An Optimal Day-Ahead Scheduling Framework for E-Mobility Ecosystem Operation with Drivers' Preferences

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***Abstract*—The future e-mobility ecosystem will be a complex structure with different stakeholders seeking to optimize their operation and benefits. In this paper, a day-ahead grid-to-vehicle (G2V) and vehicle-to-grid (V2G) scheduling framework is proposed including electric vehicles (EVs), charging stations (CSs), and retailers. To facilitate V2G services and to avoid congestion at CSs, two types of trips, i.e., mandatory and optional trips, are defined and formulated. Also, EV drivers' preferences are added to the model as cost/revenue threshold and extra driving distance to enhance the practical aspects of the scheduling framework. An iterative process is proposed to solve the non-cooperative Stackelberg game by determining the optimal routes and CS for each EV, optimal operation of each CS and retailers, and optimal V2G and G2V prices. Extensive simulation studies are carried out for two different e-mobility ecosystems of multiple retailers and CSs as well as numerous EVs based on real data from San Francisco, the USA. The simulation results show that the optional trips not only reduces the cost of EVs and PV curtailment by 8.8-24.2% and 26.4-28.5% on average, respectively, in different scenarios, but also mitigates congestion during specific hours while respecting EV drivers' preferences. Moreover, the simulation results revealed the significant impact of EV drivers preferences on the optimal solutions and cost/revenue of the stakeholders.**

***Index Terms*—E-mobility ecosystem, EV drivers' preferences, G2V and V2G operation, optional trips, three-layer optimization problem.**

NOMENCLATURE

Indices

e,i,r Index for EVs, CSs, and retailers, respectively
m, n Index of buses of distribution network
t Index for hours

Parameters

Δt Time step (s)
η_i^{GU}/η_i^{CH} Efficiency of CGU/chargers at CS i (p.u.)
η_e^{+}/η_e^{-} Efficiency of EV e's battery in G2V/V2G mode (p.u.)
γ_e Power consumed by EV e per km (kWh/km)
$\mathcal{D}_{t,e,i}$ Shortest driving distance between CS i and destination of EV e at time t, (km)
$\mathcal{G}_e$ EV e's driver preference for minimum revenue increase in V2G operation ($)
$\mathcal{K}_e$ EV e's driver preference for maximum extra distance to lower the cost compared to minimum route (in km)
$\mathcal{O}_{t,e,i}$ Shortest driving distance between origin of EV e and CS i at time t (km)
$\overline{\rho}^{-}$/$\underline{\rho}^{-}$ Maximum/Minimum electricity prices offered by CSs for V2G service ($\$/kWh$)
$\overline{\rho}^{re}$/$\underline{\rho}^{re}$ Maximum/Minimum electricity prices offered by retailers to CSs ($\$/kWh$)
$\overline{E}_i^{\mathrm{CGU}}$/$\overline{E}_i^{\mathrm{PV}}$ Capacity of CGU/PV system at CS i (kW)
$\overline{E}_i^{\mathrm{ESS}}$ Capacity of ESS at CS i (kW)
$\overline{E}_e$ Capacity of EV e's battery (kWh)
$\overline{E}_i$ Capacity of CS i (kW)
$\overline{E}_i^{\mathrm{CH}}$ Capacity of chargers at CS i (kW)
$\overline{N}_i^{CH}$ Maximum number of chargers in CS i
$\overline{P}_{m,n,t}$/$\underline{P}_{m,n,t}$ Maximum/Minimum active power flow between bus m and n (kW)
$\overline{Q}_{m,n,t}$/$\underline{Q}_{m,n,t}$ Maximum/Minimum reactive power flow between bus m and n (kVar)
$\overline{SOC}_e$/$\underline{SOC}_e$ Maximum/Minimum SOC of EV e (p.u.)
$\overline{SOC}_i^{ESS}$/$\underline{SOC}_i^{ESS}$ Maximum/Minimum SOC of ESS at CS i (p.u.)
ρ_t^{gas} Natural gas price at time t ($\$/m^3$)
ρ_t^{WM} Wholesale electricity market price at time t ($/kWh)
$\underline{\Delta V}$/$\overline{\Delta V}$ Lower/Upper limit of voltage deviation at bus m
ϑ_e EV e's driver preference for minimum cost reduction in G2V operation ($)
$\widehat{\mathcal{DO}}_{t,e}$ Driving distance of EV e to closest CS at time t (km)
$\widehat{SOC}_{t,e}$ SOC of EV e at time t if EV e charged or discharged at the closest CS (p.u.)
a SOC target
b, c, d, f Cost of battery degradation parameters
$b_{m,n}$/$g_{m,n}$ Susceptance/conductance of transmission line between bus m and n
HV Heat value of fuel on the operation of gas turbine-generator (kWh/m^3)
N^{EV}/N^{CS}/N^{re} Number of EVs/CSs/retailers
SOC_e^{end} SOC of EV e at the end of the day (p.u.)
VCS Virtual charging station
$\zeta_{t,e}$ Shortest driving route to reach the destination directly from origin of EV e at time t without stopping at any CS (km)

Sets

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B, E, R, S, T, F Sets of Buses, EVs, retailers, CSs, hours, and optional trip times, respectively

Variables

$\beta_{t,i,r}$ Binary variable for retailer r by CS i at time t
$\Delta\theta_{m,t}$ Voltage angle deviation on bus m at time t
$\Delta V_{m,t}$ Voltage magnitude deviation on bus m at time t
$\Delta\hat{V}_{m,t}$ Voltage magnitude deviation obtained from the lossless power flow solution on bus m at time t
$\Gamma_{t,e,i}$/$\Pi_{t,e,i}$ Binary variable for CS i for charging/discharging EV e at time t
$\psi_{t,i}$ Binary variable for charging/discharging ESS at CS i
$\rho^{+}_{t,i}$/$\rho^{-}_{t,i}$ Electricity price offered by CS i at time t for charging/discharging EVs (\$/kWh)
$\rho^{AG}_{t,i}$ Electricity price sold to the aggregator by CS i at time t (\$/kWh)
$\rho^{re}_{t,r}$ Electricity price sold to CSs by retailer r at time t (\$/kWh)
$\theta_{m,t}$ Voltage angle of bus m and time t
$\widehat{\rho^{+}_{t,e}}$/$\widehat{\rho^{-}_{t,e}}$ Electricity price offered by the closest CS to EV e at time t in G2V/V2G mode (\$/kWh)
$P_{m,n,t}$/$Q_{m,n,t}$ Active/Reactive power flow between bus m and n at time t (kW/kVar)
$P^{\mathrm{WM}}_{t,r}$/$Q^{WM}_{t,r}$ Active/Reactive power purchased/provided from/by the wholesale market by retailer r at time t (kW/kVar)
$SOC_{0,e}$ Initial SOC of EV e (p.u.)
$SOC_{T,e}$ SOC of EV e at the end of the day (p.u.)
$SOC_{t,e}$ SOC of EV e at time t (p.u.)
$V_{m,t}$ Voltage magnitude of bus m and time t
$X^{+}_{t,e,i}$/$X^{-}_{t,e,i}$ Charging/Discharging power of EV e at CS i at time t (kW)
$Y^{+}_{t,i}$/$Y^{-}_{t,i}$ Charging/Discharging power of ESS of CS i at time t (kW)
$Y^{GU}_{t,i}$ Power produced by CGU/PV system of CS i at time t (kW)
$Y^{PV}_{t,i}$ Local PV generation of CS i at time t (kW)
$Y^{re}_{t,i,r}$/$Q^{re}_{t,i,r}$ Active/Reactive power purchased/provided from/by retailer r by CS i at time t (kW/kVar)

I. INTRODUCTION

RECENT advances in battery storage technologies, that lowered the prices, together with unprecedented awareness towards global warming, created a momentum for electrification of the transportation sector. While offering indisputable environmental benefits and cost saving for consumers in the long term, a large penetration of electric vehicles (EVs) introduces concerns and challenges for power system operation due to uncoordinated EV charging in grid-2-vehicle (G2V) mode. This may lead to severe voltage deviations, power losses and overload of power lines and transformers [1], [2]. Electrifying transportation sector, however, provide new opportunities for the power system operators as well as the EV owners through vehicle-to-grid (V2G) technology. This is because an EV fleet is essentially a mobile storage that can supply flexibility and energy arbitrage services to the grid while creating a new revenue stream for the EV owners [3].

