This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ACFPE59335.2023.10455123.10532686, 2023 2nd Asian Conference on Frontiers of Power and Energy (ACFPE)

Low Carbon Economic Dispatch of Power Systems with Wind Power for Electric Vehicle Carbon Quotas

Gao Yang
School of Communication and Information Engineering,
Chongqing University of Posts and Telecommunications
Chongqing, China
s210101030@stu.cqupt.edu.cn

Huang Fei*
Electric Power Science Research Institute of Grid Chongqing Electric Power Company
Chongqing, China
1172506421@qq.com

Huang Zhengwen
Department of Electronic and Electrical Engineering
Brunel University
London, U.K
Zhengwen.huang@brunel.ac.uk

Li Guoquan
Group of Artificial Intelligence and System Optimization,
Chongqing University of Posts and Telecommunications
Chongqing, China
ligq@cqupt.edu.cn

Jia Jinshuo
Group of Artificial Intelligence and System Optimization,
Chongqing University of Posts and Telecommunications
Chongqing, China
s220101055@stu.cqupt.edu.cn

***Abstract*—With The rapid advancement of electric vehicles (EVs) and renewable energy technologies has opened up new possibilities for their integration into low-carbon power systems. Considering EVs as a flexible dispatch resource and incorporating them into the economic dispatch of power systems containing scenic power farms is crucial for effectively meeting low-carbon and carbon-reduction environmental requirements. This paper aims to construct an optimized dispatch model that minimizes both generation costs and carbon emissions of the power system. To address this challenge, we propose a genetic algorithm based on irregular coding as a solution to the dispatch model. Through extensive simulations, we validate that the proposed method significantly reduces computational resource requirements while achieving optimal scheduling of power generation units in the system. The method offers a cost-effective solution with low computational complexity while ensuring compliance with power constraints for scenic power generation. As a result, the approach presented in this paper holds great significance in progressively optimizing the co-dispatch of electric vehicles and renewable energy.**

Keywords—Carbon emissions, Electric vehicle, Clean energy, Economic scheduling

NOMENCLATURE

A. Abbreviations

EV	Electric Vehicle.
PV	Photovoltaic.
GA	Genetic Algorithm.

B. Sets and Indices

i,T	Index and set of time periods.
j,U	Index and set of units.

C. Parameters

a_j,b_j,c_j	Coal consumption factor of j -th unit.
Q_{coal}	Unit cost of coal consumption.
K_c	Unit price of carbon emissions.
E_c	Carbon emission factor per unit of electricity from thermal power.
δ	Carbon emission allocation factor per unit of electricity.
$P_j^{\min},P_j^{\max}$	Minimum and maximum output power of unit j .
Δt	Length of a period.
$R_j^{u,d}$	Maximum climb/slope rate of unit j .

D. Variables

C,C_{unit},C_{carbon}	Total system cost, unit cost of generation, system cost of carbon emissions.
$P_{i,j}$	Power generated by unit j at i -th period.
$P_{i,w},P_{i,pv}$	Active output power of wind and photovoltaic at i -th period.
$P_{i,l}$	Load demand of the system at i -th period.

I. INTRODUCTION

China, as the world's largest energy consumer and greenhouse gas emitter, assumes a critical role in combating global climate change[1]. To tackle this pressing issue, China has established two strategic goals: achieving "peak carbon" by 2030 and carbon neutrality by 2060[2]. With electricity emissions accounting for a growing proportion of the country's total carbon emissions, it is essential to focus on this sector amidst the transition to a low-carbon economy. Electric vehicles (EVs) have garnered increasing attention, while renewable energy sources such as hydropower, wind power,

This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ACFPE59335.2023.10455123.10532686, 2023 2nd Asian Conference on Frontiers of Power and Energy (ACFPE)

solar power, geothermal power, biomass, and wave energy are progressively contributing to electricity generation and transportation [3]. This presents an opportunity to curtail fossil fuel usage and reduce carbon emissions. However, we must acknowledge the various charging-related costs associated with EVs. As industry and the economy continue to flourish, more users are embracing electric vehicles, resulting in a substantial number of EVs being haphazardly connected to the grid, thereby exerting significant strain on grid operations. Consequently, it is imperative to explore strategies and approaches to address this challenge.

