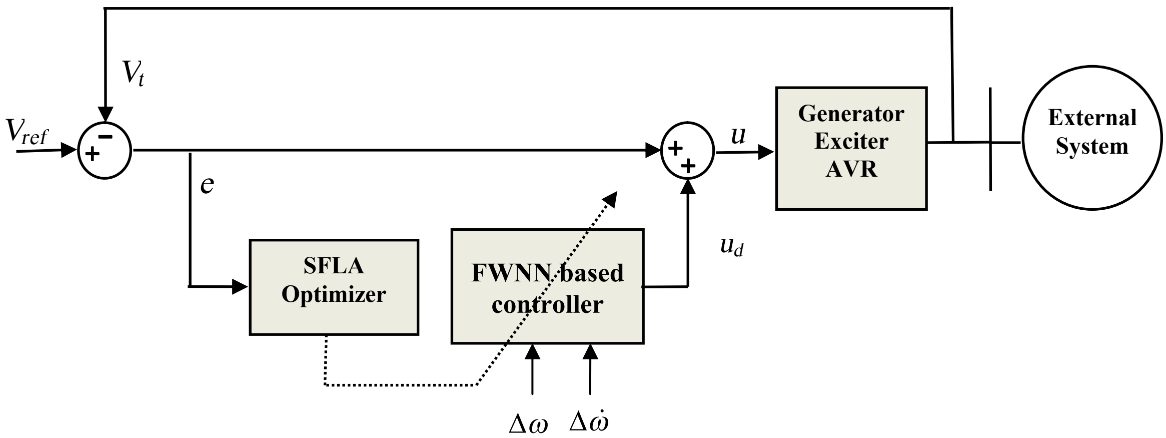

Figure 5. The proposed FWNN damping controller scheme.

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 paper, the sampling period is chosen as $10\,ms$.

According to Figure 5, 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. Here, to obtain the FWNN parameters the SFL algorithm is proposed.

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 Figure 5, the generator output voltage is measured in each iteration and will be given to the SFLA optimizer after being compared to the reference voltage. 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.

4.2 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 task 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 $(x(1), x(2), \cdots, x(s))$ for $s = 1, 2, \cdots, N$, over a time interval from 0 to t_s, where t_s 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 some measure of fitness, which is calculated from 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 Figure 6.

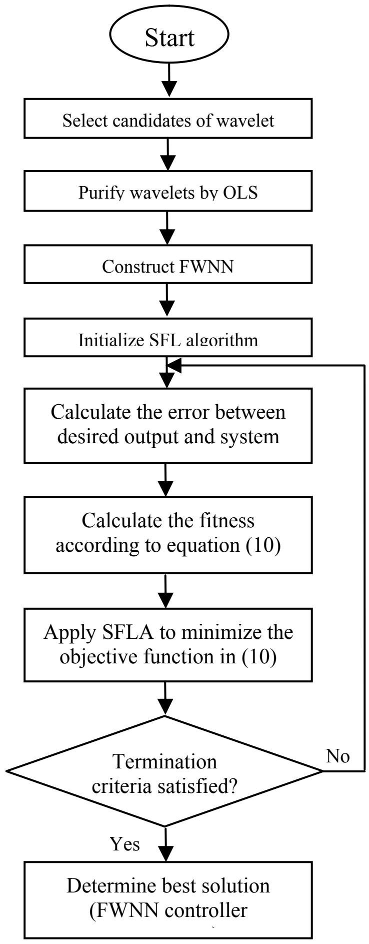

Figure 6. General principles of FWNN damping controller design.

5. Design Procedure for Conventional Damping Controller

In this section, design procedures of conventional damping controller are explained. This controller is designed by SFLA using the suggested approach in [22]. In this approach, the SFLA is employed to seek optimal settings of controller parameters using eigenvalue-based objective functions. In this study, conventional structure with two lead/lag stages is considered for damping controller, as shown in Figure 7.

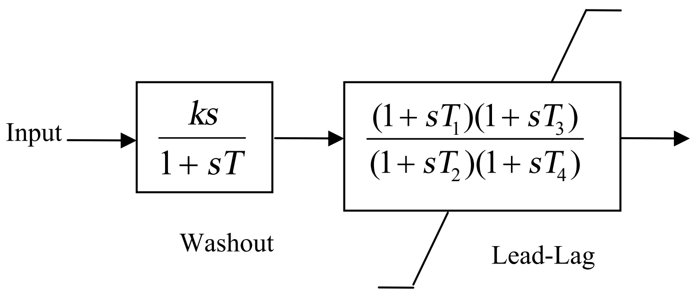

Figure 7. Conventional lead-lag block diagram damping controller.

Without damping controller the case studies are unstable. For instance, the damping ratios and electromechanical mode eigenvalues for the 2-area-4-machine system, without damping controller, are shown in Tables 1. As can be seen from this table, some of the modes are quite lowly damped and, in some cases, are unstable.

Table 1. Low Frequency modes, frequency and damping ratio of the 2-area-4-machine system without damping controller.

Low frequency modes	Frequency	Damping ratio
-0.4958 ± 7.1190i	1.330	0.064947
-0.5506 ± 6.8714i	1.0936	0.079873
0.1055 ± 3.6544i	0.5816	-0.028857
-0.3357 ± 0.6398i	0.1018	0.464622
-0.3058 ± 0.6643i	0.1057	0.418156
-0.2490 ± 0.6449i	0.1026	0.360190
-0.1957 ± 0. 5545i	0.0882	0.332811

The control strategy is to choose the best lead-lag controller parameters i.e. [k, T, T_1, T_2, T_3, T_4; k, T, T_1, T_2, T_3, T_4] in such a manner that the lightly damped and un-damped modes of the system are shifted to a prescribed zone in the left-hand side of *S*-plane as far as possible. The tuning of the controller parameters for a multi-machine power system is usually formulated as an objective function with constraints consisting of the damping factor and damping ratio. In this paper the suggested approach in [22] is adapted and applied for tuning controller parameters by using SFLA.

The parameters to be tuned through the SFLA are [k, T, T_1, T_2, T_3, T_4; k, T, T_1, T_2, T_3, T_4]. In the SFLA, each population (N frogs) represents a candidate solution for the problem. Thus, each frog is considered as [k, T, T_1, T_2, T_3, T_4; k, T, T_1, T_2, T_3, T_4], which determines the parameters of the controller. By placing each solution (controller) into the case study, related eigenvalues is obtained for the system. For each solution the worst eigenvalue is selected and the corresponding damping ratio (ξ) is calculated.

