Low-carbon dispatch of the Park IES based on the EV flexible load storage characteristics

Hui Liao[a,b,c], Yaodong Li[d], Xianfu Gong[d], Tianren Zhang[b,c,e] Yuping Huang[a,b,c,e*] ,
[a,]Guangzhou Institute of Energy Conversion, Chinese Academy of Sciences, Guangzhou 510640, China
[b,]University of Chinese Academy of Sciences, Beijing, 100049, China
[c,]Guangdong Provincial Key Laboratory of New and Renewable Energy Research and Development, Guangzhou 510640, China
[d,]Grid Planning & Research Center, Guangdong Power Grid Corporation, CSG, Guangzhou 510620, China
[e,]School of Energy Science and Engineering, University of Science and Technology of China, Hefei 230026, China

Abstract: The integrated energy system (IES) is an efficient way of utilizing energy in industry park. However, with the massive integration of renewable energy and disorganized charging of electric vehicles (EVs), the safe operation of this system faces several challenges. To address these issues, we propose a novel dispatch model that incorporates the flexible load characteristics of EV clusters. Firstly, we elucidate the operational framework for the IES in parks and establish models for users and microgrid operators incorporating carbon trading mechanisms. These models can effectively portray how an IES operates within a park setting. Secondly, using charging data from parks, we uncover potential dispatchable charging/discharging capacities for EV clusters and formulate strategies to utilize EVs as flexible loads in our dispatch operation policy. By appropriately regulating EV charging/discharging behaviors, demand-supply balance within the system can be better achieved. Subsequently, aiming to maximize benefits for all entities in the park area, we construct a master-slave game model that involves multiple users and microgrid operators. Lastly, employing reinforcement learning concepts, we establish an equivalent power output models for wind turbines(WT)，photovoltaic (PV) power generation and apply it to an IES in an industrial park in a specific city. An analysis reveals that our proposed model not only minimizes cost associated with energy storage equipment but also significantly reduces carbon emissions—yielding mutual benefits for both microgrid operators and users.

Key words: EV; IES, carbon trading, main and slave game, optimized scheduling

1 Introduction

Under the backdrop of China's "14th Five-Year" energy development plan and dual carbon goals, the energy sector is transitioning towards a safer and more efficient direction. The IES can achieve complementary energy use effects by breaking down barriers between various energy subsystems, representing a future development trend[1]. However, the complexity of IES also poses challenges to its overall safe operation[2]. With regional economic development, large quantities of renewable energy and coupled components are being added into grids, continually increasing peak shaving pressures. Moreover, the rapid increase in EV numbers further magnifies this pressure[3]. Therefore, how to fully realize the flexible load storage characteristics of the overall optimization of EVs has become an important content of the current research, which is of great significance to reduce the carbon emission of Park IES.

The Park IES aims to balance the economic interests of microgrid energy system operators and users by integrating user-side load characteristics. Ref [4] establishes an optimization scheduling model for AC-DC microgrids that includes EVs and transforms this model into a mixed integer second-order cone convex optimization problem. Sample results demonstrate that EVs, serving as mobile energy storage, can perform peak shaving and valley filling, thereby improving the economic operation of the microgrid. Ref [5] proposes a microgrid economic dispatch scheme for orderly charging and discharging of EVs. By guiding orderly charging and discharging behavior of EVs, good environmental benefits are achieved at lower power generation costs. From a load aggregator's perspective, Ref [6] improves synergy between EVs and PV—and achieves increased revenue while reducing emissions—by proposing an EV dispatch strategy that combines PV output characteristics with demand response forms. Furthermore, There are some researchers explored the coordinated operation of other devices such as energy storage[7] and concentrating solar power[8] to enhance the environmental benefits of the IES. For grid-connected microgrids aiming to achieve resource collaboration optimization. Ref [9] establishes a hierarchical optimization scheduling model considering demand response and carbon emission quotas while evaluating user satisfaction. However, most studies consider either EVs or flexible loads individually with few researching flexible loads, energy storage, and EVs collectively. Ref [10] proposes integrated dispatch strategies considering adjustable loads—establishing a scheduling model aimed at maximizing power system revenue alongside user-side income to facilitate overall optimization of power resources—though these primarily focus on economic optimization without assessing their own absorption conditions for new energies or their impact on grids. While these studies achieve goals pertaining to economical operation of microgrids alongside improved absorption rates for new energies through optimizing flexible load dispatching—they do not consider potential effects on user satisfaction following flexible load regulation.

Addressing the economic benefit issues of the Park IES, Ref [11] analyzes the impact of hydrogen energy storage equipment on electricity and heating prices based on park electricity-heat-gas characteristics. Ref[12] considers incorporating detailed heating modeling within the IES, taking into account user costs from an electricity-heating characteristic perspective. Ref[13] establishes a mixed electric/thermal storage model to improve the economy of the Park IES. However, these researches overlook the relationship between microgrid operators' pricing strategies and user energy strategies, thereby disregarding interests of microgrid operators.

Park IES requires high robustness against energy fluctuations. Due to significant variability in system energy supply and demand, a low-carbon operation model for integrated energy grounded on the flexible load storage characteristics of EVs is proposed. Ref [14] encourages users to achieve maximum benefits by employing peak-shifting charging and discharging strategies using devices with flexible load storage characteristics. On this basis. Ref [15] enhances economic efficiency by planning charging and discharging times among different stakeholders across multiple parks. However, these studies do not consider the flexible load storage characteristics of EV clusters within Park IES context. Compared to previous approaches, we utilize the "storage" characteristic of EVs to diminish investment costs associated with energy storage equipment and exploit the "load" characteristic of EVs to reduce wind and solar curtailment probability, thereby enhancing overall energy utilization rate within the IES.

At present, some scholars have explored the dispatch potential of EV clusters. Ref [16] proposes a control strategy that considers the participation of EV clusters in grid peak load regulation. Ref [17] fully exploits the dispatch potential of EV clusters by establishing a bidding model for charging stations. Ref [18] treats the dispatchable potential model of EV clusters as energy storage devices participating in the game process with microgrid operators. These studies did not consider parameter uncertainty when establishing an EV cluster model. Although Ref [19] utilized a bidirectional long-short term memory network to handle uncertainty, it did not consider the flexible load storage characteristics of EV clusters.

Addressing the carbon emission issue in Park IES, Ref [20]introduces a stepwise carbon trading mechanism during system optimization. Ref [21]proposes a novel stochastic planning model for zero-carbon multi-energy systems considering individual energy needs and environmental conditions' uncertainty. Ref [22] reduces system carbon emissions by using CO2 storage tanks. Ref [23] introduces a carbon trading mechanism with reward-penalty factors, leading to reduced energy consumption costs in the system.

