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Optimal Multi-Distributed Generators Planning Under Uncertainty using AHP and GA

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Abstract
Power system deregulation and the shortage of energy sources have led to increased interests in distributed generators (DGs). The access of DGs to the distribution networks brings advantages as well as creates adverse influences, which is related to the type, location and size of DGs. In order to fully apply the positive and restrain the negative, proper DGs planning is very important and indispensable. Based on the analysis of the uncertain factors, this paper presents the distribution features of load, WTG and PV. And According to these distribution features, the relatively accurate sampling data are obtained by different discretization methods. Furthermore, this paper also presents an uncertain planning model of DGs owned by the distribution company, which involve power loss improvement, the system voltage quality variation, environment change, etc. The optimization algorithm is based on the fusion methodology with the Monte Carlo simulation, the analytical hierarchy process (AHP) and genetic algorithm (GA). The simulation is carried out on IEEE 37-bus distribution systems and the results is presented and discussed.

***Keywords**: distributed generators, distribution network, siting and sizing, fusion methodology, uncertainty*

1. Introduction

Under the impetus of the need for more flexible electric systems, energy saving and environmental protection, etc., distributed generators (DGs) has become very important and indispensable part of developing electric utility industry [1-2]. Currently, one main method of studying and applying DGs is to access them to the distribution level. If DGs is properly planned and operated, it may provide advantages likes reduction of power losses, improvement of voltage, deferment or elimination of investments for network enforcing, etc. However, it also may create adverse influences including degradation of power quality, reliability, and control of the power system while improper DGs installment happens [1-4]. In order to fully play a part in the positive as well as restrain the negative, exactly and properly planning DGs is a very important and urgent task.

Up to now, a great quantity of research works has been carrying about siting and sizing of DGs. In order to minimize the electrical network losses and to guarantee acceptable reliability level and voltage profile, [5] presented a methodology for optimal DGs allocation and sizing in distribution systems. [6] gave an analytical method to determine the sizing and siting of DGs in radial systems.In [7], a multiobjective evolutionary algorithm was proposed so as to define the sizing and siting of DGs satisfying the the best compromise between cost of network upgrading, cost of power losses, cost of energy not supplied, and cost of energy required by the served customers. In [8], an integrated model, which aims to minimize DGs investment and operating costs, etc., was given to achieve optimal sizing and siting of distributed generation. For the purpose of peak cutting, [9] proposed an integrated distribution network planning model including feeder investments, DGs investments energy loss cost and the additional cost of DGs for peak cutting.

But previous methods mostly devoted to efforts of using the deterministic approaches, that is to say, they only consider one power system operating profile. Therefore, the result obtained by these methods may not be the optimal; especially it is outstanding when planning problem involves plenty of uncertainty factors like renewable DGs, load fluctuations, market change, etc. Thus recently published documents also have pointed out the uncertainty factors in

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the optimazation models of DGs planning. Based on chance-constrained programming, the planning model considering stochastic character of renewable DGs output is presented in [10] to evaluate the distribution network investment risk due to DGs connected to distribution network. [11] introduced the sizing of batteries in distributed power system utilizing chance constrained programming. Reference [12] proposed a chance constrained formulation to tackle the uncertainties of load and wind turbine generator in transmission network expansion planning. In [13], the planning scheme based on the chance constrained programming was proposed for siting and sizing of distributed wind generators (WGs).

With the development of power market and different DGs technology, DGs planning will become more and more complex, and consideration of uncertainties is of utmost importance so as to decrease the risk of system operation. However, it is difficult for some uncertainties (e.g. such as social, political, environmental, etc.) to establish the scientific and reasonable mathematical model [12, 17]. In addition, the complexity of the distribution network and the efficiency of power flow calculation also require the practitioners to seek simple, rapid and accuracy optimization algorithm.

