VOLTAGE STABILITY ANALYSIS USING CP_ANN AND OPTIMISED CAPACITOR BANK PLACEMENT

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***Abstract* – Voltage Stability refers to the ability of power system to maintain steady voltage at all buses in the system after being subjected to a disturbance from a given initial operating condition. In this paper, the IEEE 30-bus system is subjected to different loading and contingency conditions that simulate probable line faults and a load flow study is conducted with each configuration of load and contingency. The results are used to train a Counter Propagating Artificial Neural Network (CPANN) to classify the buses according to weakness. From the solution for the idealized system, the reduced Jacobian is used to determine the impact of the reactive power injection in the form of system voltage improvement at optimized capacitor bank locations.**

Keywords- Load flow, CP_ANN, Neural Networks, Reduced Jacobian.

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.

In general, the voltages of the buses within a power system are required to remain within a particular margin from the specified voltage [1]. Most systems have this margin as 4% or 5% of the nominal bus voltage. During conditions of disturbances e.g. faults, switching or lightning surges or load changes, there are fluctuations of voltage magnitudes on the buses. If a system is able to maintain the bus voltages within these margins even during these disturbances, then it can be said to be ***voltage stable***.

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]. CP_ANN systems provide 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. Optimum capacitor bank placement is one way of improving the voltage profile of PQ buses in the system.

In this paper, the Newton Raphson method of load flow solution is adopted due to the quadratic convergence and high accuracy. It consumes memory space but with new computation systems, memory is of little hindrance. In addition, the Jacobian matrix utilized in the solution is essential in optimizing the capacitor bank placement by deriving the reduced Jacobian matrix.

II. METHODOLOGY

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

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

The power injected into a bus is given by

$$\frac{P_i - jQ_i}{V_i^*} = I_i \qquad (2)$$

Substituting yields the following equation

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

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

$$\begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix}^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \qquad (4)$$

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. A total of 100 different training sets each from a different loading and contingency combination were used with the results being the training data for the CP_ANN system.

B. WEAK BUS ID USING CP_ANN

CP_ANN are very similar to the Kohonen Maps and are essentially based on the Kohonen approach, but combines characteristics from both supervised and unsupervised learning [5]. The CP_ANN net is based on a single layer of neurons arranged in a two-dimensional plane having a well defined topology which means that each neuron has a defined number of neurons as nearest neighbors, second-nearest neighbor, etc. There is an additional output layer with same layout as input layer.

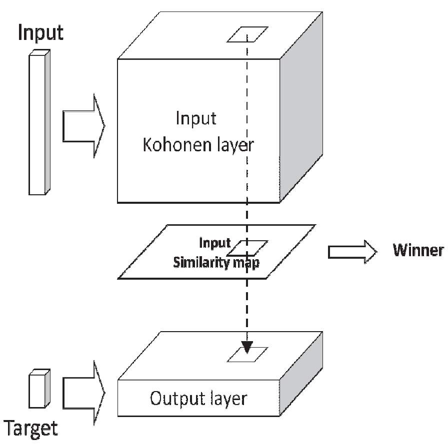

Fig 1: CP_ANN Net Layout

Principle Component Analysis (PCA) is done on the result to analyse the various weights the net appropriates to different variables. It involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

Weak buses are buses within the system that have the lowest voltage magnitude and have the least capacity of reactive power during normal operation. In case of a large disturbance, the voltage at these buses is likely to sag to unfeasible levels triggering a voltage collapse. Weak buses have previously been identified based on Fuzzy Logic [6], Load Flow Equations [7], and using power capacity [8].

The variables from the load flow set of solutions are fed into the CP_ANN net to classify the buses according to weakness. The variables chosen are |V|, δ, sub matrix elements , and the element from the Y-bus for each bus in each solution. Based on these data, the CPANN was trained for 100 epochs to produce the top map.

D. COMPUTING THE REDUCED JACOBIAN

The technique implements a simple computation on the elements of the reduced Jacobian to find the suitable bus for capacitor placement as seen in the later section. The reduced Jacobian [9] is formulated from the Jacobian of the load flow. A brief description of the formulation of the reduced Jacobian is given before proceeding further.

The load flow equations are given by

f represents the active power mismatch equation,
g represents the reactive power mismatch equation.

Equation 7 gives the known matrix model of the load flow.

P and *Q* are the active and reactive power injections,

V and θ are the state variable vectors, namely voltage magnitude and bus angle, respectively,

ΔP is the difference in active power injection,
ΔQ is the difference in reactive power injection,

$\Delta\theta$ is the change in bus angle,
ΔV is the change in bus voltage magnitude,

J1 represents $\partial f / \partial\theta$,
J2 represents $\partial f / \partial V$,
J3 represents $\partial g / \partial\theta$,
J4 represents $\partial g / \partial V$.

