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Determination of Optimal DG Allocation under Variable Load and Generation Using Genetic Algorithm to Reduce Losses and Improve Voltage Profile

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Abstract: **This paper presents a method for the optimal allocation of Distributed generation in distribution systems for voltage profile improvement and loss reduction in distribution network. Genetic Algorithm (GA) has been used as the solving tool, which referring two determined aim; the problem is defined and objective function is introduced. Considering to fitness values as sensitivity in genetic algorithm process, there is needed to apply load flow for decision-making. Load flow algorithm is combined appropriately with GA, till access to acceptable results of this operation. The suggested method is programmed under MATLAB software and applied MIPOWER software for evaluating of results correctness. Developed methodology has been implemented on two IEEE 69 and 52 node systems. The resulting operation of this method on some testing system is demonstrated improvement of voltage profile and loss reduction indexes.**

Keywords: **Distributed Generation, Voltage Profile, Transmission losses, Genetic Algorithm.**

1. INTRODUCTION

Distributed generation (DG) technologies under smart grid concept forms the backbone of our world Electric distribution networks [5]. These DG technologies are classified into two categories: (i) renewable energy sources (RES) and (ii) fossil fuel-based sources. Renewable energy source (RES) based DGs are wind turbines, photovoltaic, biomass, geothermal, small hydro, etc. Fossil fuel based DGs are the internal combustion engines (IC), combustion turbines and fuel cells. Environmental, economic and technical factors have a huge role in DG development [1-2]. Presence of Distributed generation in distribution networks is a momentous challenge in terms of technical and safety issues [3]. Thus, it is critical to evaluate the technical impacts of DG in power networks. Thus, the generators are needed to be connected in distributed systems in such a manner that it avoids degradation of power quality and reliability. Evaluation of the technical impacts of DG in the power networks is very critical and laborious. Inadequate allocation of DG in terms of its location and capacity may lead to increase in fault currents, causes voltage variations, interfere in voltage-control processes, diminish or increase losses, increase system capital and operating costs, etc.[4]. The placement of the DG units mainly the Renewable energy sources placement, is affected by several factors such as wind speed, solar irradiation, environmental factors, geographical topography, political factors, etc. For example, wind generators or turbines cannot be installed near residential areas, because of the interference in the form of public reactions and legislations from environmental organisations. Another issue is application of the plug-in electric vehicle (PEV) which is being paid more attention to [5-6]. However, there are several factors or uncertainties that can possibly lead to probable risks in determining the optimal siting and sizing of DGs in distribution system planning [6]. The optimal placement and sizing of generation units on the distribution network has been continuously studied in order to achieve different aims. The objective can be the minimization of the active losses of the feeder [7-8]; or the minimization of the total network supply costs, which includes generators operation and losses compensation [9-13], or even the best utilization of the available generation capacity [14]. In this paper, an analytical expression to calculate optimum size and an effective methodology to identify the optimum location for DG placement are proposed. The methodology is computationally less demanding. The DG is considered to be located in the primary distribution system and the objective of DG placement is to reduce the losses. The cost of DG and the other associated benefits have not been considered while solving the location and sizing problem [15]. The sizing and placement of DG is based on single instantaneous demand at peak, where the losses are maximum. The proposed methodology is suitable for allocation of single DG in a given distribution network. As a contribution to the methodology for DG economical analysis, in this paper it is presented an algorithm for the allocation of generators in distribution networks, in order to voltage profile improvement and loss reduction in distribution network. In Section 2 it is presented a brief discussion about distributed generation issues and Section 3 is an introduction to the Genetic Algorithm. The problem formulation and solution methodology is also presented in Section 3 and case study is discussed in Section 4. The conclusions is presented in section 5.

2. DISTRIBUTED GENERATION

Distributed generation is an electric power source connected directly to the distribution network or customer side of the meter [16]. It may be understood in simple term as small-scale electricity generation. The definition of distributed generation takes different forms in different markets and countries and is defined differently by different agencies. International Energy Agency (IEA) defines Distributed generation as generating plant serving a customer on-site or providing support to a distribution network, connected to the grid at distribution-level voltages [17]. CIGRE defines DG as the generation, which has the following characteristics: It is not centrally planned; It is not centrally dispatched at present; It is usually connected to the distribution network; It is smaller than 50–100 MW. Other organization like Electric Power Research Institute defines distributed generation as generation from a few kilowatts up to 50 MW [18]. In general, DG means small scale generation. There are a number of DG technologies available in the market today and few are still in research and development stage. Some currently available technologies are reciprocating engines, micro turbines, combustion gas turbines, fuel cells, photovoltaic, and wind turbines. Each one of these technologies has its own benefits and characteristics. Among all the DG, diesel or gas reciprocating engines and gas turbines make up most of the capacity installed so far. Simultaneously, new DG technology like micro turbine is being introduced and an older technology like reciprocating engine is being improved [19]. Fuel cells are technology of the future. However, there are some prototype demonstration projects. The costs of photovoltaic systems are expected to falling continuously over the next decade. This all underlines the statement that the future of power generation is DG. Supplying peaking power to reduce the cost of electricity, reduce environmental emissions through clean and renewable technologies (Green Power), combined heat and power (CHP), high level of reliability and quality of supplied power and deferral of the transmission and distribution