Difference from methodology proposed in published literature, this paper presents a new uncertain planning model of DGs to determine the allocation and sizing of DGs in distribution level. From the perspective of the distribution company owning DGs, the proposed planning models involve power loss improvement, the system voltage quality variation, environment change, etc. The optimization algorithm is based on the Monte Carlo simulation, the analytical hierarchy process (AHP) and improved genetic algorithm (GA). The simulation is carried out on IEEE 37-bus distribution system.

The organization of this paper is as follows. The models for uncertainties and objective formulation are described in the next section. The combined algorithm is introduced in section III to solve the proposed uncertain planning model. In section IV, the sample system is given to test the presented method while the simulation result is analyzed and discussed. Furthermore, conclusions are given in the last section.

2. The Description and Treatment for Uncertainties

It is well known that DGs planning involves many uncertainties such as load variations and renewable DGs fluctuation, electricity market change, policy and regulation adjustment, availability of system facilities etc. For the simplification, we only description three models including the load variations, wind turbine generators (WTGs) and photovoltaic power (PV) fluctuation. Simultaneously, this paper deals with them through their discretization so as to adapt for the complexities of the distribution network as well as improve the computational efficiency of Monte Carlo simulation.

2.1. Description and Treatment for Load Uncertainties

The uncertain model about load has been researched in some literatures [10, 12], [18-19]. The frequently-used models include interval distribution and Gaussian distribution. Here the later is employed. The model is as following:

$$L_{li} \sim N_{li}(\mu_{li}, \sigma_{li}) \tag{1}$$

Where, L_{li} is random variables about active and reactive loads at node i, $N_{li}(\mu_{li},\sigma_{li})$ is the normal distribution with mean value μ_{li} and standard deviation σ_{li}..

To meet the demands of the high-speed calculation, load uncertainties are processed on based of the central limit theorem. The algorithm steps are as follows:

Step 1: to generate a random sample of n numbers obeying uniform distribution on the interval from 0 to 1, e.g., ζ_1, ζ_2, …ζ_n.

Step 2: to calculate the number x according to Equation (2).

$$x = (\sum_{i=1}^{n} \zeta_i - \frac{n}{2}) / \sqrt{\frac{n}{12}} \tag{2}$$

Step 3: to calculate the random number y with normal distribution N (μ,σ) by Equation (3).

$$y = \mu + \sigma x \tag{3}$$

Step 4: repeat step 1 to step 3 to produce sufficient random samples.

Step 5: to divide the confidence intervals into *m* continuous and disjoint intervals and take the interval midpoint as a representative of the load discrete-data.

Step 6: to obtain the statistics of random samples falling on each interval. Then, to calculate the probabilities and their cumulative probabilities. Figure 1 is the bar graph of the discrete-data for the cumulative probability of the load uncertainty model.

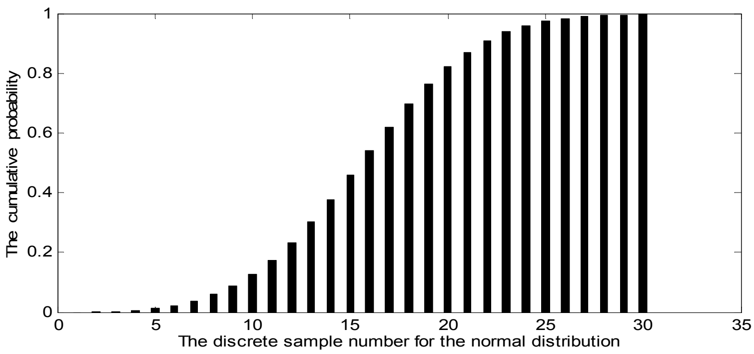

Figure 1. The Bar Graph of the Discrete-data for the Cumulative Probability of the Load Uncertainty Model

2.2. Description and Treatment for Wind Turbine Genetors

The output power of WTGs is directly related with the wind speed, which is sensitive to the natural factors, season variation, and geographic environment and so on. However, the research for the intermittent and stochastic of WTGs has been relatively mature [10, 18, 20]. Presently, the uncertain model of WTGs is expressed by the following equation.

