

RESEARCH ON CHARGING AND DISCHARGING STRATEGY OF ELECTRIC VEHICLES IN PARK MICRO-GRID BASED ON PIGEON-INSPIRED OPTIMIZATION ALGORITHM

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ABSTRACT. *To reduce the adverse impact of electric vehicles on the power grid, compensate for instabilities caused by randomness of the distributed energy, reduce user cost, and improve user satisfaction, an optimisation strategy is proposed herein for orderly charging and discharging of electric vehicles. The daily load rate of the park micro-grid, peak-valley difference of the load, and economic benefits to the users are considered as the optimisation objectives, and the uncertainty of solar power generation and energy storage are considered fully. The strategy for pigeonholing optimisation based on quantum behaviour is proposed to organise the charging and discharging behaviours of electric vehicles reasonably while realising benign interactions between the electric vehicles and grid; the feasibility and superiority of the proposed strategy are also verified by simulation experiments.*

Keywords: Electric vehicle, Vehicle-to-grid, Orderly charge and discharge, Charging station, Improved pigeon-inspired optimization algorithm

1. Introduction. The development of clean energy strategies has become a mainstream goal in recent times to address the increasing demand for environmental protection [1-3]. Several countries have increased the proportion of distributed power in their power grids, which constitute a combination of photovoltaic and wind power as well as energy storage devices; hence, related researches on micro-grids have attracted more attention. Figure 1 shows a typical photovoltaic-storage micro-grid structure. With the development of smart grids, park micro-grids have become a popular topic of research because of their advantages with respect to the control strategy and facility intelligence. Electric vehicles are an essential part of such park micro-grids [4].

Because of their environmentally friendly characteristics, electric vehicles have gradually become a preferred mode of transportation. However, an increase in the number of electric

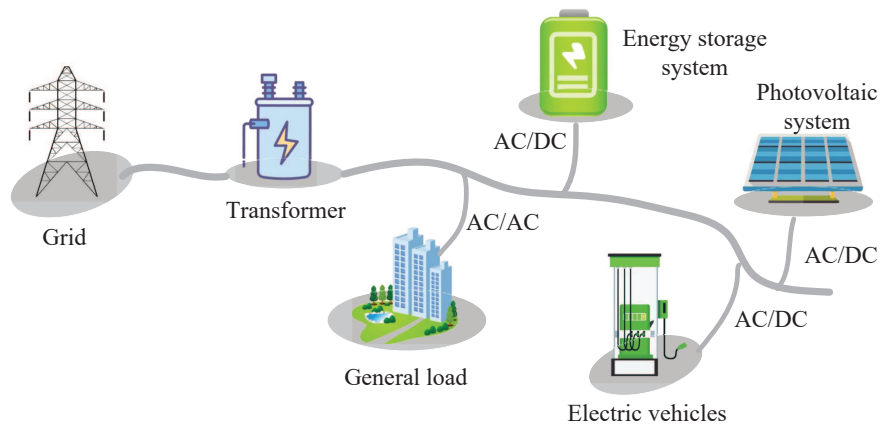


FIGURE 1. Schematic diagram of micro-grid topology in the park

vehicles also poses challenges to the distribution network. For example, load surge may lead to the phenomenon of “peak on peak”; at present, the distribution network structure does not support user needs and must be upgraded. Therefore, orderly connection of electric vehicles to a power grid has become a research hotspot [5].

The orderly connection of electric vehicles to the power grid can be regarded as an energy storage scheme to a certain extent, which can be used to absorb a part of the photovoltaic output [6]. In the traditional method, the time-of-use tariff is generally employed to guide users to charge electric vehicles in an orderly manner based on the charging cost [7]. On this basis, studies started considering user satisfaction [8] and assumed this as an optimisation goal to schedule electric vehicles. A previous study suggested a charging strategy by predicting the random distribution pattern of electric vehicle charging demand in a certain region [9] such that car owners could quickly find the best charging locations; such strategies mainly study the orderly charging of electric vehicles but do not consider discharging of the vehicles. Another study [10] investigated the two-way interactions between electric vehicles and the power grid (V2G) and considered the total load variance of the micro-grid as the optimisation goal; however, user satisfaction was ignored. Other studies have considered collaborative control of distributed energy, such as photovoltaic sources, batteries, and electric vehicles [11]; however, these consider single-objective optimisation only. A multi-objective optimisation method was explored in [12], where the total load variance and minimum cost were considered as the optimisation objectives, and the particle swarm optimisation algorithm was used to solve this problem.

In the present study, the pigeon swarm optimisation algorithm based on quantum behaviour was applied to ensuring orderly charging and discharging of electric vehicles, and the uncertain distributed energy output of photovoltaic systems and energy storage systems is considered fully. Considering an industrial park in Wuxi as an example, this study establishes a mathematical model by taking multiple indicators, such as stable operation of the micro-grid in the park and the economic benefits to the tram owners, as the optimisation objectives to organise orderly and reasonable charging of the electric vehicles; this solves the problems caused by connection of the electric vehicles to the power grid and improves the utilisation rates of the energy sources. Simulation analyses are conducted using simulation software to verify the feasibility and superiority of the proposed strategy.

