A Consumer-Oriented Incentive Mechanism for EVs Charging in Multi-Microgrids Based on Price Information Sharing

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***Abstract*—The distribution of electric vehicle (EV) charging area is affected by customer behavior, which has strong non-uniform characteristics. This will cause some areas to be in a busy state, unable to supply EV charging in time, while the areas with low passenger flow will be in an idle state, which leads to the lower charging efficiency and revenue. In order to solve such problem, this paper proposes a customer-oriented charging incentive strategy for EVs based on information sharing among multiple microgrid regions. Firstly, a customer-oriented charging incentive strategy implementation framework is proposed to realize multi regional charging coordination by sharing regional charging information with customers. Then, considering the impact of charging price on charging demand and customer transfer, the customer charging demand model is constructed. Based on this, the optimization model is constructed to maximize the interests of system operators in multi microgrid area, and solved by particle swarm optimization (PSO) algorithm. Simulation results show that the proposed mechanism can effectively alleviate the charging dissatisfaction caused by the above phenomenon, and improve the overall operating revenue of multi region.**

Keywords—EVs, customer-oriented, multi-microgrid, incentive strategy, particle swarm optimization.

I. INTRODUCTION

Due to the environmental friendly and low emission characteristics of electric vehicle (EVs), they have become the trend of future travel. Moreover, EVs have the characteristics of energy transfer in time and space, and have been paid great attention in the aspects of stabilizing the fluctuation of renewable energy, cutting peak and filling valley, and auxiliary services. Therefore, EVs have been widely used in recent years. However, with the increase of EVs, the charging demand of customers also go upward, and more research on the customer charging package and strategy has been conducted to seize customer resources, which can be mainly divided in two categories. One is to attract customers with low charging cost and build the lowest charging cost model. In this research, customers choose the appropriate charging time with Time-of-Use (TOU) price [1], real-time electricity price [2] and so on, so as to meet their own needs and spend as little electricity as possible. Later, this method gradually evolved into a charging menu based on real-time or TOU price, and its purpose is to optimize the charging cost [3]-[4]. There are also customers participating in the ancillary services market [5], where the flexible charging and discharging ability of EVs is used to balance the real-time power supply and demand, so as to obtain market revenue while meeting their own power demand. The other is, to build the optimal operation benefit model of the system with the participation of EVs from the perspective of aggregators or system operators, with the goal of minimizing the overall operating cost or maximizing the revenue of the system [6]. This research usually has two levels of optimization [7]-[9]. In the upper layer, the system operator or load aggregator evaluates the overall dispatching plan, and then issues it to the EV users. In the optimization of the lower level, price-based or incentive-based schemes are used to make profits in the charging process, so as to achieve the minimum cost goal of the upper level. It should be pointed out that, on one hand, when the above two types of research involve the customer level, the unified and shared market information such as time-sharing price and real-time price is used to guide the charging of users. However, this kind of guidance will only change the user's behavior in time, and the unified and shared price information has no effect on the change of user's spatial behavior. On the other hand, user behavior is guided, based on electricity price or incentive improved hierarchical charging package or variable electricity price. However, this kind of guidance can only prompt users to change their time behavior in the local pile and station with this kind of package. It is because this kind of package is often bound in the hardware facilities of the pile or station, and the information of the pile /station package in different regions is not directly shared, which cannot guide users to change their spatial behavior.

Therefore, even though many strategies are applied in the scenarios of EV stations or piles at present, the problem that the charging price and incentive messages are not shared for all consumers still exists. These local strategies cannot reach a better optimal point when it comes to multi-microgrids, because in single grid, the local strategies only focus on solving charging sequence of large-scale plug-in EVs but not aim at charging collaboration of multiple grids. The most typical example is when one station is busy and others are free. In this situation, it might exist an optimization to guide consumers to charge elsewhere via incentive mechanisms. Meanwhile, this optimization might contribute to the total profit due to the increase of charging amount.

Based on the above analysis, this paper innovatively proposes a charging incentive mechanism directly facing customers. The purpose is to guide customers to change their spatial behavior among different regions, and alleviate the phenomenon that some charging stations are busy while others are idle and have no revenue. The main contributions can be summarized as follows:

1) A novel consumer-oriented charging incentive mechanism in distribution network containing multiple interconnected microgrids is proposed. Compared to other station-oriented research, this is one of the rare research featured by consumer-orientation and aims at charging collaboration of multiple grids.

