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Size and Location of Distributed Generation in Distribution System Based on Immune Algorithm

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Abstract

Distributed generation can enhance energy efficiency, postpone the construction investment of distribution network, and reduce environmental costs. On the contrary, DG may also disturb the system stability. The paper proposes a dynamic model of distributed generation in the smart grid, based on environmental compensation costs, traditional DG capacity cost, DG operation and maintenance costs, purchased power cost and network loss cost. The model can reflect the DG environment-friendly features. Considering load growth, the planning problem is divided into different periods which can be solved by using the dynamic programming method, and the planning result of next period has effects on the previous one. This solution can reflect the dynamic characteristics of network planning and avoid wasting resources. Taking the immune algorithm (IA) and IEEE30-bus system as the example, the results show that the proposed model can effectively resolve the DG planning problem in smart grid and get the DG dynamic programming optimal solution.

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Keywords: distributed generation(DG); electric power network planning; smart grid; environmental economic benefits; immune algorithm

1. Introduction

As the deepening reform of the electricity market and the global depletion of fossil energy in China, a modern smart grid that can be energy-saving, environmental friendly, efficient, reliable and stable will be the main trends of the development of power grid [2], [18]. Distributed generation is an important part of the smart grid, and will be a high percentage of smart grid in the future. Distributed generation which is included in the smart grid will improve energy efficiency, delay transmission line upgrade, and can also reduce greenhouse gas emissions, increase the quality of the environment. Access of distributed power in the distribution network will impact node voltage, feeder load and system reliability. Therefore, the difficult problem of distribution network planning is to determine the capacity and access point of DG [1], [6], [8], [9], [16].

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An analytical method is proposed to determine the optimal placement and sizing of DG with only one power flow for radial systems. The derived sensitivity factor is more suitable for distribution systems to determined optimal size and location of DG [14]. Based on the indicators of voltage stability, the goal of optimization model is to reduce network losses and improve voltage quality as to solve the problem of size and location of DG [15]. The network loss minimization objective function is solved by particle swarm algorithm and output the DG location and volume [11].

In this paper, it is proposed a DG dynamic programming model under the construction of smart grid, including the capacity, the initial cost, operation and maintenance costs, purchased power costs, network losses cost and the environmental compensation cost. The conclusion can help power companies, investors and independent power regulators to make decisions to provide a scientific distributed generation in distribution system.

1.1. Environmental compensation costs

Compared to conventional thermal power, DG using natural gas and other clean energy generation, can be more efficiency, reduce emissions of greenhouse gases and dust, and has less impact on the surrounding environment [4], [17]. In the distribution network planning, the effect on the environment of traditional thermal power generation and DG is quantified as environmental compensation costs:

$$C_{Env,t} = P_{Env} \left[(E_{Trans,t} + E_{Loss,t}) \gamma_G + \sum_{i=1}^{N_{DG}} P_{DGi,t} \gamma_{DGi} \right]$$
(1)

where $C_{Env,t}$ denotes environmental compensation cost in the period of t, P_{Env} denotes the price of environmental compensation cost, $k, kg, E_{Trans,t}$ is purchased power in the period of t, $E_{Loss,t}$ denotes network losses in the period of t, γ_G denotes emissions weight of unit purchased electricity, kg/MWh, γ_{DGi} denotes emissions weight of DG, kg/MWh, N_{DG} is the number of DG, $P_{DGi,t}$ is the generation power of DG in the period of t.

1.2. Capacity cost of DG

The capacity cost of DG is allocated to the planning period t by the discount rate ζ , and the capacity cost of DG:

$$C_{INDG,t} = \frac{\eta}{8760} \cdot \sum_{i=1}^{N_{DG}} C_{Inv} \cdot P_{DGi,t}^{\max}$$

$$\eta = \frac{\zeta(1+\zeta)^{T}}{(1+\zeta)^{T}-1}$$
(2)
(3)

here
$$C_{INDG,t}$$
 denotes the capacity investment cost in the period of t, C_{Inv} denotes the price of capacity

wl investment cost, $P_{DGi,t}^{\max}$ denotes the rated capacity of DG in the period of t, η denotes capital recovery factor equal allotments, ζ denotes discount rate. T denotes planning cycle.

1.3. Operation and maintenance costs of DG

DG consumes more clean energy, and the operation cost is higher than traditional generation units[12]. Operation and maintenance costs of DG in full life-cycle:

$$C_{OMDG,t} = \sum_{i=1}^{N_{DG}} P_{OMDG} \cdot P_{DGi,t}$$

$$\tag{4}$$

where $C_{OMDG,t}$ denotes operation and maintenance costs in the period of t, P_{OMDG} denotes the price of operation and maintenance costs.