$$P_w = \begin{cases} \dfrac{P_r(v-V_i)}{(V_r-V_i)} & V_i \le v < V_r \\ P_r & V_r \le v \le V_o \\ 0 & v > V_o \ or \ v < V_i \end{cases} \tag{4}$$

Where, P_r and P_w are the rated power and active power output variables (MW) of WTGs, respectively. V_i ,V_r and V_o is orderly the cut-in wind speed, rated wind speed and cut-out wind speed(m/s). v is the wind speed variable known as the Weibull distribution whose probability density function is shown in Equation (5).

$$\varphi(v) = \frac{k}{c}(\frac{v}{c})^{k-1}\exp\left[(\frac{v}{c})^k\right] \tag{5}$$

Where, k,c are the shape parameter and the scale parameter.

The output power of WTGs is different with the change of the shape parameter and the scale parameter. In this paper, two parameters are obtained by the application of the method of mean and standard deviation on the basis of the measured wind speed samples. Simultaneously, the variation range of the wind speed is divided into n continuous and disjoint intervals. The representatives of the wind speed discrete-data select the end point on each interval and the probabilities and their cumulative probabilities on each interval is obtained according to the weibull distribution. For example, suppose V_i = 4, V_r = 14 and V_o = 25, it can be divided into 12 intervals including (0, 4], (4, 5], (5, 6], (6, 7], (7, 8], (8, 9], (9, 10], (10, 11], (11, 12], (12, 13], (13, 14], (14, 25].

2.3. Description and Treatment for Photovoltaic Power

The output power of photovoltaic power generation is also intermittent and stochastic thanks to its close correlation with the solar radiation, which is influenced by weather and season variation. The uncertain models of the output power have been studied for a long time. In [21] it is expressed as following:

$$P_s = A*\eta*r \tag{6}$$

Where, P_s is the output power of PV. A is the total area of photovoltaic panels. η is the conversion efficiency of PV. r is the solar radiation intensity.

According to statistics and integrated with Equation (6), here the output power of PV can be approximated as Equation (7)

$$P_{PV} = P_{\max} * \xi \tag{7}$$

Where P_{PV} and P_{max} are PV active output variables and peak power, respectively. ξ is the output efficiency variable of PV, which change with the weather. Here, the output efficiencies of three kinds of weather conditions are discussed, that is sunny day, cloudy day and rainy day. Their generation efficiencies are shown in Figure 2.

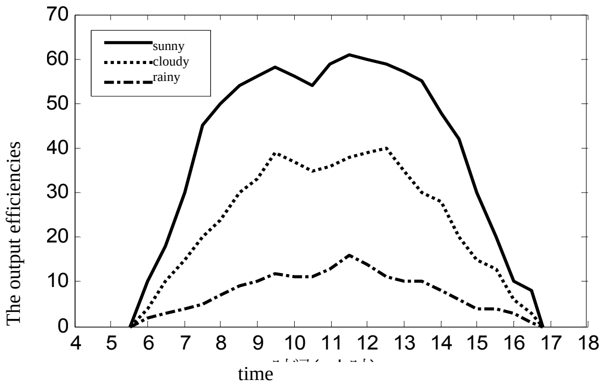

Figure 2. The Graph for the Output Efficiency of PV in Sunny Day, Cloudy Day and Rainy Day

