CHEMICAL ENGINEERING TRANSACTIONS
VOL. 71, 2018
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet
Guest Editors: Xiantang Zhang, Songrong Qian, Jianmin Xu

ISBN 978-88-95608-68-6; **ISSN** 2283-9216
DOI: 10.3303/CET1871032

Multi-Objective Grid Planning for Distributed Power Supply Considering Total Emission Control of Carbon Dioxide

Bailin Liu[a]*, Cong Jiang[b], Xiaobin Wu[c]

[a]Dean's Office, Northeast Electric Power University, Jilin Province, Jilin 132012, China
[b]Jilin Electric Power Construction Supervision Co.,Ltd., Jilin Province, Changchun 130000, China
[c]Fujian Automation Electric Power Technology Co.,Ltd., Fujian Province, Zuzhou 350012, China
liubailinnedu@163.com

Making reasonable regional carbon dioxide emission reduction plan is the only way to realize the sustainable development of China's power industry. Therefore, on the basis of fully considering the potential of energy saving and emission reduction of regional electric power, the space of structural emission reduction and the feasibility of Engineering emission reduction, and considering the power demand of regional economic development, the plan of carbon dioxide emission reduction of electric power is formulated to give full play to the environmental protection advantages of distributed generation, which has strong practical application value and guiding significance. In this paper, a multi-objective programming method for multi-distributed power grids based on quantum genetic algorithm and multi-objective optimization strategy is proposed. By planning distributed power supply reasonably, this method not only reduces carbon emissions, but also takes into account the economy of distribution network construction.

1. Introduction

Energy provides the material basis for social and economic development. In recent years, more and more countries are suffering from energy shortage due to the soaring demand, depletion of fossil energy and the restricted development of nuclear plants. The situation is worsened by the deterioration of eco-environment, the aging of traditional power system, and the growing need of high-quality energy. Facing these problems, the only way out is to develop and utilize renewable energy. The utilization of renewable energy can be promoted by distributed power supply, also known as distributed generation. As opposed to traditional centralized power supply, the distributed power supply makes full use of various scattered but accessible energy sources, including renewable ones like wind energy, solar energy, biomass energy and tidal energy and non-renewable ones like natural gas. It has a wide range of rated power, ranging from tens of kilowatts to tens of megawatts. In general, distributed power supply is located near the user, highly modularized and supported by advanced information control techniques. Previous studies agree that distributed power supply can improve the efficiency of energy use, optimize energy supply structure and ensure safe and reliable power supply (Ferdinand et al., 2017; Erolkantarci and Mouftah, 2015; Nacef et al., 2016; Zhang et al., 2016).
The impact of distributed generation on the power grid is closely related to the installation location and capacity of the distributed generation. The existing studies on distributed power supply mostly pursue the minimal loss. However, more and more objectives have been raised in recent years, such as the minimal investment, the minimal operation cost, the optimal power quality, and the minimal power loss. These goals sometimes contradict each other (Chen et al., 2013; Xing et al., 2014). In addition to flow and operation constraints, grid planning for distributed power supply must consider economic cost, power quality, system stability, environmental benefit and so on. In light of the above, this paper firstly reviews the economic and technical optimization problems involved in grid access of distributed power supply, and then establishes a distributed power supply programming model with the aim to minimize the active network loss, investment and operation cost of the grid and the voltage offset of the load node. Then, a multi-objective mixed pure quantum genetic algorithm was developed to solve the nonlinear, multi-constraint and multi-objective programming problem of grid planning for distributed power supply, and was compared with traditional multi-objective

Please cite this article as: Liu B., Jiang C., Wu X., 2018, Multi-objective grid planning for distributed power supply considering total emission control of carbon dioxide, Chemical Engineering Transactions, 71, 187-192 DOI:10.3303/CET1871032

evolutionary algorithm. Finally, the proposed model was applied to a real case to verify the effect of the proposed algorithm in solving the grid planning for distributed power supply.

