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An Electric Vehicle Flexibility Characterization Method Based on The Behavior Data of Users

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ABSTRACT

The number and penetration of electric vehicles(EVs) are increasing. Electric vehicle charging load has the two characteristics of power load and energy storage because electric vehicles are becoming a new flexible resource to participate in the auxiliary services of power systems, which can improve the operation of power systems. As the basis of electric vehicle flexibility application, the flexibility characterization of electric vehicles has become the primary problem to be solved. Therefore, an electric vehicle flexibility characterization method based on the behavior data of users is proposed. Firstly, the original data is cleaned and reconstructed, and the behavior data set of electric vehicle users is extracted. Then, based on the electric vehicle user behavior data set, an electric vehicle user flexibility potential evaluation index system is proposed, which characterizes the electric vehicle flexibility potential from the three dimensions of capacity, charging time, and charging power. Secondly, an electric vehicle flexibility controllable region construction method based on an evaluation index is proposed to describe the flexibility of electric vehicle users with different charging habits. Finally, using real user data for verification, the results show that the proposed method can accurately describe the flexibility of different electric vehicle users. The results can provide a basis for electric vehicle aggregators (EVA) to participate in power grid auxiliary services.

Keywords: behavior data, electric vehicles, flexibility, controllable region, user behavior analysis

NONMENCLATURE

Abbreviations	
EV	Electric Vehicle
EVA	Electric Vehicles Aggregator
SOC	State of Charge
Symbols	
$\overline{Cap}_{\mathrm{in}}$	Average battery capacity for accessing the power grid.
Cap_{in}	Battery capacity of accessing the power grid.
SOC_{in}^{i}	SOC value accessing the grid of i^{th} charging record.
$Cap_{\max}$	Maximum battery capacity of the EV.
N	The total number of charging records.
$Cap_{\min}$	Minimum battery capacity of the EV.
$SOC_{\min}$	Minimum SOC value set by the user.
SOC_{tra}^{i}	The SOC consumed of i^{th} trip record.
N_{tra}	The number of trips.
Cap_{exp}	Off-grid battery capacity EV users expect.
SOC_{lea}^{i}	SOC value when left the grid of i^{th} charging record.
$\overline{T}_{\mathrm{in}}$	Average on-grid time.
t_{in}^{i}	The on-grid time of i^{th} charging record.
$\overline{P}$	Average charging power.
P^{i}	The charging power of i^{th} charging record.
$t_{\mathrm{end}}^{\mathrm{c}}$	The time when the battery is fully charged.

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$t_{\mathrm{end}}^{\mathrm{d}}$	The time when the battery is discharged to Cap_{min} and ended the discharge process.
t_{st}	The time when the battery with Cap_{min} starts charging.
$Cap_{\mathrm{lea}}^{\mathrm{c}}$	The off-grid battery capacity after charging.
t_{lea}	The off-grid time.
$Cap_{\mathrm{end}}^{\mathrm{c}}$	The battery capacity after forced charging.
$Cap_{\mathrm{end}}^{\mathrm{d}}$	The off-grid battery capacity after discharging.

1. INTRODUCTION

In recent years, more and more new energy sources have been connected to the power grid, which has brought new challenges and impacts to the power grid. The flexibility and reserve provided by traditional thermal power units have made it difficult to meet the demand for flexibility. As a special energy storage device and power load, EV is also a flexible resource that can provide load reserve for the power grid. It was proved that making full use of EV flexibility can significantly reduce electricity price fluctuations, improve energy efficiency, and reduce carbon dioxide emissions in the [1]. EV flexibility was defined as the ability of electric vehicles to adjust their power load by using charge and discharge control in the [2].

Most of the existing research is based on mathematical models. The flexible charging and discharging of EVs can be characterized by establishing a flexibility model in the [3]. A flexibility evaluation model for the EVA was proposed in the [4] by dispatching EVs to participate in demand response, which can effectively reduce the imbalance risk of the power grid. An EV flexibility evaluation model considering the coordination of power system transmission and EVA was proposed in the [5], which realized the quantification of EV flexibility service under the premise of ensuring the stable operation of the power system. When describing the flexibility potential of EVs, traffic constraints were added, and the spatial constraints of EVs were considered in the [6]. The above methods rely on the simulation by setting the scene in advance to simulate the behavior of the EV or EVA. The mathematical model is more idealized and cannot truly characterize the randomness of EV behavior.

