The Calculation of Electric Power Flow Using Neural Network Systems

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The neural network system employed in this study has 3-layers structure which is composed of an input, a hidden, and an output layers. As a simulation example the calculation of electric power flow was considered. The results in this study show an idea how to construct the neural network system for fast calculation or simulation of the electric power equations.

Key words: Load flow calculation, Artificial neural network system, Direct current method

1. Introduction

The artificial neural network system^{(1)~(5)} is a mathematical model which simulates neural networks in human brain. The brain has many superior features such as parallel processing of information, learning function, self-organizing ability, etc. Therefore, it is expected that the neural network system obtained by modeling the brain has similar superior features as it has and could easily solve the problems which are difficult to be calculated by Neuman-type computers.

The neural network system, which is a nonlinear learning system, has an advantage that it is able to calculate the load flow states under both stable and unstable conditions due to heavy loads or sudden disturbances.

In this study the neural network system with the superior parallel processing property in addition to the above property is used for the load flow calculation. The neural network system is learned by the calculated values of load flow at each node and thereafter can calculate various load flow states in the power system. The analysis of the simulation study is given.

2. Application of neural network system for load flow calculation

2.1 Learning algorithms⁽¹⁾

In this study, we construct multi-input and

multi-output units in a layer and assume that the connections in each layer and the connections from the output layer to the input layer do not exist in the neural network system. This neural network system is learned by the following three learning algorithms.

(i) Sequential modified method (back propagation method)

This method modifies the synapsis weights and offsets at each acceptance of learning patterns where the sigmoid function given by

$$f(x) = 1 / \{1 + \exp(-2x/u_0)\} \quad \dots\dots\dots (1)$$

is used as the response of unit.

(ii) Moment method

This method modifies the synapsis weights and offsets by considering the contribution from the errors in the output layer. The current modification $\Delta W(t)$ is calculated from the sum of both the former modification $\Delta W(t-1)$ and the modification from the error d such that

$$\Delta W(t) = d + m\Delta W(t-1) \quad \dots\dots\dots (2)$$

where d is $\partial E / \partial W$ [refer to Ref. (1)], E is the errors between the outputs of the neural network system and the teaching signals, and m is moment coefficient. In the simulation $m=0.9$ and $\Delta W(0)$ =random value were used.

(iii) Modified moment method

This method modifies the synapsis weights and offsets in various directions and after the learning process

proceeds modifies them in the direction which is near to the former modification. The algorithm is given by

$$\Delta W(t)=d+m(t)\Delta W(t-1) \cdots \cdots (3)$$

$$m(t)=m(t-1)+\Delta m \cdots \cdots (4)$$

where $m(0)=0.6$ and $\Delta m=0.02$ were used.

2.2 Power system to be learned

In information processing the learning function of the neural network system does not require the strict mathematical model of the object to be processed and but requires only appropriate data which are available.

In this study the active power P_i and phase angle δ_i of node i calculated from the direct current method, which is an approximate load flow calculation method, are used as the data for the object to be learned. Namely, the active powers and phase angles are used as the inputs and teaching signals for the neural network system, respectively. In the neural network system only the value ranged from 0 to 1 can be learned and therefore the power unit is employed in order to express the various values in the power system.

The power system in problem 6.4 on page 186 in Ref. (6) is employed as the model of power system used for learning which is shown in Fig. 1. The values of reactance for each line are the same as in problem 6.4. For this system model we consider the convergence conditions when both the parameter u_0 in the sigmoid function and number of the units in the hidden layer are

Fig. 1. Model of electric power system with 4 nodes.

Fig. 2. Three layers neural network system.

changed in the 3-layers neural network system shown in Fig. 2.

3. Simulation study

In the simulation study on the learning of the neural network system the number of the units in the hidden layer is changed as 10, 20 and 30 and also the parameter of the sigmoid function u_0 is changed as 0.75, 2.0, 3.0, and 4.0. The number of the data used for the learning is 30 pairs which is generated randomly from the $P-\delta$ system in the problem 6.4 in Ref. (6). As the criterion of the convergence the sum of the mean square error (denoted MSE) between the teaching signals and the phase angles of the output layer is used. If the sum is less than $1.5E-5$, the learning is regarded as completed.

In Table 1 the average numbers of learning for three learning methods stated in Section 2.1 are illustrated. In Figs 3~5 the convergence properties of the modified moment method are illustrated when both the parameter u_0 and the number of units in the hidden layer are changed as 10, 20, and 30.

In Table 1 notation (—) means that the number of the learning exceeded 3,000 in one of the neural network systems with three types of units (10, 20, 30) in the hidden layer.

From this table it is seen that the modified moment method is the most effective method compared with the other two methods. Moreover, although the modified moment method with $u_0=3.0$ seems to be best among

Table 1. Average numbers of learning for three learning methods.

u_0	(i)	(ii)	(iii)
0.75	—	—	—
2.0	1,854.3	993.7	845.3
3.0	—	2,289.3	741.7
4.0	—	—	846.3

Fig. 3. Convergence process of modified moment learning method with $u_0=2.0$.

Fig. 4. Convergence process of modified moment learning method with $u_0=3.0$.

Fig. 5. Convergence process of modified moment learning method with $u_0=4$.

the others the convergence process of the method for the neural network system with 30 units in the hidden layer is oscillatory as seen from Fig. 4 and hence the number of the learning is large. Also as seen from Fig. 3 the convergence process for the neural network system with 10 units in the hidden layer is oscillatory. Consequently, it is concluded that the best learning method for the load flow calculation of the power system model is the modified moment method with $u_0=4.0$.

4. Conclusions

In this simulation study we used the 3-layers neural network system for the the load flow calculation in the power system model with 4 nodes. We discussed the effects of both the 3 different learning algorithms and the parameter u_0 of the sigmoid function on the convergence processes. It was seen from the simulation that there exists an appropriate learning method and a parameter of the sigmoid function for the load flow calculation.

The future studies are on the learning of the neural network system to calculate the load flows for the power system with the large number of nodes and on the development of the neural network system for the load flow calculation in large scale power systems. After those studies have been completed the neural network

system for the load flow calculation which is learned using the measured values from a real power system could be in practical use. In order to achieve the practical use of the neural network system for the load flow calculation further studies are necessary to overcome the difficulties stated above such as selection of the number of units in the hidden layer, the number of the nodes in the power systems to be handled, and the determination of appropriate parameters. Also in order to achieve the fast calculation of the power flows under the disturbances the application of neurocomputers or neuro hardware is inevitably necessary and this study is now in our investigations.

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