2. Mathematical Model for the Orderly Charging and Discharging of Electric Vehicles. The essential condition for the large-scale connection of electric vehicles to the grid is that the stable operation of the power grid cannot be affected. If many electric

vehicles are connected to the grid without intervention, the charging peaks of electric vehicles will overlap with the regular load peaks and cause an even more significant impact on the grid. Therefore, the optimization objectives to be modeled for the orderly charging of electric vehicles in the park need to have two aspects. The grid side usually considers the grid losses and the peak-to-valley difference, and the user side needs to consider the economic benefits to maintain the stability of power grid operation and improve user satisfaction. Therefore, this paper establishes a daily charging and discharging model for electric vehicles, and treats the daily load variance, the load peak-to-valley difference and the operating cost in the park as the optimization objectives to schedule the electric vehicles. Here, the output of the photovoltaic system is taken as a negative value and then superimposed on the other loads in the park, and the result is regarded as an equivalent load.

2.1. Objective function.

2.1.1. *Grid side.* The grid side should consider reducing system load fluctuations and improving energy efficiency. Therefore, this paper takes the minimum peak valley difference and the minimum load variance as the optimization objectives.

$$f_1 = \min \left[\max \left(P_d(j) + \sum_{i=1}^M P_i x_{ij} \right) - \min \left(P_d(j) + \sum_{i=1}^M P_i x_{ij} \right) \right] \quad (1)$$

$$P_d(j) = P_L(j) - P_{PV}(j) \quad (2)$$

$$f_2 = \min \frac{1}{96} \sum_{j=1}^{96} \left[P_d(j) + P_{es}(j) - P_{PV}(j) + \sum_{i=1}^M P_i x_{ij} - P_0 \right]^2 \quad (3)$$

$$P_0 = \frac{1}{96} \sum_{j=1}^{96} \left[P_d(j) + \sum_{i=1}^M P_i x_{ij} + P_{es}(j) \right] \quad (4)$$

where P_i represents the charging and discharging power of the i th electric vehicle, M denotes the total number of all electric vehicles in the park, x_{ij} denotes the charging and discharging states of the electric vehicles, with only three states, 1, 0, -1 , representing charging, no action and discharging respectively. $P_d(j)$ is the newly defined equivalent load, $P_L(j)$ denotes the conventional load at the moment j , $P_{PV}(j)$ denotes the output of the photovoltaic power generation system at the moment j , $P_{es}(j)$ represents the output of the energy storage system at the moment j , P_0 represents the daily average load of the micro-grid in the park after electric vehicles are connected to the park.

2.1.2. *User side.* The user side mainly considers users' regular travel and economic benefits, so the minimum charging cost is taken as the optimization goal.

$$f_3 = \min \sum_{j=1}^{96} \sum_{i=1}^N x_{ij} P_i C_j \quad (5)$$

where C_j denotes the price of electricity in the park at the j moment. It is specified that the price of buying and selling electricity is equal. Due to the fact that the magnitudes of the three objective functions are different, normalization is required to convert the multi-objective problem into a single-objective problem before solving it, as shown in Equation (6).

$$F = \min(\mu_1 f_1 + \mu_2 f_2 + \mu_3 f_3) \quad (6)$$

$$\begin{cases} p_{ij} = \frac{x_{ij}}{\sum_{j=1}^n x_{ij}} \\ E_i = -\frac{\sum_{j=1}^n p_{ij} \cdot \ln p_{ij}}{\ln n} \\ \mu_i = \frac{1 - E_i}{\sum_{i=1}^m (1 - E_i)} \end{cases} \quad (7)$$

where μ_1, μ_2, μ_3 in the above formula can be obtained according to the entropy weight method [13,14], Formula (7). Standardized value of the i th index in the j th sample is denoted as p_{ij} , E_i is the entropy of the p_i index, μ_i is the weight of the i index.

2.2. Constraint condition. In order to ensure that the control strategy has practical significance, the following constraints are given.

1) Power balance of the system.

$$P_{grid}(j) = P_d(j) + \sum_{i=1}^M x_{ij} P_i - P_{es}(j) \quad (8)$$

where $P_{grid}(j)$ is the power of the campus micro-grid interacting with the grid at the j moment.

2) Electric vehicle charging power balance. This paper assumes that when there is no intervention, the electric vehicle starts charging when it arrives at the charging station and leaves as soon as charging is complete. This paper uses a Monte Carlo algorithm to fit the time to charge an electric vehicle to data published by the NHTS in the USA in 2009 [15].

$$f_s(x, \mu, \sigma) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right) & \mu - 48 < x \leq 96 \\ \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x + 24 - \mu)^2}{2\sigma^2}\right) & 0 < x \leq \mu - 48 \end{cases} \quad (9)$$

where μ and σ denote the mean and standard deviation of the arrival time of electric vehicles at charging stations, respectively. After combining the travel habits and car usage patterns of users, it is found that most users choose to charge after they get home from work, roughly 18:00 every day. Thus, μ and σ can be assigned a value of 72 and 5, respectively.

$$\sum_{j=1}^{96} \sum_{i=1}^N x_{ij} P_i = P_{PRE} \quad (10)$$

where P_{PRE} is the total power previously predicted for uncontrolled charging of electric vehicles in the park.

3) Load change rate.

$$\frac{[P_d(j+1) - P_d(j)]}{P_d(j+1)} = \varphi\% \quad (11)$$

where $\varphi\%$ represents the limit on the rate of change of the load in the park, generally chosen as 0.6.

4) Output power constraints of photovoltaic power generation systems.

$$P_{PV\min} \leq P_{PV}(j) \leq P_{PV\max} \quad (12)$$

where $P_{PV}(j)_{\min}$ and $P_{PV}(j)_{\max}$ represent the maximum and minimum output power of the photovoltaic system, respectively.

