Lecture Notes in Electrical Engineering 833

Shu-Chuan Chu
Jerry Chun-Wei Lin
Jianpo Li
Jeng-Shyang Pan *Editors*

Genetic and Evolutionary Computing

Proceedings of the Fourteenth International Conference on Genetic and Evolutionary Computing, October 21–23, 2021, Jilin, China

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Preface

This volume composes the proceedings of the Fourteenth International Conference on Genetic and Evolutionary Computing (ICGEC 2021), which was hosted by Northeast Electric Power University and was held in Jilin City, Jilin Province, China, on October 21–23, 2021. ICGEC 2021 was technically co-sponsored by Fujian University of Technology (China), Shandong University of Science and Technology (China), Western Norway University of Applied Sciences (Norway), and Springer. It aimed to bring together researchers, engineers, and policymakers to discuss the related techniques, to exchange research ideas, and to make friends. More than sixty excellent papers were accepted for the final proceeding. We would like to thank the authors for their tremendous contributions. Furthermore, we would also express our sincere appreciation to the reviewers, program committee members, and local committee members for making this conference successful.

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Adaptive Droop Control Strategy for Island Microgrid Based on Improved Particle Swarm Optimization Algorithm

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Abstract. The isolated island microgrid with multiple distributed power sources operating in parallel cannot ensure that the voltage information is equal everywhere due to the difference in line impedance. As a result, its droop control may cause some problems such as unbalanced power distribution and bus voltage fluctuation. For this, a method to improve particle swarm optimization (IPSO) using fuzzy rule system to optimize droop control is proposed. Firstly, the principle and shortcomings of traditional droop control are analyzed. Then, in order to reach optimization of droop factor, a particle swarm (PSO) algorithm with fuzzy rule system is proposed, which can dynamically adjust the learning factor and inertia weight of the particle swarm algorithm, and effectively improve the convergence ability and search speed of the algorithm. The experiment results show that the proposed IPSO algorithm can maintain the real-time stability of bus voltage and microgrid frequency under complex operating conditions, efficaciously improve the accuracy of power balance distribution, and enhance the dynamic performance and stability of islanded microgrid.

Keywords: Microgrid · PSO algorithm · Fuzzy rule-based systems · Droop control · Power distribution

1 Introduction

As a small power system, the microgrid integrates distributed generations, energy storing equipment, energy transformers, protection devices and loads, and has two operating modes: islanding and grid-connected [1]. The control mode of microgrid is classified as master-slave control and equivalence control [2]. Compared with the master-slave control, the equivalence control mode simulates the external characteristics of the grid-connected operation of the synchronous motor. Under this control mode, the droop control of the distributed generations (DG) can automatically participate in the distribution of the output power, which is convenience for realizing the plug-and-play of the distributed generations [3, 4].

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The droop controller of the alternating current (AC) microgrid mainly includes two parts: the inner loop that uses the droop curve to generate the voltage reference quantity, and the outer voltage-current loop that tracks the reference value generated by the inner loop [5]. Whereas, the existence of line impedance and local load makes the voltage and frequency information of each DG not equal everywhere, which will lead to insufficient power allocation accuracy and bus voltage drop [6]. At present, artificial intelligence control algorithm plays an increasingly significant role in solving complex problems in power grid. Artificial intelligence control algorithm has incomparable advantages. Artificial intelligence control algorithms have been the primary way to study and settle electrical power system problems in control, modeling, operation and analysis [7].

Therefore, this paper proposed the IPSO algorithm by using the fuzzy rule-based system to optimize the droop control. The function of introducing fuzzy rule system is to dynamically adjust the learning factor and inertia weight of particle swarm algorithm, and improve the global search ability and local search ability of the algorithm. The simulation experiment results show that the proposed IPSO algorithm can sustain real-time voltage and frequency stability under different operating conditions, effectively improve the power allocation accuracy and the dynamic performance and stability of the microgrid.

2 Traditional Droop Control

The topology of the AC microgrid droop controller is similar to equivalent circuit of synchronous generator. The topology of the simplified multi-distributed power microgrid in Fig. 1 is obtained [8].

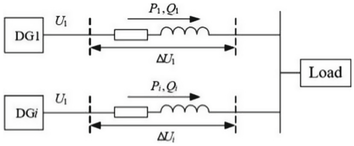


Fig. 1. Simplified structure of microgrid.

