A Neural Network-Based Model for Load Flow Solution

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ABSTRACT

Load flow study is the most frequently carried out study by power utilities and is required to be performed at almost all stages of power system planning, optimization, operation and control. Sometimes utilities are unable to perform certain functions, involving various load flow solutions in real time mode due to unavailability of fast and reliable load flow methods.

Recently, Artificial Neural Networks (ANN) are gaining popularity in many power system applications due to their high computational rates, ability to handle nonlinear functions and a great degree of robustness. This paper presents an Artificial Neural Network model for a fast load flow solution. A feedforward model of the neural network based on the stochastic backpropagation algorithm has been applied to the load flow problem and it has been tested for two sample ac systems. The first system is a 9-bus standard test power system proposed by Western Systems Coordinating Council (WSCC) in Canada while the second system is the IEEE-14 bus, 20 lines power system. The neural network model computes the value of the complex voltages at all the buses except at the slack bus as output for given real and reactive power demands at the load buses as input. The results demonstrated that the proposed model provides sufficiently accurate and fast results.

الملخص

إن دراسات سريان القدرة هامة فى عمليات التخطيط و التحكم و الأمثلة و تشغيل نظم القوى الكهربية، وهى الدراسات الأكثر استخداما والتى تحتاجها مؤسسات القوى الكهربية فى كل مراحل التشغيل. وفى

بعض الأحيان تكون هذه المؤسسات غير قادرة على حل سريان القدرة خلال الوقت الحقيقى للتشغيل نتيجة بطء طرق حل سريان القدرة التقليدية .

و حديثا بدأ استخدام الشبكات العصبية الاصطناعية فى كثير من تطبيقات نظم القوى الكهربية نتيجة لسرعتها الحسابية و مقدرتها على حل العلاقات غير الخطية . ويقدم هذا البحث نموذجا لحل سريان القدرة باستخدام الشبكات العصبية الاصطناعية و قد تم تطبيق هذا النموذج الذي يستخدم خوار زم الانتشار العكسى العشوائى علي مثالين لشبكات القوى الكهربية . وقد أظهرت النتائج سرعة و دقة هذا النموذج فى حل سريان القدرة مما يكسبه ميزة إمكانية استخدامه فى الوقت الحقيقى للتشغيل .

1. Introduction

Load flow or power flow studies are conducted to determine the static operating state of a power system in terms of its voltage profile, line flows and losses. It is the most frequently carried out study by power utilities and is required to be performed at almost all stages of power system planning, optimization, operation and control. The power flow study essentially involves the solution of a set of nonlinear algebraic equations for a given loading in the network. During the past four decades, probably almost all the relevant known methods of numerical analysis for solving a set of nonlinear algebraic equations have been applied in developing load flow algorithms. In addition, many methods based on some special features of the load flow equations have also been suggested. A detailed account of the various methods developed till 1974 is given by Stott [1]. The most recurrent question in the load flow field is how to choose the best method for a given application. The main desirable features to compare the different load flow methods are the speed of solution and the robustness or reliability of convergence. None of the available methods satisfy all the criteria of goodness. Fortunately, not all but only a particular combination of the various features is what will be needed in a given situation. For example, the memory requirement may be important only to small computer having low storage space. However, with the advent of modern digital computer, memory requirement is no more a limiting factor. Robustness or reliability of convergence of the method is required in all types of applications. However, speed of solution is more important for on line applications as compared to the off-line studies. A high degree of solution accuracy is desirable in most of the applications. However, for few applications e.g. the contingency selection studies, approximate but fast load flow methods are used.

Some of the popular conventional methods with utilities to solve the load flow problem for ac networks include Gauss-Seidel method [2], Newton-Raphson method [3] and fast decoupled load flow (FDLF) method [4-7]. These methods are iterative in nature and provide the full ac load flow solutions. Amongst them the Gauss-Seidel load flow (GSLF) method offers poor convergence in solving large and ill conditioned systems. Newton-Raphson load flow (NRLF) method and the FDLF techniques are frequently used as the general purpose load flow methods [8]. Recently, rule based artificial intelligence techniques have also been applied to the power flow problems [9]. This technique hampered in its performance by drawing out rules and making inferences from a very large data base. Moreover, it requires complete apriori knowledge about the power system to develop the knowledge base and form the inference rules.