5) Output power constraints of energy storage systems.

$$P_{es\min} \leq P_{es}(j) \leq P_{es\max} \quad (13)$$

where $P_{es}(j)_{\min}$ and $P_{es}(j)_{\max}$ represent the maximum and minimum output power of the photovoltaic system, respectively.

3. Optimization Strategy. The charging strategy of an electric vehicle can be obtained according to the ordered charging model introduced above. When the electric vehicles arrive at the charging station, the charging pile will obtain the current power of the electric vehicles, and the user's desired charging completion time, charging power, battery capacity, and other relevant information. Based on the information obtained, the control system of the charging station will determine whether the electric vehicles meet the discharge conditions and arrange the most proper charging (discharging) time for it and ensure that the electric vehicles can meet the owner's expected power when it leaves. Show the charging and discharging plan to the owner, and if the owner agrees, let the electric vehicles perform the charging and discharging actions according to the plan. Otherwise, arrange charging for the electric vehicles immediately. The charging process for an electric vehicle is shown in Figure 2.

- 1) Determine whether the electric vehicle meets the discharge conditions: The state of charge (SOC) of the battery is greater than 0.3, which indicates that the battery has standby capacity and can be discharged before charging.
- 2) Conditions for user consent to scheduling: The user agrees to the scheduling plan whether the expected departure time is greater than or equal to the planned display departure time.

4. Pigeon-Inspired Optimization Algorithm Based on Hybrid Quantum Theory.

4.1. Pigeon-inspired optimization. The pigeon-inspired optimization (PIO) [16-18] establishes a mathematical model by imitating the homing behavior of pigeons, and is generally used to solve optimization problems. Pigeons can find the correct nest location and homing route under the influence of different magnetic fields because pigeons can use geomagnetic fields and landmarks to complete their homing. The iron crystals on the beak of pigeons can detect the strength of magnetic fields to help pigeons distinguish their direction. As early as the ancient Roman era, people discovered that pigeons could identify the direction and return to the nest and were used as a communication tool. In returning to its destination, the pigeon will use the magnetic field to sense the direction in the early stage. When the pigeon approaches its destination, it will determine its flight path based on landmarks. Pigeons can easily find their destinations using magnetic fields and landmarks. The pigeon-inspired optimization algorithm proposes map and compass operators based on geomagnetic field and sun, proposes landmark operators according to landmarks.

4.1.1. Compass operator. The compass operator is built based on the geomagnetic field and the sun. In this paper, V_i^T and X_i^T represent the position vector and velocity vector of the i th pigeon, respectively, and their update formulae are

$$V_i^T = V_i^{T-1} \cdot e^{-RT} + \text{rand} \cdot (X_{gb} - X_i^{T-1}) \quad (14)$$

$$X_i^T = X_i^{T-1} + V_i^T \quad (15)$$

where T denotes the number of iterations of the pigeon-inspired optimization algorithm, X_{gb} denotes the position vector of the pigeons in the flock representing the optimal solution during that iteration, and R is the compass operator.