3. The Description for Objective Formulation

3.1. Objective Formulation

The decline of DG technology cost and gradual improvements of power market regulations result in more and more participants in DGs operation. Currently DGs operators usually include Load Customers (LC), Power Distribution Companies (PDC) and Independent Power Suppliers (IPS).Their purposes of investment in DGs are usually discriminative, so the constructed objective formulation is also distinct when planner stands in the perspective of different benefits. In this paper, DGs is taken as appendants of PDC to decrease power loss, enhance voltage profile and improve environments. Here the objective function is to maximize the expected benefits for weighted sum involving voltage, energy loss and environment improvement subject to some technical constraints of the distribution system. The expected value formulation is as follows:

$$\text{maximize} \quad Obj = w_1 * E[IP] + w_2 * E[IU] + w_3 * E[IE] \tag{8}$$

Where E[.] denotes the expected value for an event. IP,IU and IE are the improvement indices of voltage, power and environment. w_1,w_2 and w_3 are the weighted factors of IP,IU and IE, whose computations are shown in following three equations.

$$IP = \frac{P_{woi}^{Loss}}{P_{wi}^{Loss}} \tag{9}$$

$$IU = \frac{\lambda_{wi}}{\lambda_{woi}} = \frac{\sum_{i=1}^{N} U_i^{w} L_i^{w} k_i^{w}}{\sum_{i=1}^{N} U_i^{wo} L_i^{wo} k_i^{wo}} \tag{10}$$

$$IE = \frac{E_{wo}}{E_{wi}} = \frac{\sum_{i=1}^{NP} \alpha_i^{wo} E_i^{wo}}{\sum_{i=1}^{NP} \alpha_i^{w} E_i^{w}} \tag{11}$$

Where P^{Loss}, U and L is the power loss, voltage and load. k and α are the weighted factors. E and λ denotes the pollution emissions and system voltage respectively. N and NP mean the number of load node and pollution gases. Subscripts *wo* and *wi* stand for before and after installation of DGs.

3.2. Constraints

To satisfy the requirements for distribution network, the maximized objective function is subject to power flow equations constraint and some inequation limits like node voltage, branch capacity, etc. But considering the volatility of loads and DGs, here the planning scheme are allowed not to satisfy the node voltages constraints and branch transmission power in certain extreme circumstances. The various inequation constraints are discussed as follows.

Voltage Limits at the Buses:

According to the practical requirements, the probability of overvoltage at each node should be smaller than a specified confidence level. That is, the not-overvoltage-probability can be obtained:

$$\Pr\left\{V_i^{\min} \le V_i \le V_i^{\max}\right\} \ge \beta_V, i \in \phi \tag{12}$$

Where Pr{.} shows the probability of an event. V_i^{max} and V_i^{min} are the upper and the lower of voltage at node *i*. β_V gives the specified confidence level for voltage at node *i*. Φ is known as load node set in distribution network.

Feeder Capacity Limits:

DGs access maybe causes the changes of branch current or brings reverse power flow. Therefore, after DGs access to distribution system, the probability beyond feeder capacity limits should also be smaller than a specified confidence level. The expression is obtained from:

$$\Pr\left\{S_{ij} \le S_{ij}^{\max},\ S_{ji} \le S_{ji}^{\max}\right\} \ge \beta_L \qquad i, j \in \phi \tag{13}$$

Where Pr{.} shows the probability of an event. S_{ij} and S_{ji} stand for power of branch *ij*. S_{ij}^{max} and S_{ji}^{max} are forward and reverse uppers of power flow at branch *ij*. β_L is the specified confidence level for the feeder capacity. Φ is known as nodal set of system.

DGs Penetration Capacity Limits:

At present, DGs penetration capacity is constrained due to some technology impacts. To reflect these circumstances, this paper assumed that the DGs penetration capacity is subject to the following constraints:

$$E\left[\sum_{j\in\Omega_g} P_{DGj}\right] \le k\% * E\left[\sum_{i\in\Omega_L} P_{Li}\right] \tag{14}$$

where P_{Li} and P_{Dgj} show load and DGs power at node *j* and node *i*. *k*% is the penetration rate of DGs. Ω_g and Ω_L denote load node set and DGs location set in distribution network.