2. Multi-objective grid planning model for distributed power supply

2.1 Multi-objective grid planning model for distributed power supply

The typical constrained multi-objective problem can be described as follows:

$$\begin{cases} \min\ f(X) = \left[f_1(X), f_2(X), \cdots, f_n(X) \right] \\ \qquad\qquad s.t. g_q(X) \le 0 \end{cases} \tag{1}$$

where$f(X) \in R^n$ is a vector with *n* objective functions, which form the target space;$g_q(X) \le 0$ is a q inequality constraint function, which constitutes a feasible solution area; $X = [x_1, x_2, \cdots x_n,] \in R^n$is are *n* vectors with *m* decision variables, which make up the decision space.
The following are several basic definitions for multi-objective optimization:
(1) Pareto dominance: solution X_1 has Pareto dominance over solution X_2 ($X_1 < X_2$), if and only if the following conditions are fulfilled at the same time:

$$\begin{aligned} & f_i(X_1) \le f_i(X_2), \forall i = 1,2, \cdots n \\ & f_i(X_1) < f_i(X_2), \exists i \in \{1,2, \cdots n\} \end{aligned} \tag{2}$$

(2) Pareto optimality: X is the Pareto optimal solution, if and only if $\neg \exists X_i : X_i \prec X$.
(3) Pareto optimality set: the collection of all Pareto optimal solutions.
(4) Pareto optimal frontier: the area formed by all Pareto optimal solutions corresponding to the objective function value.

2.2 Objective function

A rational grid plan for distributed power supply should improve the power quality and optimize the power flow without sacrificing the economic benefits. Therefore, the objective function must include both economic and technical targets. Specifically, the economic targets are the minimal investment and operation cost and the minimal power loss, while the technical target is the minimal voltage offset of load node, that is, the maximum stability margin of static voltage (Fan et al., 2015; Fan, 2018). Considering these targets, objective function of the mathematical model of multi-objective grid planning for distributed power supply can be expressed as:

$$\left\{ \begin{aligned} & \min P_{loss} = \sum_{k=1}^{N_1} G_{k(i,j)} (U_i^2 + U_j^2 - 2U_i U_j \cos\delta_{ij}) \\ & \min C = \sum_{i=1}^{N_{DG}} X_i \left[\left(\frac{r(1+r)^n}{(1+r)^n - 1} \right) \cdot C_{aZ,i} + C_{OM,i} \right] P_{DGi} \\ & \min \Delta U = \sum_{i=d}^{Nd} \left(\frac{U_l - U_l^{spec}}{\Delta U_l^{\max}} \right)^2 \end{aligned} \right\} \tag{3}$$

where P_{loss} is the active network loss; *C* is the investment and running cost; ΔU is the voltage offest of load node; $G_{k(I,j)}$ is the conductance of branch *K*; N_{DG} is the total number of nodes in the grid for distributed power supply; N_l is number of branches in the grid; N_{dis} the number of load nodes; δ_{ij} is the voltage phase angle difference between nodes *i* and *j*; U_i and U_j are the voltage amplitudes of node *i* and *j*, respectively; U_l is the actual voltage; U_{spec} is the expected voltage; U_{max} is the maximum allowable voltage offset of load node; *n* is the service life; *r* is the discount rate; *X* is an indicator of the presence of distributed power supply (*X=0* means the distributed power supply is not installed at the corresponding position while *X=1* means the distributed power supply is installed at the corresponding position); P_{DGi}, $C_{aZ,I}$ and $C_{OM,i}$(unit: 104yuan/kWh) are the capacity, maintenance cost and installation cost of the distributed power supply at node *i*, respectively.
There are three inequality constraints and one equality constraint for our model.
The equality constraint targets the power flow of the grid:

$$\begin{cases} P_{Gi} + P_{DGi} - P_{Li} - U_i \sum_{j=1}^{n} U_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij} \right) = 0 \\ Q_{Gi} - Q_{Li} - U_i \sum_{j=1}^{n} U_j \left(G_{ij} \sin\delta_{ij} - B_{ij} \cos\delta_{ij} \right) = 0 \end{cases} \tag{4}$$

