V2G strategy incorporating charging behavior for mitigating future grid impacts of high electric vehicle adoption

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Abstract: The urgent need for the prediction of electricity demand triggered by the deep adoption of electric vehicles (EVs) contributes to the reliable electricity supply of the grid. However, an underestimated grid load would occur for peak and off-peak differences in the overwhelming EV charging context. From a behavior perspective, we aim to explore the long-term impact of EV charging on the underestimated load effect with charging behavior modification under climate goals, since the adopter's charging time and EV initial state of charge (SOC) are vital to shaping grid peak profile. Here, we propose a combined top-down and bottom-up integrated assessment model to predict the implication of EV charge on grid underestimated power supply gap under climate goals. Notes that the forward-looking behaviors are constructed through a data-driven mixture probability framework developed by EV minutely charging and driving data in Beijing. Our results indicate that under China's carbon-neutrality goals, the underestimated load increases by 15.8% relative to no climate target limitations, while guiding EV adopters to charge their vehicles in the off-peak could reduce 41 GW peak electricity demand, and thus curtail the grid load fluctuation 90 GW, 18% more than the overall coal-fired capacity increased forthcoming in the European Union and the United Kingdom combined. Coupled charging behavior guidance and Vehicle-to-grid integration are more productive. Our findings open avenues for enhancing future electricity supply security concerning deep vehicle electrification by charging behavior guidance using behaviorally realistic data.

Keywords: V2G charging, Charging behavior, grid load impact, data-driven mixture probability framework

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1. Introduction

Vehicle electrification, coupled with decarbonized electricity, is critical to reduce fossil energy carbon emissions [1, 2]. Adopting electric end-use vehicle technologies, in place of internal combustion engine counterparts, is known as the prospective solution to cope with energy crisis and climate challenges in road transportation [3]. This consensus enables the global EV sales to meet 43 million, approximately accounting for 30% of the total new vehicle sales, to achieve the climate change consensus (limiting global warming to 2°C) reached by large jurisdictions around the world in the Paris Agreement [4]. Under this urgent need, the dominant market of EV sales, China, broke new records last year to reach 5.4 million EV sales, up from 3.5 million in 2021. The momentum is expected to continue strongly for a prolonged time since this frontrunner pledged its carbon neutrality (CNCN) goal [5, 6]. In 2030, it is anticipated that market trends and policy efforts will encourage the share of EV sales to surpass 90% in the domestic market, accounting for more than 40% of total global vehicle sales [7].

However, the escalating EV adoption would trigger a sharp increase in electricity demand globally. When the light-duty vehicle fleet achieves 100% electrification in 2050, the transportation sector would consume light-duty vehicle fleet in Canada [8, 9]. If the fleet is entirely electrified in America, the annual electricity demand would be up to 1730 TWh [10], and the peak residential demand could be double [11]. Likewise, research has been estimated in the context of China. Dong et al., (2023) indicate electric vehicles will offer 66% of the electricity consumption increase according to China's climate-neutrality pursuit [12].

However, the analysis above on the consequence of EV adoption on electricity consumption and grid impact is based on the "annual average" EV charging load and electricity generation under the climate goals scenarios. "Daily-specific" EV charging needs have not yet been evaluated, which becomes critical in the long run. Specifically, if EVs are plugged at a large scale in a specific time slot, the peak load would sharply increase in this period [13-15]. Considering the average load only masks the users' heterogeneous charging behavior and thus ignores the estimation of the higher-than-average load. Therefore, this huge underestimation of grid load may occur when EVs are deep deployed under climate goals, challenging the supply of electricity grid infrastructure and its safety operations.

Conversely, although literature related to the impact of EV charging on electricity demand has focused on the detailed load fluctuation within a short time frame, e.g. one day or one year, focusing on associations between EV charging and grid under the climate goals scenarios in the long timescale has not been explored. For example, Jahromi et al. [16] forecast the residential EV charging profile in the look-ahead hours through the probability density function. Yuan et al. [17] analysis the operations of electricity use of battery EVs in various climate zones in China during the 2020s. Given that deep EV adoption driven by climate goals becomes a global consensus, when predicting the impact of EV charging on the grid, excluding the role of climate goal constraint, would increase the risk of the unreasonable expansion and planning of the power grid infrastructure [18-20].

In addition, numerous previous studies have used charging management and controls (i.e. charging behavior guidance and vehicle-to-grid technology) to estimate the impact of EV adoption on grid load and emissions in the short term at low EV adoption levels [21-25]. These frameworks are not suitable for understanding the impact of EV deployment on grid load under climate goals in the long term because they do not account for EV deployment trends and ignore heterogeneity in the charging behavior of future EV drivers [26]. The existing large-scale charging demand models are based on the behavior of early EV adopters [27, 28], but assuming similarity in charging behavior of early and future EV adopters might not be realistic to forecast long-term spatiotemporal energy demand for EVs [1]. With appropriate charging guidance, EVs can potentially smooth out the peak and off-peak difference in the grid load by providing demand transferability and flexibility, reducing the adverse effect of high EV penetration on the grid [29-31].

Here, we construct a customized top-down and bottom-up integrated model to simulate the adoption trajectory of EVs under climate targets in China, and further explore the impact of charging behavior guidance on grid electricity consumption and the underestimated power supply gap. Specifically, first, we combine the Global Change Analysis Model (GCAM) and the Bass diffusion model (Bass model) to simulate the pathway of EV adoption. Second, we fit the charging behavior model using the micro-granular data of EV adopters charging and driving at the 15-minute level. The model accounts for potential changes in charging behavior, facilitating the simulation of future charging scenarios. Finally, we model the controlled charging and vehicle-to-grid (V2G) collaboration technology in the context of deep EV deployment under climate goals to explore its impact on the power grid. Our findings underline the significance of leading EV users to adopt more sustainable charging behavior.

The overall layout of this paper is as follows: in Section 2 introduce the overall method; in Section 3, we detail the data source and scenario design; in Section 4 we describe the result; in Section 5 we conclude and discuss.

2. Methodology

In this section, we introduce the method of this study. We depict the modeling framework of this study, consisting of four main components: the EV adoption trajectory under climate goals, EV charging behavior scenario development, EV charging model, and the Vehicle-to-grid charging model.