Now, we define two vectors as follows: $\underline{\xi} = \{\xi_1,...,\xi_N\}$ and $\underline{\sigma} = \{\sigma_1,...,\sigma_N\}$ as those elements are the damping ratio of the worst eigenvalue for each solution and the real parts of the eigenvalues with the damping ratios less than 0.36, respectively. With these two vectors the following objective functions are considered:

$$f_1 = \min_{i \in \{1,...,n\}}(\xi_i) \quad (15)$$

$$f_2 = \min_{i \in \{1,...,n\}}(-\sigma_i) \quad (16)$$

The optimization problem can be formulated as maximize $\{ f_1, f_2 \}$. According to these objectives function, the damping controller is designed so that the damping ratio of the close-loop system is increased as well as shifting the eigenvalues of the close-loop system to the left hand side of *S*-plane. In other words, this fitness function will place the system closed-loop eigenvalues in the *D*-shape sector characterized by $\sigma_i < \sigma_0$ and $\xi_i > \xi_0$ as shown in Figure 8.

To implement the SFLA a weighted-sum-approach is employed for (15) and (16). The weighted-sum-approach considers the above two objective to a single objective function. Therefore to restrict the system closed-loop eigenvalues in the D-shape sector illustrated in Figure 8, the following objective function is defined:

$$\max F = f_1 + f_2 \tag{17}$$

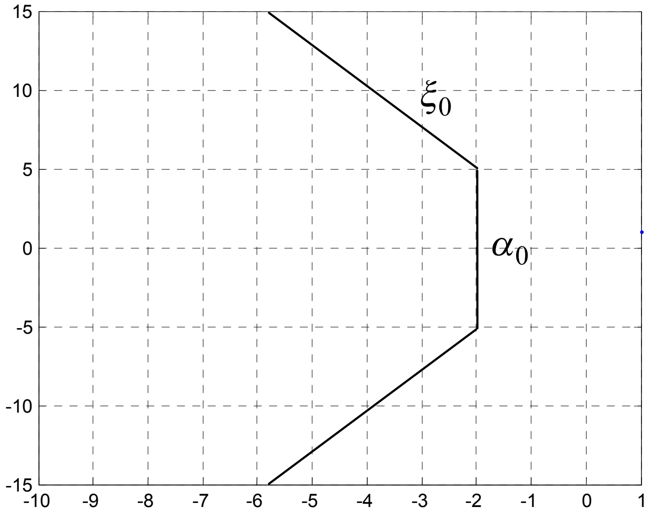

Figure 8. A D-shape sector for eigenvalues in the s-plane.

6. 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.

6.1 Two-area-Four-machine power system

Designing of damping controller using proposed FWNN based method: At first, according to Figure 6, 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 (18) is considered for the OLS algorithm and some experiments are performed using the proposed FWNN damping controller.

$$J = \int \Delta\omega^2 t^2 dt \tag{18}$$

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 Figure 5, 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 chosen as 10 and the number of evaluation for local search is set to 20. Also $D_{\max}$ considered to be 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. Also, for applying the proposed method in [19], the parameters of GA are considered as follows. The crossover rate and mutation rate are set to be 0.8 and 0.01, respectively. Also, the number of population and iterations of GA are considered as same as SFLA. The obtained FWNN membership function parameters by two approaches are shown in Table 2. For brevity, other parameters of FWNN are not presented here.

Table 2. The FWNN membership function parameters for two different methods.

FWNN-SFLA	A_1^1	$P_{11}^1 = 0.567,\ P_{12}^1 = 1.1871$	A_2^1	$P_{21}^1 = -0.9180,\ P_{22}^1 = 1.9101$
	A_1^2	$P_{11}^2 = 0.9826,\ P_{12}^2 = -0.6752$	A_2^2	$P_{21}^2 = 1.0701,\ P_{22}^2 = 0.8917$
	A_1^3	$P_{11}^3 = 1.0091,\ P_{12}^3 = 1.6718$	A_2^3	$P_{21}^3 = -1.5461,\ P_{22}^3 = 1.9301$
Proposed Method in [19]	A_1^1	$P_{11}^1 = 0.8160,\ P_{12}^1 = 1.1540$	A_2^1	$P_{21}^1 = -0.8195,\ P_{22}^1 = 1.8855$
	A_1^2	$P_{11}^2 = -0.4813,\ P_{12}^2 = 0.4517$	A_2^2	$P_{21}^2 = -.9014,\ P_{22}^2 = 0.7719$
	A_1^3	$P_{11}^3 = 1.3091,\ P_{12}^3 = 1.9918$	A_2^3	$P_{21}^3 = -1.5361,\ P_{22}^3 = 1.9286$

Designing Conventional damping controller Using SFLA: According to the fitness function defined in (17), the damping controller is designed so that the damping ratio of the close-loop system is increased as well as the eigenvalues of the close-loop system are shifted to the left-hand side. The boundaries of *D*-shape sector for eigenvalues are selected as $\alpha_0 = -0.2$ and $\xi_0 = 0.3$ .Also, the design problem can be formulated as the constrained optimization problem, where the constraints are the bounds on the controller parameters:

$$\begin{cases} 1 \le K \le 50 \\ 1 \le T \le 10 \\ 0 \le T_i \le 2 \quad , \quad i = 1,2,3,4 \end{cases} \tag{19}$$

The *initial* population size (N) to implement the SFLA is considered to be 100. The number of memeplex is chosen as 10 and the number of evaluation for local search is considered to 10. Also $D_{\max}$ is chosen as inf. Each population is a solution to the problem which determines the parameters of the controllers; i.e. [*k, T, T_1, T_2, T_3, T_4; k, T, T_1, T_2, T_3, T_4*]. Based on section 2, the local search and shuffling processes (global relocation) continue until the last iteration is met. In this paper, the number of iteration is set to be 50. The results obtained by the SFLA *k, T, T_1, T_2, T_3*, and *T_4* are shown in Table 3. Also,

Table 3. The results obtained by SFLA for damping controller.

K	T	T_1	T_2	T_3	T_4
54.9	4.46	0.765	0.657	1.998	0.817

The designed FWNN damping controllers and those obtained by SFLA are placed in the case study (Figure 2). To indicate the effectiveness of the designed damping controllers, two different operating conditions are considered as follows:

Case 1: Line-to-ground fault;

Case 2: Three phase fault;

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 illustrated in Figure 9. Also, Figures 10 and 11 show the machine angles, δ with respect to a particular machine (machine 1) as a function of time for the above fault.

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 Figure 12. Also, Figures 13 and 14 show the machine angles, δ with respect to a particular machine (machine 1) as a function of time for the above fault. Figures 9-14 show the FWNN-SFLA 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 and proposed FWNN damping controller in [19].

