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Optimal design of power system stabilizer based on multilayer perceptron neural networks using bee's algorithm

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ABSTRACT

The modern power networks are very big and have nonlinear characteristics. In these big and complicated networks, many problems and abnormal conditions may be occurring. Power system stabilizers or PSS tools are applied to produce additional control efforts for the excitation system to remove or enfeeble the inferior frequency power system fluctuation. There are many techniques for PSS control that have some shortcomings and deficiencies. To overcome the shortcoming and defect of the conventional techniques, in this paper we proposed an optimal neural network based technique using bee's algorithm. The suggested technique is applied in a power network to produce additional control effort signals to the excitation section. The proposed method has two main parts: The controller part and the optimization part. In the controller part, we proposed MLP neural network as a controller. The MLP neural network has good capability in control tasks. In the MLP neural networks, the number of hidden layers and relative neuron numbers have a high effect on its performance. For this purpose in the optimization part, we used the bee's algorithm for finding the optimal number of these parameters. To evaluate the performance of the suggested technique, some computer simulations are done and the obtained results show that the suggested method has good performance.

1. Introduction

The control of generator voltage magnitude and damping of its oscillation is one of the most important subjects in electrical engineering. In modern power networks, almost all generators are tooled to voltage controller to automatically control the voltage of generator and prevent from unwished disturbances. But these automatic voltage controllers have harmful effects on dynamic and voltage profile of electrical power network. In some cases, the inferior frequency power system fluctuation made serious problems in power transmission. Therefore these fluctuations must be eliminated as soon as possible to prevent from future damages (Supriyadi et al., 2014).

There are two category of power system fluctuation. The first one is related to synchronous generators at a producing plant. This kind of power system fluctuation is known as 'intra-area mode' fluctuation. The other type of fluctuation is called s type oscillation. This type of fluctuation is relative to connections between machines in one section of power system against to machines and other devices in other different section. This kind of fluctuation is known as 'inter-area mode' oscillations. The PSS is used to produce the control efforts to damp or eliminate these fluctuations in power networks (Nechadi et al., 2012).

There are some traditional techniques for design of power system stabilizers. In many of these power system stabilizers, the designers used phase compensation theory. In these traditional techniques, the parameters of power system stabilizers are selected based on linear model of electrical power system. In linearization of power system, some estimation is done. Therefore in this linear model some errors are available. Also the parameters of designed power system stabilizers must be selected in concern to both types of oscillations. As mentioned, the modern available electrical power networks are include numerous machines, compensators, transformers, breakers, nonlinear load and many other sections. Therefore these networks are high nonlinear characters. In this big and nonlinear network, the design of power system stabilizer is very hard on difficult problem. For this purpose, this paper suggests the application of MLP neural network as power system stabilizer. With usage of neural networks as power system stabilizer, the nonlinear and dynamic characters of electrical power networks are considered and therefore the damping of low frequency fluctuations is done better (Sun et al., 2014).

The power system stabilizer with fixed parameters may have good performance in wind boundary of power system situation, but these conventional systems cannot act properly if the operating points change. Therefore it is essential to design an adaptive technique to tune the parameters of power system stabilizer. To overcome these shortcoming in designing of power system stabilizers, different artificial intelligence based techniques are proposed. These artificial intelligence based techniques led to better performance under variable operating situations. One of the most powerful and effective of these tools is artificial neural networks (ANN).

The artificial neural networks have good capabilities in pattern recognition, classification, clustering, control, forecasting, function approximation and many other areas. The artificial neural networks have several types like MLP, radial basis function neural networks (RBFNN), probabilistic neural networks (PNN), recursive neural networks, concurrent neural networks and Elman neural networks. In this paper we used MLP neural network for tune the parameters of power system stabilizer to improve the performance of it. With application of MLP neural network, the parameters of power system stabilizer can be tuned for different load conditions and therefore the performance of power system stabilizer will be better. In MLP neural network some issues must be considered like training

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algorithm, number of hidden layers and number of neurons in hidden layers. In the proposed method, different training algorithms are tested and the best one is selected. Also the number of hidden layers and number of neurons in hidden layers are selected by optimization algorithm (Wen et al., 2015; Zhang et al., 2015; Zhaoet al., 2015).