In addition, some scholars propose a data-based flexibility analysis method. By analyzing the charging data, the EV flexibility was converted into demand-side response capability, and the EV flexibility was quantified in the [7]. Based on charging behavior data and electricity price data, the flexibility potential of EV users under different electricity prices was quantified in the [8]. The clustering algorithm was used to identify the types of EV charging behavior, and the characteristics of charging behavior under different types were analyzed in the [9]. The method combined with multi-source data such as weather, the flexibility of EVs in each period of the day was quantitatively analyzed. An EV flexibility quantification method based on the SOC curve was proposed in the [10], which realized the coordinated operation of a distributed power system with the goal of profit for all parties. However, most of the research based on EV behavior data currently focuses on numerical quantification, and the evaluation results are often weak in physical meaning and fail to visually display the EV flexibility boundary.

In summary, a single mathematical model cannot effectively describe the flexibility of EV users with different behavior habits in real situations. The existing methods based on behavioral data often quantify the results of numerical types, and the characterization of EV flexibility is vague. To solve the above problems, a method to characterize the flexibility of EVs was proposed based on user behavior data. The flexibility of EVs was characterized by constructing an EV flexibility controllable region and characterizes the flexibility of EVs as a feasible region. The region not only characterizes the flexibility of EVs but also points out the flexibility boundary of EVs, that is, the boundary where EVs adjust their electricity load. The boundary represents physical meanings such as charging capacity. The flexibility controllable region can provide a basis for EVA to make full use of EV flexibility to participate in grid services.

2. FLEXIBILITY INDEX SYSTEM OF EVS

2.1 Data preprocessing

A The original data includes the basic information of EV users, charging data, and driving data. Data preprocessing includes the processing of outliers and missing values, and the data merging and reconstruction. For the missing data, the random interpolation method is used to fill the missing data based on the data distribution. There are many outliers in the original data set. The outliers are screened based on the data distribution and are deleted from the data record. After processing the outliers and missing values in the original data, the original data is extracted and reorganized to obtain the EV user data set shown in Table 1.

Tab. 1. Data set of EV users

Data type	Data name	Note
Basic information	User id	identify users
	The purpose of the vehicle	private car, bus, and so on
	Cap_{max}	Nominal battery capacity (kWh)
Charging data	Start time	Indicates when to start
	End time	Indicates when to end
	SOC_{in}^{i}	SOC when access grid (kWh)
	SOC_{lea}^{i}	SOC when off-grid (kWh)
	P^{i}	The power of a single charge (kW)
Driving data	SOC_{tra}^{i}	SOC consumed by one trip. (kWh)

The basic information includes user ID, the purpose of the vehicle, and battery capacity; The charging data includes the start time and end time, charging power, SOC accessing power grid, and off-grid SOC for each charging behavior; the driving data includes the consumption capacity for each trip.

2.2 Flexibility index system of EVs

After cleaning and screening the data, an EV user flexibility index system is proposed. The index system not only can describe the flexibility of EV users numerically, but also be used as the basis for constructing the EV flexibility controllable region. The index system is constructed from three aspects: capacity, charging time, and charging power, as shown in Figure 1.

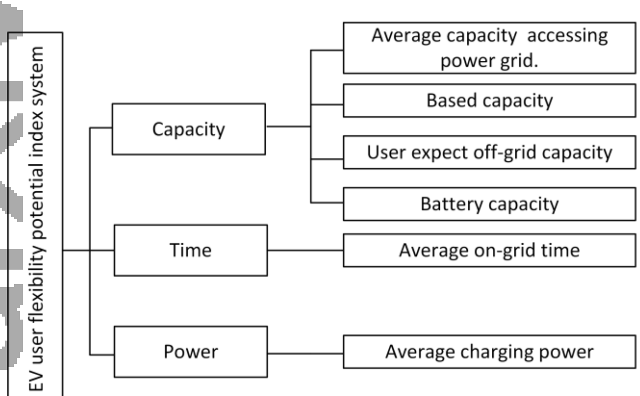

Fig. 1. *Flexibility index system of EVs*

There are a lot of uncertainties in the charging behavior of EV users. The system is an average index system. The average value in multiple charging records is used to characterize the behavior habits of EV users.

