Artificial Intelligence Technique for Identifying Proper Location & Size of Distribution Generation in Power Distribution System

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Abstract - There are numerous advantages of allocation of Distributed Generation (DG) in distribution systems. These advantages include decreasing power losses and improving voltage profiles. This paper presents a method for the optimal location and sizing Distributed generation in RDS by using ANN. In ANN, coding is developed to carry out the allocation problem, which is identification of location and size of DG. The effectiveness of the proposed methodology is demonstrated on the IEEE 33-bus radial distribution network using MATLAB software. After appropriate allocation of DG units, voltage profiles of most of the buses are increased significantly. The results also indicated that the total loss of the distribution network has reduced, and voltage stability conditions of buses are improved considerably.

Keywords - Distributed Generation (DG), Artificial Neural Network (ANN), Optimal location and sizing, Power loss, RDS

I. INTRODUCTION

Distributed or Distributed Generation refers to any electric power production technology that is integrated within distribution systems, close to the point of use. Distributed Generation (DG) refers to small electricity generation facilities ranging from few kWs to 50 MW, placed within the distribution system close to where the most power is consumed. DG placement in the distribution system is profitable. DG not only minimized the power loss of the distribution system also it improved the voltage profile.

There are a number of approaches proposed for placement and sizing of DG units. If sized and selected properly, DG can improve electrical conditions, such as improvement of voltage, loss reduction, relieved transmission and distribution congestion, improved utility system reliability and power quality in the distribution network, [1]. A second order algorithm with transformation of variables to optimally allocate DG resources in a meshed network. The convergence properties of the proposed algorithm have been examined with a six bus test system[2].A fuzzy-GA method to resolve dispersed generators placement for distribution systems with the objective to reduce power losses of distribution systems [3]. Analytical methods to determine the optimal location to place a DG in radial as well as networked systems to minimize the power loss of the system. The proposed method was tested on the IEEE 6- bus and 30-bus test systems[4]. A method for placement of DG units using continuation power flow analysis has been proposed by Hedayat et al. [5]. They have not studied about the size of DG units. Kashem et al. have discussed about optimal use of DG units to support voltage in distribution feeders [6].They have applied sensitivity analysis to determine appropriate location of voltage support DG units. A hybrid GA-OPF approach was proposed by Harrison [7] for finding optimal location for connecting a predefined numbers of DGs in a distribution network Jabr and Pal [8] presented an ordinal optimization (OO) method for specifying the locations and capacities of distributed generation (DG) such that a trade-off between loss minimization and DG capacity maximization is achieved. Acharya in[9] suggested a heuristic method to select appropriate location and optimal value of DG capacity for minimum real power losses of the system by calculating DG size at different buses.

In this paper provides the detailed analysis of optimal placement and sizing of DG in electrical power systems. The paper is organized as follows: At first, a voltage stability indicator (VSI) is developed from conventional power flow equation to determine the stability condition of buses. Then, a priority list is set up using VSI to allocate DG units. In the next section, artificial neural network (ANN) technique is used to determine the proper size of the DG units to ensure the permissible static voltage of each bus. After that, proposed methodologies tested on a 33-bus radial distribution network, and the impact of the DG units on static voltage profile is illustrated. The effectiveness of the proposed methodology is demonstrated on the IEEE 33-bus radial distribution network. Proposed methodology for the determination of appropriate size of DG units for desired voltage profile using ANN technique has emerged as a very fast and efficient tool.

II. PROPOSED METHOD

A. IEEE-33 Bus -

In IEEE-33 bus radial distribution system substation provides 12.66 KV voltage which will distributed to all 32 buses. From bus 1 to 2 total impedance of distribution system 0.0922 + j0.0470 per unit. The sectionalize switches (normally closed) are numbered from 1 to 32, Radial distribution system with 33 buses, three node (bus No. 2, 3, and 6), 5 looping and 5 branches. Load is not connected at bus number 8. The system is without distributed generation and feeder reconfiguration. In IEEE-33 bus system individual lines taken once at a time. The radial structure implies that there are five loops in bus system and one bus is connected to the source via exactly one path. IEEE-33 bus system having 100 MVA power rating and 12.66 KV voltage rating. In IEEE-33 bus system bus number 2 is connected with bus number 18 as well as bus number 3 is connected with bus number 22 also bus number 6 is connected with bus number 25 because total three path of distribution provided by IEEE-33 bus system as shown in below figure.