With increased size of power system networks, utilities face a major challenge in performing certain functions involving multiple load flows in real time mode contingency analysis and selection, security e.g. constrained optimal power dispatch etc. For contingency selection, fast non iterative approximate load flow methods such as dc load flow method, linearized ac load flow method, one iteration of Newton-Raphson load flow or decoupled Newton load flow or fast decoupled load flow methods are used. These methods offer results having inaccuracies ranging between 10-20%. However, these methods as well as full ac methods offer convergence difficulties in certain system conditions. Full ac methods are accurate but become unacceptable for such real time applications. Hence, the motivation behind the present work is to develop a fast, accurate and robust load flow model using the Artificial Neural Network concepts, which can be used in real time and to the power system problems involving several load flow runs. ANN have already been applied to some power system problems such as security assessment [10], real time control of capacitors [11], protection [12] and load forecasting [13]. From the literature survey, it appears that probably few researchers applied the neural networks to the load flow problem [14].

The features of the neural networks which make them so appealing and are felt to be advantageous in solving power flow problems are as follows:

- Neural Networks are made with interconnections between the elementary processing units (neurons), information processing may be carried out in a parallel, distributed manner. This makes real time processing of large volumes of data more readily reliable.
- Neural Networks are extremely useful in solving the problems which are inherently nonlinear as in the case of load flow problem.
- The method is non algorithmic and requires no apriori knowledge of the functions that relate the problem variables (P , Q , V , δ in case of load flow). Also being non algorithmic, they do not make any approximations as in the case with most of the mathematical models.
- Neural Networks are capable of handling situations of incomplete information, corrupted data and large data volume and are fault tolerant.

This paper presents an Artificial Neural Network model for load flow solution. The model has been applied on two example ac systems. Compared with the conventional load flow approaches, the results obtained from the model presented in this paper are quite accurate. The advantage of the approach is that it is straightforward and simple for real-time application.

2. Artificial Neural Networks

Neural networks are a relatively new information processing technique. They can be defined as " a computing system made up of a number of simple, highly interconnected processing elements, which processes information by its dynamic state response". A neural network consists of a number of very simple and highly interconnected processors called neurons which are the analogs of the neurons in the brain. The neurons are connected by a large number of weighted links, over which signals can pass. In the present application, three layers neural networks algorithms (having an input layer, a middle layer and an output layer) have been used, together with a sigmoidal activation function and supervised training via a backpropagation technique. The well known enhancement of introducing a momentum term in the weight updating formula has also been successfully applied to reduce training times and to help in avoiding premature convergence (i.e. to a local optima). Further details of ANN methods, and the various enhancements which have been used here, can be found in the extensive literature on the subject, e.g. in references [15-17].

3. Application of ANN Approach to the Load Flow Problem

In this section, the method and the procedures for application of ANN approach to the load flow problem are described. Two example systems have been chosen to apply the technique. The first system is a nine bus, three generators standard test power system proposed by Western System Coordinating Council (WSCC) in Canada. A one line diagram for the system is shown in Fig. (1), and the system characteristics are given in [18]. The second system is the IEEE 14-bus system and its data was taken from Ref. [4]. A one line diagram for the IEEE 14-bus system is shown in Fig. (2).

3.1 Generation of Training Set Samples

This is an important off-line task for the ANN approach. The quality of the training set determines the reliability of the ANN for unseen cases.

For the WSCC system, it is assumed that the loads are randomly distributed and they have a normal distribution shape with the following means:

$$[P_A , P_B , P_C] = [1.25 , 0.9 , 1.0] \text{ p.u.}$$

For load flow analysis, Bus 1 is taken as the slack (swing) bus with voltage magnitude of 1.0 p.u., and buses 2 and 3 are voltage controlled (P-V) buses with voltage magnitude of 1.025 p.u and the remaining buses are load (P-Q) buses. For each load sample, the loading of the generators is determined by economical dispatch of the total load among generators, followed by a load flow analysis using Gauss-Seidel load flow method.