3. Grid planning based on multi-objective mixed pure quantum genetic algorithm

3.1 Typical quantum genetic algorithm

In quantum computation, the information is stored physically in two-state quantum systems, i.e. qubits. Each qubit can represent the states of $|0\rangle$ and $|1\rangle$, and a random superposition state between these two strates. In other words, a qubit may be $|0\rangle$or$|1\rangle$, or the middle state between the two. Thus, a quantum state can be expressed as:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{5}$$

where α and β are the probability amplitudes of $|0\rangle$ and $|1\rangle$., respectively. Both amplitudes satisfy the normalization condition.

$$|\alpha|^2 + |\beta|^2 = 1 \tag{6}$$

where $|\alpha|^2$ and $|\beta|^2$are the probabilities of observing the quantum state of 0 and 1, respectively.
In atypical quantum genetic algorithm, the chromosome structure can be coded by qubit code as follows:

$$q_j' = \begin{bmatrix} \alpha_{11}'\alpha_{12}' \cdots \alpha_{1k}' \,|\, \alpha_{21}'\alpha_{22}' \cdots \alpha_{2k}' \,|\, \cdots \,|\, \alpha_{m1}'\alpha_{m2}' \cdots \alpha_{mk}' \\ \beta_{11}'\beta_{12}' \cdots \beta_{1k}' \,|\, \beta_{21}'\beta_{22}' \cdots \beta_{2k}' \,|\, \cdots \,|\, \beta_{m1}'\beta_{m2}' \cdots \beta_{mk}' \end{bmatrix} \tag{7}$$

where q_j' are the chromosomes of individual *j* in generation *i*; *k* is the number of qubits in each coded gene; *m* is the number of chromosomes, which corresponds the number of variables in a function.
The quantum genetic algorithm relies on quantum gate action and update to complete evolutionary search. With high search efficiency and good convergence, this algorithm can maintain population diversity and prevent pressure problem. Compared with traditional genetic algorithm, the quantum genetic algorithm achieves a high level of diversity and simultaneity through quantum chromosome coding.

3.2 Implementation of multi-objective mixed pure quantum genetic algorithm

(1) The main ideas
The multi-objective mixed quantum genetic algorithm was inspired by quantum computation and multi-objective evolution. The main ideas are as follows: improving the computing precision through qubit coding of real numbers, bolstering optimization efficiency and convergence speed based on the mixed nature of qubit probabilities and superimposed feature of quantum state, promoting population evolution through multi-objective optimization strategies like non-dominated sorting, elite retention and hierarchical clustering, and maintaining population diversity to ensure the convergence to the global optimal solution set of Pareto.
(2) Quantum chromosome coding
The variables of the proposed algorithm were represented by a real qubit instead of multiple binary qubits. Then, the quantum chromosome coding structure can be expressed as:

$$q_j' = \begin{bmatrix} x_1' x_2' \cdots x_{N_{DG}}' \\ \theta_1' \theta_2' \cdots \theta_{N_{DG}}' \end{bmatrix} \tag{8}$$

where $1 \le j \le N_p$, with Np being the population size;$x_i^t \in [x_{imin}^t, x_{imax}^t]$is a real variable;$\theta_t^i$ is the corresponding angle of the variable. This angle must satisfy the following equation:

$$\theta_i^t = \arcsin\left[\frac{x_i^t - x_{i\min}^t}{x_{i\max}^t - x_{i\min}^t}\right] \tag{9}$$

In this way, the information of each chromosome can be expressed simultaneously in real number space and phase space.
(3) Population classification
Based on non-dominated sorting, the population was classified according to the level of noninferior solutions of individuals. The non-dominated sorting algorithm needs to calculate the parameters n_i and S_i for each individual of the population, with ni being the serial number of individual i in the population, and Si being the individual set dominated by individual *i* in the population. The fast non-dominated sorting can be implemented through the following steps:
a) Identify all ni=0 individuals in the population and save them in the current set F_1.