2) Considering the impact of price, distance and capacity on consumers' decision-making and transportation, a model of electricity demand is established, in which heterogeneous parameters from different consumers are handled by stochastic scenario probabilities.

3) An optimal profit model for system operation is presented, wherein the EVs transportation caused by optimized prices in each iteration is involved. Moreover, the model is compared in 4 cases to discuss its applicability.

The remaining part of the article is organized as follows. Section II presents the description of the proposed charging pricing strategy. Section III describes the system model. Section IV presents the problem formulation. Section V presents case studies together with simulation results. Finally, conclusions are drawn in Section V.

II. Description Of The Proposed Charging Pricing Strategy

The overall structure of the proposed charging strategy is shown as Fig.1.

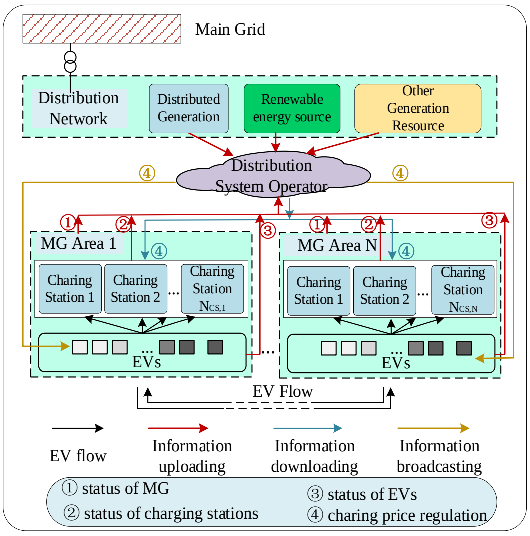

Fig.1 framework of the proposed strategy.

With distribution system operator (DSO) as the main body of information aggregation, the charging behavior of EV groups in multiple microgrid regions is guided, mainly including the following parts. 1) Collect the output of renewable energy, distributed generation and conventional resources in the covered distribution network area, and predict the overall power vacancy. 2) Collect the power supply and demand status of microgrid and the free and idle state of charging station, determine the optimal price based on the supply and demand of the whole network and the charging equilibrium degree of each region, and broadcast it to the electric vehicle users. 3) After receiving the broadcast charging price, the customer selects the charging area and uploads the charging demand to DSO. As the regional transfer of EVs takes time, the electricity price is different from that of the actual charging. The following mechanism is added in this paper: After the costumers makes a choice, he goes to the charging area within the agreed time, and will be given a discount according to the selected charging price.

III. System Model

In the above mentioned structure, when the customers receive the broadcast information from DSO, the charging behavior will be adjusted. The choice will be influenced by the following aspects. 1) Charging price. Generally, the higher the charging price is, the less the charging capacity is. 2) Charging location. Customers usually do not consider the charging point which is rather far. If it's on the way, it's always a priority. 3) Charging waiting time. For a busy charging station, the waiting time cost of costumers is high. In this case, costumers will consider changing the charging location.

A. *Impact of price on consumers*

Affected by price elasticity, costumers will actively reduce the amount of charging when the charging price is high. In this paper, the price elasticity model of [10] is used, and the charging demand of users can be described as follows:

$$v_{d,j,t}^{\text{int}} = E_{\max,j}(1-SOC_{avg,j})\left(\frac{PR_{d,t}^{\text{int}}}{PR_{d,t}^{buy}}\right)^{-\gamma_j} \tag{1}$$

where $v_{d,j,t}^{\text{int}}$ is the original charging demand of customer *j* at the time *t*. Suppose customer *j* is in area *d*. $E_{\max,j}$ is the maximum charging capacity of customer *j*. $SOC_{avg,j}$ is the average state of charge of customer j, which can be obtained by the historical data of acquisition for each charge. $PR_{d,t}^{\text{int}}$ is the original charging price of area *d* at the time *t*. γ_j is the price elasticity of the customer *j* which is non-negative. When γ_j is positive, it represents the charging demand of customer *j* has negative relation with price, which means as the price increases, the demand decreases. When γ_j is zero, it means the customer does not have elasticity. When the charging price of area *d* $\Delta PR_{d,t}$ changes, the demand of customer *j* turns to $v_{d,j,t}$, which satisfies the following equation.

$$v_{d,j,t} = E_{\max,j}(1-SOC_{avg,j})\left(\frac{PR_{d,t}^{\text{int}}+\Delta PR_{d,t}}{PR_{d,t}^{buy}}\right)^{-\gamma_j} \tag{2}$$

B. *Modeling of EVs transposition*

The transfer of EVs is influenced by the price, distance and the power supply capacity of the destination. Customers have different sensitivity on these factors.