1) Average capacity accessing power grid

$$\overline{Cap_{in}} = \frac{\sum_{i=1}^{N} SOC_{in}^{i}}{N} Cap_{max} \tag{1}$$

Where $\overline{Cap_{in}}$ is the average capacity accessing the power grid of the user; SOCi in is the SOC value accessing the power grid of ith charging record; Capmax is the maximum battery capacity of the EV; N is the total number of charging records.

2) Based capacity

$$Cap_{min} = (1\text{-}SOC_{min} + \frac{\sum_{i=1}^{N_{tra}} SOC_{tra}^{i}}{N_{tra}}) Cap_{max} \tag{2}$$

Where Cap_{min} is the lower limit of battery capacity, which ensures the travel demand of EV users. SOC_{min} is the minimum SOC value set by the user; SOC_{tra}^{i} is the SOC consumed of i^{th} trip record; N_{tra} is the amounts of trips.

3) Expect off-grid capacity

$$Cap_{exp} = Cap_{min} + \frac{\sum_{i=1}^{N} SOC_{lea}^{i}}{N} Cap_{max} \tag{3}$$

Where Cap_{exp} is users expect off-grid capacity, which contains Cap_{min} to ensure the travel needs of EV users; SOC_{lea}^{i} is SOC value when left the grid of i^{th} charging record.

4) Average on-grid time

$$\bar{T}_{in} = \sum_{i=1}^{N} t_{in}^{i} / N \tag{4}$$

Where $\bar{T}_{in}$ is the average on-grid time of the multiple charging records. t_{in}^{i} is the on-grid time of i^{th} charging record.

5) Average charging power

$$\bar{P} = \sum_{i=1}^{N} P^{i} / N \tag{5}$$

Where $\bar{P}$ is the average charging power of the multiple charging behavior; P^{i} is the charging power of i^{th} charging record.

3. CONSTRUCTION METHOD OF AN EV FLEXIBILITY CONTROLLABLE REGION

An EV flexibility controllable region construction method is proposed based on the index of section 2.2. The upper and lower boundaries of the EV flexibility controllable region are calculated by using the flexibility index value, and the closed area surrounded by the upper and lower boundaries is the EV flexibility controllable region. Figure 2 shows the EV flexibility controllable region under ideal conditions.

entire closed region representing the battery capacity feasible point set of the EV.