Previous studies on V2G and G2V operation show that coordinated/regulated charging and discharging of EVs can be beneficial for the grid operation [4]–[6]. Also, the possibility of various business models is investigated for charging stations (CSs) operation that provide V2G and G2V services at competitive prices, e.g., [7], where EVs were supposed to select a CS. At the same time, CSs need to choose a retailer to purchase energy while optimising the operation of their onsite generation and storage assets. It, therefore, portrays an ecosystem of EVs, CSs and retailers in which each participant is seeking to maximize its profit or minimize its cost. It is a challenging task to manage EVs demand, and CSs and retailers operation in the ecosystem to achieve satisfaction of all stakeholders. Thus, a day-ahead scheduling framework is required to optimize the operation of the entire system while fulfilling individual stakeholders' objectives.

Numerous studies have investigated different aspects of this problem, which are highlighted in Section I-A. Then, the contributions of this paper are listed in Section I-B.

A. Literature review

The EV scheduling problem has been investigated in numerous research papers from different perspectives in recent years. Most of the literature propose coordinated G2V and V2G operation mechanisms to minimize their impact on the grid. For instance, a two-step EV scheduling methodology was proposed in [8] to minimize EVs' charging impact on the distribution network. The optimal number of EVs to be charged during each hour was determined in the first step and the maximum number of EVs that should be charged during the next hour was obtained in the second step. An iterative two-layer optimization model was proposed in [9] based on a mixed-integer programming to alleviate the negative impact of uncoordinated charging/discharging of a large number of EVs on the grid. In [10], an optimal V2G and G2V control mechanism was offered to reduce the negative impact of EVs on the grid while minimizing EV charging cost and losses of the power system. The authors in [11] developed a two-stage scheduling optimization model including EVs, thermal power units and load demand. The day-ahead schedules of charging and discharging EVs and thermal units were determined in the first step, and charging and discharging schedules of the EVs were obtained afterwards considering demand uncertainties. A smart charging approach was presented in [12] for EV aggregator's operation to optimize power delivered to EVs during G2V mode. Three different options were considered based on electricity prices and charging power rates, and the final decision was made by the EV owners based on their waiting time preferences. In [13], a smart management and scheduling model was proposed for EVs considering desired charging electricity prices, remaining battery capacity, remaining charging time and age of the battery as EV owners' preferences. The proposed algorithms have been developed to optimize EVs operation in [10], [12], [13] and the grid in [8], [9], [11], where the impact of CSs operation is neglected. Thus, only one or two stakeholders were considered by neglecting the impact of other players in the future e-mobility ecosystem. Also, prices were treated as given parameters as opposed to obtaining them in the solutions.

Another group of studies focused on optimal pricing of G2V and/or V2G services in the future e-mobility ecosystem. For example, an optimal pricing scheme was proposed in [14] to coordinate the charging processes of EVs. Another model was developed in [15] for managing EVs in a public CS network through differentiated services including optimal pricing and routing. In their method, CSs were assigned to EVs based on their energy demand and their traveling preferences (i.e., which stations they are willing to visit) to manage waiting time and electricity prices. In [16], a pricing scheme for charging an EV was proposed including two optimization problems to maximize social welfare of CSs and EV owners. In [17], an incentive-based scheduling of EV charging among multiple CSs was studied based on game theory. It aimed to minimize the total electricity cost of the utility and to maximize the payoff of each station. In [18], a pricing methodology for CSs was developed to facilitate consumption of renewable generation. The selection of CSs by EV owners was modeled based on the charging prices, driving distance to CSs and traffic congestion information. In [19], an algorithm was proposed to schedule EVs for G2V and V2G services according to EV driving demand while planning the time and location of the services. The scheduling was based on Time-of-Use pricing. In [20], a CS operation mechanism was developed that jointly optimized pricing, charging scheduling and admission of a single CS. CS's profit was maximized by reducing waiting time at the CS. Unfortunately, the impact of retailers' operation and prices is disregarded in this group of literature, which is quite important as the major provider of electricity and thus a price maker. Also, V2G prices have not been determined in the proposed algorithms.

Game theory has also been used in several studies on this subject, which facilitates price calculation. A day-ahead G2V scheduling was proposed in [21] based on an aggregative game model accounting for the interaction between the EV charging demand and its impact on the electricity prices. In [7], a Stackelberg game was developed, where CSs (as leaders) offered their G2V prices to EVs (as followers), who then select CSs based on prices, travel distances, and expected waiting times at CSs. In [22], an optimization framework based on non-cooperative game was developed using mixed-integer linear programming to allocate CSs to EVs for G2V operation in order to minimize EV waiting times. In these papers, the proposed algorithms can only solve the scheduling problem for a subset of the players in future e-mobility ecosystem, which may lead to sub-optimal solutions, thus lower public acceptance.

Several papers proposed EV scheduling algorithms to provide various services to the grid. A decentralized algorithm was proposed to optimally schedule EV charging and discharging to fulfil load shifting in [23], [24]. In [25], an energy management problem was formulated using dynamic programming to minimize the daily energy cost of plug-in hybrid EVs. In that study, an optimal charging scheme for plug-in hybrid EVs was developed to shave the peak load and flatten the overall load profile from the distribution system operator's perspective. Nevertheless, the CSs operation has not been investigated in these studies.

Multi-objective formulation has also been used in the literature for the EV scheduling problem. In [26], a day-ahead co-optimization problem was proposed to minimize the negative effects of plug-in EVs on the distribution network by minimizing the cost of energy losses and transformer operation cost, while managing reactive and active powers. In [27], a multi-objective optimization problem was proposed to co-optimize customer and system operator objectives. The proposed model controlled the peak load from the system operator's perspective and optimized EVs' costs/revenues and the battery degradation cost from the EVs' perspective. In [28], a multi-objective optimization problem was presented to obtain optimal charging schedule of EVs regarding the operation of transportation network, power network, and CSs. In [29], a multi-objective optimization was developed for scheduling EV's V2G and G2V operation. Co-optimization of electricity cost, battery degradation, grid net exchange and CO_2 emissions has been performed. It can be seen that the proposed multi-objective methods only optimize one stakeholder's operation without accounting for the impact of optimal operation of the other ones. Also, the G2V and V2G prices for different stakeholders have not been obtained in the proposed multi-objective frameworks. Other potential challenges related to multi-objective problems are the dilemma over determining appropriate weights for different objectives and the tractability of a larger optimization problem that should be solved in a single shot [30].

A careful review of the literature shows that the proposed algorithms find the best CS based on the EV drivers' preferences such as minimum driving distance [20], minimum cost of G2V, maximum revenue of V2G [13], and minimum waiting time in CSs [12], [31] without considering diverse attitude of EV drivers to economic incentives. In addition, the EV drivers may react differently to extra driving distances required for cheaper (more expensive) G2V (V2G) services. In other words, EV drivers are modelled fully rational in the literature, which may jeopardize the EV drivers' welfare. In summary, an extensive review of the existing studies indicates the following gaps in knowledge:

- A whole system approach has not been adopted to optimize major stakeholders operation in the ecosystem. Also, the mutual impacts of the stakeholders are ignored by optimizing each stakeholder's operation individually;
- The role of retailers on the operation of the EV's scheduling system and prices has not been investigated;
- They do not offer a mechanism to determine V2G prices;
- In the proposed algorithms, some of the practical aspects of EV scheduling, e.g., EV drivers' preferences and G2V and V2G operation outside of declared trips, were not considered.

B. Main Contributions

In this paper, a comprehensive day-ahead scheduling framework is developed for an e-mobility ecosystem including EVs, CSs, and retailers (as the three major stakeholders) for V2G and G2V operation. In an attempt to improve the practical aspects of the EV scheduling formulation, we propose two major improvements. First, the optional trips (besides mandatory trips) are introduced in the formulation to provide opportunities for G2V and V2G services beyond mandatory trips, explained in Section II-A. As we will see in the simulation studies in Section IV-A, it will enhance convenience and flexibility in EV scheduling and provide an opportunity to encourage more G2V and V2G participation. Second, two new parameters, namely driver's cost/revenue threshold and driver's route preference, are defined and formulated to model diverse reaction of EV drivers to economic incentives, as described in Section II-B. The G2V and V2G prices are also obtained by considering the mutual impact of the stakeholders through an iterative process, which is presented in Section II-C.