In summary, few research consider the integration of flexible load storage characteristics based on EV clusters and the source-load characteristics of the park when optimizing and dispatching Park IES that includes large-scale EVs. In fact, with the development of Park IES and an increase in EV ownership, EVs as flexible load storage devices play an integral role in implementing a "light-storage-direct-flexible" strategy[24]. Simultaneously, most existing research focuses primarily on minimizing user costs without fully considering the interests of microgrid operators, thus failing to satisfy all stakeholders.

Therefore, this paper targets a Park IES involving microgrid operators, EVs, and users. Based on the energy prices set by the microgrid operators, an equivalent solar output prediction model is established on the source side using reinforcement learning. On the load side, considering demand response, flexible load storage characteristics of EV clusters, and stepwise carbon trading mechanisms, a low-carbon optimization model for Park IES is constructed based on master-slave game theory and flexible load storage characteristics based on dispatchable potential of EV clusters. The effectiveness of this proposed scheme is validated through case analysis.

2 Operation framework of IES based on EV flexible load storage characteristics

In order to unified planning purposes, this paper counts the scattered users within the Park IES as a user model, with EVs undergoing charging and discharging processes at a unified charging station. The energy interaction process between users, microgrid operators, the power grid, and EV charging stations is also considered. The electric load and heat load on the user side are mainly supplied by gas engine sets on the microgrid operator side, with a small proportion supplied by WT, PV, and electric heating equipment on the user side. Users can purchase electricity from EV charging stations as depicted in Figure 1.

As shown in Figure 1, a "source-load-storage" cooperative control microgrid topology is established, including renewable energy generation systems such as wind power and photovoltaics (PV), energy storage systems, EV charging and discharging systems, loads, and microgrid control systems. The microgrid control system monitors each internal system and can control the energy flow within the microgrid and the energy exchange between the microgrid and external power grid based on the internal electric energy dispatch needs. The EVs in the microgrid serve as a combination of flexible storage and flexible load. Under certain constraints, through unified scheduling by the microgrid control system, they can assist Park IES in peak shaving and valley filling functions while enhancing robustness of park's microgrids system and reducing carbon emissions.

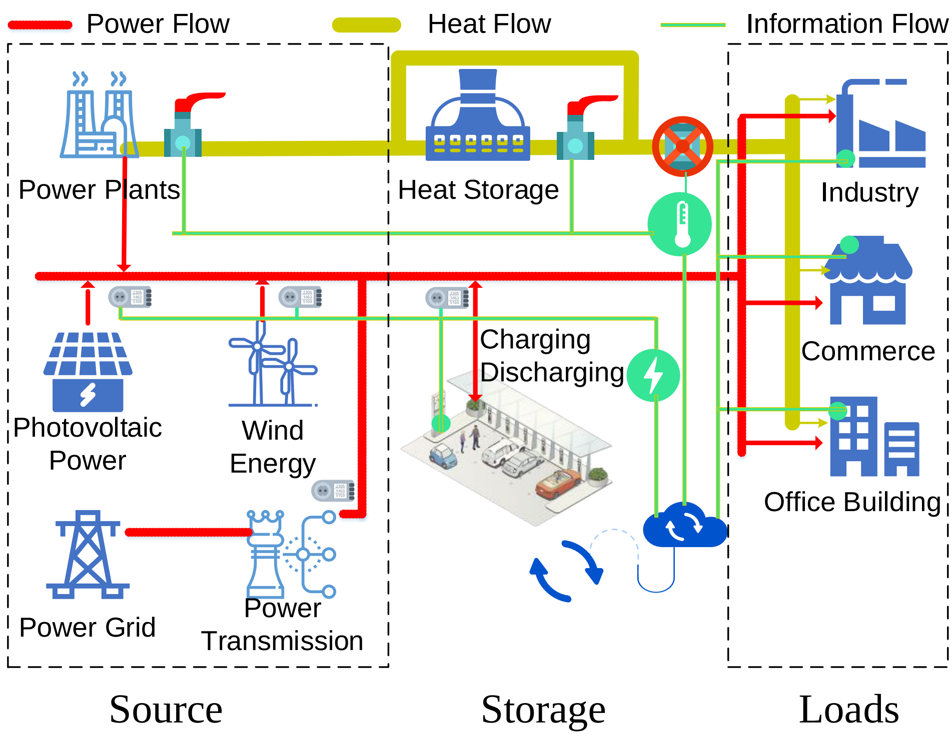

Figure 1 Framework of Park IES based on EV flexible load storage characteristics

The microgrid operator provides users with electricity and heat through combined heat and power generation, and the prices are market specific. The microgrid operator determines hourly electricity and heat prices based on information provided by users, earning revenue by selling electricity and heat to users. In addition, the microgrid operator can sell excess electricity to the grid for additional profit. Simultaneously, a stepwise carbon trading mechanism with reward-penalty factors is incorporated into the microgrid operator side to penalize systems when carbon emissions exceed quotas and reward them when emissions are below quotas, promoting a reduction in carbon emissions.

The energy demand on the user side mainly consists of electrical demand and thermal demand. Assuming that the price set by the microgrid operator does not exceed grid time-of-use rates, it is assumed in this paper that users' electrical energy comes from both the microgrid system and EVs. When PV on the user side cannot meet their power demands, users can purchase electricity from power grid or EVs. Meanwhile, when renewable energy generation on the user side exceeds user electricity consumption, EVs can be dispatched for charging or reverse discharging to the grid.

Based on these analyses, Park IES operates as follows: The microgrid operator formulates reasonable selling strategies according to purchasing/selling electric prices from/to grid and historical heating purchase prices of users. On the user side they select optimal energy usage schemes according to their electric/thermal load conditions while optimizing their distribution of electric/thermal loads. The EV charging station can charge when electricity prices are low; during higher price periods it discharges in reverse by selling stored EV power to users for profit.