In last decades, the optimization is considered as important subjects in many areas and many optimization algorithms have been proposed for this purpose. Also with advances in computer hardware, some iterative that mimic the animals manner are proposed for optimization like ant colony optimization algorithm (ACO), artificial bee colony (ABC) optimization algorithm, particle swarm optimization (PSO) algorithm, imperialist competitive algorithm (ICA), cuckoo optimization algorithm (COA) and bee's algorithm (Mernik et al., 2015; Liu et al., 2015). These nature based optimization algorithms are inspired from animal's manner in food searching. It is proven that each optimization algorithm must have two vital items: extraction and exploration. The exploration is capability of optimization algorithm in finding of best areas of food, and the extraction is capability of optimization algorithm in finding the final optimal solution. The bee's algorithm or BA has good extraction and exploration capability. Therefore in this paper we used bee's algorithm to find the best number of hidden layers and number of hidden neurons in hidden layers. The more details about the proposed method, optimization algorithm and neural network are described in following sections.

2. Optimization algorithm

The flowchart of bee's algorithm is shown in Fig. 1. This algorithm is inspired from honey bee manner. The honey bee is looking for food in nature with special way. In this process, some bee's fly to different areas of nature. These bee's select the best areas that have high amount of honey. From these areas, some have better and higher amount of honey. The related bees are known as elite bees. The elite bees are candidate to local search. This section is illustrated in Fig. 1 (Pham et al., 2006).