The main contributions of this paper are:

1) **Formulating and solving a three-layer optimization problem:** A comprehensive model is developed to consider the operation of all stakeholders in the future e-mobility ecosystem as a three-layer optimization problem. An iterative solution is proposed to solve the problem as a non-cooperative Stackelberg game.
2) **Optional trips:** This provision is expected to improve the practical aspects of EV scheduling problem and provides an opportunity for EV drivers to take advantage of cheaper G2V prices and more expensive V2G prices beyond mandatory trips' timeframe. The effect of optional trips on the cost/revenue of three stakeholders, CS congestion and PV spillage are investigated.
3) **Preferences of EV drivers:** Two important practical aspects of the EV scheduling problem are considered by adding new constraints in order to model economically-irrational decisions taken by the EV drivers in response to economic incentives. These constraints are driver's cost/revenue threshold and driver's route preference.

The rest of the paper is organised as follows: Section II presents problem definition and describes the structure of the proposed G2V and V2G framework including the three stakeholders. It is followed by the proposed three-layer optimization formulation in Section III. In Section IV, two ecosystems are proposed for simulation and a series of studies are carried out to show the effectiveness of the proposed framework. Simulation results are discussed and the paper is concluded in Section V.

II. Problem Definition

This paper presents a day-ahead scheduling framework for e-mobility ecosystems including EVs, CSs, and retailers as three major players. In the proposed ecosystem, illustrated in Fig 1, there are multiple retailers selling electricity to CSs from the wholesale electricity market. The CSs are the charging stations located in the scheduling area. They operate at the distribution system to serve EVs during G2V and V2G operation. For the sake of completeness, each CS is assumed to own and operate an onsite small gas turbine/diesel generator as a conventional generation unit (CGU), photovoltaic (PV), and energy storage system (ESS), which can be used to supply electricity to EVs during G2V operation. Also, CSs purchase V2G services from EVs and sell it in the wholesale electricity market through aggregators. It is assumed that conventional retailers are not allowed to sell electricity to the wholesale market (i.e., simultaneous buying and selling energy are prohibited).

In order to facilitate cost-effective operation of the stakeholders, to mitigate congestion and PV curtailment at CSs, and to consider EV drivers' preferences, two kinds of trips and extra constraints are defined and formulated in this paper, which are explained in detail in Sections II-A and II-B, respectively.

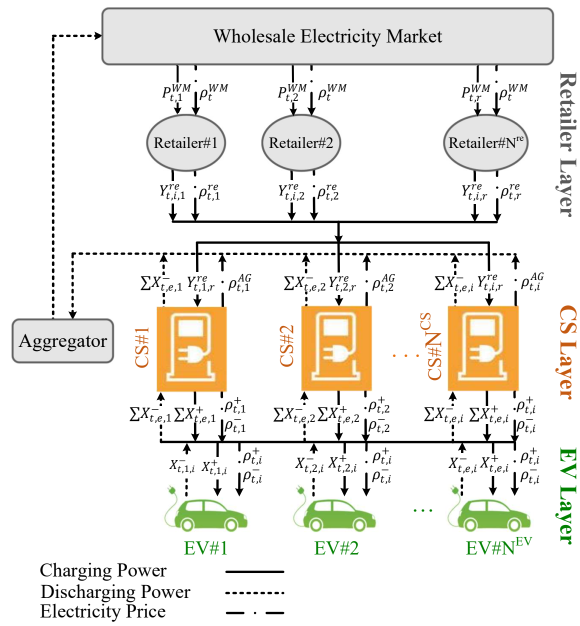

Fig. 1. Schematic diagram of the future e-mobility ecosystem.

A. Different types of trips

As shown in Fig. 2, EVs can have two kinds of trips during a typical day: mandatory trip and optional trip. Each EV can have multiple mandatory trips with known departure time, origin, and destination for each trip. These trips will be fulfilled at any cost. In other times, e.g., between two mandatory trips, EV drivers may have time for G2V and/or V2G services if the prices are right. This is the basis for what is called optional trip in this study. An optional trip, as opposed to mandatory trip, provides a chance for EV drivers to take advantage of cheap G2V or expensive V2G services outside of the mandatory trip time frame; thus reduce their overall cost. Overall, EVs with a known location and initial state of charge (SOC) seek a G2V and V2G plan for the combined mandatory and optional trips such that it minimizes their overall cost while respecting their preferences. The optional trips also help CSs to sell their excess energy, to provide services to the upper grid that generates revenue for EVs, and to enable CSs to alleviate congestion.

The scheduling problem is solved for the entire day ahead. EV drivers submit their plans for mandatory and optional trips to the scheduling centre (which could be a cloud platform with monthly subscription fee) a day before the scheduling day. As shown in Fig. 2, there are N^{CS} real CSs with known driving routes from EV origin in each trip, only one of which might be scheduled for EV e. Therefore, each CS is represented by two binary variables in the EV e problem for G2V and V2G operation at each time interval (as shown in Fig. 3).

As mentioned before, a mandatory trip should always be accomplished. Let's consider a mandatory trip in which the most economic decision for EV e is not to be charged nor discharged. In this case, none of the actual CSs should be selected and yet, the battery SOC values should be updated at the end of the trip and the shortest route should be selected. For this purpose, we introduced Virtual CS (VCS) in our model that represents the shortest route to reach the destination directly from EV's origin, as shown in Fig. 2. When VCS is selected, EV e arrives at the destination from its origin without charging or discharging, while it is ensured that the EV's preferences and constraints are satisfied. Hence, G2V and V2G power of a VCS in a mandatory trip are equal to zero for EV e. A VCS is also needed for EV e in an optional trip to correctly model the solution in which neither G2V or V2G services are recommended. The only difference between VCS in optional and mandatory trips is that the driving route of a VCS is zero in the optional trip. Thus, the EV will be idle for that optional trip.

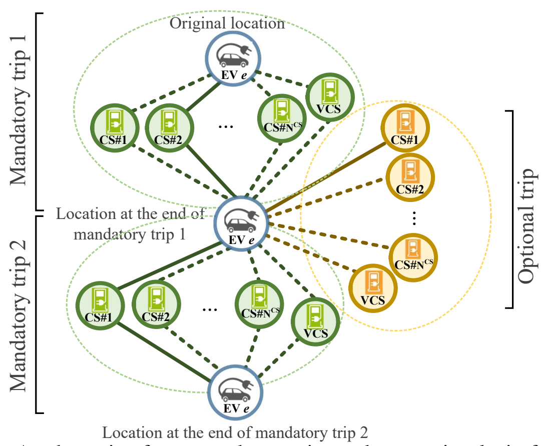

Fig. 2. A schematic of two mandatory trips and one optional trip for EV e.

B. EV drivers preferences

In this study, two practical aspects of the EV scheduling problem are modeled by defining "driver's cost/revenue threshold" and "driver's route preference" constraints. They represent economically-irrational decisions of the EV drivers, as explained in the following subsections.

1) Driver's cost/revenue threshold

We are assuming that EV drivers accept an alternative route (instead of the shortest route) only if there is an economic incentive greater than or equal to the drivers' expectation. When a CS offers a lower price than the nearest CS for G2V service, the EV driver accepts it only if the charging cost reduction is equal to or more than the driver's cost threshold. Otherwise, the EV driver would prefer to charge at the nearest CS although it may be a bit more expensive. The same argument can be made during the V2G services, where a driver chooses a CS with higher V2G prices over the nearest CS only if the increase in revenue is equal to or more than the driver's revenue threshold.

2) Driver's route preference

In addition to the cost/revenue threshold, an EV driver may accept a CS other than the nearest CS only when the required extra driving distance is equal to or less than "driver's route preference". In other words, the driver's route preference ensures that not only selecting an alternative route makes sense economically to the driver, but also the driver's desire for not being on the road for more than "driver's route preference" is fulfilled in the scheduling process.

Let's see the two preferences in an example. Consider an EV driver whose "cost/revenue threshold" and "route preference" are \$5 and 2 km, respectively. An alternative route will be selected only if the cost-benefit of the alternative route is at least \$5 **AND** the extra driving distance does not go beyond 2 km, both in comparison with the nearest CS.

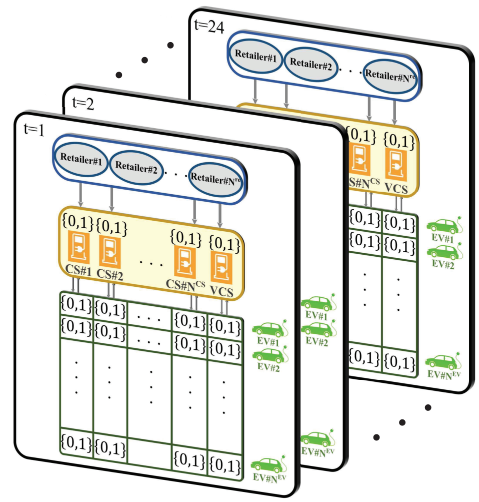

Fig. 3. The proposed framework for day-ahead G2V and V2G scheduling for all stakeholders.