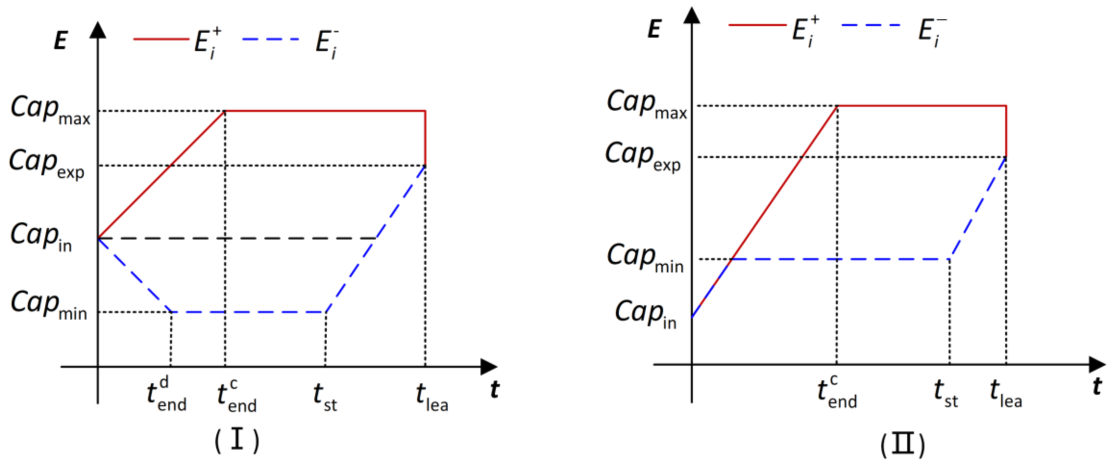

Fig. 2. *EV flexibility controllable region under ideal conditions*

In the Figure 2, E_i^+ is the upper boundary of the flexibility controllable region and E_i^- is the lower boundary of the flexibility controllable region, and i represents the serial number of the users. Cap_{max}, Cap_{exp}, Cap_{in}, *and* Cap_{min} can be obtained directly from the index values in Section 2.2. t_{end}^c is the time when the battery is fully charged; t_{end}^d is the time when the battery is discharged to Cap_{min} and ends the discharge process; t_{st} is the time when the battery with Cap_{min} starts charging; t_{lea} is the off-grid time. They can be determined by the equations (6)-(9).

$$t_{end}^c=(Cap_{max}-\overline{Cap}_{in})/\overline{P} \tag{6}$$

$$t_{end}^d=(\overline{Cap}_{in}-Cap_{min})/\overline{P} \tag{7}$$

$$t_{st}=\overline{T}_{in}-(Cap_{exp}-Cap_{min})/\overline{P} \tag{8}$$

$$t_{lea}=\overline{T}_{in} \tag{9}$$

According to whether the $\overline{Cap}_{in}$ is higher than the Cap_{min}, EV users can be divided into two categories: Figure 2(I) and (II).

For Figure 2(I), the upper boundary of Figure 2(I) consists of two straight lines: remains charging after accessing the grid until Cap_{max} and maintaining the waiting state until leaving the grid. The lower boundary of Figure 2(I) consists of three straight lines: remains discharging after accessing the grid until Cap_{min}, starts charging at the latest to meet the Cap_{exp} and waiting stage of neither charging nor discharging.

For Figure 2(II), the upper boundary of Figure 2(II) is the same as the upper boundary of Figure 2(I). The lower boundary of Figure 2(II) consists of three straight lines: remains charging after accessing the grid until Cap_{min}, starts charging at the latest to meet the Cap_{exp} and uncharged waiting stage. These lines constitute the entire closed region representing the battery capacity feasible point set of the EV.

Figure 3 shows the overall process of the construction method, which introduces the construction method of controllable regions in detail. The upper boundary will be calculated first. If the EV can be charged to Cap_{max} within $\overline{T}_{in}$ time length after accessing the grid, it is proved that the EV has an inflection point (t_{end}^c, Cap_{max}) on the upper boundary, and if not, there is only an off-grid point (t_{lea}, Cap_{lea}^c). Cap_{lea}^c indicates the off-grid battery capacity after charging. In this way, the connection of the inflection point is the upper boundary of the EV flexibility controllable region. Cap_{lea}^c can be determined by the equation (10).

$$Cap_{lea}^c=\overline{Cap}_{in}+\overline{T}_{in}\overline{P} \tag{10}$$

When calculating the lower boundary, it is necessary to consider the two types of Figure 2(I) and Figure 2(II) separately. For Figure 2(I), the lower boundary is the discharge boundary. The lower boundary also needs to calculate its inflection point. If the EV can be discharged to Cap_{min}, and charged from Cap_{min} to Cap_{exp} within $\overline{T}_{in}$ time length after accessing grid, it is proved that the EV has two inflection points on the lower boundary. That is discharge end point (t_{end}^d, Cap_{min}) and the starting charging point (t_{st}, Cap_{min}). The lower boundary off-grid point is (t_{lea}, Cap_{exp}).

