A comprehensive day-ahead scheduling strategy for electric vehicles operation

Mahsa Bagheri Tookanlou[a], S. Ali Pourmousavi Kani[b], Mousa Marzband[a,c]

[a] *Faculty of Engineering and Environment, Department of Maths, Physics and Electrical Engineering, Northumbria University Newcastle, Newcastle upon Tyne NE1 8ST, UK*
[b] *School of Electrical and Electronic Engineering, University of Adelaide, Australia*
[c] *Center of research excellence in renewable energy and power systems, King Abdulaziz University, Jeddah, Saudi Arabia*

Abstract

Distribution networks are envisaged to host significant number of electric vehicles and potentially many charging stations in the future to provide charging as well as vehicle-2-grid services to the electric vehicle owners. The main goal of this study is to develop a comprehensive day-ahead scheduling framework to achieve an economically rewarding operation for the ecosystem of electric vehicles, charging stations and retailers using a comprehensive optimal charging/discharging strategy that accounts for the network constraints. To do so, an equilibrium problem is solved using a three-layer iterative optimisation problem for all stakeholders in the ecosystem. EV routing problem is solved based on a cost-benefit analysis rather than choosing the shortest route. The proposed method can be implemented as a cloud scheduling system that is operated by a non-profit entity, e.g., distribution system operators or distribution network service providers, whose role is to collect required information from all agents, perform the day-ahead scheduling, and ultimately communicate the results to relevant stakeholders. To evaluate the effectiveness of the proposed framework, a simulation study, including three retailers, one aggregator, nine charging stations and 600 electric vehicles, is designed based on real data from San Francisco, the USA. The simulation results show that the total cost of electric vehicles decreased by 17.6%, and the total revenue of charging stations and retailers increased by 21.1% and 22.6%, respectively, in comparison with a base case strategy.

Keywords: Charging and discharging strategy, cloud scheduling system, electricity pricing, electric vehicles, three-layer optimisation problem

1. Introduction

A significant amount of private and public money has been invested in electric vehicles (EVs) in recent years in an attempt to reduce fossil fuel consumption and consequently lowering CO_2 emission in transportation sector [1–3]. While electrification of transportation sector has undeniable and significant environmental impacts, a large uptake of EVs introduces new challenges for the grid operation, the biggest of which is uncoordinated EV charging in grid-2-vehicle (G2V) mode. The system's operation will become more chal-

Email address: mahsa.tookanlou@northumbria.ac.uk (Mahsa Bagheri Tookanlou)

lenging when EVs operate in vehicle-2-grid (V2G) mode supporting the upstream grid operation. It has been investigated in several studies [4–7] by showing that a proper coordinated operation of EVs in both G2V and V2G modes can be beneficial for the grid operation. Considering other entities/agents involved in the future electrified transportation sector, e.g., charging stations (CSs) and energy providers (retailers), we will be faced with an unprecedented level of operational complexity. As a result, optimal scheduling of CSs and EVs as well as determining V2G and G2V prices by accounting for EVs driving needs are deemed as one of the significant challenges to facilitate transportation electrification. Also, distribution network service providers are expected to face with extreme voltage violations, increased power losses and overload of transmission lines and transformers [8–10] due to significant increase in demand by uncoordinated EV charging [11–13]. Therefore, a comprehensive optimal day-ahead scheduling framework is needed to overcome the outstanding economic and technical challenges by minimizing the cost of EVs operation while fulfilling their requirements, and maximising the profit of CS operators and other entities/agents while respecting technical limitations of the network.

Numerous studies partially investigated the different aspects of these challenges. Various EV's charging/discharging strategies have been proposed considering customers' preferences. In [14], an EV charging/discharging scheduling and control framework has been proposed to provide grid services considering EV drivers travel requirements. In [15], a charging algorithm has been proposed for allocating power to a large-scale plug-in hybrid EVs at a parking station. EV management and charging/discharging scheduling model have been developed for an intelligent parking lot in [16] considering economical and technical aspects of EV operation, simultaneously. In [17], a bi-level optimisation algorithm was developed based on multi-agent systems to optimise the performance of an EV aggregator and to generate optimal bids for participation in energy markets. The effects of EV's V2G and G2V operation on the power system demand profile as well as the stability and reliability of the power system were investigated in [7]. Various power levels for V2G and G2V operation were considered to estimate its impact on the system reliability. In [18], a coordination algorithm for EVs' V2G and G2V operation was proposed considering the impact of penetration of EV fleets into the power system. In [19], a multi-variant route optimisation model was presented for EVs operation incorporating G2V and V2G options in the travel path. A steady-state analysis of a distribution network was proposed in [20] to determine the nodal voltage variations considering different EVs' charging strategies. A smart charging strategy of EVs at CSs has been introduced offering multiple charging options. In [21], a combination of EV routing and charging/discharging scheduling strategy was proposed to operate an EV fleet. A mixed-integer linear program (MILP) was formulated to maximise the revenue of EV owners subject to EV and distribution network constrains. In [22], a mathematical model is developed for integration of EVs and distributed generation units in energy market under a joint aggregator. Also, the performance of the EV aggregator under the uncertainty of electricity market prices was studied through an stochastic optimisation formulation. A two-stage scheduling framework at the distribution level was proposed in [23]. In the first stage, the charging/discharging schedules of EVs were obtained. In the second stage, the resource were scheduled, i.e., usage profiles of the distributed generation units, strategy of buying electricity from the market, and final charging/discharging patterns of the EVs were obtained. In [24], a framework was presented to develop the network equilibrium traffic and charge patterns in an electric transportation network. In that study, the effects of individual CS on aggregate congestion and electricity costs were investigated. In [25], the optimal traffic-power flow model was reformulated as a mixed integer second-order cone program (MIQP) to optimise coordinated operation of transportation and electricity networks. A framework linking power network with transportation system was proposed in [26] to navigate EVs to CSs using a hierarchical game approach considering reliability of the distribution network and profit of CSs.

Furthermore, numerous studies offered approaches based on a multi-objective optimisation. In [27], a multi-objective optimisation problem was developed for scheduling EV's V2G and G2V operation. Simultaneous optimisation of electricity cost, battery degradation, grid net exchange and CO_2 emissions have been performed. Another multi-objective optimisation problem was developed in [6] to consider both power grid and EV drivers' concerns. The stochastic modelling was proposed to take into account the inherent uncertainty of EV driving activities and renewable energy output power. In [28], a day-ahead co-optimisation problem was developed to minimise the negative impacts of plug-in EVs on the power system operation by minimizing the cost of energy losses and transformer operation cost while managing active and reactive powers. In [29], a multi-objective framework was proposed to schedule EVs' charging and discharging in a smart distribution network, where total operation cost of the distribution network, including EVs and CO_2 emission from distributed generation units and the main grid, was minimised. A multi-objective optimisation problem was proposed in [30] to find optimal charging schedule of a large EV fleet considering the operation of the transportation network, power network, and CSs where the nearest CS was selected as the best option regardless of the electricity prices. A two-stage multi-objective optimisation problem was offered in [31], where the driving needs of EV owners were considered in the first stage. In that study, total energy and emission costs were optimised in the second stage under the uncertainty of solar irradiation and wind speed.

On a relevant subject, an EV charging management system was developed in [32] to guide EVs to a CS such that the negative impact of EVs on the grid is mitigated. The goal was to ensure a proper service to EVs regarding availability of chargers and minimum waiting time at the CS considering user preferences and needs. A CS selection method is proposed in [33] to minimise the travel time, waiting time, and charging cost for an EV.

A review of the existing literature indicates several gaps in research related to G2V and V2G operation as well as CSs operation, which are outlined below:

- The proposed strategies in [6, 7, 14–33] do not optimise the profit of all agents including retailers, CSs, and EVs participating in charging/discharging scheduling, whether collectively or individually. In other words, a comprehensive ecosystem has not been considered in these studies to address different aspects of the G2V and V2G operation considering the effects of optimal operation of CSs and retailers through an iterative process.

- V2G and G2V prices are considered as known parameters in [6, 21–23, 28–31] as opposed to calculating the equilibrium prices as a part of the optimisation problem;
- In [21, 22, 30, 32], the nearest CSs were selected as the optimal option without considering the cost-benefit of the services offered by CS operators.

The goal of this study is to develop a comprehensive day-ahead scheduling framework to guarantee economic and energy-efficient routing of EVs, where each EV finds the best CSs for V2G and G2V operation based on a cost-benefit analysis. It is done by proposing an ecosystem including three stakeholders (EVs, CSs and retailers) and a three-layer optimisation problem. It is formulated and optimised as an equilibrium problem such that the collective benefits of all three stakeholders are guaranteed simultaneously. The main contributions of this paper can be summarised as follows:

- Proposing a comprehensive day-ahead scheduling strategy that represents an ecosystem including the interaction between EVs, CSs, and retailers during EVs' V2G and G2V operation whilst optimising the collective welfare of all agents;
- The coordinated EVs' V2G and G2V operation is formulated and solved such that the effects of optimal operation of CSs and retailers are considered through an iterative process;
- Obtaining optimal day-ahead electricity prices of all agents during V2G and G2V operations such that the collective benefit of all three stakeholders are achieved simultaneously by solving an equilibrium problem iteratively;
- Combining cost/benefit and energy-efficient-routing problems (instead of choosing the shortest route) for each EV to select the best CS, which is integrated with the CSs operation in purchasing electricity from retailers.

