ON-LINE LOAD FLOW ANALYSIS USING RADIAL BASIS NEURAL NETWORK

J. Krishna, L. Srivastava*, M. Pandit
Electrical Engineering Department
M.I.T.S., Gwalior

S.N. Singh
Electrical Engineering Department
I.I.T., Kanpur

Abstract

Load flow (LF) study, which is performed to determine the power system static states (voltage magnitudes and voltage angles) at each bus to find the steady state operating condition of a system, is very important and is the most frequently carried out study by power utilities for power system planning, operation and control. In this paper, a radial basis function neural network (RBFN) is proposed to solve load flow problem under different loading/contingency conditions for computing bus voltage magnitudes and angles of the power system. The RBFN has many advantageous features such as optimised system complexity, minimized learning and recall times as compared to multi-layer perceptron model. The composition of the input variables for the proposed neural network has been selected to emulate the solution process of a conventional load flow program. The effectiveness of the proposed RBFN based approach for on-line application is demonstrated by computation of bus voltage magnitudes and voltage angles for different loading conditions and single line-outage contingencies in IEEE 14-bus system.

Keywords— Admittance matrix, load flow studies, security analysis, line outage contingency, radial basis function neural network, real loads, reactive loads, bus voltage magnitude, voltage angle, Gaussian function.

1.0 Introduction

Load flow or power flow studies are conducted to determine the steady state operating condition of a power system, by solving the static load flow equations (SLFE) that mathematically are represented by a set of non-linear algebraic equations for a given network. The main objective of load flow (LF) studies is to determine the bus voltage magnitude with its angle at all the buses, real and reactive power flows (line flows) in different lines and the transmission losses. It is the most frequently carried out study by power utilities and is required to be performed at almost all the stages of power system planning, optimization, operation and control.

Fast security assessment is of paramount importance in a modern power system to provide reliable and secure electricity supply to its consumers. To perform the contingency screening, which is one of the most CPU time-consuming tasks for on-line security assessment, the computation in a few minutes of many LF scenarios is required simulating the occurrence of several contingencies and different loading conditions [1].

During last four decades, almost all the known methods of numerical analysis for solving a set of non-linear algebraic equations have been applied in developing load flow algorithms [2,3]. One or more desirable features to compare the different LF methods can be the speed of solution, memory storage requirement, accuracy of solution and the reliability of convergence depending on a given situation. Though, robustness or reliability of convergence of the method is required for all types of application, the speed of solution is more important for on-line applications compared to the off-line studies.

For contingency selection, fast non-iterative approximate load flow methods such as DC load flow method, linearised AC load flow, decoupled load flow, fast decoupled load flow methods are used, which provide results having significant inaccuracies. Full AC load flow methods are accurate but become unacceptable for on-line implementation due to high computational time requirements.

With the advent of artificial intelligence, in recent years, expert systems, pattern recognition, decision tree, neural networks and fuzzy logic methodologies have been applied to the security assessment problem [4-6]. Amongst these approaches, the application of artificial neural networks (ANNs) have shown great promises in power system

* Corresponding author, email: laxmi@sancharnet.in
engineering due to their ability to synthesize complex mappings accurately and rapidly. Most of the published work in this area utilizes multi-layer perceptron (MLP) model based on back propagation (BP) algorithm, which usually suffers from local minima and over-fitting problems [5-7]. Its ability to generalise a pattern depends on the learning rate and the number of units in hidden layer. In reference [8], a neural network load flow using an ANN-based minimisation model is proposed. A separate MLP model based on Levenberg-Marquardt second order training method has been used for computation for bus voltage magnitude and for angle at each bus of power system in reference [9]. As the number of neural networks required to solve load flow problem are large, it may not be applicable to a practical power system having huge number of buses.

A radial basis neural network [7,10,11] is proposed in this paper for on-line load flow studies. The RBFN has many advantageous features such as optimised system complexity, minimised learning and recall times. RBF model has an input layer, one hidden layer and output layer. The input variables are directly fed to the hidden units without weights.

The effectiveness of the proposed RBFN based approach is demonstrated by computation of bus voltage magnitudes and angles following different single line-outage contingency at different loading conditions in IEEE 14-bus system [12].

2.0 Methodology

Figure 1 shows the architecture of the proposed radial basis function neural network. The composition of the input variables for the proposed neural network has been selected to emulate the solution process of a conventional load flow program.

![Figure 1. Proposed RBFN Architecture](image)

The input consists of the electric network parameters represented by the diagonal elements of the bus conductance and susceptance matrix, voltage magnitudes $V_g$ of generation and slack buses, the active power generations $P_g$ of PV buses. In order to speed up the neural network training, the conductance and susceptance are normalised between 0.1 and 0.9. For this RBFN based load flow model, the system loads, active and reactive power components are represented like constant admittance and they are included into the diagonal of the bus admittance matrix $[Y]= [G]+ j[B]$, where $[G]$ and $[B]$ are the bus conductance and susceptance matrices respectively.