The reduced Jacobian used in this technique assumes that change in active load i.e. $\Delta P = 0$. Substituting this in (7), we get

Putting $\Delta\theta$ from (8) in (9), we get

where is the reduced Jacobian. The reduced Jacobian serves as the tool on which the proposed methodology yields the results regarding the capacitor location.

E. REDUCED JACOBIAN TECHNIQUE

The reduced Jacobian J_R gives a relationship describing ΔQ in terms of ΔV [9]. The inverse describes ΔV in terms of ΔQ. The elements in each column of the inverse matrix J_R^{-1} can be made to represent the change in voltage of every load bus for a given injection of reactive power into the bus corresponding to that column. The concept can be explained using a sample matrix like the one in (13) which shows J_R^{-1} as a (3 X 3) matrix.

$$[\Delta V] = \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{bmatrix} [\Delta Q] \qquad (13)$$

$A_{11}, A_{21},$ *and* A_{31} represent partial derivatives of voltages of load buses 1, 2 and 3 of the system with respect to reactive power at load bus *i*,

ΔQ represents the vector of change in reactive power modeled by a fixed amount of reactive power injection,

ΔV represents the vector of change in voltage.

This implies that for studying the change in voltage ΔV as a result of the reactive power injection into load buses separately or individually, the corresponding element of ΔQ, say ΔQi alone must be made 1 p.u. and the others 0. Upon implementing this, the corresponding column *i* in J_R^{-1} directly gives ΔV [9]. Thus one needs to only study the elements of the particular column *i* of the reduced Jacobian to get the change in voltage as an effect of 1 p.u. reactive power injection at that bus *i*.

$$A_{1i} = \Delta V_{1,} \qquad (14)$$

$$A_{2i} = \Delta V_{2,} \qquad (15)$$

$$A_{3i} = \Delta V_{3,} \qquad (16)$$

The sum of the elements of that column *i* of J_R^{-1} further gives the total improvement of system voltage $\Delta Vtotali$ as an effect of the injection at the bus *i*. This is shown in (17).

$$A_{1i} + A_{2i} + A_{3i} = \Delta V_{total_i} \qquad (17)$$

On comparison of the sums of all individual columns of J_R^{-1}, the bus corresponding to the column *i* which yields maximum $\Delta Vtotali$ is determined as the bus required.

$$bus_i \ : \Delta V_{total_i} = max\{\Delta V_{total_1}, \Delta V_{total_2}, \Delta V_{total_2}\} \ (18)$$

corresponding to the matrix given in (13).

busi is not the i^{th} bus in the system but the i^{th} load bus in the system as the buses involved in the analysis are only load buses.

It should be noted that the term $\Delta Voverall$ depicts the total improvement in system voltage where as the individual change in the bus voltage information come with the individual elements of J_R^{-1}.

III. TEST RESULTS.

A. CP_ANN WEAK BUS CLASSIFICATION

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 is given in the appendix. The Newton Raphson method was used to obtain the steady state solution and the results provided the variables |V|, δ, sub matrix elements $J_{1_{ii}}$, $J_{4_{ii}}$ and the element Y_{ii} from the Y-bus for training the CP_ANN net. The resulting top map was analysed using Principle Component Analysis (PCA).

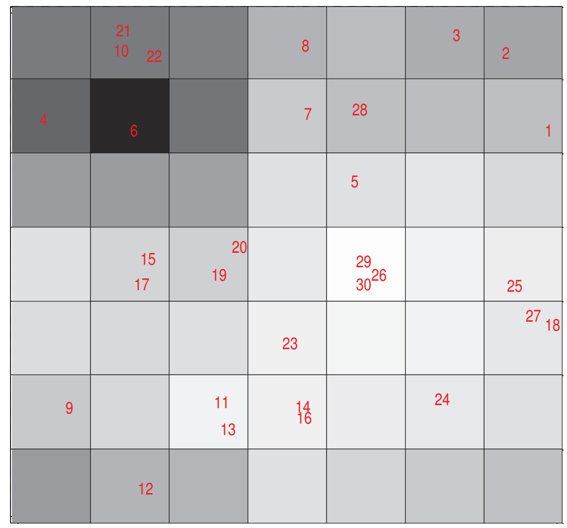

Fig 2. IEEE 30-bus CP_ANN top map

The dark neurons represent strong buses while lighter shading is an indication of weakness.