C. The proposed day-ahead scheduling framework/solution

The proposed scheduling framework is a non-cooperative Stackelberg game, which is formed among the three layers [32]. The leader of the Stackelberg game is the retailer and the first and second followers are CSs and EVs, respectively. Typically, three- or n-level non-cooperative games are solved using Karush–Kuhn–Tucker (KKT) optimality condition or strong duality theorem by replacing the lower level problem with a set of constraints in the upper level problem. In this paper, however, the lower level problem is a mixed-integer quadratic program, which doesn't satisfy the KKT optimality condition. Even if there was a differentiable objective function and constraints in the lower level, formulating the complementarity conditions of the lower level in the middle-level problem would result in a non-convex optimisation problem [33], [34].

In this study, we adopted an iterative approach to solve the Stackelberg game, which is common in three-level games in the literature [33], [35]. The solution of this formulation provides a Nash equilibrium, although the uniqueness and existence of Nash equilibrium cannot be guaranteed [33], [34].

As shown in Fig. 4, the electricity prices, estimated using historical wholesale market prices, are generated by retailers in the first iteration. Then, the prices will be given to the CS layer. In this iteration, the prices will be modified by adding CSs' profit margin. Afterwards, CSs' prices will be passed on to EV layer where the first optimization problem will be solved in the first iteration. Please note that the prices for V2G services are also estimated by the CS layer in the first iteration. In the EV layer, the decision variables are EVs' power during G2V and V2G operation, and CS selection for each trip (as shown in Fig. 3). The optimal solutions (i.e., G2V and V2G power of EVs and optimal CSs) for this iteration are sent back to the CS layer, where its optimization problem is solved. The optimal solutions in the CS layer are electricity prices for V2G service, power generation of onsite CGU and PV system, power purchased from retailers, charging/discharging power and operation mode of stationary ESS and optimal retailers for each CS. Afterwards, the EV layer problem will be solved with the updated V2G prices and new EV and CS schedules will be obtained. The inner loop (see Fig 4) will continue between CS and EV layers until the convergence criterion of the optimization problems in the CS layer is satisfied for the given retailers' prices. Since the aggregator operation is not modelled in this paper, the same V2G prices from the first iteration will be used in the inner loop. Upon convergence of the inner loop in the first iteration (of the outer loop), optimal solutions (i.e., selected retailers and power purchased from each) are passed on to Retailer layer. Then, an optimization problem is solved to identify new electricity prices offered by retailers to CSs according to the reactions of CSs and EVs to original prices. Second iteration of the outer loop starts with the new Retailers' prices (see Fig 4). The iterative process will be terminated when the change in the relevant objective functions in the last two iterations for both inner and outer loops is less than or equal to 0.001.

III. Mathematical Modeling

A. Optimization problem in the EV layer

The objective function of EV e is the net cost of EV operation to be minimized. It is the difference between cost of EV e and the revenue from selling electricity to CS i in V2G mode. The cost of EV e comprises electricity purchased from CS i in G2V mode and battery degradation cost (the term inside the bracket of Eq. (1)). We used the battery capacity degradation model from [36], which works for any arbitrary battery charging/discharging profile and captures the impact of battery SOC and charge/discharge power levels. As a result, EVs will be scheduled for V2G services only if they can recover the cost of battery degradation and make a profit. During G2V operation, the battery degradation model ensures that EVs won't be charged excessively unless the benefits of low G2V prices exceed the extra degradation cost of the battery. Please note that the objective is sum of the objective functions of all EVs in this layer.

$$\min_{\substack{X^{+}_{t,e,i},X^{-}_{t,e,i},\\ \Gamma_{t,e,i},\Pi_{t,e,i}}} \sum_{t=1}^{T}\sum_{e=1}^{E} X^{+}_{t,e,i}\cdot\rho^{+}_{t,i} + \Big[b\cdot\big(SOC_{t,e}-a\cdot(\Gamma_{t,e,i}+\Pi_{t,e,i})\big)^{2} + c.X^{+}_{t,e,i} - d.X^{-}_{t,e,i} + f.X^{-2}_{t,e,i}\Big] - X^{-}_{t,e,i}\cdot\rho^{-}_{t,i} \qquad \forall i\in S \tag{1a}$$

s.t.

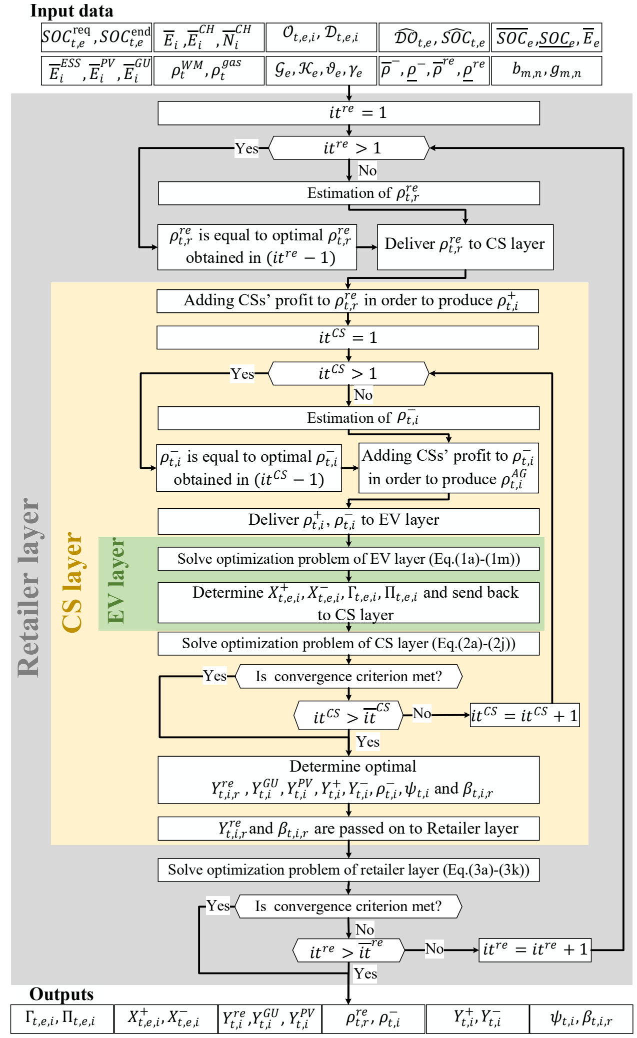

Fig. 4. Flowchart of the three-layer optimization problem.

$$SOC_{t,e} = SOC_{0e} + \frac{\eta^{+}_{e}\cdot\sum_{t=1}^{t} X^{+}_{t,e,i}.\Delta t}{\overline{E}_e} - \frac{\sum_{t=1}^{t} X^{-}_{t,e,i}\Delta t}{\eta^{-}_{e}\overline{E}_e} - \sum_{t=1}^{t}\frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}.(1-\Gamma_{t,e,i}-\Pi_{t,e,i}) - \frac{(\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i})\cdot\gamma_e}{\overline{E}_e}(\Gamma_{t,e,i}+\Pi_{t,e,i}) \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{1b}$$

$$\underline{SOC}_e \le SOC_{t,e} \le \overline{SOC}_e \qquad \forall t\in T, \forall e\in E \tag{1c}$$

$$SOC_{T,e} \ge SOC^{\text{end}}_{e} \qquad \forall e\in E \tag{1d}$$

$$0 \le X^{+}_{t,e,i} \le \overline{E}^{\text{CH}}_{i}.\Gamma_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{1e}$$

$$0 \le X^{-}_{t,e,i} \le \overline{E}^{\text{CH}}_{i}.\Pi_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{1f}$$

$$\sum_{i=1}^{S}(\Pi_{t,e,i}+\Gamma_{t,e,i}) \le 1 \qquad \forall t\in T, \forall e\in E \tag{1g}$$

$$\sum\nolimits_{e\in E}(\Gamma_{t,e,i}+\Pi_{t,e,i}) \le \overline{N}^{CH}_{i} \qquad \forall t\in T, \forall i\in S \tag{1h}$$

$$\rho^{+}_{t,i}.X^{+}_{t,e,i} \le \big(\vartheta_e + \widehat{\rho}^{+}_{t,e}.\widehat{SOC}_{t,e}.\overline{E}_e\big).\Gamma_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{1i}$$

$$\rho^{-}_{t,i}.X^{-}_{t,e,i} \ge \big(\mathcal{G}_e + \widehat{\rho}^{-}_{t,e}.\widehat{SOC}_{t,e}.\overline{E}_e\big).\Pi_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{1j}$$

$$\Gamma_{t,e,i}.(\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i})\leq(\widehat{\mathcal{DO}}_{t,e}+\mathcal{K}_e).\Gamma_{t,e,i} \quad \forall t\in T,\forall e\in E,\forall i\in S \tag{1k}$$

$$\Pi_{t,e,i}.(\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i})\leq(\widehat{\mathcal{DO}}_{t,e}+\mathcal{K}_e).\Pi_{t,e,i} \quad \forall t\in T,\forall e\in E,\forall i\in S \tag{1l}$$

$$X^+_{t,e,i}=0 \qquad \forall t\in T,\forall e\in E,\forall i=VCS \tag{1m}$$

$$X^-_{t,e,i}=0 \qquad \forall t\in T,\forall e\in E,\forall i=VCS \tag{1n}$$

$$\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i}=\zeta_{t,e}\forall t\in(T-F),\forall e\in E,\forall i=VCS \tag{1o}$$

$$\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i}=0 \quad \forall t\in F,\forall e\in E,\forall i=VCS \tag{1p}$$

