The Charging and Vehicle to Grid Flexibility of Electric Vehicles at Different Locations

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Abstract

The idea that electric vehicles (EVs) can connect to the grid to serve as energy storage energy devices is compelling, especially in situations where traditional forms of storage, back-up energy supply is unavailable or expensive, or considering the volatility of frequency. So far, the viability and reliability of vehicle-grid integration, which represents smart charging (SC) and vehicle to grid (V2G) of electric vehicles, has become a very popular research topic. Previous studies mainly focused on the maximum potential of SC and V2G capacity on account of too many assumptions, which, however, is usually unrealistic to achieve. The charging and V2G flexibility of EVs are estimated from both adjustable power and adjustable amount aspects with model derived from real-world data. Overall, the EVs at home locations have the largest charging and V2G flexibility under the uncontrolled charging (UC) strategy, only in the regular working time, the maximum adjustable charging power at home location is smaller than that at work locations. Meanwhile, the V2G flexibility, is generally larger than charging flexibility at work and public locations.

Keywords: Smart charging, vehicle to grid, electric vehicle, flexibility

Nomenclature

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<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>EVSE</td>
<td>Electric vehicle supply equipment</td>
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<td>EV</td>
<td>Electric vehicle</td>
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<td>SC</td>
<td>Smart charging</td>
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<td>UC</td>
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1. Introduction

In order to identify the impacts of EVs, there are more needs to know about the distribution and flexibility of electric vehicles (EVs) charging demands, especially their characteristics at multiple types of locations, which are crucial information for grid distribution system operation, renewable sources integration, charging station siting and so on. In order to achieve this, reliable models that capable of translating the travel patterns of a large population of EVs into the respective power demand are needed even when real-world data is available. Models need to be developed to assess impacts in conditions that do not necessarily coincide with those described by the available data.

In existing studies, the spatial and temporal distributions of EVs charging demand relate to different facilities or entities for some economic or security goals. The majority of the early studies have used a deterministic approach to model charging demands, some using expected charging time and demands directly [1] [2], some using annual travel data or averages to generated static charging pattern [3] [4]. For better understanding and recurrence of EVs characteristic, authors of [5] [6] [7] developed several archetypal driving patterns that generated from statistics to model EVs use. Even the archetype, which has specific trip schedule and energy consumption, captures the main structure of travel patterns but strongly limits capturing the effects of travel patterns variability on energy mobility. [8] simulated charging and V2G behavior of EV owners through stochastic travel pattern parameters and evaluated their impacts on the system reliability of smart grid. [9] quantified the potential of EVs to consume renewable generations through optimized charging and emphasized that trip information is essential to utilize EV flexibility. However, the stochastic model in existing researches are usually developed based on home behavior related parameters: home departure time, back home time and daily travel distance, which can be used to measure daily energy consumptions instead of charging of each trip. Therefore, a detailed loop model considering EVs location variation and temporal distribution is needed for
EVs charging demand modelling and flexibility estimation.

This work is build upon the work of [10] by utilizing the data from the American National Household Travel Survey (NHTS) [11], which provides good supports to model the sophisticated travel and charging patterns at multiple types of locations. With the novel agent-based trip chain model (ABTCM), important issues like the penetration of EV and dynamic energy consumption due to the use of EVs can be extensively investigated.

The aim of this paper is to analyze the charging demand distribution and flexibility of EVs at multiple types of locations. Flexibility usually refers to the adjustment ability of a system. In this study, we provide a benchmark assessment of the charging and discharging flexibility of a given EV fleet. Like the conventional generator flexibility definition, we utilized the maximum adjustable charging/discharging power as ramping constraint and the maximum adjustable charging/discharging amount of electricity during the parking period as the total quantity constraint. Different scenarios are developed to analyze the influences of locations, charging strategies and EVSEs on both weekdays and weekends.