Determining the power output of each generating unit to minimize the cost of power generation and carbon emissions, while fulfilling the charging demands of electric vehicles, is a fundamental aspect of economic dispatch within the power system. Currently, the most viable and advantageous solution for economic dispatch in power systems involves optimizing the combination of units with scenic power generation. This approach aims to minimize the operating costs of thermal units, meet the charging requirements of electric vehicles, and adhere to the various constraints of the thermal units, all within the limitations of scenic power generation dispatch. By substituting a portion of thermal power generation with scenic power generation, fuel consumption is reduced, and pollutant emissions are mitigated to a certain extent.

Currently, research on the optimal dispatch of electric vehicles has made significant advancements. Studies focusing on the optimal dispatch of electric vehicles, incorporating carbon trading and demand response mechanisms, have provided crucial insights and methodologies to ensure clean charging of electric vehicles, yielding notable outcomes. Referred literature [4-5] extensively elaborates on the contribution of electric vehicles to emission reduction and assesses the extent of their impact and sensitivity to emission reduction within diverse energy grid structures, underscoring the significance of adopting cleaner electric vehicle charging practices. Furthermore, other studies [6-7] delve into the influence of time-of-use tariffs on electric vehicle charging behavior, utilizing such tariffs as a basis. By optimizing charging behavior to minimize user charging costs and reduce peak-to-valley load differentials, these studies demonstrate that orderly charging schedules guided by time-of-use tariffs can diminish the overall charging costs for users and alleviate load fluctuations. Moreover, additional literature[8-9]effectively manages load fluctuations during charging by employing dynamic tariffs in conjunction with demand response mechanisms, presenting an efficient approach for flexibly controlling the charging process. This method enables the balancing of grid load and reduction of energy consumption.

Based on the aforementioned research status, it can be deduced that current studies predominantly focus on a singular electric vehicle (EV) charging scenario, primarily emphasizing orderly charging, with limited consideration given to the integration of renewable energy sources into charging practices. Although some literature has introduced scenic power generation models within these scenarios, their full utilization remains unexplored, resulting in energy wastage. Therefore, the objective of this paper is to develop an optimization model for EV charging that incorporates scenic power generation, drawing upon the aforementioned research, the work in this paper covers the following two main parts:

Part I: In terms of model, different from the traditional power system unit optimization and dispatching model, this paper integrates the power supply capacity of generating units and the charging demand of electric vehicles, builds an optimization model of electric vehicle charging with scenic power generation, and introduces a power system optimization and dispatching model that takes into account the environmental effects.

Part II: This paper uses an improved genetic algorithm with variable length coding to solve the proposed model, determining the number of coded bits of the initial population from the output range of different units and dealing with various constraints in the form of penalty functions, so as to quickly and accurately obtain the generation solution with the lowest system generation cost while meeting the charging demand of the users.

II. MATHEMATICAL FORMULATION

A. *Problem Statement*

In comparison to conventional fuel vehicles, the carbon emissions produced by electric vehicles during operation are nearly negligible. Nevertheless, it is crucial not to overlook the system operating costs associated with charging these vehicles, which constitute a significant consideration. Figure 1 gives the carbon emissions as well as the energy flow relationships between the various components of the electric vehicle charging process.

