

Reliability Improvement of Distribution System by Optimal Placement of Distributed Generator Using Genetic Algorithm and Neural Network

¹S Chandrashekhar Reddy, ²P.V.N.Prasad and ³A.Jaya Laxmi

¹Assoc.Professor, ^{2,3}Professor,

¹Christu Jyoti Institute of Technology & Science, Jangaon, Warangal, Andhra Pradesh, India

²University College of Engineering, Osmania University, Hyderabad, India,

³J.N.T.U.H College of Engineering, J.N.T.University, Hyderabad, India

¹Chandureddy6@yahoo.com

Abstract— Distributed generator (DG) is now commonly used in distribution system to reduce total power loss and to improve the power quality and reliability of the network. The major task of connecting DG is to identify their optimal placement in the system and to evaluate the amount of power to be generated by DG. By considering this objective, a hybrid technique using Genetic algorithm and Neural-network is proposed in this paper. By placing DG at optimal location and by evaluating generating power based on the load requirement then the number of generators in the network increases and so that different generator states are possible for a particular load condition. The total power loss in the system can be minimized without affecting the voltage stability of the buses. Reliability is old concept and a new discipline. Reliability is, and always has been, one of the major factors in planning, design, operation and maintenance of electric power system. Reliability of an electric supply system has been defined as the probability of providing the user with continuous service of satisfactory quality. Reliability prediction is a method of quantitatively stating what is expected to occur and can be used to indicate the relative merits of alternate design proposals with regard to a predetermined level of performance adequacy. Here considered reliability parameters are Loss of Load probability (LOLP) and Expected Energy Not Supplied (EENS). The LOLP and EENS evaluations are based on peak load consideration with load model is considered as straight line. The probability of load exceeding the generating capacity has also been considered in LOLP evaluation. The proposed method is tested for IEEE 30 bus system, by connecting suitable size of DG at the optimal location of the system. The results showed a considerable reduction in the total power loss in the system, improved voltage profiles of all the buses and Reliability parameters.

Keywords—DG, Genetic Algorithm, Neural network (NN), LOLP and EENS.

I. INTRODUCTION

In recent years, a lot of work has been done in the electric power system infrastructure and market using Distribution

Generation. It is a small-scale power generation facility that is connected to in the distribution system. While on the other hand to reduce the cost of service, the DGs use several modular technologies which are located around a utility's service area [1]. Distributed generation is a technique, which minimizes the amount of power loss which occurs during transmission by generating the power very close to load centre or maybe even in the same building [2]. Nowadays, the usage of DGs in the power distribution has become popular and is increasing at a fast rate. Some of the major advantages that are present in installing of DG units in distribution level are peak load saving, enhanced system security and reliability, improved voltage stability, grid strengthening, reduction in the on-peak operating cost, reduction of network loss etc. [3,4]. The main motive behind applying DGs in the power distribution are an energy efficiency or rational use of energy, deregulation or competition policy, diversification of energy sources, availability of modular generating plant, ease of finding locations for smaller generators, shorter construction time and lower capital costs for smaller plants, and its proximity of the generation plant to heavy loads, which can reduce the transmission costs [5].

Different technologies are used for DG sources such as photo voltaic cells, wind generation, combustion engines, fuel cells and other types of generation from the resources that are available in the geographical area [6,7]. Usually, DGs are integrated with the existing distribution system and lot of studies are done to find out the best location and size of DGs to produce utmost benefits [8,9]. The main characteristics that are considered for the identification of an optimal DG location and size are the minimization of transmission loss, maximization of supply reliability, maximization of profit of the distribution companies (DISCOs), etc [10]. Due to extensive costs, the DGs should be allocated properly with optimal size to enhance the system performance in order to

minimize the system loss as well as to get some improvements in the voltage profile while also have to maintain the stability of the system [11]. The effect of placing a DG on network indices will differ on the basis of its type and location and load at the connection point [12].

In this paper, the optimal placement of DG and amount of power being generated by DGs are computed using genetic algorithm and neural network. Here, a two stage genetic algorithm and one stage neural network which are used to identify the optimal placement of DGs and amount of power to be generated is presented. By using this method, the total power loss in the system is reduced and voltage in the system is improved and due to this the reliability of the system also increases. The rest of the paper is organized as follows: Section 2 briefly reviews the recent related works; Section 3 describes the proposed technique with sufficient mathematical models and illustrations; Section 4 explains the Reliability Evaluation; Section 5 discusses the implementation of results and Section 6 concludes the paper.

II. RELATED RESEARCHES: A REVIEW

Some of the researches related to reliability planning of power system are discussed below.