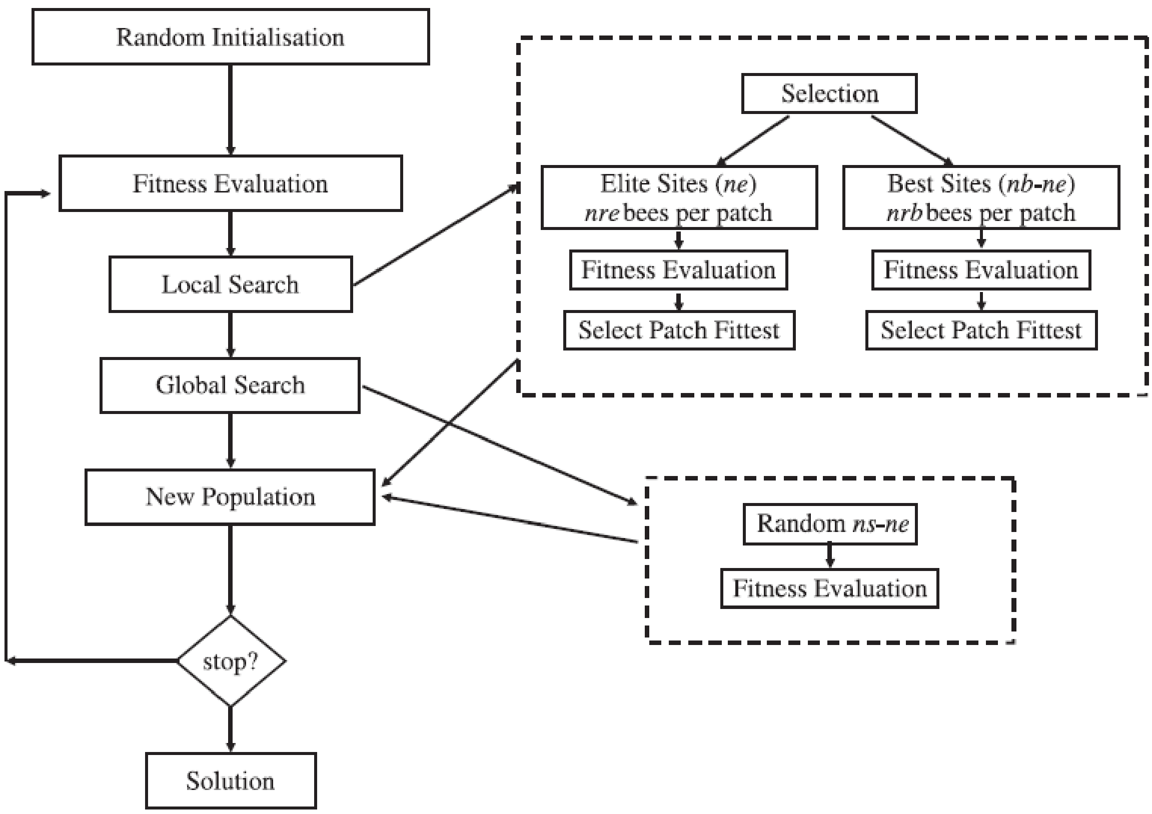

Fig. 1. The flowchart of bee's algorithm.

The remaining bees are known as global search bees. These remaining bees eliminated and reproduced randomly in search space. In the initial step of bee's algorithm, the boundaries of optimization must be defined. The elite bees and remaining bees must be move in this predetermined boundary. Each elite bee has its soldier bees. These soldier bees aid the elite bee to search the local area.

As mentioned, each optimization algorithm must have to vital features. One of them is exploration feature. This feature aims the optimization algorithm to search all points of search area. In the bee's algorithm, global search bees perform this step. With random producing of these bees, bee's algorithm avoid from trapping in local minima. Some other nature based optimization algorithm such as particle swarm optimization algorithm, imperialist competitive algorithm, artificial bee colony and ant colony optimization algorithm don't have this vital feature. Therefore the mentioned algorithms may trap in local minima.

The extraction feature is the second vital feature in each optimization algorithm. This feature assigns to find the final global answer from the found best area. This feature is satisfied by local search in bee's algorithm. It can be seen that, in the bee's algorithm some soldier bees aim to elite bees to search the best areas. This feature cause to fast convergence speed. Almost all nature based optimization algorithms have this feature. The more details and applications of bee's algorithm can be found in Pham et al. (2006) and Baykasoglu et al. (2009).

The main steps of bee's algorithm are described as follow:

1) Initialize bee's algorithm parameters, such as boundaries, number of elite bees and other parameters.
2) Produce the initial random population.
3) Step 3) Evaluate the fitness function for initial random population.
4) Choose the elite bees.
5) Perform the local search by soldier bees.

6) Perform the global search by remaining bees.
7) Check the stop condition. If the stop condition satisfied, go to next step, otherwise go to step 3.
8) The end.

3. Neural network

The artificial neural networks are effective tool to some task that need to iterative process. There are several types of neural networks such as MLPNN, RBFNN and PNN. In this paper we used MLP neural network for tuning of power system stabilizer parameters. The MLP neural network structure is illustrated in Fig. 2. It can be seen that MLP neural network has one input layer, one or multi hidden layer and one output layer. The connections between these layers are made by weights and biases. The main algorithm for selecting the value of these weights and biases is back propagation algorithm (BP).

