LOAD FLOW SOLUTION USING NEURO-FUZZY TECHNIQUES

Muriithi C. M[#1], Olan'go S. A[*2]
Department of Electrical & Electronics
Jomo Kenyatta University of Agriculture & Technology
Nairobi, Kenya
[1]cmmuriithi@eng.jkuat.ac.ke, [2]selineakinyi@yahoo.com

Abstract **- Load-flow (LF) study is the steady state solution of the power system network under existing or contemplated conditions for normal operation. In this paper, a neuro-fuzzy system is proposed to solve power flow problem under different loading/contingency conditions for computing bus voltage magnitudes and angles of the power system. The neuro-fuzzy system combines the explicit knowledge representation of fuzzy logic with the learning power of neural networks. The composition of the input variables for the proposed neural network has been selected to emulate the solution process of a conventional power flow program. The effectiveness of the proposed neuro-fuzzy based approach for solving power flow is demonstrated by computation of bus voltage magnitudes and voltage angles for different loading conditions and single line-outage contingencies in IEEE 30-bus system.**

Keywords- Load flow, Neural Networks. Fuzzy- Neural Networks.

I. INTRODUCTION

The main objectives of LF studies is to determine the voltage magnitude and phase angle at all the buses, reactive powers and at generator buses, real and reactive power flows (line flows) in the transmission line and power losses in the system.

It is used in determining the best operation of the existing power systems, for economic scheduling, in the exchange of power between utilities, in transient stability and contingency studies, and in control of an existing system. Most of the known methods of solving the load flow problem have been based on the solution of a set of non-linear equations [1, 6, 7]. The 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 computational efficiency of these methods has been improved, the speed of solution for online applications is most significant [2]. 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 many power system problems [2, 3].

A neuro-fuzzy system is proposed in this paper. The neuro-fuzzy system provides a practical approach for implementing a pattern mapping task, since learning is fast in this network [4]. The effectiveness of the proposed method based approach is demonstrated by computation of bus voltage magnitudes and angles following different single line-outage contingency at different loading conditions on IEEE 30-bus system.

II. METHODOLOGY

Figure 1 shows the architecture of the proposed neuro-fuzzy network. The composition of the input variables for the proposed method has been selected to emulate the solution process of a conventional power flow program.

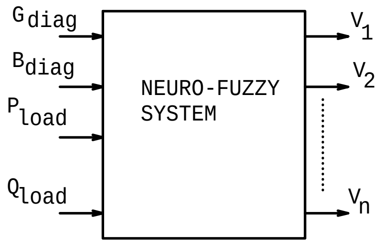

Figure 1 Proposed Neuro Fuzzy Architecture

A. POWER FLOW PROBLEM

The objective of power flow study is to determine the voltage and its angle at each bus, real and reactive power flow in each line and line losses in the power system for specified bus or terminal conditions.

From the nodal current equations, the total current entering the *i*th bus of *n* bus system is given by

$$I_i = V_i \sum_{j=0}^{n} Y_{ij} - \sum_{j=1}^{n} Y_{ij} V_j \tag{1}$$

The power injected into a bus is given by

$$\frac{P_i - jQ_i}{V_i^*} = I_i \tag{2}$$

Substituting yields the following equation

$$\frac{P_i - jQ_i}{V_i^*} = V_i \sum_{j=0}^{n} Y_{i0} - \sum_{j=0}^{n} Y_{i0} V_j \tag{3}$$

From the above relation, the mathematical formulation of the power flow problem results in a system of algebraic non linear equations which must be solved by iterative techniques.

For large power systems the Newton-Raphson method is found to be more efficient and practical. The power flow equations are solved to give

$$\begin{pmatrix} \Delta\delta \\ \Delta|V| \end{pmatrix} = \begin{pmatrix} J_1 & J_2 \\ J_3 & J_4 \end{pmatrix}^{-1} \begin{pmatrix} \Delta P \\ \Delta Q \end{pmatrix} \tag{4}$$

Where J1, J2, J3 and J4 are the elements of the Jacobian matrix while $\Delta\delta$'s and ΔV's gives the correction vector i.e $\Delta\delta$'s for all the *PV* and *PQ* type buses and ΔV's for all the *PQ* type buses, which are used to update the earlier estimates of δ's and *V*'s.

Newton-Raphson method requires more time per iteration. It provides accurate results and is the most reliable AC power flow method.

To get accuracy in power flow solution, the NR power flow program has been developed in this paper and run to generate several training / testing patterns.

B. NEURO-FUZZY SYSTEM

The neuro-fuzzy system is a hybrid of neuro-networks and fuzzy logic as shown in Figure 2.