4. The Proposed Optimation Algorithm

Many heuristic optimization techniques can be used in the siting and sizing of DGs planning. Due to high efficiency of GA, it is widely taken into account in many details. We still employ it but integrate with the Monte Carlo simulation and AHP in accordance with the constructed uncertain objective formulation. The Monte Carlo method and the improved GA are used to compute the uncertain constraints and objective, while the AHP is employed to determine the weighted factors. The flow chart of optimization algorithm is given in Figure 3.

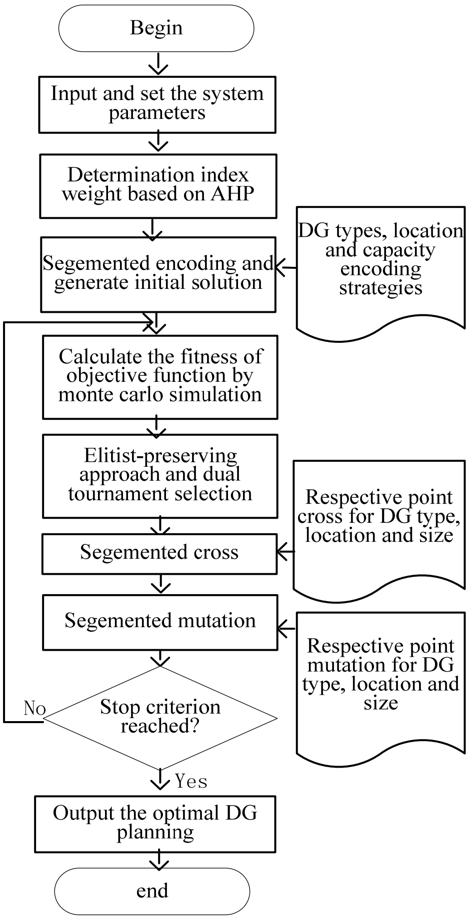

Figure 3. The Flowchart of Optimization Algorithm

4.1. GA

GA proposed by Holland has attracted considerable attention as global methods for complex function optimization. It has eight basic components: genetic representation, initial population, evaluation function, reproduction selection scheme, genetic operators, generational selection scheme, stopping criteria and GA parameter setting [14, 22]. Like any algorithm, the proposed algorithm in this article has three steps: initiation step, repeated step and stop step. But to work with high efficiency and to adapt to the proposed planning models, some operations are improved. The improved steps are described as follows.

1) *Chromosome Code*: The decimal integer codification is adopted. The chromosome includes three segments which are orderly representative for types, locations and capacities of DGs.

2) *Genetic Operation*: The new generation was selected by elitist-preserving and dual tournament approach. Both crossover operation and mutation operation is to adopt segment point crossover and segment point mutation. That is, one random point of DGs types in a chromosome exchanged with the corresponding point DGs types in another chromosome. Similarly, it is suitable for the DGs location and DGs capacity to carry out the crossover operation and mutation operation.

4.2. The Monte Carlo Simulation

On the basis of the previously established distribution function for wind power output, load and solar power, the Monte Carlo simulation [23] gives the statistical estimate of the objective and constraints. The simulation process is:

1) Set confidence level for two constraints: β_v and β_l.

2) Randomly extract much enough N samples according to the foregoing discrete-data for wind power output, photovoltaic energy and loads.

3) Aim at each sampling, both inspection of constraint and the caculation of objective function values are carried out. For each constraint, if the number satisfying conditions is more than $\beta_i \times N$, i= 1, 2, the samples is qualified; For objective function, the following estimate equation is applied.

$$\frac{\sum_{k=1}^{N} f(x,\xi)}{N} \to E[f(x,\xi)] \tag{15}$$

Where N is the number of samples. $f(x,\xi)$ stands for the objective formulation.