line investment through improved loadability are the major applications of the DG [20]. Other than these applications, the major application of DG in the deregulated environment lies in the form of ancillary services. These ancillary services include spinning and non-spinning reserves, reactive power supply and voltage control etc.

[21-24]. DG also has several benefits like reducing energy costs through combined heat and power generation, avoiding electricity transmission costs and less exposure to price volatility. Though the DG is considered as a viable solution to most of the problems that today’s utility are facing, there are many problems (e.g. DG integration into grid, pricing, change in protection scheme, nuisance tripping etc.) that need to be addressed. Furthermore, the type of DG technology adopted will have significant bearing on the solution approach. In this study, DGs capable of supplying real power only are considered.

3. GENETIC ALGORITHM

Genetic Algorithms (GAs) are versatile exploratory hunt processes focused around the evolutionary ideas of characteristic choice and genetics. A genetic algorithm is a heuristically guided random search technique that concurrently evaluates thousands of postulated solutions. Biased random selection and mixing of the evaluated searches is then carried out in order to progress towards better solutions. The coding and manipulation of search data is based upon the operation of genetic DNA and the selection process is derived from Darwin’s survival of the fittest’. Search data are usually coded as binary strings called chromosomes, which collectively form populations. Evaluation is carried out over the whole population and involves the application of, often complex ‘fitness’ functions to the string of values (genes) within each chromosome. Typically, mixing involves recombining the data that are held in two chromosomes that are selected from the whole population.

Genetic Algorithms (GAs) were invented by John Holland at the University of Michigan. This lead to Holland's book "Adaptation in Natural and Artificial Networks" published in 1975. The goals of their research have been twofold: (1) to abstract and rigorously explain the adaptive processes of natural networks and (2) to design artificial networks software that retains the important mechanisms of natural networks. The central theme of research on genetic algorithms has been ronodetness, the balance between efficiency and efficacy necessary for survival in many different environments. The basic elements of natural genetics: reproduction, crossover, mutation are used in the genetic search procedure. Genetic Algorithms differ from the traditional methods of optimization in the following respect:

1.) A population of points (trial design vectors) is used for starting the procedure instead of a single design point. If the number of design variables is n, usually the size of the population is taken as 2n to 4n. Since several points are used as candidate solutions, Genetic Algorithms are less likely to get trapped at a local optimum.

2.) Genetic Algorithms use only the values of objective function. The derivatives are not used in search procedures.

3.) In GAs the design variables are represented as strings of binary variables that correspond to the chromosomes in natural genetics. Thus the search method is naturally applicable for solving discrete and integer programming problems. For continuous design variables, the string length can be varied to achieve any desired resolution.

4.) The objective function value corresponding to design vector plays the role of fitness in natural genetics.

5.) In every new generation, a new set of strings is produced by using randomized parents selection and crossover from the old generation (old set of strings). Although randomized, GAs are not simple random search techniques. They efficiently explore the new combination with the available knowledge to find the new generation with better fitness or objective function value.

3.1 Objective Function:

A multi-objective optimization problem is consider in this distribution networks planning problem with continuous planning decision variables. The main objective is to determine an economical yet reliable network with better technical features, such as lower power loss, better node voltage profile, and better branch current/thermal limit ratio. Thus, two objective functions are formulated: minimization of (i) the total power loss (P_{loss}) of the distribution network and (ii) maximum node voltage deviation (V_{dev}) ratio. Optimization of (i) yields an economical and high efficient network and optimization of (ii) results in a reliable network with better technical features.

3.2 DG Allocation with GA strategy:

A feeder brings power from substation to load points/nodes in radial distribution networks (RDN). Single or multiple radial feeders are used in this planning approach. 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.