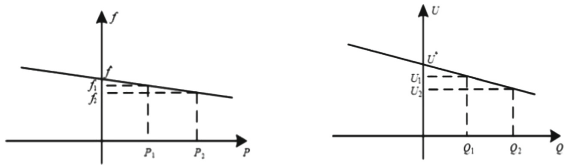
As illustrated in the picture above, the DG is connected to the microgrid through inverter and LC filter respectively and is connected to the AC bus through line impedance to supply power to the load [9]. Since $R << X$, the resistance part of the line impedance does not need to be calculated. The power output P_i and Q_i of the i-th DG are:

$$P_i = \frac{U_i U_{PCC} \sin \delta_i}{X_i} \tag{1}$$

$$Q_i = \frac{U_i U_{PCC} \cos \delta_i - U_{PCC}^2}{X_i} \tag{2}$$

In the formulas, U_i is the amplitude of the i-th DG output voltage, U_{PCC} is the amplitude of the AC microgrid bus voltage, X_i is the line reactance from the i-th DG to the AC bus, and δ_i is the phase of the i-th DG output voltage Phase difference with PCC voltage.

According to formula (1) and (2), the variation factors of active power P and reactive power Q of the DGs are voltage phase difference δ and voltage magnitude U. Thus the droop characteristics of microgrid are illustrated in the picture blow.



(a) P-f Droop characteristics. (b) Q-U Droop characteristics

Fig. 2. Droop characteristics.

From Fig. 2, we can get that the droop characteristic equation of the DG_i are

$$f_i = f^* - k_p P_i \tag{3}$$

$$U_i = U^* - k_q Q_i, \tag{4}$$

Where k_p is the frequency droop factor in the microgrid droop control, and k_q is the voltage droop factor in the microgrid droop control, f^* is the reference frequency value of the microgrid system, U^* is the reference voltage value of the microgrid system.

Therefore, the traditional droop control principle is illustrated in Fig. 3 [10].

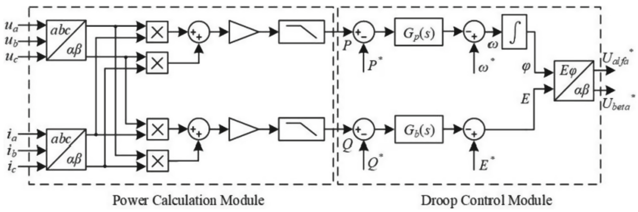


Fig. 3. Traditional droop control schematic

In the microgrid, the reactive power of the DG can 't be accurately distributed by droop control according to the local variable output voltage. Hereby, we should need to optimize the distribution of the DG reactive power output [8].

In the simplified microgrid topology diagram, the following formulas can be obtained:

$$U_i = U_{PCC} + \Delta U_i \tag{5}$$

$$\Delta U_i = \frac{X_i Q_i + R_i P_i}{U^*} \tag{6}$$

Among them, ΔU is the voltage drop of the i-th DG line impedance. As mentioned earlier, because of $R << X$, the above formula can be simplified to:

$$\Delta U_i = \frac{X_i}{U^*} Q_i \tag{7}$$

According to the simplified microgrid topology diagram in Fig. 1 and Eqs. (5) to (7), the reactive power transmission characteristic curves of each DG is shown as follows:

$$U_1 = U_{PCC} + \frac{X_1}{U^*} Q_1 = U_{PCC} + k_1 Q_1 \tag{8}$$

$$U_2 = U_{PCC} + \frac{X_2}{U^*} Q_2 = U_{PCC} + k_2 Q_2 \tag{9}$$

Among them, k_1 and k_2 are the impedance factors of the DG1 and DG2 exit line. Combined with the droop characteristic diagram shown in formula (4), the reactive power distribution relationship of double parallel distributed power sources is illustrated in the picture blow.

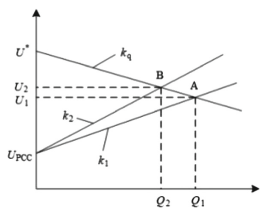


Fig. 4. Reactive power distribution relationship

When $X_1 \neq X_2$, the stable operation points of the systems are situated at A and B in Fig. 4. Assuming that there is $\Delta Q_1 = \Delta Q_2$, when $X_1 < X_2$, there is $Q_1 > Q_2$, and the reactive power output of double parallel distributed power sources cannot be accurately distributed.