But there is only one inflection point on the lower boundary of some EVs. If the EV is discharged to Cap_{min}, and cannot be charged to Cap_{exp} within $\overline{T}_{in}$ time length after accessing the grid. There is an inflection point (t_{end}^d, Cap_{min}) on the lower boundary. The inflection point indicates that the charging is started immediately after the EV is discharged to Cap_{min}. In this case, the EV cannot be charged to Cap_{exp} when leaves the power grid, and the lower boundary off-grid point is (t_{lea}, Cap_{end}^c).

There is no inflection point on the lower boundary of some EVs. If the EV cannot be discharged to Cap_{min} within $\overline{T}_{in}$ time length after accessing grid, the lower boundary off-grid point becomes (t_{lea}, Cap_{end}^{d}) directly. Cap_{end}^{c} is the battery capacity after forced charging. Cap_{end}^{d} is the off-grid battery capacity after discharging. The calculation method is as follows equations (11) and (12).

$$Cap_{end}^{c}=Cap_{min}+\left(t_{lea}-t_{end}^{d}\right)\overline{P} \tag{11}$$

$$Cap_{end}^{d}=Cap_{min}-P_{d}t_{lea} \tag{12}$$

Where, P_d is the set discharge power, and the default is 7kW.

For the lower boundary of Figure 2(II), it is still the same as its upper boundary as the charging boundary, but the lower boundary is expressed as waiting for a period to charge to Cap_{exp} after accessing the grid. If the EV can be charged to Cap_{exp} within $\overline{T}_{in}$ time length after

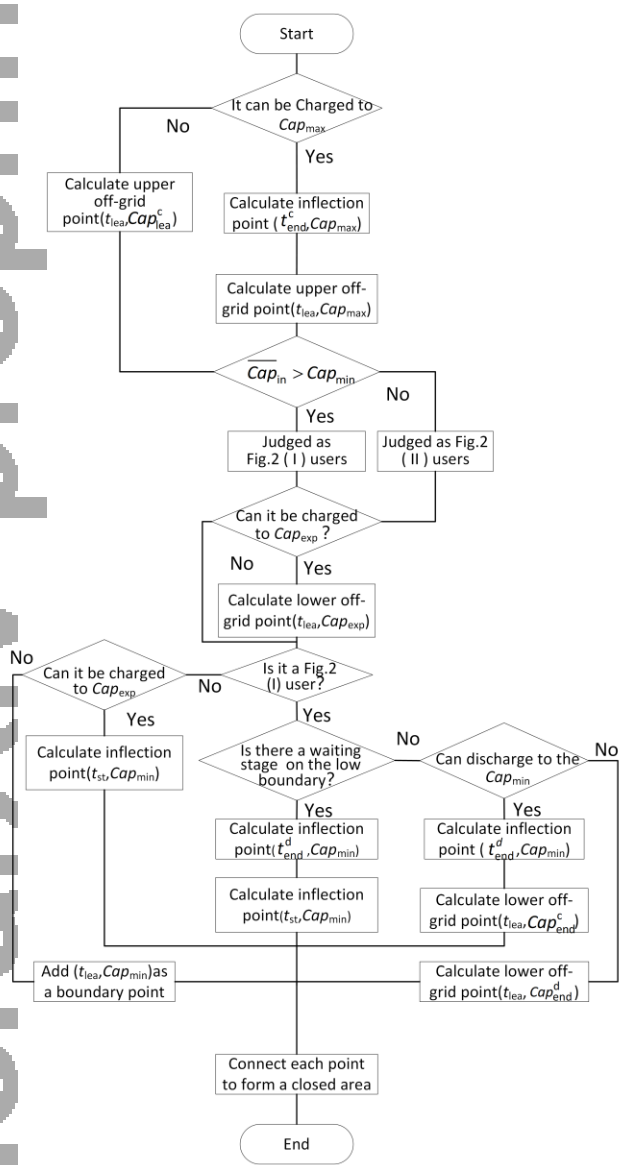

Fig. 3. EV flexibility controllable region construction process

accessing the grid, there is an inflection point (t_{st} ,Cap_{min}) and leave grid point(t_{lea},Cap_{exp}) on the lower boundary. If not there is just a leave grid point (t_{lea},Cap_{min}), the Cap_{min} just meets the EV's minimum travel needs.