2. METHODOLOGY

2.1 Agent-based trip chain model.

The agent-based trip chain model (ABTCM) is developed based on the real-world data extracted from the American national household travel survey 2017 (NHTS) [11] and The EV project [12]. It involves several kinds of locations and trip purposes to models the heterogenous travel patterns and charging patterns of EVs at multiple locations. The detail parameters could be found in [10].

![Fig.1 Overview of the model.](image)

The overview of the model structure is shown in Fig. 1. In this study, three types of EVSE are deployed based on the usage statistics in practice: Level 1 (3.3 kW), Level 2 (up to 14.4 kW but typically 6.6 kW) and Level 3 (typically 44/120 kW) [13]. In many studies, Level 1 and Level 2 SEs are usually referred to as normal/slow charging facilities and Level 3 SEs are called rapid/fast charging facilities. This study considered two charging strategies: uncontrolled charging (UC) and smart charging (SC) strategy, and the details are introduced as follows.

1. Uncontrolled charging

Under the UC strategy, EVs are charged according to their SOC and driving needs, while the electricity tariff or load management of the grid does not affect the charging behaviors.

2. Smart charging

In this study, the time-of-use (TOU) pricing mechanism is employed and thus motivates EVs to shift loads to reduce cost. The SC strategy is applied to the home location with Level 1 EVSE and the work location with Level 2 EVSE to manage EV’s charging demands. A full random dispatch algorithm, which introduced in [14], is adopted to avoid electric imbalance.

2.2 Flexibility estimation.

Flexibility usually refers to the adjustment ability of a system. The operational flexibility is studied while a consumption or generation baseline is already known and then the adjustment ability is evaluated [43]. In this study, we provide a benchmark assessment of the charging and discharging flexibility of a given EV fleet. Like the conventional generator flexibility definition, we utilized the maximum adjustable charging/discharging power at time t as ramping constraint and the maximum adjustable charging/discharging amount of electricity during the parking period as the total quantity constraint. The baseline for flexibility estimation is the original charging profile of EVs.

The maximum adjustable charging power at time t can be calculated as formulation (1), where $m$ represents the total number of EVs and $i$ represents the $i$th EV. Formulations (2)-(4) are the constraints for the charging potential calculation, where $t_{p,i}$ and $SOC_i$ represent the parking time and SOC of the $i$th EV and $C$ represents the capacity of the battery.

\[
\begin{align*}
    p_{\text{max}} &= P_{\text{charger}} \cdot \sum_{i}^{m} \alpha_{t_{p,i}} \cdot \alpha_{SOC_{i}} \cdot \alpha_{\text{state}_{i}} \quad (1) \\
    \alpha_{t_{p,i}} &= \begin{cases} 
    1 & t_{p,i} > 30 \text{ min} \\
    0 & \text{ otherwise} 
    \end{cases} \
    \text{i.e, } i \in \{1 \ldots m\} \quad (2) \\
    \alpha_{SOC_{i}} &= \begin{cases} 
    1 & (100 - SOC_{i}) \cdot C / P_{\text{charger}} > 30 \text{ min} \\
    0 & \text{ otherwise} 
    \end{cases} \quad (3) \\
    \alpha_{\text{state}_{i}} &= \begin{cases} 
    1 & \text{isParking} \cap \text{notCharging} \\
    0 & \text{otherwise} 
    \end{cases} \quad (4)
\end{align*}
\]
Constraint (2) and (3) enforce that the adjustable charging power is counted only while the parking time and the expected charging time of the ith EV are both longer than 30 minutes. The 30 minutes limitation is involved based on the interval constraint of smart charging or V2G activities in most of the related publications. Constraint (4) limits the flexibility of EVs in accordance with its state: if the EVs is charging or it is not parked, the adjustable degree is bound to zero.