2.1 Radial Basis Function Neural Network

The RBF network consists of three layers, the input layer, hidden layer and output layer. The nodes within each layer are fully connected to the previous layer as shown in Figure 2. The input variables are assigned to each node in the input layer and are passed directly to the hidden layer without weights. The hidden nodes (units) contain the radial basis functions, and are analogous to the sigmoidal function commonly used in the BP networks.

The radial basis function is similar to the Gaussian density function, which is defined by a centre position and a width parameter. The width of the RBF unit controls the rate of decrease of function. The output of the $i^{th}$ unit $a_i(X_p)$ in the hidden layer is given by
\[ a_i(X_p) = \exp \left( -\sum_{j=1}^{r} \left[ x_{jp} - \bar{x}_{ji} \right]^2 / \sigma_i^2 \right) \]  

(1)

where

- \( \bar{x}_{ji} \) = centre of \( i^{th} \) RBF unit for input variable \( j \)
- \( \sigma_i \) = width of \( i^{th} \) RBF unit
- \( r \) = dimension of input vector

The connection between the hidden units and the output units are weighted sums as shown in Figure 2. The output value \( y_{mi} \) of the \( m^{th} \) output node is given as

\[ y_{mi} = \sum_{j=1}^{H} w_{jm} a_i(X_j) + w_{om} \]  

(2)

where

- \( w_{om} \) = biasing term at \( m^{th} \) output node

The parameters of the RBF units are determined in three steps of the training activity. First, the unit centres are determined by some form of clustering algorithm. Then the widths are determined by a nearest neighbour method. Finally weights connecting the RBF units and the output units are calculated using multiple regression techniques.

Euclidean distance based clustering [7] technique has been employed in this paper to select the number of hidden (RBF) units and unit centres. The normalized input and output data are used for training of the RBF neural network.

3.0 Algorithm

A large number of load patterns are generated randomly by perturbing the load at all the buses in wide range, voltage magnitude at PV and slack buses and real power generation at PV buses. Single line outages are considered as contingencies. Newton-Raphson (NR) load flow program is run to generate training / testing patterns for different load scenarios and for all the single-line outage contingencies.

Two RBF neural networks are developed in this work, one (RBFN1) for computation of bus voltage magnitude at all the \( PQ \) type buses, while the other (RBFN2) for computation of bus voltage angle at \( PV \) type and \( PQ \) type buses. After training, the knowledge about the training patterns in form of voltage magnitudes at all the \( PQ \) buses and voltage angles at different \( PV \) and \( PQ \) buses in various contingency cases and different system operating conditions are stored in structured memory by the trained RBFNs.
3.1 Solution Algorithm

The solution algorithm for load flow problem using RBF networks is as follows:

(i) A large number of load patterns are generated randomly by perturbing the load at all the buses, real power generation at the generator buses, voltage magnitudes at \( PV \) and slack buses.

(ii) AC load flow (NR) programs are run for all the load patterns and also for contingency cases to calculate bus voltage magnitudes at all the \( PQ \) type buses and voltage angles at all the \( PV \) and \( PQ \) type buses.

(iii) Input features are selected by using diagonal elements of the bus conductance and susceptance matrix (active and reactive loads added to it), voltage magnitudes at \( PV \) and slack buses and real power generations at \( PV \) buses.

(iv) The number of hidden (RBF) units and unit centres are determined using Euclidean distance based clustering technique. Then width of the RBF unit is determined.

(v) For training of the RBF network, initialize all the connection weights between hidden nodes and output nodes.

(vi) Compute the Gaussian function at the hidden node using equation (1).

(vii) Calculate the output of the RBF network using equation (2).

(viii) Calculate the Mean Squared Error \( e_p \) for the \( p^{th} \) pattern using

\[
e_p = \frac{1}{2} \sum_{j=1}^{NO} \left( t_{jp} - o_{jp} \right)^2
\]

where \( NO = \) number of neurons in output layer

\( t_{jp} = \) target value at \( j^{th} \) neuron of output layer

\( o_{jp} = \) actual output at \( j^{th} \) neuron for \( p^{th} \) pattern

(ix) Repeat steps (vi) to (viii) for all the training patterns.