This paper is organized as follows. Section 2 describes the structure of the proposed EV charging and discharging strategy incorporating the three agents. Section 3 presents the proposed three-layer optimisation formulation. Salp swarm algorithm (SSA) is used in this study for solving optimisation problems (and compared with particle swarm optimisation (PSO) algorithm), which is explained in Section 4. The case study is introduced in Section 5. The simulation results are presented and discussed in Section 6. Finally, in Section 7, conclusion and recommendation of future work are given.

2. The structure of the proposed ecosystem

In this paper, a comprehensive ecosystem is envisaged for the future electrified transportation sector by considering all three agents, as shown in Figure 1. In this ecosystem, retailers purchase electricity from the wholesale market and sell it to CSs aiming to maximise their profit. The CSs are charging stations with known locations in a given area and operate at the distribution system level as the point of connection of EVs to the main grid in G2V and V2G modes. Similar to retailers, CS operators are looking to maximise their profit in this framework. Both CSs and EVs are entitled to choose their energy providers based on their economic benefits. For the sake of completeness, the CSs are assumed to have onsite conventional generation unit (CGU), photovoltaic (PV), and energy storage system (ESS), which might be used to supply electricity to EVs. An CGU could be a small gas turbine-generator. In this study, conventional retailers are assumed; thus they are not able to sell energy back to the wholesale market by purchasing it from CS operators. Therefore, V2G service is purchased from EVs by CS operators and sold in the wholesale market through an aggregator. Please note that the aggregator optimal operation has not been considered in this study to avoid further complexity and will be considered in our future work.

EVs are the end-users, as shown in Figure 1. During a typical day, EVs might have multiple trips with different waiting times between each trip. EVs with known location and initial state of charge (SOC) plan their charging/discharging depending on the shortest driving route and a cost/benefit analysis based on the CSs prices. Please note that each EV can only be charged or discharged during each trip if there is an economic benefit to do so while respecting the EV's constraints. In this case, EVs require an algorithm to select proper CSs for G2V and V2G operation to minimise their cost.

In order to satisfy the objectives of different agents, a top-to-bottom coordinated method is proposed that solves a day-ahead scheduling problem for all agents. The formulated problem is an equilibrium one that is solved in three layers sequentially and iteratively, where the leader is the retailer agent. The solution to the equilibrium problem is inspired by Walrasian tâtonnement, which leaves the price invariant if and only if it is an equilibrium price [34, 35]. Through the iterative three-layer optimization problem, the operation of each player in the framework is changed by receiving new information from other players to reach the equilibrium point. The proposed solution can be offered to the agents as a cloud scheduling system, which is operated by a non-profit entity (aka price-setter). Its role is to collect required information from all agents, as shown in Figure 2, run the top-to-bottom coordinated scheduling method, and ultimately dispatch the results to relevant agents. Since power system topology is needed to ensure the feasibility of the solutions against network constraints, distribution system operators or distribution network service providers could be the best candidates to take on this role. Since the scheduling system operator does not seek any profit in the proposed framework, accessing to the information of the three stakeholders does not compromise fair operation of the scheduling system. It is assumed that all agents have communication links with the cloud scheduling system. All information exchanged between the stakeholders and the scheduling operator can be end-to-end encrypted, so that it becomes more difficult to compromise the information. The information exchanged between three agents and the cloud scheduling system are detailed in Figure 2. The following assumptions are made in developing the proposed strategy:

- All agents are economically rational within their personal preferences and limitations, which means that they change their behaviour in response to economic incentives;
- It is assumed that each EV can only be charged or discharged during each trip if there is an economic benefit to do so while respecting the EV's constraints. Therefore, there is an implicit constraint in the optimisation formulation that is limiting the number of charge/discharge events, which is based on the EV owner's preferences (as in their day-ahead plan);

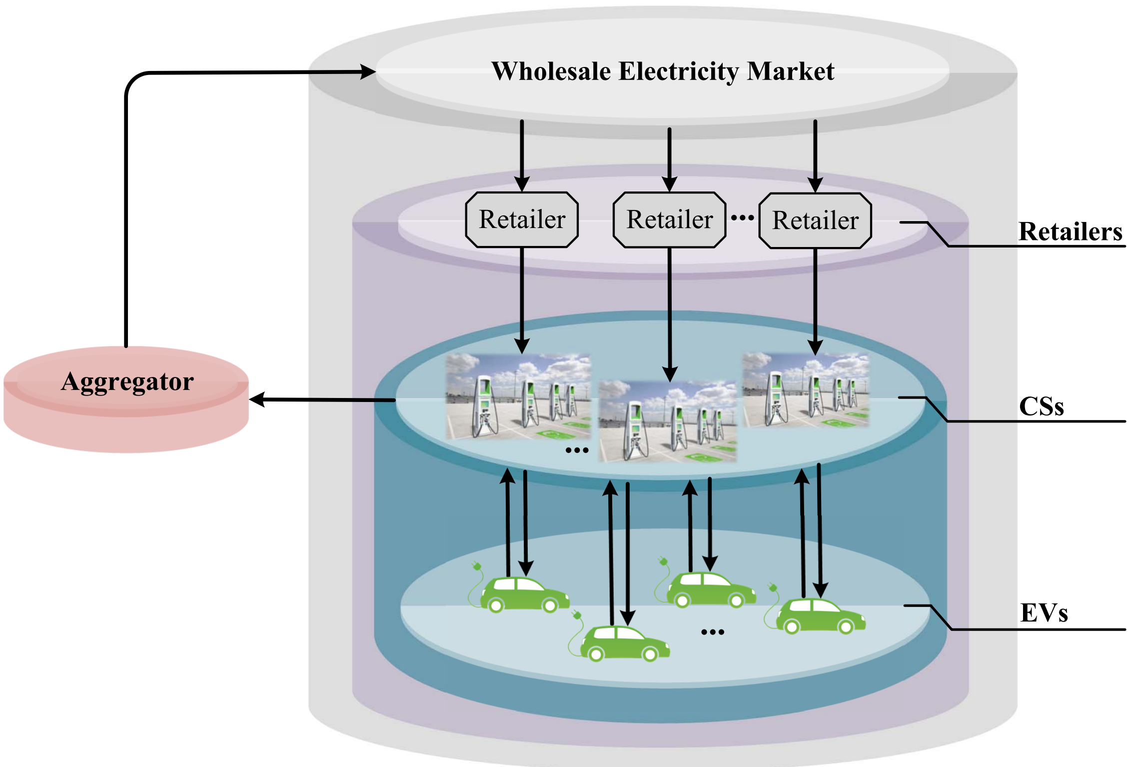


Figure 1: Conceptual structure of the proposed ecosystem including interactions between wholesale electricity market, retailers, aggregator, CSs, and EVs.

- In order to consider EV owners' preferences, a minimum SOC level is specified by the EV owner as the minimum battery SOC at the end of the day;
- All CSs have fast DC charger (22kW and 50kW). This is to ensure that the scheduled G2V or V2G operation will be fulfilled within an hour for any type of EVs;
- In each hour, the number of EVs assigned to a CS is smaller or equal to the number of EV chargers in that station. Therefore, no queuing is required.

There are four steps to implement the proposed strategy, as depicted in Figure 3, that should be followed:

Step 1: At the beginning of the scheduling period, the cloud scheduling system collects required parameters and data from each agent for every hour of the next day. The input parameters that should be communicated to the cloud scheduling system from each agent and decision variables of each agent are summarized in Table 1. It is worth mentioning that some of the parameters do not change on a daily basis; they will be updated when needed by the agent, e.g., number and capacity of available EV chargers in each CS. This way, the amount of required communication bandwidth can be reduced significantly.