b) For each individual *i* in the current set *F1*., save the individuals dominated by individual i in the set Si. Traverse each individual ω in *Si*, execute $n_\omega = n_\omega - 1$, and, if $n_\omega = 0$, save ω in the set *H*.
c)Taking the individuals in *F1*.as the first non-dominated individuals, and *H* as the current set, repeat the above steps until the whole population is stratified.
d)According to the serial number, assign a virtual fitness value to each level of individual. The target value is positively correlated with the non-dominance degree of the individual.
(4) Elite retention
The elite retention aims to save the good individuals in the parent generation directly into the child generation. According to hierarchical clustering, the crowding distance was calculated and *F1*. was sorted in the following steps:
a) Let $Z^t(Z^t = Q^t \cup R^t)$ be the population synthesized from parent population Q^t and child population R^t. Perform non-dominated sorting of Z and determine all the non-dominated solutions by $F = (F_1, F_2, \cdots)$.
b) Calculate the crowding distance of Fi and execute$Q^{t+1} = Q^t \cup F_i$ and i=i+1until $|Q^{t+1}| + |F_i| \le N_p$.
c)According to the niche theory, introduce crowding distance$\sigma(i)$is introduced to sort all the non-inferior front-end *F1*.. Then rank is negatively correlated with the crowding distance. Select the best $(N_p - |Q^{t+1}|)$ solutions in *F1*. that is, $Q^{t+1} = Q^{t+1} \cup F_i[1{:}(N_p - |Q^{t+1}|)]$.
d)Assign a virtual fitness value to each level of individual according to the non-inferior stratification and crowding distance. The target value is positively correlated with the non-dominance degree of the individual.
Meanwhile, the niche was adjusted automatically to protect the good individuals, resulting in evenly distributed results in the target space. Specifically, the crowding distance can be calculated as:

$$\begin{cases} \sigma(i) = \sum_{o=1}^{n} \sigma(i,o) \\ \sigma(i,o) = \dfrac{f_{inext,o} - f_{iform,o}}{f_{o\max} - f_{o\min}} \end{cases} \tag{10}$$

where $\sigma(i)$ is the crowding distance of individual *i* in the population; $\sigma(i, o)$ is the crowding distance of individual irelative to the target individual *o*; $f_{inext,o}$ is the next adjacent value to $f_{i,o}$,;$f_{iform,o}$ is the next adjacent value to $f_{i,o}$; f_{omax} and f_{omin} are the maximum and the minimum values, respectively. The crowding distance of individual *i* relative to the target individual o needs to be sorted in ascending order by the value of *o*.
(5)Quantum probabilities of crossover and chaotic mutation
The non-dominated sorting and allocation of virtual fitness values shows that the fitness-based traditional methods cannot determine the evolution direction of non-dominated individuals with the same rank. Therefore, the objective function value in the target space was regarded as the vector in the n-dimensional space, a vector modulus fitness function was adopted as the evaluation criterion, and the model of the vector was viewed as the fitness value of the individual to guide the evolution. In this way, the following equation can be established:

$$F(q_j') = \|\bar{f}_j\| = \sqrt{f_{j1}^2(x) + f_{j2}^2(x) + \cdots + f_{jo}^2(x)} \tag{11}$$

where $f_{jo}(x)$ represents the zeroth is the o-th objective function in target space *j*.
According to cross probability, the next generation can be produced from a real number of chromosomes as follows:
If $\|\bar{f}_i\| > \|\bar{f}_j\|$,

$$\begin{cases} \Delta\theta_i^t = \theta_i^t - \theta_j^t \\ q_i^{t+1} = q_i^t \cos^2(\Delta\theta_i^t) + q_j^t \sin^2(\Delta\theta_i^t) \end{cases} \tag{12}$$

Considering the ergodicity and initial value sensitivity of chaos, the chaotic sequence *C* was introduced to restrict the amplitude perturbation of the angle θ corresponding to all the real chromosomes in the current generation.
The variation in the phase angle can be expressed as

$$\lambda_i = \exp[(i - N_p)/N_p] \tag{13}$$

$$\Delta\theta_i^t = \lambda_i \cdot C(i) \tag{14}$$

3.3 Grid planning for distributed power supply based on the proposed algorithm

In this paper, the position and capacity of distributed power supply are mixed with the integer and real numbers of qubit chromosome. Then, the decision variable can be expressed by the integer variable and the real number angle defined in equations (13) and (14), respectively. Taking the target grid as a power quality reporting node, the active network loss, economic cost and voltage offset of load node were solved, together with the power flow. Figure 1 illustrates the application of the proposed algorithm in the grid planning for distributed power supply.