3 Modeling of Park IES

3.1 Modeling of the EV flexible source charge characteristics

3.1.1 Modeling of individual EV flexible source charge characteristics

After entering the charging station, EV will charge and discharge according to its own energy demand and economic benefits. The individual EV charge-discharge model is as follows:

$$\begin{cases} 0 \le P_{n,t}^{cha} \le P_n^{cha,max} \times i_{n,t}^{cha} \\ 0 \le P_{n,t}^{dis} \le P_n^{dis,max} \times i_{n,t}^{dis} \\ S_{n,t} = S_{n,t-1} + \left(\eta^{EV,cha} \cdot P_{n,t}^{cha} - \dfrac{P_{n,t}^{cha}}{\eta^{EV,dis}} \right) \Delta t \\ S_{n,t}^{min} \le S_{n,t} \le S_{n,t}^{max} \\ 0 \le i_{n,t}^{cha} + i_{n,t}^{dis} \le i_{n,t}^{EV} \quad t \in [T_{arrive}, T_{leave}] \end{cases} \tag{1}$$

Where:$P_{n,t}^{cha}, P_{n,t}^{dis}$ are the charge and discharge power of different types of EV at time t; $P_n^{cha,max}, P_n^{dis,max}$ are the allowable limits of EV charge and discharge power; $i_{n,t}^{cha}, i_{n,t}^{dis}$ are Boolean variables for the EV charge-discharge states; The EV cannot be conducted charge and discharge simultaneously; $i_{n,t}^{EV}$ is the status of the EV location. When $i_{n,t}^{EV} = 1$, it means that the EV_n can be charged and discharged in the charging station at time t;$S_{n,t}$ is the state of the EV battery; The n is the number of the EV;$\eta^{EV,cha}$,$\eta^{EV,dis}$ are the charge-discharge efficiency of EV; Δt is the time period of the EV cluster; $S_{n,t}^{min}$,$S_{n,t}^{max}$ are the minimum and maximum power of EV; T_{arrive},T_{leave} are the arrival time and the departure time of the EV.

3.1.2 EV cluster schedulable potential modeling

Due to the considerable uncertainty in individual EV arrival and departure times at charging stations, as well as their initial SOC, the flexible load storage characteristics of EVs cannot be fully utilized. Therefore, this paper constructs a dispatchable potential model for an EV cluster. The larger the sample size within the cluster, the more accurate is its dispatchable potential. Dispatchable potential refers to predicting historical data such as EV arrival and departure times at charging stations and initial SOC, thereby clearly defining real-time EV flexible load storage capacity range and charging-discharging power.

This paper aggregates an EV cluster into a flexible load storage characteristic model using Mincowsky sum theory and calculates envelope space boundaries for dispatchable potentials of the EV cluster. As Boolean variables are considered when calculating individual EV charging-discharging power, their station entry-exit times belong to the same feasible domain; therefore, individual EVs possess Mincowsky sum additivity. The upper and lower boundaries of an aggregated EV cluster can be formulated as:

$$\begin{cases} 0 \le \sum_{n \in N^{EV}} P_{n,t}^{cha} \le \sum_{n \in N^{EV}} \left(P_n^{cha,max} \times i_{n,t}^{cha}\right) \\ 0 \le \sum_{n \in N^{EV}} P_{n,t}^{dis} \le \sum_{n \in N^{EV}} \left(P_n^{dis,max} \times i_{n,t}^{dis}\right) \\ \sum_{n \in N^{EV}} S_{n,t} = \sum_{n \in N^{EV}} \left(S_{n,t-1} + \left(\eta^{EV,cha} \cdot P_{n,t}^{cha} - \frac{P_{n,t}^{cha}}{\eta^{EV,dis}}\right) \Delta t\right) \\ \sum_{n \in N^{EV}} S_{n,t}^{min} \le \sum_{n \in N^{EV}} S_{n,t} \le \sum_{n \in N^{EV}} S_{n,t}^{max} \end{cases} \tag{2}$$

Where: N^{EV} represents a collection of EV sets, Equation (2) not only establishes the flexible load storage model of EV cluster with physical significance, but also realizes the aggregation of individual EV decision space from the perspective of optimizing the feasible domain. In conclusion, the flexible load storage model of EV sets can be expressed as follows:

$$\begin{cases} P_{n,t}^{cha,EV} = \sum_{n \in N^{EV}} P_{n,t}^{cha} \\ P_{n,t}^{dis,EV} = \sum_{n \in N^{EV}} P_{n,t}^{dis} \\ S_{n,t}^{EV} = \sum_{n \in N^{EV}} S_{n,t} \end{cases} \tag{3}$$

Where:$P_{n,t}^{cha,EV}$ $P_{n,t}^{dis,EV}$ $S_{n,t}^{EV}$ are the charging discharging power and SOC of EV_n at time t, which participate in the scheduling as a decision variable.

3.1.3 Probabilistic modeling of the charge-discharge time distribution of EVs

According to the Ref [25], large number of statistics can be obtained, the probability density function of EV started charging time follows a normal distribution, and the probability density function of EV stopped charging class follows a log-normal distribution.

$$f^{arrive}(t) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(t-\mu)^2}{2\sigma^2}\right] & \mu - 12 \le t \le 24 \\ \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(t+24-\mu)^2}{2\sigma^2}\right] & 0 \le t \le \mu - 12 \end{cases} \tag{4}$$

$$f^{leave}(t) = \frac{1}{t\sqrt{2\pi\sigma'}} \exp\left[-\frac{(lnt - \mu')^2}{2\sigma'^2}\right] \tag{5}$$

Where:$\mu, \sigma$are the mean and standard deviation of the normal distribution; μ', σ' are the mean and standard deviation of the lognormal distribution, t is the moment of the beginning or end of EV charging.

3.1.4 Prediction EV's parameters based on GBDT

From Equations(2) and (3), it can be discerned that once historical data such as the maximum charging-discharging power and energy storage limits of EVs within the charging station are known, the range of real-time energy storage potential parameters for EVs can be calculated. Predicting these real-time data using algorithms with strong calculation capabilities can help minimize the impact of uncertainties. Therefore, this paper employs Gradient Boosting Decision Tree (GBDT) method to analyze three historical datasets: initial SOC, entry-exit times of EV clusters.

Compared to other prediction methods, GBDT can further explore the connection between current data and past or future time-related data, enhancing prediction accuracy. The GBDT algorithm and its associated parameters refer to Ref[26].

The power purchase cost of EV charging stations to the power grid can be expressed as follows:

$$E_{out}^{EV}=\sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_c\times P_{n,t}^{cha,EV} \tag{6}$$

Where: E_{out}^{EV} represent the daily purchase cost of EV charging station; λ_c is the charging cost coefficient of EV and the N is the total number of EV.

At the same time, the revenue of EV charging station sales to Park IES can be expressed as:

$$E^{EV}=\sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_d\times P_{n,t}^{dis,EV} \tag{7}$$

Where:E_{in}^{EV} is the revenue obtained by EV charging station from Park IES; λ_d is the cost coefficient of EV discharge.

Therefore, the revenue of EV charging station within one day can be expressed as:

$$E_{in}^{EV}=E_{in}^{EV}-E_{out}^{EV} \tag{8}$$

3.2 WT -PV power model

The power output of WT is influenced by the wind speed and blade angle. In this research, we focus on the impact of wind speed, and divided into three categories, the active power output of WT is calculated according to the following formula[27,28].

$$P^{WT}(v)=\begin{cases}0 & v<v_{step_{in}} \text{ or } v>v_{step_{out}}\\ P_0\,arctan(\omega_1 v+\omega_2)+\omega_3 & v_{step_{in}}\le v<v_{set}\\ P_0 & v_{step_{out}}\ge v\ge v_{set}\end{cases} \tag{9}$$

Where: $P^{WT}(v)$ is the power out of WT, P_0 is the maximum power of WT; $v_{step_{in}}, v_{set}, v_{step_{out}}$ are the minimum operational wind speed, rated wind speed, and cut-out wind speed of WT. $\omega_1,\omega_2,\omega_3$ represent the fitting coefficients for wind speed and WT power and can get from Ref[27,28].