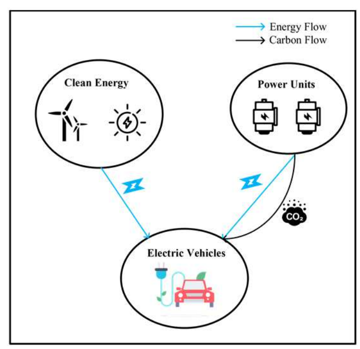

Fig.1 Energy flow and Carbon flow of the model

One of the primary contributors to these costs is the consumption of coal by thermal power units, along with the accompanying carbon emissions resulting from coal combustion. Therefore, it has become a major concern to determine the output power values of the different units in each dispatch time interval during the system operating cycle in order to minimize the carbon emissions generated by supplying electricity to electric vehicles and to minimize the charging costs.

To address this issue, several key factors need to be taken into consideration. Firstly, it is essential to dispatch the power system effectively to determine the power output of each generating unit during specific time intervals. This dispatch should consider both the power supply capacity of the system and the charging demand of electric vehicles. Secondly, an

This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ACFPE59335.2023.10455123.10532686, 2023 2nd Asian Conference on Frontiers of Power and Energy (ACFPE)

appropriate optimization model must be employed, which includes an optimal dispatch model for the power system, taking into account environmental factors. This ensures that the system can meet the charging demand while minimizing carbon emissions and operating costs. Lastly, in order to solve this model, optimization algorithms such as genetic algorithms can be utilized to obtain the most cost-effective power generation solution that fulfills the users' charging requirements.

Through the above research and optimization, we can effectively address the issues of carbon emissions and charging costs when powering electric vehicles. This will help to promote the popularity and sustainable development of electric vehicles and contribute to the reduction of environmental pollution and energy consumption.

B. Objective Function

The optimization objective of the proposed model in this paper is to minimize the generation costs and carbon emissions associated with supplying power to electric vehicles. To achieve this goal, a multi-objective function is designed, represented by (1) as follows:

(1) Total system cost

$$\min C = \min(C_{unit} + C_{carbon}) \tag{1}$$

In the case of thermal power units, the cost of generating electricity is closely related to the coal consumption factor of the unit and the output power of the unit. The coal consumption coefficients of different units are determined internally by the respective units. For unit j, the total coal consumption required can be calculated using equation (2) for different operating periods and output powers.

(2) Cost of system generation

For thermal units, the cost of generating electricity is directly related to the coal consumption factor of the unit and the corresponding output power of the unit, which is determined by the unit itself. For unit j, the total coal consumption required for different operating hours and output powers can be calculated by (2):

$$f_j(Q_{i,j}) = a_j P_{i,j}^2 + b_j P_{i,j} + c_j \tag{2}$$

where $Q_{i,j}$ is the output state of unit j in time period i.

After obtaining the required coal consumption for different units, the exact generation cost of the unit can be calculated by (3) based on the unit coal consumption cost in the current scenario and combined with (2) to give an accurate generation cost C_{unit}.

This calculation process ensures that the coal consumption requirements of the unit and the unit coal consumption cost are considered together to give an accurate generation cost.

$$C_{unit} = \sum_{i=1}^{T}\sum_{j=1}^{U}[Q_{coal} f_j(Q_{i,j})] \tag{3}$$

where Q_{coal} is the cost per unit of coal consumed and has a value of RMB 800/t.

(3) Cost of carbon emissions

In the process of power generation, the source of carbon emissions from thermal power units is mainly the carbon dioxide released during the operation of coal-fired power plants. In this paper, carbon dioxide allowances and the price of carbon trading are used as the main indicators to measure the cost of carbon emissions, and the cost of carbon emissions from the system can be calculated by (4):

$$C_{carbon} = K_c\left(\sum_{j=1}^{U} P_{i,j}E_c - \sum_{j=1}^{U} P_{i,j}\delta\right) \tag{4}$$

K_c is the carbon emission factor per unit of electricity of thermal power units, which is set as 0.9109 kg/kWh, and δ is the carbon emission allowance allocation factor, which is set as 0.8112 kg/kW.