Generation of samples is performed by changing loading conditions of the system. A group of 27 samples is generated at three different load levels (1.5 , 1.0 , 0.5) p.u. for each of the three loads of the power network under study.

For the IEEE-14 bus system in [4], bus-1 is taken as the slack bus having prespecified voltage as $1.06 \angle 0$ p.u, buses 2,3,4 and 8 are voltage controlled buses and buses 5,6,7, 9-14 as load buses. Newton-Raphson load flow program is used to generate 15 sets of training patterns with real and reactive power load values picked up at random ranging between 0 to 1.0 p.u. and -0.05 to 0.25 p.u. respectively.

3.2 The Construction of the Neural Networks Used

The neural network model used for the load flow solution presented in this paper computes the value of complex voltages at all the buses except at the slack bus as output for given real and reactive power demands at the load buses as input.

The first ANN model for the WSCC system has 6 input neurons and 16 output neurons. The number of neurons in the hidden layer is varied from 5 to 50 and it is found that 10 neurons in the hidden layer give the best solution according to this construction.

The second ANN model for the IEEE-14 bus system has 18 input neurons and 26 output neurons. The number of neurons in the hidden layer is varied from 10 to 100 and it is found that 32 neurons in the hidden layer give the best solution according to this construction.

The two neural networks are trained for an average error of 0.001 and 10000 iterations using the Neural Desk Package with a stochastic back propagation algorithm. The learning rate (β) and the momentum constant (α) are taken as 0.1 and 0.9 respectively.

Fig. (3) presents a schematic diagram of the construction of the adopted neural networks used for the load flow problem.

3.3 Testing the Proposed Approach

The last step in the approach is the generalization process by which a complete verification of the capabilities of the approach in solving the load flow problems is performed. The generalization ability is best estimated using the absolute error between the actual values obtained from the conventional load flow programs and the values calculated from the neural networks models. The accuracy of neural network models for solving load flow problems is tested for the cases (which are not used for training).

This can serve as an index of satisfactory performance of the models in unknown situations. This step is conducted by testing the approach using an adequate test sets. The samples of the test set should cover a wide spectrum of operating conditions. The generation of samples for the test sets was performed in a similar way to the training set. 64 samples are generated as a test set for the WSCC system and 40 samples are generated as a test set for the IEEE 14-bus system.

Reliability testing of the neural network models is done by comparing the models results against that obtained from the load flow programs. This is illustrated in Tables (1) and (2) for the sake of comparison.

Table (1) Comparison of Load Flow Results of WSCC System

Voltage magnitude (p.u) and angle (rad.)	Gauss- Seidel method	Neural network model	Absolute error
V_2	1.025	1.02496	0.00004
V_3	1.025	1.02503	0.00003
V_4	0.940	0.94123	0.00123
V_5	0.876	0.87736	0.00136
V_6	0.899	0.89901	0.00001
V_7	0.968	0.96641	0.00159
V_8	0.939	0.93904	0.00004
V_9	0.983	0.98203	0.00097
δ_2	0.242	0.2409	0.0011
δ_3	0.101	0.1014	0.0004
δ_4	-0.082	-0.0834	0.0014
δ_5	-0.153	-0.1532	0.0002
δ_6	-0.137	-0.1368	0.0002
δ_7	0.081	0.0808	0.0002
δ_8	-0.013	-0.0136	0.0006
δ_9	0.025	0.0241	0.0009

Table (2) Comparison of Load Flow Results of IEEE-14 Bus System

Voltage magnitude (p.u) and angle (rad.)	Newton -Raphson method	Neural network model	Absolute error
V_2	1.0450	1.0432	0.0018
V_3	1.0380	1.0367	0.0013
V_4	1.0100	1.0100	0.0000