Billinton *et.al.*[13], Endreyni *et.al.*[14], Dhilon and Singh *et.al.*[15] Bansal *et al*[16], Saket and Bansal *et.al.*[17], Wang and Billinton *et.al.*[18], Li and Billinton *et.al.*[19] and Wang *et al*[20] have been discussed. Loss of load probability (LOLP) is one of the most commonly used index for planning generation capacity. This index is generally obtained by convolving generation model with a load model. The generation system model used is known as capacity outage probability table. The traditional and well accepted algorithms for generation system modeling based on recursive procedures. Such procedures are theoretically accurate for calculating the discrete probability distribution of the generation capacity outages. These discrete probability distributions are the outcome of (i) failure density functions, (ii) repair density functions, and (iii) derived availability and unavailability functions. Moreover, in such modeling the failure and repair distribution functions of each unit is assumed to be independent. Hence, for identical units binomial distribution is adopted. Recently many researchers have used continuous probability distribution as an approximation for capacity outage probability distribution

Alavi-Sereshki and Singh *et.al.*[21] have presented a generalized approach to use continuous distribution approximation for generating capacity reliability evaluation. Gram-Charlier's expression is shown to have a special of this formulation. Potential of this method lies in the fact that any continuous distribution function can be examined for its suitability for modeling generation systems or in fact any discrete distribution functions. LOLP distribution is based on two and three parameters Gamma distribution functions. Loss

of load expression in days per year has been calculated based on daily peaks.

Tian *et al.*[22] *approach* is based on Laguerre polynomials, which uses Gamma distribution as the basic building blocks.

Saket *et al.*[23] have presented a methodology for evaluating the probability of failure based on continuous load and generation model at safety factor considerations.

Kim and Singh[24] have been developed A frequency and duration approach for generation reliability evaluation using methods of stages. Their approach postulates multi parameter distribution for the probability and frequency of generating capacity outages and parameters of these distributions are obtained from the generating unit parameters by using the moment matching techniques.

Malik *et al*[25] have modeled adequately pumped storage units and used proper estimates of their load leveling benefits in generation capacity planning. The technique used is frequency and duration approach coupled with the equivalent load duration curve method.

III. RELIABILITY IMPROVEMENT OF DISTRIBUTION SYSTEM BY OPTIMAL PLACEMENT OF DG

The optimal placement of DG units on the buses of distribution network at minimum power loss and the amount of power to be generated by these units is the main objective. By fixing DGs at suitable locations and generating power based on the load requirement, the quality of power of the system can be increased. By considering the above problem, a new method is proposed for optimal placement of DGs and computing the amount of power to be generated by DGs using Genetic algorithm and Neural-network. The proposed method consists of three stages. In the first stage, Genetic algorithm is used to generate the training dataset for various number of DGs to be connected in the system; in the second stage Neural network is used to identify the best location for the given number of DGs to be connected in the system and in the third stage Genetic algorithm is used to compute the amount of power to be generated by the DGs to reduce the power losses. The three-stage process is shown in Figure 1.

Initial step for identification of optimal locations of DGs is computation of power flow between the buses. Power flow between the buses is calculated using Newton-Raphson method. It is the commonly used method for load flow calculation because it has the advantage of lesser number of iterations, when compared to other methods. The real and reactive power flows in the buses mainly depends on voltage and angle values and are computed using the Eq. (1) and Eq. (2)

$$P_i = \sum_{k=1}^N V_i \times V_k (G_{ik} \times \cos \theta_{ik} + B_{ik} \times \sin \theta_{ik}) \quad (1)$$

$$Q_i = \sum_{k=1}^N V_i \times V_k (G_{ik} \times \sin \theta_{ik} - B_{ik} \times \cos \theta_{ik}) \quad (2)$$

where, N is the total number of buses, V_i & V_k are the voltage at i^{th} bus and k^{th} bus respectively, θ_{ik} is the angle between i^{th} bus and k^{th} bus and G_{ik} & B_{ik} are the values of conductance and susceptance respectively. After calculating the real and reactive power flow between the buses, the total power losses in the system can be computed using Eq. (3).

$$P_{loss} = \sum_{i,j=1}^N \text{Real}[Conj((V_m(i)) \times (V_m(j))) \times Y_{ij} \times B] \quad (3)$$

where, V_m is the voltage magnitude, Y_{ij} is the Y-bus matrix and B is the base MVA.

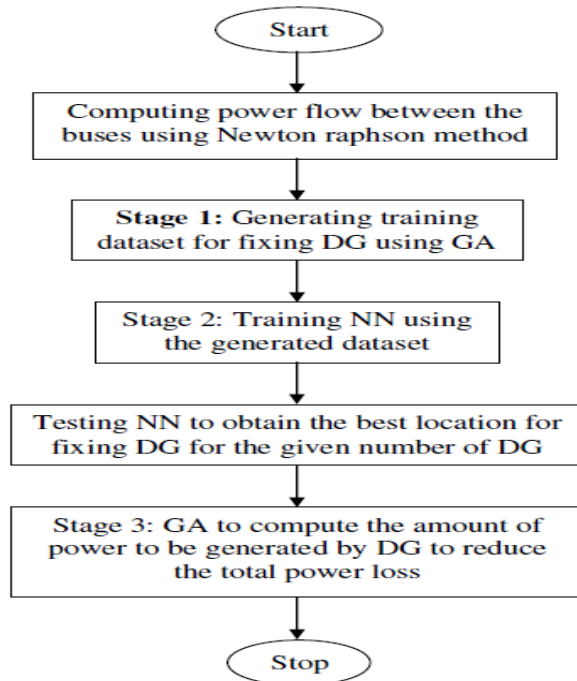


Figure 1. Overall process takes place in the proposed method

The Y-bus matrix mainly depends on the values of resistance and reactance. After computing the total power loss in the system, the suitable locations needed to be identified for fixing the DGs is obtained using GA and NN and the amount of power to be generated by DG is computed by GA. The initial process of identifying the buses which satisfy the active and reactive power constraints is discussed using the following Genetic algorithm. The process that takes place in the proposed method consists of: (i) Generating training dataset using GA (ii) Neural-network to identify optimal placement of DGs (iii) Computing power to be generated by DG. This process is discussed in the following sections.