The equivalent PV power generation is controlled by the maximum power tracking, and the active power output is affected by factors such as ground radiation and temperature, and the active power output is calculated according to the following formula.

$$\begin{cases}V^{mp}(G,T)=V^{mp,STC}+K_V(T-T_{STC})+V_t\,ln(G/G_{STC})\\ I^{mp}(G,T)=(I^{mp,STC}+K_I(T-T_{STC}))G/G_{STC}\\ P^{mp}(G,T)=V^{mp}(G,T)I_{mp}(G,T)\\ P^{PV}(G,T)=\eta_{pv}P^{mp}(G,T)\end{cases} \tag{10}$$

Where: $V^{mp}(G,T), I^{mp}(G,T)$are the voltage and current corresponding to the maximum power; $G_{\mathrm{STC}}, T_{\mathrm{STC}}$ are the ground radiation and temperature under the standard test conditions; $V^{mp,STC}, I^{mp,STC}$and are the voltage and current corresponding to the maximum power under the standard test conditions; $K_V, K_I$are the temperature coefficient of the voltage and current; V_t is the diode thermal voltage and can according to the calculation $V_t=kT/q$, k is the Boltzmann constant, q is the amount of electronic charge, T is the temperature and the unit is Kelvin; η_{pv} is the conversion efficiency of the inverter.

3.3 Modeling of CHP

CHP units are primarily categorized into back-pressure and extraction types, with this study focusing on the latter. Figure 2 illustrates the thermal-electrical characteristics of an extraction-type CHP unit[29]. In this figure, $P_{h,max}$ represents the maximum heat output of the CHP, while $P_{h,min}$ refers to the heat power when the unit operates at minimum electrical output. $P_{el,max}$、$P_{el,min}$, respectively, denote the maximum and minimum electrical output under pure condensation conditions. The overall operation range is represented by ABCDA in a graphical form.

It can be inferred that when thermal load is fixed (as represented by P_h), adjustments can be made within the range PE~PF for CHP unit output. However, as heating power increases, there is a corresponding decrease in the adjustable range of electrical power. Consequently, during periods of low EV demand at night, forced escalation in Park IES output results in insufficient peak regulation capacity for electricity networks. This inability reduces wind energy absorption capacity leading to wind curtailment phenomena.

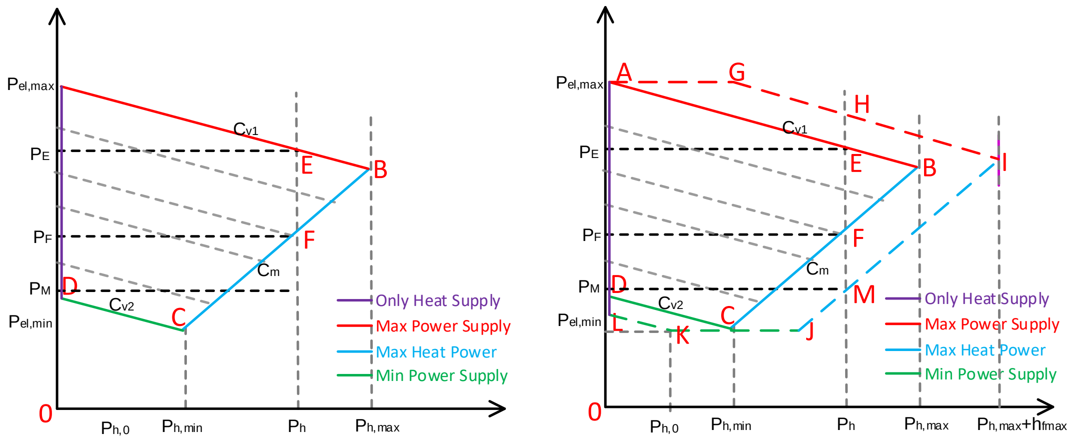

Figure 2 Working characteristics of the cogeneration unit

Upon the installation of a thermal storage device, the electrical-thermal characteristic curve of the CHP unit changes, and the operation range expands from ABCD to AGHIJCKL. The heat release from the thermal storage device lowers the minimum heat output to $P_{h,0}$ and raises the maximum heat output to$P_{h,max} + h_{fmax}$. As depicted in Figure 2, when thermal load is fixed (as represented by P_h), adjustments can be made within PM~PH for CHP unit electrical output due to regulation by thermal storage. Compared with PE~PF range without storage, there is no longer a need for matching with thermal demand, significantly weakening strong coupling between electrical and heating outputs. This allows for more flexible adjustment ranges, thereby achieving decoupling of "heat-determined-electricity" constraints. At this time, excess or insufficient heating can be stored or released by thermal storage devices to meet heat load requirements, thereby enhancing system peak-shifting capability.

In Park IES environments, produced thermal energy from CHP equipment is utilized to fulfill park user demands. When combined electricity outputs from this equipment and renewable energy devices exceed park electricity needs, surplus power will be fed back into the main grid. Contrarily if electricity supply falls short of demand levels it will be necessary to purchase additional power from major networks. The gas consumption cost of CHP units and its corresponding electric power output can be represented as:

$$E_t^{CHP} = \frac{P_t^{el}}{\eta_e^{CHP}} \times P_{gas} \tag{11}$$

$$P_{el,min} \le P_t^{el} \le P_{el,max} \tag{12}$$

Where: E_t^{CHP} is the gas consumption cost of CHP during the period t, η_e^{CHP} is the power generation efficiency of CHP, P_t^{el} *is* the electric power output of CHP during the period t, and P_{gas} means the price of natural gas.

Among them, the relationship between heating and power supply in CHP can be expressed as follows:

$$P_t^h = \eta_{he} \times P_t^{el} \tag{13}$$

Where: P_t^h it is the thermal power of CHP during the period t, and η_{he} is the thermoelectric ratio coefficient.

4 Thermoelectric pricing model and solution strategy based on main and slave game

4.1 Modeling the Principal-Agent Game among Different Entities within the Park

Microgrid operators chose the best energy selling scheme through a main and slave game with park users. Park users, by comparing the electricity sale scheme and EV charging station prices, make rational use of EV charging station services and electric heating equipment while dynamically adjusting their flexible electrical and thermal loads. If the price set by the microgrid operator does not align with expectations, park users will adjust their proportion of flexible load and energy purchase; meanwhile, microgrid operators will also dynamically adjust pricing schemes based on changes in park user's energy purchases. It is evident that there is an order to their decision-making: microgrid operators are main players while park users are slaves in this game. The game process of this model is shown in Figure 3.