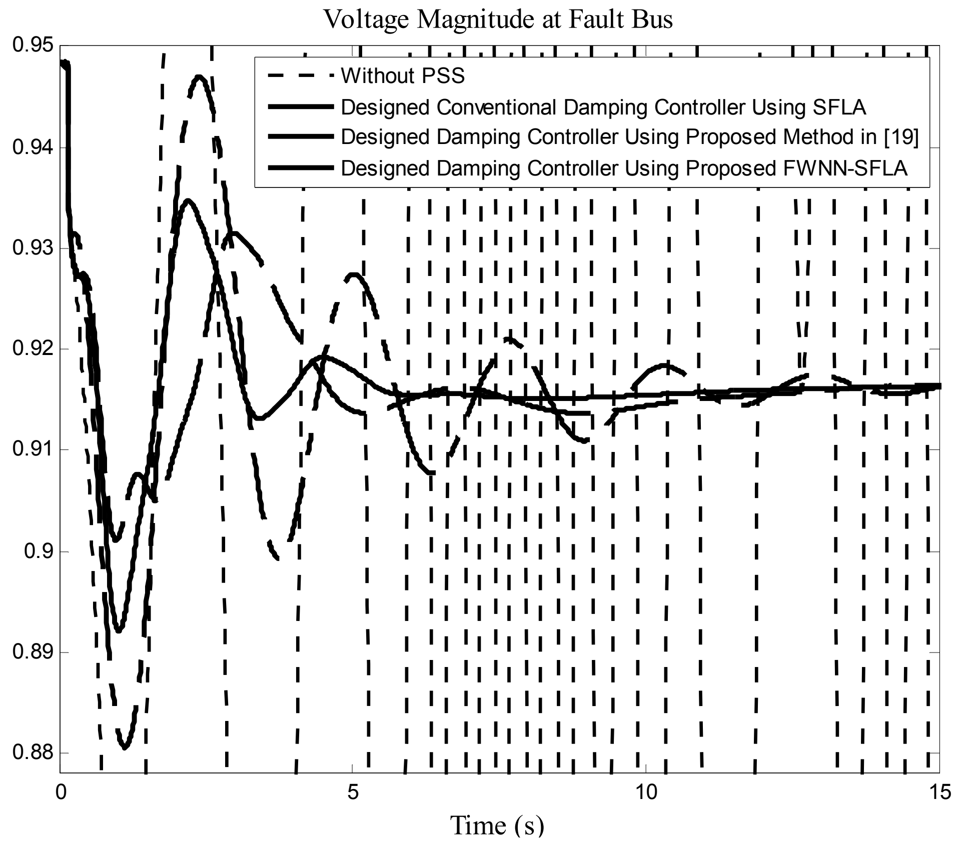

Figure 9. The voltage response of the system to a line-to-ground fault at bus 3.

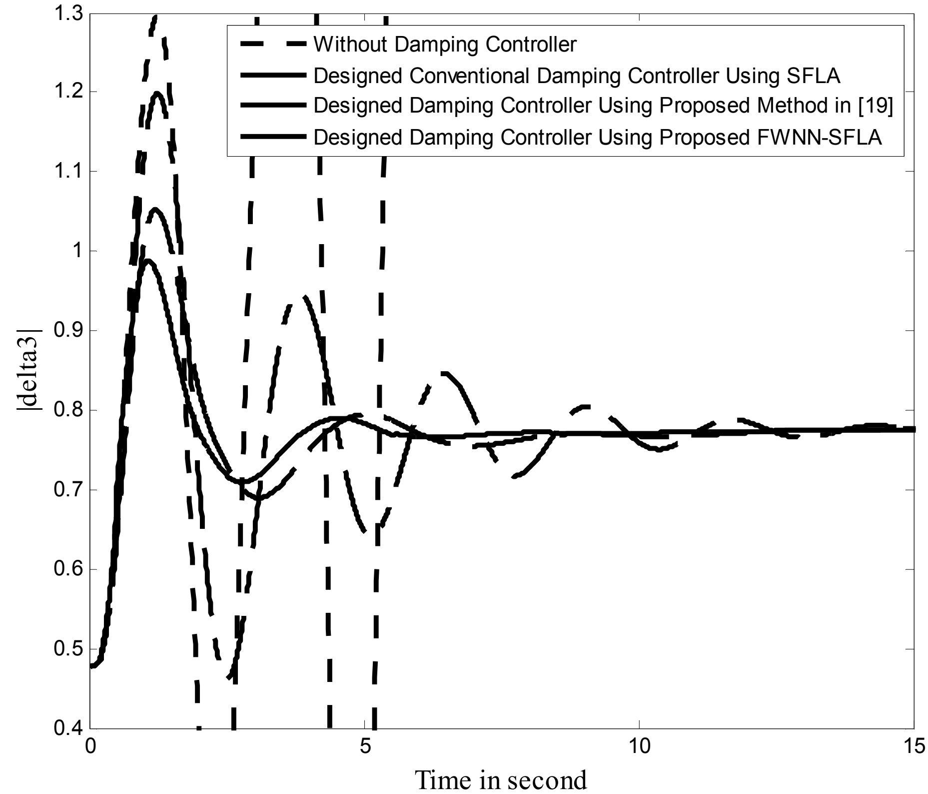

Figure 10. The response of generator 3 to a line-to-ground fault.

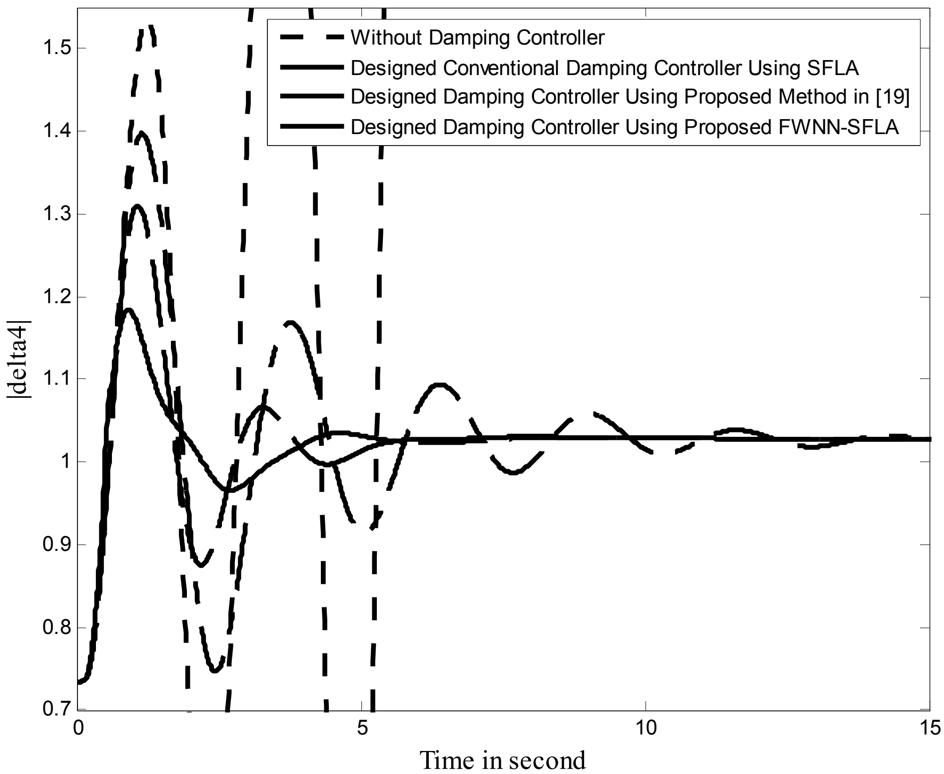

Figure 11. The response of generator 4 to a line-to-ground fault.

