Pricing Scheme Design for Vehicle-to-Grid Considering Customers Risk-aversive Behaviors

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Abstract

The increasing penetration of plug-in electric vehicles (PEVs) brings both opportunities and challenges to the power grid. Vehicle-to-grid (V2G) proposes a promising solution that enhances grid resilience, reduces carbon emissions and saves facility investment. However, the actual motivation of drivers to participate in such programs is questionable: they may have to unexpectedly depart earlier than anticipated, thus risking that their vehicles are not adequately charged. As a consequence, they may refuse to accept the flexible charging plan even though it is attractive in the explicit cost. In this work, we formulate a bi-level model where EV charging station (EVCS) and drivers are considered as distinct entities, both having their own utility functions to maximize. We make extensive discussion on the stochasticity in actual cost of a session, including the energy cost and potential dissatisfaction, of choosing different charging modes. We challenging the widely-adopted assumption that all customers are risk-neutral, and characterize the behavioral differences among different customers with varying time value $\nu$ and risk preference factor $\rho$. Accordingly, we propose a novel pricing/service scheme, denoted as double commitment (DC) to alleviate customers' concerns on energy short when engaging V2G. The name of the scheme suggests that besides the single commitment (SC) on full charge by stated departure, it also allows users to specify a safety window within which EV charge for basic mobility is ensured. We demonstrate that by introducing double commitment, 15% more customers change their charging modes from ASAP to FLEX/V2G. As a consequence, EVCS gains flexibility to save energy costs, which is mainly realized from a reduction of demand charge. Hence, it also helps enhance grid reliability and stability.

Key innovations

- Formalize a risk analysis framework for explaining why customers not choose V2G even with incentives.
- Introduce the game-theoretic perspective to analyze and optimize EVCS pricing schemes.
- Propose a novel scheme as double commitment (DC) to encourage more V2G engagements.

Practical implications

Simulating EVCS and EV owners as a single entity may over-claim the impacts of some operational strategies like V2G. We need to deepen our understanding on customer behaviors for better mechanism design.

Introduction

Background

The dramatic adoption diffusion of plug-in electric vehicles (PEVs) brings both opportunities and challenges to the power infrastructures. On the one hand, stochastic PEV charging demands may increase the grid load fluctuations. On the other hand, if operating coordinately, PEVs can serve as controllable resources to help grid peak shaving. As many PEVs stay at EVCS much longer than their minimum required charging time (Wolbertus et al., 2018), they are even possible to charge the (micro-)grids when bi-directional charging is enabled. It is especially important for grids with high penetration of renewables, because its generation is intrinsically stochastic and time-varying.

We categorize charging plans into three types:

- ASAP (as-soon-as-possible mode): always charging with maximum power till fully-charged
- FLEX (flexible mode): the station coordinates and optimizes charging powers of each PEV, but discharging is not allowed
- V2G (vehicle-to-grid mode): station may even discharge PEVs at certain time slots if it finds it profitable and feasible

V2G¹ proposes a promising solution that enhances grid resilience, reduces carbon emissions and saves investment (Színai et al., 2020; Sovacool et al., 2018; Haupt et al., 2020), since nowadays, to balance the supply and demand, grids have to turn on peaking plants with high emissions, and/or invest intensively in energy storage systems.

Related work

To promote V2G, both hardware and market design innovations are required (Hannan et al., 2022; Das et al., 2020). Price menu design of charging fees is an important component of charging station management, and remains an active area of research. Several price menu

¹Since most benefits and concerns of FLEX and V2G are shared conceptually, we sometimes use them interchangeably in the introduction part.
design strategies have suggested that it can be beneficial to all three parties in numerical simulations (Limmer, 2019). EVCS managers incentivize PEVs to accept flexible charging schedules, so that they can be managed as controllable loads (Zeng et al., 2021; Xu et al., 2018). Some recent works explore fairly sophisticated frameworks as dynamic (time-varying) and heterogeneous (same time for different requests), e.g., (Lu et al., 2022).

However, their real performance is largely remain untested since high-quality empirical data on customers’ behavioral model is very limited (Huang et al., 2021). Most existing literature is stated preference (SP) analysis, i.e., enrolling participants to complete online questionnaire of choice experiments with imaginary scenarios. Parsons et al. (2014) is among the earliest research on willingness to keep a V2G contract (which is long term in its context), and find that the required incentive is very high for the acceptance. Wolinetz et al. (2018) points out that a groundless over-optimistic on V2G willingness may lead to biased estimation on various operation innovations and facility investments. It is a particular challenge on how to acquire the necessary empirical data given the heterogeneity of the population and the diversity of pricing schemes.