A. First Stage: Generating training dataset using GA

The various possible optimal placements of DGs in the system is identified using Genetic algorithm which consists of five sub-stages, namely, generation of initial chromosomes, fitness function, crossover operation, mutation operation and termination. The first step in Genetic algorithm operation is initializing the chromosome. Initially the number of input and output variables and the range of each variable are identified. In the present method, there are one input and three output genes. The input gene is the total number of DGs to be connected in the system and the output gene is the possible locations of connecting DGs and their corresponding real and reactive powers. The real and reactive powers are randomly generated within a certain power limits. The constraints of active & reactive powers of DG units are shown in Table 1.

Table I. Active and Reactive Power Constraints

Constraints	Maximum	Minimum
Active Power	10.0 MW	0.0 MW
Reactive Power	5.0 MVAR	0.0 MVAR

Fitness function used in the proposed method is total power loss. The fitness function is calculated for the entire chromosomes generated in the above stage and the initial chromosome is ordered based on reduction of total power loss. The crossover operation is done based on the crossover rate. By applying crossover between two parent chromosomes, a new chromosome is generated which is the combination of two parent chromosomes. This crossover operation is applied for all the chromosomes, so that one can obtain a new set of chromosomes. Then the fitness function using Eq.3 is applied for these chromosomes and arranged based on lowest total power loss.

The mutation is done based on the mutation rate by randomly selecting the genes in the chromosome to obtain a new set of chromosomes. In this stage, the best chromosome is selected based on the fitness function. The above process is repeated until it reaches the maximum number of iterations.

After completing the process, a best set of chromosome is obtained based on reduction in power loss. The best set of chromosome obtained is the optimal placement for connecting one DG to the system. The above process is repeated by increasing the total number of DGs to be connected as two so the output genes become six. From this Genetic algorithm, best set of chromosomes for placing one and two number of DGs in the system can be obtained. After generating training

dataset, the next step is to train the Neural-network using the above generated training dataset.

B. Second Stage: NN to identify optimal placement of DGs

The Neural-network is used for identifying the optimal placement of DGs for the given number of DGs to be connected. NN is used to select the best location from the few locations computed in the first stage, which satisfy the active and reactive power constraints. Usually, Neural-network consists of two stages, namely training stage and testing stage. In the training stage, the network is trained based on the training dataset and in the testing stage, if the number of DGs to be connected as input, it gives the best location of installation of DGs in the system.

Neural network training consists of three layers, namely input layer, hidden layer and output layer. Here input layer consists of x layers, hidden layer consist of n layers and output layer consists of $3x$ layers. The configuration of Neural-network used in the proposed method is shown in Fig 2. In the proposed method, the network is trained based on back propagation algorithm.

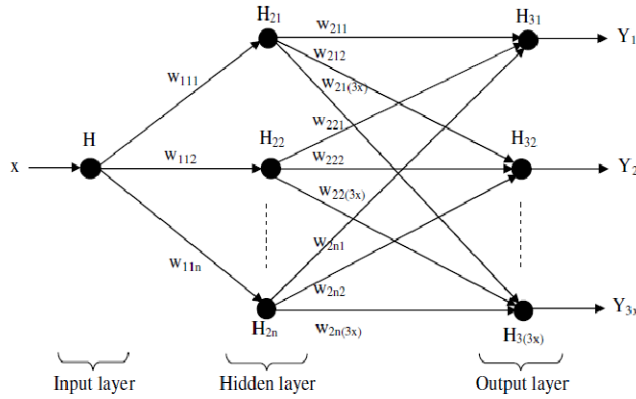


Figure 2. Neural Network

The steps for training the Neural-network are: (i) Initialize the input weight of each neuron (ii) Apply the training dataset to the network. Here, x is the input to the network and $Y_1, Y_2, \dots, Y_{3x}$ are the outputs of the network. Eq. (4), Eq. (5) and Eq. (6) represent the activation functions performed in the input and output layers. (iii) Adjust the weights of all neurons. (iv) Determine the optimal placement of DGs to be connected.

$$Y_1 = \sum_{r=1}^n W_{2r1} Y_1(r) \quad (4)$$

$$Y_2 = \sum_{r=1}^n W_{2r2} Y_2(r) \quad (5)$$

$$Y_{(3x)} = \sum_{r=1}^n W_{2r(3x)} Y_{(3x)}(r) \quad (6)$$

Where

$$Y(r) = \frac{1}{1 + \exp(-W_{11r} \cdot x)}$$

In the testing stage, if the total number of DGs to be connected in the system is given as input, it gives the output as optimal placement of DGs and their real and reactive powers. The next process is to identify the power to be generated by the corresponding generator to reduce the total power loss in the system.