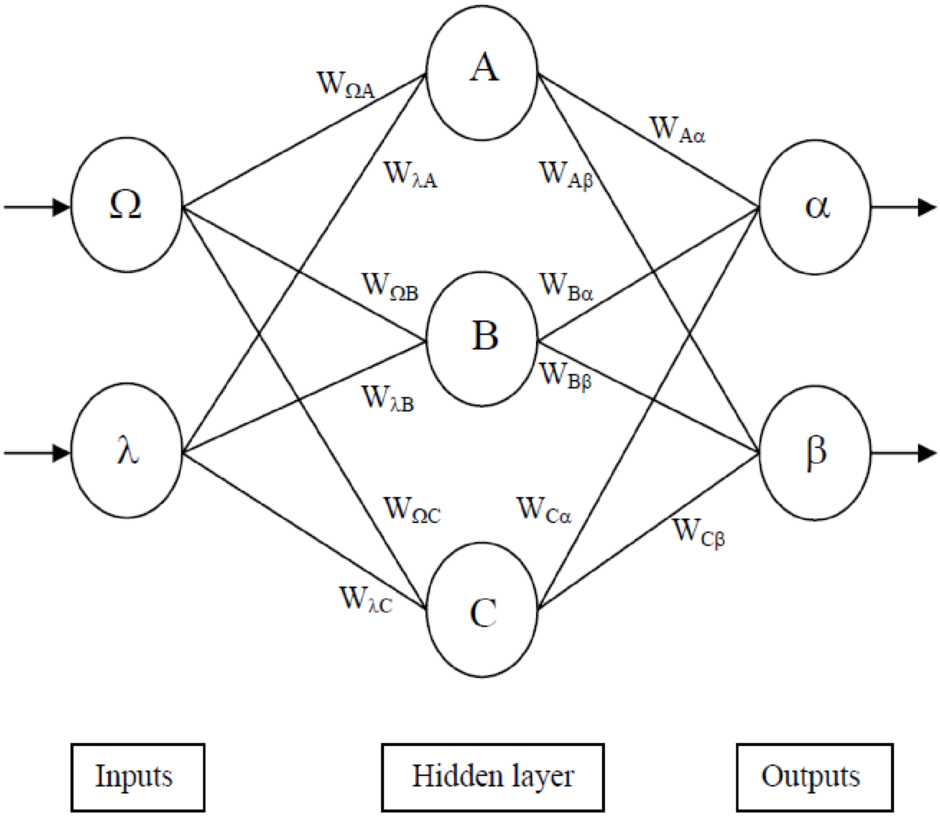

Fig. 2. MLP neural network structure.

In the following lines, the BP is described:

First step) Compute the value of error in output neurons.

$$\delta_\alpha = out_\alpha(1 - out_\alpha)(Target_\alpha - out_\alpha) \quad (1)$$
$$\delta_\beta = out_\beta(1 - out_\beta)(Target_\beta - out_\beta) \quad (2)$$

Second step) Update the value of weights and biases in output layer.

$$W^+{}_{A\alpha} = W_{A\alpha} + \eta\delta_\alpha out_A \quad (3)$$
$$W^+{}_{B\alpha} = W_{B\alpha} + \eta\delta_\alpha out_B \quad (4)$$
$$W^+{}_{C\alpha} = W_{C\alpha} + \eta\delta_\alpha out_C \quad (5)$$
$$W^+{}_{A\beta} = W_{A\beta} + \eta\delta_\beta out_A \quad (6)$$
$$W^+{}_{B\beta} = W_{B\beta} + \eta\delta_\beta out_B \quad (7)$$
$$W^+{}_{C\beta} = W_{C\beta} + \eta\delta_\beta out_C \quad (8)$$

Third step) Compute the value of errors in hidden layers (Back propagation process)

$$\delta_A = out_A(1 - out_A)(\delta_\alpha W_{A\alpha} + \delta_\beta W_{A\beta}) \quad (9)$$
$$\delta_B = out_B(1 - out_B)(\delta_\alpha W_{B\alpha} + \delta_\beta W_{B\beta}) \quad (10)$$
$$\delta_C = out_C(1 - out_C)(\delta_\alpha W_{C\alpha} + \delta_\beta W_{C\beta}) \quad (11)$$

Forth step) Update the value of weights and biases in hidden layer or hidden layers.

$$W^+{}_{A\lambda} = W_{A\lambda} + \eta\delta_A in_\lambda \quad (12)$$
$$W^+{}_{B\lambda} = W_{B\lambda} + \eta\delta_B in_\lambda \quad (13)$$
$$W^+{}_{C\lambda} = W_{C\lambda} + \eta\delta_C in_\lambda \quad (14)$$
$$W^+{}_{\Omega A} = W_{\Omega A} + \eta\delta_A in_\Omega \quad (15)$$
$$W^+{}_{\Omega B} = W_{\Omega B} + \eta\delta_B in_\Omega \quad (16)$$
$$W^+{}_{\Omega C} = W_{\Omega C} + \eta\delta_C in_\Omega \quad (17)$$

In last decades, some improvement in BP algorithm is performed and new versions of it are proposed. In this paper we used from the following versions of BP. More details regarding MLP neural network and training algorithms can be found in Haykin (1994), Kalteh et al. (2013), and Park et al. (1996).