The sensitivity of user *j* to price is defined by a quadratic function, which can be described as:

$$f_j^{PR}(PR) = \left(PR - PR_{ep,j}\right)^2 \tag{3}$$

where $f_j^{PR}(\cdot)$ is the function of the j^{th} user's willingness to change behavior influenced by the price, which means the lower the charging price is than the customers' expected price, the more motivated the customers are to choose low-cost charging. $PR_{ep,j}$ is the expected charging price of customers. Generally, in order to motivate customers to change their behavior, the value of PR is lower than the expected value.

Except the influence of price, the sensitivity of customer *j* on the distance can be defined as:

$$f_j^{rt}(\Delta R) = \Delta R^{-2\theta_j} \tag{4}$$

where $f_j^{rt}(\cdot)$ is the function of the j^{th} customer's willingness to change behavior influenced by distance. θ_j is the distance influence factor of customer *j*. When θ_j is large, it means the further the distance is, the more unwilling the customers are to change the charging location.

Then, the power supply capacity can be modelled with $f_j^{cc}(D^{atl})$:

$$f_j^{cc}(D^{atl}) = \lambda_j D^{atl} \tag{5}$$

where $f_j^{cc}(\cdot)$ is the function of the j^{th} customer's willingness to change behavior influenced by power supply capacity of destination. λ_j is the power supply influence factor, which is positive. It means that the larger the capacity is, the higher the chance of being selected.

Then, the behavior of customer *j* transferring from area d_w to area d_v is the result of the comprehensive influence of price, distance and power supply capacity of destination. The comprehensive influence can be defined as:

$$\lambda_{d_w,d_v,j,t} = f_j^{PR}\left(PR_{d_v,t}\right) f_j^{rt}\left(\Delta R_{d_w,d_v}\right) f_j^{cc}\left(D_{d_v}^{atl}\right) \tag{6}$$

Furthermore, the transition probability of customers selecting charging area according to the degree of comprehensive influence is described as:

$$\rho_{d_w,d_v,j,t} = \lambda_{d_w,d_v,j,t} / \left(\sum_{d_v=1}^{N_D} \lambda_{d_w,d_v,j,t}\right) \tag{7}$$

where N_D is the sum of the areas. $\rho_{d_w,d_v,j,t}$ is the transfer probability of customer *j* from area d_w to area d_v.

C. Modeling of electricity demand

Due to the different sensitivity of customers on the price, distance and the power supply capacity, the customers with the same characteristics are classified in one type and there is a total of N_J types of customers.

Considering the difference of different types, the number of EVs after transfer in area d can be described as:

$$N_{d,t} = \sum_{d_w=1}^{N_D} \sum_{j=1}^{N_J} N_{d_w,t} \vartheta_j \rho_{d_w,d,j,t} \tag{8}$$

where ϑ_j is the proportion of the j^{th} type of customers. $N_{d_w,t}$ and $N_{d,t}$ are respectively the number of EVs of area d_w and area d_v at the moment *t*. Then, the total charging demand of area *d* is:

$$D_{d,t} = N_{d,t} \sum_{j=1}^{N_J} \vartheta_j v_{d,j,t} \tag{9}$$

D. Scenarios discussion and simplification

System model (1)-(9) involves many parameters of users, such as γ_j, $E_{\max,j}$, $SOC_{avg,j}$, $PR_{ep,j}$, θ_j, λ_j, etc. For these parameters, almost every user has different values, which results in a large number of heterogeneous parameters, which is difficult to deal with in the actual model. The conventional method is to simulate the above user data through Monte Carlo, and divide the parameters of similar features by clustering algorithm, and finally form several typical scenarios [11]. On this basis, the scene probability distribution ϑ_j can be obtained from the clustering results.

In addition, we set forth the following assumptions:

Assumption1: for user *j*, the charging demand determined at time *t* is not affected by the subsequent price. This is because there is an agreement in the framework: after the user makes a choice, he will go to the charging area within the agreed time, and still give the user a discount according to the selected charging price.