2.1. Overview modeling framework

The impact of deep EV deployment under climate goals on the power grid is assessed via a customized top-down and bottom-up integrated model, whose overall formulation is presented in Fig.1. In detail, we begin with joint use of the Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) in GCAM model to obtain the key parameters of population, economic development level, carbon price, and energy and fuel price. These macroscopically up-down parameters are part of the data source of the EV Bass model, which provides the EV development trajectories under different climate goals. Next, we use real-world charging and driving data of EV adopters, at a 15-minute resolution, to cluster the current EV charging patterns in China. To exploit the effect of charging behavior control, these currently diverse patterns are the foundation to simulate future charging patterns via mixed probability modeling. This model captures the charging tendency of EV adopters in the long run, which is determined by the real-world observed charging and driving patterns. Note that this method could help us extend the charging behavior scenarios to perform more latent behavior simulation, rather than on the assumption that EV adopters' charging preference is fixed. This means it is conducive for us to provide a charging guidance strategy for the mitigation of EV's adverse effects on the grid and energy system. Utilizing this method, we could generate the data of charging behavior scenarios in 2050. The newly generated data are used to estimate the distribution of EV charging behavior (start time and initial state of charge) under long-term charging conditions.

For the future EV charging module, a Monte Carlo simulation conveyed by scalable charging and driving profile is conducted for individual EVs with a time resolution of 15 minutes on a typical day. To quantify the impact of the V2G strategy on the grid load, we employ Monto Carlo simulation under various conditions, such as the state of driving, charging and discharging, charging and discharging price, and electric current.

The net electricity demand caused by composite EV fleets requires the combination of charging individual EVs and aggregated EV ownership. The overall picture regarding the impact on the grid from EV development under climate goals is depicted. By defining the underestimated load, we could examine the peak-than-average electric demand for urging the grid to provide sufficient electricity supply.

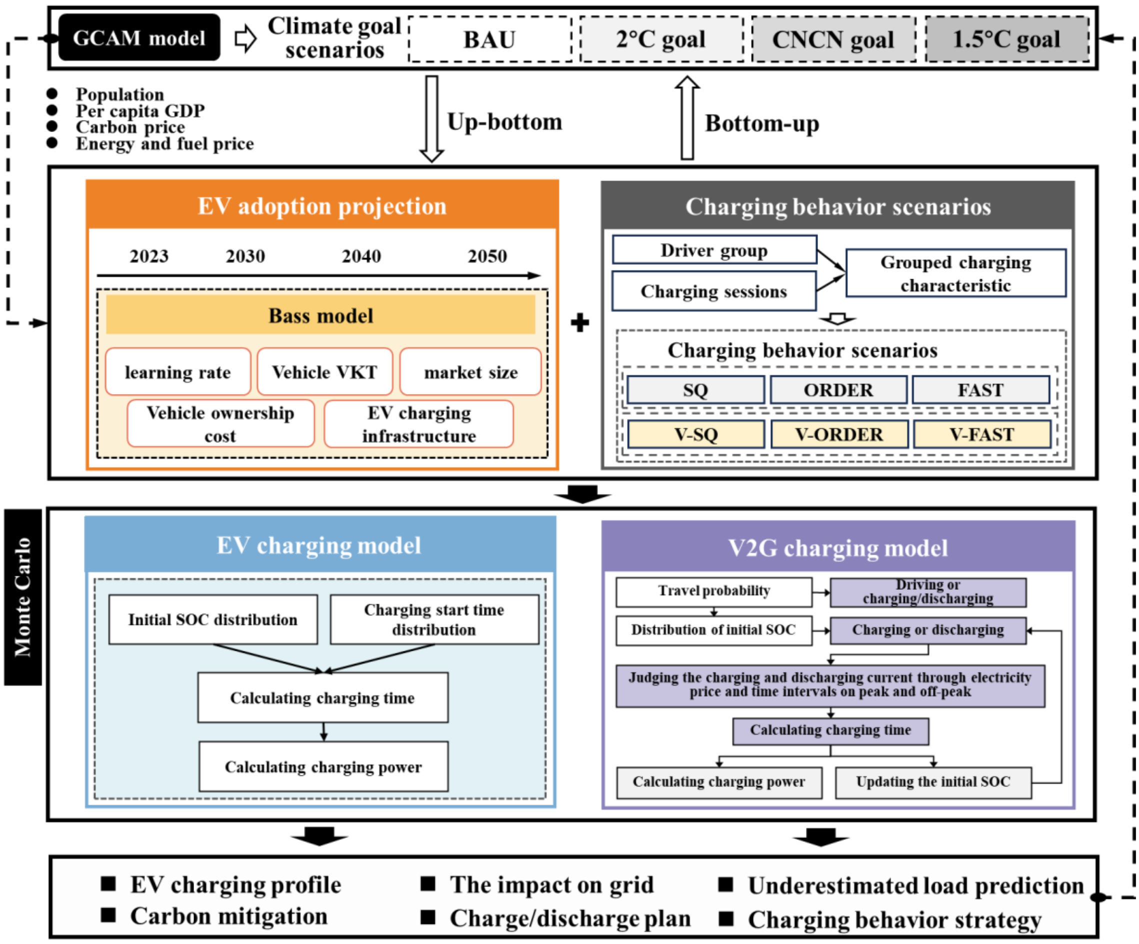

Fig. 1. Modeling framework and scenarios for the integrated model.

2.2. EV ownership prediction under climate goals

We combine the top-down Global Change Analysis Model (GCAM) model and bottom-up Bass model to predict the EV adoption tendency under the three climate goal scenarios (1.5°C goal, 2°C goal, China's carbon neutrality goal) and one scenario without the carbon mitigation constraint (business-as-usual, BAU scenario). To do this, we combined the Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) in the GCAM model, and input macroscopically up-down parameters from GCAM to the EV Bass model. Our modified Bass model has two parameters: (i) the innovation coefficient p form the external impact of EV manufacturers; and (ii) the imitation coefficient q, which results from the internal impact of EV buyers. By model running, we could capture the long-term EV S-shape growing trend triggered by technological breakthroughs, reform of advertising and marketing system, as well as attribution of group population. The Bass model can be expressed as follows:

$$\frac{dY(t)}{dt} = [p + \frac{q}{m(t)} Y(t)][m(t) - Y(t)]x(t) \tag{1}$$

where the left side of the equation, $\frac{dY(t)}{dt}$, is the rate of EV adoption, meaning the sales of EVs; $Y(t)$ is the cumulative adoption at time t, meaning the stock of EVs. The EV automobile market space $m(t)$, indicates the future demand potential. Here, we evaluate the yearly market space, which is the function of population and the vehicle ownership per 1,000 capita. This dynamic vehicle ownership is adjusted based on the income changes, which are obtained from the outputs of GCAM. The term of $\frac{q}{m(t)} Y(t)[m(t) - Y(t)]$ is the expression of Logistic model, and therefore Bass model is a more general model considering the technology and incentive policies force. The lifespan of an EV is assumed 10 years [32], and we use Weibull distribution to depict the EV annual scrappage rate [33].

