Soheil GANJEFAR, Morteza TOFIGHI

Department of Electrical Engineering, Bu-Ali Sina University, Hamedan, Iran

A fuzzy wavelet neural network stabilizer design using genetic algorithm for multi-machine systems

***Abstract**. This paper presents a new method to design power system stabilizer (PSS) using fuzzy wavelet neural network (FWNN) for stability enhancement of a multi-machine power system. In the proposed approach, Wavelet Neural Network (WNN) is used to construct a well localized in both time and frequency domains consequent part for each fuzzy rule of a Takagi-Sugeno-Kang (TSK) fuzzy model. In designing the FWNN stabilizer the activation function of hidden layer neurons is substituted with dilated and translated Mexican Hat wavelet function. In the proposed method, an efficient genetic algorithm (GA) approach is used to obtain the optimal values of such parameters as translation, dilation, weights, and membership functions. These parameters are tuned through simulation of non-linear model of power system under chosen disturbance by minimizing a non-explicit based objective function. Results are promising and demonstrate the capabilities of the proposed FWNN stabilizer in damping of overall power oscillations in the system. It is worth noting that the proposed FWNN stabilizer, moreover, significantly improves the dynamic response characteristics, reducing the number of fuzzy rules as well as a fast convergence of network.*

***Streszczenie.** W artykule opisano metodę projektowania stabilizatora systemu elektroenergetycznego z wykorzystaniem sieci neuronowej bazującej na rozmytej teorii falkowej. W celu optymalizacji parametrów sieci zastosowano algorytm genetyczny oraz wykonano symulacje uwzględniające odpowiednie zakłócenia w sieci. Wykonane badania wykazały, że proponowany algorytm pozwala na skuteczne tłumienie oscylacji mocy w systemie elektroenergetycznym. (**Zastosowanie sieci neuronowej z falkami rozmytymi oraz algorytmu genetycznego w stabilizacji elektrycznego systemu wielomaszynowego**).*

Keywords: Fuzzy wavelet neural network stabilizer; Wavelet neural network; Genetic algorithm.
Słowa kluczowe: stabilizator FWNN, Falkowa sieć neuronowa, algorytm genetyczny.

Introduction

Power system stabilizers (PSS) have been extensively used in large power systems for stabilizing and damping low frequency oscillations caused by disturbances in the power network. It provides an additional control loop that generates an auxiliary stabilizing signal to the excitation system generators, in-phase with the synchronous rotor speed deviations, in order to improve power system dynamic performance [1]. The conventional fixed structure PSS [2, 3] designed using a linear model obtained by linearizing the nonlinear model considering a single operating point provides optimum performance for the same operating condition and system parameters. However, the performance becomes suboptimal following deviations in system parameters and loading condition from their nominal values.

During the last two decades, several methods have been proposed to design a PSS that could get better performance in comparison to the conventional ones. These methods use techniques such as Gain-Scheduling [4], Adaptive Control [5, 6], Neural Networks [7, 8] and Fuzzy Logic Systems [9, 10, 11]. Each of these techniques has their own advantages and disadvantages. For instance, although adaptive control based power system stabilizers resulting in a better dynamic performance for different operating conditions, but bearing from the major drawback of requiring parameter model identification, state observation, as well as feedback gain calculations in online mode [12]. Fuzzy logic controllers (FLC) are capable of coping with nonlinear uncertain systems effectively but their design basically is based on a trial-and-error method. The main disadvantage of neural networks is that a large number of neurons are required when dealing with the intricate problems. Moreover, they also lead to slow convergence rate and convergence to a local minimum.

In recent years, wavelet neural networks (WNN), which combine neural networks with wavelet functions have become very popular and have been applied in many scientific and engineering research areas such as system identification [12], signal processing and function approximation [13]. The activation functions such as sigmoid and Gaussian functions which have non-local properties in time are swapped with the wavelet functions in hidden layers neurons of the WNN. Unlike the multilayer perceptron which is a global network, WNN is a local network in which the output function is well localized in both time and frequency domains. The training of the network in one part of the input space does not corrupt that which has already been learned in more distant regions. Thus, the learning speed of the local network is generally much faster than the global network. Furthermore, local minima can be eliminated in the local network [14].

A Fuzzy wavelet neural network (FWNN) combines Takagi-Sugeno-Kang (TSK) fuzzy model with wavelet neural networks. The synthesis of a fuzzy wavelet neural inference system includes the determination of the optimal definitions of the premise and the consequent part of fuzzy IF–THEN rules. Several papers have discussed the synthesis of a fuzzy wavelet neural inference system for time series prediction, function approximation, system identification, and control problems [15–19]. In [15], the fuzzy wavelet neural networks are proposed for identification and control of dynamic plants, and in [16], the chaotic time-series prediction using adaptive wavelet-fuzzy inference system is presented. Using combines TSK fuzzy models with wavelet transform and ROLS learning algorithm a fuzzy wavelet network is proposed to approximate arbitrary nonlinear functions in [17]. In [18] each fuzzy rule is represented by a sub-WNN, existing for all the dimensions of each wavelet single-scaling wavelets with the same dilation parameters. The constructed network is used for function approximation and control of nonlinear systems. A wavelet and neuro-fuzzy conjunction model are used for the application of short-term and long-term streamflow forecasting in [19].