Nevertheless, suppose we have a decent model characterizing customers’ utility functions, researcher usually integrate it into a bi-level optimization model, aka a Stackelberg game to seek for optimal policy of the EVCS, or for social welfare maximization. Applied game-theoretic research specific to V2G context can be dated back to a decade ago, e.g., Wu et al. (2012) and Tushar et al. (2012). However, since different models hold different assumptions on customer utilities, market structures, and operational constraints, there are still plenty of real-world phenomenon lacking good understanding.

We state an inspiring example here: During a one-year field experiment in two pilot charging stations in California (Smart Learning Pilot for EV Charging Stations (SLEpEV), Zeng et al. (2021)), where ASAP and FLEX modes are available, 59% of charging sessions were selected to be ASAP even though it would be more expensive. The rest 41% sessions were FLEX mode (note that discharge is not allowed in this program). For sessions in ASAP mode, EVs overstayed for 2.41 hours (52% of duration) on average, indicating a large potential in charging power optimization. For sessions in FLEX mode, 28% of them departed half an hour earlier or longer, and 14.5% were earlier for more than one hour. Consequently, only 28% of FLEX sessions met at least 90% of required charge, and 54% of them were short in more than 20% of charge. These field data suggests that: (1) participation rate of FLEX charging program was relatively low; (2) overstay issue was common and reduced station’s service capacity and efficiency; (3) for PEVs chose the FLEX plan, many of them departed earlier than claimed and failed to get fully-charged.

Contribution
In this work, we propose a novel price menu design approach to encourage FLEX / V2G engagement. Specifically, our main contributions are as follows:

- We formalize risk analysis which emphasizes the stochasticity of FLEX/V2G charging modes and customers’ risk-averse behaviors. We propose simple and universal personal attributes, e.g., value of time and risk preference factor, to capture the heterogeneity across the population.
- We introduce a game-theoretic framework where both EVCS and EV drivers have their own utility functions to maximize. Particularly, we compute the “actual” cost of a charging session including potential dissatisfaction caused by energy shortage. We model customers’ choices with risk proxy CVaR (conditional value-at-risk) besides mean value.
- We propose a novel scheme as double commitment (DC) to encourage more V2G engagements. The scheme allows users to specify a safety window within which EV charge for basic mobility is ensured. We analyze its impact on both customers’ decision making and EVCS’s energy management.

Methods

Customers’ decision model
For PEV $i$, arriving at $t^i$, its actual departure time is $t^i_d$, which is unknown by either its own driver or EVCS at its arrival. The driver only knows its distribution, say a Gaussian $N(t^i_d, \sigma^2)$. The driver decides the stated departure time $t^i_d$ and charging mode $m \in \{\text{ASAP, FLEX, V2G}\}$, to maximize her utility, defined as:\footnote{In this section, since we are discussing single PEV, the subscript $i$ is omitted for simplicity. Further, without loss of generality, we assume $\tau = 0$ and $E^{\text{init}} = 0$, thus $\tau^i, t^i_d$ and $c^i$ actually means the duration / fueled energy, etc.}

$$U(t^i_d, m) = \rho \mathbb{E}\left\{\Phi \mid t^i_d, m\right\} + (1 - \rho) \text{CVaR}_\alpha \left\{\Phi \mid t^i_d, m\right\}$$

(1)

where $\mathbb{E}\{\cdot\}$ is the expectation of a random variable, and CVaR$_\alpha \{\cdot\}$ is its conditional value-at-risk at cutoff $1 - \alpha$. If the customer is assumed to be risk-neutral, the expected return. CVaR arises from the interest to also incorporate customers’ risk-averse decision patterns. Its value assembles the tail distribution of the cost, i.e., those “worst” events. $\rho \in [0, 1]$ is risk-preference factor, which is one of the individual attributes. By our definition of (1), a $\rho$ close to 1 indicates the customer is almost risk-neutral, while a $\rho$ approaching 0 represents she is more risk-averse.\footnote{We assume customers are never risk-aggressive. However, choosing other risk proxies, e.g., VaR, allows such extensions.}

Realized utility
$\Phi$ in (1) is a random variable$^4$, whose value, the actual utility of a charging session, is revealed once the actual $t^i_d$.