1.4. Purchased power costs

Electricity transmission network mainly transmits electricity from the generation side to the distribution network. Power distribution companies maximize their own interests by purchasing power from multiple power transmission company. Purchased power costs of distribution network includes active power costs and reactive power costs:

$$C_{E,t} = \sum_{i=1}^{G} P_{p \ it} \cdot P_{Gi,t} + \sum_{i=1}^{G} P_{q \ it} \cdot Q_{q \ it}$$
(5)

where $C_{E,t}$ denotes the purchased power cost in the period of t, $P_{pi,t}$ denotes active power price in the period of t, $P_{qi,t}$ denotes reactive power price in the period of t, $P_{Gi,t}$ denotes active power, $Q_{qi,t}$ denotes reactive power, G denotes the number of nodes connected to the transmission network.

1.5. The cost of network losses

DG located in the vicinity of end-user and used for peak periods. Thereby DG can reduce the power flow in transmission and distribution lines, the impact of transmission congestion and network losses, and can also improve energy efficiency[7],[10]. Cost of distribution system network:

$$C_{loss,t} = E_{loss,t} P_{pi,t} \tag{6}$$

$$E_{loss,t} = \sum_{i} \sum_{j} P_{ij}$$
(7)

$$P_{ii} = V_i^2 Y_{ii} \cos(\theta_{ii}) - V_i V_i Y_{ii} \cos(\delta_i - \delta_i + \theta_{ii})$$

$$\tag{8}$$

where $C_{loss,t}$ denotes the cost of network loss in the period of t, P_{ij} denotes line loss between i and j.

1.6. The objective function

The access point and the capacity of DG is included in the cost-minimizing objective optimization problem, the objective function is:

$$\min C_{Total} = \min \sum_{i=1}^{T} (C_{Env,t} + C_{INDG,t} + C_{OMDG,t} + C_{loss,t})$$
(9)

where C_{Total} denotes the total system optional cost in the planning period, \$, T denotes planning cycle, t = 1, 2, 3...T.

1.7. Constraints

In the planning cycle, the system need meet certain security constraints and network constraints. Power balance constraints:

$$(P_{DGi} + P_{Gi}) - P_i^d - \sum_{j=1}^{d} P_{ij} = 0$$
⁽¹⁰⁾

$$Q_{Gi} - Q_i^d - \sum_{j=1}^{d} Q_{ij} = 0 \tag{11}$$

Purchased power constraints:

$$0 \le P_{Gi} \le P_{Gi}^{\max} \tag{12}$$

Branch capacity constraints:

$$\left|S_{ij}\right| \le S_{ij}^{\max} \tag{13}$$

Node voltage constraint:

$$V_i^{\min} \le V_i \ \le V_i^{\max} \tag{14}$$

Capacity constraints of DG:

$$0 \le \sum_{t=1}^{T} P_{DGi,t} \le P_{DGi}^{\max}$$

$$(15)$$

where P_i^d denotes demand of active power at node *i*, Q_i^d denotes demand of reactive power at node *i*.

 $\sum_{j=1}^{i} P_{ij} \text{ denotes line power loss between } i \text{ and } j, \sum_{j=1}^{i} Q_{ij} \text{ denotes line reactive loss between } i \text{ and } j,$ $S_{ii}^{\max} \text{ denotes line maximum transmission capacity, } P_{Gi}^{\max} \text{ denotes the maximum capacity of DG } i.$

2. Immune Algorithm

Immune Algorithm (IA) is a biomimetic intelligent calculation from imitating intelligent behavior of biological immune system. The objective function and constraints corresponds to antigen, and the feasible solution corresponds to the antibody. Adaptive immune algorithm is chosen to solve programming problems of DG [3],[5].

2.1. Coding

The genes of each chromosome is divided into two series, binary and decimal encoding respectively. Binary code gene string represents the access of DG, 1 denotes yes, 0 denotes no. Decimal string represents the size and location of DG [13]. the period of t.

2.2. Clonal selection of antibody-based incentive

Affinity is the antibody incentives degree of the final evaluation results. Antibodies that have low concentration and high density will be given a greater degree of motivation.

The number of antibody is M, the affinity of antibody is

$$f(x_i) = \frac{1}{1 + C_{Total}(x_i)} \qquad i = 1, 2, \dots M$$
(16)

The clonal selection probability based on Antibody affinity

$$P_r(x_i) = f(x_i) / \sum_{i=1}^M f(x_i) \qquad i = 1, 2, \dots M$$
(17)

where x_i denotes the planning program, $C_{Total}(x_i)$ denotes the corresponding total cost of planning.

