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Resident Carbon Credit Incentive Decision-Making Method to Promote Valley Filling

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***Abstract*—Establishing a reasonable, feasible, and directional incentive carbon points operation model for residents is an effective means to enhance the low-carbon awareness of residents. This paper introduces dynamic carbon emission factors and power characteristics of carbon valley, and a carbon credit-oriented incentive decision-making method for residents to promote valley filling is proposed. Firstly, based on the carbon quota allocation model, considering three factors: monthly carbon quotas, basic carbon emission and incentive carbon credits, a residential carbon credits-oriented incentive model is proposed to promote carbon valley filling. Secondly, the carbon valley electricity consumption ratio is established, and the K-means algorithm is used to cluster residents. Then, considering the constraints, such as the average monthly carbon credits of residents, the proportion of below-zero credit residents and difference between the mean carbon credits of different clusters, a resident carbon credit decision-making model is constructed, and the Grey Wolf Optimization is utilized to solve it. Finally, a numerical example is given to verify the rationality and target incentive of the proposed model.**

Keywords*—*carbon credit, carbon valley characterization, valley filling, incentive decision-making

I. Introduction

The carbon market, as a crucial policy to combat climate change, can contribute to achieving peak carbon and carbon-neutral strategic goals [1-2]. The carbon trade method has effectively addressed local air pollution [3]. Recent research has focused on firm-level carbon trade [4-6]. Bayer and Aklin [4] confirmed that a carbon market can be effective if it is a credible institution, and firms might cut emissions even though market prices are low. Yu et al. [5] pointed out that the implementation of the market-based climate policies improves the firm's financial performance. However, so far, studies have yet to be conducted on the carbon trade on the residential side. Wang et al. [6] estimated marginal abatement cost curves using a database of more than two million firms covering over 500 four-digit industries and suggested that the next sector be included in China's emissions trading scheme.

The residential carbon-inclusive method can be significantly complementary to the carbon emission reduction. Zhang and Hanaoka [7] researched the impacts on energy consumption and emissions that emerged following EV adoption in China at the provincial level. Helveston and Davidson [8] estimated the global construction of distributed PV and its contribution to achieving carbon neutrality. Due to the characteristics of dispersion of residents, residents can turn carbon credits into cash through aggregators, consequently raising the awareness of carbon saving. Relevant studies are carried out based on the aggregation of carbon credits of residents. Wang et al. [9] introduced air conditioner aggregators for air conditioners to participate in regulation. The aggregators can provide conditions for residents to participate in carbon markets and promote the response abilities of residents, satisfying scheduling requirements [10-11].

Considering the demand response of residents has the double-edged characteristic of considerable variation and uncertainty [12-13]. Its potential to reduce total carbon emissions cannot be ignored. Zhang et al. [14] optimized the dynamic energy price formulated with both supplier and demander participation by analyzing the characteristics of multi-entities joint pricing. Li et al. [15] coordinated the uncertainty of renewable generations with demand response strategies, thus obtaining an optimal scheduling plan and the real-time prices. However, few studies have been focused on the newly proposed "peak load shaving" policy. The duration of coal power generation can be reduced after the policy is implemented, promoting the growth of sustainable energy sources and keeping the grid stable [16].

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To solve such issues, an incentive decision-making method to promote valley filling is proposed for residential carbon credits. Firstly, a residential carbon credits-oriented incentive model is introduced for "peak load shaving" behavior. Then, residents are classified according to the carbon valley electricity consumption ratio to achieve targeted incentives. Lastly, the performance of the proposed method is verified by numerical examples.