C. Constraints

The objective of economic dispatch in power systems is to effectively allocate the output of thermal power units during the operating cycle in order to minimize the overall operating costs while satisfying all relevant constraints. However, the operation of thermal power units is subject to various constraints that pose challenges. In this particular scenario, the following key constraints need to be considered predominantly:

(1) System power balance constraint

In the model presented in this paper, the power output of thermal units, along with photovoltaic and wind power generation, collectively form the electricity supply scheme to meet the overall demand of the system. To minimize carbon emissions and promote the utilization of clean energy, constraints such as those represented in equation (5) are introduced. These constraints ensure the maximum utilization of renewable energy sources within the model. This design approach aims to optimize the electricity supply scheme, fostering the efficient use of renewable energy and reducing dependence on conventional energy sources.

$$\sum_{j=1}^{U} P_{i,j} + P_{i,w} + P_{i,pv} = P_{i,l} \tag{5}$$

This constraint is implemented to guarantee the complete utilization of wind and photovoltaic power during each dispatch interval.

(2) Thermal power unit output and climbing constraints

$$\begin{cases} P_j^{\min} \le P_{i,j} \le P_j^{\max} \\ \left|P_{i,j} - P_{i,j-1}\right| \le R_j^{u,d} \Delta t P_j^{\max} \end{cases} \tag{6}$$

Δt is the length of a scheduling interval, set as 1h.

III. SOLUTION METHOD

A. Introduction of GA

Genetic algorithms are a versatile class of optimization algorithms widely used in intelligent optimization. They mimic the biological evolutionary process to find the optimal solution, employing the principle of "survival of the fittest." The key components of a genetic algorithm include parameter encoding, initial population generation, fitness function design, genetic

This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ACFPE59335.2023.10455123.10532686, 2023 2nd Asian Conference on Frontiers of Power and Energy (ACFPE)

operation composition, and control parameter configuration. Operating on a population of individuals, genetic algorithms employ randomization techniques to efficiently explore the encoded parameter space and locate the optimal individual. The genetic operation consists of three main steps: selection, crossover, and mutation. By combining these core elements synergistically, genetic algorithms can effectively identify the best solution to an optimization problem[10].

The execution process of a traditional genetic algorithm consists of the following steps:

Step 1: Determine the objective function and the solution space of the problem and create the population.

Step 2: The individuals in the population are evaluated and assigned different fitness values based on the set objective function.

Step 3: Select, crossover and mutate individuals based on their fitness values to obtain the next generation population.

Step 4: Repeat steps 2-3 until the algorithm reaches the number of iterations.

Traditional genetic algorithms perform well in solving function extremes and solving optimization problems, and are able to find high precision optimal solutions quickly. However, traditional genetic algorithms are limited in certain usage scenarios and can lead to a dramatic increase in computational complexity in multi-constrained scenarios.

In this paper, we apply genetic algorithms to address low carbon economic dispatch scenarios in power systems. To enhance the performance of traditional genetic algorithms, we propose an irregular coding-based genetic algorithm by improving the coding method and population construction form. The details of our improvement scheme are described below:

B. *Encoding scheme*

Traditional genetic algorithms usually choose a specific coding method based on the characteristics of the problem, such as binary coding or real number coding. However, considering the range of output of different units, this paper proposes an irregular coding method that better meets the requirements of low-carbon economic dispatch of power systems while adapting to the needs of this specific scenario.

$$2^{l_j} \geq P_j^{\max} - P_j^{\min} \tag{7}$$

The minimum number of binary coding bits required for each unit is calculated from the power output of the unit and Equation (7) and is denoted l_j . Using this coding method to construct the initial population, the initial population $initialpop$ is obtained in the following form:

$$initialpop = \begin{pmatrix} a_{1,1}^1, a_{1,2}^1, \ldots, a_{1,l_1}^1, a_{2,1}^1, a_{2,2}^1, \ldots, a_{2,l_2}^1, \ldots, a_{j,1}^1, a_{j,2}^1, \ldots, a_{j,l_j}^1 \\ \vdots \\ a_{1,1}^N, a_{1,2}^N, \ldots, a_{1,l_1}^N, a_{2,1}^N, a_{2,2}^N, \ldots, a_{2,l_2}^N, \ldots, a_{j,1}^N, a_{j,2}^N, \ldots, a_{j,l_j}^N \end{pmatrix} \tag{8}$$

The size of $initialpop$ is $N * \sum_{j=1}^{U} l_j$.