By calculating the number and location of inflection points on the upper and lower boundaries of the user and connecting each inflection point into a region. This region is the flexibility controllable region of the EV and represents the set of feasible points that an EV can reach after accessing the grid. EVA can utilize the flexibility of EV in this controllable region.

4. RESULT AND ANALYSIS

The example used in this paper is the behavior data of 6903 EV users in a city in China from May 2021 to May 2022, including charging and driving. The total number of data is nearly 1.4 million.

4.1 Analysis of the characteristics of the controllable region

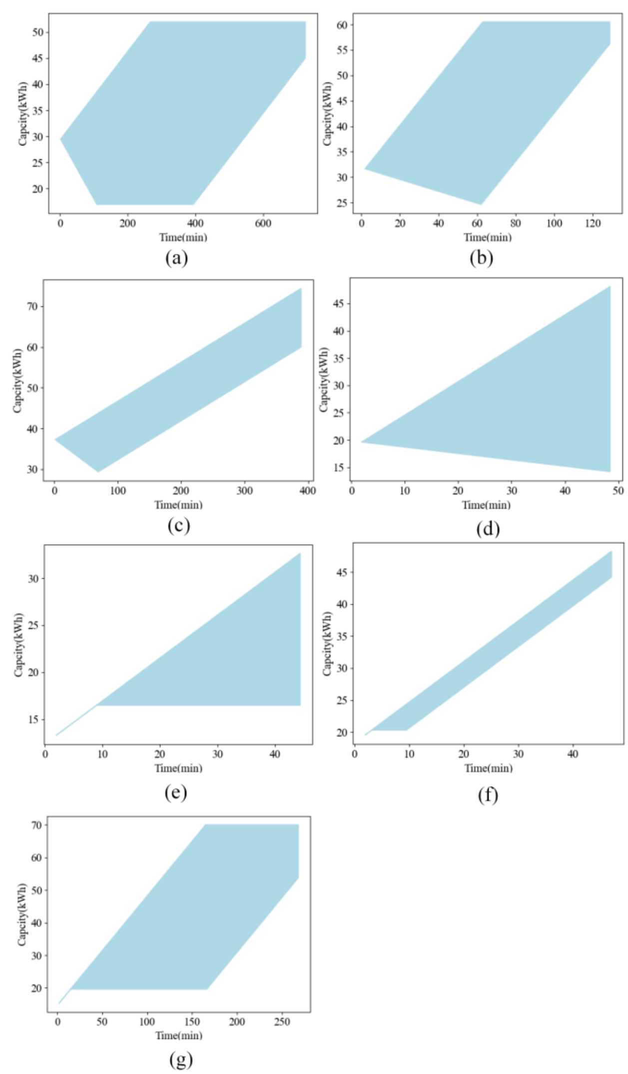

Fig. 4. EV user flexibility controllable domain construction

Figure 4 shows the user flexibility controllable regions constructed based on the method proposed in this paper. According to the different boundary shapes of the controllable regions, seven types of flexibility controllable regions can be obtained. Among them, Figure 4(a), Figure 4(b), Figure 4(c), and Figure 4(d) are similar to that of Figure 2(I) region mentioned above, $\overline{Cap}_{in}$ is higher than Cap_{min}, the upper boundary is the charging boundary and the lower boundary is the discharge boundary. Figure 4(e), Figure 4(f), and Figure 4(g) are similar to that of Figure 2(II) region mentioned above, $\overline{Cap}_{in}$ is lower than Cap_{min}, and the upper/lower boundaries are charge boundaries. The following will analyze the characteristics of each region.

There is a stage of waiting on the upper/lower boundary of the Figure 4(a) user, and which indicates that the user has a high probability of waiting for the scheduling when charging. Figure 4(a) belongs to the priority user during the scheduling and the user whose controllable region conforms to Figure 2(I). Compared with Figure 4(a) users, Figure 4(b) users haven't a stage of waiting on the lower boundary, because it is necessary to meet the Cap_{exp} within $\overline{T}_{in}$ time length. Figure 4(c) users haven't a stage of waiting on the upper/lower boundary. Because the users cannot be charged to Cap_{max} within $\overline{T}_{in}$ time length, and be charged immediately after being discharged to Cap_{min}. Such boundary construction is to meet the travel needs of users. Figure 4(d) users are fast-charging and fast-leaving users. They charge to the end after accessing the grid on the upper boundary, and discharge to the end after accessing the grid on the lower boundary.