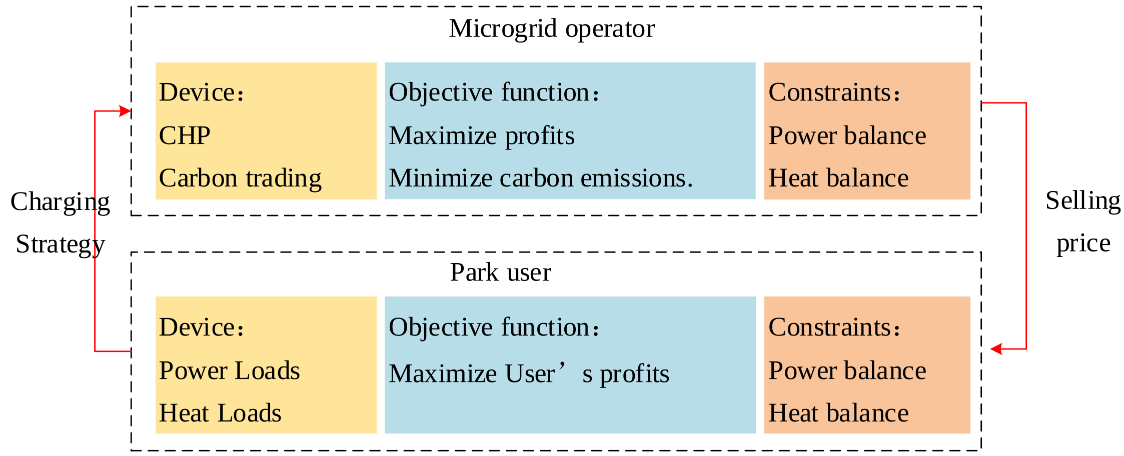

Figure 3 Schematic diagram of the master and slave game process of the IES

There is no other heat source in the Park IES, and the heat production of CHP is all used to meet the heat needs of users.L_t^h So there are:

$$P_t^h \ge L_t^h \tag{14}$$

The strategy set of the micro grid operator provides heat and electric energy for users, and obtains the optimal selling price strategy set by using the master and slave game. The electricity price and thermal price constraints are as follows:

$$P_t^{CHP\_el,b} < P_t^{CHP\_el} < P_t^{CHP\_el,s} \tag{15}$$

$$P_t^{CHP\_h,min} < P_t^{CHP\_h} < P_t^{CHP\_h,max} \tag{16}$$

Where: $P_t^{CHP\_el}, P_t^{CHP\_h}$ are the electricity sale price and heat sale price set by the micro grid system after the master and slave game; $P_t^{CHP\_el,b}, P_t^{CHP\_el,s}$ are the electricity purchase price of the power grid; and $P_t^{CHP\_h,min}$, $P_t^{CHP\_h,max}$ are the upper and lower limits of the heating price of the user.

The income and cost of the micro grid system mainly consists of the following parts: the income from the electricity sale and heat sale of the micro grid system $E^{L,e}, E^{L,h}$; the income generated by the micro grid and the electricity sale to the large power grid $E^{G,e}$; the gas cost of the micro grid $E_t^{CHP}$and the cost generated by the carbon trading mechanism E^{CET}; and the net profit of the park.E_{profit}

$$E^{L,e} = \sum_{t=1}^{T} P_t^{CHP\_el} \times L_t^e \tag{17}$$

$$E^{G,e} = \begin{cases} \sum_{t=1}^{T} P_t^{CHP\_el,b} \times \left(L_t^e - P_t^{el} - P_t^{PV} - P_t^{WT}\right) & L_t^e < P_t^{el} + P_t^{PV} + P_t^{WT} \\ \sum_{t=1}^{T} P_t^{CHP\_el,b} \times \left(P_t^{el} + P_t^{PV} + P_t^{WT} - L_t^e\right) & L_t^e \geq P_t^{el} + P_t^{PV} + P_t^{WT} \end{cases} \tag{18}$$

$$E^{L,h} = \sum_{t=1}^{T} P_t^{CHP\_h} \times L_t^h \tag{19}$$

$$E^{CET} = \left(e_s^{chp} \times \frac{P_t^{el}}{\eta_e^{CHP}} + \sum_{t=1}^{T} e_s^{Grid} \times \left(L_t^e - P_t^{el} - P_t^{PV}\right) - E_{al}\right) \times \delta_{step}^{carbon} \tag{20}$$

$$E_{profit} = E^{L,e} + E^{L,h} + E^{G,e} - E^{CET} - \sum_{t=1}^{T} E_t^{CHP} \tag{21}$$

Where: T is the synthesis of all periods of the day; P_t^{PV} is the power generation of PV; $P_t^{WT}$the power generation of WT; E_{al} is the overall carbon emission quota of the Park IES, e_s^{chp} represents the emission coefficient of CHP; e_s^{Grid} indicate the indirect emission coefficient of purchased power; and δ_{step}^{carbon} is the stepped carbon trading price with reward and penalty factors.

4.2 Model solving equation and process of master and slave game

The objective of Park IES operators is to maximize revenue, based on which they design the optimal electricity and heat pricing schemes. The pricing strategy of the upper-level MGO is initialized and updated by a genetic algorithm. After receiving prices from the upper-level MGO, the lower-level UA uses CPLEX solver to determine the optimal revenue. The process flow diagram is shown in Figure 4.

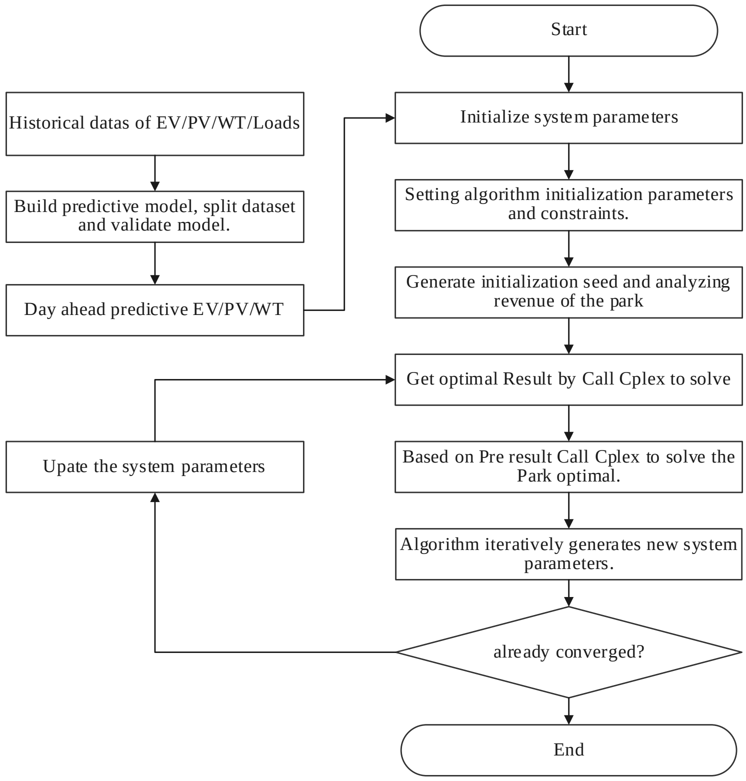

Figure 4 Solving method and process of multi-agent master and slave game model in the park