C. *Actual objective function*

In genetic algorithms, the main indicator of the degree of merit of an individual is the value of that individual's objective function. Genetic algorithms basically do not use external information in evolutionary search, but only use the fitness function as the basis, using the fitness value of each individual in the population to search. Therefore, the selection of the fitness function will directly affect the convergence speed and the search effect of the genetic algorithm[11]. Before determining the objective function of the algorithm, it is important to determine in advance how to deal with the multiple constraints in the scenario involved.

Various constraints, particularly those related to system power balance, are present in the operational scenarios of thermal power units with scenic generation. To address these constraints, this paper proposes an optimization scheme that employs a penalty function. The penalty function helps ensure better satisfaction of these constraints. Specifically, the resulting penalty function is represented as (9):

$$punish = \sum_{i=1}^{T} \left(\left| \sum_{j=1}^{U} P_{i,j} - P_{i,l} \right| \right) \tag{9}$$

Combining equation (1) and equation (8), the actual objective function of the algorithm for this scenario can be derived as shown in (10):

$$Obj = C + \mu * punish \tag{10}$$

Obj is the objective function value of a power allocation scheme and μ is the penalty factor, which is determined by the user. The fitness value of each scheme corresponds to the value of the objective function calculated by the algorithm, the correspondence in this example being that the lower the total cost of running the system, the higher the fitness value.

D. *Introduction of improved GA*

In this paper, the improved GA is applied to the low carbon economic dispatch scenario of power system, starting from the coding method and population construction form of traditional genetic algorithm, a genetic algorithm based on irregular coding is proposed, and the flow chart of the proposed improved genetic algorithm is shown as Fig. 2:

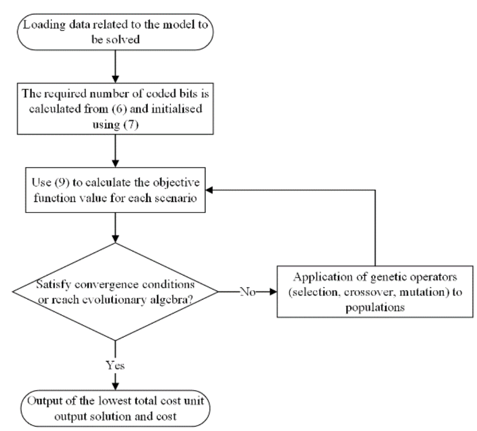

Fig.2 Improved genetic algorithm flow chart

IV. Result and Discussion

A. Data access

In this paper, we divide the time period involved in the scheduling of scenarios into 24 periods from 0:00 to 24:00. Within each time period, we will dynamically adjust the power output of the individual units according to the power demand of the customers and the output of the scenery farm. For the power data of the thermal units, we will refer to the classical 8-unit arithmetic and use the unit parameters and 24-hour customer demand data from [12] shown in TABLE I. and TABLE II. . Forecast data for wind and photovoltaic generation from [13] will be provided in TABLE III.