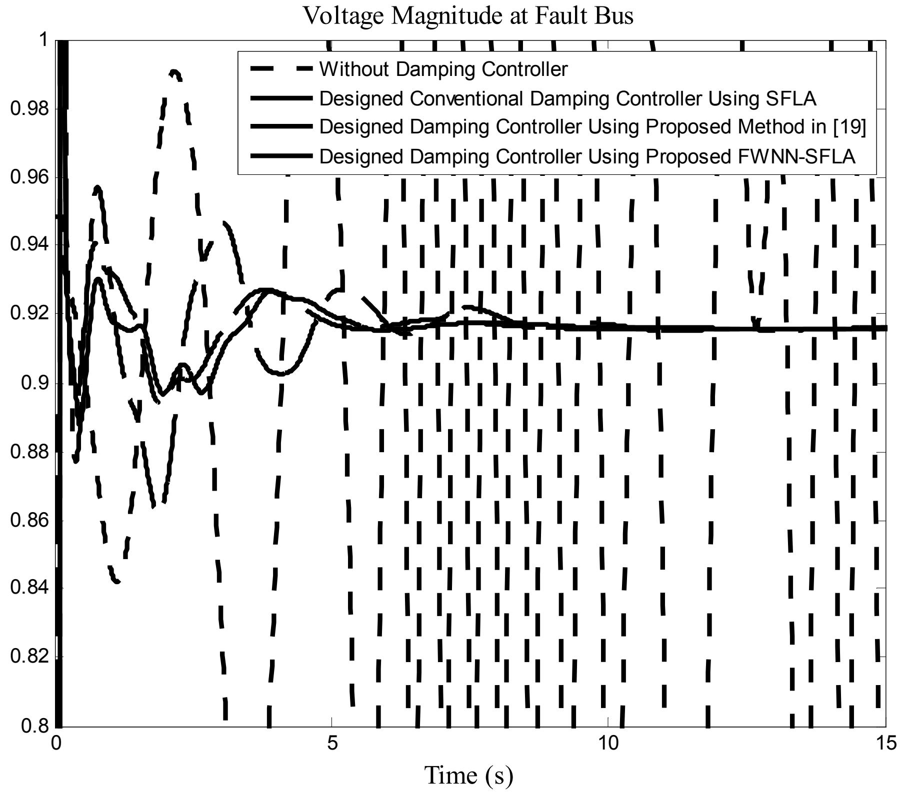

Figure 12. The response of the system to a three-phase fault at bus 3.

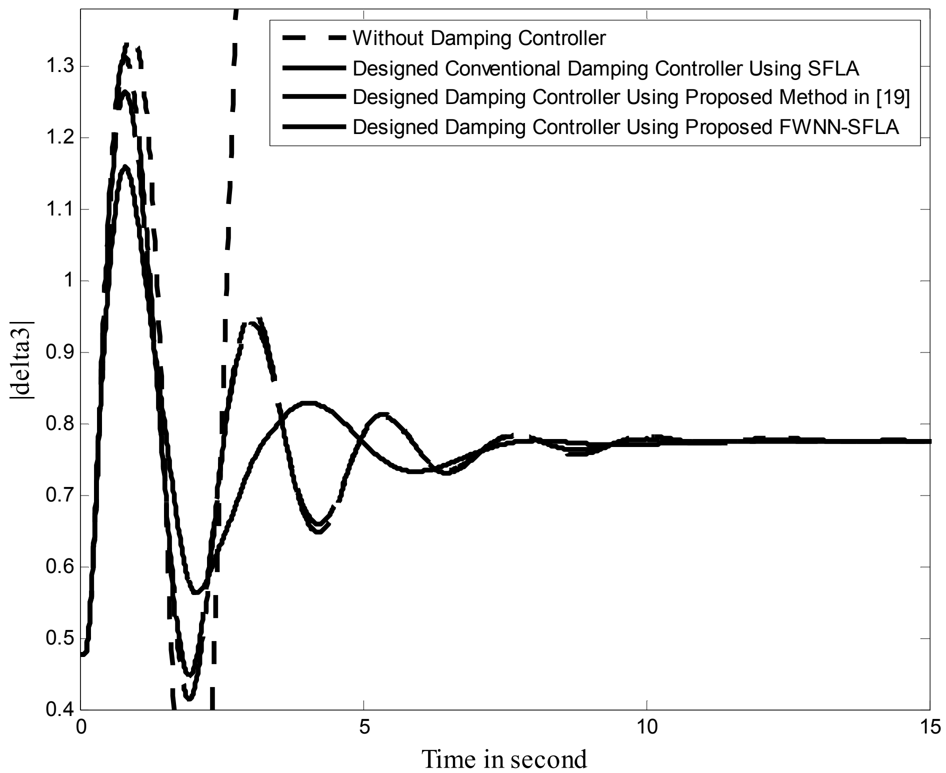

Figure 13. The response of generator 3 to a three-phase fault.