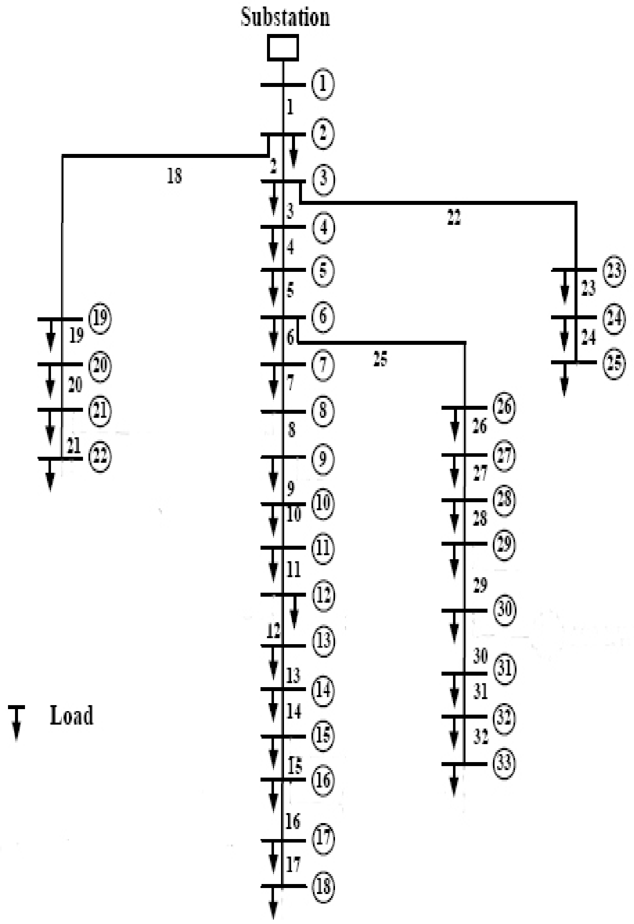

Figure 1: IEEE- 33 Bus System

B. Load Flow of Radial Distribution Networks –

A feeder brings power from substation to load points/nodes in radial distribution networks (RDN). Basically, the RDN total power losses can be minimized by minimizing the branch power flow or transported electrical power from transmission networks (i.e. some percentage of load are locally meeting by local DG). To determine the total power loss of the network or each feeder branch and the maximum voltage deviation are determined by performing load flow. The Forward/Backward Sweep Load Flow technique is used in this case. The impedance of a feeder branch is computed by the specified resistance and reactance of the conductors used in the branch construction. The Forward/Backward Sweep Load Flow method consist two steps (i) backward sweep and (ii) forward sweep.

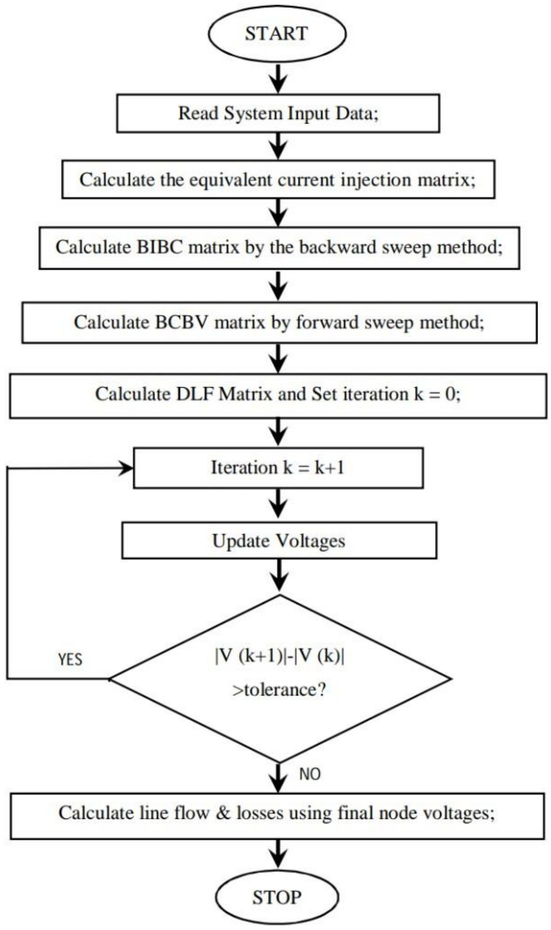

Figure 2: Flowchart for load flow solution for radial distribution networks.