The maximum adjustable charging amount during the parking period is calculated with formulation (5) and (6), where SOCmax,i is the maximum SOC that the ith EV can be charged to during the parking time. As shown in formulation (7) and (8), it is then translated into an integral over a certain length of time for handling the sum of adjustable amount over different time scales, where $P_{\text{charge},t}$ is the equivalent charging power at time $t$. Formulation (9) is the additional time related constraint for adjustable charging amount, where $t_{d,i}$ represents the departure time of the ith EV.

$$C_{\text{charge}} = C \cdot \sum_i (SOC_{\text{max},i} - SOC_i) \cdot a_{t_{p,i}} \cdot a_{soc,i} \cdot a_{state,i}$$  

(5)

$$SOC_{\text{max},i} = \min (100\% \cdot P_{\text{charger}} \cdot t_{p,i} / C + SOC_i)$$  

(6)

$$P_{\text{charge},t} = \int_0^{t_{d,i}} C \cdot \sum_i (SOC_{\text{max},i} - SOC_i) / t_{p,i} \cdot a_{t_{p,i}} \cdot a_{soc,i} \cdot a_{state,i} \cdot a_{td,i} \cdot dt$$  

(7)

$$a_{td,i} = \begin{cases} 1 & t_{d,i} - t_{p,i} < t < t_{d,i} \\ 0 & \text{otherwise} \end{cases} \quad i \in \{1 \ldots m\}$$  

(8)

The flexibility of V2G is calculated with similar processes of charging demand. The maximum adjustable V2G power and amount is calculated with formulation (10)-(13), where SOCrest,i represents the necessary energy consumption of the rest trips in the day, SOCanx,i represents the range anxiety of EV drivers, V2Gmax,i is the maximum SOC that the ith EV can discharge to the grid during the parking time and 20% SOC is designed for battery protection.

$$P_{\text{V2G}}^{\text{max}} = P_{\text{V2G}} \cdot \sum_i (SOC_{\text{max},i} - SOC_{\text{rest},i} - SOC_{\text{anx},i} - 20\%) \cdot C / P_{\text{V2G}} > 30 \text{ min}$$  

(10)

$$V2G_{\text{max},i} = \min (SOC_i - SOC_{\text{rest},i} - SOC_{\text{anx},i} - 20\% , P_{\text{V2G}} \cdot t_{p,i} / C)$$  

(11)

$$C_{\text{V2G}} = C \cdot \sum_i V2G_{\text{max},i} \cdot a_{t_{p,i}} \cdot a_{V2G,i} \cdot a_{state,i}$$  

$$= \int_0^{t_{d,i}} P_{\text{V2G}} \cdot t_{d,i} \cdot dt = C \cdot \int_0^{t_{d,i}} (SOC_{\text{max},i} - SOC_i) / t_{p,i} \cdot a_{td,i} \cdot dt$$  

(12)

$$a_{V2G,i} = \begin{cases} 1 & (SOC_i - SOC_{\text{rest},i} - SOC_{\text{anx},i} - 20\%) / C / P_{\text{V2G}} > 30 \text{ min} \\ 0 & \text{otherwise} \end{cases}$$  

(13)

3. RESULTS AND DISCUSSION

3.1 Charging flexibility of EVs

The charging flexibility is evaluated by the maximum adjustable charging power, $P_{\text{max}}^{\text{charge}}$, and the maximum adjustable charging amount of electricity, $C_{\text{charge}}^{\text{max}}$. In Fig.2 and 3, the profiles of maximum adjustable charging power and the equivalent adjustable power, $P_{\text{charge},t}$, for amount estimation at different locations are given, in which the adjustable power at public locations is represented by the stacking of the potential for different purposes. Under the UC strategy, the adjustable charging power and amount of EVs at home location are already utilized and thus only the profiles at work and public locations are illustrated. The maximum adjustable charging amount of EVs on an average daily perspective is shown in Table 1.

