### LOW CARBON DISPATCH OF THE PARK INTEGRATED ENERGY SYSTEM BASED ON THE ELECTRIC VEHICLES FLEXIBLE LOAD STORAGE CHARACTERISTICS

#### by

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The integrated energy system is an efficient way of utilizing energy in industry park. However, with the massive integration of renewable energy and disorganized charging of electric vehicles, 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 electric vehicles clusters. Firstly, we elucidate the operational framework for the integrated energy system in parks and establish models for users and microgrid operators incorporating carbon trading mechanisms. These models can effectively portray how an integrated energy system operates within a park setting. Secondly, using charging data from parks, we uncover potential dispatchable charging/discharging capacities for electric vehicles clusters and formulate strategies to utilize electric vehicles as flexible loads in our dispatch operation policy. By appropriately regulating electric vehicles 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, photovoltaic power generation and apply it to an integrated energy system 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: electric vehicles, integrated energy system, carbon trading, main and slave game, optimized scheduling

#### Introduction

Under the backdrop of China's 14<sup>th</sup> Five-Year energy development plan and dual carbon goals, the energy sector is transitioning towards a safer and more efficient direction. The integrated energy system (IES) can achieve complementary energy use effects by breaking

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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 electric vehicles (EV) numbers further magnifies this pressure [3]. Therefore, how to fully realize the flexible load storage characteristics of the overall optimization of EV 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. Tamura and Kikuchi [4] establishes an optimization scheduling model for AC-DC microgrids that includes EV and transforms this model into a mixed integer second-order cone convex optimization problem. Sample results demonstrate that EV, serving as mobile energy storage, can perform peak shaving and valley filling, thereby improving the economic operation of the microgrid. Al-Ogaili et al. [5] proposes a microgrid economic dispatch scheme for orderly charging and discharging of EV. By guiding orderly charging and discharging behavior of EV, good environmental benefits are achieved at lower power generation costs. From a load aggregator's perspective, Yan et al. [6] improves synergy between EV and photovoltaic (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 co-ordinated 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. Cao et al. [9] establishes a hierarchical optimization scheduling model considering demand response and carbon emission quotas while evaluating user satisfaction. However, most studies consider either EV or flexible loads individually with few researching flexible loads, energy storage, and EV collectively. Yhu and Gao [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, Li *et al.* [11] analyzes the impact of hydrogen energy storage equipment on electricity and heating prices based on park electricity-heat-gas characteristics. Zhang *et al.* [12] considers incorporating detailed heating modelling within the IES, taking into account user costs from an electricity-heating characteristic perspective. Zhao *et al.* [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 EV is proposed. Gao *et al.* [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. Alabi *et al.* [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 EV to diminish investment costs associated with energy storage equipment and exploit the *load* characteristic of EV 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. Chen *et al.* [16] proposes a control strategy that considers the participation of EV clusters in grid peak load regulation. Guo *et al.* [17] fully exploits the dispatch potential of EV clusters by establishing a bidding model for charging stations. Liu *et al.* [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 Xu *et al.* [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, Chen *et al.* [20] introduces a stepwise carbon trading mechanism during system optimization. Alabi *et al.* [21] proposes a novel stochastic planning model for zero-carbon multi-energy systems considering individual energy needs and environmental conditions' uncertainty. Alabi *et al.* [22] reduces system carbon emissions by using  $CO_2$  storage tanks. Cheng *et al.* [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 EV. In fact, with the development of park IES and an increase in EV ownership, EV 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, EV, 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.

## 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 EV 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 wind turbines (WT), PV, and electric heating equipment on the user side. Users can purchase electricity from EV charging stations as depicted in fig. 1.

As shown in fig. 1(a) *source-load-storage* co-operative control microgrid topology is established, including renewable energy generation systems such as wind power and 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 EV 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 EV. When PV on the user side cannot meet their power demands, users can purchase electricity from power grid or EV. Meanwhile, when renewable energy generation on the user side exceeds user electricity consumption, EV can be dispatched for charging or reverse discharging to the grid.

Based on these analyses, park IES operates: 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.

#### **Modelling of park IES**

#### Modelling of the EV flexible source charge characteristics

Modelling 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:

$$0 \leq P_{n,t}^{cha} \leq P_n^{cha,max} \times i_{n,t}^{cha}$$

$$0 \leq P_{n,t}^{dis} \leq P_n^{dis,max} \times i_{n,t}^{dis}$$

$$S_{n,t} = S_{n,t-1} + \left(\eta^{EV,cha} P_{n,t}^{cha} - \frac{P_{n,t}^{cha}}{\eta^{EV,dis}}\right) \Delta t$$

$$S_{n,t}^{min} \leq S_{n,t} \leq S_{n,t}^{max}$$

$$0 \leq i_{n,t}^{cha} + i_{n,t}^{dis} \leq i_{n,t}^{EV} \quad t \in [T_{arrive}, T_{leave}]$$
(1)

where  $P_{n,t}^{cha}$  and  $P_{n,t}^{dis}$  are the charge and discharge power of different types of EV at time t,  $P_n^{cha,max}$  and  $P_n^{dis,max}$  – the allowable limits of EV charge and discharge power, and  $i_{n,t}^{cha}$  and  $i_{n,t}^{cha}$  – the 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. The  $S_{n,t}$  is the state of the EV battery, n – the number of the EV,  $\eta^{EV,cha}$  and  $\eta^{EV,dis}$  are the charge-discharge efficiency of EV,  $\Delta t$  is the time period of the EV cluster,  $S_{n,t}^{min}$  and  $S_{n,t}^{max}$  are the minimum and maximum power of EV, and  $T_{arrive}$  and  $T_{leave}$  – the arrival time and the departure time of the EV.