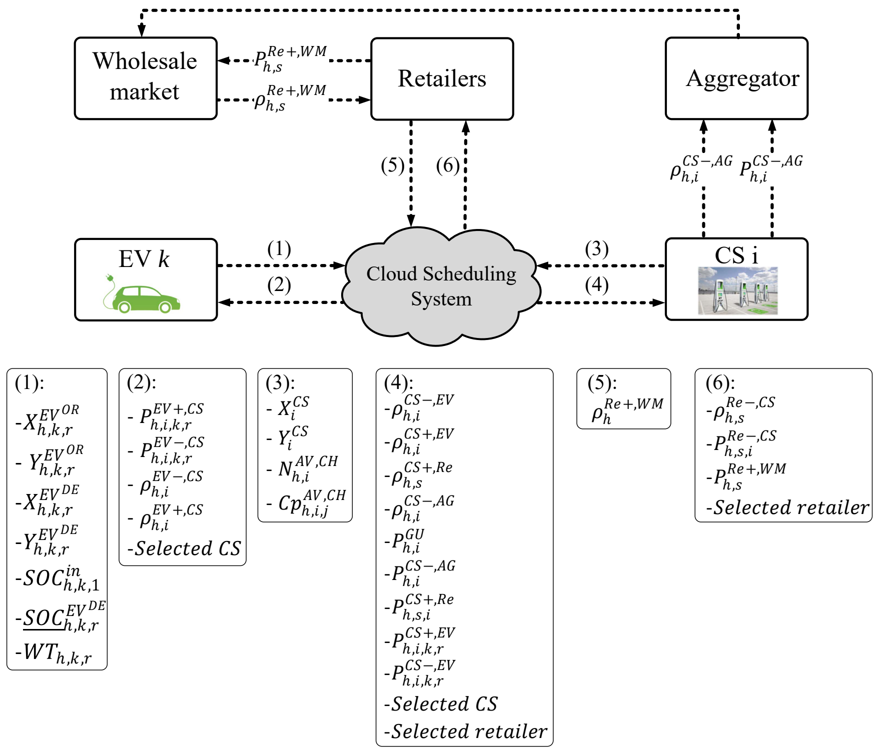


Figure 2: The cloud scheduling system and the required communication links with other agents.

Table 1: Input parameters and decision variables for each agent

Agent	Input Parameters	Decision Variables
Retailers	$\rho_{h,s}^{Re+,WM}$	$\rho_{h,s}^{Re-,CS}$
CSs	X_i^{CS}, Y_i^{CS} $N_{h,i}^{AV,CH}$, $Cp_{h,i,j}^{AV,CH}$	$P_{h,i}^{GU}$, $P_{h,s,i}^{CS+,Re}$, $P_{h,i}^{CS-,AG}$
EVs	$X_{h,k,r}^{EV^{OR}}$, $Y_{h,k,r}^{EV^{OR}}$, $X_{h,k,r}^{EV^{DE}}$, $Y_{h,k,r}^{EV^{DE}}$ $SOC_{h,k,1}^{in}$, $WT_{h,k,r}$, $\underline{SOC}_{h,k,r}^{EV^{DE}}$	$P_{h,i,k,r}^{EV-,CS}$, $P_{h,i,k,r}^{EV+,CS}$

Step 2: Let's assume that each EV is allowed to plan T trips per day where each trip $r \in \{1, \ldots, r, r+1, \ldots, T\}$. The shortest driving route for each trip is determined by a network analyst toolbox called ArcGIS [36] as a navigation platform in the cloud scheduling system. For each hour, the longitude and latitude of each CS, origin and destination of each EV for each trip are used to determine the shortest route considering the traffic pattern in each hour. Five potential shortest driving routes will be identified in step 2: **Route#1**: the shortest driving route between the origin and destination of EV k for trip r; **Route#2**: the shortest driving route between the origin of EV k and the location of CS i for trip r/trip $r+1$; **Route#3**: the shortest driving route between the destinations/origin of EV k for trip r/trip $r+1$ and destination of EV k for trip $r+1$; **Route#4**: the shortest driving route between the location of CS i and destination of EV k for trip r; **Route#5**: the shortest driving route between the location of CS i and the destination of EV k

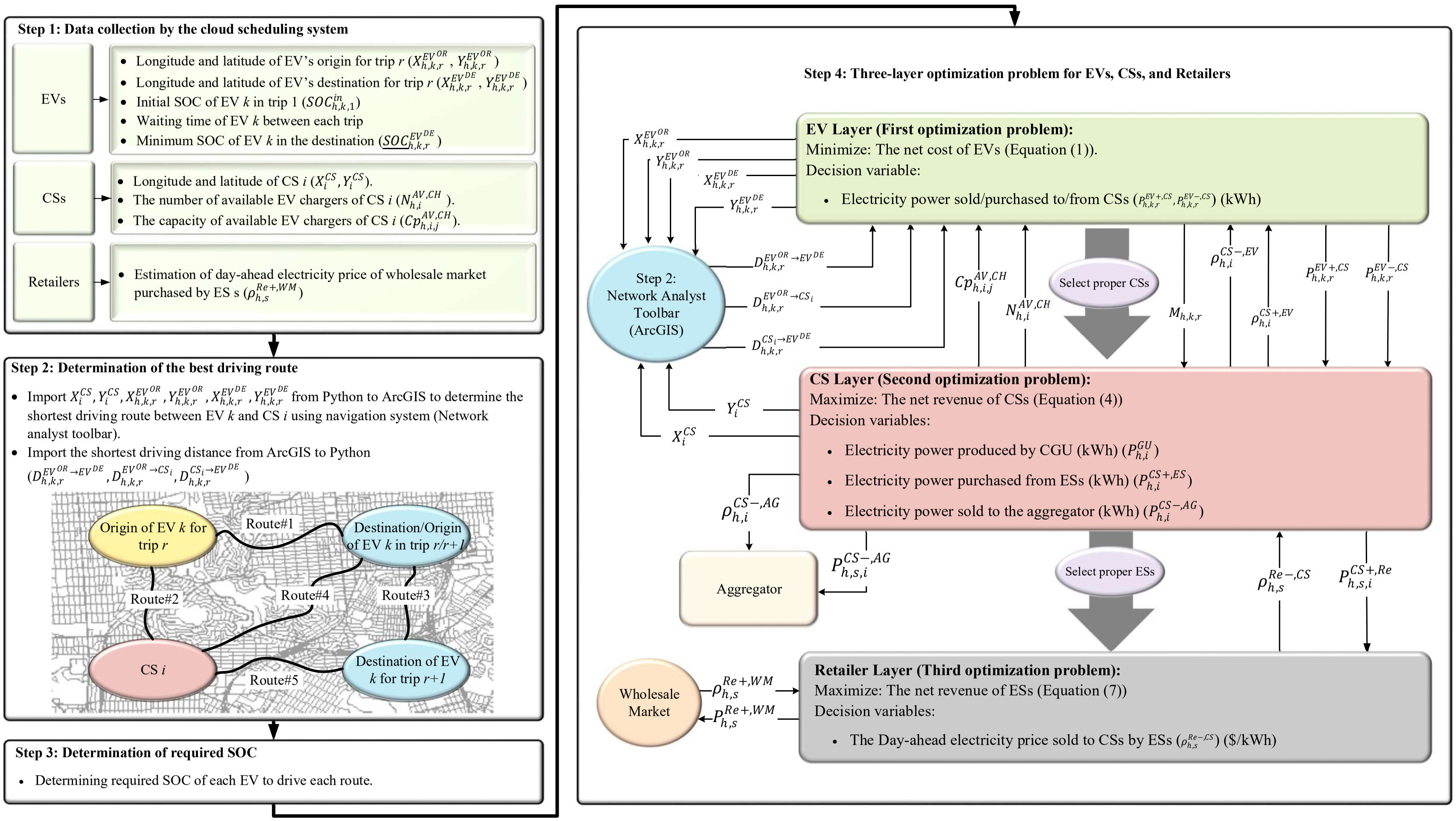


Figure 3: Step-by-step process of implementing the proposed strategy

for trip $r + 1$. As shown in Figure 3, the driving distances corresponding to the five possible driving routes will be used in Step 3.

Step 3: Required energy (in terms of battery SOC changes) to drive each set of the five routes will be calculated in this step for each EV.

Step 4: The framework of the three-layer optimisation problem for EVs, CSs, and retailers is implemented in this step, as shown in Figure 3. Three layers in the framework correspond to the optimisation problem that should be solved for each of the three agents. As shown in Figure 2, parameters are received by the cloud scheduling system, as explained in Table 1. The three optimisation problems are solved iteratively for 24 hours ahead, which is summarised in Algorithm 1. The optimisation problems formulation and the optimisation technique are explained in Section 3 and 4, respectively. Through the iterative three-layer optimization problem, the profit of all agents are optimised as an equilibrium problem. It essentially leads to collective optimisation which can be called social welfare optimisation of the ecosystem. In the equilibrium problem, the iterative algorithm is used to solve, and consequently, update the position of each player in the framework by receiving new information (e.g., new prices) from other players to find the equilibrium point in which the prices do not change. This way, we are able to obtain the prices of V2G and G2V at different level of the system. Since the scheduling system is operated in day-ahead, wholesale market price estimation is needed for the entire next day.