4In mathematics, a random variable is actually a function mapping from the sample space to $\mathbb{R}$.}
and delivered charge $e^d$ are known:

$$
\Phi(t^d, e^d | t^d, m) = -\theta_m^{\text{ch}}(t^d) - \omega^{\text{m}}(E^{\text{req}} - e^d) \quad (2)
$$

where $\theta_m^{\text{ch}}$ is the charging rate for mode $m$, and it is non-increasing in $t^d$, since longer duration gives the station more flexibility. $\omega^{\text{m}}$ is the (monetized) dissatisfaction with the session, increasing with the short in request energy. We further assume:

$$
\begin{align*}
\theta_m^{\text{ch}}(t^d) &= \beta \left[ 1 - \beta_m^\prime \left( 1 - e^{-\beta_m^\prime(t^d - d_m^\prime)^+} \right) \right] \quad (3) \\
\omega^{\text{m}}(E^{\text{req}} - e^d) &= \kappa \nu (E^{\text{req}} - e^d) + (1 - \kappa) \nu \left[ \kappa^\prime E^{\text{req}} - e^d \right] \quad (4)
\end{align*}
$$

where $\beta, \beta_m^\prime, \beta_m^{\prime\prime}$ are parameters in the EVCS price menu, and $\kappa, \kappa^\prime$ parameterize the customers’ dissatisfaction. $\beta$ is the baseline price, and also the constant price for ASAP mode. $d_m^\prime$ is the minimum time to meet the request energy, and only the slack $t^d - d_m^\prime$ will be incentivized if choosing FLEX or V2G.

![Figure 1: Breakdown of the “actual” cost of a charging session.](image)

**Figure 1:** Breakdown of the “actual” cost of a charging session. **left:** energy cost, which depends on the amount of energy delivered, stayed duration hours and selected charging mode. **right:** monetized dissatisfaction (may partly interpreted as value of time) that depends on the energy short at departure and customer’s value of time.

By writing customers’ dissatisfaction in the form of (4), we hope to capture customers’ diminishing marginal utility in delivered energy. $\kappa^\prime \in [0, 1]$ indicates a turning point below which the basic mobility will be restricted, thus the marginal penalty is higher. $\nu$ is considered to be proportional to the “value of time” (VoT) of the customer, since she needs to take some extra time to refuel her vehicle if the target charge is not met. Particularly, when $e^d < \kappa^\prime E^{\text{req}}$, she has to wait at the EVCS until basic level of energy is charged.$^6$

**Estimation of CVaR** For simplicity, let $X(.) = \Phi( | \cdot | t^d, m)$. Let $F_X$ be the distribution function of $X$. CVaR is defined as$^7$:

$$
\text{CVaR}_\alpha \{ X \} = \lambda \alpha \text{Var}_\alpha \{ X \} + (1 - \lambda \alpha) \mathbb{E} \{ X | X > \text{Var}_\alpha \{ X \} \} \quad (5)
$$

where:

$$
\begin{align*}
\text{Var}_\alpha \{ X \} &= \inf \{ z : F_X(z) \geq \alpha \} \\
\lambda \alpha &= \frac{F_X(\text{Var}_\alpha \{ X \}) - \alpha}{1 - \alpha} \quad (6)
\end{align*}
$$

We can hardly use the definition directly to calculate $U(t^d, m)$ given its complexity. Instead, we estimate it by Monte-Carlo simulation. Sample $N$ values of $X$ i.i.d., and sort them such that $x_1 \leq x_2 \leq ... \leq x_N$, then

$$
\begin{align*}
\mathbb{E} \{ X \} &\approx \frac{1}{N} \sum_{n=1}^{N} x_n \\
\text{CVaR}_\alpha \{ X \} &\approx \frac{1}{N} \frac{N}{N'} \sum_{n=1}^{N} x_n, \quad N' = \lfloor \alpha N \rfloor \quad (9)
\end{align*}
$$

We need further know the distribution of $e^d$ in order to draw samples. We assume that, given $t^d$, any feasible state is equally likely, that is: $e^d \sim \text{Unif}(e(t^d), \tau(t^d))$, where $e(t^d), \tau(t^d)$ are the lowest and highest possible SoE at $t^d$. Hence, the joint density $f$ of $(t^d, e^d)$ is

$$
f(t^d, e^d) = \frac{f_X\left(\frac{t^d - e^d}{\sigma^2(t^d)}\right)}{\tau(t^d) - e(t^d)} \leq e^d \leq \tau(t^d) \quad (10)
$$

where $f_X$ is the density of the standard normal distribution $N(0,1)$.