Forward/Backward sweep load flow with DG:

To study the impact of the DG allocation in distribution networks, the DG model is incorporated in the forward-backward sweep load flow algorithm, which consists of two steps:

Backward sweep: In this step, the load current of each node of a transmission network having *N* number of nodes is determined as:

$$\overline{I_L}(\mathrm{m}) = \frac{P_L(m) - jQ_L(m)}{\overline{V^*}(m)} \qquad (\mathrm{m}=1,2,3.........\mathrm{N}) \qquad (1)$$

where, $P_L(m)$ and Q_L(m) represent the active and reactive power demand at node *m* and the over bar notation($\bar{x}$) indicates the phasor quantities, such as $\overline{I_L}$ *and* $\overline{V^*}$. Then, the current in each branch of the network is computed as:

$$\bar{I}(\mathrm{mn}) = \overline{I_L}(\mathrm{n}) + \sum_m \overline{I_L}(m) \qquad (2)$$

To incorporate the DG model, the active and reactive power demand at the node at which a DG unit is placed, say, at node *i*, is modified by:

$$P_{D\,i}^{with\,DG} = P_{D\,i}^{without\,DG} - P_{G\,i}^{DG} \qquad (3)$$

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$$Q_{D\,i}^{with\,DG} = Q_{D\,i}^{without\,DG} \mp Q_{G\,i}^{DG} \tag{4}$$

***Forward sweep*:** This step is used after the backward sweep so as to determine the voltage at each node of a distribution network as follows:

$$\bar{V}(\mathrm{n}) = \bar{V}(\mathrm{m}) - \bar{I}(mn)Z(mn) \tag{5}$$

where, nodes *n* and *m* represent the receiving and sending end nodes, respectively for the branch *mn* and Z(mn) is the impedance of the branch.

GA Optimization for DG allocation:

In this analysis proposed adaptive GA is used for optimization of DG location and size. The flowchart for the uncertainty in load and generation approach is presented below.