In the first iteration, retailers generate the prices that they would like to offer to CSs based on their profit margin. Then, the prices will be passed on to CS layer in this iteration. The prices increase in CS layer considering their profit margin. Then, CSs communicate the prices to EV layer where the first optimisation problem, i.e., (1)-(2c) with the constraints in (9a)-(14), will be solved for the first time. The optimisation solutions, i.e., energy sold/purchased to/from CSs in each trip, will be sent to the CSs layer, where the operation of CSs will be scheduled by solving the optimisation problem in (4)-(6c) with the constraints given in (15a)-(19c). Ultimately, the optimisation solutions including energy produced by CGUs as well as the electricity traded with retailers and aggregators will be used in Retailer layer to obtain optimal operation of the retailers using the optimisation problem in (7)-(8b) and the constraints in (20a)-(26). As a result, the optimal day-ahead electricity prices sold to CSs by retailers is determined in Retailer layer. The newly generated prices will then be used in the second iteration to repeat the optimisation problems of the EV and CS layers. This iterative process will go on until a certain convergence criterion is met. In this study, the convergence criterion is defined as the change in the objective function in the two consecutive iterations, which should be less than 10^{-3} for all three optimisation problems.

Algorithm 1 **Three-layer optimisation problem for EVs, CSs, and Retailers**

```
▷ Retailer layer
it^Re = 1
while it^Re ≤ \overline{it}^Re do
    Initialize the decision variables in Retailer layer.
    ▷ CS layer
    it^CS = 1
    while it^CS ≤ \overline{it}^CS do
        it^CS = 1
        Initialize the decision variables in CS layer.
        ▷ EV layer
        it^EV = 1
        while it^EV ≤ \overline{it}^EV do
            if it^EV = 1 then
                Initialize the decision variables in EV layer.
                Calculate the objective function in EV layer (Eq. (1))
            else
                Determine the best value of decision variables in EV layer
                Solving optimisation problem of EV layer
                it^EV = it^EV + 1
        Import the optimal value of decision variables from EV layer.
        Calculate the objective function in CS layer (Eq. (4)).
        Determine the best value of decision variables in CS layer
        Solving optimisation problem of CS layer
        it^CS = it^CS + 1
    Import the optimal value of decision variables from CS layer
    Calculate the objective function in Retailer layer (Eq. (7)) for each salp
    Determine the best value of decision variables in Retailer layer
    Solving optimisation problem of Retailer layer
    it^Re = it^Re + 1
```

The cloud scheduling system finds the charging/discharging schedules of all EVs at once, which depends on the V2G and G2V prices in each trip throughout a day and the minimum expected SOC level of EVs by the owners. To identify V2G and G2V mode of each EV during a day, a rule-based approach is developed in this study as follows:

- If G2V prices in trip r is less than V2G prices in trip $r+1$, EV k will be charged in trip r and discharged in trip $r+1$ with regards to the minimum expected SOC level of EV k throughout a day;
- If V2G prices in trip r is more than G2V prices in trip $r+1$, EV k will be discharged in trip r and charged in trip $r+1$ with regards to the minimum SOC level of EV k at the end of the trip.

3. Mathematical modeling

In this section, objective functions and technical constraints for each layer in Step 4 of Figure 3, namely EVs, CSs, and retailers, are presented and explained. For the sake of clarity, objective functions and constraints are presented in separate sub-sections for the three agents.

3.1. *Objective function of EV layer*

The net cost of EV operation must be minimised in this layer, which is the difference between the cost of EVs (including electricity purchased from CSs, $\mathbb{C}^{\text{EV+,CS}}$, and battery degradation cost during V2G operation, $\mathbb{C}^{\text{DEG,EV}}$) and the revenue from selling electricity to CSs, $\mathbb{R}^{\text{EV-,CS}}$, as per below equation:

$$\mathbb{C}^{\text{EV}} = \mathbb{C}^{\text{EV+,CS}} + \mathbb{C}^{\text{DEG,EV}} - \mathbb{R}^{\text{EV-,CS}} \tag{1}$$

The individual cost and revenue terms can be computed as follows:

$$\mathbb{C}^{\text{EV+,CS}} = \sum_{h=1}^{24} \sum_{k=1}^{N^{\text{EV}}} \sum_{r=1}^{N^{\text{T}}} \frac{1}{2} \times M_{h,k,r} \times (M_{h,k,r} + 1) \times P_{h,i,k,r}^{\text{EV+,CS}} \times \rho_{h,i}^{\text{EV+,CS}} \tag{2a}$$

$$\mathbb{C}^{\mathrm{DEG,EV}} = \sum_{h=1}^{24}\sum_{k=1}^{N^{\mathrm{EV}}}\sum_{c=1}^{N^{\mathrm{CYC}}}\sum_{r=1}^{N^{\mathrm{T}}}\frac{1}{2}\times M_{h,k,r}\times(M_{h,k,r}-1)\times c_{p.u}^{\mathrm{BAT}}\times Cp_k^{\mathrm{nom}}\times\frac{\mathbb{D}_{h,k,r}^{\mathrm{EV}}(T^{\mathrm{CYC}})}{Cp_k^{\mathrm{nom}}-Cp_k^{\mathrm{re}}} \tag{2b}$$

$$\mathbb{R}^{\mathrm{EV-,CS}} = \sum_{h=1}^{24}\sum_{i=1}^{N^{\mathrm{CS}}}\sum_{k=1}^{N^{\mathrm{EV}}}\sum_{r=1}^{N^{\mathrm{T}}}\frac{1}{2}\times M_{h,k,r}\times(M_{h,k,r}-1)\times P_{h,i,k,r}^{\mathrm{EV-,CS}}\times\rho_{h,i}^{EV-,CS} \tag{2c}$$

To avoid uneconomical V2G operation, battery degradation should be quantified and its cost should be included in the objective function. As a result, EV owners will be remunerated for V2G services only if they can recover the cost of battery degradation and make some profit. In (2b), the battery degradation cost is considered for EVs during discharging period, which is obtained from the cycling degradation for a given discharge profile using the following equations [37]. The cost considers cycle number, depth of discharge, and discharge rates in optimal scheduling:

$$Cp_k^{\mathrm{re}} = 0.8\times Cp_k^{\mathrm{nom}} \tag{3a}$$

$$\begin{aligned}\mathbb{D}_{h,k,r}^{\mathrm{EV}}(T_c^{\mathrm{CYC}}) =& (\sigma_1\times[DOD_{h,k,r}^{\mathrm{EV}}(T_c^{\mathrm{CYC}})]^2+\sigma_2\times DOD_{h,k,r}^{\mathrm{EV}}(T_c^{\mathrm{CYC}})+\sigma_3)\\ &\times(\phi_1\times[DR_{h,k}^{\mathrm{EV}}(T_c^{\mathrm{CYC}})]^3+\phi_2\times[DR_{h,k}^{\mathrm{EV}}(T_c^{\mathrm{CYC}})]^2+\phi_3\times DR^{\mathrm{EV}}(T_c^{\mathrm{CYC}})+\phi_4)\end{aligned} \tag{3b}$$

3.2. *Objective function of CS layer*

As it was explained in Section 2, it is assumed that CS operators purchase electricity from retailers only if the onsite generation and storage is not sufficient to meet EVs charging demand, or the onsite generation is more expensive compared to the electricity supplied from retailers. In addition, to provide services to the upper grid for added revenue, CS operators are allowed to purchase electricity from EVs and sell to the wholesale market through aggregators. Therefore, the objective function in this layer is defined as the net revenue of CS operators, which has to be maximised. The net revenue (profit) of CS operators can be calculated by subtracting revenues of selling energy to the aggregators, $\mathbb{R}^{\mathrm{CS-,AG}}$, and EVs, $\mathbb{R}^{\mathrm{CS-,EV}}$, from the expenses including onsite operational costs, $\mathbb{C}^{\mathrm{Op,CS}}$, cost of energy purchased from retailers, $\mathbb{C}^{\mathrm{CS+,Re}}$, and EVs, $\mathbb{C}^{\mathrm{CS+,EV}}$, expressed by:

$$\mathbb{R}^{\mathrm{CS}} = \mathbb{R}^{\mathrm{CS-,AG}}+\mathbb{R}^{\mathrm{CS-,EV}}-\mathbb{C}^{\mathrm{Op,CS}}-\mathbb{C}^{\mathrm{CS+,Re}}-\mathbb{C}^{\mathrm{CS+,EV}} \tag{4}$$

The revenue terms in (4) can be calculated as follows:

$$\mathbb{R}^{\mathrm{CS-,AG}} = \sum_{h=1}^{24}\sum_{i=1}^{N^{\mathrm{CS}}}\sum_{s=1}^{N^{\mathrm{Re}}}P_{h,i}^{\mathrm{CS-,AG}}\times\rho_{h,i}^{\mathrm{CS-,AG}} \tag{5a}$$

$$\mathbb{R}^{\mathrm{CS-,EV}} = \sum_{h=1}^{24}\sum_{i=1}^{N^{\mathrm{CS}}}\sum_{k=1}^{N^{\mathrm{EV}}}\sum_{r=1}^{N^{\mathrm{T}}}\frac{1}{2}\times M_{h,k,r}\times(M_{h,k,r}+1)\times P_{h,i,k,r}^{\mathrm{CS-,EV}}\times\rho_{h,i}^{\mathrm{CS-,EV}} \tag{5b}$$