SOC of EV e after each charge and discharge is calculated by Eq. (1b), while Eq. (1c) ensures that the SOC level is maintained within a lower and upper bound at all times. The SOC of EV e must be greater than or equal to the desired SOC level specified by the driver at the end of the day, as expressed in Eq. (1d). Maximum and minimum charging and discharging capacity of the chargers at CS i are enforced by Eqs. (1e) and (1f). Sum of the binary variables of CSs must be less or equal to one for EV e in order to select one CS for either G2V or V2G operation at time t, imposed by Eq. (1g). Equation (1h) ensures that the number of used chargers in a CS during G2V and V2G operation does not exceed the number of existing chargers. Equations (1i) and (1j) enforce drivers' cost/revenue preferences. Based on Eq. (1i), an EV will be assigned an alternative CS from the nearest CS only if the driver's cost reduction is greater than or equal to her/his expected cost reduction. In V2G mode, Eq. (1j) guarantees a minimum incentive greater than or equal to drivers' revenue expectation for a CS that is not on the shortest route. Equations (1k) and (1l) enforce the driver's route preference in G2V and V2G mode, respectively. In this case, an alternative route will be selected only if the extra driving distance (in comparison with the shortest route) is less than or equal to the specified value. Equations (1m) and (1n) set the VCSs' G2V and V2G power to zero. Based on Eq. (1o), the driving route assigned to VCS for the mandatory trip is equal to the shortest route to reach the destination directly from EV's origin. Equation (1p) set the driving route distance to zero between the EV and VCS in the optional trips.

B. Optimization problem in CS layer

The objective function of CS i is the net revenue of the CS. The revenue of CS i comes from selling electricity to EV e and aggregator during G2V and V2G operation, respectively. We assumed that the electricity purchased from EV e is equal to the electricity sold to the aggregator. The expenses of CS i consists of onsite operational costs [37] and cost of energy purchased from retailer r and EV e during G2V and V2G services, respectively. The overall objective function is the sum of the individual CSs' objective functions.

$$\max_{\substack{Y^{re}_{t,i,r},Y^{GU}_{t,i},Y^{\mathrm{PV}}_{t,i}\\ Y^+_{t,i},Y^-_{t,i},\rho^-_{t,i},\\ \beta_{t,i,r},\psi_{t,i}}} \sum_{t=1}^{T}\sum_{i=1}^{S}\sum\nolimits_{e\in E}(X^+_{t,e,i}.\rho^+_{t,i}+X^-_{t,e,i}.\rho^{\mathrm{AG}}_{t,i}) -Y^{re}_{t,i,r}.\rho^{re}_{t,r}-\sum\nolimits_{e\in E}X^-_{t,e,i}.\rho^-_{t,i} -\frac{Y^{GU}_{t,i}.\rho^{\mathrm{gas}}_t}{\eta^{\mathrm{GU}}_i.HV} \qquad r\in R \tag{2a}$$

s.t.

$$Y^{\mathrm{PV}}_{t,i}+Y^{GU}_{t,i}+Y^{re}_{t,i,r}+Y^-_{t,i}+\sum\nolimits_{e\in E}X^-_{t,e,i}=\frac{\sum_{e\in E}X^-_{t,e,i}}{\eta^{\mathrm{CH}}_i} +\frac{\sum_{e\in E}X^+_{t,e,i}}{\eta^{\mathrm{CH}}_i}+Y^+_{t,i} \qquad \forall t\in T,\forall i\in S,r\in R \tag{2b}$$

$$0\leq Y^{GU}_{t,i}\leq\overline{E}^{\mathrm{GU}}_i \quad \forall t\in T,\forall i\in S \tag{2c}$$

$$0\leq Y^{PV}_{t,i}\leq\overline{E}^{\mathrm{PV}}_i \quad \forall t\in T,\forall i\in S \tag{2d}$$

$$0\leq Y^{re}_{t,i,r}\leq\overline{E}_i.\beta_{t,i,r} \quad \forall t\in T,\forall i\in S,r\in R \tag{2e}$$

$$\sum_{r=1}^{R}\beta_{t,i,r}\leq 1 \quad \forall t\in T,\forall i\in S \tag{2f}$$

$$0\leq Y^+_{t,i}\leq\overline{E}^{\mathrm{ESS}}_i.\psi_{t,i} \quad \forall t\in T,\forall i\in S \tag{2g}$$

$$0\leq Y^-_{t,i}\leq\overline{E}^{\mathrm{ESS}}_i.(1-\psi_{t,i}) \quad \forall t\in T,\forall i\in S \tag{2h}$$

$$\underline{SOC}^{\mathrm{ESS}}_i\leq\frac{\sum_{t=2}^{t}(Y^+_{t,i}-Y^-_{t,i}).\Delta t}{\overline{E}^{ESS}_i}\leq\overline{SOC}^{\mathrm{ESS}}_i \quad \forall t\in T,\forall i\in S \tag{2i}$$

$$\underline{\rho}^-\leq\rho^-_{t,i}\leq\overline{\rho}^- \quad \forall t\in T,\forall i\in S \tag{2j}$$

During G2V and V2G operation, the power balance between supply and demand at CS i will be maintained at all times by Eq. (2b). Therefore, the total power produced by PV system, CGU, stationary ESS during discharging, and power purchased from retailer r and EVs must be equal to the total power demand, including power of stationary ESS in charging mode, power sold to the aggregator and EVs during V2G considering chargers' efficiency. CGU and PV upper and lower capacity limits at CS i are enforced in Eqs. (2c) and (2d), respectively. The power purchased from retailer r is limited by Eq. (2e). $\beta_{t,i,r}$ is a binary variable showing if retailer r is selected by CS i. Equation (2f) ensures that only one retailer is selected by CS i at time t. Charging and discharging power of the stationary ESS at CS i are enforced by Eqs. (2g) and (2h). The upper and lower limits of ESS' SOC in CS i at time t are guaranteed by Eq. (2i). The electricity prices offered by CS i to EV e for V2G services are confined by Eq. (2j).

C. Optimization problem in Retailer layer

The objective function in this layer is the net revenue of all retailers to be maximized. It includes the difference between revenue obtained by selling electricity to CS i, and the cost of electricity purchased from the wholesale market, as given by:

$$\max_{\rho^{\mathrm{re}}_{t,r}} \quad \sum_{t=1}^{T}\sum_{r=1}^{R}\sum\nolimits_{i\in S}Y^{re}_{t,i,r}.\rho^{\mathrm{re}}_{t,r}-P^{\mathrm{WM}}_{t,r}.\rho^{\mathrm{WM}}_t \qquad \forall i\in S \tag{3a}$$

s.t.