V_5	1.0644	1.0633	0.0011
V_6	1.0247	1.0238	0.0009
V_7	1.0041	1.0030	0.0011
V_8	1.0252	1.0236	0.0016
V_9	1.0186	1.0176	0.0010
V_{10}	1.0020	1.0011	0.0009
V_{11}	1.0159	1.0146	0.0013
V_{12}	1.0214	1.0196	0.0018
V_{13}	1.0147	1.0132	0.0015
V_{14}	0.9898	0.9879	0.0019
δ_2	-0.0790	-0.0776	0.0014
δ_3	-0.2102	-0.2106	0.0004
δ_4	-0.2091	-0.2104	0.0013
δ_5	-0.2110	-0.2114	0.0003
δ_6	-0.2110	-0.2121	0.0011
δ_7	-0.2367	-0.2373	0.0006
δ_8	-0.1371	-0.1367	0.0004
δ_9	-0.1618	-0.1593	0.0025
δ_{10}	-0.2373	-0.2379	0.0006
δ_{11}	-0.2261	-0.2275	0.0014
δ_{12}	-0.2273	-0.2284	0.0011
δ_{13}	-0.2294	-0.2314	0.0020
δ_{14}	-0.2526	-0.2543	0.0017

The maximum and minimum absolute errors of voltage magnitude are found to be 0.00159 p.u and 0.00003 p.u and those in angles are 0.0014 rad. and 0.0002 rad. respectively for the WSCC system. Corresponding values for the IEEE-14 bus system are 0.0019 p.u and 0.0 p.u for the voltage magnitude and 0.0025 rad. and 0.0004 rad. respectively for the voltage angles. In fact, the errors at all the buses are less than 1% in voltage magnitude for both the two systems and voltage angles for the WSCC system. The error in voltage angles in the IEEE-14 bus system are also less than 1% at most of the buses except at few where it is slightly more than 1%.

In a comparison with the load flow model of the IEEE-14 bus system in [14], a simple construction is presented here using less number of inputs rather than the model in [14] which used the complex voltage of the slack bus as input to the neural network beside the values of the real and reactive power demands at the load buses. There is no meaning for that as the complex voltage of the slack bus is almost a constant value. Also, the model presented in this paper contains only 32 neurons in the hidden layer instead of a complex one containing 125 neurons in the hidden layer and auxiliary nodes in [14]. Consequently, the total number of weights is reduced by 74.4 % which results in simpler construction and faster convergence time of solution. However, better results are obtained in this work. Also, the stochastic backpropagation algorithm which has been used in this work enhanced the performance of the solution and consequently promising in the load flow solution of more complicated networks.

Thus the neural network models are found to provide results quite close to the full load flow methods. The errors can be further reduced by selecting more training sets and trying more number of iterations to stabilize the weights.

4. Conclusions

- A new artificial neural network model for load flow analysis has been developed. The model provides a fast and accurate solution.
- The model is quite robust. The load flow convergence difficulties, faced with conventional methods, do not arise in neural network models. This is because the question of convergence arises in the training phase only which has to be carried out in off-line mode. Once the training is over, the only parameters that are of any consequence are the weights which have been fixed during the training phase. So, there is no need for solving a set of nonlinear algebraic equations and forming the bus admittance matrix Y_{bus} to solve the load flow problem.
- The model will prove to be quite useful for real time applications to the power system problems especially involving large number of load flows.

5. References

[1] Stott, B. , "Review of Load Flow Calculation Methods", Proceeding of IEEE, Vol. 62, pp. 916-929, July (1974).

[2] Ward, J.B. and Hale, H. W., "Digital Computer Solution of Load Flow Problems", AIEE Trans., Vol. PAS-75, pp. 398-404, June (1956).

[3] Tinney , W. and Hart, C.E. "Power Flow Solution of Newton's method", IEEE Trans. on PAS, Vol. 86, pp. 583-588, Nov. (1967).

[4] Freris, L. and Sasson, A. M., "Investigation of the Load Flow Problems", Proc. IEE, Vol. 115, pp. 1458-1469, Oct. (1968).