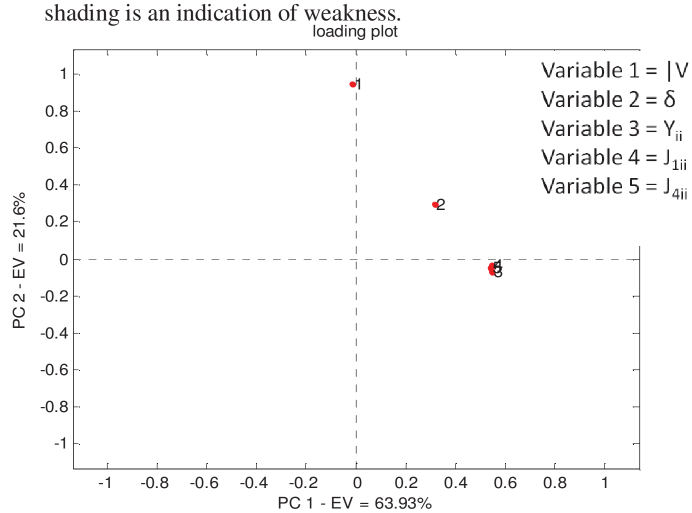

Fig 3. PCA Analysis on IEEE top map

The PCA shows that the first axis extracted almost 3/5th of the variation in the entire data set. In addition, Y_{ii}, $J_{1_{ii}}$ and $J_{4_{ii}}$ are clustered together implying that they play a greater role than the voltage magnitude and angle in determining the strength of a bus, from the variables fed into the CP_ANN net for the load flow study.

Further analysis of the top map shows bus 6 to be the strongest. An evaluation of that neuron's weight (Fig. 4) shows strong values of , $Y_{ii}, J_{1_{ii}}$ and $J_{4_{ii}}$.

Fig 4. Neuron Weights for bus 6

This is seen as bus 6 is heavily interconnected and thus can be considered voltage stable even though its voltage magnitude and angle weights are low. It's also interesting that bus 6 is not loaded and has a direct connection with bus 2 which has a generator. Next to the neuron with bus 6 is bus 4 which is also well interconnected, has direct connections to generators at bus 2 and bus 1 and is thus considered a strong bus.

In contrast, buses 26, 29 and 30 are clustered together in one neuron as the weakest buses in the system. An evaluation of the neuron weights (Fig. 5) shows weak weights for , $Y_{ii}, J_{1_{ii}}$ and $J_{4_{ii}}$.

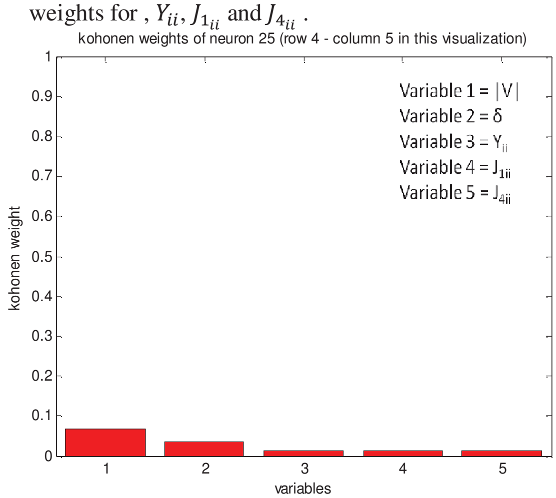

Fig 5. Neuron Weights for buses 26, 29 and 30

These buses are not only far from the generator but also very weakly interconnected. This makes them particularly susceptible to voltage sags and hence their classification as weak buses.

Bus 5 is placed next to these buses and ranks low in weakness yet it has synchronous condensers connected to it. This is explained by its heavy loading that greatly reduces its voltage stability margin.

This idea can be extended for 100 different loading and contingency arrangements. These were run using the Newton Raphson load flow solution method by creating a random line contingency and randomizing the loading to within ±50% of the nominal loading. The CP_ANN net was trained with the 100 epochs and had 49 neurons. The top map generated was as in (Fig. 6).