1) Back-propagation with momentum (BP with momentum)
2) Resilient back-propagation (RPROP) algorithm
3) LM algorithm
4) scaled conjugate gradient algorithm (SCG),
5) Conjugate gradient back propagation with Fletcher-Reeves updates (CGBFR)
6) BFGS quasi-Newton back propagation (BFGSQB)
7) One-step secant back propagation (OSS)

4. Proposed method and simulation results

4.1. Structure of proposed power system stabilizer system

The proposed power system stabilizer is one lead- lag controller that its mathematical formulation is presented by Eq. 18. The main structure of the proposed method is shown in Fig. 3.

$$V_p(s) = \frac{sT_w}{1+sT_w} K_p \frac{1+sT_1}{1+sT_2} \frac{1+sT_3}{1+sT_4} \Delta w \quad (18)$$

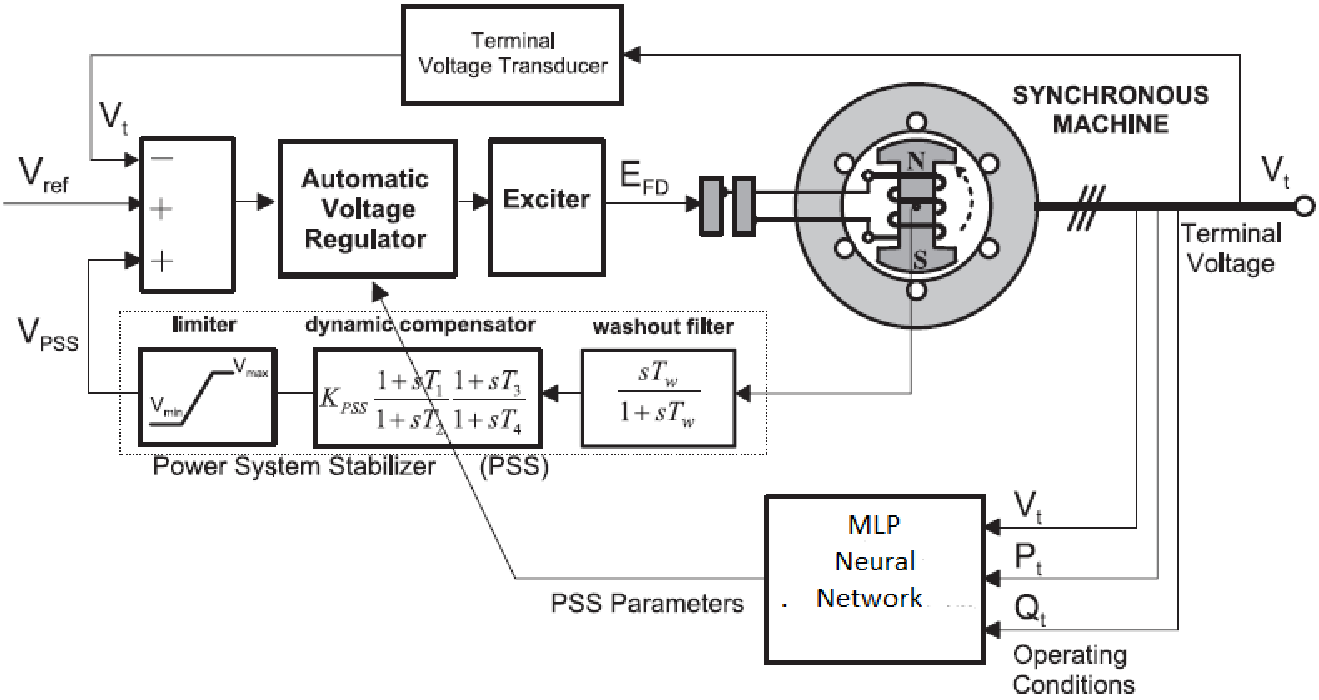

Fig. 3. The main structure of proposed power system stabilizer.