[5] Stott, B. , "Decoupled Newton Load Flow", IEEE Trans. , Vol. PAS-91, pp. 1955-1959, Sept. (1972).

[6] Stott, B. and Alsac, O., "Fast Decoupled Load Flow", IEEE Trans. , Vol. PAS-83, pp. 859-869, June. (1974).

[7] El-marsatawy, M. , Menzies, R. W. and Mathur, R. M., "A New, Exact, Diakoptic, Fast Decoupled Load Flow Technique for Very Large Power Systems", IEEE Trans. , Vol. PAS-98, (1979).

[8] Arillaga, J., Arnold, C.P. and Harker , B.J., "Computer Modelling of Electrical Power Systems" , John Wiley and Sons, (1983).

[9] Keyhani, A. and Abur. A., "Knowlege based Power Flow Models", Electrical Power Systems Research Journal, Vol. 9, pp. 183-191, (1985).

[10] Hobson, E. and Allen, G.N., "Effectiveness of Artificial Neural Networks for First Swing Stability Determination of Practical Systems" , IEEE Trans. on Power Systems, Vol. 9, No. 2 , pp. 1062-1068, May (1994).

[11] Santoso, I. and Tan, O., "Neural -Net Based Real Time Control of Capacitors Installed on Distribution Systems", IEEE Trans. on Power Delivery, Vol. PWRD-5, No. 1 , pp. 266-271, Jan. (1990).

[12] Abdelaziz, A.Y., Irving, M.R., El-Arabaty, A.M. and Mansour, M.M. "Out-of-step Prediction Based on Artificial Neural Networks", Electrical Power Systems Research Journal, Vol. 34, No. 2 , pp. 135-142, Aug. (1995).

[13] Hsu, Y. and Yang, C. ," Design of Artificial Neural Networks for Short Term Load Forecasting", IEE Proceedings-C, Vol. 138, No.5, pp. 407-418, Sept. (1994).

[14] Klara, P., Srivastava, S., Joshi., S., Kumar, N. and Wagneo, R., " Artificial Neural Network Based Load Flow Models", Proceedings of ESAP'93, Australia, pp. 56-61, Jan. (1993).

[15] Rumelhart, D.E. and McClelland, J.L., "Parallel Distributed Processing", Explorations in the Microstructure of Cognition, Vol. 1: Foundation, (The MIT Press, London, England, (1986).

[16] Lippmann, R. P., "An Introduction to Computing with Neural Nets", IEEE ASSP Magazine, pp. 4-22, April (1987).

[17] Caudill, M. and Butler, C., "Understanding Neural Networks", Vol. I: Basic Networks, The MIT Press, London, England, (1992).

[18] Anderson, P. M. and Fouad, A.A., "Power System Control and Stability", Iowa State University Press, Iowa, (1977).