In Eq. (1), the speed of diffusion is also influenced by the change in price $x(t)$ and is given by the equation as follows:

$$x(t) = 1 + \beta_1 \frac{\Delta Cr(t)}{Cr(t-1)} + \beta_2 \frac{\Delta P(t)}{P(t-1)} \tag{2}$$

where $Cr(t) = \frac{C_{ev}(t)}{C_{icev}(t)}$ denotes the shifting of EV costs from internal combustion engine vehicle (ICEV), represented by Equ. (3). In which $\frac{\Delta Cr(t)}{Cr(t-1)}$ is the influence of price element, and $\frac{\Delta P(t)}{P(t-1)}$ is the influence from charging infrastructure. Correspondingly, the β_1 and β_2 represent the coefficient of price and charging infrastructure, respectively. Additionally, $\Delta Cr(t) = Cr(t) - Cr(t-1)$ measures the change in relative costs from the last year. The $\Delta P(t) = P(t) - P(t-1)$ measures the growth in charging infrastructure alike.

Note that we take EV annual ownership cost into consideration, that is, not only the economic cost but also the environmental cost (significance for handling climate change) is absorbed in our model. The economic cost aggregates the purchase cost, usage cost, and recycling revenue. Specifically, the purchase cost contains EV sale price, maintenance expenditure, and subsidy; the usage cost incorporates electricity consumption cost; and the recycling revenue comes from the EV and its battery salvage value. With regard to the environmental cost, the life-cycle cost related to raw material production, automobile assembly, usage, and recycling is evaluated. Multiplying the carbon price from GCAM outputs together, is efficient to merge environmental cost and economic cost both.

Referring the Nykvist and Nilsson (2015) [34], we evaluate the EV future sale price by learning effect, which explains the decline of production cost with the increase of production experience. Therefore, the EV future sale price, $C_{ev,t} = C_{ev,0} \cdot Y(t)^{-b}$, is affected by the EV sale price in the baseline year, the number of EV owners, and the learning rate b [34].

2.3. Long-term charging behavior simulations

The mixed probability framework is employed to simulate EV adopters' charging propensity, wherein connects two key elements: the driver groups G and charging session situations s. The distribution over EV adopter groups, $p(G)$, is on behalf of the proportion of the total number of drivers in each group. Once the charging session in a group is given, the charging load will fall into place deterministically. The electricity demand is zero before the EV arrives and after the total session energy has been delivered. The specifically conditional probability for each charging session within the framework can be constructed as:

$$P(s,G) = P(s \mid G)P(G) \tag{3}$$

To capture the heterogeneity of charging behavior among EV adopters, we aim to divide them into diverse groups applied by the k-means clustering algorithm. To describe each EV driver as a sample in the clustering we create a feature vector based on the driver's charging session s. According to our notation, the session s_i is the i-th charging session, and the session vector for the session i contains the start time before charging, t_i, charging duration, d_i, initial SOC, ss_i, SOC after charging, es_i, charged power, p_i, and maximum current, c_i:

$$s_i = [t_i, d_i, ss_i, es_i, p_i, c_i]^T \tag{4}$$

For each session, we define a vector x^d to represent the mean behavior of EV adopters when charging in a specific group:

$$x^d = \frac{1}{n^d}\sum_i s_i^d \tag{5}$$

The decision of each adopter belongs to which cluster depends on minimizing the increase in the within-cluster sum of squares. Using the Euclidean distance, the objective is to find:

$$\sum_{l=1}^{L}\sum_{x^d \in c_l} \| x_d - x_c \|_2^2 \tag{6}$$

In which c_l is the set of points in cluster l, x_c is the centroid of points in c_l, and there are L clusters. We implement this algorithm in Python in the scikit-learn package.

After grouping the diverse categories in terms of the driver's charging feature vector, we make an attempt to describe charging behavior. That means when the EV adopter in group G has a charging session s, we build the conditional probability defining the session $P(s \mid G)$. GMM has been shown well-fitting the joint distribution of multiple charging parameters. It can be regarded as a weighted sum of k multiple multivariate Gaussians. Where μ_k, σ_k^2 donated the expectation and covariance matrix in independent sub-models, respectively. φ denotes the density function of a single Gaussian distribution, and π_k is the mixture coefficient of component k in the mixture, satisfying $\sum_{k=1}^{K}\pi_k = 1$ and $0 \le \pi_k \le 1$. The likelihood of the GMM for sessions s can be obtained as:

$$L(\pi, \mu, \sigma) = \prod_{i=1}^{n} \sum_{k=1}^{K} \pi_k \varphi(s_i \mid u_k, \sigma_k^2) \tag{7}$$

GMM attempts to find a mixed representation of the probability distribution of the multivariate Gaussian model, so as to fit the charging data distribution of any shape. We apply this clustering algorithm in Python using the Gaussian Mixture feature in the scikit-learn package. That helps us to recognize the charging regularity of EV adopters since it is insusceptible to noise and outliers than non-density-based clustering methods. The Bayesian Information Criteria (BIC) is selected for determining the number of components K in GMM.

On the base of capturing the charging propensity in diverse groups, the mixed probability framework facilitates to generate potential, large-scale charging scenarios. First, we calculate the EV adopter number in every group determined by Eq. (8), wherein the D means the total number of EV adopters (the equivalent of the number of EV adoption), and $P(G_i)$ represents the probability distribution over every group, determined in line with the probable assumption of prospective charging preference.

$$D_i = P(G = G_i) \cdot D \tag{8}$$

Second, we simulate charging sessions through GMM, implemented for charging sample generation based on the results of parameter estimation, for each group. Finally, we aggregate the simulated charging data across all EV adopter groups to formulate the all charging behavior profile in a typical day.