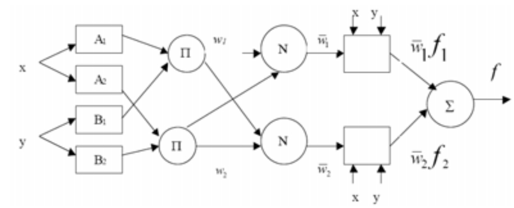

Figure 2.

This paper uses the Adaptive Neuro Fuzzy Inference System (ANFIS). Fuzzy Inference System (FIS) forms are a useful computing framework based on the concepts of fuzzy set theory, fuzzy if–then rules and fuzzy reasoning. The ANFIS is a FIS implemented in the framework of an adaptive fuzzy neural network. It combines the explicit knowledge representation of a FIS with the learning power of ANNs [5].

Two fuzzy inference systems are developed in this work, one (FIS1) for computation of bus voltage magnitudes at all the *PQ* type buses, while the other (FIS2) for computation of bus voltage angles at *PV* type and *PQ* type buses. After training, the knowledge about the voltage magnitudes at all the *PQ* buses and voltage angle at different *PV* and *PQ* buses for various contingencies under different system operating conditions (training patterns) are stored in the structured memory by the trained FISs.

C. SOLUTION ALGORITHM

The algorithm of the proposed neuro-fuzzy load flow system may be summarized as follows:

i. A large number of load patterns are generated randomly by perturbing the load at all the buses.

ii. AC power 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 angle at all the *PV* and *PQ* type buses except the slack

iii. The diagonal elements of the bus conductance and susceptance matrix, the active and reactive loads, are selected as input features.

iv. The voltage magnitudes and the voltage phase angles are selected as the outputs

v. Two fuzzy inference systems are developed, one (FIS1) for mapping the bus conductances, active loads to the voltage phase angle, while the other (FIS2) for mapping the bus susceptances, reactive loads to the bus voltage magnitudes.

vi. A model parameter optimization method is selected: either backpropagation or a mixture of backpropagation and least squares (hybrid method). In this paper the hybrid method was used.

vii. Choose the number of training epochs and the training error tolerance

viii. Train the FIS model by adjusting the membership function parameters until all the input-output

III. TEST RESULTS.

A. *NEURO FUZZY LOAD FLOW ALGORITHM*

The IEEE-30 bus system, which is composed of 30 buses has been used to test the proposed methodology. The data for IEEE-30-bus system were taken from [1].

One FIS1 was trained to provide bus voltage magnitude at all the PQ buses, while the other neural network (FIS2) was trained to compute the bus voltage angles at all the PV and PQ type buses.

The total number of inputs is 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 CPNN, 500 load scenarios were generated by perturbing the load at all the buses in the range of 50% to 150%. Single-line outages were considered as contingencies. Newton-Raphson (NR) power flow program was used to generate training / testing patterns for the 1000 load scenarios and for all the single-line outage contingencies.

The NR method converged for 863 different loading conditions and line outage cases. Out of 863 generated patterns, 432 patterns were arbitrarily selected and used for training of the ANFIS, while the rest were used for testing the performance of the trained ANFIS.

The test results for one load scenario (loosing transmission line between buses 12 & 16) are shown in Figure 3 and Figure 4 for voltage magnitude computation at PQ buses and voltage angle computation at all the buses except slack bus respectively.

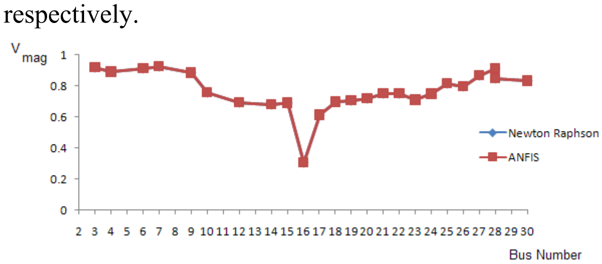

Figure 3. Voltage Magnitude at each bus

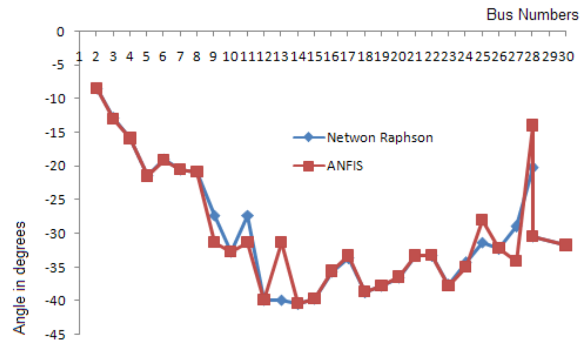

Figure 4. Voltage Phase Angle at each bus

B. *CONCLUSION*

The two FISs were trained, one for computation of voltage magnitude at all the *PQ* type buses and other for voltage angle at all the *PV* and *PQ* buses. The trained FISs 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. However for some buses the mapping was not accurate enough for the phase angles.

When the FISs 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. This goes well with online applications.

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