II. Resident Carbon Credit-Oriented Incentive Model for Promoting Carbon Valley Response

The calculation of residential carbon credits involves such elements as carbon quotas, dynamic carbon emission factor, and electricity consumption of residents at different periods. According to the existing carbon market trading framework, the monthly carbon credits of residents as shown in (1):

$$C_i = C_i^{\text{given}} - \sum_{d\in D}\sum_{t\in T}\lambda_t p_{d,t,i} \tag{1}$$

where C_i are the monthly carbon credits of resident i, which can be used to participate in carbon trading, carbon finance, carbon commercial markets, etc. C_i^{given} are the monthly initial carbon quotas for the resident, which is related to the population of the resident; λ_t is the dynamic carbon emission factor of power grid, $p_{d,t,i}$ is the electricity consumption of resident i at time t in day d. The time step is 1h.

Considering the population of the resident in China, residents are categorized into three categories, so that m=1,2,3 represent the population of the resident are four and below four, five and above, seven and above respectively. The initial number of carbon quotas for the residents of the m category are:

$$C_m^{\text{given}} = \begin{cases} C_1^{\text{given}} \\ C_2^{\text{given}} \\ C_3^{\text{given}} \end{cases} \tag{2}$$

The monthly initial carbon quotas should be met $C_1^{\text{given}} < C_2^{\text{given}} < C_3^{\text{given}}$.

Under the framework of the carbon market, in order to promote the residents to shift their electricity consumption to the carbon emission valley period, a carbon credit accounting method for residents oriented to the carbon valley response is further designed.

Residential carbon credits consist of three categories: carbon quotas, basic carbon emission, and incentive carbon credits. Basic carbon emission refers to calculating residents' actual carbon emission according to the dynamic carbon emission factor and power consumption during the period. The incentive carbon credits are mainly used to encourage residents to transfer the load to the carbon valley period, which is related to the power consumption during the carbon emission valley period and belongs to carbon emission reduction.

The incentive carbon credits are related to the carbon emission valley period. In this paper, according to the dynamic carbon emission factor of the power grid, T^{valley} is selected as the carbon emission valley period, as is shown in Fig. 1.

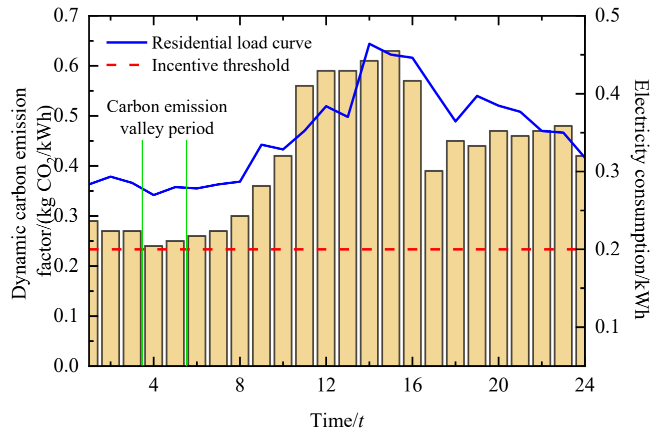

Fig. 1. Schematic diagram for carbon emission valley period

The monthly carbon credits of resident i in group m is shown in (3).

$$C_{m,i} = C_{m,i}^{\text{given}} - \sum_{d\in D}\sum_{t\in T}\lambda_t p_{d,t,m,i} + C_{m,i}^{\text{inc}} \tag{3}$$

where $C_{m,i}^{\text{given}}$ are the carbon quotas of resident i in group m. $C_{m,i}^{\text{inc}}$ are the incentive carbon credits of resident i in group m during carbon emission valley period.

III. Resident Carbon Credits Decision-Making Model

A. *Residential Clustering Method Considering the Carbon Valley Electricity Consumption Ratio*

Based on the residential daily load curve, the carbon valley electricity consumption ratio is used to characterize the residential carbon valley electricity consumption characteristics. K-means clustering method is used to classify residents according to the ratio.

The carbon valley electricity consumption ratio w_i of resident i is shown in (4).

$$w_i = \frac{\sum_{d\in D}\sum_{t\in T^{\text{valley}}} p_{d,t,i}}{\sum_{d\in D}\sum_{t\in T} p_{d,t,i}} \tag{4}$$

where T^{valley} is the valley period of carbon emission divided by the power grid side.