$$P^{\mathrm{WM}}_{t,r}=\sum\nolimits_{i\in S}Y^{re}_{t,i,r} \tag{3b}$$

$$Q^{\mathrm{WM}}_{t,r}=\sum\nolimits_{i\in S}Q^{re}_{t,i,r} \tag{3c}$$

$$P_{m,n,t}=g_{m,n}.(1+\Delta\hat{V}_{m,t}).(\Delta V_{m,t}-\Delta V_{n,t}) -b_{m,n}.(\theta_{m,t}-\theta_{n,t}) \quad \forall m,n\in B,\forall t\in T \tag{3d}$$

$$Q_{m,n,t} = -b_{m,n}.(1+\Delta\hat{V}_{m,t}).(\Delta V_{m,t}-\Delta V_{n,t}) -g_{m,n}.(\theta_{m,t}-\theta_{n,t}) \quad \forall m,n \in B, \forall t \in T \tag{3e}$$

$$V_{m,t} = 1+\Delta V_{m,t} \quad \forall m \in B, \forall t \in T \tag{3f}$$

$$\theta_{m,t} = 0+\Delta\theta_{m,t} \quad \forall m \in B, \forall t \in T \tag{3g}$$

$$\underline{\Delta V}_m \leq \Delta V_{m,t} \leq \overline{\Delta V}_m \quad \forall m \in B \tag{3h}$$

$$\underline{P}_{m,n} \leq P_{m,n,t} \leq \overline{P}_{m,n} \quad \forall m,n \in B, \forall t \in T \tag{3i}$$

$$\underline{Q}_{m,n} \leq Q_{m,n,t} \leq \overline{Q}_{m,n} \quad \forall m,n \in B, \forall t \in T \tag{3j}$$

$$\underline{\rho}^{\text{re}} \leq \rho^{\text{re}}_{t,r} \leq \overline{\rho}^{\text{re}} \quad \forall t \in T, \forall r \in R \tag{3k}$$

Equations (3b) and (3c) maintain the balance of active and reactive power at all times. Thus, sum of the electricity purchased from wholesale electricity market through retailer r must be equal to the electricity purchased by CS i from retailer r for active and reactive power at time t. Equations (3d) and (3e) represent real and reactive power flows in the network based on voltage magnitude and angle deviations [38]. Voltages and angles deviations are obtained by Eqs. (3f) and (3g). Equation (3h) guarantees that bus voltages are within permissible range. Active and reactive power of the line are constrained by Eqs. (3i) and (3j). The electricity prices offered by retailers are limited by Eq. (3k) based on their profit margin.

IV. Simulation Results

To assess the effectiveness of the proposed model and the impact of new practical constraints and optional trips on the solutions, a comprehensive simulation study is carried out. The first simulation model contains three retailers, nine CSs, and 600 EVs in San Francisco, the USA, and IEEE 37-bus distribution test system. Without loss of generality, all CSs are assumed to have 30 bidirectional fast DC chargers (50kW). Other simulation parameters are:

- A 65 kW CGU for each CS;
- 16kW, 19.2kW, 24kW, 27.2kW, and 32kW of PV systems randomly assigned to CSs;
- Five one-hour ESS with the capacity of 45kW, 50kW, 65kW, 70kW, and 85kW randomly assigned to CSs;
- Four types of EVs with battery capacity of 14.5kWh, 16kWh, 28kWh, and 40kWh are considered; and
- The initial SOC of EVs is randomly generated between 10% and 95% with mean value of 28%; and
- The desired SOC of EVs at the end of day specified by the drivers is randomly selected between 70% and 90%.

Without loss of generality, it is assumed that each EV plans two mandatory trips and one optional trip in a typical day. The first mandatory trip of 90% of EVs in the fleet is randomly scheduled between 06:00 to 10:00. The optional trip of 90% of EVs is randomly planned between 11:00 to 15:00. Finally, the second mandatory trip of 90% of EVs is assumed to take place between 16:00 to 20:00. The shortest routes between origin of EV e, location of CS i, and destination of EV e for each trip are determined by ArcGIS® prior to optimization. Since end-users should pay network maintenance costs, ancillary services costs, taxes, and etc., the day-ahead electricity prices of the wholesale market (California ISO [39]) is multiplied by 4.5 homogeneously to obtain the prices offered to the CS operators by the retailers. The profit margin of the retailers is assumed to be 5-30%, while the CSs profit margin is varied between 10% to 30%. In addition, electricity prices offered for the V2G service is between 60-85% less than prices offered by retailers. The electricity prices sold to the aggregator by CSs is 10% more than what CSs pay for V2G service to the EV owners. Four simulation scenarios are defined, see Table I, to assess the impact of optional trips and EV drivers' preferences on the cost/revenue of all stakeholders, explained in subsections IV-A and IV-B. The optimization problems are solved by Branch-and-Bound method using Gurobi® solver in Python on a laptop with Intel Core i7 CPU with 1.80GHz processor and 8GB RAM. The MIP optimality gap is set to 0.0001 for all optimization problems.

A larger ecosystem with 1000 EVs, 18 CSs, and three retailers on IEEE 69-bus distribution test system is also simulated, where the simulation parameters and results are explained in Section IV-E.

TABLE I
Different simulation scenarios

Scenario	Optional trip?	EV drivers' preferences?
s_1	Yes	Yes
s_2	Yes	No
s_3	No	Yes
s_4	No	No

TABLE II
Total daily net cost and revenue of the stakeholders with MIP optimality gap

Scenario	Total net cost of EVs [$] (relative MIP gap)	Total net revenue of CSs [$] (relative MIP gap)	Total net revenue of retailers [$] (relative MIP gap)
s_1	1153.4 (0.0097%)	256.4 (0%)	958.1 (0%)
s_2	1000.1 (0.002%)	418.9 (0%)	1333.9 (0%)
s_3	1240.5 (0%)	238.0 (0%)	1040.5 (0%)
s_4	1118.8 (0.0044%)	389.4 (0%)	1382.6 (0%)

TABLE III
Total number of charged and discharged EVs

Scenario	Total # of EVs		# of EVs charged (*discharged*)	
	Charged	Discharged	Mandatory trips	Optional trip
s_1	688	32	434 (*30*)	254 (*2*)
s_2	739	327	448 (*320*)	291 (*7*)
s_3	566	27	566 (*27*)	–
s_4	556	297	556 (*297*)	–

A. The impact of optional trips

In order to quantify the significance of optional trips on the net cost of EVs and the net revenue of CSs and retailers, s_1 and s_2 can be compared with s_3 with s_4, respectively. Table II shows the cost/revenue of each stakeholder obtained in each scenario, where the total net cost of EVs decreased from $1240.5 to $1153.4 and the total revenue of CSs increased from $238.0 in s_3 to $256.4 in s_1. The reduction in retailers' revenue is due to less PV curtailment at CSs (see Fig. 8) in s_1 and thus less energy purchase from the retailers by the CSs. Also, it can be seen from Table III that the number of EVs participated in G2V (V2G) increased from 566 (27) in s_3 to 688 (32) in s_1, and from 556 (297) in s_4 to 739 (327) in s_2. The impact of optional trips on the congestion can be seen in Fig. 5, where more EVs are scheduled to charge in the middle of the day rather than early morning.

A similar pattern has been observed by comparing scenarios s_1 and s_3. It shows that the consideration of optional trips can eliminate/reduce G2V congestion during the hours of mandatory trips, which consequently affect power system operation as a whole by avoiding new peaks and voltage issues, although its impact on V2G is negligible. The optimal hourly averaged electricity prices offered by retailers and CSs during V2G and G2V operation for scenario s_1 are shown in Fig. 6. Since unique prices will be obtained for each stakeholder in this framework, only stakeholders with non-zero prices in an hour are considered in the hourly average calculation. Zero price in an hour shows that no G2V or V2G activity was scheduled in that hour. The prices in Fig. 6 are aligned with the G2V and V2G operation in Fig. 5. Note that the higher G2V prices of CSs from 18:00 to 21:00 is consistent with high V2G prices of CSs and zero prices of retailers to encourage services to the grid by EVs.

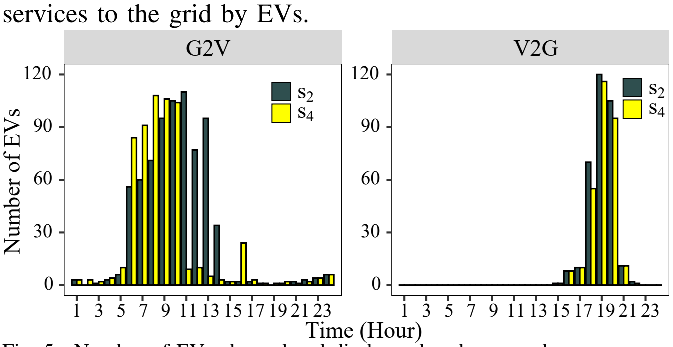

Fig. 5. Number of EVs charged and discharged under s_2 and s_4.