3 Improved Particle Swarm Algorithm

3.1 Basic Particle Swarm Algorithm

The PSO algorithm has the characters of structure simplification and good optimization effect, and can search for appropriate parameters without establishing an accurate mathematical model [12]. The initial parameters of PSO are quantitative random particles. In the PSO running process, the particles update the parameters of individual extremum and global extremum through each iteration in order to find the optimum result [13].

In PSO algorithm, the particle velocity and position update formula are as follows:

$$v_{id} = \omega \times v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 \left(p_{gd} - x_{id}\right) \tag{10}$$

$$x_{id} = x_{id} + v_{id} \tag{11}$$

Among them, c_1 and c_2 are study rates of the PSO algorithm; r_1 and r_2 are symmetrical random numbers in [0,1]; ω is the adaptive weight value.

3.2 Introduction of Fuzzy Rule System

Despite of simple structure of the basic PSO algorithm, when optimizing complex nonlinear microgrids based on droop control strategy, the basic PSO algorithm has the shortcomings of insufficient global search and detection ability. Therefore, a series of improvements to the basic PSO are required.

This thesis introduces a fuzzy rule-based system on the basis of the proposed method in the reference [14] to enhance the performance of the PSO algorithm, and dynamically adjusts the learning factor c_1 and c_2 of the particle swarm algorithm through fuzzy inference and the inertia weight ω. Among them, the iteration coefficient λ of each particle is the ratio of the current iteration number to the maximum iteration number, and the iteration coefficient λ of each particle is between 0 and 1. The calculation formula is:

$$\lambda = \frac{t}{t_{max}} \tag{12}$$

Among them, t is the particle current iteration number, and t_{max} is the maximum iteration number of the particle. During the initial operation of the algorithm, λ approaches 0. With the change of the iteration number, λ gradually increases and approximates 1.

The particle similarity γ is the reciprocal of the square root of the average value of the optimum result of all particle distances in the whole world, and its value is between 0 and 1. The calculation formula is:

$$r = \frac{1}{\sqrt{\frac{1}{m}\sum_{i=1}^{m}\sqrt{\sum_{j=1}^{d}\left(x_{ij}(t-1) - gbest_i(t-1)\right)^2} + 1}} \tag{13}$$

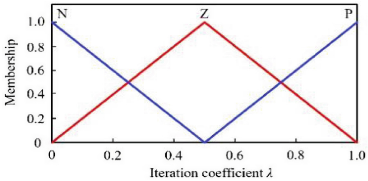
Among them, m is the total particle number, d is the search space dimension, x_{ij} is the position of the i-th particle in the j-th dimension during the previous iteration, and $gbest_j$ is the j-th dimension of the optimum result found in the previous iteration. When the distance between the particle and the optimum result in the algorithm is larger, the average value is also larger, and the particle similarity is smaller, until it is 0; otherwise, the particle similarity is larger, until it is 1.

The fitness error ε of a particle is the difference between the average of the ratio of the fitness value of the global optimal particle to the fitness value of all particles and 1, and its value is between 0 and 1. The calculation formula is:

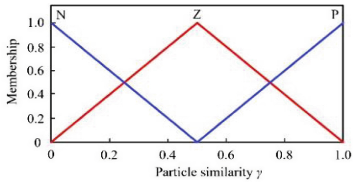
$$\varepsilon = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{f_{gbest}}{fit(i)} \tag{14}$$

Among them,f_{gbest} is the fitness value of the algorithm's global optimal particle, and $fit(i)$ is the adaptation degree of the i-th particle in the IPSO algorithm. When the algorithm has a good convergence effect, the particles approach the global optimum result, the ratio of f_{gbest} and $fit(i)$ becomes larger, approaching 1, and the fitness error approaches 0. Conversely, the difference between f_{gbest} and $fit(i)$ The ratio becomes smaller and approaches 0, and the fitness error approaches 1.