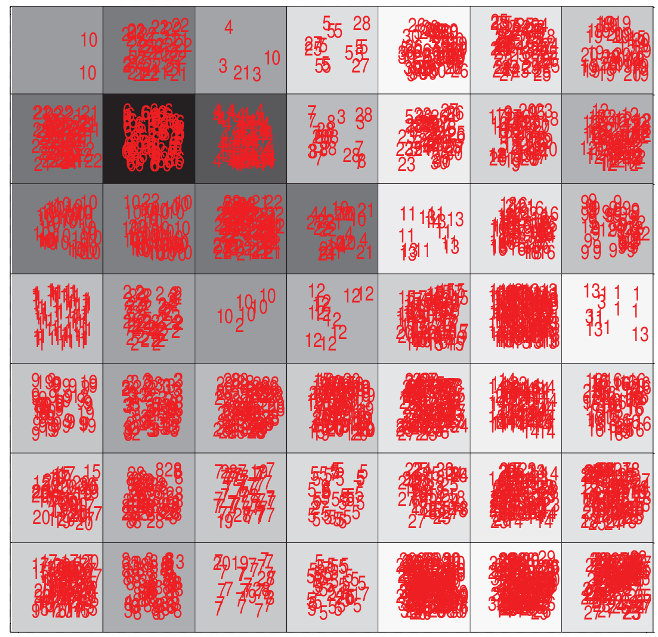

Fig 6. IEEE 30-bus CP_ANN top map for 100 LF solutions

The PCA was similar as that for 1 solution as shown in Fig. 7

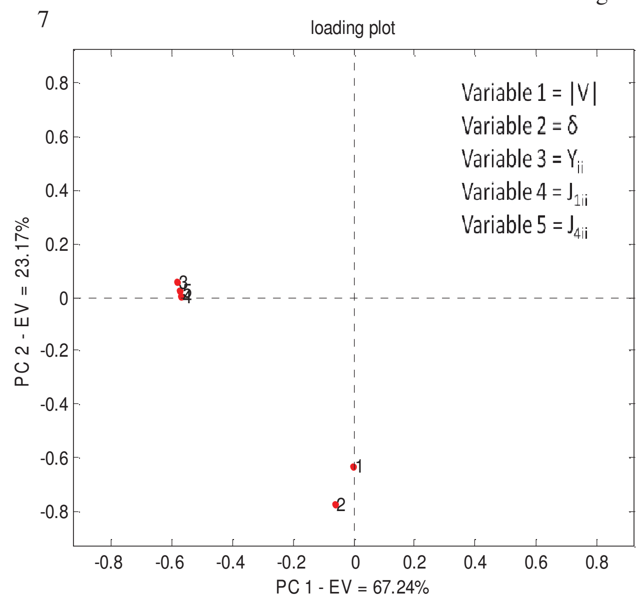

Fig 7. PCA Analysis on IEEE top map for 100 LF solutions

Again, the variables Y_{ii} , $J_{1_{ii}}$ and $J_{4_{ii}}$ are clustered together and account for about 4/5th of all the variation.

They thus carry more weight in determining if a bus is weak or strong.

From the top map, bus 6 is still ranked as the strongest bus within the system. The neuron weight for bus 6 is (Fig. 8)

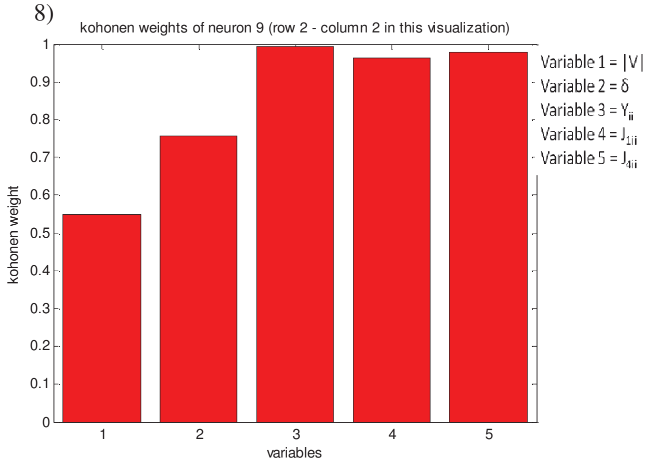

Fig 8. Neuron Weights for bus 6

The voltage magnitude and angle weights improve and the other variable weights are still high. Bus 4 is still clustered near bus 6 as a strong bus. The factors for this clustering remain the same even with line contingencies within the system namely the close proximity to generator buses, light loading and many interconnections.

The top map still classifies buses 26, 29 and 30 as weak buses. Their neuron weight is shown in (Fig. 10).

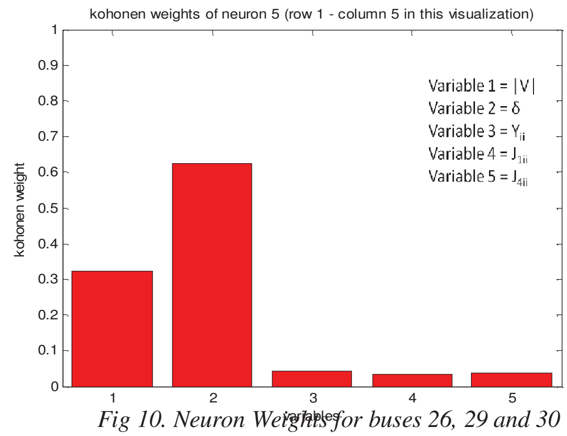

Fig 10. Neuron Weights for buses 26, 29 and 30

Their variables for buses 26, 29 and 30have very low weights but the weightings for voltage magnitude and voltage angle improve. Bus 5 is still clustered next to them.

B. OPTIMUM CAPACITOR BANK PLACEMENT

From the ideal IEEE 30-bus system, the reduced Jacobian was constructed and the optimum capacitor location identified as bus 26 while the least effect was at bus 7. An idealized static capacitor VAR value of 5MVAR was introduced and the load flow solution obtained for both locations. The voltage profile for the PQ buses showed marked improvement with capacitors at bus 26 and little improvement with capacitors at bus 7. The voltage profile increased with increase in injected VARs (Fig. 11).