In this system, the MLP neural network tunes the parameters of power system stabilizer. The MLP neural network uses from three important variables that are real power value or P_t, reactive power value Q_t, and V_t, that assign the terminal voltage of generator. These three parameters were MLP neural network inputs. The output of MLP neural network is power system stabilizer parameters. For obtaining the train data, the power system stabilizer is simulated in different load conditions and those parameters are used for training data. Generally, 5000 sample date or input- output vector was generated for MLP neural network training. The high amount of training data led to better training of MLP neural network. The obtained data divided into two groups: the training data and the test data. The test data is used for evaluate the proposed system.

As mentioned in MLP neural network, the number of hidden layer and the number of neurons in hidden layer have high effects on its performance. Therefore in this paper we used bee's algorithm to select the optimal number of these parameters. The schematic of this method is illustrated in Fig. 4. Also in Fig. 5, the sample bee is shown. In this sample bee, the first variable assign to the number of hidden neurons and the remaining variables indicate the number of neurons in hidden layers.

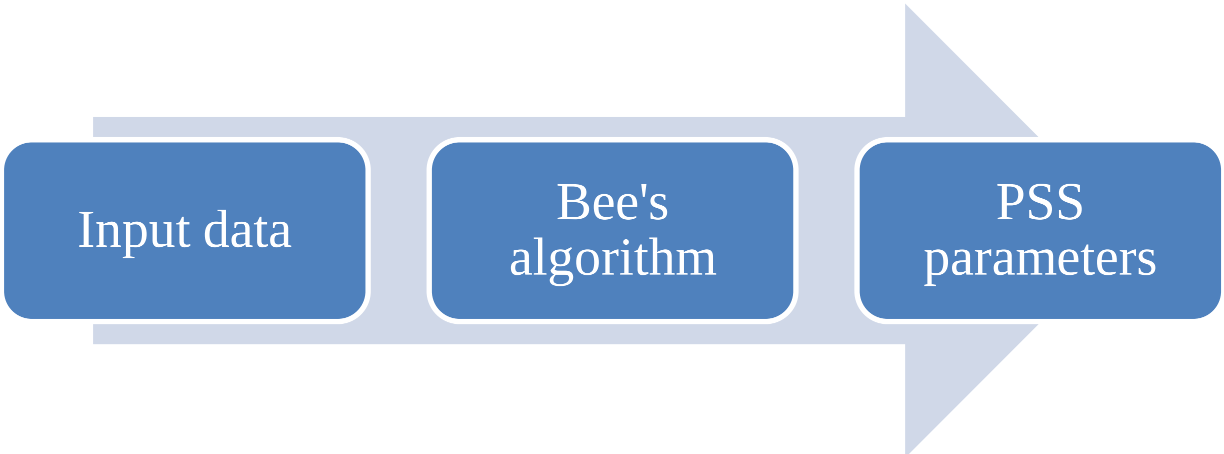

Fig. 4. The schematic of proposed method.

$$Samplebee = [x_1 x_2 x_3 x_4]$$
$$x_1 = Numberofhiddenlayers$$
$$x_2, x_3, x_4 = Numberofneuronsinhiddenlayers$$

Fig. 5. Sample bee.

4.2. Obtained results

In this section, some simulations are performed to evaluate the performance of proposed optimal power system stabilizer. As mentioned, in the proposed MLP neural network based power system stabilizer, the parameters of power system stabilizer are adopted by MLP neural network. Also for enhance the performance of proposed method; bee's algorithm is applied to select the optimal number of hidden layers and hidden neurons.