Input the carbon valley electricity consumption ratio of I residents, set the number of clusters J and corresponding cluster centers $\{\mu_1, \mu_2, \cdots \mu_J\}$. From the first cluster to the final, the cluster center decline. By calculating the distance between the carbon valley electricity consumption ratio of every single resident and the cluster center, it can be divided into the nearest cluster. The distance calculation formula is as follows:

$$\begin{cases} dis(w_i, \mu_j) = \left| w_i - \mu_j \right| \\ \mu_j = \dfrac{\sum_{i \in S_j} w_i}{S_j} \end{cases} \tag{5}$$

where μ_j is the center value of cluster j, which is the average percentage of the carbon valley electricity consumption ratio of all residents in the cluster; S_j is the number of residents of cluster j.

Finally, a cluster set of residents based on the power consumption characteristics during carbon valley period is obtained. The specific process is shown in Fig. 2.

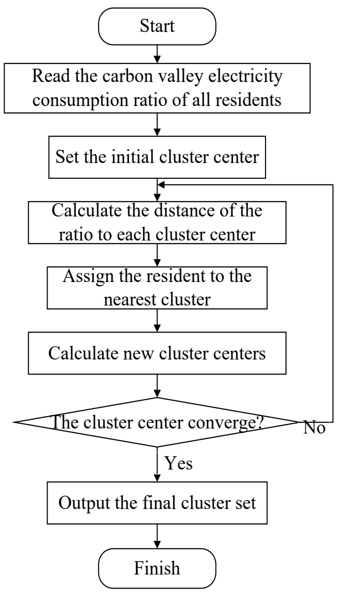

Fig. 2. Solution process based on K-means cluster

After classifying residents into J categories, the incentive carbon credits for carbon valley period are introduced for residents.

p_m^{inc} is the incentive threshold for electricity consumption of group m residents (shown in Fig. 1). Therefore, the incentive carbon credits for resident i in group m cluster j is shown in (6).

$$C_{m,j,i}^{\mathrm{inc}} = \sum_{d \in D} \sum_{t \in T^{\mathrm{valley}}} \alpha_j \cdot (p_{d,t,m,j,i} - p_m^{\mathrm{inc}}) \tag{6}$$

where α_j are the incentive coefficients for residents in cluster j, which satisfies $\alpha_1 > \alpha_2 > \cdots > \alpha_J$.

The final form of monthly carbon credits for resident i in group m cluster l is shown in (7).

$$C_{m,l,i} = C_{m,i}^{\mathrm{given}} - \sum_{d \in D} \sum_{t \in T} \lambda_t p_{d,t,m,l,i} + \sum_{d \in D} \sum_{t \in T^{\mathrm{valley}}} \alpha_j (p_{d,t,m,l,i} - p_m^{\mathrm{inc}}) \tag{7}$$

B. Model Construction

In order to improve the enthusiasm of residents to standardize the behavior of electricity consumption, the residents with a higher carbon valley electricity consumption ratio should get more incentive credits, that is:

$$F = \max \sum_{m \in M} \sum_{i \in I} C_{m,j,i}^{\mathrm{inc}} \tag{8}$$

The constraints include the following three aspects.

1) At the initial stage of application, residential carbon credits are dominated by the governments, and the balance between government costs and residential credit benefits should be considered when the incentive coefficients are optimized. In order to enhance residents' interest in participating in the carbon market and consider that the initial carbon quotas are allocated free of charge, the average monthly carbon credits of residents should below a certain threshold.

$$\sum_{i \in I} C_i / I \le C^{\max} \tag{9}$$

where $C^{\max}$ is the maximum carbon credits allowed.

2) Restriction on the proportion of below-zero credit residents. In order to avoid the decrease in residents' enthusiasm due to too many residents' below-zero credit, the proportion of residents with zero credit should not exceed a certain threshold.

$$f(C_i \le 0) \le \eta \tag{10}$$

where $f(C_i \le 0)$ are the proportion of below-zero credit residents, η are the minimum proportion of below-zero credit residents.