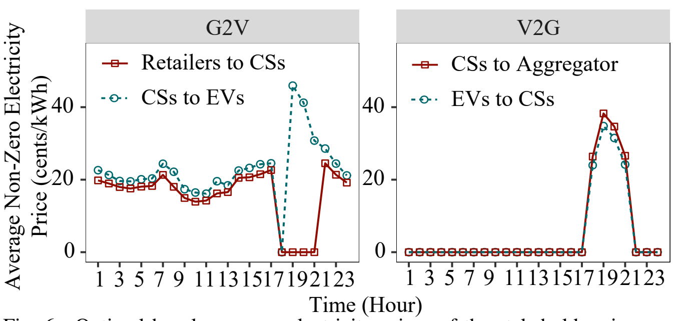

Fig. 6. Optimal hourly average electricity prices of the stakeholders in s_1

The number of EVs who selected VCS during V2G and G2V operation in the mandatory and optional trips is shown in Fig. 7 in s_1. EVs selected VCS 347 times during optional trips, which means that they didn't participate in either G2V or V2G program in those hours. Also, EVs are not scheduled for G2V or V2G 766 times during mandatory trips (176 EV in the first mandatory and 590 in the second mandatory trip) in a day of simulation. In the remaining 687 times, EVs have been scheduled for either G2V or V2G operation.

The impact of optional trips on the total PV curtailment is shown in Fig. 8 for CS#1, CS#2, and CS#6, where considering optional trips led to significant reduction (49.8%, 16.3%, and 13%, respectively,) in PV curtailment. In other CSs, no PV generation was curtailed in the four scenarios.

B. The impact of EV drivers' travel preferences

In this subsection, the impact of drivers' cost/revenue and extra driving distance preferences are investigated. The simulation results in Table II show that when the constraints

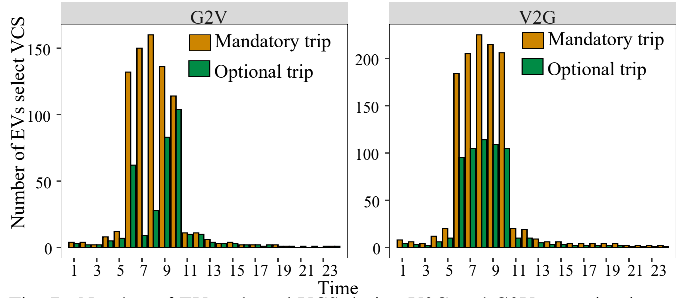

Fig. 7. Number of EVs selected VCS during V2G and G2V operation in s_1.

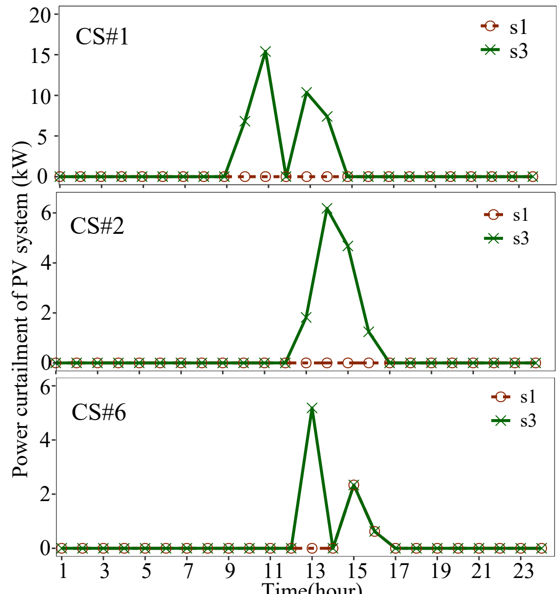

Fig. 8. CS#1, CS#2, and CS#6 PV curtailment in scenario s_1 and s_3.

in Eqs. (1i), (1j), (1k), and (1l) are enforced, the total net cost of EVs increased from \$1000.1 in s_2 to \$1153.4 in s_1. Also, the total net revenue of CSs and retailers decreased from \$418.9 and \$1333.9 in s_2 to \$256.4 and \$958.1 in s_1, respectively. Also, Fig. 9 shows that significantly fewer EVs participated in the V2G program due to drivers' preferences. In particular, the number of EVs participated in V2G increased from 32 in s_1 to 327 in s_2, and from 27 in s_3 to 297 in s_4. Therefore, eliminating these preferences leads to significant overestimation of the G2V and V2G services and revenue of retailers and CS, and underestimation of EV's costs.

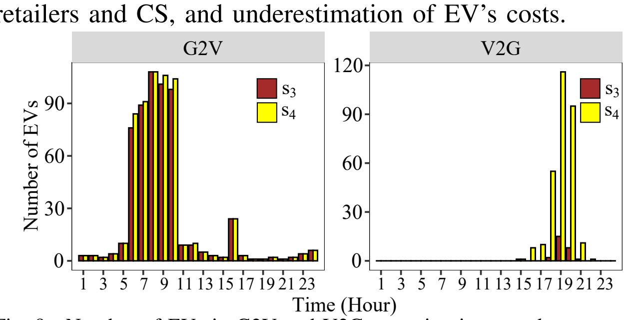

Fig. 9. Number of EVs in G2V and V2G operation in s_3 and s_4.

C. The impact of V2G services

To show the impact of V2G services, the iterative three-layer optimization problems is solved in all scenarios by eliminating V2G services from the framework. A comparison between Table II and Table IV reveals 6.8% increase in the total net cost of EVs on average, and 26.5% and 16.2% decrease in the total net revenue of CSs and retailers on average, respectively, in the absence of V2G services. It depicted the sheer magnitude of V2G impact on the financial interests of all stakeholders in the ecosystem.

TABLE IV
TOTAL DAILY NET COST AND REVENUE OF THE STAKEHOLDERS AFTER ELIMINATING V2G SERVICE

Scenario	Total net cost of EVs [$]	Total net revenue of CSs [$]	Total net revenue of retailers [$]
s_1	1166.1 (0%)	245.8 (0%)	941.3 (0%)
s_2	1154.7 (0.007%)	242 (0%)	933.7 (0%)
s_3	1250 (0%)	235.1 (0%)	1037.4 (0%)
s_4	1249 (0%)	234.1 (0%)	1037.7 (0%)

D. The impact of three-layer iterative optimization

Table V shows a comparison between cost/revenue of three stakeholders for two different cases as defined below:

- ◇ Case I: This the case in which the proposed three-layer optimization problem is solved iteratively to find equilibrium based on the flowchart in Fig. 4.
- ◇ Case II: The optimization problems in the three layers are solved individually, not iteratively. Thus, G2V and V2G prices are not updated and the impact of G2V prices offered by retailers and V2G prices offered by CSs are not considered.

Similar optional trips and EV drivers' preferences are considered in both cases. It can be observed in Table V that the total net cost of EVs in Case II increased by 1.65% and the total net revenue of CSs and retailers decreased by 22.5% and 3.95%, respectively, compared to Case I. It should be mentioned that when the optimization problems in the three layers are solved individually, fewer EVs participated in G2V and the V2G program, which led to significant decrease in the total net revenue of CSs.

TABLE V
TOTAL NET COST AND REVENUE OF ALL STAKEHOLDERS IN s_1

Cost/Revenue	Case I	Case II
Total net cost of EVs ($)	1153.4	1172.4
Total net revenue of CSs ($)	256.4	198.7
Total net revenue of retailers ($)	958.1	920.3

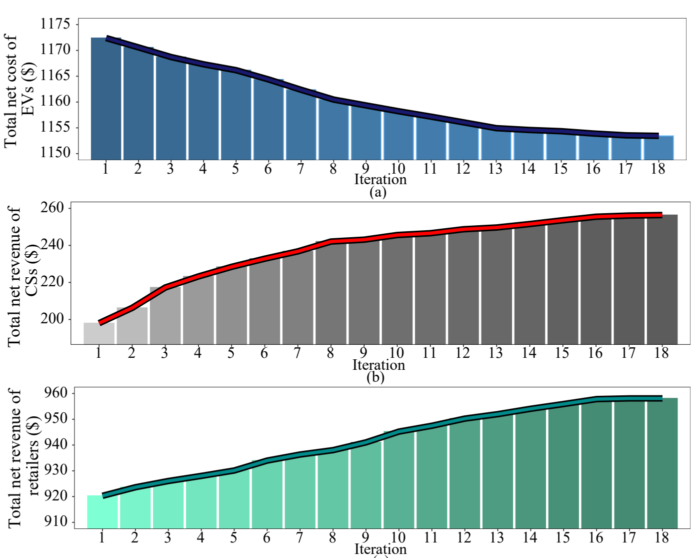

Fig. 10. (a) EV layer, (b) CS layer, and (c) Retailer layer objective function values at different iterations

The optimization algorithms convergence for the three layers is shown in Fig. 10 in scenario s_1, where optimal results are obtained after 18 iterations of the outer loop in 37 minutes.