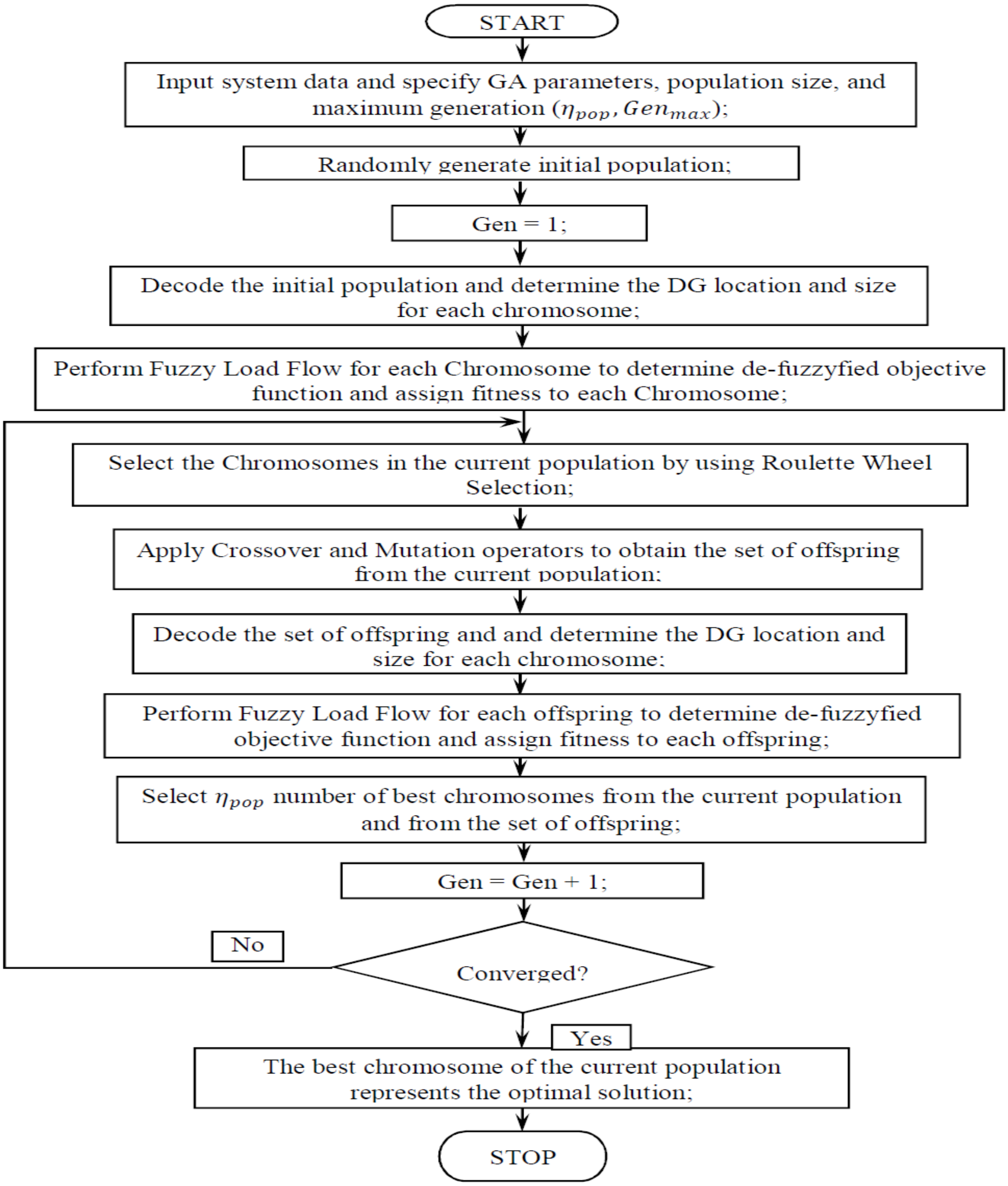

Fig.1 Flow chart for uncertainty in load and generation with GA optimization

4. CASE STUDY FOR UNCERTAINTY IN LOAD AND GENERATION

4.1 Deterministic Load and Generation Analysis:

Table 1 Study for deterministic load of 0.6 p.u. on test system with GA#6 optimization

Different Cases	Different systems	No. of DG	Total DG Power		No. of Tap	No. of CB	Total CB Reactive Power (kW)	Minimum Active Power Loss (kW)	Minimum Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
			Active Power (kW)	Reactive Power (kVAR)							
Base	System # 1	-	-	-	-	-	-	75.5264	34.4477	0.94755	0.28777
	System # 2	-	-	-	-	-	-	241.251	103.794	0.84120	1.24020
Case # 1 (a)	System # 1	5	1398.0	-	-	-	-	17.115	7.994	0.98560	0.18710
	System # 2	4	1394.0	-	-	-	-	22.128	9.520	0.96155	0.85695
Case # 1 (b)	System # 1	4	1118.4	838.8	-	-	-	4.032	3.636	0.99234	0.14046
	System # 2	5	1115.2	836.4	-	-	-	24.488	10.535	0.97053	0.87447
Case # 1 (c)	System # 1	3	1019.2	-764.4	-	-	-	66.918	29.960	0.96530	0.27684
	System # 2	3	1093.6	-820.2	-	-	-	125.231	53.878	0.88240	1.36410
Case # 2 (a)	System # 1	4	1397.0	-	10	-	-	4.814	2.742	0.99419	0.14526
	System # 2	4	1394.0	-	19	-	-	11.874	5.108	0.96789	0.76714
Case # 2 (b)	System # 1	4	1118.4	838.8	10	-	-	0.164	2.028	0.99487	0.12917
	System # 2	5	1145.2	836.2	20	-	-	14.859	6.393	0.97164	0.78049
Case # 2 (c)	System # 1	3	1115.2	-836.4	9	-	-	36.222	16.880	0.97204	0.23973
	System # 2	3	1115.2	-834.4	20	-	-	104.621	45.011	0.89680	1.30790
Case # 3	System # 1	-	-	-	-	4	1396	41.750	18.292	0.96443	0.23564
	System # 2	-	-	-	-	3	1394	218.801	94.135	0.85533	1.16640
Case # 4	System # 1	-	-	-	10	4	1398	37.337	16.783	0.96768	0.23472
	System # 2	-	-	-	20	3	1390	200.815	86.397	0.87695	1.10720
Case # 5	System # 1	-	-	-	10	-	-	49.156	22.526	0.95545	0.23938
	System # 2	-	-	-	20	-	-	218.739	94.108	0.86491	1.15550

System # 1 and system # 2 with a deterministic load of 0.6 p. u. base load; case#1 (a), unity p. f. DG; case # 1(b), DG operating at 0.8 p. f. leading; case#1(c), DG operating at 0.8 p. f. lagging; case#2(a), unity p. f. DG with OLTC; case#2(b), DG operating at 0.8 p. f. leading with OLTC; case#2(c), DG operating at 0.8 p. f. lagging with OLTC; case #3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

Table 2 Study for deterministic load of 0.6 p.u. on test system with GA#6 optimization