4.3. AHP

AHP is employed to give a scientific and reasonable weighted vector in accordance with the expert experience or DGs investors prefer. The first step of determining weighted vectors is to construct a judgment matrix formed by experts or investors scoring. Then matrix's maximized eigenvalue and corresponding eigenvectors are calculated. Finally the weighted factors is obtained by:

$$w_i = \frac{v_i}{\sum_{k=1}^{3} \boldsymbol{v}_k} \quad i = 1,2,3 \tag{16}$$

Where v_i is the ith number of eigenvectors $v.w_i$ is the represents for improvements of power loss, voltage and environment respectively.

5. Example Studies

5.1. Test Sysetem and Simulation Parameters

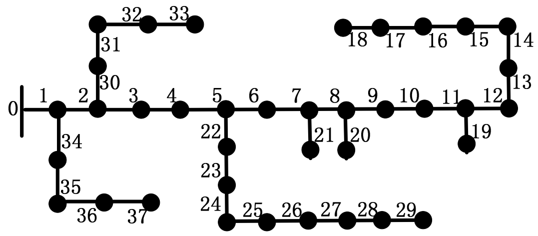

Figure 4. The Topological Structure for IEEE 37-bus System

To demonstrate the performance of the proposed method, simulation is carried out on IEEE 37-bus system. Its topological structure is shown in Figure 4 and the branch, load parameters can be found in [14]. But considering the uncertainty as well as for sake of simplicity, all loads is equal to the sum of base case data and a normal random variable. And here assume that 0 and 0.01 is the mean and standard deviation at every load node. Let take the bus 30 as an example, its load can be divided into 10 intervals under the confidence level of 95%.The discrete-data is given in Table 1.

Table 1. The Discrete-Data of the Load on Bus 30 Node

intervals	load（p.u.）	Cumulative probability interval
[0.06, 0.066]	0.063	(0, 0.0068]
(0.066, 0.072]	0.069	(0.0068, 0.0346]
(0.072, 0.078]	0.075	(0.0346, 0.1137]
(0.078, 0.084]	0.081	(0.1137, 0.2729]
(0.084, 0.09]	0.087	(0.2729, 0.4987]
(0.09, 0.096]	0.093	(0.4987, 0.7244]
(0.096, 0.102]	0.099	(0.7244, 0.8836]
(0.102, 0.108]	0.105	(0.8836, 0.9627]
(0.108, 0.114]	0.111	(0.9627, 0.9905]
(0.114, 0.12]	0.117	(0.9905, 0.9973]

In Monte Carlo simulation, 1000 is taken as the random sample number. The main GA parameters in our tests are: 0.9 for select rate; 0.9 for crossover rate; 0.05 for mutation rate; 100 for chromsome numbers; 30 for max genetic generation.

Total rated capacity of DGs is equal to thirty percent of total base load in distribution network. For WTG: WTG output active power is one or more integer times than 100kW and the power factor is 0.8; wind speed parameters V_i,V_o ,V_r ,k and c are orderly 4, 10, 25, 2 and 8. The discrete-data is presented in Table 2. For PV: Maximum active power output is the integer multiples of 40kW; the calculation method of reactive power is the same as that of WTG; PV generation efficiency parameters are a=0.1, b=0.6. The discrete-data for PV is illustrated in Table 3.

Furthmore, Power flow calculation is to use the improved back/forward sweep method proposed in [16]. And we assume that voltage base is 10 kV, power base is 10MW and convergence accuracy is 10^{-4}.

Table 2. The Discrete-Data for The Wind Speed and the Output Power of the Wind Turbines

intervals	Wind speed（m/s）	Output power	Cumulative probability interval
[0，4]	4	0	(0.4013,0.5987]
（4，5]	5	10	(0.5987,0.6462]
（5，6]	6	20	(0.6462,0.6915]
(6, 7]	7	30	(0.6915,0.7340]
(7, 8]	8	40	(0.7340,0.7734]
(8, 9]	9	50	(0.7734,0.8092]
(9, 10]	10	60	(0.8092,0.8413]
(10, 11]	11	70	(0.8413,0.8697]
(11, 12]	12	80	(0.8413,0.8944]
（12，13]	13	90	(0.8944,0.9154]
（13，14]	14	100	(0.9154,0.9332]
（14，25]	25	100	(0.9332,0.9980]

5.2. Results and Discussion

The program is simulated with Matlab 2008rb on a personal computer. The weighted factors obtained by AHP is w_1=0.37,w_2=0.36,w_3=0.27. Table 4 list the results of DGs planning under specified confidence levels: β_V=0.9 and β_L=0.9.