(x) Calculate the error function \( E_k \) using

\[
E_k = \frac{1}{2} \sum_{p=1}^{P_{max}} \sum_{j=1}^{NO} \left( t_{jp} - o_{jp} \right)^2
\]

(xi) The connection weights \( w_{ji} \) between the hidden and output layers at \( K^{th} \) iteration are updated using equations

\[
w_{ji}(K+1) = w_{ji}(K) + \Delta w_{ji}(K)
\]

where

\[
\Delta w_{ji}(K) = \eta(K) \delta_j A_i + \alpha \Delta w_{ji}(K-1)
\]

\( \delta_j = T_j - W_j A_i \)

\( \eta(K) = \) learning rate or adaptive size at \( K^{th} \) iteration

\( \delta_j = \) error signal for unit \( j \)

\( \alpha = \) Momentum term

\( T_j = [t_{j1}, t_{j2}, \ldots, t_{jp_{max}}] \)

\( W_j = [w_{j1}, w_{j2}, \ldots, w_{jH}, w_{j0}] \)

\( A_i = [a_i(X_1), a_i(X_2), \ldots, a_i(X_{p_{max}})] \)


\[
\text{for} \quad i = 1, 2, \ldots, H+1
\]

\( H = \) number of hidden layer (RBF) nodes

(xii) The procedure is continued till the error becomes negligible.

4.0 Application Results

The IEEE-14 bus system, which is composed of 14 buses and 20 lines, has been used to test the proposed methodology. The data for IEEE-14-bus system were taken from reference [12] with buses renumbered to make bus-
1 as slack bus having pre-specified voltage as 1.06∠0° p.u., buses 2-5 as PV buses and buses 6-14 as load (PQ) buses. One RBF model (RBFN1) was trained to provide bus voltage magnitude at all the PQ buses, while the other neural network (RBFN2) was trained to compute the bus voltage angles at all the PV and PQ type buses.

The total number of inputs are 29, including diagonal values of G and B, real and reactive loads, real bus power generation at bus no. 2, bus voltage magnitudes at 4 PV and the slack buses. For training and testing of RBFNs, 25 load scenarios were generated by perturbing the load at all the buses in the range of 60% to 140%, PV bus voltage magnitudes between 0.9 to 1.10 and real power generation in the range of 80% to 120%. Single-line outages were considered as contingencies. Newton-Raphson load flow program was used to generate training / testing patterns for 25 load scenarios and for all the single-line outage contingencies. The NR method converged for different loading conditions and for 19 line outage cases i.e. for 500 cases. Out of 500 generated patterns, 400 patterns corresponding to 20 load scenarios were arbitrarily selected and used for training of the RBF, while 100 patterns corresponding to 5 load scenarios were used for testing the performance of the trained RBF networks.

Two RBFNs were developed, one for computation of bus voltage magnitudes at 9 PQ type buses, while the other for computation of bus voltage angles at 4 PV type buses and 9 PQ type buses (total 13). The number of hidden neurons (nodes) could be decided using some trial and error method. The optimum structures of the neural networks were found to be 29-118-9 for RBFN1 and 29-147-13 for RBFN2. The trained RBFNs were tested for 100 unknown patterns and were found to give accurate and fast computation of bus voltage magnitudes and voltage angles. The test results for one load scenario for outage of line no.18 (which has maximum testing error) are shown in Table 1 and Table 2 for voltage magnitude computation at 9 PQ buses and voltage angle computation at all the 13 buses respectively.

### Table 1: Comparison of NR and RBFN1 (29-118-9) outputs corresponding to the case of maximum test error

<table>
<thead>
<tr>
<th>Voltage Mag.(pu)</th>
<th>NR Method</th>
<th>RBF Model</th>
<th>Absolute Error</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>V6</td>
<td>0.9907</td>
<td>0.9887</td>
<td>0.0020</td>
<td>0.202</td>
</tr>
<tr>
<td>V7</td>
<td>1.0275</td>
<td>1.0254</td>
<td>0.0021</td>
<td>0.204</td>
</tr>
<tr>
<td>V8</td>
<td>0.982</td>
<td>0.9842</td>
<td>-0.0022</td>
<td>0.224</td>
</tr>
<tr>
<td>V9</td>
<td>0.9903</td>
<td>0.9942</td>
<td>-0.0039</td>
<td>0.394</td>
</tr>
<tr>
<td>V10</td>
<td>0.9935</td>
<td>0.9934</td>
<td>0.0001</td>
<td>0.010</td>
</tr>
<tr>
<td>V11</td>
<td>1.0241</td>
<td>1.026</td>
<td>-0.0019</td>
<td>0.186</td>
</tr>
<tr>
<td>V12</td>
<td>1.0447</td>
<td>1.0445</td>
<td>0.0002</td>
<td>0.019</td>
</tr>
<tr>
<td>V13</td>
<td>1.0332</td>
<td>1.0333</td>
<td>-0.0001</td>
<td>0.010</td>
</tr>
<tr>
<td>V14</td>
<td>0.9479</td>
<td>0.9591</td>
<td>-0.0112</td>
<td>1.182</td>
</tr>
</tbody>
</table>