TABLE I. The Unit Paraemeters

Unit	*Pmin* /MW	*Pmax* /MW	a_i /t·MWh^{-2}	b_i /t·MWh^{-2}	c_i /t·MWh^{-2}
1	150	405	0.000015	0.12	5.25
2	150	405	0.000016	0.13	5.1
3	20	147	0.000017	0.14	3.37
4	20	147	0.000021	0.14	3.37
5	25	152	0.00003	0.16	2.77
6	20	83	0.00004	0.16	2.78
7	25	88	0.000029	0.2	3.6
8	15	46	0.00005	0.19	4.95

TABLE II. Load Data In Different Periods

Period	Load/MW	period	Load/MW	period	Load/MW
1	700	9	1300	17	1000
2	750	10	1400	18	1100
3	850	11	1450	19	1200
4	950	12	1500	20	1400
5	1000	13	1400	21	1300
6	1100	14	1300	22	1100
7	1150	15	1200	23	900
8	1200	16	1050	24	800

TABLE III. Outputs Prediction Of Pv And Wind Power

Period	P_w /MW	P_{pv} /MW	period	P_w /MW	P_{pv} /MW	period	P_w /MW	P_{pv} /MW
1	165	0	1	35	65	1	150	25
2	145	0	2	10	100	2	195	5
3	120	0	3	75	115	3	140	0
4	160	0	4	85	125	4	240	0
5	140	0	5	50	115	5	140	0
6	120	0	6	115	110	6	70	0
7	130	6	7	125	80	7	10	0
8	80	25	8	170	50	8	80	0

B. Simulation Results

The convergence process of the improved genetic algorithm is depicted in Fig.2 of this paper. It demonstrates a reduction of approximately 240 coding bits, leading to a decrease in computational complexity. From the observation of Fig.3, it is evident that the algorithm proposed in this study can surpass the initial population and converge to the optimal solution in around 40 generations. This indicates the algorithm's excellent convergence performance.

Details of the power output of the eight units for each time period after scheduling are given in Fig.4. Furthermore, TABLE IV. presents the carbon emission costs and unit generation costs associated with the power output scheme before and after optimization. Upon examining TABLE IV. , it is evident that the method proposed in this paper results in significant savings for the customer, approximately RMB 280.4 per day. This indicates that the proposed method offers substantial benefits in achieving low carbon economic dispatch.

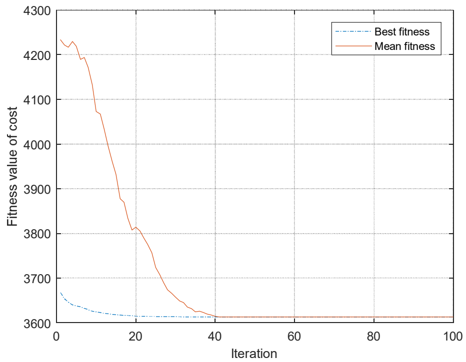

Fig.3 The convergence process of improved GA

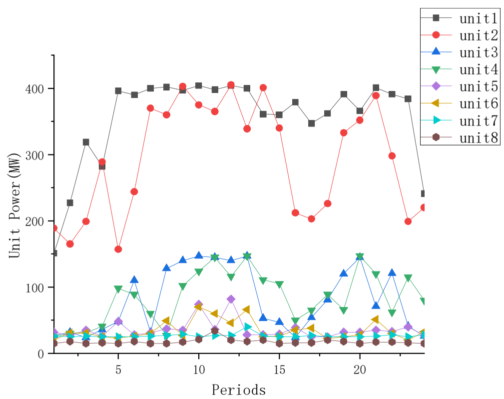

Fig.4 Units output power for each time period

TABLE IV. SIMULATION RESULTS COMPARISON

Optimization	Carbon Cost	Units Cost	Total Cost	Cost reduction/yuan
Before	586.5	3307.4	3893.9	280.4
After	556.6	3056.9	3613.5	

V. CONCLUSITION

The issue of electric vehicle charging is a key concern in achieving low-carbon economic dispatch in power systems. By appropriately allocating the output power of thermal power units, the strain on the grid caused by the widespread adoption of electric vehicles can be alleviated, and charging operating costs can be reduced. This paper begins by conducting a detailed analysis of relevant parameters for thermal power units and power generation data from scenic power stations. Subsequently, a model is constructed to represent the output power of eight units that include scenic power stations. The model is solved using a genetic algorithm, employing different coding strategies for the output of units across various time periods and constructing an initial population.