C. ANN -

Artificial Neural Network (ANN) is one of AI Technique. It intended to simulate the behaviour of biological systems composed of “neurons”. ANNs are computational models inspired by an animal’s central nervous systems. An Artificial Neural Network is an information processing technique. It works like the way human brain processes information. ANN includes a large number of connected processing units that work together to process information. They also generate meaningful results from it.

ANN can be trained to generate control parameters for minimizing power losses and determining the optimal solution for DG implementation in the distribution network. For the purpose of ANN training, a training data set has to be generated. Selecting the amount and type of training data is extremely important since the wrong selection could reduce the learning ability of the ANN or even provide an incorrect solution. For better accuracy, all dependent parameters have to be taken into account.

For a particular bus, as the size of the DG unit is increased beyond its appropriate size, network losses start increasing rather than decreasing. So, appropriate size evaluation of DG is very significant. The use of ANN [10] is capable of indicating the best solution for a given distribution system. This is because of the advantage of high computation rate of three-layered feed forward ANN in approximating a complex nonlinear mapping. A feed forward ANN works on the basis of Artificial Neural networks (ANN).

D. DG Size and Location -

A feed forward ANN works on the basis of voltage stability indicator. Propagation of signal in only one direction from an input stage to an output stage through intermediate neurons. The number of hidden layer is chosen to match the complexity of the function. Error back propagation learning algorithm is used to train the ANN for the faster learning and reliable convergence. The error function chosen for the learning process is mean square error (MSE) of outputs. The appropriate size of a DG unit for a particular bus can be determined for desired voltage profile of that bus. With random change of DG unit at that bus, values of voltage magnitudes are determined from power flow solutions. Feed forward ANN is trained rigorously with DG size corresponding to voltage magnitudes at poor-voltage stable bus obtained from load flow solution. Then, for any required bus voltage, the appropriate size of the DG unit (MVA) for that particular bus is evaluated. The proposed methodology for the allocation and size evaluation of the DG units is shown in figure. In the flowchart of Figure 3, the iteration starts with calculating the VSI of each bus at base case of the network. After iterations, on view point of voltage profile improvement of buses beyond 0.90 p.u., the appropriate size and location of the DG units are obtained at modified network.

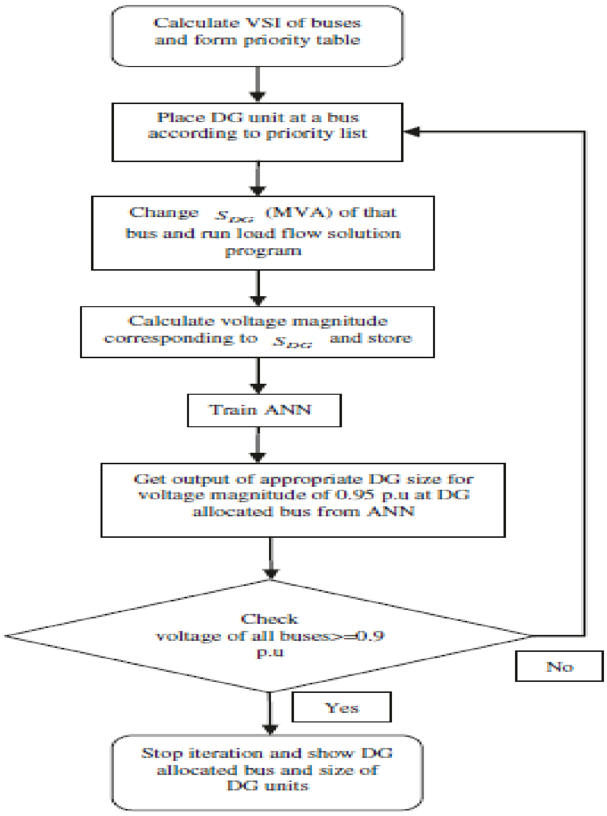

Figure 3: Flow chart How to find DG Size and location.