2.4. Methodology for simulating charging of EVs

Monte Carlo simulation is selected to model the adopter's charging behavior according to the large-scale real-world data. The future EV fleet charging profile under the climate goal is formulated by aggregating the charging demand of individual vehicles.

We take different simulation strategies to deal with one-way charging and V2G charging (Fig. 2). In terms of one-way charging, the charging start time for an individual EV is generated by Monte Carlo simulations, and then the charging duration is deduced by initial SOC, which is subjected to the probability distribution obtained from real-world data. We assume each vehicle begins charging instantaneously once the EV plugs in, with 90% charging efficiency, and ends until its battery is fully charged. After the number of iterations is reached in Monte Carlo simulations, the whole fleet loads are superimposed to obtain the total charging load profile.

In terms of one-way charging, electricity flows from the electric grid into the EV, while in V2G charging, electricity can flow both ways. Therefore, we are first required to judge the state of the EV in charge or discharge. Two steps are required to do this. Our first step one is judging whether the EV is traveling or not by the travel probability of the electric vehicle. If the EV is in the non-travel state, it is in the power access state by default. The travel probability is extracted from the travel interval distribution of the driver based on large-scale real-world driving data. In the second step, determining whether the electric vehicle is charging or discharging is based on its initial SOC. If the random number of initial SOC is greater than 0.8, EV is under discharge state; if initial SOC is less than 0.5, EV is under charge state; otherwise, the state is uncertain and both of them may be possible. After identifying the EV state, the key to simulating electricity load is figuring up the charging (or discharging) current. According to the comparison between the charge (or discharge) price of an EV and the time-of-use price, and combining the charging time (dividing daily into three periods of peak time, flat time and valley time), the magnitude of charge (or discharge) current would be determined. Multiplying by alternating voltage, the charging power could be calculated. The peak and off-peak periods are divided according to the time-of-use tariff policy in Beijing, and we assume EV adopters are prone to choose to charge their vehicles during the off-peak period in the wee hours and discharge their vehicles during the peak period at night. Charging or discharging time is calculated by the relationship between the charging current, initial SOC, and capacitor. After that, the initial SOC is updated and used in the next iteration to start a new round of charging or discharging judgment. Finally, when the specified number of iterations (equal to the number of EVs under climate goals) is reached, we aggregate the load profiles across all EV fleets to calculate the total charging and discharging demand with the V2G strategy.

3. Data and scenario designs

This section first introduces the high-solution data used in the model, including the minute-level charging and driving data of 10,000 EVs and more than 4 million charging and driving sessions over one year in 2018. Secondly, we elaborate on the charging behavior scenario in 2050, and consider the potential change in future charging behavior.

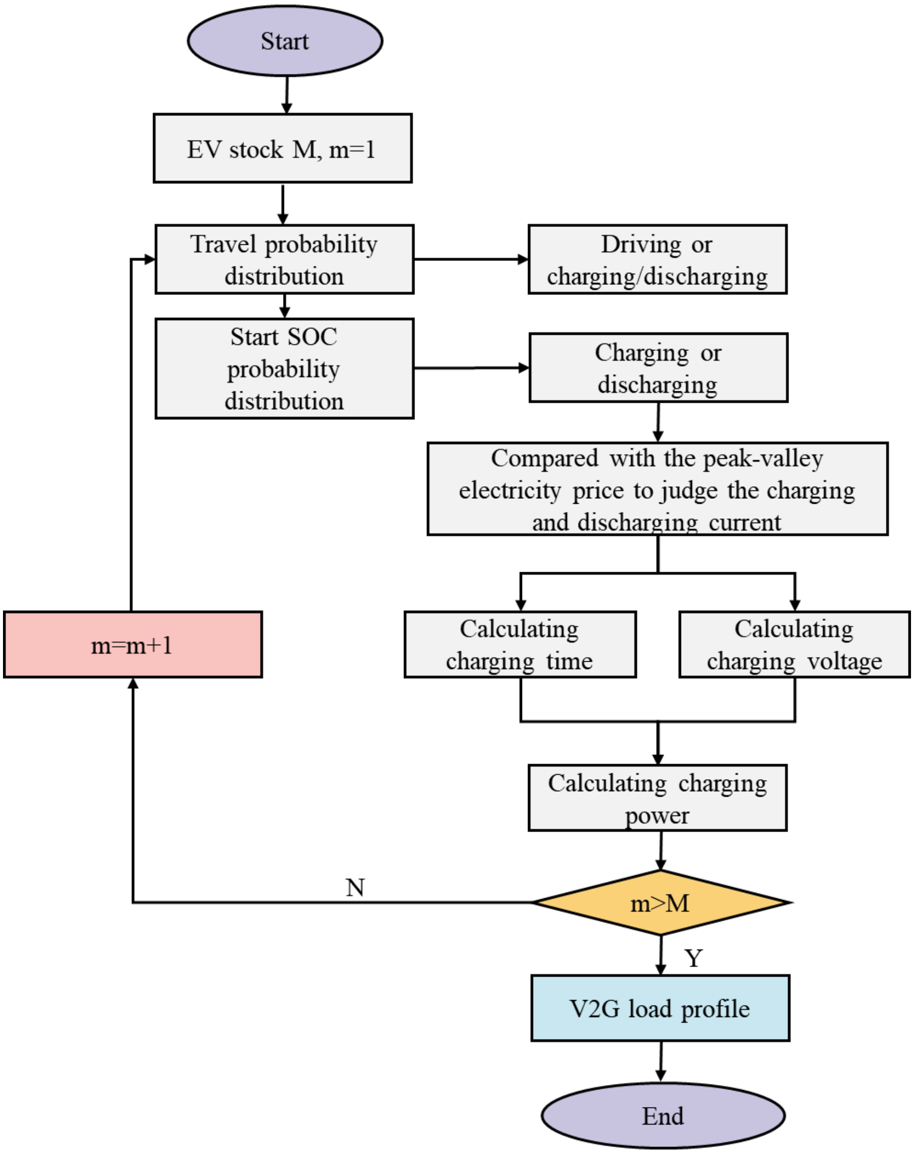

Fig. 2. Monte Carlo for V2G charging strategy.