3) In order to achieve targeted incentive, the difference between the mean carbon credits of cluster $j-1$ and that of cluster j residents should be higher than a certain threshold, as shown in (9).

$$\overline{C_{m,j-1,i}} - \overline{C_{m,j,i}} > C^{\mathrm{thr}} \tag{11}$$

where $\overline{C_{m,j,i}}$ are the mean carbon credits of cluster j, C^{thr} is the certain threshold.

C. Model Solving

Grey Wolf Optimizer (GWO) inspired by grey wolves. The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature [17]. In order to make the algorithm easier to obtain the optimal solution, an optimized GWO is employed. Three types of grey wolves are used for simulating the leadership hierarchy, to realize three main steps of hunting, searching for prey, encircling prey, and attacking prey. The specific process is shown in Table I.

TABLE I. THE SPECIFIC PROCESS OF THE OPTIMIZED GWO

Initialize constraints and coefficients: grey Wolf population, parameter $\vec{E_x}$, a, $\vec{A}$, and the number of iterations K (12)-(14)
Optimization begins
1: Calculate the optimization function value of the wolves (8), and pick out three wolves closest to the prey $\vec{\beta}$, $\vec{\chi}$ and $\vec{\delta}$
2: **For** k=1 to K
3: Update the position of grey wolves (15)-(17)
4: Update $\vec{E_x}$, a and $\vec{A}$
5: Calculate the optimization function value of the wolves (8), and update three wolves closest to the prey $\vec{\beta}$, $\vec{\chi}$ and $\vec{\delta}$
6: Calculate the position of $\vec{\beta}$, $\vec{\chi}$ and $\vec{\delta}$
7: **End for**
8: Get the optimal elements of the grey wolf $\vec{\beta}$
Optimization ends

$$\vec{\mu}(k) = (\alpha_1, \alpha_2, \cdots \alpha_J) \tag{12}$$

where $\vec{\mu}(k)$ is a collection of incentive coefficients of all clusters of residents of single grey wolf $\vec{\mu}$.

$$\vec{E_x} = 2\vec{r_x} \tag{13}$$

where $\vec{r_x}$ is a random vector in [0,1]. x=1,2,3.

$$\vec{A_y} = a \cdot \vec{r_y} \tag{14}$$

where $\vec{r_y}$ is a random vector in [0,1]. y=4,5,6. The value of $\vec{A_y}$ is between [-a,a]. $a = 2 - 2 \cdot k / K$, which converges from 2 to 0 with the number of iteration k.

$$\begin{cases} D_\beta = |\vec{E_1} \cdot \vec{\beta} - \vec{\mu}(k)| \\ D_\chi = |\vec{E_2} \cdot \vec{\chi} - \vec{\mu}(k)| \\ D_\delta = |\vec{E_2} \cdot \vec{\delta} - \vec{\mu}(k)| \end{cases} \tag{15}$$

$$\begin{cases} \vec{\mu_1} = \vec{\beta} - D_\beta \cdot \vec{A_1} \\ \vec{\mu_2} = \vec{\beta} - D_\chi \cdot \vec{A_2} \\ \vec{\mu_3} = \vec{\beta} - D_\delta \cdot \vec{A_3} \end{cases} \tag{16}$$

$$\vec{\mu}(k+1) = \frac{\vec{\mu_1} + \vec{\mu_2} + \vec{\mu_3}}{3} \tag{17}$$

where D_β, D_χ and D_δ are the distances between grey wolf $\vec{\mu}$ and $\vec{\beta}$, $\vec{\chi}$, $\vec{\delta}$.