Antibody density expresses the diversity of population. When antibody density is too high, it means that the individual of populations are very similar. The research will focus on the optimization range of a feasible solution area which is not conducive to global optimization. When antibody density is too low, it means that the scattered distribution of antibody is not conducive for improving efficiency. The distance of x_i on clone populations M:

$$d(x_i) = \sum_{j=1}^{M} \left| f(x_i) - f(x_j) \right| \quad i = 1, 2, \dots M$$
(18)

The Corresponding antibody concentration:

$$\rho(x_i) = \frac{1}{d(x_i)} = \frac{1}{\sum_{j=1}^{M} \left| f(x_i) - f(x_j) \right|}$$
(19)

Clonal selection probability based on antibody concentration:

$$P(x) = \frac{d(x)}{\sum d(x)} = \frac{\sum |f(x) - f(x)|}{\sum \sum |f(x) - f(x)|}$$
(20)

Clonal selection probability base on the degree of antibody incentives:

$$P(x_i) = \delta P_r(x_i) + (1 - \delta) P_d(x_i) \tag{21}$$

where δ denotes weighting coefficients of incentive Degree.

The number of cloning in population:

$$N_{c}(x_{i}) = P(x_{i})S' = [\delta P_{r}(x_{i}) + (1 - \delta)P_{d}(x_{i})]S'$$
(22)

where $N_c(x_i)$ denotes the cloning number of x_i , S' denotes the population scale after cloning.

2.3. Mixed mutation operator

Gaussian mutation operator and Cauchy mutation operator are used for mutation of the antibody population in this paper. Gaussian mutation operator is selected for the high affinity of outstanding individual of cloned populations, so individuals can make a higher probability of variation in small-scale. Cauchy mutation operator is selected for the low affinity of individuals in cloned populations, so individuals can have a variation in the smaller probability and larger scale.

Gaussian mutation operator:

$$\lambda_i = \lambda_i + \alpha_i \cdot \exp\left[\frac{N(0,1)}{\sqrt{2}} + \frac{N_i(0,1)}{\sqrt{2}}\right] N_i(0,1)$$
⁽²³⁾

Cauchy mutation operator:

$$\lambda = \lambda + \alpha \cdot \exp\left[\frac{\eta(0,1)}{\sqrt{2}} + \frac{\eta(0,1)}{\sqrt{2}}\right] \eta(0,1)$$
(24)

where λ_i denotes antibody *i*, α_i is variation step, N(0,1) and $N_i(0,1)$ denote standard normal distribution, $\eta(0,1)$ and $\eta(0,1)$ denote standard Cauchy distribution.

2.4. Algorithmic process

Immune algorithm flow is shown in Figure 1.



Fig. 1. Flow chart of immune algorithm

3. Example analysis

IA and IEEE30-bus system are used for case study to determine the optimal DG capacity and access points. The structure of system network is shown in Figure 2.



Fig. 2. Chart of IEEE30 bus system

The level of system voltage is 33kV. Load demand is 268.8MVA. Planning cycle is 5 years. Purchased electricity price is 70\$/MWh. Gas unit construction cost is 0.5M\$/MW. The cost of operation and maintenance is 55M\$/MWh. The largest DG capacity of distribution network is 20MVA. Single DG capacity is 1MW. Maximum number of each node is 4. Voltage of each node range is 0.96u-1.05u. Price of environmental compensation cost is 0.007\$/kg. Emissions standard of purchased electricity is 1000kg/MWh. Emissions standards of DG is 500kg/MWh.

Table 1. An example of a table

location	DG capacity/MW	location	DG capacity/MW
14	2	23	3
15	3	24	1
18	3	26	3
19	3	30	3

Table 1 shows the best location and capacity of DG. After the accessing of DG, the purchased power of electricity system reduced to 329.2MW, which was decrease by 5.94%. The total costs of environmental compensation reduced to 6.13×105 . Network losses reduced 15.76MW, which was decreased by 2.9%. The price decreased to 69.61/MWh.



Fig. 3. Changes of system voltage profiles without and with DG in the planning period T

Figure 3 shows the voltage profiles without and with DG in the planning period T. Before DG installation, voltages are violated at buses 8, 24, 29 and 30 at the planning period. After DG installation, the system voltage profiles is improved and satisfy the voltage constraints.

4. Conclusion

The development of DG meets the requirements of energy saving policies in smart grid construction. In this paper, it proposes a DG dynamic programming model. Several examples show that, after the access of DG, environmental compensation costs, marginal price and network losses can be effectively reduced. The voltage level of each node is improved. According to the programming model, the system can effectively clarify the cost of DG and promote the further use of grid enterprises.

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