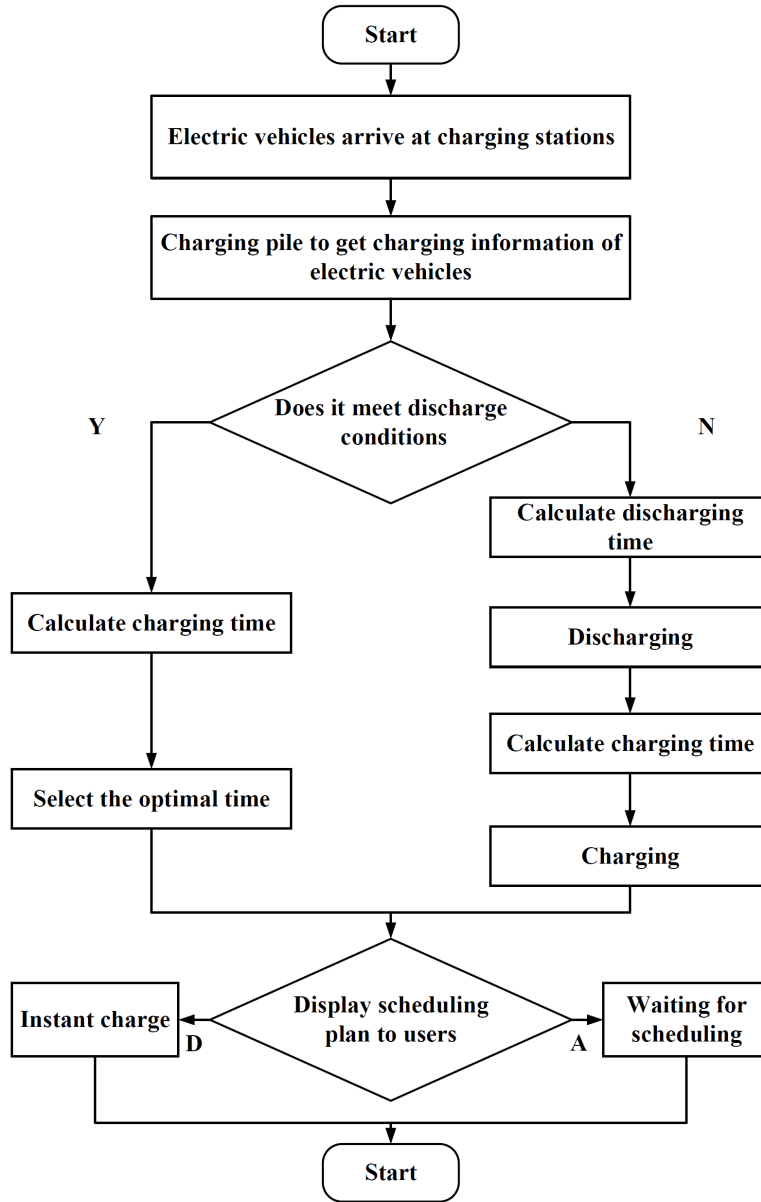


FIGURE 2. Self control flow diagram of charging pile

From the above, it can be seen that the velocity of the corresponding pigeon of the previous generation and the position of the optimal solution of the flock during this current iteration together determine the vector of the velocity of the i th pigeon. Furthermore, the position of the i th pigeon is determined by the previous position and the current velocity. All pigeons in the flock adjust their flight direction towards the optimal solution according to Equation (14) and change their position according to Equation (15).

4.1.2. *Landmark operator.* The landmark operator is built based on landmarks. During the flight of a pigeon, when it is close to the destination, the pigeon will determine its flight path based on the flight status of nearby pigeons and landmarks. N_u denotes the number of one-half pigeons in each iteration, X_c^T is the central position of the flock in the

T th generation, and $\text{fitness}(x)$ is defined as the mass of the pigeons. Assuming that all pigeons fly along a straight line between their position and the destination, the following equation will be given:

$$N_u^T = \frac{N_u^{T-1}}{2} \tag{16}$$

$$X_c^T = \frac{\sum X_i^T \cdot \text{fitness}(X_i^T)}{N_u \cdot \sum \text{fitness}(X_i^T)} \tag{17}$$

$$X_i^T = X_i^{T-1} + \text{rand} \cdot (X_c^T - X_i^{T-1}) \tag{18}$$

During the iteration, the destination of all pigeons is the center position in that iteration, so that the half of the pigeons that are far from the destination will determine their position vector and velocity vector by referring to the flight state of the pigeons close to the destination, while the other half of the pigeons can reach the destination with the fastest speed.

4.2. Pigeon-inspired optimization algorithm based on quantum behavior. Quantum entanglement is a mechanical phenomenon describing particles' entanglement independent of localization. That is, far away quantum will also have an impact. [19] combined quantum theory with particle swarm to propose a particle swarm optimization algorithm (PSO) with quantum behavior, which solved the problem of poor convergence of the traditional particle swarm algorithm. Inspired by this thinking, this paper applies quantum theory to the PIO, which makes the PSO more perfect. Quantum behavior based pigeon-inspired optimization algorithm [20-25] (QPIO) abandons the original pigeon-inspired algorithm in which the guide operator updates the speed, instead of using the wave function in quantum theory to determine the position of the pigeon. Hence, the mathematical expression of the guide operator becomes

$$\alpha = \frac{(1 - 0.5)(T_a - t)}{T_a} + 0.5 \tag{19}$$

$$\mathbf{P} = \frac{\text{rand}_1 \mathbf{X}_{\text{pb}_i}^{T_b-1} + \text{rand}_2 \mathbf{X}_{\text{gb}}^{T_b-1}}{\text{rand}_1 + \text{rand}_2} \tag{20}$$

$$\mathbf{X}_i^{T_b} = \mathbf{P} \pm \alpha \left| \mathbf{X}_{\text{mb}}^{T_b-1} - \mathbf{X}_i^{T_b-1} \right| \ln \left(\frac{1}{\text{rand}} \right) \tag{21}$$

where α represents the contraction-expansion coefficient, T_a represents the number of iterations of the guide operator, T_b represents the current iteration number of the improved algorithm, and \mathbf{X}_{mb}^T represents the average of all pigeon positions in the flock.

In order to increase the optimization speed of the algorithm, a learning factor is introduced, and the expression of the landmark operator becomes

$$\beta = \text{round}(1 + \text{rand}) \tag{22}$$

$$\mathbf{X}_{\mathbf{n}_i} = \mathbf{X}_i^{T-1} + \text{rand} (\mathbf{X}_{\text{gb}}^{T-1} - \beta \mathbf{X}_{\text{mb}}^{T-1}) \tag{23}$$

$$\mathbf{X}_i^{T_b} = \begin{cases} \mathbf{X}_{\mathbf{n}_i} & F(\mathbf{X}_{\mathbf{n}_i}) < F(\mathbf{X}_i^{T-1}) \\ \mathbf{X}_i^{T_b-1} & F(\mathbf{X}_{\mathbf{n}_i}) > F(\mathbf{X}_i^{T-1}) \end{cases} \tag{24}$$

The schematic diagram of the improved landmark operator is shown in Figure 3.