IV. SIMULATION RESULTS AND ANALYSIS

A. Inputs and Assumptions

The simulation analysis is carried out with 2000 residents in Changzhou in August 2020. Residential electricity consumption is measured per hour. The population of the resident cannot be confirmed due to data limitations. The example assumes that the population are the same. Adopt carbon emission factor 0.42kg CO_2/kWh, uniform carbon quotas of 88.2kg are granted for each resident, the dynamic carbon emission factor is shown in Fig. 3. Set the carbon valley period as 4-5 a.m., the maximum carbon credits $C^{\max}$ as 80, the minimum proportion of the minimum proportion of below-zero credit residents η as 20%, the threshold C^{thr} as 20kg CO_2/kWh, and the number of iterations as 50.

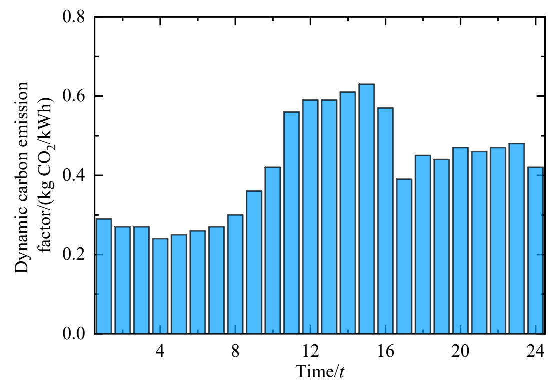

Fig. 3. Dynamic carbon emission factor

B. Clustering Results

The k-means clustering method is used to cluster the carbon valley characteristics of residents, and the number of clusters is 3. The average electricity consumption curves of various clusters of residents and the average electricity consumption curves of 2000 residents are shown in Fig. 4.

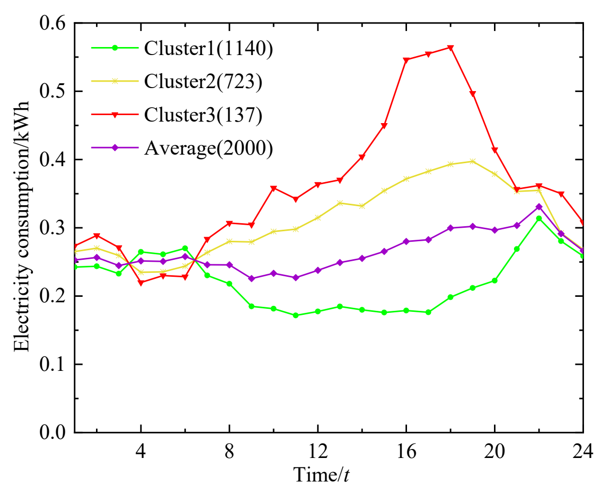

Fig. 4. The average electricity consumption curves

It is observed that from cluster 1 to cluster 3, the carbon valley electricity consumption ratio gradually increases, and the total electricity consumption and peak-valley difference increased in turn. According to the residential electricity consumption curve, the incentive threshold of cluster 1 is set as 0.1kWh per hour, that of cluster 2 is set as 0.12kWh per hour, and that of cluster 3 is set as 0.16kWh per hour.

C. Results of Carbon Credit Optimization

The optimized GWO is used to solve the incentive coefficients for the residents in each cluster. After optimization, α_1 , α_2 α_3 are respectively 2.8kg CO_2/kWh, 2.7kg CO_2/kWh, and 2.4kg CO_2/kWh. The distribution of the monthly carbon credits of the residents are calculated as shown in Fig. 5.

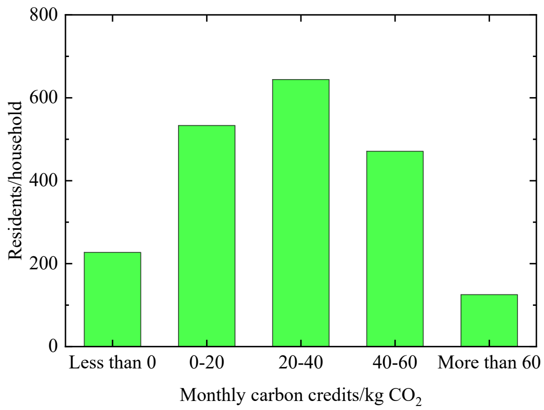

Fig. 5. Monthly average carbon credits distribution and number of residents

The monthly average carbon credits of residents are 23.73 kg CO_2, with the most of residents falling into the range between 0-20 kg CO_2 and 20-20 kg CO_2, 533 and 644 respectively. There are 227 residents with monthly carbon credits below zero and 125 residents with monthly average carbon credits more than 60 kg CO_2.