Different Cases	Different systems	No. of DG	Total DG Power		No. of Tap	No. of CB	Total CB Reactive Power (kW)	Minimum Active Power Loss (kW)	Minimum Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
			Active Power (kW)	Reactive Power (kVAR)							
Base	System # 1	-	-	-	-	-	-	224.995	102.198	0.90919	0.49031
	System # 2	-	-	-	-	-	-	887.181	381.694	0.68442	2.43820
Case # 1 (a)	System # 1	4	2088.0	-	-	-	-	50.557	24.0396	0.96953	0.32060
	System # 2	5	2095.0	-	-	-	-	92.600	39.839	0.92560	1.30910
Case # 1 (b)	System # 1	5	1678.4	1258.8	-	-	-	17.624	13.135	0.98035	0.25856
	System # 2	6	1679.2	1259.4	-	-	-	89.619	38.557	0.93813	1.30910
Case # 1 (c)	System # 1	3	1433.6	-1075.6	-	-	-	190.731	85.864	0.93621	0.46614
	System # 2	4	1650.4	-1237.8	-	-	-	535.504	230.391	0.82221	2.11770
Case # 2 (a)	System # 1	5	2087.0	-	8	-	-	16.598	9.694	0.97902	0.23973
	System # 2	6	2095.0	-	19	-	-	77.164	33.059	0.93456	1.30910
Case # 2 (b)	System # 1	5	1676.0	1257.0	9	-	-	7.698	4.534	0.98803	0.21735
	System # 2	6	1678.4	1258.8	20	-	-	76.789	33.037	0.95106	1.30830
Case # 2 (c)	System # 1	4	1634.4	-1225.8	10	-	-	128.582	56.112	0.95070	0.36631
	System # 2	4	1658.4	-1243.8	20	-	-	483.191	207.885	0.84036	1.9143
Case # 3	System # 1	-	-	-	-	4	2099	128.676	57.0404	0.93814	0.40236
	System # 2	-	-	-	-	4	2096	786.995	338.591	0.71626	2.25760
Case # 4	System # 1	-	-	-	7	4	2091	120.470	56.114	0.94519	0.39981
	System # 2	-	-	-	20	4	2090	716.607	308.308	0.75746	2.12410
Case # 5	System # 1	-	-	-	10	-	-	169.244	77.768	0.91721	0.43167
	System # 2	-	-	-	20	-	-	796.285	342.588	0.73196	2.26360

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System # 1 and system # 2 with a deterministic load of 1.0 p. u. load; case#1 (a), unity p. f. DG; case # 1(b), DG operating at 0.8 p. f. leading; case#1(c), DG operating at 0.8 p. f. lagging; case#2(a), unity p. f. DG with OLTC; case#2(b), DG operating at 0.8 p. f. leading with OLTC; case#2(c), DG operating at 0.8 p. f. lagging with OLTC; case #3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

4.2 Probabilistic load and Generation analysis:

Table 3 Study for probabilistic load of 0.4 p. u. to 1.4 p. u. On test system with GA#6 optimization

Different Cases	Different systems	No. of DG	Total DG Power		No. of Tap	No. of CB	Total CB Reactive Power (kW)	Minimum Active Power Loss (kW)	Minimum Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
			Active Power (kW)	Reactive Power (kVAR)							
Base	System # 1	-	-	-	-	-	-	201.193	91.435	0.91416	0.46444
	System # 2	-	-	-	-	-	-	764.177	328.774	0.70890	2.25270
Case # 1 (a)	System # 1	7	2213.0	-	-	-	-	49.174	21.871	0.98114	0.29830
	System # 2	7	2207.0	-	-	-	-	59.896	25.769	0.94218	1.24160
Case # 1 (b)	System # 1	6	1770.4	1327.8	-	-	-	10.003	9.095	0.98860	0.22293
	System # 2	9	1765.6	1324.2	-	-	-	58.806	25.300	0.95715	1.18690
Case # 1 (c)	System # 1	4	1529.6	-1147.2	-	-	-	176.867	78.843	0.94305	0.44430
	System # 2	6	1759.2	-1319.4	-	-	-	480.434	206.698	0.83001	1.88320
Case # 2 (a)	System # 1	6	2213.0	-	10	-	-	12.781	6.527	0.98875	0.19997
	System # 2	6	2206.0	-	18	-	-	39.247	16.885	0.94462	1.24160
Case # 2 (b)	System # 1	5	1766.4	1324.8	10	-	-	4.004	2.892	0.99454	0.18590
	System # 2	8	1765.6	1324.2	19	-	-	47.984	20.644	0.95665	1.24280
Case # 2 (c)	System # 1	5	1700.0	-1275.0	10	-	-	133.115	59.834	0.95312	0.40433
	System # 2	5	1763.2	-1322.4	20	-	-	436.000	187.581	0.86231	1.87720
Case # 3	System # 1	-	-	-	-	5	2213.0	116.100	50.726	0.94395	0.37919
	System # 2	-	-	-	-	4	2207.0	675.519	290.630	0.73967	2.08190
Case # 4	System # 1	-	-	-	8	5	2212.0	108.008	47.871	0.94566	0.37645
	System # 2	-	-	-	20	5	2203.0	621.814	267.525	0.77587	1.97270
Case # 5	System # 1	-	-	-	10	-	-	148.999	68.500	0.92255	0.40624
	System # 2	-	-	-	20	-	-	691.949	297.699	0.75144	2.10830