4.3. Charge and discharge control of electric vehicles. The mathematical model and optimization strategy of electric vehicle charging and discharging are introduced above. Now the pigeon-inspired optimization algorithm based on quantum behavior is applied to the optimization strategy. According to the mathematical model proposed in

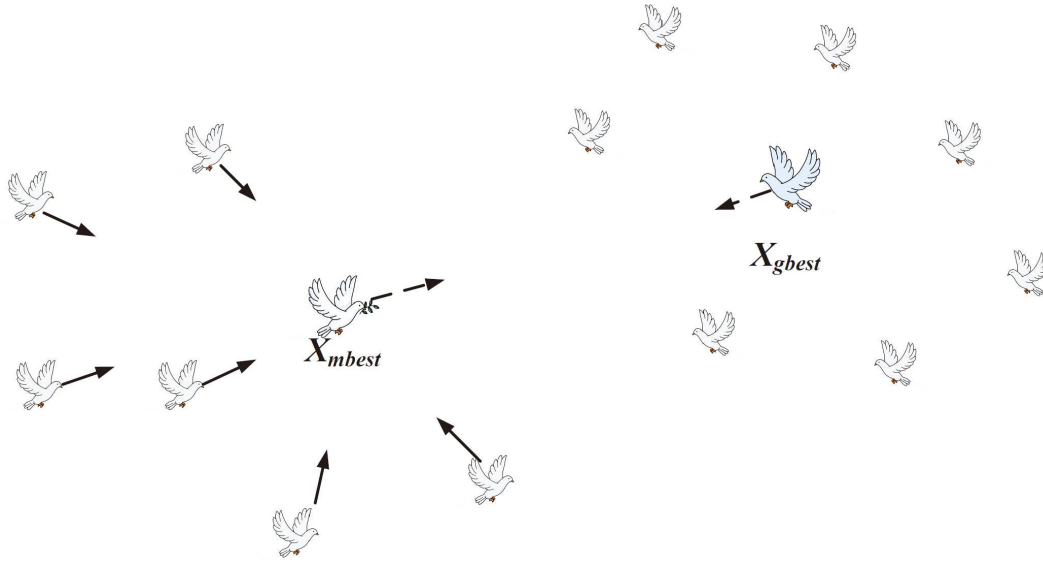


FIGURE 3. Schematic diagram of improved landmark operator

TABLE 1. QPIO algorithm framework

Begin**1. Initialization**

Set initial values for T_a , T_b and T the search range

Set initial path X_i^T and V_i^T velocity for each pigeon individual randomly

Remove pigeons that do not meet the requirements

Calculate fitness values of different pigeon individuals

$X_g = \arg \min[F(X_{pi})]$

2. Compass operations

For T to T_a do

Remove pigeons that do not meet the requirements

Update the guide operator, update the position vector of the flock X_i^T according to Equations (19), (20), and (21)

Update the value of the fitness function for each pigeon

Find the global optimal solution X_{gb}

End for

3. Landmark operations

For T to T_b do

Remove pigeons that do not meet the requirements

Update the landmark operator, update the position vector of the flock X_i^T according to Equations (22), (23), and (24)

Calculate the individual fitness values of the pigeons and rank them

Keep half of the individuals with better fitness value, and abandon the other half according to Equation (16)

Find the global optimal solution X_{gb} and evaluate it

End for

4. Output

X_{gb} is output as the global optima of the F

End

this paper for the quantum behavior-based pigeon-inspired algorithm set the initial value of the search range of the flock, the value of the fitness function of each pigeon, and the measure of the global optimal solution. Secondly, the rules for updating the number of pigeon flocks are determined using the optimization idea of the optimization strategy. Table 1 shows the specific process of the QPIO algorithm.

5. Example Analysis.

5.1. **Parameter setting.** This paper takes a business park in Wuxi City, Jiangsu Province, China, as a reference case. The topology of the micro-grid is the same as that shown in Figure 1. The park contains photovoltaic power generation facilities and hybrid energy storage devices of batteries and supercapacitors. Table 2 is the electricity price table of the district.

TABLE 2. Time of use tariff

Time frame	Price (yuan/(kW·h))
23-6	0.38
10-15	1.37
7-9,21,22	0.87
16-20	1.55

5.1.1. *Basic parameters of electric vehicles.* Assume that there are 1000 electric vehicles willing to participate in the scheduling. The battery capacity of electric vehicles in the market is generally between 20 kW and 30 kW. Suppose the battery capacity of these 1000 vehicles is evenly distributed between 20 kW and 30 kW. All these electric vehicles are charged (discharged) with 4 kW constant power and the efficiency is 0.9. The electric vehicle owner wants to leave the electric vehicle with SOC of 1, the electricity price in the park is time-sharing tariff, and the electric vehicles buy and sell electricity at the same price. The price is the same, and the charging station in the park has the function of information collection and information processing, which can satisfy all electric vehicles for charging and discharging simultaneously.

5.1.2. *Output of photovoltaic system.* The photovoltaic panels laid in the park are taken as the average daily power generation of the photovoltaic power generation system in the park for one month to obtain the daily output curve of the photovoltaic system, as shown in Figure 4.

5.1.3. *Parameter settings of QPIO algorithm.* According to the mathematical model of orderly charging and discharging of electric vehicles above, the pigeon-inspired optimization algorithm based on quantum theory is used for simulation analysis. Table 3 shows the parameters of QIPO.