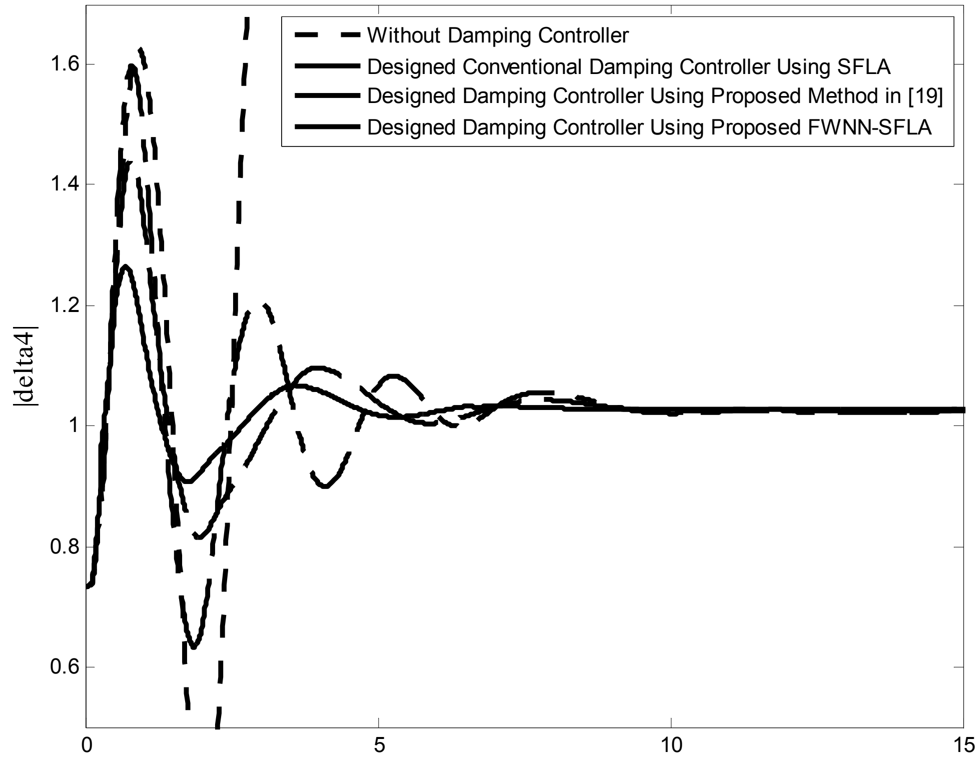

Figure 14. The response of generator 4 to a three-phase fault.

Table 4 shows the worst low frequency modes of the system when it is without damping controller and when it is equipped with the designed damping controllers by classical based method, FWNN based genetic algorithm introduced in [19] and proposed FWNN-SFLA approach under two different operating conditions. As can be seen, the system is unstable when it is without damping controller. Also, FWNN-SFLA method produces better damping comparing to other approaches.

Table 4. The system closed-loop eigenvalues with minimum damping ratio for designed damping controller by different methods, under different operating conditions.

	Method	Low frequency mode	Frequency	Damping ratio
Line-to-Ground Fault	Without Damping Controller	0.112± 2.456i	0.3909	-0.0456
	Conventional Damping Controller	-2.987±3.768i	0.5997	0.6212
	Proposed FWNN-GA in [19]	-3.113±4.786i	0.7617	0.5452
	Proposed FWNN-SFLA	-3.768±4.191i	0.6670	0.6686
Three-Phase Fault	Without Damping Controller	0.345± 2.779i	0.4423	-0.1232
	Conventional Damping Controller	-1.343±7.934i	1.2627	0.1669
	Proposed FWNN-GA in [19]	-2.718±6.894i	1.0972	0.3668
	Proposed FWNN-SFLA	-3.099±4.501i	0.6670	0.5671

6.2 Five-area-Sixteen-machine power system

In order to indicate the stabilization effects of proposed damping controller for large-scale power system, a 16-machine 5-area test system (see Figure 6) is simulated in this subsection.

Designing of damping controller using proposed FWNN based method: A similar procedures that introduce for the first case study, is applied to design damping controller for 5-are-16-machine system. By applying OLS algorithm, four fuzzy rules with five selected wavelets are represented for constructing the FWNN controller. Then in the learning step, SFLA is used to train parameters of the FWNN. In SFLA, initial number of frogs (N) is set to 400. The number of memeplex is considered to be 20 and the number of evaluation for local search is set to 30. Also $D_{\max}$ is chosen as inf. Also, the stopping criterion is set to be 7500 iterations. Also, for applying the proposed method in [19], the parameters of GA are considered as previous and the number of its population and iterations are considered as same as SFLA. The obtained FWNN membership function parameters are shown in Table 5. For brevity, other parameters of FWNN are not presented here.

Table 5. The FWNN membership function parameters for two different methods.

FWNN-SFLA	A_1^1	$P_{11}^1 = 1.5743,\ P_{12}^1 = 1.1133$	A_2^1	$P_{21}^1 = -0.8824,\ P_{22}^1 = 0.6451$
	A_1^2	$P_{11}^2 = 1.9274,\ P_{12}^2 = -0.0019$	A_2^2	$P_{21}^2 = 0.3019,\ P_{22}^2 = 0.1119$
	A_1^3	$P_{11}^3 = 0.8924,\ P_{12}^3 = -0.0991$	A_2^3	$P_{21}^3 = -0.3344,\ P_{22}^3 = 0.6712$
	A_1^4	$P_{11}^4 = 1.7503,\ P_{12}^4 = 19987$	A_2^4	$P_{21}^4 = 0.9536,\ P_{22}^4 = -0.2561$
Proposed Method in [19]	A_1^1	$P_{11}^1 = 0.1907,\ P_{12}^1 = 0.3452$	A_2^1	$P_{21}^1 = -0.7761,\ P_{22}^1 = 0.6655$
	A_1^2	$P_{11}^2 = 1.3571,\ P_{12}^2 = -0.3895$	A_2^2	$P_{21}^2 = 1.0563,\ P_{22}^2 = 0.3674$
	A_1^3	$P_{11}^3 = 0.8954,\ P_{12}^3 = 1.5773$	A_2^3	$P_{21}^3 = -0.9335,\ P_{22}^3 = 1.0910$
	A_1^4	$P_{11}^4 = 0.6658,\ P_{12}^4 = 1.9181$	A_2^4	$P_{21}^4 = 0.3460,\ P_{22}^4 = 0.4439$

Designing Conventional damping controller Using SFLA: the same procedures as explained for the first case study is performed here. The initial population size is considered to be 200. The number of memeplex is considered to be 10 and the number of evaluation for local search is set to 10. Also D_{max} is chosen as inf. Furthermore, the number of iteration is set to be 100. The results obtained by the SFLA *k, T,* T_1, T_2, T_3, and T_4 are shown in Table 6. Also, α and β, the boundary of *D*-shape sector for eigenvalues, are considered as −0.16 and 0.049, respectively. Table 7 shows the system close-loop eigenvalue with minimum damping ratio for designed damping controller by SFLA.

Table 6 . The results obtained by SFLA for damping controller.

K	T	T_1	T_2	T_3	T_4
46.7	9.14	1.014	0.788	0.787	0.435

The designed FWNN damping controllers and those obtained by SFLA are installed in the power system (Figure 3). To show the effectiveness of the designed controllers, a line-to-ground fault is applied in one of the tie lines at bus 26. The fault cleared after 70.0 *ms*. The behavior of the system was simulated for 20 *s*. Figure 15 shows the voltage magnitude at the faulted bus. Also, Figures 16 and 17 show the angles difference between different generators and G1 (chosen as the reference generator) under a line-to-ground fault with damping controller. These figures show that the controller designed by FWNN-SFLA method improves the transient response characteristics and has a better performance in terms of overshoot, settling time and rise time compared to two others methods.