To further analyze the effect of clustering, the distribution of residents' carbon credits of 3 clusters is shown in Fig. 6.

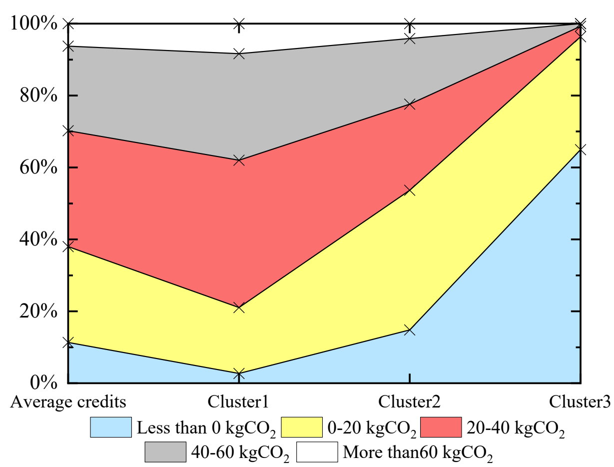

Fig. 6. The distribution of residents' carbon credits of 3 clusters

From the figure, it is evident that most residents in cluster 1 are distributed with more carbon credits. With the increase of clustering level, the residents gather in intervals with fewer carbon credits because of more unreasonable use of electricity.

The users with below-zero carbon credits are further analyzed in Fig. 7.

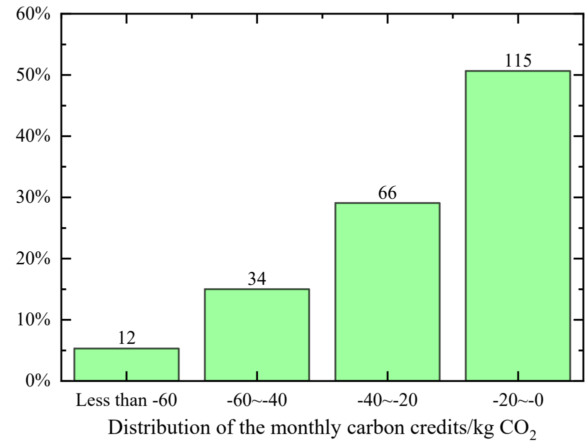

Fig. 7. Distribution and share of below-zero carbon credits

There are 227 residents with less than zero carbon credit, including 31 residents in cluster 1 with below-zero carbon credits, 107 residents in cluster 2 with below-zero carbon credits, and 89 residents in cluster 3 with below-zero carbon credits. The number of users with carbon credits between -20 kg and 0 kg CO_2 are the largest, accounting for 46.25%, and most of the residents with below-zero carbon credits in all clusters are in this interval. This means there is some potential for further incentive. The ratio of different intervals is gradually decreasing subsequently. At the initial stage of the application, in order to improve the satisfaction of residents, this category of residents can be treated with zero carbon credit finally.

V. Conclusion

In this paper, firstly, the monthly carbon quotas, basic carbon emission and incentive carbon credits are fully considered for resident carbon credit-oriented incentive model. Secondly, by using the clustering method, different clusters of residents are set up to set different incentive threshold and incentive coefficients. Moreover, through case study, it is found that the monthly carbon credits of residents are mostly in the interval of 0-40 kg CO_2. It can not only reduce government investment, but also increase the residents' satisfaction. Besides, more carbon credits can be obtained for residents with higher carbon valley electricity consumption ratio. Therefore, effective targeted incentives are met. Lastly, it is concluded that there is some potential for further incentive.

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