3.1. Data descriptions

For this work, it is worth emphasizing that we simulate the hourly charging demand for individual EVs on a typical day in 2050 based on the nearly million observations of real-world charging and driving data of 10,000 EVs, obtained from the National Big Data Alliance of New Energy Vehicles (NDANEV) – the biggest monitoring platform of new energy vehicles. Each charging session contains the following charging characteristics: (i) vehicle information involving vehicle type and anonymous plate number; and (ii) charging information, such as charging start time, charging end time, charging duration, SOC before charging, SOC after charging, maximum charging current, longitude, latitude. Each driving record contains time, SOC, distance, and position information before and after driving. In the data preprocessing for high-quality data, we filter out data whose battery power added is less than 0.5 kWh or erroneous SOC measurements before charging exceeding SOC after charging.

3.2. Scenario design

We design three climate goal scenarios in the EV adoption model, in addition to the business-as-usual scenario (BAU, not bound by climate targets). The stricter temperature rise control targets are associated with prompt and extensive EV deployment due to the more pressing emission reduction policy. We use the learning curve to link the EV deployment with its manufacturing cost under three learning rates reflecting different climate goal scenarios. Additionally, we consider three charging scenarios: (i) SQ scenario, which is the same as current charging patterns; (ii) ORDER scenario, where a high proportion of EV adopters charge their vehicle during the off-peak period in favor of grid electricity regulation; and (iii) FAST scenario, where majority adopters prefer fast charge due to availability batteries with high capacity, thanks to the battery technology evolution. Specifically:

SQ Scenario: This scenario serves as the baseline for charging behavior scenarios. Its creation is based on the assumption that the distribution of charging behavior patterns in 2050 remains consistent with historical trends.

ORDER Scenario: This represents an optimistic future charging scenario. We assume that in this scenario, the majority of EV users (60%) adopt an ordered charging behavior, utilizing slow charging during the early morning when the grid load is low.

FAST Scenario: This represents a pessimistic scenario where the majority of EV users adopt fast charging, and the majority of EV users have fast charging habits.

Correspondingly, combined with the charging behavior scenarios and V2G charging strategy, we develop three V2G charging scenarios: (i) V-SQ scenario, meaning when EV adopters charge their vehicle with current charging behavior; (ii) V-ORDER scenario, donating that EV adopters charge their vehicle with grid-friendly charging behavior; and (iii) V-FAST scenario, assuming that EV adopters prefer the fast charging technology even though they agree to participate in V2G charging strategy.

4. Results

4.1. Characteristics of predicted EV charging behavior

We construct a data-driven model of future charging behavior by adopting a probabilistic mixture modeling framework. We first classify the EV adopters into five groups, where each group has a distinct charging practice. In contrast to assuming the homogeneous charging behavior of all users, this approach effectively captures the heterogeneity among them. We then represent charging sessions by group-specific Gaussian Mixture Model (GMM) based on detailed historical charging data, including charging start time, initial SOC, and charging duration. Eventually, to simulate heterogeneous EV charging demand under the three considered future scenarios, SQ, ORDER, and FAST, and three V2G charging scenarios coupled with these three charging behaviors, the GMM-based predicted probability distribution is applied to the forecasted EV adopter groups.

The generated distribution of charging start time and SOC are vital in simulating charging behavior, which is shown in Fig. 3. Our first observation is that current EV users are prone to charge their EV between 18:00-22:00, i.e., when drivers return home from work. Meanwhile, the SOC shows a bimodal distribution, meaning that a high proportion of EV adopters choose to charge at around 35% and 75% battery levels, depending on their risk preferences. Under the ORDER scenarios, as expected, a majority of drivers charge during 0:00-3:00 to better spread charging events throughout the day, reducing charging during evening peak hours. Encouraging drivers to charge at an off-peak time through national policy interventions reduces the difference between peak and off-peak grid load and pacifies electricity security issues. In this scenario, The SOC at the start of EV charging approximately follows the normal distribution. In the FAST scenario, the charging sessions of EV adopters concentratedly take place after work along with the lowest battery level of EV, and the peak load yielded by PEVs will be even higher.

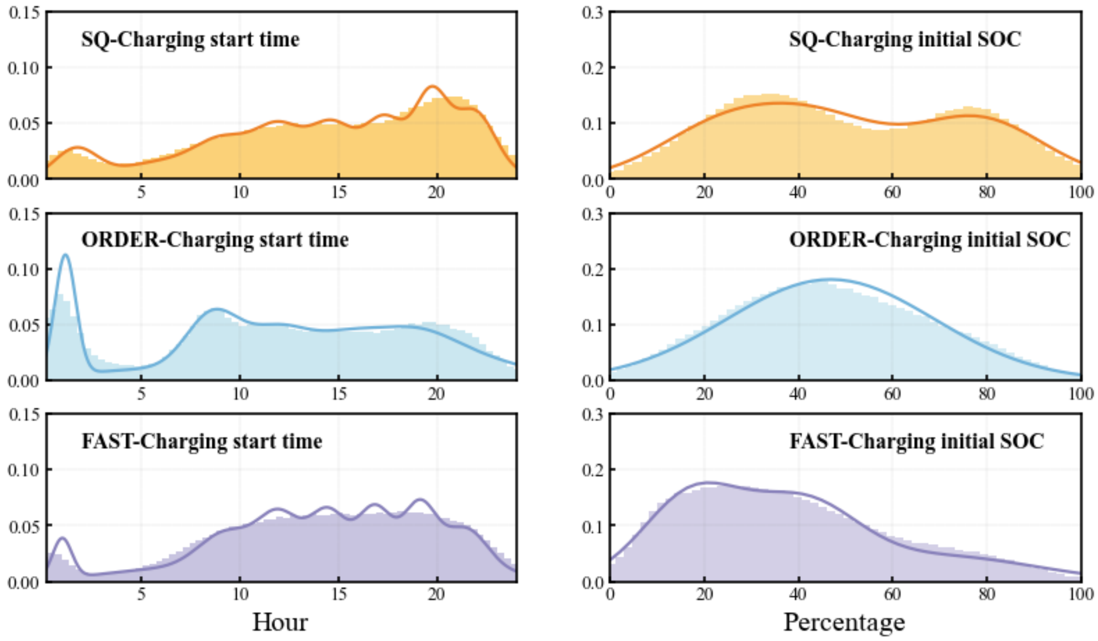

Fig. 3. Charging behavior characteristic in three charging behavior scenarios.