5 case analysis

The study's example is a Park IES in a city of Guangdong China. Assuming one day is divided into T=24 periods, The power characteristics of WT obtained by calculating, based on the wind speeds of the park IES, according to the Ref[30], the characteristics of thermal and electric loads, PV output, parameters of CHP from microgrid operators, time-of-use electricity price from the grid and upper and lower limits of thermal and electric loads from park users are referred to in Ref[31]. The relevant parameters of EVs and GBDT algorithm are cited from Ref[26]. To reflect the reality that there are multiple users in the park, calculations are carried out for different user energy demands. The historical data of the EV cluster is processed using GBDT method. For the introduced model of Park IES featuring reward-penalty mechanism for carbon trading as well as flexible storage load characteristic of EVs, comparison analyses were made among four scenarios through MATLAB simulation. Moreover, relative advantages of proposed models were analyzed from economic perspective and carbon emission aspect regarding Park IES. The four scenarios are set up as follows:

Scenario 1: no EV, excluding the stepped carbon trading mechanism; Scenario 2: consider EV, no the stepped carbon trading mechanism; Scenario 3: consider the stepped carbon trading mechanism, no EV; and Scenario 4: consider EV and the stepped carbon trading mechanism. The optimized run results for the 4 scenarios are shown in Table 1.

Table 1 Benefit and cost analysis of different scenarios

scene	Operator revenue / yuan	User revenue / yuan	EV revenue / yuan	Carbon trading cost / yuan	carbon emission /kg

1	11876	25357			39308
2	13581	23928	2688		38089
3	7768	27087		5291	33101
4	7328	27651	2609	4683	30927

According to data presented in Table 1, it indicates that considering either carbon trade (scenario 3) or charging station for EV(scenario 2), compared with considering regular storage device without considering EV charging station or mechanism for carbon trade (scenario 1), can lead to higher Profits for Park IES operators. Specifically, scenario 2's model based on flexible storage load brought about by Electric Vehicles resulted in a CO2 emission reduction by as much as 1219 kg compared with scenario 1, while income from park users and EVs increased by 1429 yuan. This outcome is due to the addition of EVs, as park users can opt to purchase electricity from EV charging stations when the price offered by Power Gid operators is relatively high, thereby reducing their energy purchasing costs. This also encourages a reduction in CHP output and decreases carbon emissions from Park IES.

In Scenario 3, by considering the carbon trading mechanism, compared with scenario 1, the carbon emissions of the park IES are reduced by 6207 kg. This is because after the addition of the carbon trading mechanism, in order to promote the system emission reduction, the output of CHP on the side of the micro grid operator decreases. Users in the park give priority to power supply for their own electric load, reduce the charge time of EVs, increase the heat purchase from the CHP, and increase the energy cost.

Combining the advantages of scenario 2 and 3, scenario 4 reduces the carbon emission by 7162 kg and 2174 kg respectively compared with scenario 2 and scenario 3, greatly reducing the carbon emission of the park IES; Meanwhile, compared with scenario 3, the revenue of park users in scene 4 is increased by 564 yuan after joining EV. It is proved that the carbon emission of the system can be greatly reduced by adding the flexible load storage model based on EV. In addition, the overall income of the park IES has been increased to a certain extent. Compared with the traditional energy storage equipment, it not only reduces the early investment cost of the park, but also brings additional economic income to the users and the park IES.