C. Third Stage: Computing DG Power generation using GA

The amount of power to be generated by each generator is computed using GA in this stage, after obtaining optimal location of DGs in the second stage. The initial chromosome is taken from the output of neural network and the real and reactive power variables are changed. The real and reactive power values are randomly generated within a certain power limit for N chromosomes. Then for this power values, the total power loss in the system is computed in the evaluation stage and the chromosomes are ordered based on the total power loss.

Then crossover operation is applied to the above set of chromosomes with a crossover rate and so a new set of chromosomes are obtained and for that newly generated chromosome, fitness function is computed and arranged based on the total power loss. After applying crossover operation, then mutation operation is applied with a mutation rate. After completion of mutation, the termination process is executed. In the termination process, the real and reactive power with lowest total power loss is taken as the best power values to be generated by the DGs. By fixing DGs in the load bus with power generation, the total power loss reduces and the bus voltages remain stable, indicating improvement of power quality of the system.

IV. RELIABILITY EVALUATION

Reliability of the meshed distribution system can be evaluated before and after placement of DG based on the mainly two parameters such as Loss of Load Probability (LOLP) and Expected Energy Not Supplied (EENS)

A. Evaluation of LOLP

The capacity and load models are essentially merged using a suitable analytical technique to obtain a reliability index. Various load models very often used in reliability study [13] are:

1. Constant Load: This indicates that load remains constant throughout the period of study. This is a very simplified model of load and is not true especially for modern large power network, which is interconnected, and possesses very diversified loads.

2. Load Having Normal Distribution: It includes loads, which have variations around constant mean. Applicability of such loads can be where isolated system needing a specific or non diversified load pattern.

3. Load Duration Curve: This is one of the most practical load model used in practice to evaluate LOLP index. It is constructed from chronological daily load curve.

4. Two Level Representation of Daily Load: In two levels daily load duration curve, which is a cumulative curve of daily peak loads, the variation of load within a day are not recognized in it. Hence, LOLP is a crude approximation of system failure probability and, hence, system failure frequency is not calculated using load duration curve. For system failure frequency calculations a two level load representation is used and Markov modeling is used to represent transition of load from one load level to another. It is assumed that low load is always same every day and designated as Lo. The peak load 'Li' vary daily and may occur in random sequence with relative frequency of occurrence. The mean duration t_i of the peak is described by the exposure factor $e = t_i / do$. Where 'do' is the length of the load cycle typically may be hours. The factor 'e' is considered the same every day, its magnitude lies between 0 and 1. It has been observed that results are not much sensitive to the value of 'e'.

Loss of Load probability has been evaluated with more realistic model as load duration curve as shown in Figure 3. The generation system model used is known as capacity outage probability table [13]. The traditional and well accepted algorithms for generation system modeling based on recursive procedures. Such procedures are theoretically accurate for calculating the discrete probability distribution of the generation capacity outages. The LOLP has been evaluated for a load model as load duration curve as a straight line load duration curve shown in Figure 4 (based on curve fitting technique)

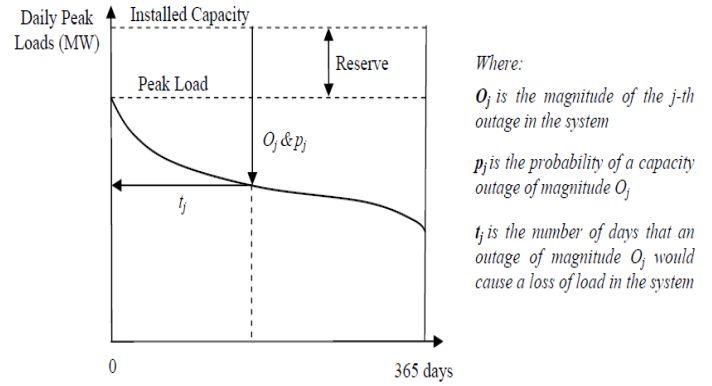


Figure 3. LOLP Calculation using Load Duration Curve

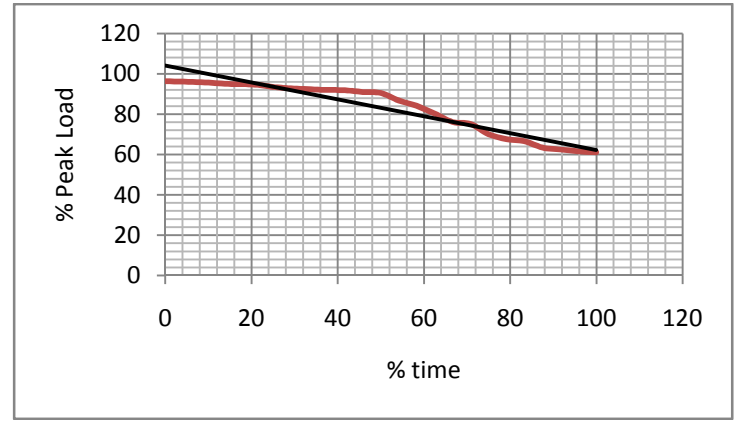


Figure 4. Load duration curve as straight line

LOLP can be calculated considering the daily peak loads for 1 year duration or sometimes on each hour's load for a 24 hours day. Therefore, the same system may have two or more values of LOLP depending on how the calculation is being done. The mathematical formula for the calculation of LOLP is shown in Equation 7.