#### The EV cluster schedulable potential modelling

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 EV 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 EV possess Mincowsky sum additivity. The upper and lower boundaries of an aggregated EV cluster can be formulated as:

$$0 \leq \sum_{n \in N^{EV}} P_{n,t}^{cha} \leq \sum_{n \in N^{EV}} \left( P_n^{cha,max} \times i_{n,t}^{cha} \right)$$

$$0 \leq \sum_{n \in N^{EV}} P_{n,t}^{dis} \leq \sum_{n \in N^{EV}} \left( P_n^{dis,max} \times i_{n,t}^{dis} \right)$$

$$\sum_{n \in N^{EV}} S_{n,t} = \sum_{n \in N^{EV}} \left[ S_{n,t-1} + \left( \eta^{EV,cha} P_{n,t}^{cha} - \frac{P_{n,t}^{cha}}{\eta^{EV,dis}} \right) \Delta t \right]$$

$$\sum_{n \in N^{EV}} S_{n,t}^{min} \leq \sum_{n \in N^{EV}} S_{n,t} \leq \sum_{n \in N^{EV}} S_{n,t}^{max}$$

$$(2)$$

where  $N^{EV}$  is the collection of EV sets, eq. (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:

$$P_{n,t}^{cha,EV} = \sum_{n \in N^{EV}} P_{n,t}^{cha}$$

$$P_{n,t}^{dis,EV} = \sum_{n \in N^{EV}} P_{n,t}^{dis}$$

$$S_{n,t}^{EV} = \sum_{n \in N^{EV}} S_{n,t}$$
(3)

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

#### Probabilistic modelling of the charge-discharge time distribution of EV

According to the [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:

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

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

where  $\mu$ ,  $\sigma$  are the mean and standard deviation of the normal distribution,  $\mu'$ ,  $\sigma$  and – the mean and standard deviation of the lognormal distribution, t – the moment of the beginning or end of EV charging.

## Prediction EV's parameters based on gradient boosting decision tree

From eqs. (2) and (3), it can be discerned that once historical data such as the maximum charging-discharging power and energy storage limits of EV within the charging station are known, the range of real-time energy storage potential parameters for EV 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 [26].

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

$$E_{\text{out}}^{EV} = \sum_{t=1}^{I} \sum_{n=1}^{N} \lambda_c \times P_{n,t}^{\text{cha}, EV}$$
(6)

where  $E_{\text{out}}^{EV}$  is the daily purchase cost of EV charging station,  $\lambda_c$  – the charging cost coefficient of EV, and the N – the total number of EV.

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

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

where  $E_{in}^{EV}$  is the revenue obtained by EV charging station from park IES and  $\lambda_d$  – the cost coefficient of EV discharge.

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

$$E_{\rm in}^{EV} = E_{\rm in}^{EV} - E_{\rm out}^{EV}$$
(8)

#### The 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].

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

where  $P^{WT}(v)$  is the power out of WT,  $P_0$  – is the maximum power of WT,  $v_{\text{stepin}}$ ,  $v_{\text{set}}$ ,  $v_{\text{stepout}}$  are the minimum operational wind speed, rated wind speed, and cut-out wind speed of WT, and  $\omega_1$ ,  $\omega_2$ ,  $\omega_3$  – the fitting coefficients for wind speed and WT power and can get from [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:

$$V^{\rm mp}(G,T) = V^{\rm mp,STC} + K_V \left(T - T_{\rm STC}\right) + V_t \ln\left(\frac{G}{G_{\rm STC}}\right)$$

$$I^{\rm mp}(G,T) = \left[I^{\rm mp,STC} + K_I \left(T - T_{\rm STC}\right)\right] \frac{G}{G_{\rm STC}}$$

$$P^{\rm mp}(G,T) = V^{\rm mp}(G,T) I_{\rm mp}(G,T)$$

$$P^{PV}(G,T) = \eta_{\rm ny} P^{\rm mp}(G,T)$$
(10)

where  $V^{\text{mp}}(G, T)$ ,  $I^{\text{mp}}(G, T)$  are the voltage and current corresponding to the maximum power,  $G_{\text{STC}}$ ,  $T_{\text{ST}}C$  – the ground radiation and temperature under the standard test conditions,  $V^{\text{mp,STC}}$ ,  $I^{\text{mp,STC}}$  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,  $V_t$  – the diode thermal voltage and can according to the calculation  $V_t = kT/q$ , k – the Boltzmann constant, q – the amount of electronic charge, T[K] – the temperature, and  $\eta_{\text{pv}}$  – the conversion efficiency of the inverter.