Table 3. The Discrete-Data of the Power Efficiency of PV

intervals	Output efficiency	Output power	Cumulative probability interval
[10%，15%]	12.5%	5	(0.1667, 0.2500]
(15%，20%]	17.5%	7	(0.2500, 0.3333]
(20%，25%]	22.5%	9	(0.3333,0.4167]
(25%，30%]	27.5%	11	(0.4167，0.5000]
(30%，35%]	32.5%	13	(0.5000,0.5833]
(35%，40%]	37.5%	15	(0.5833,0.6667]
(40%，45%]	42.5%	17	(0.6667,0.7500]
(45%，50%]	47.5%	19	(0.7500,0.8333]
(50%，55%]	52.5%	21	(0.8333,0.9167]
(55%，60%]	57.5%	23	(0.9167,1.0000]

Table 4. The Discrete-Data of the Power Efficiency of PV

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[10%，15%]	12.5%	5	(0.1667, 0.2500]
(15%，20%]	17.5%	7	(0.2500, 0.3333]
(20%，25%]	22.5%	9	(0.3333,0.4167]
(25%，30%]	27.5%	11	(0.4167，0.5000]
(30%，35%]	32.5%	13	(0.5000,0.5833]
(35%，40%]	37.5%	15	(0.5833,0.6667]
(40%，45%]	42.5%	17	(0.6667,0.7500]
(45%，50%]	47.5%	19	(0.7500,0.8333]
(50%，55%]	52.5%	21	(0.8333,0.9167]
(55%，60%]	57.5%	23	(0.9167,1.0000]

The simulation shows that the scheme of DGs planning considering with the uncertainties is distinct from that of with the certainties, which indicates that it is necessary to concern with the uncertainties when carrying on DGs planning. And plenty of simulation also shows that the results of DGs planning are closely related with sampling frequency and specified confidence levels including. For sampling frequency, the larger the sampling number is, the more reasonable the DGs planning scheme is. So sampling frequency must be large enough in order to receive the reasonable scheme. For specified confidence levels, Here simulation examples shows that DGs planning changes with the different confidence level, and the change coming from the voltage confidence level is different from that coming from branch capacity confidence level. DGs planning have little change under different voltage confidence level due to the less DGs penetration. Distinct change of DG planning will happen under different branch capacity confidence level due to different branch capacity limit in 37 bus system. Generally speaking, the higher the confidence level is, the larger the simulation timer is. In order to ensure the accuracy of the results and improve the algorithm efficiency, this paper recommends the confidence level of 0.9 as the reference by plenty of simulations.

6. Conclusion

The diversity and uncertainty of DGs brings out all kinds of new problems and make DGs planning become more and more complex. Aiming at these circulations, this paper presents a new method of DGs planning in distribution networks considering with uncertainty. According to the probability distribution of load, WTG and PV, the relatively accurate sampling data are obtained by different discretization methods. This not only can accurately and fully consider the uncertainties, but also can the sample space reduce the computational difficulty of the Monte Carlo simulation. The proposed model from the aspect of Distribution Company can reflect the influences of DGs on the distribution networks involving power loss, the system voltage quality and environment. The simulation results of complicated example optimization also show that the employment of the the Monte Carlo simulation, AHP and GA can quickly and efficiently solve DGs planning considering uncertainty. And improved crossover and mutation operation is much more effective than the standard crossover and mutation operation. The simulation results can provide reference of DGs planning under the uncertain environments for Distribution Company.

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