$$LOLP = \sum_j P[C_A = C_j] \cdot P[L > C_j] = \sum_j \frac{p_j t_j}{100} \quad (7)$$

Where,

L	expected load
C _A	available generation capacity
C _j	remaining generation capacity
P _j	probability of capacity outage
t _j	percentage of time when the load exceeds C _j

It must be noted that an LOLE expectation index is more often used than the LOLP probability index in practical applications. The relationship between LOLE and LOLP is shown in Eq. 8

$$LOLE = LOLP * T \quad (8)$$

Where

$T=365$ days (if the load model is an annual continuous load curve with day maximum load; the LOLE unit is in days per year).

$T=8760$ hours (if the load model is an hourly load curve; the LOLE unit is in hours per year).

A level of LOLP is normally set and to be use as a reliability criteria for generation capacity planning. A common practice was to plan the power system to achieve an LOLP of one-day-in- ten-years or less. This does not mean a full day of shortages once every 10 years, but refers to the total accumulated time of shortages that should not exceed one day in 10 years or equivalently 0.0274% of a day.

B. Loss of Energy

Loss-of-energy method is another measure for generation reliability assessment. The measure of interest in this case is the ratio of the Expected Energy Not Served (EENS) during some long period of observation to the total energy demand during the same period. A mathematical formula for the Expected Energy Not Served (EENS) or Loss of Expected Energy (LOEE) calculation is shown in Equation 9.

$$LOLE = EENS = \sum_k E_k p_k \quad (9)$$

E_k is energy not supplied due to a capacity outage O_k
 P_k is Individual probability of the capacity outage O_k

The value obtained will have a unit of MWh/year and is also known as the Loss of Energy Expectation (LOEE) since it is an expected value rather than a probability. Similar to the loss-of- load method, a load duration curve can be used to determine the LOEP for installed capacity evaluation. Any capacity outage exceeding the reserve will result in load interruption and energy curtailment. The energy not served, E_k , is the shaded area shown under the load duration curve in Figure 5. LOEE can be calculated from Equation 9. In some ways, the loss of energy index gives a more real representation of the system than the LOLP index [14]. It will show the severity of an event by giving a higher value for more serious events than for marginal failures, even if their probabilities and frequencies are the same. However, the true loss of energy cannot be accurately computed on the basis of the cumulative curve of daily peaks As a result, the LOEP index is seldom used for reliability evaluations of for Generation capacity planning.

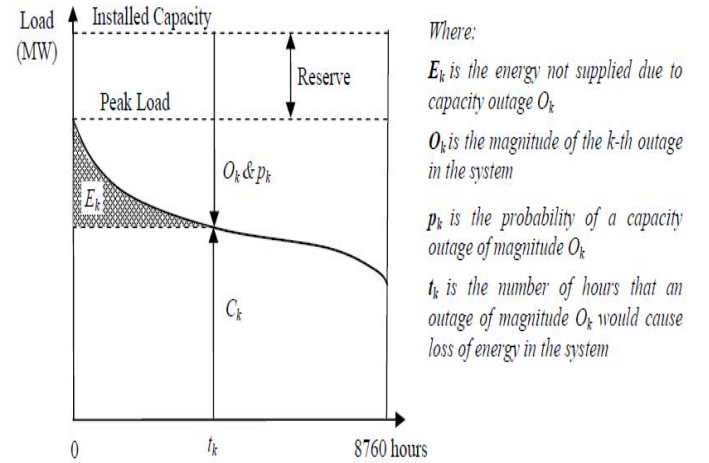


Figure 5. LOEE Calculation using Load Duration Curve

V. RESULT AND DISCUSSIONS

The proposed method is implemented in MATLAB 7.11 for IEEE 30 bus system and is shown in Fig 6. In the test system, bus 1 is considered as the slack bus and the base MVA of the system is 100 MVA. Buses 2, 13, 22, 23 and 27 are generator buses and remaining all other buses are load buses. Table 2 shows the active & reactive powers, power factor and power loss after the installation of DG units.