This paper presents a new method for stability enhancement of a multi-machine power system using FWNN stabilizer. The proposed framework combines several soft computing (SC) techniques such as a TSK fuzzy system, wavelet transform, neural networks (NN), and GA. In order to avoid trial-and-error and time-consuming processes, the GA method is used as an optimization technique to obtain the optimal values of parameters of translation, dilation, weights, and membership functions. In the proposed method, the search capability of the GA is enhanced by introducing an improved evolutionary direction operator (IEDO) [20], which leads to a higher probability of getting global or near global optimal solutions. Simulation results demonstrate the capabilities of the proposed FWNN stabilizer in damping of overall power oscillations in the system. Moreover, compared with the existing methods, it can also reduce the number of fuzzy rules as well as a fast convergence of network.

Overview of genetic algorithm

A genetic algorithm based evolutionary process is an optimization technique that is often able to locate near optimal solutions to complex problems. To achieve this aim, it preserves a set of trial solutions often called as individuals and forces them to evolve towards an admissible solution. Although the binary representation is frequently applied to power system optimization problems, the real-valued representation scheme is adopted in our study for the solution. The use of real-valued representation in the GA is claimed by Wright [21], has a number of benefits in numerical function optimization with respect to binary encoding. The design procedure of the GA approach is described as follows:

Step 1) Initialization of individuals

Set generation *t* = 0. In the initialization process, a population of individuals (chromosomes) is randomly created within user-specified bounds (boundary constraints).

Step 2) Evaluation

Each chromosome in the population will be evaluated by a defined fitness function. The better chromosomes will return higher values in this process.

Step 3) IEDO

The idea behind IEDO is to choose the three best solutions in each generation in order to implement the evolutionary direction operator (EDO) algorithm, and then obtain a new solution that is superior to the original best solution [20].

Step 4) Selection

Selection is the process of determining the number of trials for a particular individual for reproduction and, thus, the number of offspring that an individual will produce. The selection used in this paper depends on individual fitness. The best individuals of the present population are kept for the next population.

Step 5) Crossover

This is a basic operator for producing new chromosomes in genetic programming. Crossover produces new individuals that have some parts of both parents' genetic properties. A binomial mutual crossover is used to increase the local diversity of the individual [22]. The probability of crossover is set to 0.4.

Step 6) Mutation

The individual will then undergo the mutation operation, which changes the genes of the chromosomes. In this paper, non-uniform mutation operator is employed [22]. The mutation rate is set to 0.008.

Step 7) Verification of stop criterion

Set the generation number for *t* = *t* + 1. Proceed to Step 2 until a stopping criterion is met, usually a predefined maximum number of generations.

Wavelet neural network

A wavelet network corresponds to a three-layer structure including the wavelet functions in the neurons of the hidden layer of the network as activation functions [23]. A wavelet is a waveform of effectively finite duration with a zero average value. Wavelet analysis includes the decomposition of a signal into shifted and scaled versions of a single prototype function, known as the original or mother wavelet. The structure of wavelet network with one output θ, n inputs ($x_1, x_2, \ldots, x_n$) and m nodes in the hidden layer, is given in Fig. 1. The wavelet form is defined as follows:

(1) $$\psi_{ij}(x_i) = \frac{1}{\sqrt{|a_{ij}|}}\psi(z_{ij}) \quad for \quad a_{ij} \neq 0$$

where

(2) $$z_{ij} = \frac{x_i - b_{ij}}{a_{ij}}$$

Here, b_{ij}, a_{ij}, and $\psi_{ij}(x)$ stand for the translation parameters, dilation parameters, and family of wavelets obtained from the single $\psi(x)$ function, respectively. The subscript of ij denotes the i^{th} input and the wavelet function between the j^{th} hidden layer neuron for $i = 1, 2, ..., n$ and $j = 1, ..., m$. The output signal of network in Fig. 1 is calculated as

(3) $$\theta = \sum_{j=1}^{m} w_j \sum_{i=1}^{n} x_i \, \psi_{ij}(x_i)$$

where

(4) $$\psi_{ij}(x_i) = \frac{1}{\sqrt{|a_{ij}|}}(1 - z_{ij}{}^2)\exp\left(-\frac{z_{ij}{}^2}{2}\right)$$

and w_j are the weight coefficients between hidden and output layers. Notice that the Mexican Hat function $\psi(x) = (1 - x^2)\exp(-x^2/2)$, is used as the mother wavelet function in this paper.