Assumption2: the charging price strategy of a microgrid is the same. This is because when a microgrid has multiple charging prices, it can be treated as multiple regions. In the framework of the previous part, when there are multiple charging stations in the microgrid, and the charging price is the same, it can be equivalent to a virtual charging station. In this regard, we aim to optimize the charging price of each region.

IV. Problem Formulation

A. Objective function

The purpose of the DSO is transferring the EVs that may be queued for a long time from the busy charging area to the idle charging area, so as to sell more electricity to users to increase the overall revenue. The income of DSO can be composed of the following parts:

$$\max OF = F_{income} - C_{buy} - C_{prd} \tag{10}$$

In the formula, F_{income} is the total revenue of DSO, C_{buy} is the cost of purchasing electricity from the external grid, C_{prd} is the operating cost of DSO, including distributed generation costs C_{DGs} and renewable energy operating costs C_{RESs}. The formula for each sub-item is as follows:

$$F_{income} = \sum_{t=1}^{N_T} \sum_{d=1}^{N_D} \left(\phi_{d,t} PR_{d,t}^{sell} P_{d,t}^{sell} \Delta t + D_{d,t} PR_{d,t}\right) \tag{11}$$

$$D_{d,t}^{atl} = \min\{D_{d,t}, D_{d,t}^{\max}\} \tag{12}$$

In the formula, $D_{d,t}^{atl}$ is the actual total consumption of area d in time period t, $D_{d,t}^{\max}$ is the maximum charging capacity of area d in time period t, $\phi_{d,t}$ is the binary variable of supply and demand in area d at time *t*, 1 represents oversupply, and 0 represents the opposite. $PR_{d,t}^{sell}$ represents the electricity purchase price of area d at time t, and $P_{d,t}^{sell}\Delta t$ represents the capacity of electricity sold at time *t*. Correspondingly, the cost of DSO buying electricity from the main network is as follows:

$$C_{buy} = \sum_{t=1}^{N_T} \sum_{d=1}^{N_D} (1-\phi_{d,t}) PR_{d,t}^{buy} P_{d,t}^{buy} \Delta t \tag{13}$$

where $PR_{d,t}^{buy}\Delta t$ indicates the capacity of electricity purchased of area d at time t. The operating costs in the distribution network area include distributed power costs and renewable energy costs, as described below:

$$C_{prd} = C_{DGs} + C_{RESs} \tag{14}$$

$$C_{DGs} = \sum_{t=1}^{N_T}\left(\sum_{i=1}^{N_{DG}} C_i(P_{i,t}) + SU_{i,t} + SD_{i,t}\right)\Delta t \tag{15}$$

$$C_{RESs} = \sum_{t=1}^{N_T}\left(\sum_{w=1}^{N_W} PR_{w,t}P_{w,t} + \sum_{v=1}^{N_V} PR_{v,t}P_{v,t}\right)\Delta t \tag{16}$$

where C_{DGs} and C_{RESs} are the operating costs of distributed power and renewable energy, respectively. $C_i(\cdot)$ is the cost function of the i^{th} unit, usually is a quadratic function. $P_{i,t}$ is the output of the i^{th} unit at time t, $SU_{i,t}$ and $SD_{i,t}$ are the start and stop costs of the i^{th} unit at time t. $PR_{w,t}$ and $PR_{v,t}$ are the operating costs of wind turbines and photovoltaics at time t. $P_{w,t}$ and $P_{v,t}$ are the output of wind turbines and photovoltaics at time t. N_W, N_V and N_{DG} are the number of wind turbines, photovoltaics, and distributed power sources respectively.

B. Constraints of the problem

The objective function mentioned in this paper needs to satisfy the operating state constraints of the distribution network, user charging constraints, charging price and risk constraints, as follows:

1) Distribution network operating status constraints: including power balance constraints (17), microgrid tie line capacity constraints (18), each microgrid output unit capacity constraints (19)-(21), and the charging capacity provided per unit time constraint (22), described as follows:

$$\sum_{d=1}^{N_D} P_{d,t}^{buy} + \sum_{w=1}^{N_W} P_{w,t} + \sum_{v=1}^{N_V} P_{v,t} + \sum_{i=1}^{N_{DG}} P_{i,t} = \sum_{d=1}^{N_D}\left(P_{d,t}^{sell} + \frac{D_{d,t}^{atl}}{\Delta t}\right), \forall t \tag{17}$$

$$\left|\begin{matrix}(1-\phi_{d,t})P_{d,t}^{buy} - \dfrac{D_{d,t}}{\Delta t} + \displaystyle\sum_{w=1}^{N_{W,d}} P_{w,d,t} \\ + \displaystyle\sum_{i=1}^{N_{DG,d}} P_{i,d,t} - \phi_{d,t}P_{d,t}^{sell} + \displaystyle\sum_{v=1}^{N_{V,d}} P_{v,d,t}\end{matrix}\right| \le \sum_{\substack{d_w=1,\\ d_w\neq d}}^{N_D} P_{d_w,d,t}^{line} \tag{18}$$

$$0 \le P_{d,t}^{buy} \le P_{d,t}^{\max,buy} \tag{19}$$

$$0 \le P_{d,t}^{sell} \le P_{d,t}^{\max,sell} \tag{20}$$

$$0 \le P_{w/v,t} \le P_{w/v}^{\max} \tag{21}$$

$$P_i^{\min} \le P_{i,t} \le P_i^{\max} \tag{22}$$

2) Charging price constraints in each region: The charging price should be higher than the selling price of electricity to the grid, meeting the constraint (23). Moreover, in order to prevent the charging price from fluctuating too much, the variation of the charging price should be limited to fluctuations within a certain percentage of the original price, satisfying (24).

$$PR_{d,t}^{sell} \le PR_{d,t}^{\text{int}} + \Delta PR_{d,t} \tag{23}$$

$$\frac{\Delta PR_{d,t}}{PR_{d,t}^{\text{int}}} \le \varepsilon_1 \tag{24}$$

C. Problem Solution Methodology

In order to solve the described problem, this paper uses the Monte Carlo method to simulate the uncertainty distribution of users. Monte Carlo generates random parameters of each customer forming a total of 2.7×10^5 scenarios. In order to reduce the number of scenarios and facilitate the calculation, the k-means algorithm is used to cluster users with similar characteristics, and finally 20 scenarios are formed, and applied to the proposed random optimization model. Since the proposed model contains many variables, especially when $D_{d,t}$ is a high-order variable and there are multiple nonlinear constraints, conventional nonlinear programming algorithms are difficult to solve and time-consuming. In this paper, particle swarm optimization (PSO) algorithm is selected to solve the model, because PSO is not complicated and has a faster convergence effect, which can better adapt to the real-time characteristics required by the price optimization strategy of this paper. The particles are the charging price and DG output of each area in each time.

V. Simulation And Numerical Results

A. Case study and simulation parameters

The strategy proposed in this paper is applied to a multi-microgrid interconnected distribution system, in which the parameters of distributed generation and renewable generation in microgrid adopt unified specifications, as shown in Table I.

TABLE I. INFORMATION OF GENERATING UNITS

Unit	**Min-Max Generation**	**Marginal Cost**	**Start-up Cost**	**Shut-down Cost**	**Amounts**
DG	25-150	0.045	0.09	0.08	15
WT	0-80	0.055	-	-	20
PV	0-75	0.040	-	-	15

Assume that this part of power generation resources only supplies power to EVs. Each customer in EVs group is equipped with edge communication module, which is used to receive DSO broadcast information and upload charging plan. The wind and solar output data in the microgrid is obtained from the power generation data of a certain area in China, which is shown in Fig.2. 300 EV users are generated by Monte Carlo method, all of which are fast charging customers. The parameters are evenly distributed according to the range in the table and 20 typical scenes are clustered by the k-means algorithm, which is shown in Fig.3. The other parameters are listed in Table II.

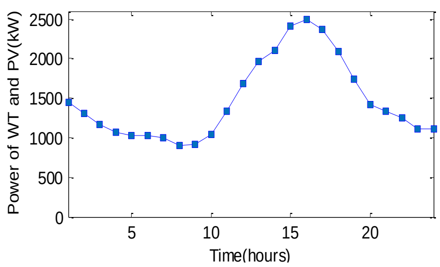

Fig. 2 total output of WT and PV generation

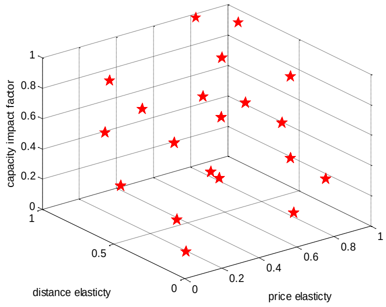

Fig. 3 cluster centers of 20 typical scenarios

TABLE II. OTHER GLOBAL PARAMETERS

Parameters	Value	Parameters	Value
PR^{sell}	4.0	γ	[0.3,3]
PR^{buy}	6.8	θ	[0.5,2]
PR^{int}	9.34	λ	[1,2]
ε_1	20%	SOC_{avg}	0.3