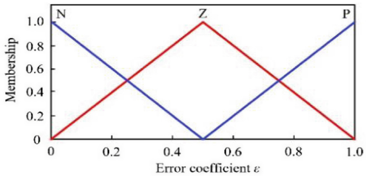
In the fuzzy rule-based system, the inputs are the iteration coefficient λ, the particle similarity γ and the particle fitness error ε, and the output is the learning factor c_1, c_2



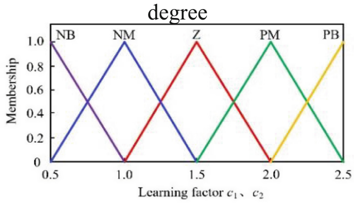
(a) Iteration coefficient λ membership degree



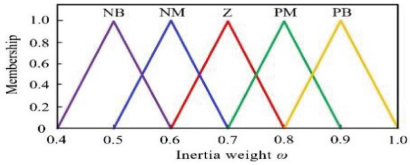
(b) Particle similarity γ membership degree



(c) Error coefficient ε membership degree



(d) Learning factors c_1 and c_2 membership degree



(e) Inertial weight ω membership degree

Fig. 5. Fuzzy rule system membership degree

and the inertia weight ω of the PSO algorithm, and there are 27 rules. For one thing, this article sets the delimited region of iteration coefficient λ, particle similarity γ and particle fitness error ε to [0,1], the delimited region of ω to [0.4,1], and the delimited region of c_1 and c_2 to [0.5,2.5]. Afterwards, this article set the number of input fuzzy divisions to 3. The number of output fuzzy divisions is 5. The fuzzy inference system adopts the Mamdani type system and the centroid method of gravity for the defuzzification [10]. Otherwise, because of the excellent performance and good application result, the triangular membership function is applied to the IPSO algorithm proposed in the thesis.

The application of fuzzy rule-based system must meet two requirements as follow. In the early stage of the IPSO operation, the large distance between the particle and the optimum result and the small value of the particle iteration coefficient λ, the particle similarity γ, and the particle fitness error ε can make the IPSO algorithm obtain the better exploration ability. In the late stage of the IPSO operation, the small distance between the particles and the optimum result, and the large value of the particle iteration coefficient λ, the particle similarity γ and the particle fitness error ε can make the IPSO algorithm obtain the local searching capability.

3.3 Fitness Function

In this paper, an island microgrid with double parallel distributed power sources is the research object, considering the power balanced distribution, bus voltage fluctuations and frequency oscillations, a control method using an IPSO algorithm to find the optimal droop factor is proposed.

The fitness function optimized for the IPSO algorithm is:

$$F = \Delta P + \Delta Q + \Delta U + \Delta f \tag{15}$$

In the above formula, ΔP can be expressed as:

$$\Delta P = |P_1 - P_2| \tag{16}$$

$$\Delta Q = |Q_1 - Q_2| \tag{17}$$

Among them, P_1 and P_2 are the active power output, and Q_1 and Q_2 are the reactive power output.

Similarly, ΔU can be expressed as:

$$\Delta U = \Delta U_1 - \Delta U_2 = |U_1 - U_0| + |U_2 - U_0| \tag{18}$$

Among them, ΔU and ΔU_2 are the output voltage deviations, U_1 and U_2 are the output voltages, and U_0 is the system rated voltage.

Similarly, Δf can be expressed as

$$\Delta f = \Delta f_1 - \Delta f_2 = |f_1 - f_0| + |f_2 - f_0| \tag{19}$$

Among them, Δf_1 and Δf_2 are the frequency deviations, f_1 and f_2 are the frequencies and f_0 is the power frequency of 50 Hz.

4 Simulation Analysis

4.1 System Control Structure and Parameter Design

There is the IPSO algorithm present in the second section of this article in application to the droop control of the island microgrid as demonstrated in Fig. 6. Among them, DG i is the i-th distributed power supply put into operation in the system, and droop control gives control signals for inverter i. The IPSO optimization module and the droop control part achieve the intercommunication of the microgrid system: when the microgrid is running, the measured system deviation information is input into the IPSO part, and the IPSO part receives the input signal to optimize the particles, and at the same time fuzzy rules the system Through the calculated particle information, the parameters of IPSO can be dynamically adjusted to speed up the convergence speed of the algorithm, and then update its own speed and position. After completing the final optimization to get the optimum result of the particle, the obtained two values d_p and d_q will be used as the input of the droop control strategy to get the new droop factor, and then the reference voltage and reference current are obtained to generate inverter control signal through the voltage and current loop.

The frequency band of the current and voltage loop are set to 200 Hz and 26.6 Hz, and their parameters are set to: $k_{pc} = 0.3$, $k_{ic} = 6$ and $k_{pv} = 4$ and $k_{iv} = 82.8$.

The parameter settings of the microgrid system are demonstrated in the table blow.