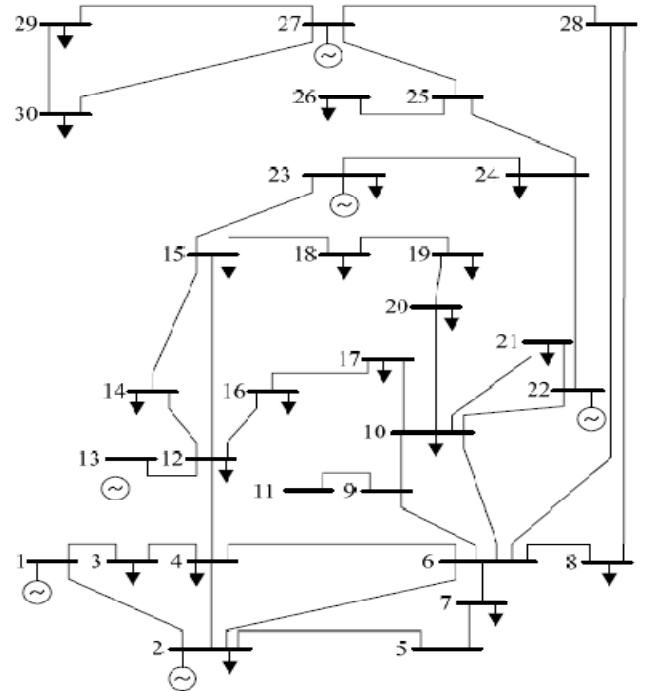


Figure 6. IEEE 30 Bus System

Table II. Power Loss with Installation of DG Sets

No. of DGs	DG Bus No.	Active Power of DG (MW)	Reactive Power of DG (MVAR)	Power Factor of DG	Total Power Loss (MW)	% Reduction of Power Loss
Zero	-	-	-	-	10.563	-
One	5	9.9505	1.4230	0.990	9.3717	13.3%
Two	7	9.8020	1.1669	0.993	8.6876	19.6%
	21	9.6635	4.1939	0.922		
Three	18	9.1255	3.2840	0.950	8.2197	24.0%
	26	8.4990	0.5604	0.998		
	30	9.9800	3.1268	0.954		

From Table 2, it is clear that the power loss in the system reduces after connecting DGs in the system. The power loss in the system without connecting DG is 10.563 MW. But after connecting one DG, the total power loss is reduced by 13.3%. In this case, the best location obtained from the present method is bus number 5 and power generated by that DG is 9.9505 MW. After connecting two DGs in the system, the optimal locations obtained are bus numbers 7 & 21 and the power generated by those DGs are 9.802 MW & 9.6635 MW respectively. The total power loss in the system is reduced to 8.6876 MW i.e., reduced by 19.6%. When three DGs are connected in the system, the best placement obtained are bus numbers 18, 26 & 30 and the power generated by DGs are 9.1255 MW, 8.499 MW & 9.98 MW respectively, and the total power loss is reduced to 8.2197 MW. Thus, there is 24% reduction of power loss with three DGs when compared to without DG in the system. All the DGs are found to be operating at good power factors between 0.922 and 0.998. It can be seen that after connecting DGs in the system, the voltages in the buses remained stable well within the margins. The maximum and minimum voltages are 1.082 per unit and 1.01 per unit respectively. Compared with the voltage of the slack bus (1.06 per unit), the upper and lower percentage variations of all the other bus voltages are 5.1% and -2.1% respectively for the three cases of DG installations. These variations are shown in Fig. 7. Also there are no changes in the voltages at the buses 1, 5, 8, 11 and 13. Hence, after connecting DG units in the system, the total power loss is reduced considerably and bus voltages remained stable within permissible limits.

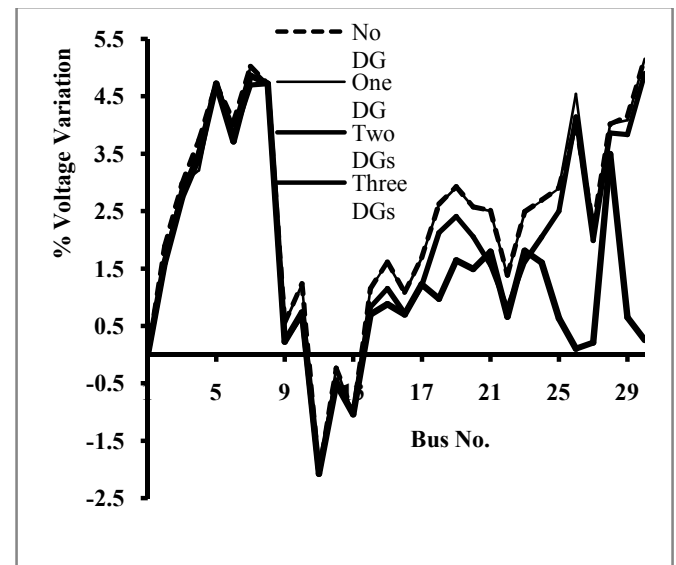


Figure 7. Percentage Variations of Bus Voltages Compared with Slack Bus Voltage

In this method, 50 iterations have been performed to identify the amount of power to be generated by DGs and also to evaluate the total power loss. The variation of power loss reduction with number of iterations for the installation of one DG and two DGs are shown in Fig. 8 & Fig. 9. Table 3 shows the performance of reliability parameters before and after connecting DG units.