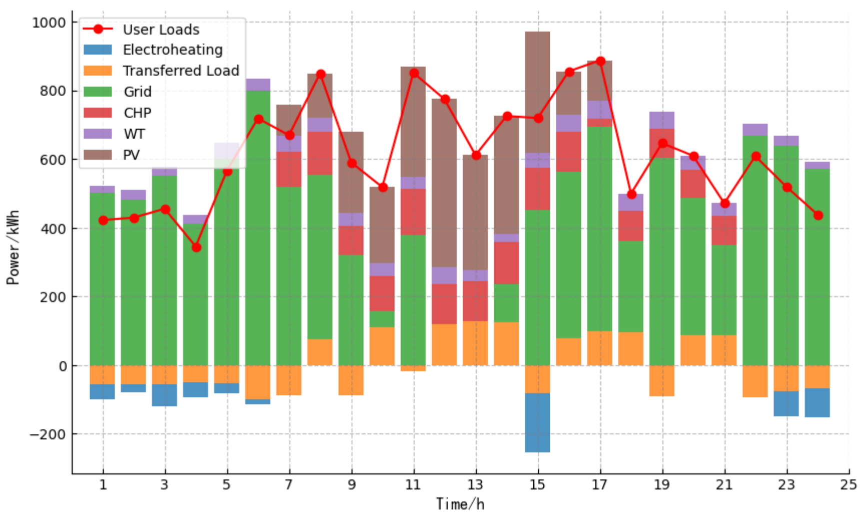

Figure 5 Optimal power balance strategy in scenarios 1

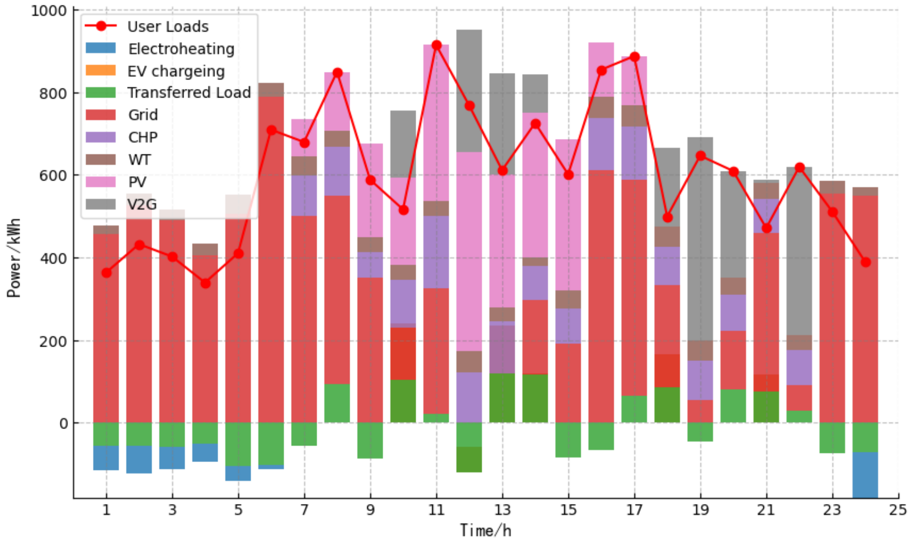

Figure 6 Optimal power balance strategy in scenarios 4

Figure 5 and Figure 6 shows power balance curves for electricity and heat among Park Users under scenarios one and four respectively. Compared with scenario one that considers energy storage devices replacing them in park IES with models based on flexible storage load brought about by EVs while considering stepwise carbon trading featuring rewards-penalties factor (scenario four) reveals more available periods where transferable loads or reduced loads are available for user three under scenario four. This is because to reduce their own energy costs, park users opt to transfer flexible load from high energy price periods to low energy price periods, proving that models based on flexible storage load characteristic brought about by EVs can improve flexibility of loads on Park User side. At the same time within periods where heat supply price from microgrid operators exceeds their power supply price compared with scenario one there are more instances in scenario four where park users choose to use electric heating devices indicating a higher degree of flexibility in their electric-thermal loads and that incorporating stepwise carbon trading mechanism featuring rewards-penalties factor can better encourage park users to use electric heating devices thereby reducing both system's CO2 emissions as well as energy costs.

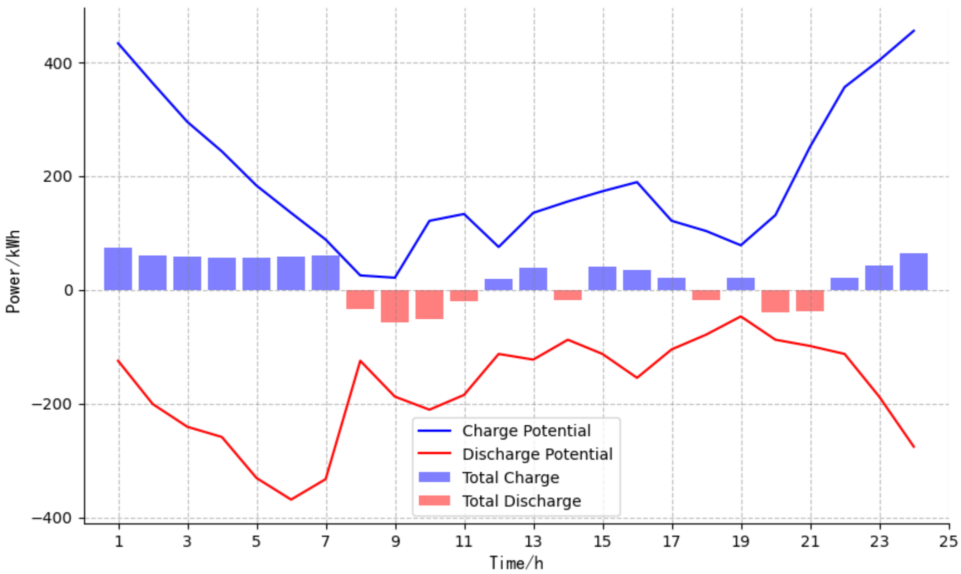

Figure 7 Optimal power balance strategy in the park in different scenarios

Figure 7 presents the total energy storage capacity changes in EV charging stations and the charging-discharging power variations across different stations. According to the electricity variation diagram of the sets, it is observed that the EVs opts for charging during 00:00—09:00, 14:00—18:00, and 21:00—24:00 periods. This is due to lower time-of-use electricity prices during these periods, which allows for cost reduction through charging. During periods with higher prices from10:00—14:00 and18:00—21:00, varying degrees of discharging operations are observed among EVs. This indicates that park users choose to obtain electricity from EVs when prices are high which consequently reduces their own energy purchasing costs. Moreover, Figure 7 also demonstrates that when the charging-discharging power of the EV cluster is within dispatchable potential boundaries, models based on flexible storage load characteristic brought about by EVs exhibit strong robustness offering surplus energy storage for future planning in parks.

6 conclusion

This study constructs a IES suitable for industrial park. In light of issues such as high initial investment in park energy storage devices, it proposes using the flexible load characteristics based on the dispatchable potential of EV sets to participate in the dispatch process. Simultaneously, a master-slave game model between microgrid operators and park users is established, effectively increasing park user income, and significantly reducing system carbon emissions, achieving a win-win situation for both parties. The main conclusions obtained are as follows:

1) The proposed model fully exploits the flexible load characteristics of EV sets. EV charging stations autonomously decide their charging and discharging processes, bringing benefits to the park while also reducing its carbon emissions. Furthermore, models based on flexible storage load characteristic brought about by EVs exhibit strong robustness and extendibility, providing surplus energy storage for future planning in parks.

2) The incorporation of models based on flexible storage load characteristic brought about by EVs can enhance the flexibility of loads from park users' side, lower their energy costs and provide insights for upper-level microgrid operators' pricing strategies.

3) After introducing a carbon trading mechanism, microgrid operators change their own energy selling strategy by adjusting CHP unit outputs. After comparison, carbon emissions from the system fell 15%, proving that introducing stepwise carbon trading mechanism with reward-penalty factor has some advantages in reducing carbon emissions. The strategy proposed in this article utilizes EV's flexible load characteristics to reduce park's energy costs which is conducive to building IES under "dual-carbon" goals within parks.

If there are no gas turbine units among park IES operators then this paper's model can be simplified: Park IES operators purchase power from grid then sell it to users to gain profits; thermal part would depend on each user's situation where they either generate heat or purchase it externally while models based on flexible storage load characteristic brought about by EVs will still provide users with energy storage services. Future research will further explore the application of EV route planning in IES within parks and the cooperative game process among users within park users.

Acknowledgements

This work was supported by the Science and Technology Program of Science and Technology Project of China Southern Power Grid Co., Ltd. (037700KK52220041(GDKJXM20220904)).

Reference

[1] Zhao Pan, Gou Feifei, Xu Wenpanet al. Energy, exergy, economic and environmental (4E) analyses of an integrated system based on CH-CAES and electrical boiler for wind power penetration and CHP unit heat-power decoupling in wind enrichment region[J]. Energy, 2023, 263: 125917.

[2] Song Dongran, Meng Weiqi, Dong Miet al. A critical survey of integrated energy system: Summaries, methodologies and analysis[J]. Energy Conversion and Management, 2022, 266: 115863.

[3] Xu Jie, Huang Yuping. The short-term optimal resource allocation approach for electric vehicles and V2G service stations[J]. Applied Energy, 2022, 319: 119200.