Fuzzy wavelet neural network Structure

The FWNN model is a feed-forward multi-layer network which integrates traditional Takagi-Sugeno-Kang fuzzy model with wavelet neural networks. The kernel of the fuzzy system is the fuzzy knowledge base that consists of the input-output data points of the system interpreted into linguistic fuzzy rules. The consequent parts of TSK-type fuzzy IF–THEN rules are represented by either a constant or a linear function of input variables. TSK-type systems generally cannot model the complex processes with desired accuracy using a certain number of rules. In the classic TSK-type neuro-fuzzy networks [24], which are linear polynomial of the input variables, the system output is locally approximated by the rule hyper-planes.

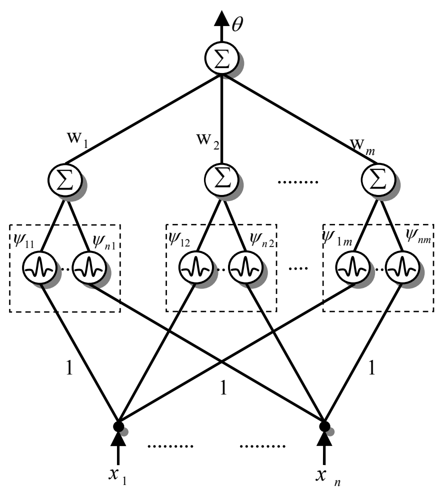

Fig. 1. Architecture of WNN

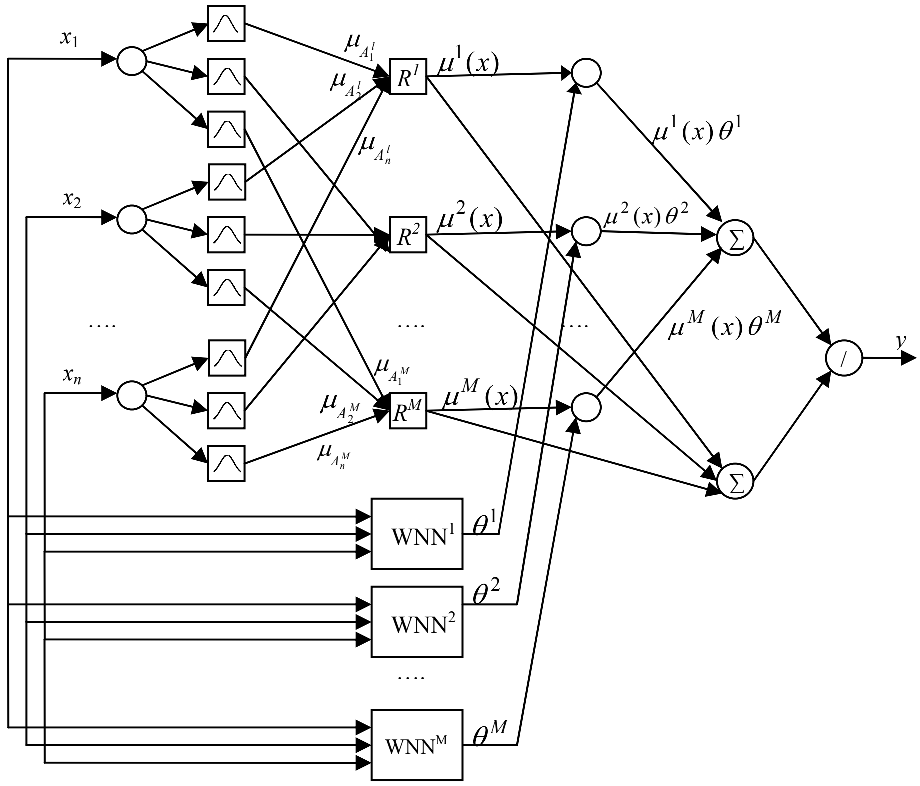

Fig. 2. Structure of fuzzy wavelet neural network

Nevertheless, the traditional TSK-type neuro-fuzzy networks do not take full advantage of the mapping capabilities that the consequent part might offer. In the FWNN, constant or linear functions in consequent part of the rules in TSK fuzzy system are substituted with wavelet functions. Using these functions instead of common activation functions in neural networks with one-hidden layer leads to increase computational power of neuro-fuzzy system regarding the fact that wavelets have time-frequency localization properties. Now suppose that there are M fuzzy IF–THEN rules in the following form:

(5) $R^l : IF\ x_1\ is\ A_1^l\ AND\ x_2\ is\ A_2^l\ AND\ ... x_i\ is\ A_n^l\ THEN\ y^l\ is\ \theta^l$

where x_i is the i^{th} input variable of the system for $i = 1{:}n$ and A_i^l is a linguistic term characterized by a fuzzy membership function $\mu_{A_i^l}(x_i)$ *for* $l = 1,2, ..., M$. By applying fuzzy product inference engine, singleton fuzzifier, and Gaussian membership functions, the output of whole network can be calculated as

(6) $$y = \frac{\sum_{l=1}^{M} \theta^l \prod_{i=1}^{n} \mu_{A_i^l}(x_i)}{\sum_{l=1}^{M} \prod_{i=1}^{n} \mu_{A_i^l}(x_i)}$$

where $\mu_{A_i^l}(x_i)$ is the Gaussian membership function defined by

(7) $$\mu_{A_i^l}(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - c_i^l}{\sigma_i^l}\right)^2\right]$$

where c_i^l denotes the center parameters, and σ_i^l denotes the scaling parameters for membership function associated with rule l. The structure of fuzzy wavelet neural network is given in Fig. 2, and the structure of each sub-WNN is presented in Fig. 1. Notice that $\mu^l(x)$ in Fig. 2 is calculated as

(8) $$\mu^l(x) = \prod_{i=1}^{n} \mu_{A_i^l}(x_i)$$

where $x = [\, x_1, x_2, \dots, x_n]$ is the input vector presented to the network for $i = 1, 2, ..., n$ and l is the total number of fuzzy rules for $l = 1, 2, ..., M$.

The network optimization

The training of the parameters is the main problem in designing a fuzzy wavelet neural network. To solve this problem, back-propagation (BP) training algorithm is extensively used [24, 25] as a powerful training method which can be applied to the forward network architecture. Since the steepest descent method is used in BP training algorithm to minimize the error function, sometimes the algorithms may reach the local minima quickly and thus never find the global optimal solution. Furthermore, BP training algorithm is slow to converge, and its overall performance depends on initial starting point values. The GA is an efficient technique for optimization problem which can be used to improve the training of FWNN and prevent sticking to local minima [19]. During the network training process, the center parameters (c_i^l) and scaling parameters (σ_i^l) of Gaussian membership functions in antecedent part of the rules, and translation (b_{ij}^l), dilation (a_{ij}^l) parameters of wavelet functions, and weight (w_j^l) parameters in the consequent part of the rules are optimized.

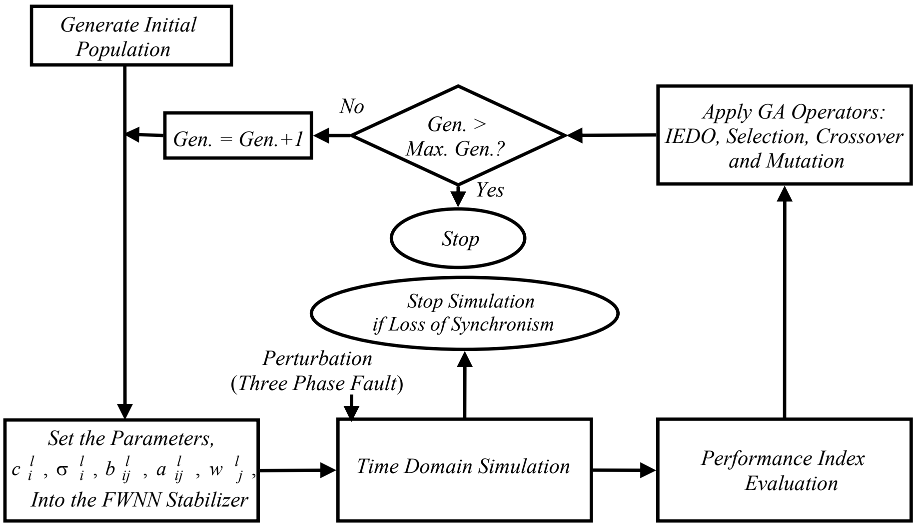

Fig. 3. Flow chart of the GA optimization approach

One of the common problems for an interconnected power system is the existence of lightly-damped power oscillations between interconnected areas; these oscillations are associated with the dynamics of inter-area power transfers which, under heavy transfer of load, often exhibit a low-damping condition. To achieve an overall effective damping improvement, lightly damped inter-area oscillations on the tie-lines between interconnected areas in a power system must be considered in the tuning procedure. This can be realized through adding the active power deviations, $\Delta p_{tie,d}$, on relevant tie-lines into the performance index. Thus, we adopt a non-explicit performance index involving the active power deviations of both Δp_{Ge} on each individual generator and $\Delta p_{tie,d}$ on the relevant tie-lines. In a multi-machine power system with h generators and r selected tie-lines, the performance index J can be defined as