VI. CONCLUSION

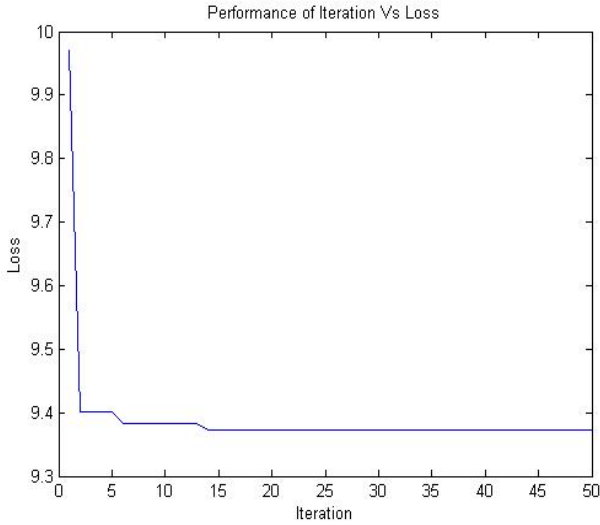


Figure.8. Loss reduction in each iteration for one DG installation.

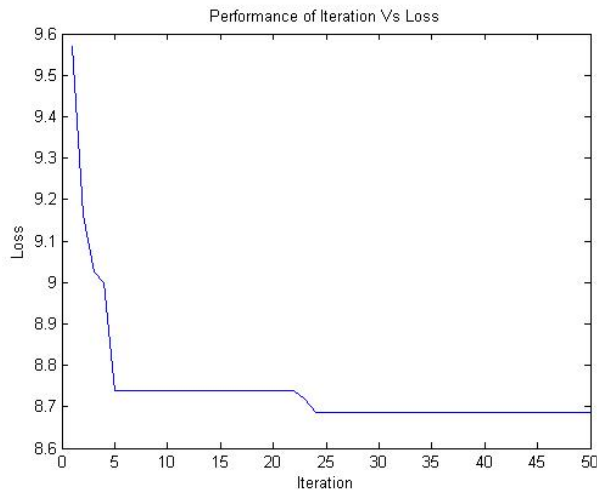


Figure 9. Loss reduction in each iteration for two DG installation.

In this paper, optimal locations of DG units were computed for IEEE 30 bus system using GA and NN methods at minimum power loss. In the first stage GA is used to find the locations which satisfy the active and reactive power constraints. In the second stage NN is used to obtain the best location of DGs at minimum power loss and in the third stage generation capacities of DGs were evaluated using GA. The optimal locations for DG installations are bus 5 for one DG, buses 7 & 21 for two DGs and buses 18, 26 & 30 for three DGs. The total power loss without connecting a DG was 10.809 MW. When one DG is connected in bus 5 with 9.9505 MW power generations, the total power loss was 9.3717 MW. With two DG installations connected to buses 7 & 21 generating 9.802 MW and 9.6635 MW respectively; the total power loss was reduced to 8.6876 MW. After connecting three DGs in buses 18, 26 & 30 with respective power generations of 9.1255 MW, 8.499 MW & 9.98 MW, the total power loss was reduced further to 8.2197 MW. Thus there is a considerable reduction of power loss from 13% to 24% (from 1.4373 MW to 2.5893 MW) with the installation of DG units when compared with the system without DG. The Reliability parameters of LOLE and EENS values before connecting DG was 157.12 hrs/year and 255.42 Mwh/year respectively and after connecting one DG above values are reduced to 121.08 hrs/year and 237.09 Mwh/year and after connecting two DGs reliability indices further reduced to 98.06 hrs/year and 220.12 Mwh/year respectively. Hence there will be a reduction in the LOLE and EENS indicates improvement in the performance of reliability parameters. Thus there is a considerable percentage improvement in LOLE and EENS as 37.58% and 13.98 % respectively. In all the above three cases, the voltage profile of the buses remained stable within tolerable limits and the power factor of the DGs is maintained at more than 0.92. From the results, it can be concluded that the proposed method can be used effectively to find the optimal location of buses for installing DG sets in the system network to minimize total power loss maintaining the bus voltages within permissible margins. Thus there is considerable improvement in power loss and reliability.

Table III. Performance of Improvement in Reliability Parameters

No. of DG	LOLE in hrs/year	Percentage Improvement in LOLE	EENS in Mwh/year	Percentage Improvement in EENS
No DG	157.12		255.42	
One DG	121.08	22.93	237.09	7.26
Two DG	98.06	37.58	220.12	13.98

REFERENCES

- [1] Ramalingaiah Varikuti and M.Damodar Reddy : Optimal Placement of DG Units using Fuzzy and Real Coded Genetic Algorithm. Journal of Theoretical and Applied Information Technology, Vol. 7, No. 2, pp. 145-151(2009)
- [2] Wichit Krueasuk and Weerakorn Ongsakul : Optimal Placement of Distributed Generation using Particle Swarm Optimization. In Proceedings of Power Engineering Conference in Australasian Universities, Australia, (2006)
- [3] M.F.Kotb, K.M.Shebl, M. El Khazendar and A. El Hussein : Genetic Algorithm for Optimum Siting and Sizing of Distributed Generation. In Proceedings of 14th International Middle East Power Systems Conference, pp. 433-440, Egypt, (2010)