TABLE 3. Algorithm parameters

Parameter	Numerical value
Total number of pigeons	40
Dimension of solution space	96
Maximum iteration times of guide operator	400
Maximum iteration number of landmark operator	200

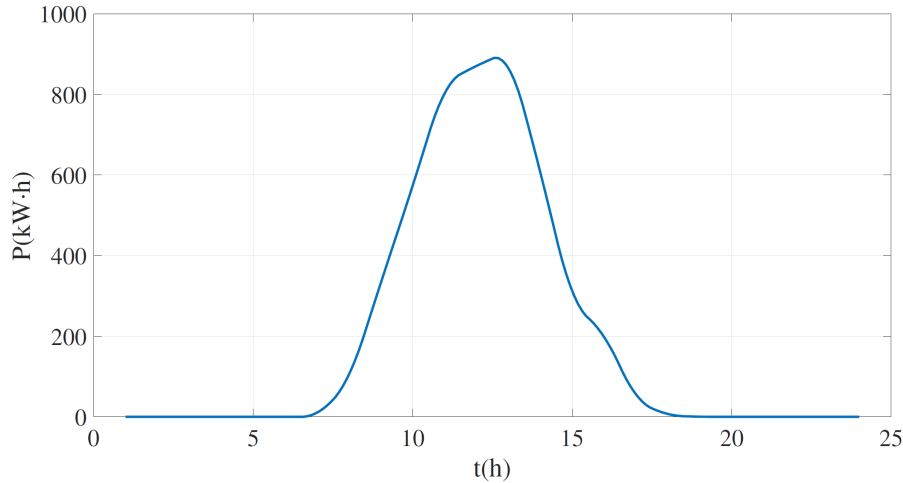


FIGURE 4. Average daily load of the photovoltaic system

5.2. Simulation analysis. In order to more vividly describe the impact of a large number of electric vehicles without intervention on the power grid, this paper simulates the disorderly charging of electric vehicles in the park according to the method of load forecasting of electric vehicles proposed in reference. The daily load of electric vehicles is superimposed with the conventional load and the output of new energy systems in the park, and the daily load curve in the park is obtained as shown in Figure 5.

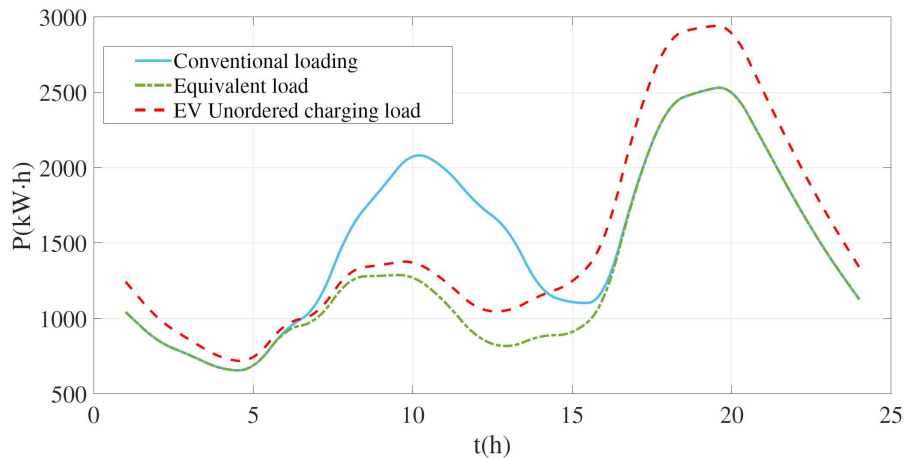


FIGURE 5. Daily load curve of the park under disorderly charging of electric vehicles

It can be seen from Figure 5 that the equivalent load of the micro-grid system is relatively small because of the high solar light intensity and high temperature at noon. When electric vehicles are connected to the micro-grid in the park without interference, because most users choose to charge directly after work, which is superimposed with the conventional load in the park, the phenomenon of peak increase occurs, which makes the peak-valley difference of the daily load curve in the park more significant, and seriously affects the stability of the grid. It can be seen from the figure that when the charging time of most users is high, the cost increases.

In order to verify that the pigeon-inspired optimization based on quantum theory can quickly and accurately find the optimal scheme, genetic algorithm, the pigeon-inspired optimization and the improved pigeon-inspired optimization are used for simulation experiments under the same conditions.

TABLE 4. Algorithm parameters

Charging modes	Peak-valley difference (kW·h)	Charging cost (yuan)
Disordered charging	2242.733	66705
QPIO	630.457	60024
PIO	1253.933	61203
GA	1202.235	61542

Note: Charging cost = Charging cost – Discharging cost

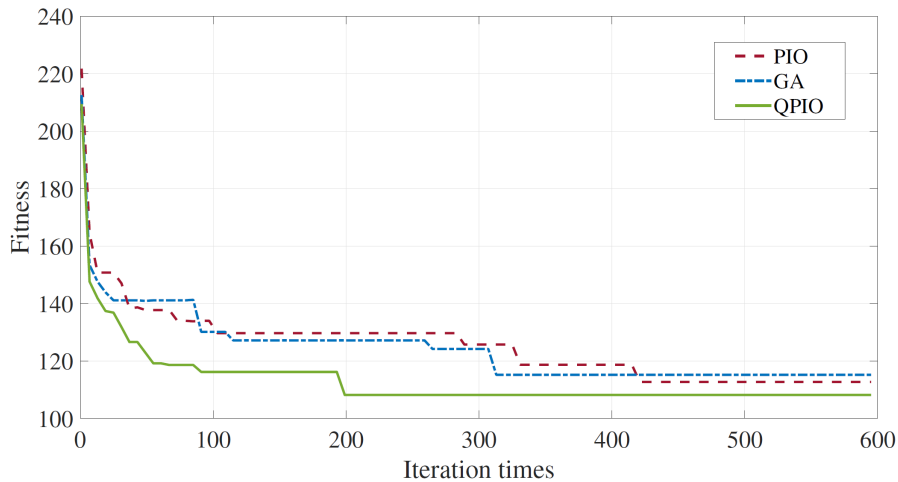


FIGURE 6. Comparison of iterative effects of GA, PIO and QPIO algorithms

Figure 6 is the iterative effect of GA, PIO and QPIO. It can be seen from the figure that QPIO can effectively avoid the problem that PIO is easy to fall into local optimum and GA has slow iteration speed. It can not only ensure the iteration speed, but also find the global optimal solution. This is because after the introduction of quantum theory, the change of guide factor has greatly improved the search ability of pigeons, and the change of landmark operator can make pigeons reach their destination at the fastest speed, so the superiority of the algorithm is greatly improved.