$$J=\sum_{q=1}^{N}\left[\sum_{e=1}^{h}\left(\frac{P_{Ge}(q)-P_{Ge}(0)}{P_{Ge}(0)}\right)^2+\sum_{d=1}^{r}\left(\frac{P_{tie,d}(q)-P_{tie,d}(0)}{P_{tie,d}(0)}\right)^2\right] \tag{9}$$

where N is the total number of the sample, $P_{Ge}(q)$ for $e = 1,2, ..., h$ is the accelerating power of the e^{th} generator at sample q, $P_{Ge}(0)$ is the corresponding initial state, $P_{tie,d}(q)$ for $d = 1,2, ...,r$ is the active power on the d^{th} health tie-line at sample q, and $P_{tie,d}(0)$ is its initial state. The FWNN training is carried out through minimizing the above-discussed performance index.

Assume that there are N samples $(x(1), x(2), ..., x(q))$ for $q = 1, 2, ..., N$, over a time interval from 0 to t_s. Accordingly, the network output for the k^{th} chromosome associated with sample q, can be calculated as follows:

$$y^{(k)}(x(q))=\frac{\sum_{l=1}^{M}\theta^{l,(k)}\left[\prod_{i=1}^{n}\exp\left(-\frac{1}{2}\left(\frac{x_i(q)-c_i^{l,(k)}}{\sigma_i^{l,(k)}}\right)^2\right)\right]}{\sum_{l=1}^{M}\left[\prod_{i=1}^{n}\exp\left(-\frac{1}{2}\left(\frac{x_i(q)-c_i^{l,(k)}}{\sigma_i^{l,(k)}}\right)^2\right)\right]} \tag{10}$$

where

$$\theta^{l,(k)}=\sum_{j=1}^{m}w_j^{l,(k)}\sum_{i=1}^{n}x_i(q)\psi_{ij}^{l,(k)}(x_i)=\sum_{j=1}^{m}w_j^{l,(k)}\sum_{i=1}^{n}x_i(q)\ldots$$
$$\frac{1}{\sqrt{\left|a_{ij}^{l,(k)}\right|}}\left(1-\left(\frac{x_i(q)-b_{ij}^{l,(k)}}{a_{ij}^{l,(k)}}\right)^2\right)\exp\left(-\frac{1}{2}\left(\frac{x_i(q)-b_{ij}^{l,(k)}}{a_{ij}^{l,(k)}}\right)^2\right) \tag{11}$$

Therefore, the k^{th} chromosome is represented as

$$U^k=[c_i^{l,(k)}\ \sigma_i^{l,(k)}\ b_{ij}^{l,(k)}\ a_{ij}^{l,(k)}\ w_j^{l,(k)}]$$
$$for\ \ i=1,2,\ldots,n,\ j=1,2,\ldots,m,\ l=1,2,\ldots,M \tag{12}$$

where

$$c_i^{l,(k)}=[c_1^{1,(k)}\cdots c_n^{1,(k)}\cdots c_1^{M,(k)}\cdots c_n^{M,(k)}] \tag{13}$$

$$\sigma_i^{l,(k)}=[\sigma_1^{1,(k)}\cdots\sigma_n^{1,(k)}\cdots\sigma_1^{M,(k)}\cdots\sigma_n^{M,(k)}] \tag{14}$$

$$b_{ij}^{l,(k)}=[(b_{11}^{1,(k)}\cdots b_{n1}^{1,(k)}\cdots b_{1m}^{1,(k)}\cdots b_{nm}^{1,(k)})\cdots$$
$$(b_{11}^{M,(k)}\cdots b_{n1}^{M,(k)}\cdots b_{1m}^{M,(k)}\cdots b_{nm}^{M,(k)})] \tag{15}$$

$$a_{ij}^{l,(k)}=[(a_{11}^{1,(k)}\cdots a_{n1}^{1,(k)}\cdots a_{1m}^{1,(k)}\cdots a_{nm}^{1,(k)})\cdots$$
$$(a_{11}^{M,(k)}\cdots a_{n1}^{M,(k)}\cdots a_{1m}^{M,(k)}\cdots a_{nm}^{M,(k)})] \tag{16}$$

and

$$w_j^{l,(k)}=[w_1^{1,(k)}\cdots w_m^{1,(k)}\cdots w_1^{M,(k)}\cdots w_m^{M,(k)}] \tag{17}$$

can all be considered as free design parameters. Thus, the total number of free unknown parameters to be optimized is $M(m(2n+1)+2n)$. The designing FWNN stabilizer is, therefore, equivalent to determination of the above-mentioned parameters. The computational flow chart of the GA optimization approach is shown in Fig. 3. After applying the GA approach, the best individual of the final generation is the solution. The constructed FWNN stabilizer is used to damp out the power system oscillations more effectively.