- [4] Naveen Jain, S.N. Singh and S.C. Srivastava : Particle Swarm Optimization Based Method for Optimal Siting and Sizing of Multiple Distributed Generators. In Proceedings of 16th National Power Systems Conference, Osmania University, Hyderabad, pp. 669-674, (2010)
- [5] Amin Hajizadeh, Ehsan Hajizadeh: PSO-Based Planning of Distribution Systems with Distributed Generations : International Journal of Electrical and Electronics Engineering, Vol. 2, No. 1, pp. 33-38, (2008)
- [6] Deependra Singh, Devender Singh, and K. S. Verma : GA based Optimal Sizing & Placement of Distributed Generation for Loss Minimization. International Journal of Electrical and Computer Engineering, Vol. 2, No. 8, pp. 556-562, (2007)
- [7] Rashid H. Al-Rubayi and Azhar M. Alrawi : Optimal Size and Location of Distributed Generators using Intelligent Techniques. Eng. & Tech. Journal, Vol. 28, No. 23, pp. 6623-6633, (2010)
- [8] M.F. Akorede, H. Hizam, I. Aris and M.Z.A. Ab Kadir : A Review of Strategies for Optimal Placement of Distributed Generation in Power Distribution Systems. Research Journal of Applied Sciences, Vol. 5, No. 2, pp. 137-145, (2010)
- [9] O. Amanifar and M.E. Hamedani Golshan : Optimal Distributed Generation Placement and Sizing for Loss and THD Reduction and Voltage Profile Improvement in Distribution Systems using Particle Swarm Optimization and Sensitivity Analysis. International Journal on Technical and Physical Problems of Engineering, Vol. 3, No. 2, pp. 47-53, (2011)
- [10] R.Jahani, A. Shafighi Malekshah, H. Chahkandi Nejad and A. H. Araskalaei. Applying a New Advanced Intelligent Algorithm for Optimal Distributed Generation Location and Sizing in Radial Distribution Systems: Australian Journal of Basic and Applied Sciences, Vol. 5, No. 5, pp. 642-649, (2011).
- [11] S. Kumar Injeti and Navuri P Kumar : Optimal Planning of Distributed Generation for Improved Voltage Stability and Loss Reduction. International Journal of Computer Applications, Vol. 15, No.1, pp. 40-46, (2011)
- [12] M. Padma Lalitha, V.C.Veera Reddy, V.Usha and N.Sivarami Reddy : Application of Fuzzy and PSO for DG Placement for Minimum Loss in Radial Distribution System. ARPN Journal of Engineering and Applied Sciences, Vol. 5, No. 4, pp. 30-37, (2010)
- [13] Billinton, R. 1970. *Power system reliability evaluation*. Gordon and Breach Publishers, New York.
- [14] Endreyne, J. 1978. *Reliability modeling in electric power systems*. John Wiley and Sons, New York.
- [15] Dhillon, B.S. and Singh, C. 1981. *Engineering reliability*. John Wiley, New York.
- [16] Bansal, R.C. Bhatti, T.S. and Kothari, D.P. 2002. Discussion of bibliography on the application of probability method in power system reliability evaluation. *IEEE Trans. Power Systems* 17(3), 924.
- [17] Saket, R.K. and Bansal, R.C. March 2006. Reliability evaluation of interconnected composite power system considering voltage stability at continuation power flow. *International Conference on Power System Operation in Deregulated Regime*, Department of Electrical Engineering, Institute of Technology, Banaras Hindu University, Varanasi, India, 339-348.
- [18] Wang, P., Billinton, R. and Goel, L. 2002. Unreliability cost assessment of an electric power system using reliability network equivalent approaches. *IEEE Transactions on Power Systems* 17(3), 549-556.
- [19] Li, W. and Billinton, R. 2003. Common cause outage models in power system reliability evaluation, *IEEE Transactions on Power Systems* 18(2), 2003, 966-968.
- [20] Wang, P. and Billinton, R. 2003. Reliability assessment of restructured power system using reliability network equivalent techniques. *IEEE Proc.- Generation Transmission and Distribution* 150(5), 555-560.
- [21] Alavi-Sereshki, M.M. and Singh, C. 1991. A generalized continuous distribution approach For generating capacity reliability evaluation and its applications. *IEEE Trans. Power Systems* 6(1), 16-21.
- [22] Tian, W.D., Sutanto, D., Lee, Y.B. and Outhred, H.R. 1989. Cumulant based probabilistic power system simulation using laguerre polynomials, *IEEE Trans. Energy Conversion* 4(4), 567-574.
- [23] Saket, R.K. Arya, L.D. and Choube, S.C. 2001. Generation system adequacy evaluation using probability theory. *Journal of the Institution of Engineers (India)* 81, 170- 174.
- [24] Kim, J.O. and Singh, C. 1993. A frequency and duration approach for generation reliability evaluation using the method of stages. *IEEE Trans. Power Systems* 8(1), 207- 215.
- [25] Malik, A.S. and Cory, B.J. 1997. An application of frequency and duration approach in generation planning. *IEEE Trans. Power Systems* 12(3), 1076-1081.

