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The application of artificial intelligence for power flow problem in power networks

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ABSTRACT

Power flow problem is one of the most important issues in power networks. Artificial neural networks (ANN) are new and efficient tools in many applications. In last decades artificial neural networks have vastly applied in control systems, pattern recognition problems, prediction problems, noise cancellation, function approximation, and many other problems. The artificial neural networks have excellent capabilities in function approximation and solving of nonlinear problems. Therefore, in this study application of artificial neural networks has been proposed for the power flow solution. There are some methods and algorithms for power flow solution, such as the Newton method. But these methods and algorithms are very sensitive to initial solutions of the problem. Therefore the algorithm simply traps to local minima. For evaluating the proposed intelligent method, the one real world power system is applied. The mentioned power system has ten generators and thirty nine terminals. The obtained results show that the proposed hybrid system has good performance and capability in solving of a power flow problem.

1. Introduction

With increasing the demand of electrical energy, the power networks become bigger and more complicated. The electrical energy is the best type of energy that has no pollution. In new and modern electrical power networks, the number of generators, transformers, breakers, loads, compensators, FACTS devices and other power devices are very plenty. In this large and complicated system, the calculating of lines current and node voltages are very difficult problem. The other studies about power system are based on power flow problem. After power flow solution, the current of transmission lines, the amplitude of terminal voltages, the angle of terminal voltages and power transmission is achieved. By computing the power flow for one case study system, the normal and steady state situation are achieved (Ghasemi et al., 2015; Rao and Kumar, 2015; Abdelouadoud et al., 2015; Kamel et al., 2015; Pinheiro et al., 2015).

The classical and traditional power flow methods, such as Newton method, are based on initial solution and the repetitive process to achieve the satisfying solution. With development of computers in last decades, the application of these tools is vastly used in many areas. The computers have high calculation speed and excellent sensitivity to detailed problems. Therefore many time consuming algorithms become applicable for usage in many areas by aid of new computers. One of the most effective and efficient concepts in artificial intelligence is artificial neural networks or neural networks. This concept is inspired from human neural system. Like human neural system, artificial neural networks try to train the one special issue. The artificial neural networks have many application s in much area such as control systems, pattern recognition problems, prediction problems, noise cancellation, function approximation and many other problems. The artificial neural networks have excellent capabilities in function approximation and solving of nonlinear problems (Wen et al., 2015; Bao and Cao, 2015; Zhang et al., 2015a; 2015b; Vuković and Miljković, 2015; Qin et al., 2015a; 2015b; Woodward et al., 2015; Jiang et al., 2015; Goles and Ruz, 2015; Lin et al., 2015; Kao et al., 2015; Sun et al., 2015; Kokkinos and Margaritis, 2015; Zhao et al., 2015). The artificial neural networks have simple structure and training algorithm. The artificial neural networks have some types such as radial basis function neural networks (RBFNN), multi-layer neural networks (MLPNN), probabilistic neural networks (PNN), concurrent neural networks, recursive neural networks, adaptive neural networks and Elman neural networks. Each of these types of artificial neural networks has its special features and capabilities. For example MLPNN has good features in pattern recognition and classification problems. The Elman neural networks have high capability in dynamic problems. The PNN has good features in forecasting problems. In the proposed method, MLPNN is applied for power flow solution.

In last decades, the artificial neural networks vastly applied for power network problems. For example, the artificial neural networks have been applied successfully in power network security improvement. Also artificial neural networks are applied in FACTS device control problems. For example, artificial neural networks can be used as controller to control the fire angle of SVC, STATCOM, UPFC and other power electronic devices (Modi et al., 2007; Alizadeh and Tofighi, 2013; Fairbank et al., 2014; Hassan et al., 2013; Nagalakshmi and Kamaraj, 2013; Al-Masri et al., 2015; Sharifian and Sharifian, 2015; Gomes and Medeiros, 2015; He et al., 2014; Chitsaz et al., 2015; Yap et al., 2014; Khamis et al., 2015; Karami and Esmaili, 2013; Xiong et al., 2013; Yeh et al., 2014). Also artificial neural networks can be applied as classifier for power network fault detection. The artificial neural networks have been successfully applied for induction motor fault detection. In Aloui et al. (2013) is applied for underground cables fault detection.