4.2. The underestimated grid load prediction

Vehicle ownership is another vital element in catching on charging-behavior changes and its impact on grid load. We use top-down and bottom-up integrated models to simulate the deep adoption trajectory of EVs under climate targets in China. From the bottom-up point, a modified bass model is employed to project vehicle ownership, and we collect the national statistics of vehicle sales, its ownership, EV market size, and charging infrastructure convenience, as well as calculate the vehicle ownership cost. Notably, we input the population and vehicle penetration optimized by the GCAM model under diverse climate goals to modify the Bass model to forecast the EV market size. Besides, obtaining the carbon price from this top-down model allows us to consider the life-cycle EV ownership cost, containing not only economic costs but also environmental ones. The EV ownership estimated from 2023 to 2050 is shown in Fig. 4. In our prediction, the more stringent goal of carbon mitigation, the more EV ownership there is. For China's carbon neutrality (CNCN) goals, the electric passenger vehicle ownership would be 300~302 million by the end of 2050, at least up to 99 million related to BAU (with three learning rates). The EV ownership in total domestic passenger vehicles would reach 388 million and 277 million under 1.5°goal and 2°goal in China respectively (with a middle learning rate).

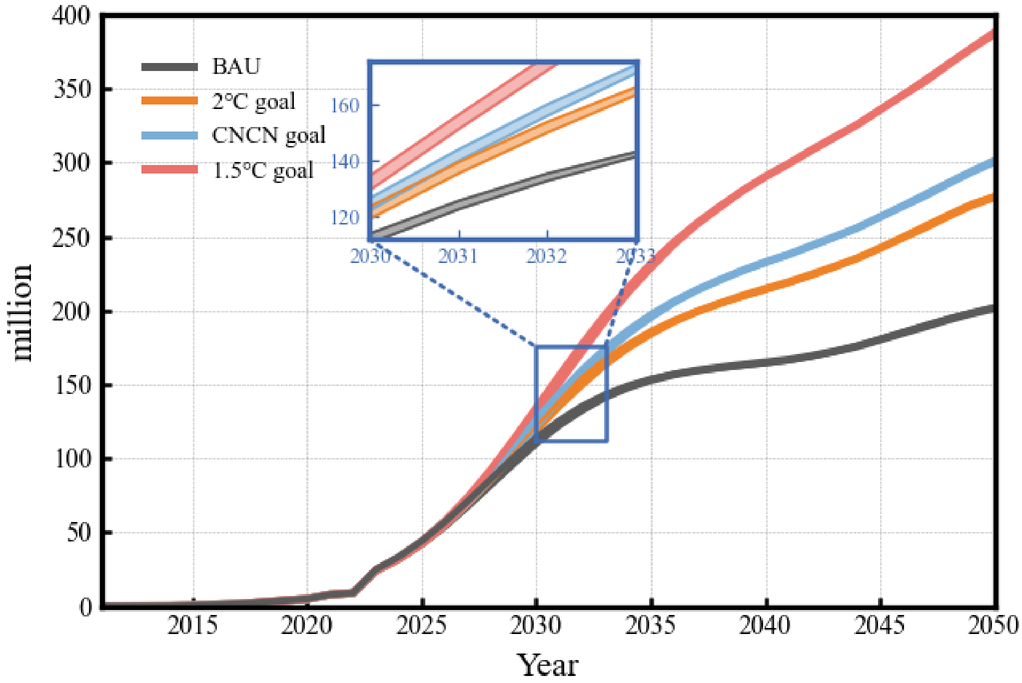

Fig. 4. The projection of electric vehicle ownership under climate goals.

It is vital to emphasize the peak-than-average electric demand for power security. Here, we define the underestimated load as the daily actual charging load of an EV minus the annual average charging load. Based on the deep adoption trajectory of EVs, the estimated grid load profile and the potentially underestimated load, are shown in Fig. 5. Results show that the stringent climate goal will lead to greater electricity consumption and underestimated implication on trends, owing to the transportation electrification continue to accelerate. Under the BAU scenario where there is no carbon mitigation constraint, the peak demand takes place at 20:00 and is modeled to be around 2433 GW in 2050. The responding underestimated electricity supply reached 273 GW. Deeper EV adoption adds peak demand because that aligns with the grid baseline shape. Considering the CNCN scenario, typically peak demand increases by 4.6% in comparison with BAU. That means at least 100 new large-sized generating units are needed to meet the demand for electricity at peak times. The underestimated load increases by 15.8%, indicating an extra 138 billion (CNY) in power storage project investment every year to make up such a huge electricity gap [35]. In the most stringent case (1.5°C goal), that gap develops further and underestimation rises by 22.7%.

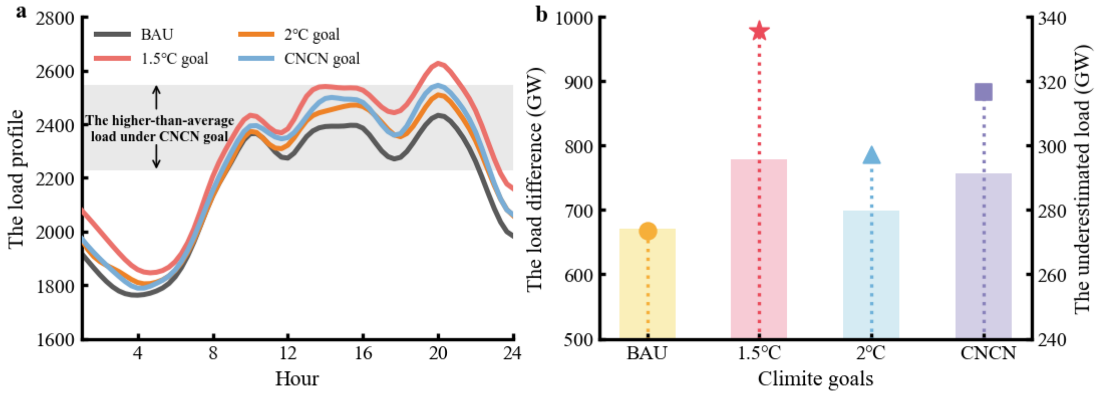

Fig. 5. The impact on the grid and the underestimated load when high electric vehicles deployed under climate goals.