The test system is simulated in different load conditions in presence of high disturbances. The details of test system can be found in Park et al. (1996). The test system is one synchronous generator that has IEEE standard excitation system. This system is jointed to infinite terminal using two parallel lines which is illustrated in Fig. 6. The parameters of conventional power system stabilizer are tuned for operating point 1 P.U and 0.97 PF lag. The parameters of this system are gained by phase compensation theory and are fixed for all load conditions.

In this section, for evaluating the performance of proposed method, two different abnormal conditions are considered. For demonstrate the performance of proposed method, we used non optimized MLP neural network. As mentioned, in neural networks the training algorithm has high effect on its performance. In this paper we used different training algorithms and based on extensive simulations select the best algorithm. The parameters of bee's algorithm are listed in Table 1. Also the best MLP neural network structure is listed in Table 2.

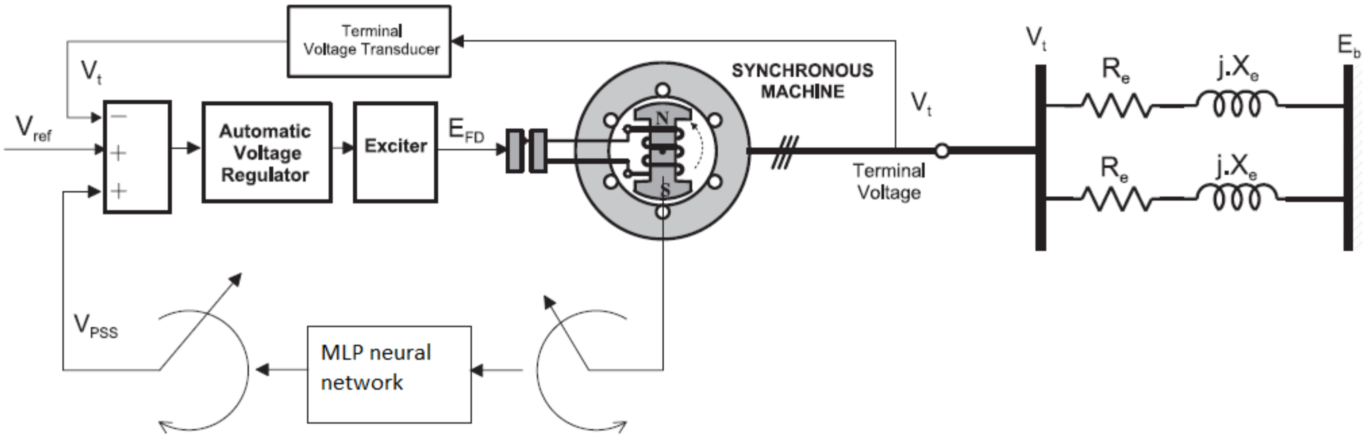

Fig. 6. The structure of test system.

Table 1
Bee's algorithm parameters.

Number of bees	50
Number of elite bees	10
Number of soldiers	5
Number of iterations	1000

Table 2
MLP structure.

Training algorithm	LM
Number of hidden layer	3
Number of neurons in 1st layer	12
Number of neurons in 2nd layer	17
Number of neurons in 3rd layer	22
Transfer function in input layer	Tangent- Sigmoid
Transfer function in hidden layer	Log- Sigmoid
Transfer function in output layer	Linear

In this experiment, the generator work in 1 P.U, 0.97 power factor and occurs 25% variation in input torque value. This decrease in input torque value is occurs in 0.22 second. The speed deviations for three power system stabilizers are shown in Fig. 7. It can be seen that the proposed optimal power system stabilizer has better performance rather than others.

In next experiment, we change the network condition to evaluate the proposed system capability. In this experiment real power is 062 P.U. The obtained results are shown in Fig. 8. It can be seen that the proposed method has good performance. This experiment, show that the proposed method is adaptive and can change the parameters of power system stabilizer in each condition and each abnormal situation.