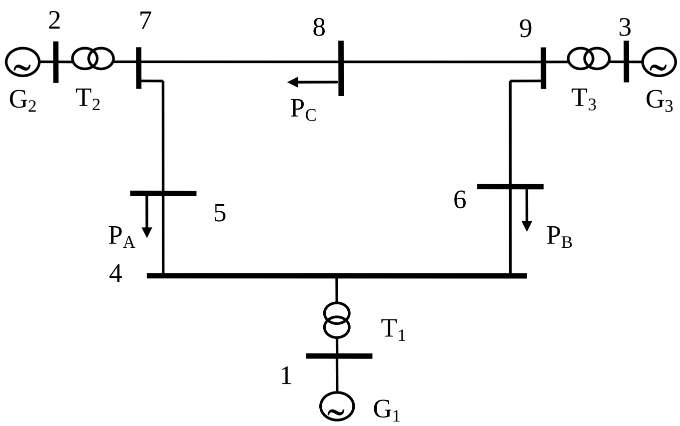

Fig. (1) WSCC power system

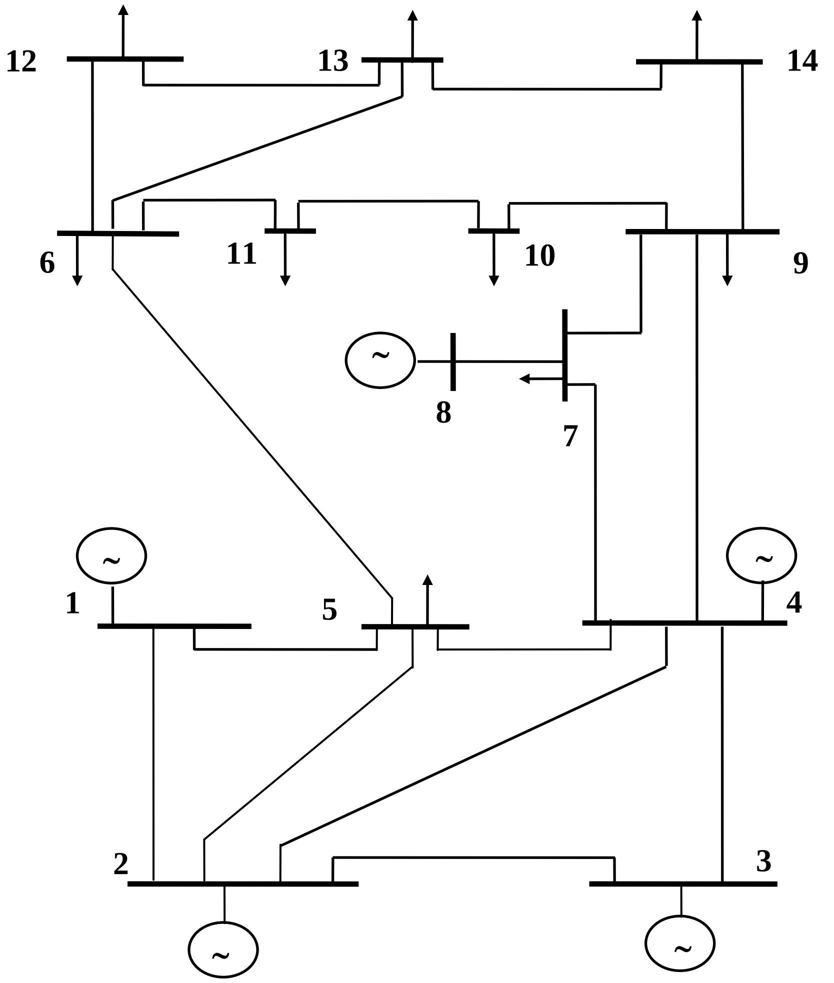

Fig. (2) IEEE 14-bus power system

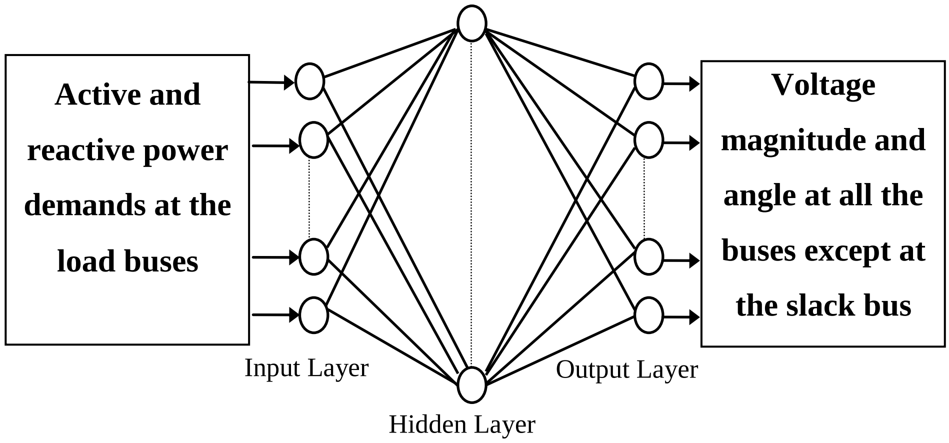

Fig. (3) Schematic diagram of the construction of the adopted neural network model used for load flow problem