In this paper, four examples are set to verify the superiority of the proposed strategy under different EV initial distribution and different charging requirements. The settings of the four examples are shown in Table III.

TABLE III. CASES SETTINGS

Index	Initial EVs distribution	EV types
1	Uniform distribution	BYD E5 with 40kWh
2	Uniform distribution	BYD E6 with 80kWh
3	Non-uniform distribution	BYD E5 with 40kWh
4	Non-uniform distribution	BYD E6 with 80kWh

Finally, our simulation selects 24 hours as the cycle, and the time scale is 1 hour. The optimization results include the electricity price, distributed unit output, power purchase and capacity sale in each period. The simulation is based on MATLAB 2019b running a win 10 system with 16GB memory and AMD 4800U@4.2GHzprocessor.

B. *Case study of three MG areas*

In the three micro-grid areas, the distance can be described by the matrix $\Delta R = [5\ 15\ 25;\ 15\ \ 5\ 20;\ 25\ 20\ 5]$. The original distribution of EVs in Case 1 and Case 2 are $[100\ 100\ 100]$, and those in Case 3 and Case 4 are $[200\ 40\ 60]$. Meanwhile, the tie-line power of the three microgrids is limited to 7000kw and the power supply capacity is $D^{atl} = [5000\ 5000\ 7000]$. The optimization goal of this strategy is to maximize the benefits of system operators, while the comparison strategy adopts the single region local optimization under the condition that the price information is not shared. The optimized results of the two methods are shown in Fig.4. It can be seen from Fig.4 that the overall benefits of the proposed strategy are higher than the one without it, which means the strategy in this paper is very effective in improving the overall efficiency. Based on Fig.4, the rate of revenue increase is counted in Table IV.

It can be illustrated in Fig.4 and Table V that, in Case 1 and Case 3, the increase of the proposed strategy is relatively low. This is because that the charging capacity of BYD e5 is small and the microgrids can satisfy the charging demand of it and the situation that one area has insufficient capacity and another area has excess power is relatively less. Reversely, in Case 2 and Case 4, the charging capacity of BYD E6 is large.

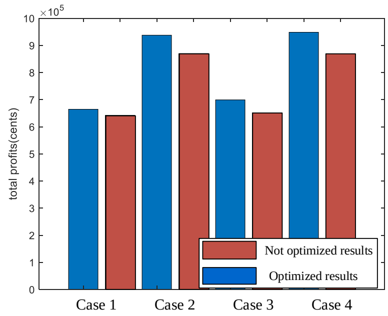

Fig.4 profits comparisons before and optimization

TABLE IV. PROFITS IMPROVEMENT RATIO AFTER OPTIMIZATION

Case	1	2	3	4
Improvement Ratio	3.46%	7.81%	4.45%	10.28%

When the EVs in the areas increase, area1 and area2 will be busy due to insufficient power supply. In this case, our strategy will guide some vehicles to the area 3 with large power supply capacity, increasing more revenue from electricity sales, so as to improve the overall revenue. Therefore, this strategy has more advantages in the scenario where some areas are busy and some areas are idle. Earnings of each period in different cases are depicted in Fig.5. When the charging demand is high, the volatility of revenue in each period is greater than when the charging demand is low. Comparing Case 1 and Case 3, when the charging demand is low, this strategy can reduce the volatility of revenue in each period, but also slightly improve the revenue. However, with the comparison of Case 2 and Case 4, when the charging demand is high, this strategy does not improve the volatility of each period, but significantly increases the income. Furthermore, combined with Fig.5 and Table V, comparing case 1 and case 3, case 2 and case 4, we can find that the overall revenue of system operators is higher when the initial distribution is uneven. It means that this strategy is more suitable for the non-uniform distribution of EVs.