#### **Modelling of CHP**

The 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. The  $P_{el,-}$ max and  $P_{el,min}$ , respectively, denote the maximum and minimum electrical output under pure condensation conditions. The overall operation range is represented by ABCDA in a graphical form.



Figure 2. Working characteristics of the cogeneration unit

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.

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  $P_{h,max} + h_{f,max}$ . As depicted in fig. 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:

$$E_t^{\text{CHP}} = \frac{P_t^{et}}{\eta_e^{\text{CHP}}} \times P_{\text{gas}}$$
(11)

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

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where  $E_t^{\text{CHP}}$  is the gas consumption cost of CHP during the period t,  $\eta_e^{\text{CHP}}$  – the power generation efficiency of CHP,  $P_t^{el}$  – the electric power output of CHP during the period t, and  $P_{\text{gas}}$  – the means the price of natural gas.

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

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

where  $P_t^h$  it is the thermal power of CHP during the period t and  $\eta_h e$  – the thermoelectric ratio coefficient.

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

#### Modelling 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 fig. 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. The  $L_t^h$  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:

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

$$\tag{15}$$

$$P_{t}^{CHP}h_{min} < P_{t}^{CHP}h < P_{t}^{CHP}h_{max}$$

$$\tag{16}$$

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 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 ECET, and the net profit of the park  $E_{\text{profit}}$ :

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

$$E^{G,e} = \begin{cases} \sum_{t=1}^{T} P_{t}^{CHP_{-}el,b} \times \left(L_{t}^{e} - P_{t}^{el} - P_{t}^{PV} - P_{t}^{WT}\right) & L_{t}^{e} < P_{t}^{el} + P_{t}^{PV} + P_{t}^{WT} \\ \sum_{t=1}^{T} P_{t}^{CHP_{-}el,b} \times \left(P_{t}^{el} + P_{t}^{PV} + P_{t}^{WT} - L_{t}^{e}\right) & L_{t}^{e} \ge P_{t}^{el} + P_{t}^{PV} + P_{t}^{WT} \end{cases}$$
(18)

$$E^{L,h} = \sum_{t=1}^{T} P_t^{CHP_h} \times L_t^h$$
<sup>(19)</sup>

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

$$E_{\text{profit}} = E^{L,e} + E^{L,h} + E^{G,e} - E^{CET} - \sum_{t=1}^{I} E_{t}^{CHP}$$
(21)



Figure 4. Solving method and process of multiagent master and slave game model in the park

where *T* is the synthesis of all periods of the day,  $P_t^{PV}$  – the power generation of PV,  $P_t^{WT}$  – the power generation of WT,  $E_{al}$  – the overall carbon emission quota of the Park IES,  $e_s^{CHP}$  – the emission coefficient of CHP,  $e_s^{Grid}$  – the indicate the indirect emission coefficient of purchased power, and  $\delta_{step}^{carbon}$  – the stepped carbon trading price with reward and penalty factors.

## 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 fig. 4. Liao, H., et al.: Low Carbon Dispatch of the Park Integrated Energy ... THERMAL SCIENCE: Year 2024, Vol. 28, No. 1B, pp. 659-673

#### **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 [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 [31]. The relevant parameters of EV and GBDT algorithm are-cited from [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 EV, 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:

- 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.
- Scenario 4: consider EV and the stepped carbon trading mechanism.

The optimized run results for the four scenarios are shown in tab. 1.

Scenario	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

 Table 1. Benefit and cost analysis of different scenarios

According to data presented in tab. 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 EV resulted in a  $CO_2$  emission reduction by as much as 1219 kg compared with Scenario 1, while income from park users and EVsincreased by 1429 Yuan. This outcome is due to the addition of EV, 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 EV, increase the heat purchase from the CHP, and increase the energy cost.

Combining the advantages of Scenarios 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 Scenario 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.

Figures 5 and 6 shows power balance curves for electricity and heat among park users under Scenarios 1 and 4, 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 EV while considering stepwise carbon trading featuring rewards-penalties factor (Scenario 4) reveals more available periods where transferable loads or reduced loads are available for user three under Scenario 4. 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 EV can improve flexibility of loads on Park



Figure 5. Optimal power balance strategy in Scenario 1



Figure 6, Optimal power balance strategy in Scenario 4

user side. At the same time within periods where heat supply price from microgrid operators exceeds their power supply price compared with Scenario 1 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  $CO_2$  emissions as well as energy costs.

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 EV 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 from 10:00-14:00 and 18:00-21:00, varying degrees of discharging operations are observed among EV. This indicates that park users choose to obtain electricity from EV when prices are high which consequently reduces their own energy purchasing costs. Moreover, fig. 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 EV exhibit strong robustness offering surplus energy storage for future planning in parks.



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

#### Conclusions

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.

• 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 EV exhibit strong robustness and extendibility, providing surplus energy storage for future planning in parks.

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

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