4.3. EV charging strategies to mitigate load impact under China's CNCN goal

The long-term charging behavior of EV adopters is uncertain and charging patterns substantially shape the different grid load profiles at the national level. To investigate which charging behavior could mitigate the grid net demand and how to effectively coordinate with the grid in the CNCN context, quarter-hourly charging behavior for the EV adopter group is simulated via Monte Carlo coupling with the developed future charging behavior scenarios. For evaluating the electricity demand under these scenarios, we input the random number of charging start times and initial SOC generated from our mixture probabilistic framework. With respect to each EV electricity demand under the V2G scenario, if the EV connects to the power supply (judged by the probability of EV trip obtained from real-world driving data), we assume the vehicle is charging or discharging, otherwise, is driving. Judging whether the EV is charging or discharging according to the initial SOC. When the state of the EV (charging or discharging) is identified, we further consider the current and responding power determined by electricity price and time intervals on peak and off-peak. Note that we divide the peak and off-peak periods according to the time-of-use tariff policy in Beijing, and we assume EV adopters prone to choose to charge their vehicle during the off-peak period in the wee hours, and discharge their vehicle during the peak period at night. We deduce the charging or discharging time according to the relationship between the charging current, initial SOC, and charging capacitor. Then the initial SOC is updated and used for the next iteration. Integrating the charging power of each vehicle, the impact of the V2G technology strategy on grid demand under CNCN goals is simulated.

We focus on the significance of behavior management on the electricity demand and underestimated grid load mitigation, comparing diverse behavior guidance modes with baseline. The results are illustrated in Fig. 6 (a, b). As indicated, effective charging behavior guidance offers a promising opportunity for peak shaving. Guiding EV adopters to charge their cars in the off-peak through subsidy or policy intervention could reduce 41 GW peak electricity demand relative to the SQ scenario (following the current charging pattern), and thus curtail the difference between peak and off-peak 90 GW, 18% more than the overall coal-fired capacity increased forthcoming in the European Union and the United Kingdom combined [7]. Coordinating EV charging with the grid will be in favor of falling off the underestimated load as well (reduced by 46 GW), protecting the grid from an abrupt shortage of electricity supply. On the contrary, the pursuit of fast charging in the long term would present another prospect. When fast charging is widely adopted by EV drivers, the peak power demand will be increased by 11.1% (283 GW) in comparison with BAU. One primary reason is that drives tend to choose high-power chargers in the period after work overlapping significantly with the daily peak power demand. At the same time, provided that a majority of EV adopters prefer to fast charge pattern, the underestimated load doubles (556 GW) as much as ORDER scenarios.

Greater advantages for the grid would occur provided that guiding EV adopters to charge their vehicles during the off-peak time and discharge during the peak time (See Fig. 6(c) and (d)). In the ideal case (V-ORDER scenario), we expect to see the 2272 GW in peak demand on a typical day at 2 p.m. by 2050, reduced by over 7.2% compared with the SQ scenario. Meanwhile, the difference between peak and off-peak load is significantly reduced by 45.8%, demonstrating when the majority of EV adopters with V2G strategy coupled with charging coordinating behavior effectively contribute to smooth load fluctuations. Even though in case EV adopters have a fast charging preference, the V2G strategy still helps markedly decrease the peak electricity demand of 331 GW in comparison with the situation without the technology of bidirectional charge and discharge. As the impact of relieved underestimated load (Fig. 6d), using the V2G charging could at most realize 132 GW of the underestimated load relieved, reduced 31.4% relative to the non-adoption of the V2G strategy. Here, we provide the planning of charging and discharging time when guiding order charging would be widely accepted by EV adopters (Fig. 6e). We find a promising way for them to arrange their charging agenda is to discharge vehicles from 2 p.m. to 10 p.m., which is in peak time of grid, and charge their vehicle at off-peak time in wee hours (before 7 a.m.).