E. Scalability and convergence of the proposed solution

In this section, a larger e-mobility ecosystem with 1000 EVs, 18 CSs, three retailers on the IEEE 69-bus distribution test system is designed to show the scalability of the proposed solution. In this simulation study, the first mandatory trip of 88.5% of EVs in the fleet is randomly scheduled between 06:00 to 10:00. The optional trip of 85% of EVs is randomly planned between 11:00 to 15:00. Finally, the second mandatory trip of 76.8% of EVs is assumed to take place between 16:00 to 20:00. Simulation parameters of CSs and EVs are identical to the first simulation study with 600 EVs. The optimal results are obtained after only 19 iterations of the outer loop in 113 minutes on average. The total net cost of EVs and total net revenue of CSs and retailers for all scenarios are given in Table VI. It shows that the proposed solution can manage to solve scheduling problem of a larger ecosystem in a reasonable time. The trends in the cost and revenue changes of the stakeholders from one scenario to another are similar to those observed in the smaller ecosystem in Section IV-A.

TABLE VI
TOTAL DAILY NET COST AND REVENUE OF THE STAKEHOLDERS FOR LARGER E-MOBILITY ECOSYSTEM

Scenario	Total net cost of EVs [$] (relative MIP gap)	Total net revenue of CSs [$] (relative MIP gap)	Total net revenue of retailers [$] (relative MIP gap)
s_1	1653.2 (0%)	400.8 (0.0015%)	1422.61 (0%)
s_2	1413.3 (0.0083%)	649.3 (0%)	1960.8 (0%)
s_3	2050.1 (0.0096%)	375.5 (0.0016%)	1545.5(0%)
s_4	1986.7 (0.0041%)	417.2 (0%)	1612.1 (0%)

Furthermore, a sensitivity analysis is performed for 10 cases with different simulation parameters to demonstrate the convergence of the proposed iterative algorithm. The simulation parameters (# of EVs and CSs and trips planning) are presented in Table VII. The total net cost of EVs and total net revenue of CSs and retailers as well as the corresponding relative MIP Gap are reported in Table VII for s_1. In Fig. 11, the convergence rates for total net cost of EVs and optimal total net revenue of CSs and retailers are illustrated. The average computation time for c_1-c_6 and c_7-c_{10} was 39 and 115 minutes, respectively. It can be seen that the proposed solution solved all cases in a reasonable time with a near-zero relative MIP gap.

V. CONCLUSION

In this study, a comprehensive day-ahead scheduling framework is proposed for the future e-mobility ecosystem including EVs, CSs, and retailers by considering both G2V and V2G operation. Two kinds of trips, namely mandatory and optional trips, as well as EV drivers' preferences are formulated to enhance practical aspects of the proposed algorithm. The proposed tool finds the best CS for EV's G2V and V2G operation and the best retailers for CSs to purchase electricity. Also, electricity prices offered by CSs for G2V and V2G services and optimal charging and discharging scheduling of

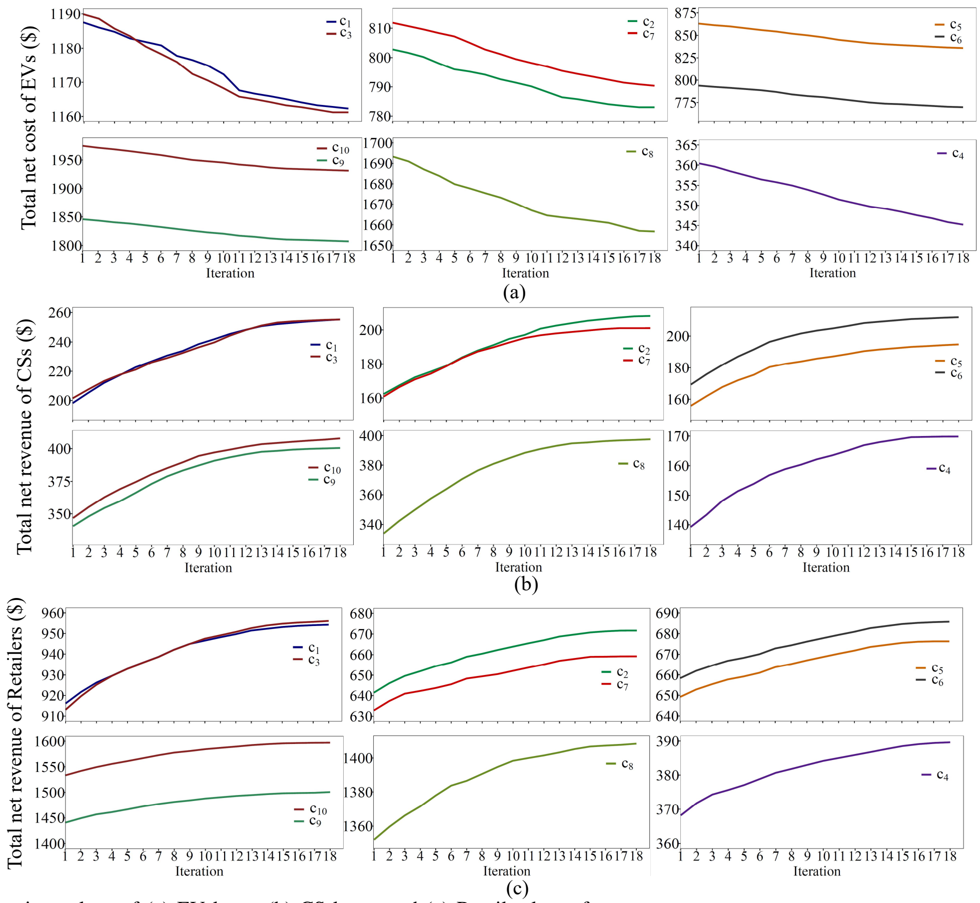

Fig. 11. Objective function values of (a) EV layer, (b) CS layer, and (c) Retailer layer for cases c_1 to c_{10}

TABLE VII
SIMULATION PARAMETERS AND THE TOTAL DAILY NET COST AND REVENUE OF THE STAKEHOLDERS FOR CASES c_1 TO c_{10}

Case	Total # of EVs	Total # of CSs	% of EVs Optional Trip (11:00-15:00)	% of EVs Second Mandatory Trip (16:00-20:00)	Distribution network	Initial SOC (Mean value)	Total net cost of EVs [$] (relative MIP gap)	Total net revenue of CSs [$] (relative MIP gap)	Total net revenue of retailers [$] (relative MIP gap)
c_1	600	9	90%	70%	37-bus system	10-95% (28%)	1162.3 (0%)	255.3 (0%)	954.3 (0%)
c_2	600	9	65%	80%	37-bus system	25-95% (38%)	783.0 (0.0072%)	208.1 (0%)	671.7 (0%)
c_3	600	9	94%	80%	37-bus system	10-95% (28%)	1161.2 (0%)	255 (0%)	956.1 (0%)
c_4	600	9	90%	70%	37-bus system	15-100% (56%)	345 (0%)	169.8 (0%)	389.6 (0%)
c_5	600	9	94%	60%	37-bus system	15-86% (36%)	835.8 (0.0078%)	194.8 (0.0089%)	676.3 (0%)
c_6	600	9	70%	90%	37-bus system	10-74% (37%)	769.3 (0%)	211.6 (0%)	685.8 (0%)
c_7	600	9	60%	60%	37-bus system	25-95% (38%)	789.9 (0%)	201 (0%)	659.2 (0%)
c_8	1000	18	75%	65%	69-bus system	10-100% (33%)	1655.5 (0.009%)	397.5 (0.0015%)	1408.4 (0%)
c_9	1000	18	65%	55%	69-bus system	10-80% (30%)	1806.2 (0.0082%)	400.5 (0%)	1500.6 (0%)
c_{10}	1000	18	55%	45%	69-bus system	10-70% (27%)	1930.4 (0.0077%)	407.9 0.0056%	1597.1 (0%)

EVs are determined considering the impacts of prices offered by retailers through a three layer optimization problem. An iterative solution is proposed to solve the three-level Stackelberg game. Simulation results confirm the value of optional trips to reduce total cost of EVs and congestion at CSs during early morning peak. Furthermore, the proposed scheduling system helped to reduce the cost of EVs and to increase the revenue of CSs and retailers. The drivers' preferences are proven to have an immense impact on the solutions and financial benefits of the stakeholders. In the future study, we plan to model different sources of uncertainties, e.g., EV drivers and PV generation, and solve a stochastic optimization.

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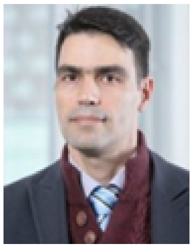

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