**EVCS energy management**

In this section, we assume EVCS price menu, i.e., parameters of $\beta, \beta_m^\prime, \beta_m^{\prime\prime}$, is fixed. Thus, customers’ decision on charging mode selection is exogenous to EVCS operations. The decision variables of EVCS are charging schedules for onsite PEVs, aligning with their chosen charging modes.

Specifically, consider PEV $i$, arriving at $t^i$, whose initial charge is $E^{\text{init}}$ and rated charging power is $P$. Suppose its driver chooses charging mode $m$ with stated energy request $E^{\text{req}}$ and departure time $t^d$, then the charging power $p_t$ and state of energy $e_t$ at time $t$ are subjected to the following constraints:

$$
\begin{align*}
e_{t+1} &= e_t + p_t \Delta t \\
e_t &= E^{\text{init}}, \quad e_t \geq E^{\text{init}} + E^{\text{req}}
\end{align*}
$$

We denote $\mathcal{P}_t$ and $\mathcal{P}_d$ as the charging limits specific to time step $t$, and let $I_t = \{ t^e \leq t < t^d \}$ as an indicator on whether the PEV is in the EVCS at $t$, then we derive a

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$^5$In general, this requires $\omega^{\text{m}}(\cdot)$ to be non-decreasing and convex in $x$, where $x$ is the short in energy delivery.

$^6$Numerical example: $\beta = 1.00$ [$/\text{kWh}$] as the base charging rate. $\beta_m^{\text{ASAP}} = 0$ thus $\theta_m^{\text{ch}} = \beta_m^\prime = 0.2, \beta_m^{\text{FLEX}} = 0.3, \nu = 0.2, \kappa = 0.8, \nu = 5$ [kWh], $\nu$ can be interpreted as value of time, if normalizing the energy with the maximum power (e.g., VoT = 30$/\text{hr}$ if charging rate is 6 kW). A visual example can be found in Fig.1.

$^7$If $X$ is continuous, i.e., $F_X$ is continuous, then $\lambda \alpha = 0$, thus $\text{CVaR}_\alpha \{ X \} = \mathbb{E} \{ X | X > \text{Var}_\alpha \{ X \} \}$. However, this assumption does not always hold.

$^8$In case $e(t^d) = \tau(t^d)$, $f(t^d, e(t^d)) = f_X\left(\frac{t^d - e(t^d)}{\sigma^2(t^d)}\right)$.

$^9$Still, all $t$ are omitted for simplicity.
unified method to describe constraints of different charging modes:

\[ \mathcal{P}_i \leq p_i \leq \mathcal{P}_i \]

(13)

where

\[ \mathcal{P}_i = \mathcal{P} \cdot \mathbb{1}_i, \quad \text{and} \]

(14)

\[ [\text{ASAP}] \quad \mathcal{P}_i = \min \{ \mathcal{P}, \Delta_i^{-1} (E_{\text{req}} - e_i) \} \cdot \mathbb{1}_i \]

(15)

\[ [\text{FLEX}] \quad \mathcal{P}_i = 0 \]

(16)

\[ [\text{V2G}] \quad \mathcal{P}_i = -\mathcal{P} \cdot \mathbb{1}_i \]

(17)

It should be noticed that such \( \mathcal{P}_i \) and \( \mathcal{P}_i \) are parameters whose values can be determined before charging profile optimization.