III. SIMULATION AND RESULTS

For the purpose of ANN training, a training data set has to be generated. Selecting the amount and type of training data is extremely important since the wrong selection could reduce the learning ability of the ANN or even provide an incorrect solution. For better accuracy, all dependent parameters have to be taken into account. Figure 4 obtained from the simulation of ANN model shows training set data at bus-33.

If well trained, an ANN can provide reasonable outputs for a new set of inputs enabling network training on a representative set of inputs with output correction. The training should be done on the largest possible set. Generally, the precision of ANN is increased by the larger training set with more input variables.

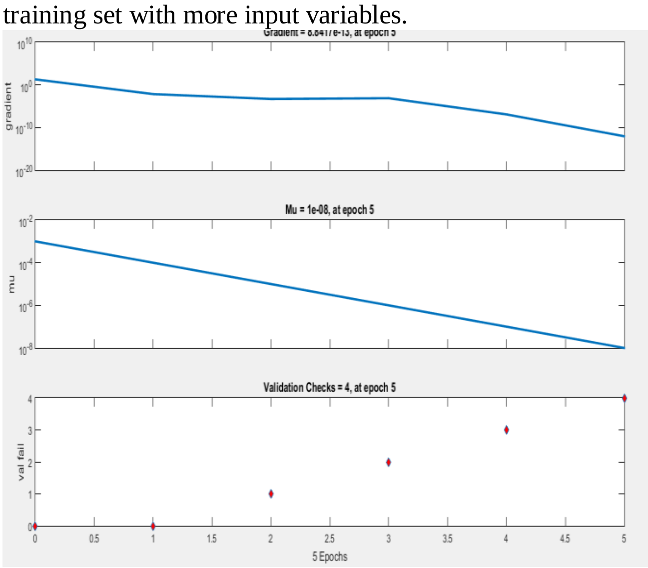

Figure 4: Gradient Training State

Figure 5 obtained from the simulation of ANN model shows Performance of ANN training at bus-33.Very low MSE (10-20) confirms the validation of the proposed model.

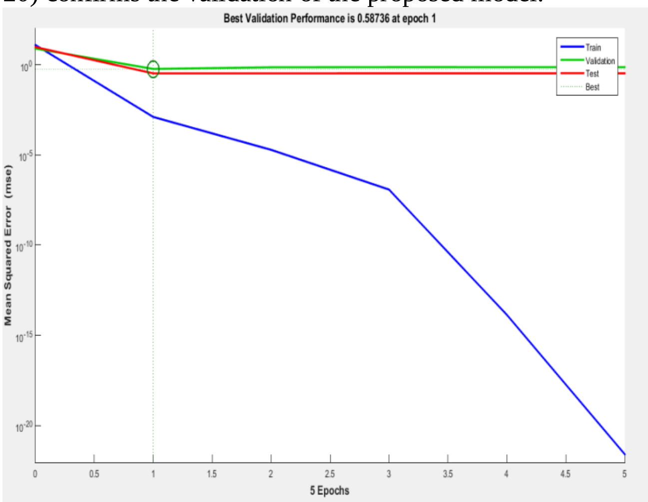

Figure 5: Performance of ANN training

Bus Voltages of IEEE-33 bus system with DG's at each buses

Table1: Bus Voltages of IEEE-33 bus system with DG1

Bus No.	**Bus Voltage (Vbus in pu)**	**Bus No.**	**Bus Voltage (Vbus in pu)**
1	1.0000	18	0.9036
2	0.9970	19	0.9965
3	0.9828	20	0.9929
4	0.9753	21	0.9922
5	0.9679	22	0.9915
6	0.9493	23	0.9792
7	0.9458	24	0.9725
8	0.9322	25	0.9692
9	0.9258	26	0.9474
10	0.9199	27	0.9449
11	0.9191	28	0.9334
12	0.9175	29	0.9251
13	0.9113	30	0.9216
14	0.9091	31	0.9174
15	0.9077	32	0.9164
16	0.9063	33	0.9162
17	0.9042		