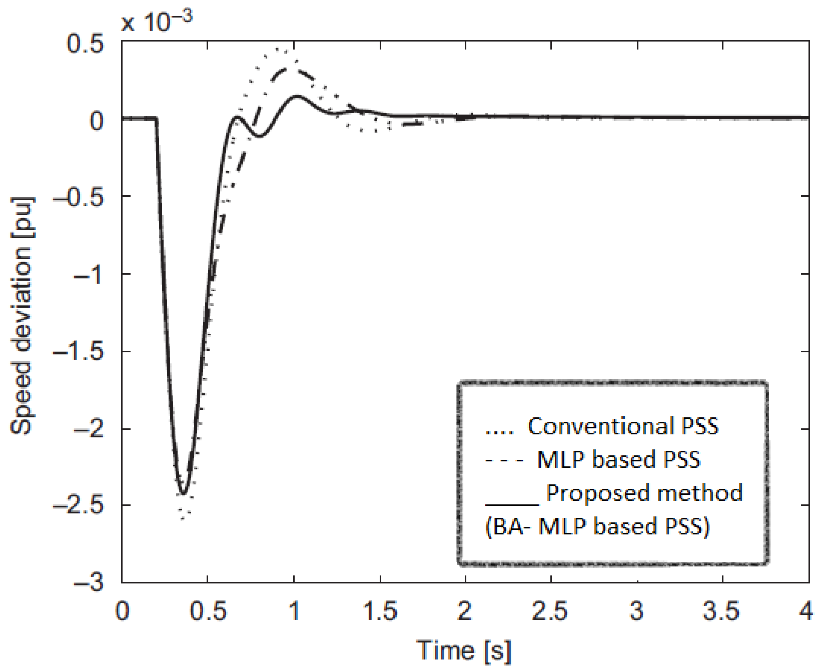

Fig. 7. Obtained result in case 1.

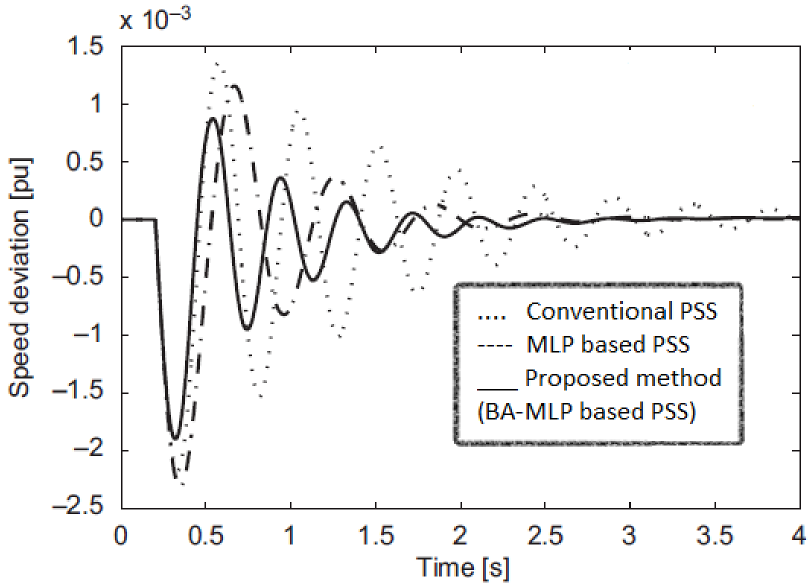

Fig. 8. Obtained result in case 2.

5. Conclusion

In this paper, optimal design of power system stabilizer is investigated. For this purpose we used artificial neural networks as adaptive parameter tuner. The MLP neural network has good features in function approximation and forecasting problems. Therefore in this paper we proposed the usage of this neural network for tune the parameters of power system stabilizer in different load conditions. In MLP neural network, the number of hidden layers and relative neuron numbers have high effect on its performance. For this purpose in optimization part, we used bee's algorithm for finding the optimal number of these parameters. The obtained results show that the suggested method has good performance.

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