Once again to show the robustness of the designed controller, a three-phase fault is applied at bus 26. Figures 18-20 show the voltage magnitude at the fault bus and angles difference between different generators and G1 (chosen as the reference generator) under above fault with damping controllers. These figures show the robustness of the designed controllers. Also as can be seen from these figures, that both methods provide a good damping for the case study, but the damping controllers designed by FWNN-SFLA method improve the transient response characteristics and has a better performance in terms of overshoot, settling time and rise time compared to others methods.

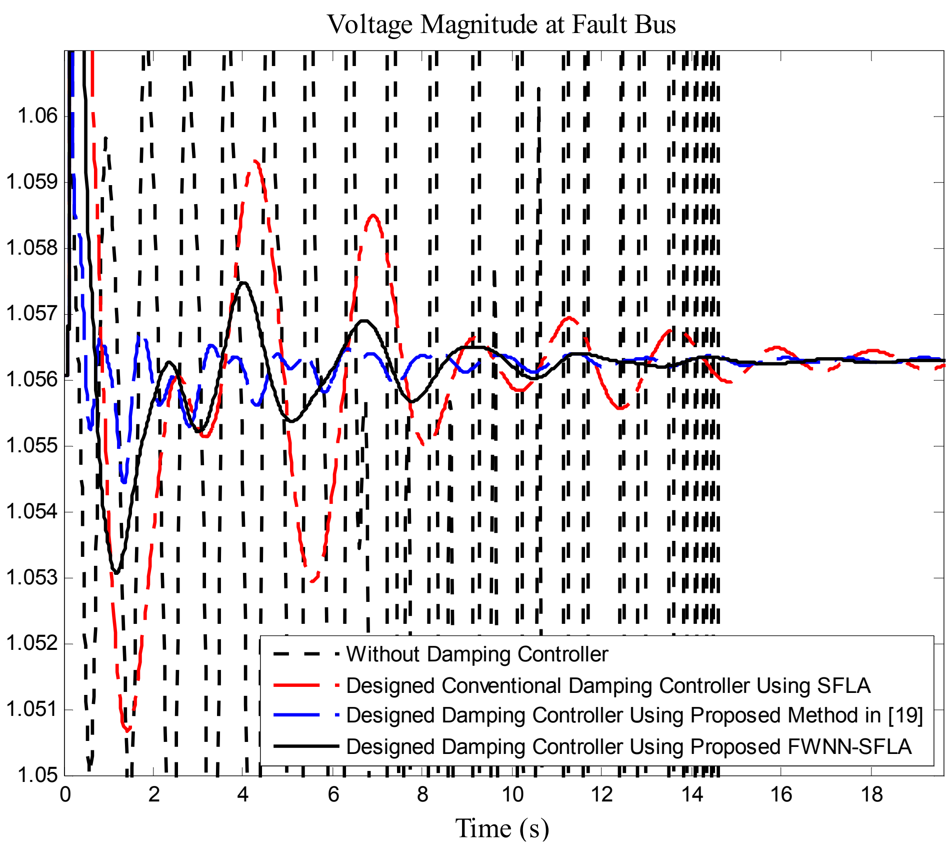

Figure 15. The response of the system to a line-to- ground fault at bus 26.

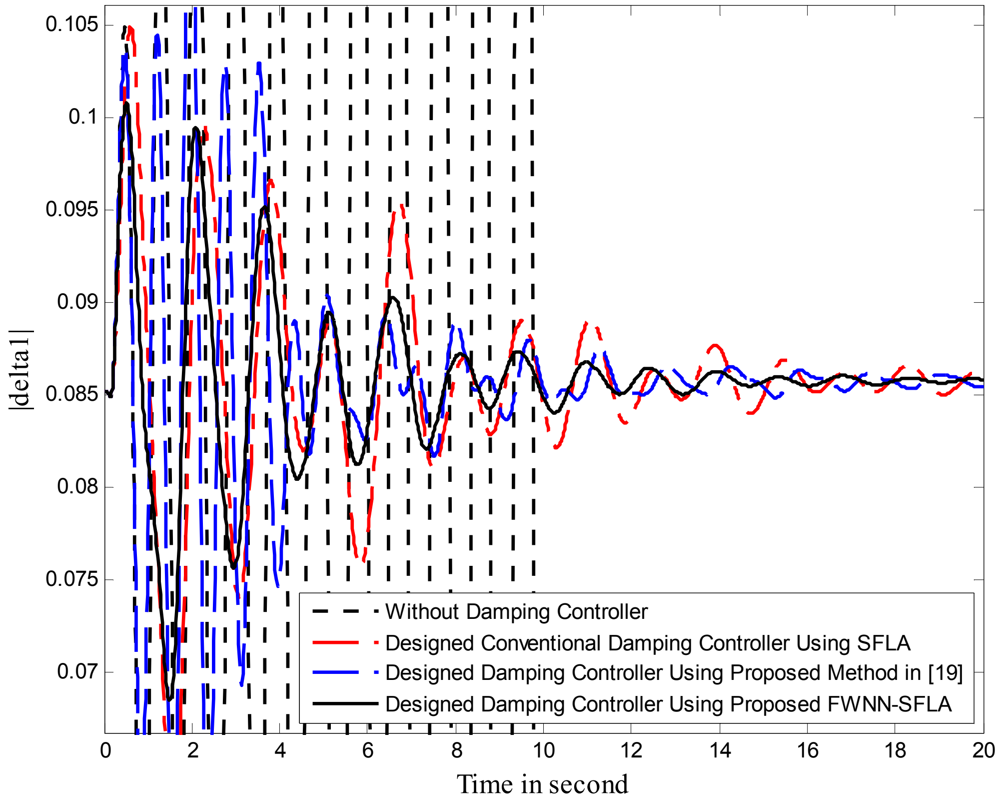

Figure 16. The response of generator 1 to a line-to-ground fault at bus 26.