From Fig.2, the EVs at home location have the largest $P_{\text{max}}^{\text{charge}}$ under UC strategy, only except the 9:00-15:00 on weekday, during which the $P_{\text{max}}^{\text{charge}}$ at work location is the largest. Under UC strategy, the pattern of $P_{\text{max}}^{\text{charge}}$ are like that under UC strategy, but the profiles at work and public locations have proportionally reduced by about 20% and 15%, respectively. Due to the variation of travel patterns on different dates, the peak of $P_{\text{max}}^{\text{charge}}$ on weekend is about 20% of that on weekdays and that at public locations is nearly double of that on weekday.

Caused by the parking duration time of EVs at different locations, the difference between $P_{\text{charge},t}$ and $P_{\text{max}}^{\text{charge}}$ at public locations is much smaller than that at home and work locations. Thus, the $P_{\text{charge},t}$ at public locations is larger than that at other locations during peak hours (Fig.3), especially on weekend, the $C_{\text{charge}}^{\text{max}}$ at public locations is 7 times larger than that at work locations (Table 1).

With the maximum adjustable charging power and adjustable amount results, the ramping and total amount constraints of flexibility at corresponding time are decided. This gives important guidance for load management or renewable integration at specified time.

3.2 Vehicle to grid flexibility of EVs

Similar to the charging flexibility estimation, the V2G flexibility is evaluated by the maximum adjustable V2G power, $P_{\text{max}}^{\text{V2G}}$, and the maximum adjustable V2G amount of electricity, $C_{\text{max}}^{\text{V2G}}$. Compared the $P_{\text{V2G}}^{\text{max}}$ profiles in Fig 4 to the $P_{\text{max}}^{\text{charge}}$ profiles in Fig.5, the adjustable V2G power and charging power have similar patterns over a day at different locations, since they are all closely connected the travel patterns, especially the parking flow. However, the $P_{\text{max}}^{\text{V2G}}$ is overall larger than $P_{\text{max}}^{\text{charge}}$ at specific time, and the peak of $P_{\text{max}}^{\text{V2G}}$ at different locations have a 30%-90% increase compared to that of $P_{\text{max}}^{\text{charge}}$ under UC strategy. When it comes to the quantity of V2G flexibility, the $C_{\text{V2G}}^{\text{max}}$ at home location is
lower than $C_{\text{max}}^{\text{charge}}$, which may be caused by the lower...
SOC of EVs after a daily trip, while the $C_{V2G}^{max}$ is larger.
than their $C_{\text{max}}^{\text{charge}}$ at other locations. Thus, a larger adjustable power does not automatically mean a larger adjustable amount, which is applied not just for the flexibility at one location, but also for the comparison between different locations, these two parameters are both important and individual for flexibility estimation. Furthermore, the OPC strategy has an opposite influence on the V2G flexibility compared to that on the charging flexibility, the $C_{\text{max}}^{\text{V2G}}$ raises by 52% and by 32% at work location and public locations with a larger SOC state of EVs after OPC (Table 10). From Fig.4 and 5, the difference between the maximum adjustable power and equivalent power at home and work locations are further magnified compared to that between Fig 2 and 3, while that at public locations has a reverse tendency. This is the reason why the adjustable amount at public locations becomes the largest only except the situation on weekday under UC strategy.

4. CONCLUSION
An agent-based trip chain model (ABTCM) is used to simulate and analyze the charging profiles of electric vehicles (EVs) at multi-locations. The charging and discharging flexibility of EVs are estimated from both the ramping and quantity aspects. The difference between the adjustable power and equivalent power at public locations is much smaller than that of other locations, this is the reason why EVs at public locations have considerable flexibility even with a lower adjustable power. The SC strategy has an opposite influence on the charging and discharging flexibility. The charging flexibility at work and public locations have reduced by about 20% and by 15%, respectively and their discharging flexibility have raised by about 50% and by 30%. The flexibility results give important guidance for load management or renewable integration at specified time, along with the traffic flow information, the limitations of vehicle-grid integration can be defined clearly.

5. ACKNOWLEDGEMENTS
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6. REFERENCE
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