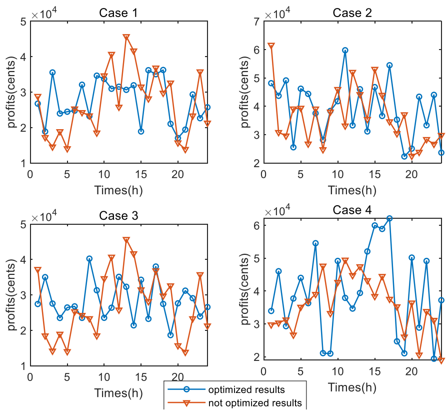

Fig. 5 Total profits of three MG areas in different cases

Fig.6 makes a comparison of the EVs transfer in each area among different cases. It can be seen that no matter how the EVS are initially distributed, the transfer of EVs tends to be consistent without using the optimization strategy in this paper. It is in line with the transfer law between regions in real life because customers will drive in a relatively regular way without knowing the price of other regions. However, In the case of using the proposed strategy, the transfer between regions is guided by the price. The driving law of users will change when they get the price information of other regions, which is not regular and is helpful to alleviate some charging areas, which have been busy for a long time.

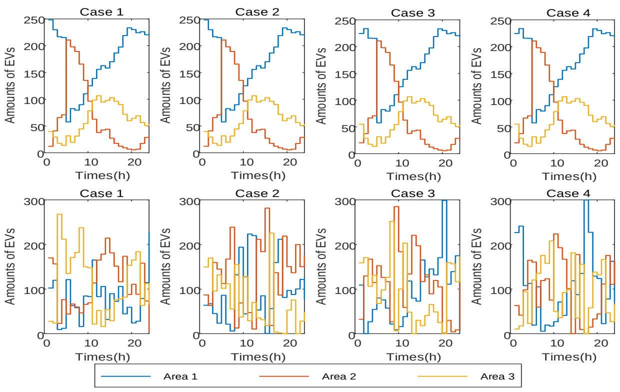

Fig.6 The distribution of EVs over a whole period

Fig. 7 shows the revenue of different regions under different scenarios, where the above is before optimization, and the below is after optimization.

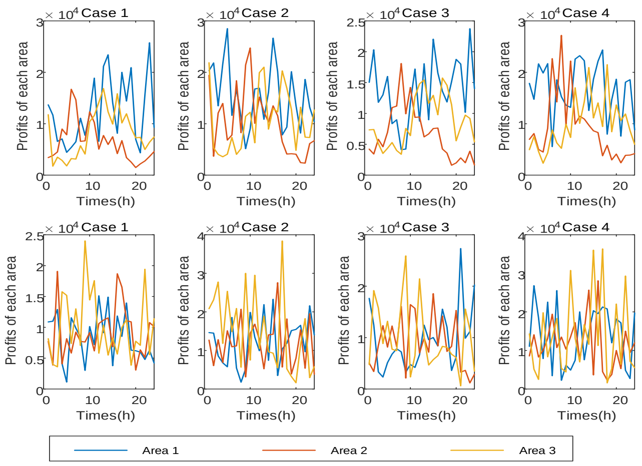

Fig.7 Profits of each MG area in different cases

It can be seen that, without the proposed strategy, the income of the three regions is relatively fixed. Area 1 gains the most, followed by area 2 and area 3. When the power supply capacity is insufficient, especially in Case 2 and Case 4, the revenue of area 1 will be limited, which cannot exceed 3×10^4cents/h. In contrast, after using the proposed strategy, the revenue of each region is relatively balanced, and the revenue of region 3 with stronger power supply capacity is higher than that of other regions. Especially in Case 2 and Case 4, the revenue of region 3 is more than 3×10^4 cents / h, which means the strategy is beneficial for EVs to transfer from the busy charging area to the area with larger power supply capacity, so as to improve the overall benefit of all areas.

VI. Conclusion

In this paper, a charging incentive mechanism for electric vehicles was proposed. By optimizing the charging price of each region and realizing information sharing, customers could be guided to change the spatial driving behavior, so as to change the distribution of EVs, promote the charging business in the edge areas, and achieve the optimal operation benefit of all microgrid regions. Simulation results showed that the proposed strategy can improve the operation efficiency in four cases, and its effect could become more visible with the increase of charging demand. In practice, it is helpful to improve the phenomenon that some areas are busy while others are idle with little revenue, and promote the balance of charging map.

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