Simulation and case studies

In order to demonstrate the validity of the proposed FWNN stabilizer, and to tune its parameters in the way presented in this paper, simulation studies are performed based on two different nonlinear models. The first model is a single-machine infinite-bus (SMIB) model applied here to facilitate finding the optimal number of fuzzy rules and the optimal number of wavelets in each sub-WNN. The second model is a four-machine two-area system used as a benchmark problem in the literature. In the proposed design procedure, the stabilizing signal, y, is computed by the FWNN stabilizer using the generator speed deviation $(\Delta\omega)$ and acceleration $(\Delta\dot{\omega})$ as the input signals to FWNN stabilizer during each sampling period. In practice, only shaft speed deviation is readily available. Hence, the acceleration signal can be derived from the speed signals measured at two successive sampling instants as follows:

(18) $$\Delta\dot{\omega}(qT) = \frac{\Delta\omega(qT) - \Delta\omega[(q-1)T]}{T}$$

where T is the sampling period and q is the sampling count. A sampling period of 10 ms is chosen for the present studies. The input vector of FWNN is selected as $[x_1, x_2] = [(\Delta\omega), (\Delta\dot{\omega})]$, meaning the FWNN stabilizer has only two inputs. Also, in Fig. 2 the output of FWNN, y, generates the stabilizing signal to the excitation system of the generator.

Selecting wavelets and fuzzy rules

The study in this section is carried out on a SMIB power system [26], and the results obtained are used in designing the FWNN stabilizer in a multi-machine power system. To find the optimal number of fuzzy rules and the optimal number of wavelets in each sub-WNN, several cases are investigated. For this purpose, experiments are conducted using the proposed FWNN stabilizer by increasing the number of fuzzy rules (M) from 1 to 7, and decreasing the number of wavelets in each sub-WNN (m) from 7 to 1. For each combination of values regarding these parameters (M, m), the training of the network is repeated 20 times for different random initializations of the proposed FWNN stabilizer to bring out the optimal values of M and m.

The boundary constraints for generating the initial population are provided in Table 1. It should be noted that the use of normalized domain, i.e. universes of discourse (UOD) requires a scale transformation which maps physical values of process variables into a normalized domain. A performance index $J = \int \Delta w^2 t^2 dt$ is selected for the optimization, evaluated through simulation of the system dynamic model considering a three phase fault at the generator terminal. The maximum generation number is set as 100. The maximum, average, and minimum performance index obtained for each parameters combination are shown in Table 2. According to the data in Table 2, we can easily find that the proposed FWNN stabilizer provides the best results in case M = 3 and m = 5. It is worth noting that for other parameters combination, we also have an optimum of the generalization ability, though worse than that obtained for M = 3 and m = 5. Also, the best chromosome corresponding to the smallest fitness value at each generation is presented in Fig. 4. It clearly shows that the gradient rate of convergence properties of the proposed FWNN stabilizer during the network training is dramatic.

Table 1. The lower and upper bounds for generating the initial population

Part of the rules	*Parameters*	*Lower bounds*	*Upper bounds*
Antecedent	Center (c_i^l)	-1	1
	Scaling (σ_i^l)	0	1
Consequent	Translation (b_{ij}^l)	-1	1
	Dilation (a_{ij}^l)	0	1
	Weight (w_j^l)	-1	1

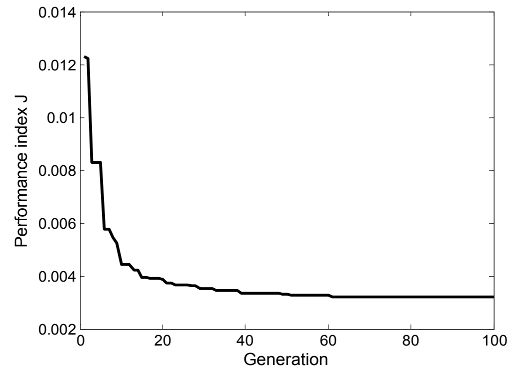

Fig. 4. Variation of performance index J on each generation.

Simulation results in a multi-machine power system

The benchmark two-area model shown in Fig. 5 is adopted for simulation studies. The test system [1] consists of two symmetrical areas linked together by two 230 kV lines of 220km length. It was specifically designed to study low frequency electromechanical oscillations in large interconnected power systems. Despite its small size, it mimics very closely the behavior of typical systems in actual operation. Each area is equipped with two identical round rotor generators rated 20kV/900MVA. The synchronous machines have identical parameters, except for inertia which is H = 6.5s for generators in area 1 and H = 6.175s for generators in area 2. Thermal plants having identical speed regulators are further assumed at all locations, in addition to fast static exciters with a 200 gain. The loads are assumed everywhere as constant impedance load models. The performance of the designed FWNN stabilizer is compared with both multi-band power system stabilizer (MB-PSS) and Conventional PSS. The MB-PSS is represented by the IEEE St. 421.5 PSS 4B type model [27] and the Conventional PSS is taken from P. Kundur [1].