System # 1 and system # 2 with a deterministic load of 0.4 p. u. to 1.4 p. u. load; case#1 (a), unity p. f. DG; case # 1(b), DG operating at 0.8 p. f. leading; case#1(c), DG operating at 0.8 p. f. lagging; case#2(a), unity p. f. DG with OLTC; case#2(b), DG operating at 0.8 p. f. leading with OLTC; case#2(c), DG operating at 0.8 p. f. lagging with OLTC; case #3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

4.3 Multiple run for probabilistic and deterministic load and generation:

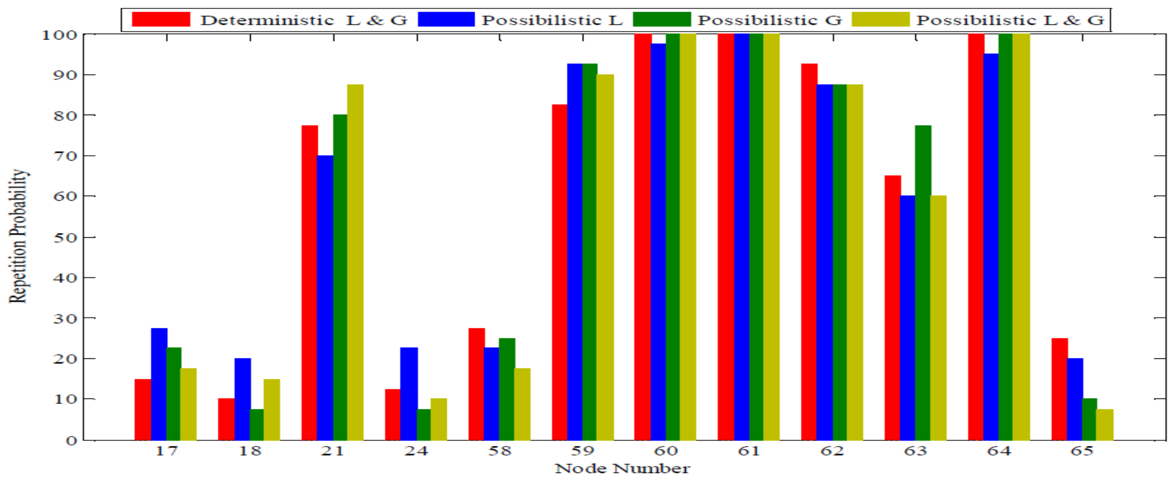

Fig. 2 System #1 DG location repetition probability for multiple run for the case#1(b); case#1(b), DG operating at 0.8 p. f. leading

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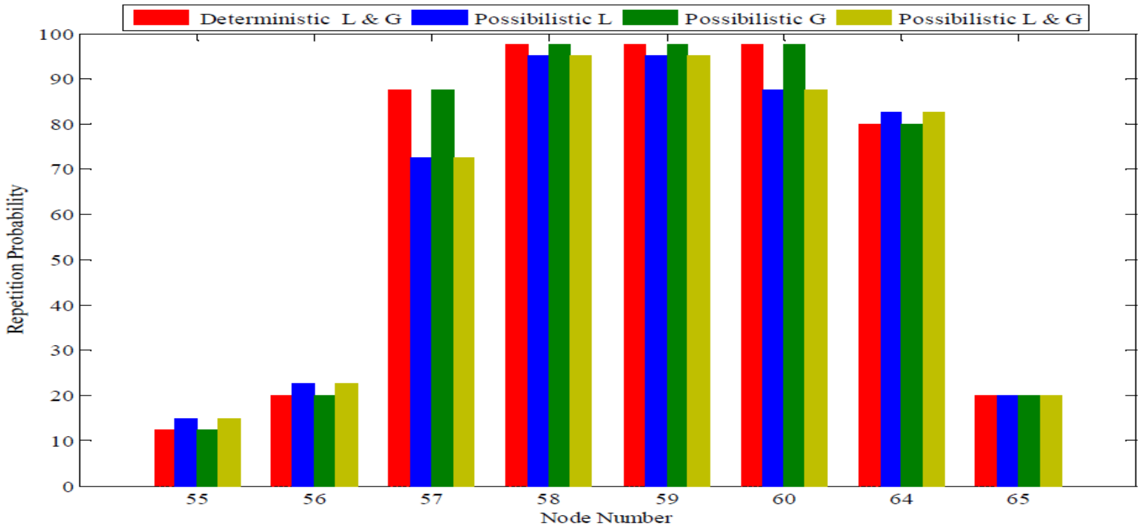