Figure 7 is the result comparison graph of the three algorithms. It can be seen that the optimization results of the pigeon-inspired optimization based on quantum theory are significantly better than the others. The peak-valley difference and fluctuation of the load curve of this algorithm are significantly lower than those of the other two algorithms.

Table 4 also shows that the pigeon-inspired optimization algorithm based on quantum theory has the highest economy in the four cases, which fully shows the superiority of the algorithm.

In Figure 8, it can be seen that the pigeon-inspired optimization algorithm based on quantum theory can effectively alleviate the fluctuation of the grid when the electric vehicle is charging disorderly, and realize the peak shaving and valley filling. By dispatching some vehicles to charge at noon, it can not only absorb the energy generated by the photovoltaic system, but also alleviate the pressure of the excessive load of the micro-grid in the evening, so that the interaction power fluctuation between the micro-grid in the park and the large power grid is small, which can be more stable operation, and can effectively reduce the potential safety hazard due to the simultaneous charging of a large number of electric vehicles.

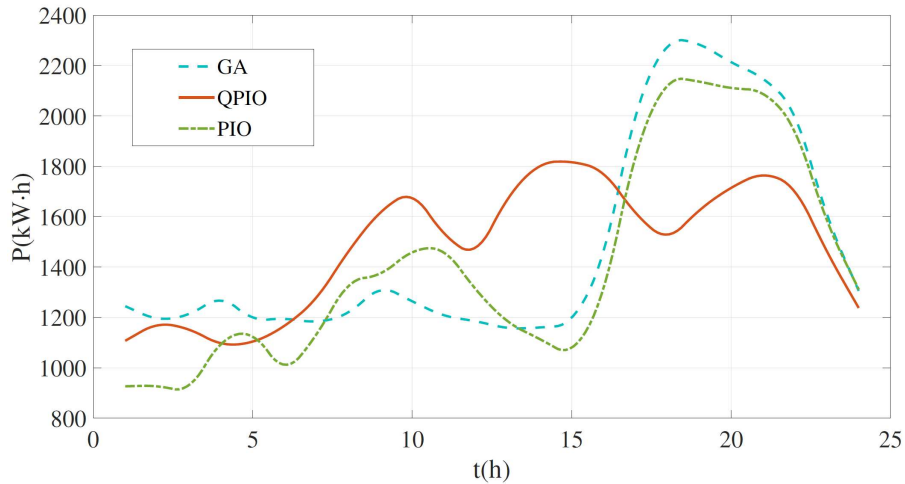


FIGURE 7. Comparison of three algorithms

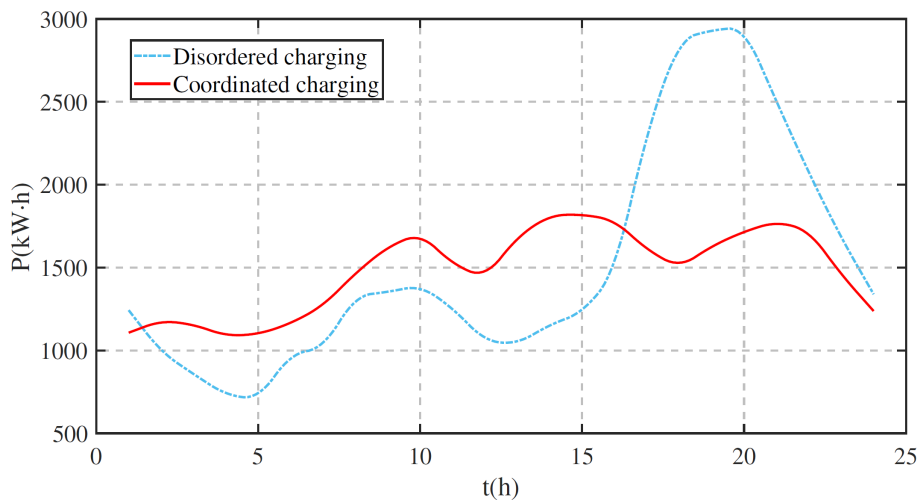


FIGURE 8. Daily load curve under disordered and orderly charging and discharging

6. Conclusions. In this work, photovoltaic power generation and energy storage systems are organically combined with the orderly charging and discharging of electric vehicles. Considering stable operation of the power grid and economic benefits to the participants, the micro-grid in the park is modelled, and the pigeon swarm optimisation method based on quantum theory is used to guide orderly charging by users. The simulations verify that orderly charging and discharging of the electric vehicles can solve the problem of peak to peak addition to the micro-grid in the park caused by charging of electric vehicles, improve the stability of the micro-grid, reduce the potential safety hazards, and greatly improve the ability of the micro-grid to absorb new energy, which is conducive to green development of the park.

However, some limitations of this work still remain. For example, the influences of season on the charging and discharging laws of the electric vehicles as well as the photovoltaic output are not considered. In future research, the effects of the environment on the control strategy must be considered. Distributed energy, such as wind power generation, can also be added to the system so as to achieve an improved control strategy.