### Table 2 : Comparison of NR and RBFN2 (29-147-13) outputs corresponding to the case of maximum test error

<table>
<thead>
<tr>
<th>Bus Angle (Deg.)</th>
<th>NR Method</th>
<th>RBF Model</th>
<th>Abs. Error</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>δ2</td>
<td>-5.1986</td>
<td>-5.2443</td>
<td>0.0457</td>
<td>0.879</td>
</tr>
<tr>
<td>δ1</td>
<td>-15.7247</td>
<td>-15.7112</td>
<td>-0.0135</td>
<td>0.086</td>
</tr>
<tr>
<td>δ4</td>
<td>-13.9797</td>
<td>-13.9961</td>
<td>0.0164</td>
<td>0.117</td>
</tr>
<tr>
<td>δ5</td>
<td>-12.1803</td>
<td>-12.2344</td>
<td>0.0541</td>
<td>0.444</td>
</tr>
<tr>
<td>δ6</td>
<td>-9.1608</td>
<td>-9.2523</td>
<td>0.0915</td>
<td>0.999</td>
</tr>
<tr>
<td>δ7</td>
<td>-12.1749</td>
<td>-12.2301</td>
<td>0.0552</td>
<td>0.453</td>
</tr>
<tr>
<td>δ8</td>
<td>-7.0813</td>
<td>-7.1071</td>
<td>0.0258</td>
<td>0.364</td>
</tr>
<tr>
<td>δ9</td>
<td>-13.7942</td>
<td>-13.8455</td>
<td>0.0513</td>
<td>0.372</td>
</tr>
<tr>
<td>δ10</td>
<td>-14.0071</td>
<td>-14.0376</td>
<td>0.0305</td>
<td>0.218</td>
</tr>
<tr>
<td>δ11</td>
<td>-18.8335</td>
<td>-18.6293</td>
<td>-0.2042</td>
<td>1.084</td>
</tr>
<tr>
<td>δ12</td>
<td>-14.6863</td>
<td>-14.6859</td>
<td>-0.0004</td>
<td>0.003</td>
</tr>
<tr>
<td>δ13</td>
<td>-24.0712</td>
<td>-24.1284</td>
<td>0.0572</td>
<td>0.238</td>
</tr>
<tr>
<td>δ14</td>
<td>-30.3637</td>
<td>-30.2265</td>
<td>-0.1372</td>
<td>0.452</td>
</tr>
</tbody>
</table>
As can be observed from Table 1 and Table 2, the maximum absolute error is approx. 1.2% for bus voltage magnitude and angle computation, which is within acceptable limits. Both the trained RBF networks are able to compute voltage magnitudes and voltage angles accurately. The results of voltage magnitude at bus nos. 7 & 11 and voltage angle computation at bus nos. 4 & 13 for all the testing patterns are compared in Figures 3, 4, 5 and 6 respectively. From these figures, it is clear that the trained radial basis neural networks are able to solve load flow problem accurately for unknown load patterns.
5.0 Conclusion

Radial basis neural networks have been developed to solve load flow problem in an efficient manner. In the commonly used multi-layer feedforward neural network, the training process is slow, and its ability to generalise a pattern-mapping task depends on the learning rate and the number of neurons in the hidden layer. On the other hand
training of a radial basis neural network is very fast, at the same time the generalization capability of the RBF network allows it to produce a correct output even when it is given an input vector that is partially incomplete or partially incorrect.

Two RBF neural networks were trained, one for computation of voltage magnitude at all the PQ type buses and other for voltage angles at all the PV and PQ buses. The trained RBFNs were able to compute bus voltages magnitudes and voltage angles accurately for previously unseen patterns having changing load / generation conditions of the power system and for single-line outage contingencies as well.

Full AC load flow takes long time, as it should be run for any change in load/ generations and topology. On the other hand, once the RBF models are successfully trained they provide accurate values of bus voltage magnitudes at all the PQ buses and voltage angles at all the PV and PQ type buses almost instantaneously. These values of voltage magnitudes and voltage angles can be used to compute line-flows and line losses etc. The radial basis neural networks based load-flow method can be implemented for on-line security assessment in Energy Management Systems.

6.0 Acknowledgement

The authors sincerely acknowledge the financial support provided by University Grant Commission (UGC), New Delhi, India, under Research grant no. F 14-16/2003 dated 27/03/03 and Director, MITS, Gwalior, India to carry out this work.

7.0 References