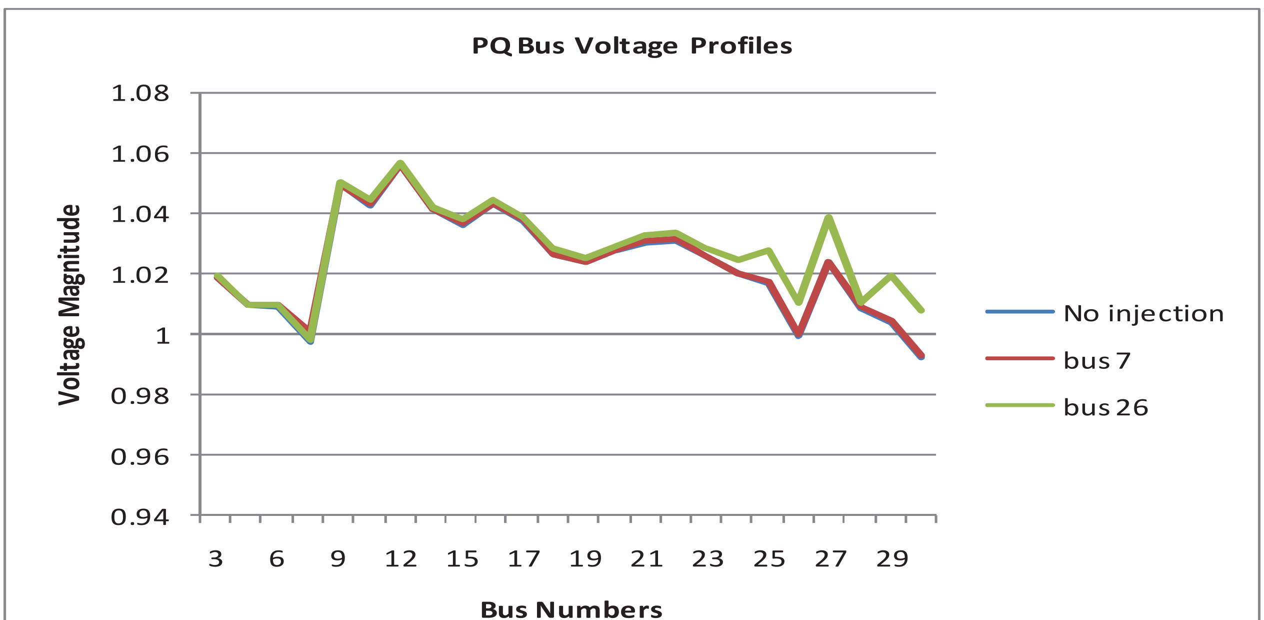

Fig. 11. Voltage profiles for PQ buses

C. CONCLUSION

The CP_ANN net was trained with data from load flow studies and was able to give a classification of buses according to weakness. This shows that neural networks can be used to predict bus weakness in an online situation and prevent voltage collapse. The variables for prediction can be increased to give a stringer indication of bus strength.

For the reduced Jacobian, the improved voltage profile for optimized capacitor placement shows that optimization may be taken as a tool in improving PQ bus voltages in large systems, saving costs of widespread VAR injection. Optimization spreads the effect of capacitors to other buses within the system. This could be important for developing countries.

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APPENDIX

Table A1: IEEE 30 Bus system Load Bus Data

Bus No	Load	
	MW	MVAr
2	21.7	12.7
3	2.4	1.2
4	7.6	1.6
5	94.2	19
7	22.8	10.9
8	30	30
10	5.8	2
12	11.2	7.5
14	6.2	1.6
15	8.2	2.5
16	3.5	1.8
17	9	5.8
18	3.2	0.9
19	9.5	3.4
20	2.2	0.7
21	17.5	11.2
23	3.2	1.6
24	8.7	6.7
26	3.5	2.3
29	2.4	0.9
30	10.6	1.9

Table A2: IEEE 30 Bus system Line Data

Bus No	Bus No	R	X	B/2	Transformer tap setting
		pu	pu	pu	
1	3	0.0452	0.1852	0.0204	1
2	4	0.057	0.1737	0.0184	1
3	4	0.0132	0.0379	0.0042	1
2	5	0.0472	0.1983	0.0209	1
2	6	0.0581	0.1763	0.0187	1
4	6	0.0119	0.0414	0.0045	1
5	7	0.046	0.116	0.0102	1
6	7	0.0267	0.082	0.0085	1
6	8	0.012	0.042	0.0045	1
6	9	0	0.208	0	0.978
6	10	0	0.556	0	0.969
9	11	0	0.208	0	1
9	10	0	0.11	0	1
4	12	0	0.256	0	0.932
12	13	0	0.14	0	1
12	14	0.1231	0.2559	0	1
12	15	0.0662	0.1304	0	1
12	16	0.0945	0.1987	0	1
15	18	0.1073	0.2185	0	1
18	19	0.0639	0.1292	0	1
19	20	0.034	0.068	0	1
10	20	0.0936	0.209	0	1
10	17	0.0324	0.0845	0	1