Fig.3 system#1 DG location repetition probability multiple run for the case#1(c); case#1(c), DG operating at 0.8 p. f. lagging

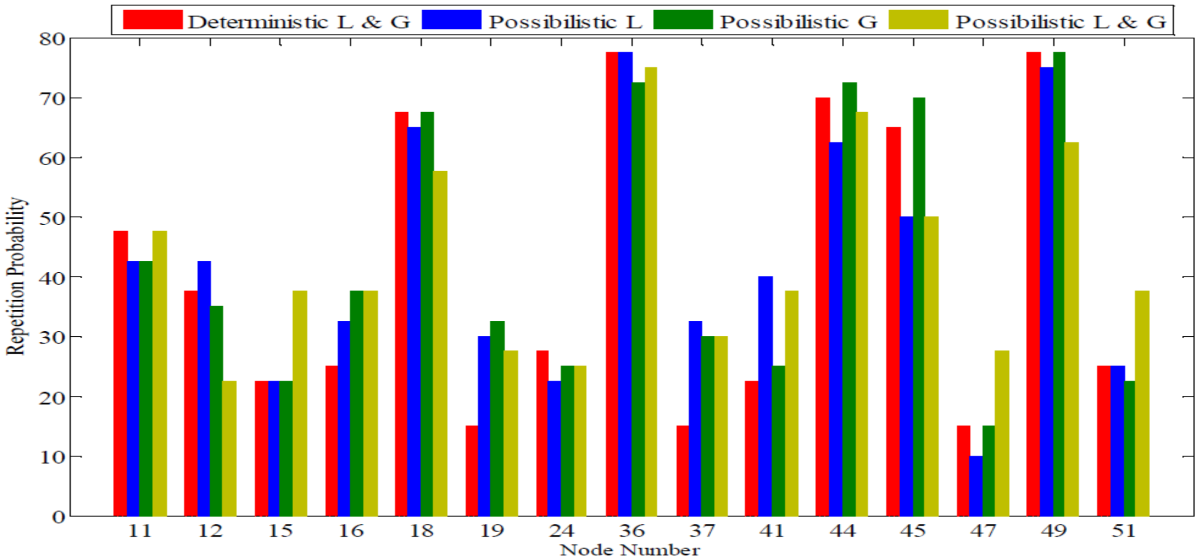

Fig.4 system#2, DG location repetition probability multiple run for the case#1(b); case#1(b), DG operating at 0.8 p. f. leading

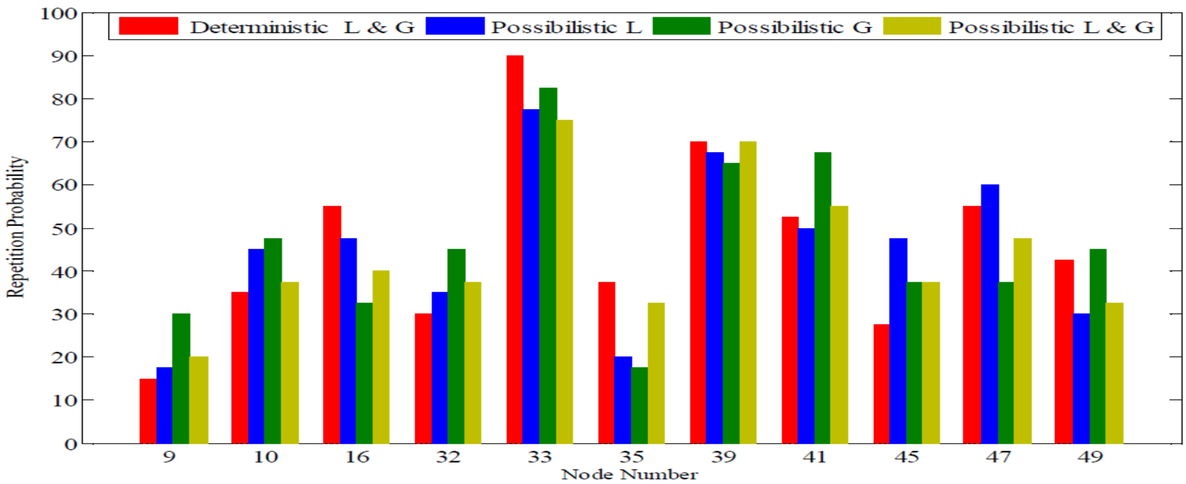

Fig.5 system#2 DG power rating variation for candidate notes in multiple runs for the case#1(c); case#1(c), DG operating at 0.8 p. f. lagging