EVCS attempts to minimize its operational expenditure (OPEX) with all PEVs’ charging requirements stratified:

\[ \min \sum_{i} \gamma \cdot p_i^{\text{agg}} \Delta_i + \gamma \cdot p_{i}^{\text{max}} \sum_{i} \theta_{i} E_{i}^{\text{req}} \]

(18)

\[ \text{s.t.} \quad p_i^{\text{agg}} = p_i^{\text{base}} + \sum_i p_{i,t} \quad \forall t \]

(19)

\[ p_{i}^{\text{max}} \geq p_i^{\text{agg}} \quad \forall t \]

(20)

\[ \mathcal{P}_i \leq p_{i,t} \leq \mathcal{P}_i \quad \forall i, t \]

(21)

\[ e_{i,t+1} = e_{i,t} + p_{i,t} \Delta t \quad \forall i, t \]

(22)

\[ e_{i}^{\text{init}} \geq E_{i}^{\text{init}} + E_{i}^{\text{req}} \quad \forall i \]

(23)

\[ e_{i}^{\text{init}} \geq E_{i}^{\text{init}} + E_{i}^{\text{req}} \quad \forall i \]

(24)

where \( \gamma \) is the time-of-use tariff (TOU) of electricity from the grid, and \( \sum \) is the demand charge rate, and accordingly, \( p_{i}^{\text{max}} \) is the maximum consumed power within the billing cycle. One can easily extend this model with more facility configurations, e.g., adding a battery system or PV panels, specifying a transformer capacity, or allowing trading surplus energy with the grid.

**Double commitment**

We propose a novel pricing scheme as *double commitment (DC)* to reduce the uncertainty of customers’ choosing FLEX or V2G modes. We name it as double commitment in contrast to the *single commitment (SC)* which the EVCS currently ensures: fully charged by stated departure time \( t^d \). Under DC, the EVCS further ensures customers that their PEVs have certain amount of energy within the safe window \( t \geq t^d - \delta \), in order to release their concern of considerable energy short if departing a bit earlier than their stated departure times.

Formally, introducing DC requires two more variables \( \zeta, \delta \) to indicate the committed energy level and safe window length respectively. Both of them can be either set by the EVCS, or as customer options. We assume \( \zeta \) is fixed, but customers can declare their own safety window \( \delta \). A larger \( \delta \) provides customers more determinacy, but they need to pay for such determinacy \[^{10}\] as it restricts EVCS’s flexibility in energy management. We adopt the following pricing scheme:

\[ \theta_{m}^{\text{DC}} (t^d, \delta) = \zeta \cdot \theta_{m}^{\text{SC}} (t^d - \delta) + (1 - \zeta) \cdot \theta_{m}^{\text{SC}} (t^d) \]

(25)

and replace \( \theta_{m}^{\text{SC}} \) in (3) and (18) with \( \theta_{m}^{\text{DC}} \).

Correspondingly, EVCS needs to keep its commitment, by introducing new constraints:

\[ e_{i,t} \geq E_{i}^{\text{init}} + \zeta E_{i}^{\text{req}} \quad \forall i \geq t^d - \delta \]

(26)

Similar as discussed earlier, when the price parameters are fixed, and customers’ decisions have been revealed, the energy management operations of EVCS is a linear programming (LP) problem.\[^{11}\]

**Results**

**Data source & configurations**

We conduct numerical studies to better demonstrate our ideas and conceptual analyses. We use StrpEV (Zeng et al., 2021) data, which includes detailed energy demand, actual arrival, departure time, and rate (maximum) charging power. For users chose FLEX mode, their scheduled departure times were also recorded. We use the total 773 sessions as our dataset, and randomly associate each of them with time value \( \nu \sim U (10, 30) \) [S/h] and risk preference factor \( \rho \sim U (0,1) \). To simulate more realistic situation for V2G, we assume the PEV battery capacities are 80 kWh, or that of their target energy, whichever is larger, and initial charge \( E_{\text{init}} \) is \( U (0,0.5) \) of the capacities.

For parameters in EVCS pricing scheme and customer dissatisfaction structure, we take the following values: \( \beta = 0.8 \) $/kWh, \beta_{\text{FLEX}} = 0.2, \beta_{\text{V2G}} = 0.25, \beta_{\text{FLEX}}^{\text{V2G}} = 0.3. \) For the energy market configuration, we use day-ahead TOU of California Independent System Operator (CAISO), and shift it a bit in order to make the peak hours of charging load across the TOU peaks. We also set a demand charge rate at 18 $/kWh per billing cycle (month).

When estimating mean and CVaR values, 1000 samples are drawn for each session.