Table 2. The maximum, average, and minimum performance index obtained for each combination of parameters (M, m).

Number of fuzzy rules (M)	1	2	3	4	5	6	7
Number of wavelets in each sub-WNN (m)	7	6	5	4	3	2	1
Number of optimization parameters	39	68	87	96	95	84	63
Maximum performance index ($\times 10^2$)	0.3492	0.3486	0.3449	0.3494	0.3650	0.3657	0.4164
Minimum performance index ($\times 10^2$)	0.3201	0.3162	0.3084	0.3080	0.3102	0.3093	0.3122
Average performance index ($\times 10^2$)	0.3355	0.3342	**0.3291**	0.3334	0.3366	0.3378	0.3516

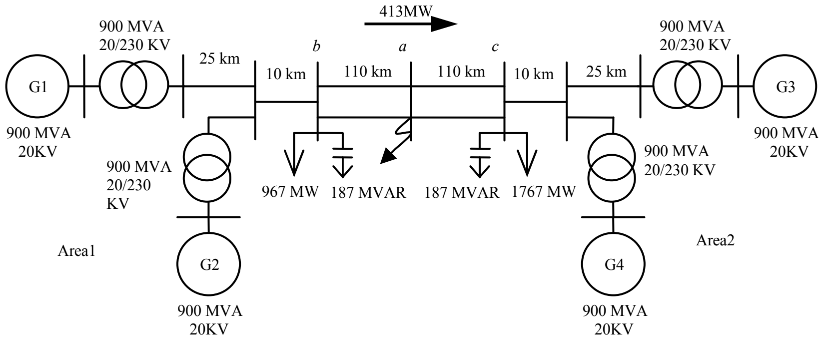

Fig. 5. Diagram of the four-machine power system.

Table 3. The parameters of membership functions after learning algorithm in case M = 3 and m = 5.

A_1^1	$c_1^1 = -0.8416$	$\sigma_1^1 = 0.4231$	A_2^1	$c_2^1 = -0.3827$	$\sigma_2^1 = 0.8502$
A_1^2	$c_1^2 = 0.7683$	$\sigma_1^2 = 0.9458$	A_2^2	$c_2^2 = -0.5921$	$\sigma_2^2 = 0.1840$
A_1^3	$c_1^3 = 0.0453$	$\sigma_1^3 = 0.8157$	A_2^3	$c_2^3 = -0.6290$	$\sigma_2^3 = 0.3492$

Based on the statistic results shown in Table 2, the parameters are chosen as follows: number of fuzzy rules M = 3 and number of wavelets in each sub-WNN m = 5. The population size and the maximum generation number are set to 40 and 100, respectively. With these parameters, the training of the network is repeated 20 times from different initial populations and select the best result as the final optimization solution. The parameters of the Gaussian membership functions obtained at the end stage of training algorithm are given in Table 3. In order to validate the feasibility and effectiveness of the proposed FWNN stabilizer for improving the stability of a multi-machine power system, its dynamic performance is examined under small disturbance and large disturbance.

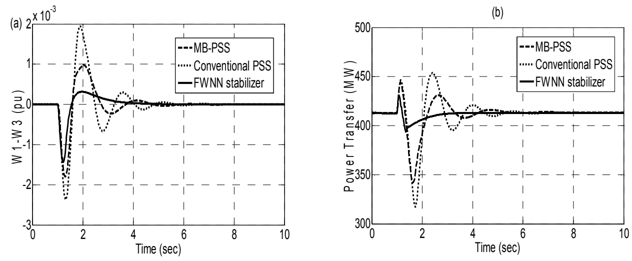

Fig. 6. (a) Gen. 1 swing against Gen. 3 for small disturbance. (b) Power transfer from area 1 to area 2 for small disturbance.

Small disturbance test

The performance of the proposed FWNN stabilizer is evaluated by applying a small disturbance in the form of a 10% increase in AVR reference voltage of generator G1 for 0.2 second and then returns to 1 *pu*. For comparison purposes, the actual speed difference between the two generators, G1and G3, in area 1 and area 2 is monitored. The power transfer from area 1 to area 2 is also monitored. The performance of proposed FWNN stabilizer is compared with both the MB-PSS and the Conventional PSS. Fig. 6 shows the dynamic characteristics of the system for the above-mentioned contingency. The simulation results reveal that the proposed FWNN stabilizer can provide improved dynamic performance compared with both the MB-PSS and the Conventional PSS. It is clear from the Fig. 6 that the proposed FWNN stabilizer significantly suppresses the oscillations in the system, providing more desirable damping characteristics to low frequency oscillations through quicker stabilization of the system.