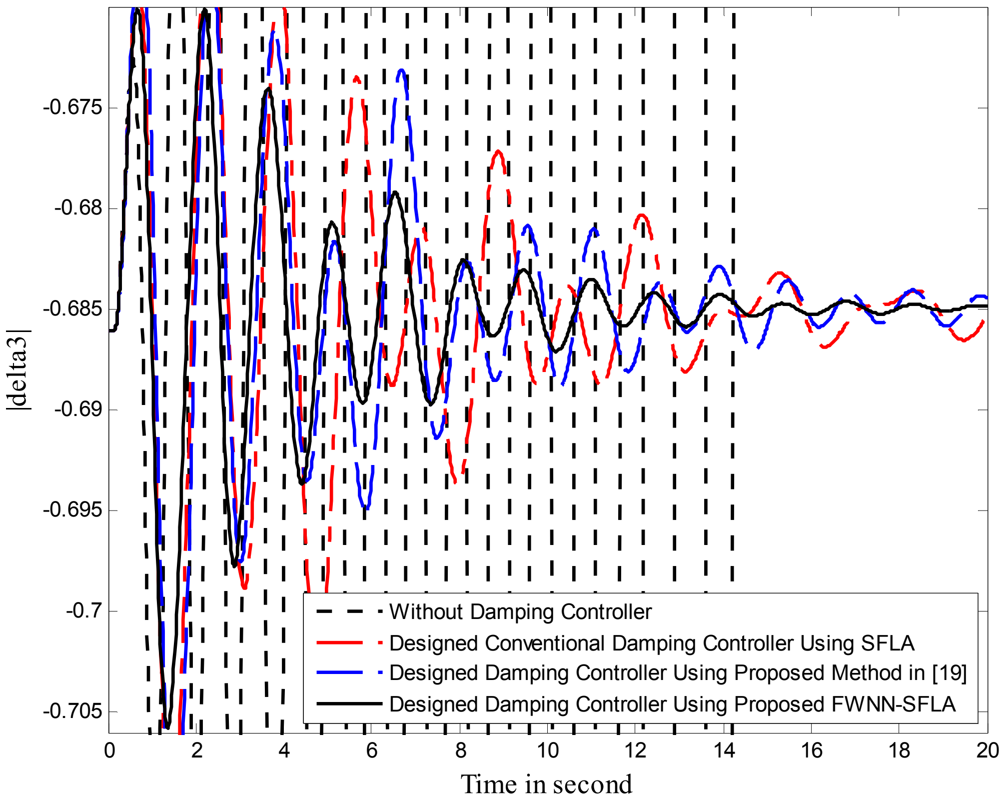

Figure 17. The response of generator 3 to a line-to-ground fault at bus 26.

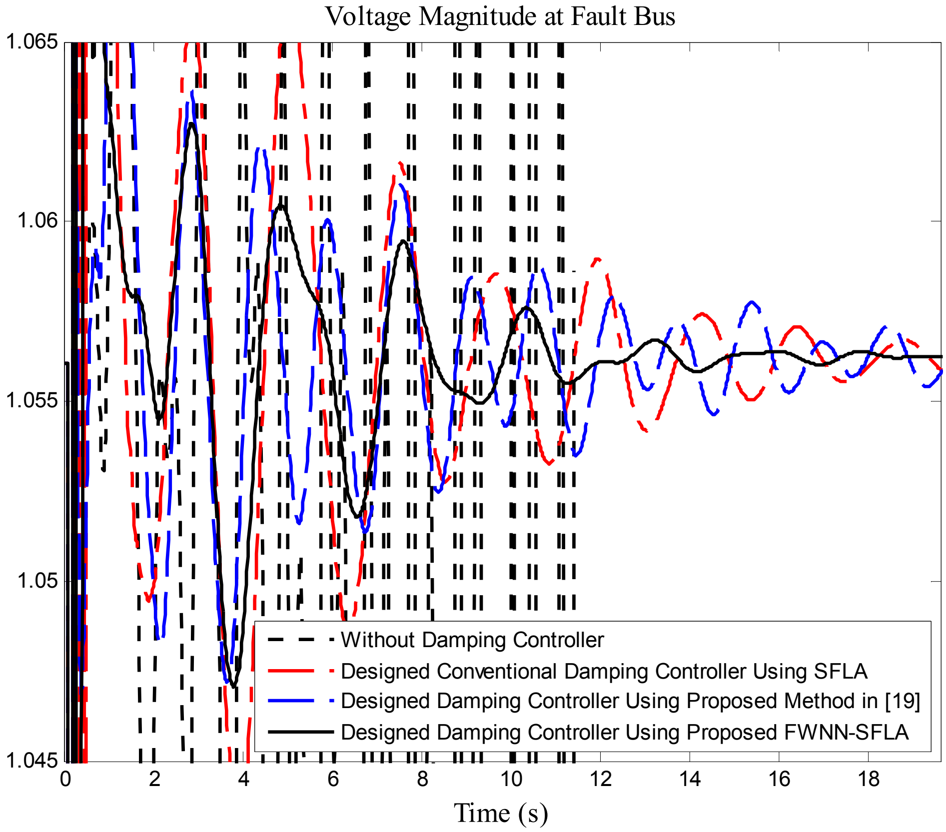

Figure 18. The response of the system to three-phase fault at bus 26.

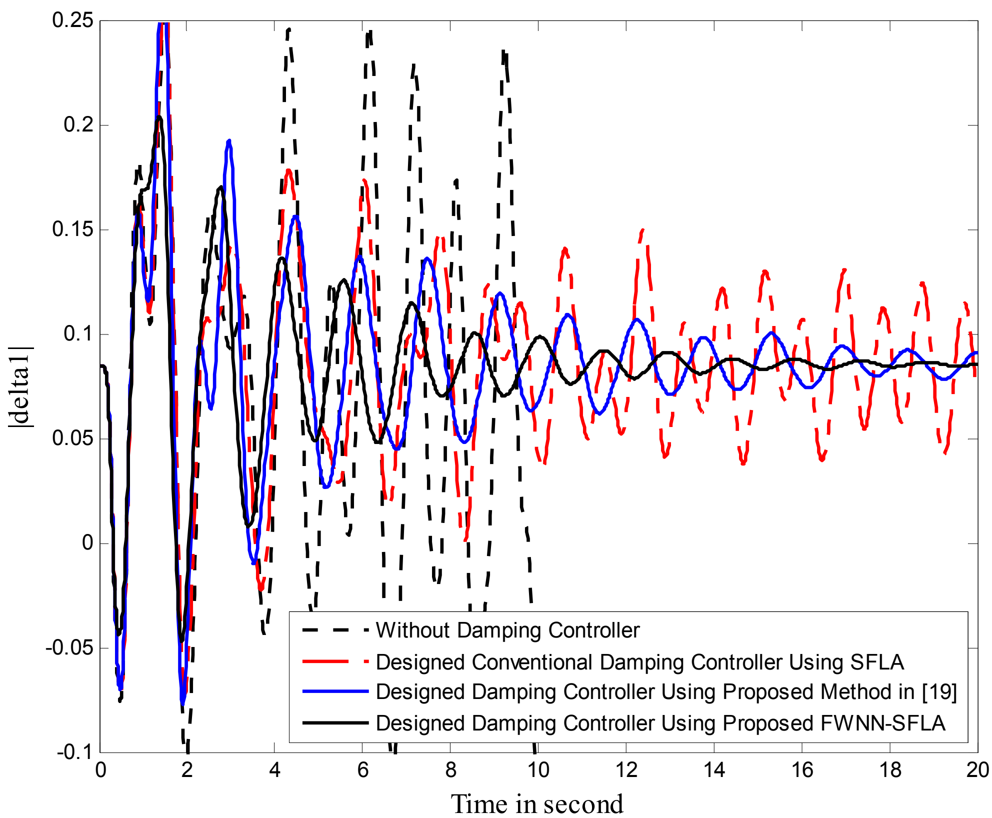

Figure 19. The response of generator 1 to a three-phase fault at bus 26.