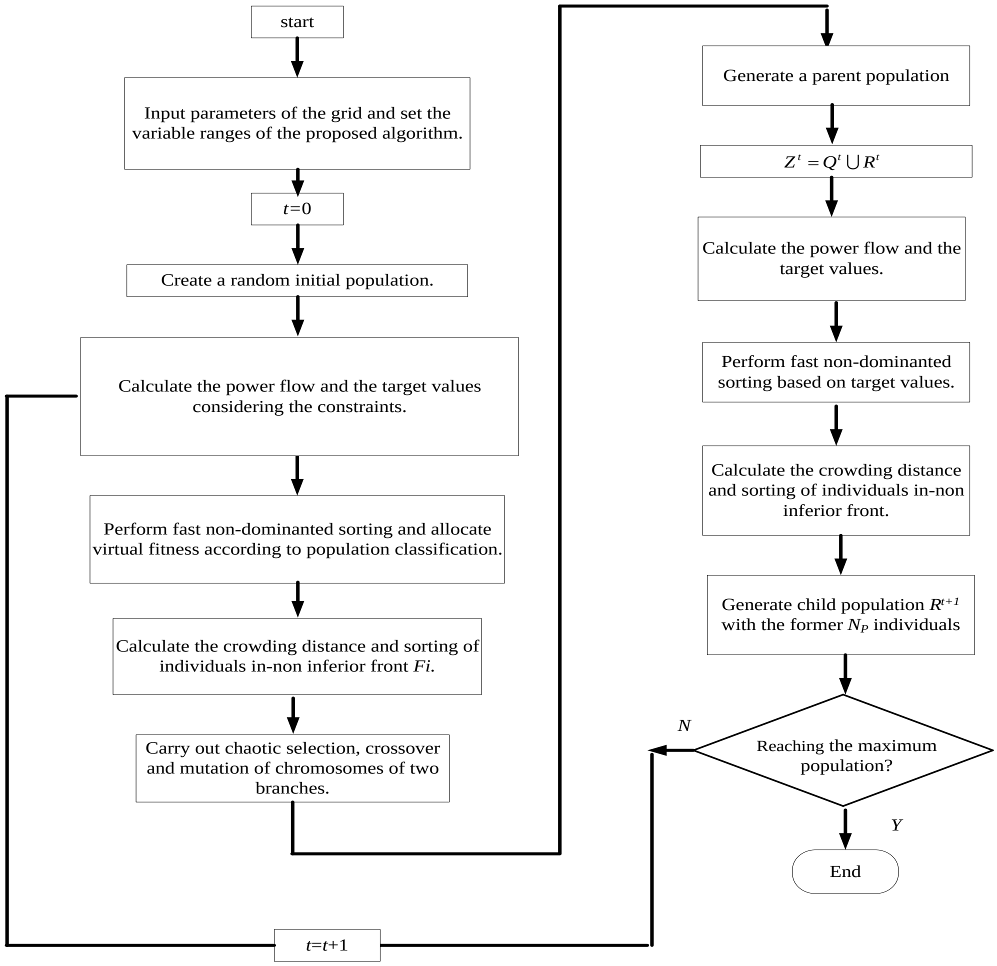

Figure 1: Workflow of the proposed algorithm

4. Case study

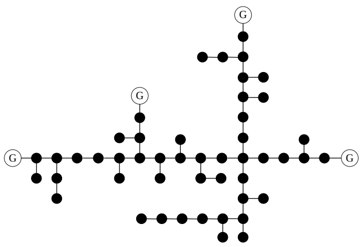

Figure 2: Structure of Dunhua grid

The proposed algorithm was applied to Dunhua Grid of Jilin Province, China, and the results were discussed in details. The structure of the said grid in early 2018 is displayed in Figure 2. As the operator of the grid, Dunhua Rural Electric Power Co., Ltd. supplies over 130 million kWh power annually to 501 enterprises and