Various cost terms are calculated by:

$$\mathbb{C}^{\mathrm{Op,CS}} = \sum_{h=1}^{24}\sum_{i=1}^{N^{\mathrm{CS}}}\frac{P_{h,i}^{\mathrm{GU}}\times\rho_h^{\mathrm{gas}}}{\eta_{h,i}^{\mathrm{GU}}\times HV}+\sum_{i=1}^{N^{\mathrm{CS}}}c_{p.u,i}^{\mathrm{PQ}}\times\lambda_i\times\kappa_i\sum_{j=1}^{N_i^{\mathrm{CH}}}\beta_{i,j}\times\alpha_{i,j}\times\frac{P_{i,j}^{\mathrm{CH}}}{\eta_{\mathrm{i,j}}^{\mathrm{CH}}\times PF_{i,j}^{\mathrm{CH}}} \tag{6a}$$

$$\mathbb{C}^{\text{CS+,Re}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\text{CS}}} P_{h,i,s}^{\text{CS+,Re}} \times \rho_{h,s}^{\text{CS+,Re}} \tag{6b}$$

$$\mathbb{C}^{\text{CS+,EV}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\text{CS}}} \sum_{k=1}^{N^{\text{EV}}} \sum_{r=1}^{N^{\text{T}}} \frac{1}{2} \times M_{h,k,r} \times (M_{h,k,r} - 1) \times P_{h,i,k,r}^{\text{CS+,EV}} \times \rho_{h,i}^{\text{CS+,EV}} \tag{6c}$$

The operation cost of each CS in (6a) includes the operation costs of the CGU and chargers related to active power filtering and reactive power compensation cost, as given in [25, 38, 39]. Charger efficiency is considered because of the internal conversion losses, where input power to the charger is more than the power sold to EVs. For the other terms, the cost is simply the product of the traded energy by the prices obtained from previous optimisation layer.

3.3. ***Objective function of Retailer layer***

The net revenue of retailers in this layer must be maximised, which is defined as the difference between the revenue obtained by selling electricity to CSs and the cost of electricity purchased from the wholesale market, as given by:

$$\mathbb{R}^{\text{Re}} = \mathbb{R}^{\text{Re-,CS}} - \mathbb{C}^{\text{Re+,WM}} \tag{7}$$

The collective daily revenue and cost of retailers are expressed in the following equations:

$$\mathbb{R}^{\text{Re-,CS}} = \sum_{h=1}^{24} \sum_{s=1}^{N^{\text{Re}}} \sum_{i=1}^{N^{\text{CS}}} P_{h,s,i}^{\text{Re-,CS}} \times \rho_{h,s}^{\text{Re-,CS}} \tag{8a}$$

$$\mathbb{C}^{\text{Re+,WM}} = \sum_{h=1}^{24} \sum_{s=1}^{N^{\text{Re}}} P_{h,s}^{\text{Re+,WM}} \times \rho_{h}^{\text{Re+,WM}} \tag{8b}$$

3.4. ***Constraints of EV layer***

The SOC evolution after each charge and discharge and each trip for hour h can be determined by (9a), while (9b) ensures that the battery SOC level is maintained within a lower and upper bound for EV k for the safety and longevity of the battery:

$$SOC_{h,k,r}^{\text{EV}} = SOC_{h-1,k,r}^{\text{EV}} + \frac{P_{h,k,r}^{\text{EV+,CS}} \times \eta^{\text{BAT+}} \times \Delta \text{t}}{Cp_k^{\text{EV}}} - \frac{P_{h,k,r}^{\text{EV-,CS}} \times \Delta \text{t}}{Cp_k^{\text{EV}} \times \eta^{\text{BAT-}}} \tag{9a}$$

$$\underline{SOC}_k^{\text{EV}} \le SOC_{h,k,r}^{\text{EV}} \le \overline{SOC}_k^{\text{EV}} \tag{9b}$$

Charging and discharging power of the chargers at each CS are limited, which is enforced by (10a) and (10b). At each hour h, an EV can only adopt one of the charging or discharging mode, which is achieved by (10c).

$$0 \le P_{h,k,r}^{\text{EV+,CS}} \le Cp_{h,i,j}^{\text{CH}} \tag{10a}$$

$$0 \le P_{h,k,r}^{\text{EV-,CS}} \le Cp_{h,i,j}^{\text{CH}} \tag{10b}$$

$$P_{h,k,r}^{\text{EV+,CS}} \times P_{h,k,r}^{\text{EV-,CS}} = 0 \tag{10c}$$

During charging period, the required energy (in terms of battery SOC) is calculated by (11) in a way to guarantee the minimum SOC level, $\underline{SOC}_{h,k,r}^{EV^{DE}}$, at the next destination, which is specified by the EV owner. The required SOC of EV is determined by the minimum driving distance obtained in Step 2 of Section 2.

$$\begin{aligned} SOC_{h,k,r}^{\mathrm{R,EV+}} &= SOC_{h,k,r}^{\mathrm{R,EV^{OR}\rightarrow CS^{SE}}} + SOC_{h,k,r}^{R,CS^{\mathrm{SE}}\rightarrow EV^{\mathrm{DE}}} + SOC_{h,k,r}^{R,EV^{\mathrm{OR}}\rightarrow EV^{\mathrm{DE}}} \\ &\quad + \underline{SOC}_{h,k,r}^{EV^{DE}} - SOC_{h,k,r}^{in} \\ &= \frac{(D_{h,k,r}^{\mathrm{EV^{OR}\rightarrow CS^{SE}}} + D_{h,k,r}^{\mathrm{CS^{SE}\rightarrow EV^{DE}}} + D_{h,k,r}^{\mathrm{EV^{OR}\rightarrow EV^{DE}}}) \times \gamma_k}{Cp_k^{\mathrm{EV}}} \\ &\quad + \underline{SOC}_{h,k,r}^{EV^{DE}} - SOC_{h,k,r}^{\mathrm{in}} \end{aligned} \tag{11}$$

Similarly, the maximum available energy of an EV that can be sold to a CS, depends on the EV's travel plan and the distance of the routes, which is calculated in (12).

$$\begin{aligned} SOC_{h,k,r}^{\mathrm{R,EV-}} &= SOC_{h,k,r}^{\mathrm{in}} - SOC_{h,k,r}^{\mathrm{R,EV^{OR}\rightarrow CS^{SE}}} - SOC_{h,k,r}^{R,CS^{SE}\rightarrow EV^{DE}} \\ &\quad - SOC_{h,k,r}^{\mathrm{R,EV^{OR}}\rightarrow EV^{\mathrm{DE}}} - \underline{SOC}_{h,k,r}^{\mathrm{EV^{DE}}} \\ &= SOC_{h,k,r}^{in} - \frac{(D_{h,k,r}^{\mathrm{EV^{OR}\rightarrow CS^{SE}}} + D_{h,k,r}^{\mathrm{CS^{SE}\rightarrow EV^{DE}}} + D_{h,k,r}^{\mathrm{EV^{OR}\rightarrow EV^{DE}}}) \times \gamma_k}{Cp_k^{\mathrm{EV}}} \\ &\quad - \underline{SOC}_{h,k,r}^{EV^{DE}} \end{aligned} \tag{12}$$

For EV k in both charging or discharging mode, the SOC at the departure time from selected CS must be higher than the required SOC of the EV to reach the next destination, as expressed in (13):

$$SOC_{h,k,r}^{\mathrm{DP,EV}} \geq SOC_{h,k,r}^{\mathrm{R,EV\pm}} \tag{13}$$

At the final destination, the SOC of EV k must be more than the final SOC level that is specified by the EV owner, which is achieved by:

$$SOC_{h,k,r}^{EV^{\mathrm{DE}}} \geq \underline{SOC}_{h,k,r}^{EV^{\mathrm{DE}}} \tag{14}$$

3.5. *Constraints of CS layer*

Balance between supply and demand within a CS should be maintained at all times during charging and discharging, which is achieved by (15a). Charger efficiency is considered for the sake of accuracy. Equation (15b) ensures that the number of operational chargers in a CS does not exceed the number of existing chargers in that station.

$$P_{h,i}^{\mathrm{PV}} + P_{h,i}^{\mathrm{GU}} \pm P_{h,i}^{\mathrm{ESS\pm}} + \sum_{k=1}^{N^{\mathrm{EV}}} P_{h,i,k,r}^{\mathrm{CS+,EV}} + \sum_{s=1}^{N^{\mathrm{Re}}} P_{h,s,i}^{\mathrm{CS+,Re}} = \frac{P_{h,i}^{\mathrm{CS-,AG}}}{\eta_i^{\mathrm{CH}}} + \sum_{k=1}^{N^{\mathrm{EV}}} \frac{P_{h,i,k,r}^{\mathrm{CS-,EV}}}{\eta_i^{\mathrm{CH}}} \tag{15a}$$

$$N_{h,i}^{\mathrm{AV,CH}} \leq \overline{N}_i^{\mathrm{CH}} \tag{15b}$$

The onsite PV generation is estimated by (16a) from meteorological data and PV panel specifications. Equation (16b) ensures that the PV dispatch at time h is lower than or equal to the maximum available PV at the same time. Therefore, PV curtailment is allowed in the CS operation.