**Reachable sets, risks, & safety windows**

We develop a visualization object as reachable sets to help understand the stochasticity in actual departure times, terminal energy states, and corresponding costs. Fig.2 illustrates reachable sets of different charging modes under SC and DC. The shaded polytopes are the range a time-energy pair may appear, compatible with all constraints in (13)- (17) (as well as (26) for DC). Any state outside the shaded polytopes is either unreachable from the initial state, or cannot reach the commit state(s). Then, time-energy pairs are sampled based on the distribution (10) to simulate potential terminal states (at the actual departure time \( t^d \)), as green dots. For those dots distant from requested energy, a large dissatisfaction penalty will be applied. For ASAP

\[^{10}\]just as what they do for ASAP, but milder or more continuous.

\[^{11}\]When price menu is also to be optimized, which further requires to integrate customers’ behavioral models, the problem is much harder.
Each row for a distinct charging mode, labeled on the left. Columns: left: SC. middle: DC. x-axis is time since arrival. y-axis is the battery charge. Red dashed line is the stated departure time. Green shaded “bell” area is the probability density of actual departure time. (Blue/pink) Polytope is the reachable set, where charge state might be at that time. Green dots are sampled “departure time - departure charge” pairs. right: histogram of actual charging costs, for the same session, with sampling in its reachable set based on its departure time distribution (green dots). Blue for SC and pink for DC. Note that the y-axis is log-scaled. Mean & CVaR values are marked.

Figure 3: Charging cost metrics (mean, CVaR) for different charging modes with varying safe window $\delta$. This is for one session (one driver) whose VoT = 20 $/h, \hat{T}_{d} = 5$ h, and $\bar{\sigma} = 0.75$ h. Solid lines for mean values and dotted lines for CVaR values. This is for one session (one driver) whose VoT = 20 $/h, \hat{T}_{d} = 5$ h, and $\bar{\sigma} = 0.75$ h. Solid lines for mean values and dotted lines for CVaR values.

Impacts on customers, EVCS, and beyond

Both Fig.2 and Fig.3 are conceptual analyses and visualizations on only one single session. Fig.5 validates our approach with large-volume real-world data. Given the price menu, we simulate customers’ choices under SC and DC schemes. With our configurations, around 15% (80 more sessions) more customers would choose FLEX/V2G (mainly V2G) when DC is available. Fig.5 also reveals how their choices are correlated with their personal attributes. The colorbars in each subplot are estimations on one customer’s probability to choose V2G, given her risk preference factor (horizontal) or value of time (vertical) by logistic regression. The results are rather intuitive: the more risk-aversive a person is, or the higher her value of time the person is, the more likely she will value determinacy over economy, and tend to choose ASAP. However, in general, more customers choose V2G modes when DC is available, since with a proper safe window, the “risk” of
Figure 4: EVCS charging profiles under different SC & DC. Blue (SC) and pink (DC) lines are the EVCS optimal aggregated charging profiles over one week, as each driver chooses the charging mode and safety window per the price menu and her own utility function. Gray shades are grid TOU curves, whose value is on the right axis.

V2G is significantly lowered.

When we put the simulated choices into EVCS energy management model, we find that it has a significant impact on the aggregate charging profiles. From Fig.4 we can see that, compared with the SC case, a notable change is the maximum aggregate power is lowered with DC, which is related with a reduction of demand charge. This is because more V2G engaged PEVs provide the station with more flexibility to shape its load in order to reduce its energy cost, especially demand charge. Another interesting observation is the SC profiles show more oscillations, while in the DC scenario, the charging profile during daytime is more stable. This is mainly because that under ASAP mode, the charging power is high while the duration is short. Both changes indicate that the operations of the EVCS, though not directly instructed to do so, become more friendly to the power grid.

Conclusion

In this work, we investigate how the stochasticity in FLEX/V2G charging will arise customers’ concern on energy shortage, which further discourages them from choosing such modes. We formulate a bi-level model where EVCS and drivers are considered as distinct entities, both having their own utility functions to maximize. We make extensive discussion on the stochasticity in actual cost of a session, including the energy cost and potential dissatisfaction, of choosing different charging modes, and develop visualization tools for demonstration.

Then, we propose a novel pricing/service scheme as double commitment (DC) which allows users to specify a safety window within which EV charge for basic mobility is ensured. Our numerical simulation with real-world charging session data shows that by introducing DC, 15% more customers change their charging modes from ASAP to FLEX/V2G. As a consequence, EVCS gains flexibility to save energy costs, which is mainly realized from a reduction of demand charge. Therefore, it also helps enhance grid reliability and stability.

References