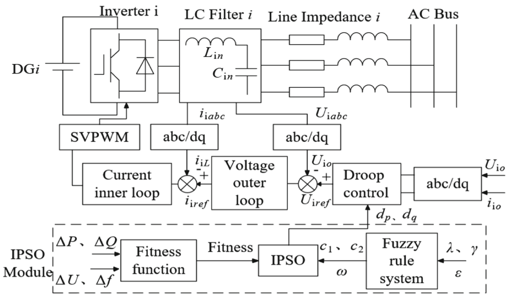


Fig. 6. Microgrid droop control structure diagram based on IPSO

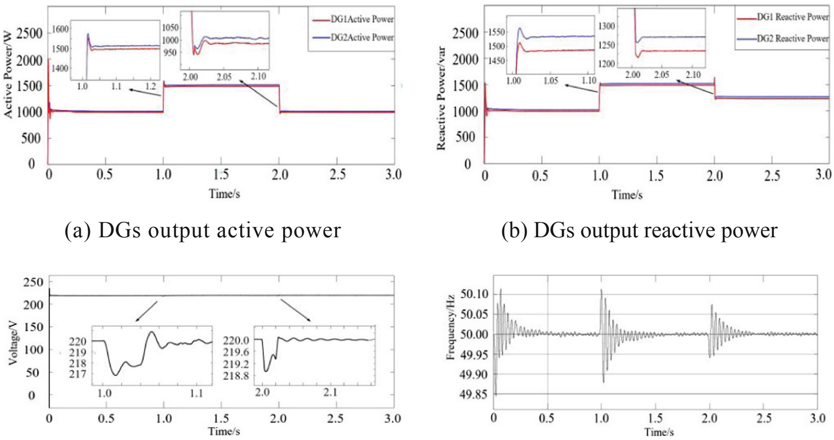
Table 1. Parameter setup of simulation experiment

Parameter	Value
DC voltage source/V	700
Initial active power droop factor	2×10^{-4}
Initial reactive power droop factor	1×10^{-5}
Inverter resistance/Ω	0.3
System frequency/Hz	50
Filter inductance/mH	3
Simulation time/s	3
Initial load power/VA	2000 + j2000
Filter capacitor/μ_F	15
Effective value of bus voltage/V	220
DG1 line impedance/Ω	$0.642 + j2.64 \times 10^{-4}$
DG2 line impedance/Ω	$0.321 + j1.32 \times 10^{-4}$

4.2 Simulation Results

In the thesis, an island microgrid with double parallel distributed power source is used as the experimental subject. In the simulation experiment, DG1 and DG2 have the same capacity, the power distribution ratio of DG1 and DG2 is set to 3:2 [15]. The other parameters are illustrated in the above table. The initial active and reactive power are set to 2000W and 2000var. The load active and reactive power are 1000W and 1000var in 1s, but the reactive power become 500var in 2s. The simulation result under original droop control is demonstrated in the pictures.

In accordance with the first section of this article, the active power corresponding to the DG output can be accurately allocated according to the droop curve, as shown in Fig. 7(a), the overall distribution accuracy of the distributed power source active power output is high, and its fluctuation is small, but due to the inherent inflexibility of the droop factor, the active power output by DG1 and DG2 still has a small amplitude difference,