$$P_{h,i}^{\mathrm{PV}} = \eta_i^{\mathrm{PV}} \times A_i^{\mathrm{PV}} \times Ra_h \times (1 - 0.005 \times (Tm_h^{\mathrm{am}} - 25)) \tag{16a}$$

$$P_{h,i}^{\mathrm{PV}} \le P_i^{\mathrm{PV,nom}} \tag{16b}$$

In (17a), onsite stationary ESS operation and its SOC evolution is characterised. The SOC upper and lower limits are enforced by (17b). Moreover, simultaneous operation of the ESS in the two modes (i.e., charge and discharge) is prohibited by (17c).

$$SOC_{h,i}^{\mathrm{ESS}} = SOC_{h-1,i}^{\mathrm{ESS}} + \frac{P_{h,i}^{\mathrm{ESS+}} \times \eta^{\mathrm{ESS+}} \times \Delta \mathrm{t}}{Cp_i^{\mathrm{ESS}}} - \frac{P_{h,i}^{\mathrm{ESS-}} \times \Delta \mathrm{t}}{Cp_i^{\mathrm{ESS}} \times \eta^{\mathrm{ESS-}}} \tag{17a}$$

$$\underline{SOC}_i^{\mathrm{ESS}} \le SOC_{h,i}^{\mathrm{ESS}} \le \overline{SOC}_i^{\mathrm{ESS}} \tag{17b}$$

$$P_{h,i}^{\mathrm{ESS+}} \times P_{h,i}^{\mathrm{ESS-}} = 0 \tag{17c}$$

Equation (18a) ensures that electricity produced by a CGU at time h does not exceed its nominal capacity [40]. Moreover, based on (18b), it is not reasonable to operate the CGU below 30% of its rated power due to low efficiency and high greenhouse gas emission at the lower operating ranges. Therefore, the CGU will be turned off, as in [40].

$$P_{h,i}^{\mathrm{GU}} \le Cp_i^{\mathrm{GU}} \tag{18a}$$

$$P_{h,i}^{\mathrm{GU}} = \begin{cases} P_{h,i}^{\mathrm{GU}} & P_{h,i}^{\mathrm{GU}} \ge 0.3 \times Cp_i^{\mathrm{GU}} \\ 0 & P_{h,i}^{\mathrm{GU}} < 0.3 \times Cp_i^{\mathrm{GU}} \end{cases} \tag{18b}$$

Total charge/discharge capacity of CS i is calculated by (19a) [33]. Electricity purchased from retailers by CS i at the point of common coupling is limited by (19b). Based on (19c), CS i is not allowed to sell CGU power to the aggregator. In other words, the power sold to the aggregator should be equal or lower than the power purchased from EVs. This is because of the existing regulations in many electricity markets and the desire to limit emissions from CGU.

$$Cp_i^{\mathrm{CS}} = \lambda_i \times \sum_{j=1}^{N^{\mathrm{CH}}} \frac{P_{i,j}^{\mathrm{CH}}}{\eta_{i,j}^{\mathrm{CH}} \times PF_{i,j}^{\mathrm{CH}}} \tag{19a}$$

$$P_{h,s,i}^{\mathrm{CS+,Re}} \le Cp_i^{\mathrm{CS}} \tag{19b}$$

$$P_{h,i}^{\mathrm{CS-,AG}} \le \sum_{k=1}^{N^{\mathrm{EV}}} P_{h,i,k,r}^{\mathrm{CS+,EV}} \times \eta_i^{\mathrm{CH}} \tag{19c}$$

3.6. ***Constraints of Retailer layer***

Active and reactive power should be balanced at all times. Therefore, sum of the electricity purchased from the wholesale electricity market through retailers must be equal to the sum of the electricity purchased by CSs from retailers, load demand and power losses of the distribution network for active and reactive power at hour h:

$$\sum_{s=1}^{N^{\mathrm{Re}}} P_{h,s}^{\mathrm{Re+,WM}} = \sum_{s=1}^{N^{\mathrm{Re}}} \sum_{i=1}^{N^{\mathrm{CS}}} P_{h,s,i}^{\mathrm{Re-,CS}} + \sum_{b=1}^{N^{\mathrm{b}}} P_{D_b,h} + P_{L_h}^{\mathrm{DN}} \tag{20a}$$

$$\sum_{s=1}^{N^{\text{Re}}} Q_{h,s}^{\text{Re+,WM}} = \sum_{s=1}^{N^{\text{Re}}} \sum_{i=1}^{N^{\text{CS}}} Q_{h,s,i}^{\text{Re−,CS}} + \sum_{b=1}^{N^{\text{b}}} Q_{D_b,h} + Q_{L_h}^{\text{DN}} \tag{20b}$$

Active and reactive power demands at bus b and hour h are determined by:

$$P_{D_b,h} = \frac{S_{D_0,b}}{\sum_{b=1}^{N^{\text{b}}} S_{D_0,b}} \times P_{D_0,h} \tag{21a}$$

$$Q_{D_b,h} = tan(\cos^{-1}(PF_{h,b})) \times P_{D_b,h} \tag{21b}$$

Power losses are given by:

$$P_{L_h}^{\text{DN}} = \sum_{m=1}^{N^{\text{M}}} \mid I_{h,m} \mid^2 \times R_m \tag{22}$$

Total electricity purchased from the wholesale electricity market must not exceed substation transformation capacity [41]:

$$\sum_{s=1}^{N^{\text{Re}}} P_{h,s}^{\text{Re+,WM}} \leq Cp^{\text{TR}} \tag{23}$$

Bus voltages must be within permissible range in order to guarantee a secure operation of the distribution network while maintaining power quality at a standard level:

$$\underline{V_b} \leq \mid V_{h,b} \mid \leq \overline{V_b} \tag{24}$$

Active and reactive power balance are maintained for bus b at hour h by [42]:

$$P_{G_b,h} - P_{D_b,h} = V_{b,h} \sum_{a=1}^{N^{\text{b}}} V_{a,h}(G_{ba}cos(\theta_{b,h} - \theta_{a,h}) + B_{ba}sin(\theta_{b,h} - \theta_{a,h})) \tag{25a}$$

$$Q_{G_b,h} - Q_{D_b,h} = V_{b,h} \sum_{a=1}^{N^{\text{b}}} V_{a,h}(G_{ba}sin(\theta_{b,h} - \theta_{a,h}) + B_{ba}cos(\theta_{b,h} - \theta_{a,h})) \tag{25b}$$

The electricity price offered by retailers to CSs is limited by minimum and maximum bounds for the optimisation problem at this layer.

$$\underline{\rho}^{\text{Re−,CS}} \leq \rho_{h,s}^{\text{Re−,CS}} \leq \overline{\rho}^{\text{Re−,CS}} \tag{26}$$

4. Optimisation Model

Despite the fact that evolutionary algorithms might not be able to guarantee global optimal solutions and that they might only reach near-optimal solutions, an evolutionary algorithm, called SSA, is preferred in this study because of the non-linear nature of the three optimisation problems. SSA is an evolutionary computation technique that is inspired by swarming behaviour of salps when they navigate in deep oceans within chains of salp searching for a food source as the swarm's target. In literature, the most popular swarm-inspired algorithms are Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) [33, 43–45]. However, it was discovered in a few studies. e.g., [46, 47], that the SSA is able to explore the search space more effectively, and that the optimisation technique benefits from high exploration and convergence speed to obtain the true global solutions [46]. In order to obtain a mathematical model of salp chains, the population of salps is divided into two groups: the first group is the leader where the salp at the front of the chain guides the swarm and the second group includes the followers, as the rest of salps, chasing the leader. In every iteration, the leader changes its position around the food source and the followers chase the leader. The position of salps is defined as an n-dimensional search space, where n is the number of decision variables of the optimisation problem at hand. The position of all salps are stored in a two-dimensional matrix, $x_{n,it}$. The position of the first salp as the leader is updated with respect to the food source, $F_{n,it}$, based on [46, 48]:

$$x^{\mathrm{L}}_{n,it} = \begin{cases} F_{n,it} + c_{1,it}\left(\left(ub_n - lb_n\right) c_{2,it} + lb_n\right) & c_{3,it} \geq 0 \\ F_{n,it} - c_{1,it}\left(\left(ub_n - lb_n\right) c_{2,it} + lb_n\right) & c_{3,it} < 0 \end{cases} \tag{27}$$

where $c_{1,it}$ is a variable that will exponentially decrease throughout the iterations, as obtained by (28); and $c_{2,it}$ and $c_{3,it}$ are random numbers uniformly distributed on the interval of [0,1] at iteration it.

$$c_{1,it} = 2e^{-\left(\frac{4 \times it}{\overline{it}}\right)^2} \tag{28}$$

The position of the follower f in the dimension n is updated by:

$$x^{\mathrm{f}}_{n,it} = \frac{1}{2}\left(x^{\mathrm{f}}_{n,it} + x^{\mathrm{f}-1}_{n,it}\right) \tag{29}$$

To determine optimal day-ahead electricity prices sold to CS operators by retailers, we have $N^{\mathrm{Re}} \times 24$ decision variables to optimise in Retailer layer. The number of decision variables in the CS layer is $3 \times N^{\mathrm{CS}} \times 24$ considering three sets of variables that correspond to the power produced by CGU, power purchased from retailers, and power sold to the aggregator for 24 hours ahead. In the EV layer, the optimisation problem includes $2 \times 24 \times N^{\mathrm{EV}}$ decision variables that correspond to the power sold/purchased to/from EVs.