10	21	0.0348	0.0749	0	1
10	22	0.0727	0.1499	0	1
21	22	0.0116	0.0236	0	1
15	23	0.1	0.202	0	1
22	24	0.115	0.179	0	1
23	24	0.132	0.27	0	1
23	24	0.132	0.27	0	1
24	25	0.1885	0.3292	0	1
25	26	0.2544	0.38	0	1
25	27	0.1093	0.2087	0	1
28	27	0	0.396	0	0.968
27	29	0.2198	0.4153	0	1
27	30	0.3202	0.6027	0	1
27	30	0.3202	0.6027	0	1
29	30	0.2399	0.4533	0	1
8	28	0.0636	0.2	0.0214	1
6	28	0.0169	0.0599	0.065	1
14	15	0.221	0.1997	0	1
16	17	0.0824	0.1923	0	1

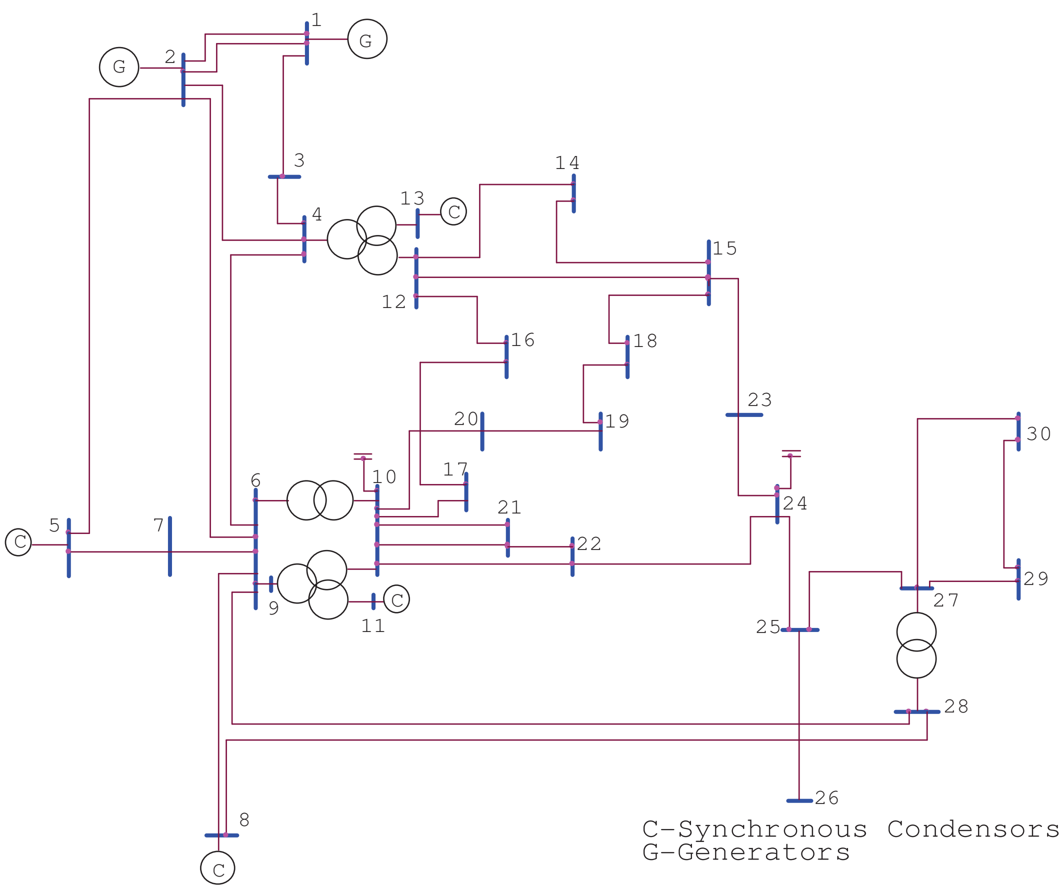

Figure A1 : IEEE 30-bus system

POWER SYSTEM LOAD FLOW SOLUTION USING FUZZY LOGIC

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Abstract – **One of the most significant problems in Power System Engineering is the fast solution of load flow problems under both normal and abnormal system conditions. Conventional methods exist for performing the load flow solutions. These include the Gauss Seidel and Newton Raphson methods. The fast decoupled method is a modified Newton Raphson method based on the observations that the active power changes affect primarily the voltage angle while the reactive power changes affect primarily the voltage magnitudes. To obtain the changes in the voltage angle and magnitude, an inverse calculation of the susceptance matrix is performed. This paper seeks to use a fuzzy logic controller to obtain these changes and hence reduce the time taken in performing this time-consuming procedure. Fuzzy logic is a convenient way to map an input space to an output space and proves to be a very powerful tool for dealing quickly and efficiently with imprecision and nonlinearity. The use of the fuzzified controller is tried out in the standard IEEE 2-bus system.**

***Index terms*- Load flow, Fuzzy logic controller, Fast Decoupled power flow method.**

I. INTRODUCTION

Conventional load flow solution methods normally encounter problems of nonlinear functions of arbitrary complexity and a long computation time that may not meet the demands of the very dynamic load flow problems. Also, imprecise data from the system would be very difficult to analyze using these methods.