75,000 residents in 543 villages and 16 towns. The entire grid consists of 16 power supply units, 91,953 <10kV distribution transformers, 1,596 10kV distribution transformers, 1,369km <0.4kV lines and 1,772m 10(6)kV lines.
The data on power generation and load between September 2017 and February 2018 were collected from Dunhua grid. Considering the three targets of reliable supply, low cost and greenness, two grid plans were prepared as follows:
Plan 1: Optimizing the design of micro-grid system for cooling, heating and power supply, and stopping the operation of micro-gas turbine unit.
Plan 2: Optimizing the design of micro-grid system for combined cooling, heating and power supply system, and operating micro-gas turbine unit at fixed thermal power.
The two plans were compared in terms of the three targets. As shown in Table 1, the micro-grid system for combined cooling, heating and power supply systemin Plan 2 outperformed the micro-grid system for cooling, heating and power supply in Plan 1 by 1.736 million yuan in economic cost, although it costed 3,755 more than the latter in operation. The good performance of Plan 2 is attributable to the efficiency of power generation and utilization of the cogenerated energy.

Table 1: Comparison between the two plans

	Investment (10^6yuan)	Running (10^6yuan)	Total Cost (10^6yuan)
Plan1	7.43646	0.00159	7.43805
Plan2	5.69271	0.03914	5.70185

5. Conclusions

After reviewing the economic and technical optimization problems in grid access of distributed power supply, this paper sets up a distributed power supply programming model with the aim to minimize the active network loss, investment and operation cost of the grid and the voltage offset of the load node. Then, a multi-objective mixed pure quantum genetic algorithm was developed to solve the nonlinear, multi-constraint and multi-objective programming problem of grid planning for distributed power supply. Finally, the proposed model was applied to a real case to verify the effect of the proposed algorithm in solving the grid planning for distributed power supply. Suffice it to say that the established model can desirably complete the grid planning for distributed power supply.

Acknowledgment

This paper is supported by The PhD Start-up Found of Northeast Electric Power University, China

References

Chen G., Dai P., Zhou H., 2013, Distribution system reconfiguration considering distributed generators and plug-in electric vehicles, Power System Technology, 37(1), 82-88, DOI: 10.1007/978-3-642-35314-7_42
Erolkantarci M., Mouftah H.T., 2015, Energy-efficient information and communication infrastructures in the smart grid: a survey on interactions and open issues, IEEE Communications Surveys&Tutorials,17(1), 179-197, DOI: 10.1109/COMST.2014.2341600
Fan M.T., Zhang Z.P., Su A.X., 2015, Enabling technologies for active distribution systems, Proceedings of the CSEE, 33(22), 12-18.
Fan Q., 2018, Multi-target location of infrared image of power equipment, Chemical Engineering Transactions, 66, 859-864. DOI: 10.3303/CET1866144
Ferdinand P., Pouillé F., Ricque B., 2017, When the remote measurement instrumentation works to improve the monitoring of the reactor building of nuclear power plants in case of severe accident, Instrumentation Mesure Metrologie, 16(1-4), 183-211, DOI: 10.3166/I2M.16.1-4.183-211
Nacef I., Ben Kilani K., Elleuch M., 2016, Impact of power system controls on damping wind induced inter-area oscillations, European Journal of Electrical Engineering, 18(5-6), 399-412, DOI: 10.3166/EJEE.18
Xing H., Cheng H., Hong S., 2014, Minimize active power loss with distribution network reconfiguration considering intermittent renewable energy source uncertainties, 2014 International Conference on Power System Technology (POWERCON). Chengdu, China: IEEE, 127-133
Zhang S.X., Yuan J.Y., Cheng H.Z., Li K., 2016, Optimal distributed generation planning in active distribution network considering demand side management and network reconfiguration, Electric Power Automation Equipment, 36(9), 1-9, DOI: 10.13334/j.0258-8013.pcsee.160333