5. Simulation Study

In order to examine the performance of the proposed method, a comprehensive simulation study is carried out, as shown in Figure 4, using a selected area of San Francisco [49]. The IEEE 37-bus distribution test system [50] is mapped over the area to represent the CSs connection to the upper grid. It is assumed that there are three retailers to provide electricity to CSs and one aggregator is considered to sell energy back to the wholesale market by purchasing it from CSs. The nominal voltage of the network is 480 V and the minimum and maximum voltage limits are 0.95 and 1.05 p.u., respectively. Node 1 is connected to the distribution transformer as the slack bus. Total active and reactive power demand (without EV) at the peak hour are equal to 8.7 MW and 4.3 MVAr, respectively. As depicted in Figure 4, the CSs are randomly placed at nodes 2, 8, 10, 11, 16, 22, 29, 32, and 35. The origin and destination of EVs in each trip is assumed to be contained in this area. 600 EVs are randomly situated over the area, each of which is assumed to complete two trips per day with different waiting times between each trip, without loss of generality. Furthermore, four types of EVs with battery capacity of 14.5kWh, 16kWh, 28kWh, and 40kWh are considered. In this study, the base case is defined in such a way that no optimisation is carried out for scheduling and every EV selects the closest CS without considering prices. Also, V2G and G2V prices in the base case strategy are equal to the initial prices in the first iteration of the proposed three-layer optimisation problem for each agent.

Input parameters and their corresponding values for the distribution network, CSs, and EVs are given in Table 2. Due to lack of daily load profile at each node in the IEEE 37-bus distribution test system, the daily hourly load profile of California ISO [51] is used by re-scaling the values in proportion to the test network load demand using (21a) and (21b). Also, day-ahead electricity prices of the wholesale electricity market for a typical day are extracted from California ISO [51], which are used in the simulation studies.

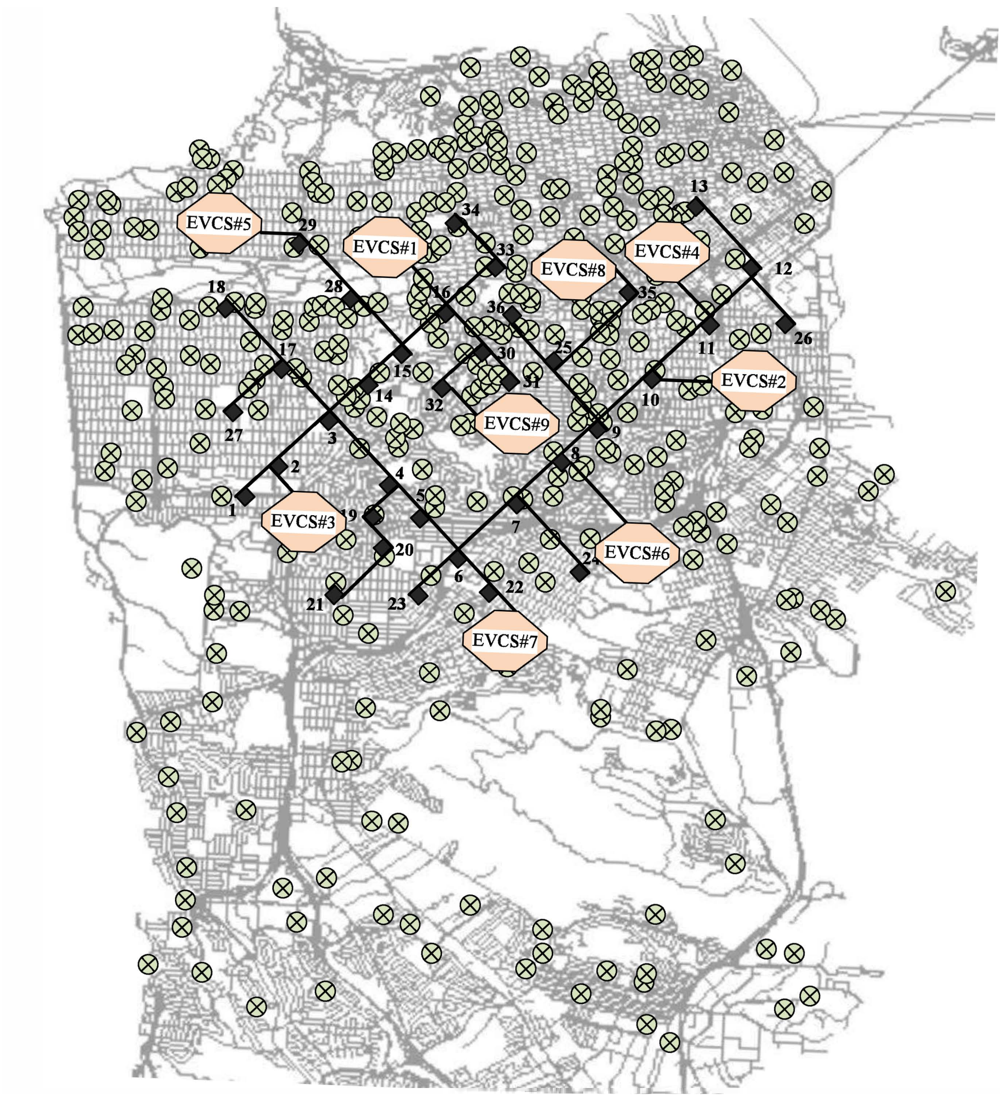


Figure 4: IEEE 37-bus distribution test network and location of some of the EVs and all CSs in San Francisco, the USA [49] and [50].

In order to take into account ancillary services costs, network maintenance costs, taxes, and etc. (which

Table 2: Input parameters of distribution network, CSs, and EVs [39, 52, 53]

Parameter	Value	Parameter	Value
$M_{h,k,r}$	± 1(+1: G2V, -1: V2G)	Cp^{EV}	14.5, 16, 28, 40 (kWh)
Δt	1 hr	$\underline{V}_b/\overline{V}_b$	0.95/1.05
$c_{p.u}^{\text{PQ}}$	10.16 (\$/kVA)	HV	0.7 (kWh/m^3)
η^{CH}	0.9	η^{PV}	0.157
PF^{CH}	0.95	A^{PV}	800 (m^2)
Cp^{GU}	65 (kW)	Cp^{ESS}	50 (kWh)
$\overline{N}_i^{\text{CH}}$	5	ρ^{gas}	13.07 (cents/m^3)
α	0.03	β	1.05
κ	0.61	λ	1
$\underline{SOC}^{\text{ESS}}$/ $\overline{SOC}^{\text{ESS}}$	0.1/0.9	γ	0.2 (kWh/km)

are normally included in the retail electricity tariffs), the day-ahead electricity prices of the wholesale market is multiplied by 4.5 homogeneously. The new prices will serve as the electricity prices that is paid by CS operators to the retailers. The electricity prices sold to EVs by CSs and electricity prices purchased from EVs by CSs are obtained by:

$$\rho_{h,i}^{CS-,EV} = rand(1.1, 1.5) \times \rho_{h,i}^{Re-,CS} \tag{30}$$

In (30), it is assumed that CSs' asking prices are 10–50% more than what they pay to the retailers in order to make profit. In addition, CS operators offer prices to EVs for V2G services that will be sold to the wholesale market through aggregators. The performance of a CS in this case depends on the prices offered to the EVs. Therefore, a sensitivity analysis is carried out using the following three scenarios:

Scenario I (Low-price scenario): $\rho_{h,i}^{CS+,EV} = \frac{1}{4.5} \times \rho_{h,i}^{Re-,CS} \times rand(0.1, 0.9)$

Scenario II (Medium-price scenario): $\rho_{h,i}^{CS+,EV} = \rho_{h,i}^{Re-,CS} \times rand(0.6, 0.85)$

Scenario III (High-price scenario): $\rho_{h,i}^{CS+,EV} = \rho_{h,i}^{Re-,CS} \times rand(1.05, 1.3)$

It can be seen that the optimal day-ahead electricity prices for discharging EVs increase from scenario I to scenario III. In fact, in scenario I to scenario III, V2G prices are getting closer to G2V prices to encourage more EVs in V2G operation, and consequently, determine the range of V2G prices in which the collective benefit of all agents is maximised. In all scenarios, $\rho_{h,i}^{CS-,AG} = 1.1 \times \rho_{h,i}^{CS+,EV}$ where the aggregator expects maximum of 10% profit based on the price offered by CSs.