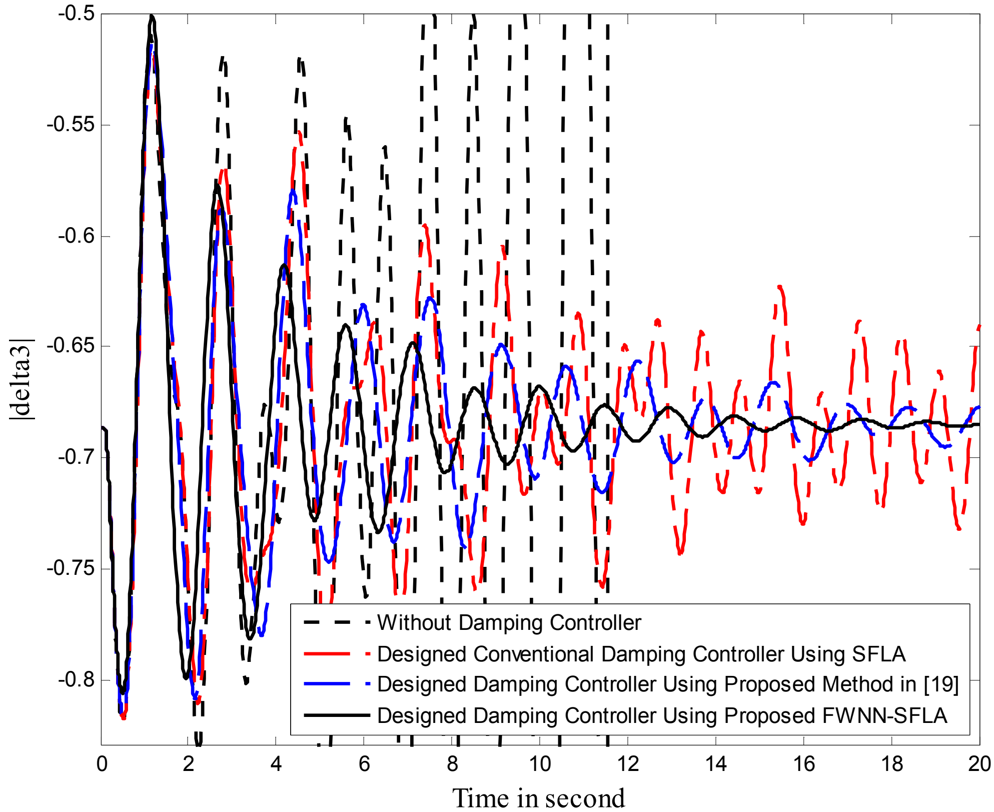

Figure 20. The response of generator 3 to a three-phase fault at bus 26.

Table 7 shows the worst low frequency modes of the system when it is without damping controller and when it is equipped with the designed damping controllers by classical based method, FWNN based genetic algorithm in [19] and proposed FWNN-SFLA approach under two different operating conditions. As can be seen, the system is unstable when it is without damping controller. Also, FWNN-SFLA method produces better damping comparing to other approaches.

Table 7. The system closed-loop eigenvalues with minimum damping ratio for designed damping controller by different methods, under different operating conditions.

	Method	Low frequency mode	Frequency	Damping ratio
Line-to-Ground Fault	Without Damping Controller	0.566 ± 3.988i	0.6347	-0.1405
	Conventional Damping Controller	-2.098±4.788i	0.5997	0.7620
	Proposed FWNN-GA in [19]	-3.019±4.498i	0.7159	0.5573
	Proposed FWNN-SFLA	-3.324±4.356i	0.6933	0.6066
Three-Phase Fault	Without Damping Controller	0.984± 5.009i	0.7972	-0.1928
	Conventional Damping Controller	-1.201±3.9874i	0.6346	0.2884
	Proposed FWNN-GA in [19]	-2.099±5.715i	0.9096	0.3448
	Proposed FWNN-SFLA	-2.655±5.044i	0.8028	0.4658

To have a better perceptiveness about the improvement of the systems by the proposed method comparing to others, two performance indices, PI_1 and PI_2 given in (19) and (20) are calculated for the obtained results:

$$PI_1 = \sum_{i=1}^{m} \int_{t=0}^{t=t_{sim}} (t\Delta\delta_i)^2 dt \tag{19}$$

$$PI_2 = \sum_{i=1}^{m} \int_{t=0}^{t=t_{sim}} (\Delta\delta_i)^2 dt \tag{20}$$

Where m is the number of machines, and t_{sim} is the simulation time. It should be noted that, lower value for the indices shows better performance of the system in terms of the settling time and overshoots. Also, the CPU time of the FWNN-GA [19] and proposed FWNN-SFLA in finding the optimal control moves are given in Table 8. Table 8 shows that the values of two considered indices with the proposed FWNN-SFLA approach are much smaller than other approaches (Conventional method and FWNN-GA). Also, the obtained results reveal that a more accurate control signal (u) is obtained in shorter time by suggested method.

Table 8. The obtained values of the performance indices and CPU time for finding optimal control moves.

	Method	PI_1	PI_2	CPU Time(s)
2-area power system	Conventional Damping Controller	0.765	0.876	-
	Proposed FWNN-GA in [19]	0.678	0.767	1093
	Proposed FWNN-SFLA	0.543	0.594	948
5-area power system	Conventional Damping Controller	2.761	2.909	-
	Proposed FWNN-GA in [19]	2.019	2.255	1408
	Proposed FWNN-SFLA	1.747	1.896	1133

7. 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 and a 5-area-16 machine system. The robustness and effectiveness of the proposed FWNN damping controllers are verified under different disturbances. It is shown that the FWNN damping controllers damp satisfactorily low frequency oscillations of system. Also, conventional damping controller are designed and the FWNN based GA approach is adopted from literature for comparison. The simulation results show the superiority and capability of proposed FWNN-SFLA damping controllers in improving the stability of the power system.

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