[4] Tamura Shigeru, Kikuchi Takuro, V2G Strategy for Frequency Regulation Based on Economic Evaluation Considering EV Battery Longevity[M], 2018

[5] Al-Ogaili Ali Saadon, Tengku Hashim Tengku Juhana, Rahmat Nur Azzammudinet al. Review on Scheduling, Clustering, and Forecasting Strategies for Controlling Electric Vehicle Charging: Challenges and Recommendations[J]. IEEE Access, 2019, 7: 128353-128371.

[6] Q. Yan, B. Zhang, M. Kezunovic. Optimized Operational Cost Reduction for an EV Charging Station Integrated With Battery Energy Storage and PV Generation[J]. IEEE Transactions on Smart Grid, 2019, 10（2）: 2096-2106.

[7] Hemmati Reza, Hooshmand Rahmat-Allah, Khodabakhshian Amin. Market based transmission expansion and reactive power planning with consideration of wind and load uncertainties[J]. Renewable and Sustainable Energy Reviews, 2014, 29: 1-10.

[8] T. Xu, N. Zhang. Coordinated Operation of Concentrated Solar Power and Wind Resources for the Provision of Energy and Reserve Services[J]. IEEE Transactions on Power Systems, 2017, 32（2）: 1260-1271.

[9] Cao Jun, Crozier Constance, McCulloch Malcolmet al. Optimal Design and Operation of a Low Carbon Community Based Multi-Energy Systems Considering EV Integration[J]. IEEE Transactions on Sustainable Energy, 2019, 10（3）:

1217-1226.
[10] Zhu Gang, Gao Yan. Multi-objective optimal scheduling of an integrated energy system under the multi-time scale ladder-type carbon trading mechanism[J]. Journal of Cleaner Production, 2023, 417: 137922.
[11] B. Li, M. Chen, Z. Maet al. Modelling integrated power and transportation sectors decarbonization with hydrogen energy storage[J]. IEEE Transactions on Industry Applications, 2021: 1.
[12] Zhang Youjun, Ge Zhihua, Yang Yunxiet al. Carbon reduction and flexibility enhancement of the CHP-based cascade heating system with integrated electric heat pump[J]. Energy Conversion and Management, 2023, 280: 116801.
[13] Zhao Teng, Zheng Yanan, Li Gengyin. Integrated unit commitment and economic dispatch of combined heat and power system considering heat-power decoupling retrofit of CHP unit[J]. International Journal of Electrical Power & Energy Systems, 2022, 143: 108498.
[14] S. Gao, T. E. Song, S. Liuet al. Joint Optimization of Planning and Operation in Multi-Region Integrated Energy Systems Considering Flexible Demand Response[J]. IEEE Access, 2021, 9: 75840-75863.
[15] Alabi Tobi Michael, Lu Lin, Yang Zaiyue. Improved hybrid inexact optimal scheduling of virtual powerplant (VPP) for zero-carbon multi-energy system (ZCMES) incorporating Electric Vehicle (EV) multi-flexible approach[J]. Journal of Cleaner Production, 2021, 326: 129294.
[16] Le Chen, Zhang Hongzhi, Lin Xiangninget al, Reliability and economic evaluation model of power distribution network under large scale EV's access[M], 2017: 2042-2047.
[17] Guo Song, Qiu Zejing, Xiao Chupenget al. A multi-level vehicle-to-grid optimal scheduling approach with EV economic dispatching model[J]. Energy Reports, 2021, 7: 22-37.
[18] Zifa Liu, Yixiao Chen, Ranqun Zhuoet al. Energy storage capacity optimization for autonomy microgrid considering CHP and EV scheduling[J]. Applied Energy, 2018, 210
[19] Wei Xu, Wang Zhiling, Li Chaoet al. Analysis of prediction and clustering for uncertainty of EV charging station behavior on V2G platform[J]. Energy Reports, 2022, 8: 1344-1349.
[20] Yingying Chen, Jian Zhu. A Graph Theory-Based Method for Regional Integrated Energy Network Planning: A Case Study of a China–U.S. Low-Carbon Demonstration City[J]. Energies, 2019, 12（23）
[21] Alabi Tobi Michael, Lu Lin, Yang Zaiyue. Stochastic optimal planning scheme of a zero-carbon multi-energy system (ZC-MES) considering the uncertainties of individual energy demand and renewable resources: An integrated chance-constrained and decomposition algorithm (CC-DA) approach[J]. Energy, 2021, 232: 121000.
[22] Alabi Tobi Michael, Lu Lin, Yang Zaiyue. Data-driven optimal scheduling of multi-energy system virtual power plant (MEVPP) incorporating carbon capture system (CCS), electric vehicle flexibility, and clean energy marketer (CEM) strategy[J]. Applied Energy, 2022, 314: 118997.
[23] Yaohua Cheng, Ning Zhang, Daniel S. Kirschenet al. Planning multiple energy systems for low-carbon districts with high penetration of renewable energy: An empirical study in China[J]. Applied Energy, 2020, 261（C）
[24] Jie Yan, Jing Zhang, Yongqian Liuet al. EV charging load simulation and forecasting considering traffic jam and weather to support the integration of renewables and EVs[J]. Renewable Energy, 2020, 159（prepublish）
[25] Calearo Lisa, Marinelli Mattia, Ziras Charalampos. A review of data sources for electric vehicle integration studies[J]. Renewable and Sustainable Energy Reviews, 2021, 151: 111518.
[26] Zhang Tianren, Huang Yuping, Liao Huiet al. A hybrid electric vehicle load classification and forecasting approach based on GBDT algorithm and temporal convolutional network[J]. Applied Energy, 2023, 351: 121768.
[27] J. F. Medina Padron, A. E. Feijoo Lorenzo. Calculating Steady-State Operating Conditions for Doubly-Fed Induction Generator Wind Turbines[J]. IEEE Transactions on Power Systems, 2010, 25（2）: 922-928.
[28] Fernández L. M., García C. A., Saenz J. R.et al. Equivalent models of wind farms by using aggregated wind turbines

and equivalent winds[J]. Energy Conversion and Management, 2009, 50（3）: 691-704.
[29] Jiang-Jiang Wang, You-Yin Jing, Chun-Fa Zhang. Optimization of capacity and operation for CCHP system by genetic algorithm[J]. Applied Energy, 2009, 87（4）
[30] C. Sahin, M. Shahidehpour, I. Erkmen. Allocation of Hourly Reserve Versus Demand Response for Security-Constrained Scheduling of Stochastic Wind Energy[J]. IEEE Transactions on Sustainable Energy, 2013, 4（1）: 219-228.
[31] Liao H., Huang Y., Zhao D., An Optimal Strategic Portfolio of Biomass-Based Integrated Energy System[M], 2019: 1-6.

Submitted: 20.10.2023.
Revised: 16.11.2023.
Accepted: 25.12.2023.