As a result, determining the necessary course of action in case of a perturbation in the system would take longer hence compromising the stability of the system [1, 3, 4]. This problem can be solved if a faster method of solving the power flow problems of whichever complexity is adopted. In addition to improving the computation speed, the method should tolerate the imprecise data as well [2].

There are physical limitations to the amount of reactive power that can be drawn from a given bus. In a similar manner, the bus voltage magnitudes can only vary within a specified range. The phase angles for all the buses cannot exceed the critical value if a power system network is to maintain its stability.

All these factors are continuously varying for a given power system. The amount of both active and reactive power drawn varies with the time of day and the type of loads connected. Also, perturbations in the system are random and cannot be eliminated entirely even in a well designed power system [1]. Due to this fact, a fast method of monitoring all these variables and their effects has to be employed to ensure the specifications at all the buses are within limits and hence, the system is stable.

Power flow analytical tools are well recognized in solutions of stability analysis, AVR management and optimization. The basic requirement of a power flow program is to organize a set of input data describing the bus parameters, line parameters, bus injections and initial state variables. Conventionally, these inputs are crisp in nature. However, this may prove not to be practical as these parameters may be imprecise and uncertain. Ill-conditioned system data complicates the matter even further in computing the inverse matrix [1]. In such cases, the information needs to be qualitatively soft and natural.

The proposed fuzzy load flow method requires the repeated solution of load flow equations set through fuzzy logic control. The computational iterations will not terminate until the maximum real and reactive power mismatches are within the specified error margin. The active power mismatches per voltage angle and reactive power mismatches per voltage magnitude at the nodes are the crisp input values of the designed fuzzy load flow controller [5, 6].

The number and shapes of the fuzzy membership functions and the rules are selected from computational experience to minimize the computing time and number of iterations required for convergence of the solution. The calculations executed per iteration are greatly reduced in fuzzy load flow controllers compared to the fast decoupled load flow method. This reduces the computing time in arriving at a solution.

II. CONVENTIONAL POWER FLOW METHOD

The modified Newton-Raphson method is employed in this research paper. The power flow solution using this method is computed from the equations:

$$\left[\frac{\Delta P}{|V|}\right] = [-B][\Delta\delta] \quad \dots (1)$$

$$\left[\frac{\Delta Q}{|V|}\right] = [-B][\Delta V] \quad \dots (2)$$

From equations 1 and 2, the changes in the phase angles are calculated using the real power mismatches only while the changes in voltage magnitudes are computed using the reactive power mismatches only. This is the conventional fast decoupled power flow method.

[B] is symmetrical and with non-zero elements which are constant real numbers, exactly equal to the negative of the susceptances of the Y bus matrix. The state vector, V, is fixed. The whole calculation will terminate only if the errors of both these equations are within acceptable tolerances.

The conventional and modified methods are applied on the standard IEEE 2-bus system represented by figure 1.

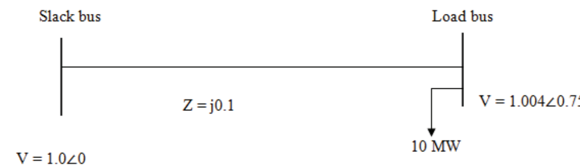


Figure 1: Standard IEEE 2-bus system.

I. ANALYSIS OF FUZZY POWER FLOW

Since for each iteration the state vector |V| is fixed, equations 1-2 can be simplified to:

$$[\Delta\delta] \quad = [-B]^{-1}[\Delta P] \dots (3)$$

$$[\Delta V] \quad = [-B]^{-1}[\Delta Q] \dots (4)$$

The fuzzy power flow equations for both active and reactive power mismatches are derived from equations 3-4 as equation 5.

$$\Delta X = B.\Delta Y \dots (5)$$

Equation 5 shows that the change in state vector, ΔY is directly proportional to state vector $\Delta X.$ The proposed method uses a fuzzy logic controller, FLC, to match the changes in the state vector input to the state vector output, as depicted in equation 6.

$$\Delta Y = fuzzy(\Delta X) \dots (6)$$

The fuzzy logic controller represented by equation 6 is illustrated schematically in figure 2.