Simulation results demonstrate that the algorithm proposed in this paper can rapidly determine the output power of each unit while optimizing objectives such as carbon emissions and generation costs. This approach provides an effective solution to the low-carbon economic dispatch problem in power systems that incorporate scenic power generation.

The model and algorithm proposed in this paper are suitable for solving the electric vehicle charging scheduling problem in some small-scale scenarios, and for obtaining clean energy output data, which are not real-time, so we hope to do more in-depth research on the model and algorithm in the future in order to obtain a real-time power system scheduling optimization method that can work in more complex and diversified scenarios.

ACKNOWLEDGEMENT

This work was supported in part by the funding of Electric Power Science Research Institute of Grid Chongqing Electric Power Company (Grant No. SGCQDKOOSBJS2100407).

REFERENCES

[1] H.L. Dai, Y.N. Su, J.Z. Liu, D.Z. Gu, L.C. Kuang and C.C. Zou, "Strategic thinking of Chinese energy development under the carbon neutrality goal," Petroleum Science and Technology Forum, pp. 1-8, 2022.

[2] D. Huang, "Carbon footprint and green supply chain management of transportation enterprises," Logistics Technology and Application, pp. 71-72, 2009.

[3] Rui Freire, Joaquim Delgado, Joáo M. Santos and Aníbal T. de Almeida, "Integration of renewable energy generation with EV charging strategies to optimize grid load balancing", IEEE 13th International IEEE Conference on Intelligent Transportation Systems, September 2010.

[4] D. Y. Yu, H. L. Huang, M. Lei, et al., "CO2 reduction benefit by coordinated dispatch of electric vehicle charging and wind power," Automation of Electric Power Systems, vol. 36, no. 10, pp. 14-18, 2012.

[5] Z. Z. Wang, N. Jia, J. H. Li, et al., "Impact factors and sensitivity analysis of electric vehicle emission reduction under different energy grid architectures," Energy Saving Technology, 2020.

[6] Z. Y. He, Y. Y. Gao, H. T. Huang, et al., "Energy management of microgrid based on grid time-sharing tariff mechanism considering flexible charging of electric vehicles," Low Voltage Electronics, vol. 2022, no. 005, 2022.

[7] A pricing strategy for electric vehicle charging in residential areas considering the uncertainty of charging time and demand, "Computer Communications," vol. 199, pp. 153-167, 2023.

[8] W. Yin, T. Wen, C. Zhang, "Cooperative optimal scheduling strategy of electric vehicles based on dynamic electricity price mechanism," Energy, vol. 263, 2023, pp. 125627.

[9] K. Wang, H. Wang, J. Yang, et al., "Electric vehicle clusters scheduling strategy considering real-time electricity prices based on deep reinforcement learning," Energy Reports, vol. 8, 2022, pp. 695-703.

[10] D. E. Goldberg, "Genetic Algorithm in Search, Optimization, and Machine Learning," Addison-Wesley Pub. Co., 1989.

[11] K. Deb, "Genetic Algorithm in Search and Optimization: The Technique and Applications," Proceedings of International Workshop on Soft Computing & Intelligent Systems, 1999.

[12] X.Q. Nan, Q. Z. Li, Y. Z. Zhao, et al., "Economic dispatching and auxiliary decision-making methods for wind power prediction with confidence," Power System Automation, vol. 37, no. 19, 2013.

[13] H. Xiong, T. Y. Xiang, H. K. Chen, et al., "Study of fuzzy chance-constrained unit combinations containing large-scale intermittent power supplies," Chinese Journal of Electrical Engineering, vol. 33, no. 13, pp. 36-44, 2013.