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The concept of power flow solution is very hard on difficult problem. This problem is very time consuming and has high computing load. For this purpose the applied artificial neural networks must have simplest and optimized structure to have good calculation time. In MLPNN the number of hidden layers and hidden neurons changes its performance. This parameters determine the neural networks architect. In order to have best performance, the value of these parameters are selected by trial and error. Based on vast simulations and experiments, the best network is selected as final neural network or power flow solution tool. The needed concepts are described in next sections.

2. Multi-layer perceptron neural network

The MLP neural network is one of the most effective and fast artificial neural networks. This type of artificial neural network has three main layers. The first layer is input layer. The second layer is hidden layer and the third layer is output layer. There are connections between the layer by weights and biases. The main structure of MLP neural network is shown in Fig. 1.

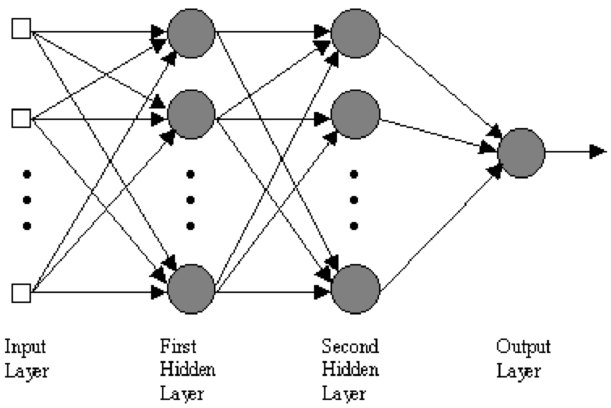

Fig. 1. The main structure of MLPNN.

As mentioned, the first layer is input layer. In this layer the input data is fed to MLP neural network. The unprocessed data have its predetermined dimension such as n. The input data transfer to second layer or hidden layer. The input data is fed to first layer neurons. In the neurons, the transfer function is applied to each input data variable. The output of transfer function in each neuron is transferred to hidden layers. This action is done by weights and biases.

The number of hidden layers and hidden neurons must be selected by user. These parameters have high effect on MLP neural network performance. The final layer is output layer.

3. Proposed method

The proposed method to solve the power flow in power network is presented in this section. The proposed intelligent method is applied in real world standard system. The test system contains ten generator node and thirty nine terminals. The mentioned power network is located in England. The details about the power network can be found in Pai (2012). The proposed method can be used for any power network system in each country. The main scheme of test system is shown in Fig. 2.

The MLP neural network has excellent features in function approximations. In the proposed intelligent method, the target of neural network is to approximate the power network operation. In the proposed method, we used the power networks operating situations as input of neural network. The output of the neural network is the power flow results. In each approximation problem, the input variables must be selected cleverly. For this purpose, the extracting the satisfying collection of input parameters is performed. This process is done as follow.

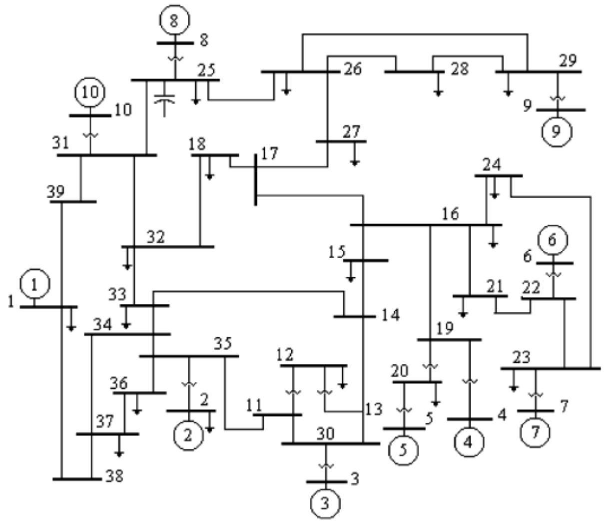

Fig. 2. The main scheme of test system.