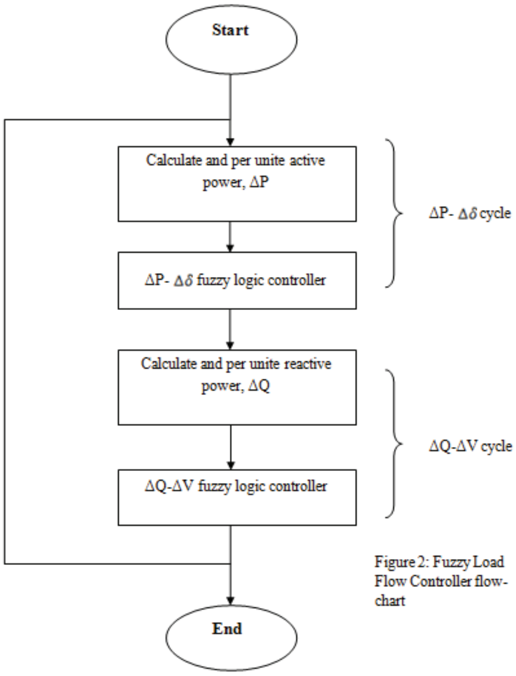


Figure 2: Fuzzy Load Flow Controller flow-chart

The power parameters ΔP and ΔQ are calculated and introduced to the P-δ FLC and Q-V FLC respectively. The FLCs generate the correction of the state vector ΔX namely, the correction of voltage angle $\Delta\delta$ for the P-δ cycle and the correction of voltage magnitude ΔV for the Q-V cycle.

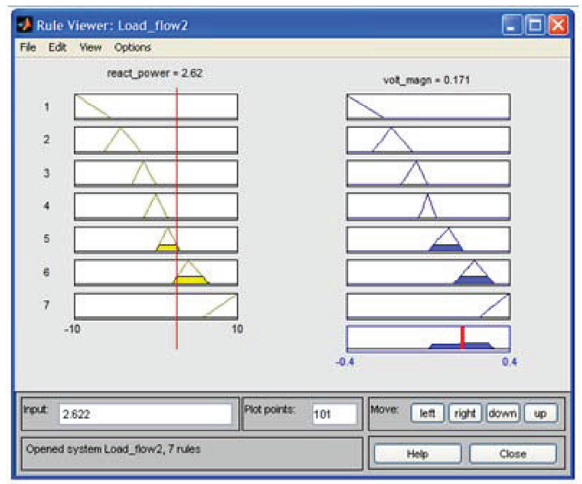
The principal components of the FLC in figure 1 are: fuzzification interface, a rule base, a process logic and defuzzification. The power parameters are selected as crisp input signals. The worst power parameters determine the range of scale mapping that transfers the input signals into the accompanying universe of discourse at each iteration.

The fuzzy rules are selected such that the changes in output state vectors are proportional to that in the state input vectors. This information is sent to the process logic which generates output fuzzy signals. The output fuzzy sets for each rule are then aggregated into a single output fuzzy set. Finally the resulting set is defuzzified, or resolved to a single number.

The centroid-of-area defuzzification strategy is adopted and the state vector updated for each output. No definite rule is available hence the number, range and parameters of the membership functions is heuristically selected but with the aim of minimizing overall computing time while ensuring that the solution converges.

I. SIMULATION RESULTS

A rule viewer developed for the reactive power-voltage magnitude controller is as shown in figure 3. An almost similar rule viewer applies to the active power-load angle controller except for the ranges of the variables.



A comparison of a bus-out load flow solution employing the conventional fast decoupled method versus the fuzzified fast decoupled method is as shown in tables 1 and 2.

Power Flow Solution by Fast Decoupled Method
Maximum Power Mismatch = 0.000412324
No. of Iterations = 2

Bus No.	Voltage mag.	Angle degree	Load MW	Load MVAR	Gen. MW	Gen. MVAR	Injected Mvar
1	1.000	0.00	0.00	0.000	9.959	0.135	0.000
2	1.000	-0.573	10.0	0.000	0.00	0.000	0.000
Total			10.0	0.000	9.959	0.135	0.000

Elapsed time is 0.203856 seconds.

Table 1: Power Flow Solution by Fast Decoupled Method

Power Flow Solution by Fuzzified Fast Decouple Method
Maximum Power Mismatch = 0.00940089
No. of Iterations = 7

Bus No.	Voltage mag.	Angle degree	Load MW	Load MVAR	Gen. MW	Gen. MVAR	Injected Mvar
1	1.000	0.000	0.000	0.000	9.060	0.134	0.000
2	1.000	-0.656	10.000	0.000	0.000	0.000	0.000
Total			10.000	0.000	9.060	0.134	0.000

Elapsed time is 0.107653 seconds.

Table 2: Power Flow Solution by Fuzzified Fast Decouple Method

III. CONCLUSION

Two fuzzy logic controllers are developed to match the active and reactive loads to the load angles and voltage magnitudes respectively.

The results from the simulation show that computation of load flow problems can be performed much faster if a fuzzy logic controller is employed while still ensuring convergence of the solution. The computation time is reduced in the proposed fuzzy logic controller compared to the conventional fast-decoupled method with all the other variables differing by only a small margin.

Therefore, this method of load flow solution can be developed and applied for any established system with more than two buses with an overall reduction in computation time of the solution.

IV. REFERENCES

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