The Figure 4(e) user is a fast-charging user with a short time in the grid. The upper boundary represents charging to leave immediately after accessing the gird, and the lower boundary represents charging to the Cap_{min} after accessing the gird. There is a stage of waiting on the lower boundary of the Figure 4(f) user. Compared with Figure 4(e), they have greater flexibility controllable regions. Figure 4(g) users are ideal users whose controllable region conforms to Figure 2(II). The EV can be charged to Cap_{max} after accessing the grid. There is a wide stage of waiting on the lower boundary, which has the largest controllable region range.

By obtaining the flexibility controllable region of EV users, EVA can acknowledge the flexibility boundary of a user. Based on this, users with similar controllable regions can be divided into user clusters. By analyzing the composition of user clusters, EVA can help EVA acknowledge the target user during scheduling and more targeted scheduling.

4.2 User Composition Analysis

By dividing users with the same controllable region characteristics into the same category, all users can be divided into 7 categories. Table 2 shows the number of various types of vehicles in each type of user cluster

Tab. 2 Distribution and composition of user controllable region types (unit: vehicles)

Catalog	(a)	(b)	(c)	(d)	(e)	(f)	(g)	Sum
Taxi	157	384	23	32	698	37	69	1400
Private vehicle	152	1146	762	477	144	114	195	2990
Bus	3	73	166	11	2	1	34	290
Rental cars	215	687	225	101	271	167	118	1784
Official car	37	219	107	25	33	9	9	439
Sum	564	2509	1283	646	1148	328	425	6903

Horizontally, the distribution of vehicle controllable region types for different purposes has different tendencies. Because of work needs, the Cap_{in} of taxi is generally low and the time on the grid is short. Figure 4(e) users are the most, and Figure 4(a) and Figure 4(b) taxi users are used to slow charge after returning home and have a longer time on the grid. They can provide a capacity reserve for the power grid. The travel and charging behavior of private cars is relatively irregular, and it is concentrated in the three types of user groups Figure 4(b), Figure 4(c), and Figure 4(d), which indicate that most private cars can provide a certain capacity reserve, but it does not conform to the ideal model. The bus is a special kind of vehicle. Its battery capacity is larger and the walking route is fixed. It is charging from accessing the grid to leaving the grid. It is concentrated in two types of users: Figure 4(b) and Figure 4(c). The user habits of rental cars and official cars are similar to private cars. The difference is that the distribution of rental cars is more uniform than that of private cars, while the user habits of official cars are highly similar to private cars.

In general, considering the number of users and EV flexibility controllable region type distribution, EVA should take the private car user as the priority scheduling object and combine the user's controllable region type to schedule for different power grid scenarios. At the same time, other users can be scheduled according to actual needs. For example, when the grid frequency rises, taxi users can be scheduled for fast charging to offset the impact of rising frequency; when EVs need to be connected to virtual power plants as energy storage, a large number of private car users can be dispatched as energy storage equipment to give full play to their discharge characteristics and provide support for the power grid while satisfying users ' travel.

5. CONCLUSION

A method to describe the flexibility of EVs based on user behavior data is proposed. Firstly, an evaluation index system of EV user flexibility potential is established to quantify the flexibility of user capacity, charging time, and charging power. Then, based on the index system, the controllable region of EV user flexibility is constructed. The real data is used to verify the example, and the users are divided into 7 categories, which realizes the description of user flexibility with different behavior habits.

The user composition of different flexibility controllable regions is analyzed. From the two aspects of the number of users and flexibility controllable region type, it is concluded that private car users are the priority scheduling objects, which provides a certain reference value for EVA to identify target users from the perspective of flexibility.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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