In each power network system, one node usually selected as slack terminal. In the studied case, the first node or terminal 1 is selected as slack terminal. In computing process, the amplitude of voltage for this terminal is fixed in 1. Also the angle of voltage for this terminal is clear parameter. Also the other terminals that are generator or machine nodes, the value of active and reactive power is known parameter. These nodes are known as PV buses. Other remaining nodes are known as PQ terminals. It can be seen that in terminal 25, one compensating capacitor is installed. This terminal is considered as PV bus. For simplicity, some conditions are considered. These conditions are as follow:

a) The amplitude of voltage in PV terminals is called $V_n \quad and\ n = 2, 3, \dots, 10$
b) The real power in generator terminals is called $PG_n \quad and\ n = 2, 3, \dots, 10$
c) The magnitude of real power in load terminals is called $PD_n \quad and\ n = 2, 3, \dots, 39$
d) The magnitude of reactive power in load terminals is called $QD_n \quad and\ n = 2, 3, \dots, 39$
e) The magnitude of reactive power in compensating terminal (terminal 25) is called Q_c .

With considering all the above mentioned parameters, we have fifty nine power network operating situation. The target of the proposed method in this paper is to approximate the relation function between the inputs and outputs by radial basis function neural networks. In the proposed method, the output will be achieved by one RBFNN. The main scheme of the proposed method is illustrated in Fig. 3.

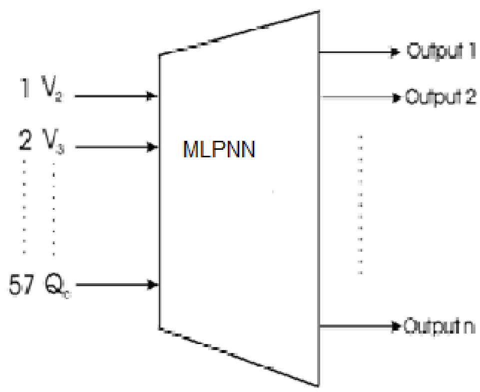

Fig. 3. The main scheme of the proposed method.

From Fig. 3, it can be seen that the inputs variables are: $V_2, V_3, \dots, Q_c$. It can be seen that we have fifty seven input variables. The inputs are voltage of nodes, the active and reactive of PV terminals and reactive power of compensator. The outputs are real and reactive power magnitudes in generator terminals, the real and reactive power value in slack node and the voltage amplitude in load terminals. With summing these parameters, it can be seen that we have seventy eight output parameters. The main step in neural network application in each problem is the training phase. For training we need to training data. The training data is achieved with simulating the test system. The test system is shown in Fig. 2. After training phase, the radial basis function neural network is ready to use in real world system. The training phase may take some computing time, but after training, the operating of trained network is very fast. The input parameters for each condition can be achieved from control room. The main steps for achieving the input parameters are as follow:

Step 1) the boundaries for produced reactive power is fixed to [-0.2, 0.7].
Step 2) all simulation and calculations are based on following assumptions:

1. The value of voltage in nine generator terminals is varying independently.
2. The value of real power in nine generator terminals is varying independently.
3. The real and reactive power magnitude in all load terminals is varying independently.
4. The compensator bus, generate reactive power, independently.
5. The boundaries for voltage changes in PV terminals are [0.9, 1.1].
6. The boundaries for other operating situations can be changed in [0.6, 1.1].

Step 3) for each of variables that mentioned in previous step, an accidently value is assigned.
Step 4) the produced data from above procedure, the RBFNN can be trained. In each step, the all terms and conditions must be checked carefully.

4. Simulation results

In this section, the performance of proposed method is evaluated. As mentioned before, for this purpose we used real world standard power network system. This power network is placed in England and has ten generator terminals and thirty nine load nodes. The test system is simulated in four hundred different situations. This data set is used for training and testing the proposed method. The 75% of this data set is used for training the neural network and the 25% is used for testing the proposed method. For simplicity, the collected data set is normalized between [0, 1].

In MLP neural network, the number of hidden layers and number of hidden neurons have high effects on the network accuracy. Therefore these parameters are selected based on vast experiments and simulations. The mean square error (MSE) criterion is chosen as fitness function. Equation 1 shows the MSE mathematical formulation:

$$MSE = \sum_{i=1}^{n} (RBFNN_{output} - TARET)^2 \tag{1}$$

The obtained results are shown in Tables 1-3. In this experiment, effect of number of hidden layers and number of hidden neurons are investigated. It can be seen that the number of hidden layers has high effect on MLPNN performance. Therefore this parameter must be selected carefully. In Fig. 4 the effect of hidden neurons is illustrated. The best hidden neurons is 18. It is clear that there is no linear relation between MSE and hidden neurons.