(a) DGs output active power

(b) DGs output reactive power

(c) Effective value of Bus voltage

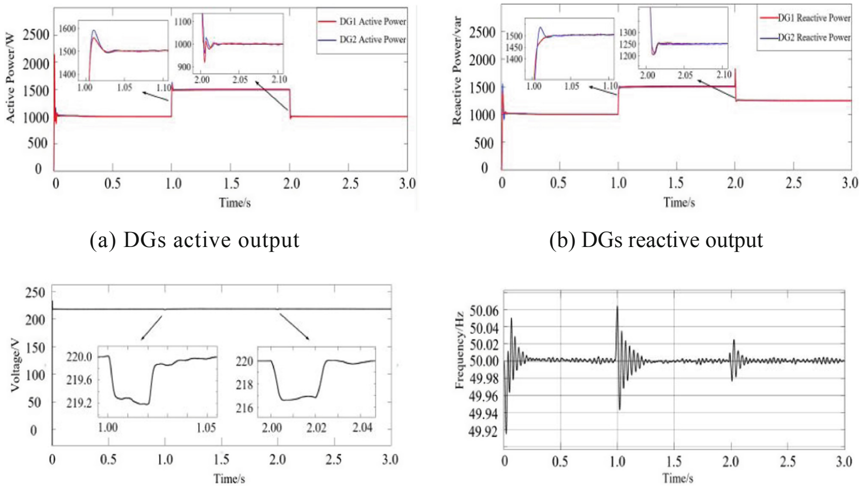
(d) System frequency

Fig. 7. Simulation results of original droop control

with a power difference of 20 W. On the contrary, the reactive power cannot be accurately distributed through the original control strategy. As shown in Fig. 7(b), because of the different line impedance, the reactive power output by the two power supplies has a large difference, which is 50W, and the fluctuation range is large, and the reactive output of the two sources is unstable. Therefore, the reactive distribution under the traditional control needs to be optimized urgently. In addition, as shown in Fig. 7(c) and (d), as the load varies in the traditional control, the system frequency and bus voltage will have large fluctuation in value, and the duration will be longer, and the bus voltage fluctuation time will continue 0.1s, the fluctuation size reaches 3V, the system frequency fluctuation time lasts 0.5 s, and the fluctuation range is 0.1 Hz.

Figure 8 gives the experiment results of the IPSO optimized droop control present in this thesis. We could learn that the active and reactive output by DG1 and DG2 can be distributed in a high-precision and balanced manner in the above picture, and the output power is relatively stable with little fluctuation, realizing the coordinated output between the two power sources. In Fig. 8(c) and (d), under the improvement of the algorithm present in the thesis, when the load changes, the bus voltage and frequency are significantly improved in comparison with the traditional control strategy. The voltage fluctuation is controlled within 1V, and the frequency fluctuation is within 0.05 Hz, the bus voltage recovery time is also shortened from 0.1 s to 0.05 s, and the system frequency fluctuation time is shortened from 0.5 s to 0.2 s, which meets the requirements of system operation.

To sum up, the improved control strategy present in the thesis has great advantages in power allocation, voltage and frequency stability, and can enhance the performance of system operation.



(a) DGs active output

(b) DGs reactive output

(c) Effective value of bus voltage

(d) System frequency

Fig. 8. Adaptive droop control simulation results based on IPSO

5 Conclusion

This thesis presents a power distribution control strategy for parallel multi-distributed power source microgrid based on an IPSO algorithm. The introduction of fuzzy rule system can make the PSO algorithm obtain better droop factor and enhance the convergence and optimization ability of the original algorithm. Then the IPSO algorithm is used to find the optimum droop factor. The simulation effects demonstrate that the present strategy realizes the intercommunication between the PSO part and the control part, and the optimalization and allocation of power under the condition of unequal impedance, and achieves the non-difference power control, and effectively enhances the performance and stability in all aspects of the microgrid.

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Coordinated Optimization Control Technology of Clean Energy Consumption Based on Spatiotemporal Characteristics of Controllable Load

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Abstract. As controllable load, electric vehicles (EVs) have great adjustable ability. This paper mainly analyzes how to charge EVs orderly according to the obtained state information, in order to shrink the power fluctuation and peak-to-valley gap of power grid. This paper analyzes the spacio-temporal characteristics of the travel of EV owners, and sets up the spacio-temporal model of the travel of EV owners based on the travel chain. The state information of the EV in the spacio-temporal model is obtained through the PLC communication system between the EV and the charging pile. Firstly, this paper analyzes the spacio-temporal characteristics of EV travel on the basis of the travel chain; Secondly, the Monte Carlo technique is applied to count the charging power of a certain number of EVs during disorderly charging; Finally, considering the basic load of residential area, genetic algorithm is introduced to shorten the charging time of EVs, the simulation experiment is carried out with the peak valley difference as the optimization objective.

Keywords: Electric vehicle · Space-time characteristics · Genetic algorithm · Orderly charging

1 Introduction

By 2020, there will be more than 5 million EVs in China. It can be predicted that with the popularity of EVs in next years, large-scale EVs connected to the power grid charging will have great influence on power system planning and operation. Among them, one of the important impacts is that large-scale EV charging will bring a new round of load growth, especially in the peak period of EV charging, which will farther increase the peak-valley gap of power grid load. Accordingly, there is an urgent need to study and lead the charging behavior of EVs to enhance the economy and reliability of power grid operation.

In [1], a space-time forecasting model of EV charging load for user travel simulation on the condition of the traffic network restrictions is proposed. Reference [2] present

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