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Table 4 Effective nodes DG rating median values for various cases

System #1 (69 node)					System #2 (52 node)				
Case#1(b)					Case#1(b)				
Node no.	#AA	#BB	#CC	#DD	Node no.	#AA	#BB	#CC	#DD
21	293.5	262.5	325.5	300.5	18	282.5	217	288	233
59	351	337	382	324	36	303	218	260	258.5
60	373.5	365	356	366	44	140	107.5	170.5	108
61	377.5	363	385	371	45	284.5	141	336	129.5
62	362	373	343	328	49	454	452	460	389
63	155.5	124	277.5	139.5					
64	368.5	369	376	374					
Case#1(c)					Case#1(c)				
57	397.5	395	397.5	395	16	149.5	0	0	0
58	398	398	398	398	33	557.5	425.5	480.5	322.5
59	397	397	397	397	39	369.5	401	351.5	392
60	357.5	384.5	357.5	384.5	41	100	37	317.5	241
64	364	361	364	361	47	115.5	159.5	0	0

Case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging and #AA; Deterministic load and Generation; #BB; Possibilistic Load; #CC; Possibilistic Generation; #DD; Possibilistic Load and Generation.

Multiple run and uncertainty analysis with different system and GA parameters:

With a new system and GA parameter the optimization is carried out for three different cases (i.e. case#1(a),case#1(b) and case#1(c)). This system and GA parameters are also taken for the analysis of uncertainty with different DG rating.

Table 5 GA and network parameters considered for the optimization process

GA parameter		Network parameter	
Population size (I_{max})	80	DGs power rating range (P_{DG}):	(50 – 600) kW
Maximum Generation (Gen_{max})	270	Minimum Voltage (V_{min}):	System#2: 0.90 p.u.
Crossover probability (Ω_c)	adaptive	Maximum Thermal Limit (I_{max}):	System#2: 1.2 p.u.
Mutation Probability (Ω_m)	0.005	Maximum number of DG (ψ_n):	5
Maximum iteration for load flow	300	DG penetration limit	Max 50% of total load
Accuracy label in load flow	10^{-9}		

Table 6 Effective nodes DG rating median value for various cases

System #2 (DG range 50-600)				
Case#1(a)				
Node no.	**#AA**	**#BB**	**#CC**	**#DD**
11	0	0	147.5	0
16	0	483.5	249	0
18	329.5	0	117.5	198
36	0	0	0	0
45	519	502.5	445.5	528.5
47	501.5	466.5	508.5	453.5
49	540.5	543	554.5	518.5
Power Loss	133.03	110.56	103.15	182.39
Minimum Voltage	0.85937	0.88407	0.89363	0.83514
Case#1(b)				
11	217	439.5	225	446
16	463	0	466.5	0
18	0	278.5	0	114.5
36	311.5	0	184.5	208
41	0	510	471.5	529
49	527	552	557.5	552
Power Loss	194.04	132.47	113.38	122.78
Minimum Voltage	0.86286	0.90697	0.92554	0.90436
Case#1(c)				
33	506.5	347.5	263.5	550.5
39	139	512.5	50.5	488.5
41	439.5	78.5	546	114.5
47	0	298.5	0	0
Power Loss	592.16	563.34	626.14	584.27
Minimum Voltage	0.78064	0.78370	0.76967	0.77897

Case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging and #AA; Deterministic load and Generation; #BB; Possibilistic Load; #CC; Possibilistic Generation; #DD; Possibilistic Load and Generation.

5. CONCLUSIONS

In this paper the results of application of GA algorithm to the optimal allocation of DGs in distribution network is presented. developed algorithm calculate the optimum size of DG at various buses and proposes a fast methodology to identify the best location corresponding to the optimum size for reducing total power losses in primary distribution network. The benefit of the proposed algorithm for size calculation is that a look up table can be created with only one power flow calculation and the table can be used to restrict the size of DG at different buses, with the view of minimizing total losses. However, if a DG is installed in the system, the look up table needs to be updated with new calculation. The proposed methodology for location selection correctly identifies the best location for single DG placement in order to minimize the total power losses. In practice, the choice of the best site may not be always possible due to any constraints. However, the analysis here suggests that the losses arising from different placement varies greatly and hence this factor must be taken into consideration while determining appropriate location. The paper also shows that the loss sensitivity factor approach for location selection may not lead to the best choice.

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