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REFERENCES

- [1] C. Weiller and A. Neely, Using electric vehicles for energy services: Industry perspectives, *Energy*, vol.77, pp.194-200, 2014.
- [2] Y. H. Cheng, Y. H. Chang and I. J. Lu, Urban transportation energy and carbon dioxide emission reduction strategies, *Applied Energy*, vol.157, pp.953-973, 2015.
- [3] L. Ye, Y. Mo, M. Chen et al., Evaluation model on schedulable potential of electric vehicles based on Monte Carlo Simulation, *2018 International Conference on Power System Technology (POWERCON)*, pp.1-8, 2018.
- [4] C. Rottondi, G. Neglia and G. Verticale, Complexity analysis of optimal recharge scheduling for electric vehicles, *IEEE Transactions on Vehicular Technology*, vol.65, no.6, pp.4106-4117, 2016.
- [5] J. Yang, W. Hao, L. Chen et al., Risk assessment of distribution networks considering the charging-discharging behaviors of electric vehicles, *Energies*, vol.9, no.7, 2016.
- [6] J. Zhang, C. Yang and F. Ju, Optimization of ordered charging strategy for large scale electric vehicles based on quadratic clustering, *2017 4th International Conference on Information Science and Control Engineering (ICISCE)*, pp.1080-1084, 2017.
- [7] Y. Luo, G. Feng, S. Wan et al., Charging scheduling strategy for different electric vehicles with optimization for convenience of drivers, performance of transport system and distribution network, *Energy*, vol.194, 116807, 2020.
- [8] Y. He, B. Venkatesh and L. Guan, Optimal scheduling for charging and discharging of electric vehicles, *IEEE Transactions on Smart Grid*, vol.3, no.3, pp.1095-1105, 2012.
- [9] J. Garcia Alvarez, M. Á. González, C. Rodriguez Vela et al., Electric vehicle charging scheduling by an enhanced artificial bee colony algorithm, *Energies*, vol.11, no.10, 2752, 2018.
- [10] C. B. Robledo, V. Oldenbroek, F. Abbruzzese et al., Integrating a hydrogen fuel cell electric vehicle with vehicle-to-grid technology, photovoltaic power and a residential building, *Applied Energy*, vol.215, pp.615-629, 2018.
- [11] T. N. Le, B. J. Choi, H. Liang et al., DCD: Distributed charging and discharging scheme for EVs in microgrids, *2014 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp.704-709, 2014.
- [12] J. Teng, T. Chen and W. D. Fan, Integrated approach to vehicle scheduling and bus timetabling for an electric bus line, *Journal of Transportation Engineering, Part A: Systems*, vol.146, no.2, 2020.
- [13] Y. Wu, Fuzzy comprehension evaluation of potential energy saving and emission reduction on regional power grid using entropy weight, *Journal of Huazhong University of Science and Technology (Natural Science Edition)*, vol.38, no.11, pp.115-118, 2010.
- [14] Y. Huang, W. Fang and S. Chen, Assessment on operational risk of power grid enterprises based on entropy weight and improved grey relation analysis, *2010 2nd International Workshop on Education Technology and Computer Science*, pp.448-451, 2010.
- [15] D. L. Brucker and N. G. Rollins, Trips to medical care among persons with disabilities: Evidence from the 2009 National Household Travel Survey, *Disability and Health Journal*, pp.539-543, 2016.
- [16] B. Hqa and A. Hd, A multi-objective pigeon-inspired optimization approach to UAV distributed flocking among obstacles, *Information Sciences*, vol.509, pp.515-529, 2020.
- [17] X. Xu and Y. Deng, UAV power component – DC brushless motor design with merging adjacent-disturbances and integrated-dispatching pigeon-inspired optimization, *IEEE Transactions on Magnetics*, pp.1-7, 2018.
- [18] H. Duan, M. Huo and Y. Shi, Limit cycle based mutant multi objective pigeon inspired optimization, *IEEE Transactions on Evolutionary Computation*, no.99, pp.948-959, 2020.
- [19] C. H. Chiang, A symbolic controller based intelligent control system with quantum particle swarm optimization based hybrid genetic algorithm, *2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence)*, pp.1356-1363, 2008.
- [20] H. Li and H. Duan, Bloch quantum-behaved pigeon-inspired optimization for continuous optimization problems, *Proc. of 2014 IEEE Chinese Guidance, Navigation and Control Conference*, pp.2634-2638, 2014.

- [21] S. Zhang and H. Duan, Multiple UCAVs target assignment via Bloch Quantum-Behaved Pigeon-Inspired Optimization, *2015 34th Chinese Control Conference (CCC)*, pp.6936-6941, 2015.
- [22] N. Xian and Z. Chen, A quantum-behaved pigeon-inspired optimization approach to explicit non-linear model predictive controller for quadrotor, *International Journal of Intelligent Computing and Cybernetics*, vol.11, pp.47-63, 2018.
- [23] S. Q. Li and Y. M. Deng, Quantum-entanglement pigeon-inspired optimization for unmanned aerial vehicle path planning, *Aircraft Engineering and Aerospace Technology*, 2018.
- [24] C. Hu, Y. Xia and J. Zhang, Adaptive operator quantum-behaved pigeon-inspired optimization algorithm with application to UAV path planning, *Algorithms*, vol.12, no.3, 2019.
- [25] W. Sun, Constrained role-engineering optimization using Boolean matrix decomposition and integer linear programming techniques, *International Journal of Innovative Computing, Information and Control*, vol.18, no.4, pp.1037-1053, 2022.

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