Table2: Bus Voltages of IEEE-33 bus system with DG2

Bus No.	**Bus Voltage (Vbus in pu)**	**Bus No.**	**Bus Voltage (Vbus in pu)**
1	1.0000	18	0.9546
2	0.9991	19	0.9985
3	0.9958	20	0.9949
4	0.9964	21	0.9942
5	0.9974	22	0.9936
6	1.0004	23	0.9922
7	0.9969	24	0.9855
8	0.9832	25	0.9822
9	0.9768	26	0.9985
10	0.9709	27	0.9959
11	0.9701	28	0.9844
12	0.9685	29	0.9761
13	0.9623	30	0.9726
14	0.9600	31	0.9684
15	0.9586	32	0.9674
16	0.9572	33	0.9672
17	0.9552		

Voltages stability index

Table 3: Bus Voltages stability index of DG 1

Bus No.	**Voltage stability index (DG size)**	**Bus No.**	**Voltage stability index (DG size)**
1	1.0000	18	0.6686
2	0.9994	19	0.9383
3	0.9846	20	0.9859
4	0.9314	21	0.9718
5	0.9033	22	0.9691
6	0.8739	23	0.9149
7	0.8119	24	0.9191
8	0.7987	25	0.8944
9	0.7545	26	0.8173
10	0.7343	27	0.8055
11	0.7161	28	0.7959
12	0.7134	29	0.7585
13	0.7085	30	0.7325
14	0.6899	31	0.7211
15	0.6830	32	0.7082
16	0.6787	33	0.7054
17	0.6746		

Table 4: Bus Voltages stability index of DG 2

Bus No.	**Voltage stability index (DG size)**	**Bus No.**	**Voltage stability index (DG size)**
1	1.0000	18	0.8323
2	1.0075	19	0.9888
3	1.0363	20	0.9940
4	1.0135	21	0.9799
5	1.0172	22	0.9771
6	1.0701	23	0.9963
7	1.0005	24	0.9686
8	0.9830	25	0.9430
9	0.9326	26	1.0065
10	0.9089	27	0.9931
11	0.8885	28	0.9801
12	0.8851	29	0.9369
13	0.8785	30	0.9071
14	0.8572	31	0.8938
15	0.8492	32	0.8792
16	0.8442	33	0.8760
17	0.8392		

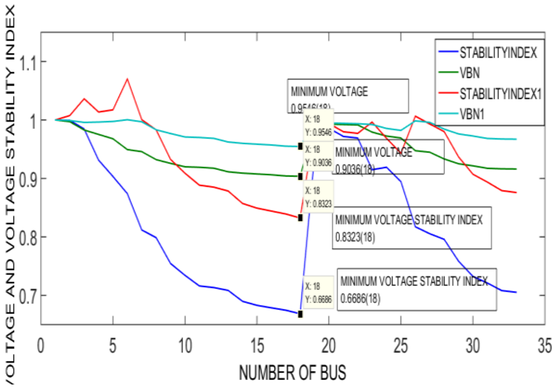

Figure 6: Voltage & Voltage Stability Index

Performance of 33 Bus system with DGs

Total real demand is	3715.0000 kW
Total reactive demand is	2295.000 kVAR
Minimum voltage with DG 1 is 0.9036 pu at Bus	18.0000 (location)
Minimum voltage with DG 2 is 0.9546 pu at Bus	18.0000 (location)
Minimum Voltage stability index DG 1 is 0.6686 pu at bus	18.0000
i.e size of DG 1 is	0.6686 pu
Minimum Voltage stability index DG 2 is	0.8323 pu at bus 18.0000
i.e size of DG 2 is	0.8323 pu
Total real power loss base case	0.503 pu
Total real power loss index with DG 1 placement case	0.178 pu
Total real power loss index with DG 2 placement case	0.134 pu

IV. CONCLUSION

ANN method to find the optimal DG sizing and placement in a distribution network was proposed, DG placement in the distribution system is profitable. DG not only minimized the power loss of the distribution system also it improved the voltage profile. In ANN, coding is developed to carry out the allocation problem, which is identification of location and size of DG. The effectiveness of the proposed methodology is demonstrated on the IEEE 33-bus radial distribution network. The simulation results shows that reduction of power loss in distribution system is possible and all node voltages variation can be achieved within the required limit if DG are optimally placed in the system.

V. REFERENCES

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