Large disturbance test

In order to investigate the effectiveness of the proposed FWNN stabilizer under more severe conditions, a three phase fault is imposed at three different locations of the tie-line. Location "a" is at the middle of the tie-line while locations "b" and "c" are considered to be within areas "1" and "2", respectively. The fault occurs at t = 1.0 sec and cleared after 6 cycles. The original system is restored after the fault clearance. The performance of the proposed FWNN stabilizer is compared with both the MB-PSS and the Conventional PSS. For fair comparison, all simulation results consider saturation limits of ±0.15 pu on the control signals provided either by the MB-PSS and the Conventional PSS or by the proposed FWNN stabilizer. Figs. 7-9 show the generators' actual speed responses when the system is simulated at a 413 MW power transfer level from the area 1 to the area 2. From these figures, one can conclude that the proposed FWNN stabilizer provides good damping to the system oscillations, not only in damping of the generator rotor modes but also in damping of oscillations on the tie-line between the two areas. Furthermore, simulation results demonstrate the superiority of the proposed FWNN stabilizer over the MB-PSS and the Conventional PSS both in the transient and the steady-state responses.

Conclusions

Using the GA approach, the structure of FWNN stabilizer is proposed in this paper for damping low frequency oscillations in a multi-machine power system. The proposed FWNN stabilizer incorporates the advantages of fuzzy concepts, neural networks, and wavelet functions. In the presented method, constant or linear combinations of input variables in consequent part of the rules in TSK fuzzy system are substituted with wavelet functions. Using these functions instead of common activation functions in neural networks with one-hidden layer leads to increase computational power of neuro-fuzzy system regarding the fact that wavelets have time-frequency localization properties. The parameters of the proposed FWNN stabilizer are tuned through a GA approach. The nonlinear simulation results demonstrate the capabilities of the proposed FWNN stabilizer in damping of overall power oscillations in the system. This method is also compared with both the MB-PSS and the Conventional PSS, showing better response behavior to damp out low frequency oscillations and significantly improves the dynamic stability of the power system. Additionally, this study shows that the proposed FWNN stabilizer provides other advantages such as fast convergence rate, considerable decrease in the number of fuzzy rules and easy algorithm.

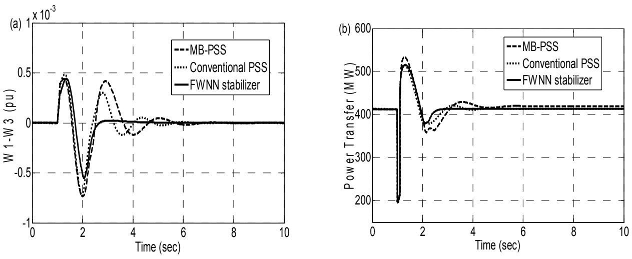

Fig. 7. (a) Gen. 1 swing against Gen. 3 for large disturbance, fault location "a". (b) Power transfer from area 1 to area 2 for large disturbance, fault location "a".

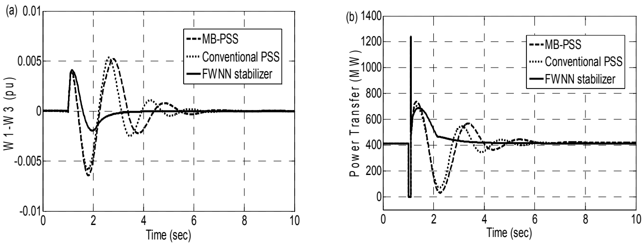

Fig. 8. (a) Gen. 1 swing against Gen. 3 for large disturbance, fault location "b". (b) Power transfer from area 1 to area 2 for large disturbance, fault location "b".

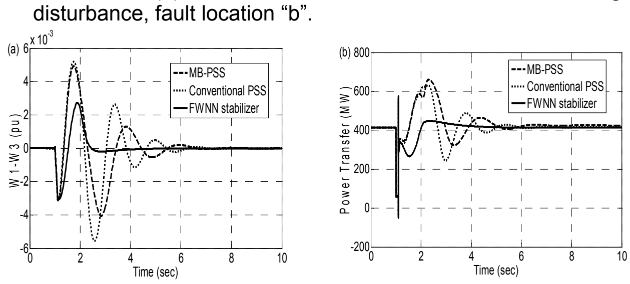

Fig. 9. (a) Gen. 1 swing against Gen. 3 for large disturbance, fault location "c". (b) Power transfer from area 1 to area 2 for large disturbance, fault location "c".

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***Authors**: Dr. Soheil Ganjefar and Morteza Tofighi*, *Department of Electrical Engineering, Bu-Ali Sina University, Hamedan, Iran. Email: s_ganjefar@yahoo.com, tofighi_morteza@yahoo.com*