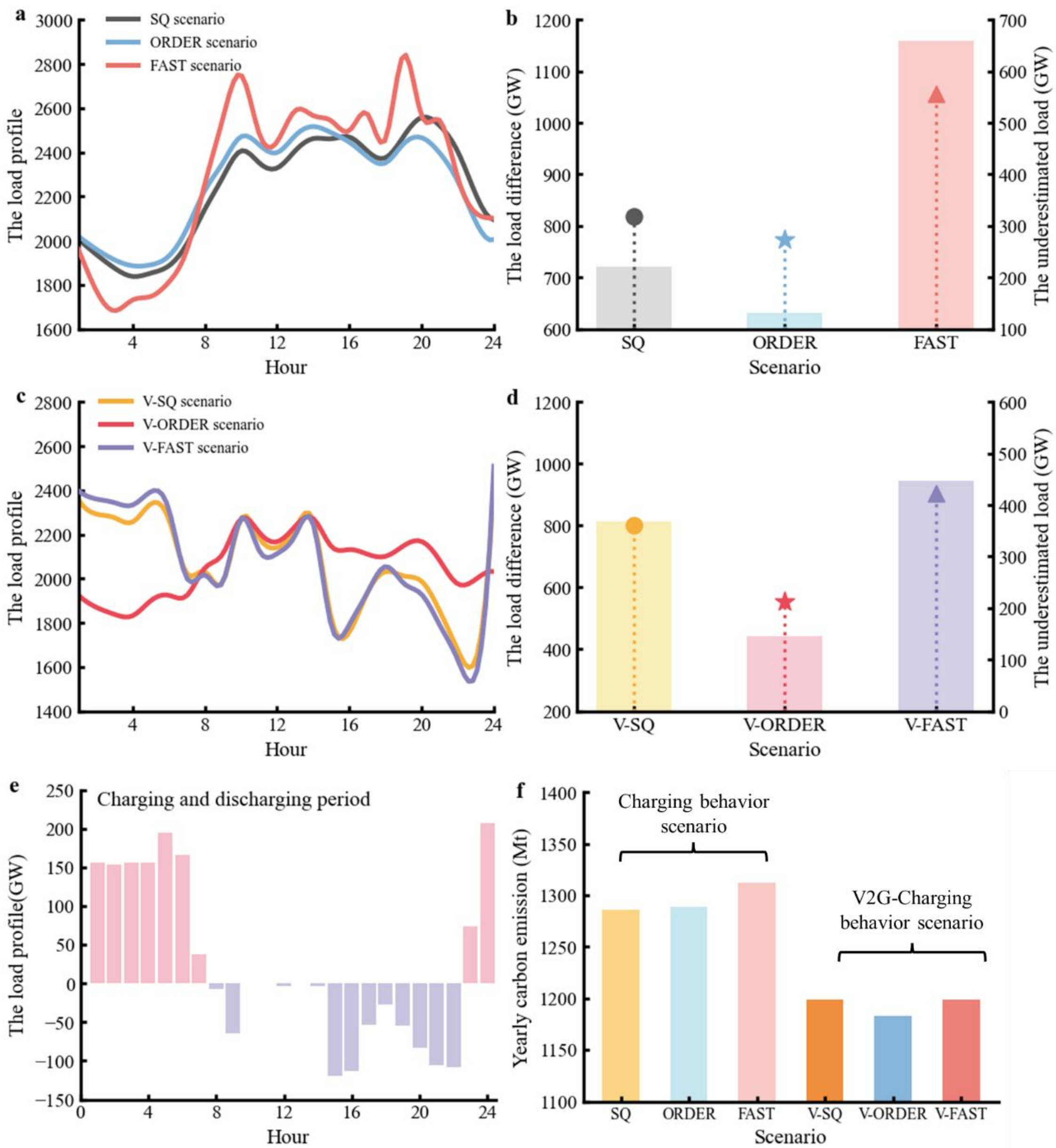

Fig. 6. The impact on the grid and the underestimated load in charging behavior and V2G scenarios under the carbon neutrality goal.

Annual electricity generation emissions of CO_2 caused by deep EV deployment for different EV charging strategies under China's carbon neutrality goal are assessed based on the hourly charging simulation results (Fig. 6f). In the ORDER scenario, CO_2 emissions are nearly identical relative to SQ scenario (1286 Mt) in 2050. However, EV adopters' fast charging preference leads to emit in the electricity sector over 1312 Mt CO_2, far greater than 2.1% compared with net emissions of the SQ scenario. Collectively, the potentials for reduction of CO_2 emissions corresponding to different combinations of V2G strategy and charging behavior are 6.8%-8/0% relative to baseline, indicating the V2G technology provides the most effective latent breakthrough to not only be beneficial for grid load but also for coping with climate change.

5. Conclusion and discussion

This work analyzes the impact on the grid and potentially underestimated electricity demand when EVs are deep employed driven by China's carbon neutrality goal, and explores to what extent these challenges would be settled down by charging behavior guidance and V2G integration. EV adopters who received guidance tended to exhibit more sustainable charging habits, such as charging during off-peak hours, which can help alleviate stress on the grid and reduce carbon emissions. In addition, by expanding the climate scenario to 1.5°C and 2°C goals, we could carry out our analysis framework and the scalable charging behavior scenarios to a broader global context, providing the behavior guidance strategy of EV charging to other countries and districts with similar situations.

Firstly, the most immediate effect on the grid of deep electric vehicle adoption driven by climate goals is the surging electricity demand. Particularly in a stricter climate scenario, China will face an even larger electricity supply gap. Our study shows typically peak demand typically increases by 4.6% under China’s CNCN goals in comparison with the BAU scenario. That suggests that if China realizes its carbon mitigation goal, at least 100 new large-sized generating units are needed to accommodate the growing number of EVs and their charging needs at peak times. When it comes to the potential effect on the grid, the underestimated load will emerge due to the peak-than-average electric demand. Under the CNCN goal, this underestimated load increases by 15.8% compared with no climate goal, indicating an extra 138 billion (CNY) energy storage project investment every year to make up such a huge electricity gap. In the most stringent case, namely, the 1.5°C goal, that gap develops further and underestimation rises by 22.7%.

Secondly, encouraging grid-friendly charging behavior has more co-benefits in terms of power grid security and carbon mitigation. In detail, when we guide EV users to charge their vehicles during the off-peak time of the grid, the peak load fluctuation would sharply decrease. Implementing a charging demand response program and attaching importance to the EV user’s behavior, leads to lower underestimated grid load as well, preventing the grid from temporary shortages of electricity supply in case sudden demand surges from multiple EVs charging simultaneously. On the contrary, dominant fast charging behavior impelled by battery technology and larger battery capacity in the long run, the peak electricity demand will be increased by 11.1%, and the underestimated load doubles in comparison with guiding drivers to stagger their charging times at the off-peak time. Moreover, the predicted situation would get worse if higher EV adopters manifest fast charging habits. Based on the analysis above, the grid should take measures to promote demand response and smart charging programs.

Thirdly, combining the vehicle-to-grid technology and the charging behavior of EV adopters is an effective measure to reduce the grid peak load and the underestimated load under China's CNCN goal. In the ideal situation (V-ORDER scenario), the peak demand would decrease by 7.2% related to our baseline scenario (SQ), bringing about the co-benefits of carbon mitigation. Moreover, even though EV users adopt the fast charging behavior, the V2G strategy contributes to decreasing the peak load substantially. Therefore, taking into account the V2G and the charging behavior in the context of deep EV adoption could be a necessary way to enhance future grid reliability and environmental benefits.

We focus on the EV charging behavior in China, whereas our charging behavior model is useful to other communities and districts, especially those which is experiencing a rapid electrification process, such as the U.S., Norway, and Germany. Owing to our flexible and scalable mixture probability framework, we could develop a large amount of charging behavior scenarios that rely on real-world individual charging and driving data. Combined with the likely charging behavior propensity, the long-term EV adopter's charging scenarios are generated. That depends on the key features of the start time before charging, charging duration, initial SOC, final SOC, charged power, and maximum current. Thus, using these characteristics could help scholars promptly generate large-scale possible charging behavior scenarios.

This study also has some limitations. Our analysis is subject to certain limitations, which provide directions for future research. Firstly, the exogeneity of grid load in our EV charging load forecasting model coupled with the charging behavior model prevents real-time feedback between electric vehicles and grid load. A notable feature of future grids is the maximization of utilizing highly volatile renewable energy sources. Consequently, this study does not account for the coordination between EV electric vehicle charging behavior and periods of renewable energy output, and thus, cannot assess the impact of EV electric vehicle charging behavior on the integration of renewable energy into the grid.

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