Table 1
The obtained result or proposed method with different hidden neuron numbers.

Run	Number of hidden neurons	MSE
1	5	0.0043
2	6	0.0041
3	7	0.0039
4	8	0.0038
5	9	0.0037
6	10	0.0034
7	11	0.0030
8	12	0.00291
9	13	0.0029
10	14	0.00289
11	15	0.0027
12	16	0.0022
13	17	0.0021
14	18	0.00201
15	19	0.0019
16	20	0.0023
17	21	0.00231
18	22	0.0024
19	23	0.0025
20	24	0.0026
21	25	0.0027
22	26	0.00271
23	27	0.00276
24	28	0.0025
25	29	0.00243
26	30	0.0028
27	31	0.0029
28	32	0.0032
29	33	0.0033
30	34	0.0035

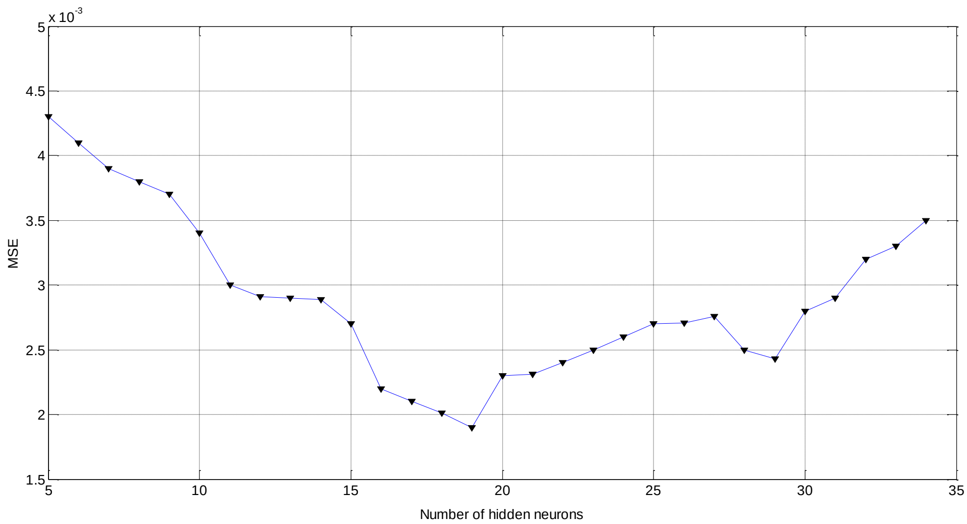

Fig. 4. The effect of hidden neurons numbers on MSE.

Table 2
The obtained result or proposed method with different hidden neuron numbers.

Run	Number of hidden neurons		MSE
	First layer	Second layer	
1	22	7	0.0040
2	11	23	0.0041
3	16	21	0.0036
4	32	11	0.0038
5	12	16	0.0037
6	17	18	0.0034
7	9	9	0.0031
8	11	10	0.00291
9	10	19	0.0023

Table 3
The obtained result or proposed method with different hidden neuron numbers.

Run	Number of hidden neurons			MSE
	First layer	Second layer	Third layer	
1	22	7	5	0.0027
2	11	23	11	0.00271
3	16	21	16	0.00276
4	32	11	14	0.0025
5	12	16	18	0.00243
6	17	18	19	0.0028
7	9	9	19	0.0029
8	11	10	22	0.0032
9	10	19	15	0.0033

5. Conclusion

In this paper, the application of MLP neural networks for solving the power flow in power networks is investigated. The MLPNN has good features in function approximations. In this type of neural networks, the number of hidden layers and hidden neurons have high effect on its performance. Therefore in this study, these parameter selected carefully. The main step in application of neural network or each machine learning concept is the obtaining the training data. In the proposed method we used a proper collection of control variables that can be gained from control room. The proposed method is tested on real world standard power network system. The simulation results show that the proposed method has good performance in approximating the power flow.

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