It is assumed that different retailers are looking for up to 30% profit. As a result, the minimum and maximum value of the day-ahead electricity prices sold to CSs by retailers are expressed as:

$$1.05 \times 4.5 \times \rho_{\mathrm{h}}^{\mathrm{Re+,WM}} \leq \rho_{\mathrm{h,s}}^{\mathrm{Re\text{-},CS}} \leq 1.3 \times 4.5 \times \rho_{\mathrm{h}}^{\mathrm{Re+,WM}} \tag{31}$$

The cloud scheduling system specifies the charging/discharging plan of all EVs at once. Four plans can be expected for EV charging and discharging with two trips. The flowchart for choosing a proper plan for EVs is shown in Figure 5, which are explained below:

- **Plan 1**: The initial SOC of EV k at the beginning of trip 1 is not sufficient to complete this trip. Therefore, EV k must be charged in trip 1. If it is profitable, it will be discharged in trip 2.
- **Plan 2**: The initial SOC of EV k at the start of trip 1 is more than the total energy needed to finish trip 1 and the minimum SOC of the EV at the end of the trip. If charging prices in trip 1 are less than discharging prices in trip 2, EV k will be charged in trip 1 and discharged in trip 2.
- **Plan 3**: The initial SOC of EV k at the beginning of trip 1 is more than the total energy required for the trip and the minimum SOC of EV at the end of the trip. If discharging prices in trip 1 are more than charging prices in trip 2, EV k will be discharged in trip 1 and charged in trip 2.
- **Plan 4**: The initial SOC of EV k at the beginning of trip 1 is more than the required energy to complete the trip and minimum SOC of EV at the end of the trip. However, charging prices in trip 1 are more than discharging prices in trip 2. In addition, discharging price in trip 1 is less than charging price in trip 2. In this case, EV k will not be charged nor discharged. However, if the initial SOC of EV k at the beginning of trip 2 is not more than the required energy to complete the trip and minimum SOC of EV at the end of the trip, the EV k must be charged in trip 2.

6. Simulation Results and Discussion

In this section, simulation results for a typical day will be presented and explained for the case study introduced in Section 5.

6.1. V2G and G2V operation and prices

The optimal day-ahead electricity prices offered by the most and least profitable CS are shown in Figure 6. It can be seen that the most profitable CS is CS#8 in scenario II and the the least profitable CS is CS#1 in scenario I. The number of EVs charged and discharged in each scenario for each hour is depicted in Figure 7. No EVs is planned for V2G service in Scenario I due to the extremely low prices offered by the CSs. However, by increasing the V2G prices (assuming that the cost of ancillary services, taxes, etc. are reduced or we experience high prices in the wholesale market), the number of EVs participating in V2G increases and reaches its maximum in Scenario III. Also, it can be seen from Figure 7 that the number of EVs in charging mode has increased substantially because it is economically beneficial for the EVs to charge in one trip and discharge in the next one (i.e., energy arbitrage).

The number of EVs in each charge and discharge mode in each scenario for **Plan 1**, **2**, and **3** is depicted in Figure 8. For **Plan 1**, the number of EVs planned for V2G service in the second trip is raised by increasing V2G prices because it is economically rewarding for EVs to make profit from the high SOC level of batteries in the second trip. For **Plan 2**, the results show that by increasing V2G prices, when G2V prices in the first trip is lower than V2G prices in the second trip, the number of EVs that prefer to charge in the first trip and discharge in the second trip increases because they can make more profit. As explained in Section 5, for **Plan 1**, EVs must be charged in trip 1, and if it is profitable, they will be discharged in trip 2. However, for **Plan 2**, EVs are charged in trip 1 and discharged in trip 2 to make profit if the prices are right. Furthermore, in **Plan 3**, more EVs discharged in the first trip with higher prices and charge in the second trip with lower prices.

Figure 9 depicts the routes for an EV that is specified by ArcGIS in the base case and the proposed strategy in this study. In this example, EV k selects the nearest CSs (CS#8 and CS#3) in the base case without running a cost-benefit analysis, which leads to \$4 extra cost for EV k in comparison with the proposed three-layer optimal strategy.

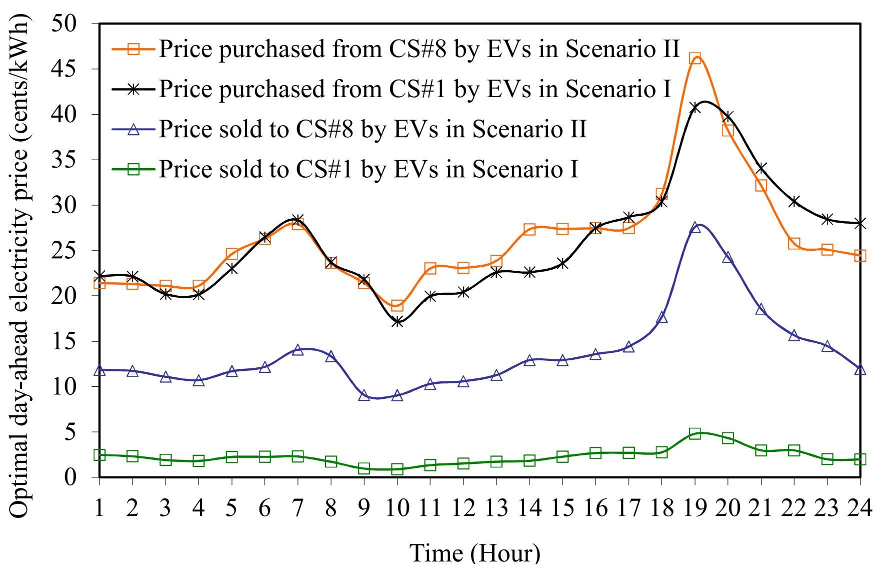
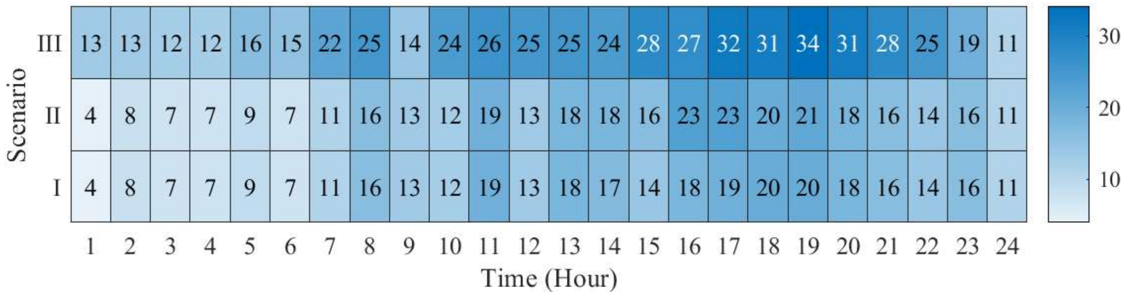
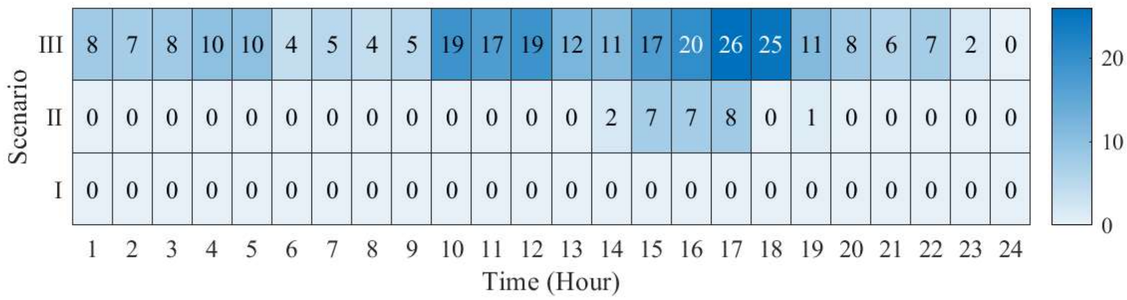


Figure 6: Optimal day-ahead electricity prices offered by the least (CS#1) and the most profitable CS (CS#8) during charging and discharging of EVs among all Scenarios.



(a)



(b)

Figure 7: Number of EVs planned to participate in (a) G2V and (b) V2G in each scenario.

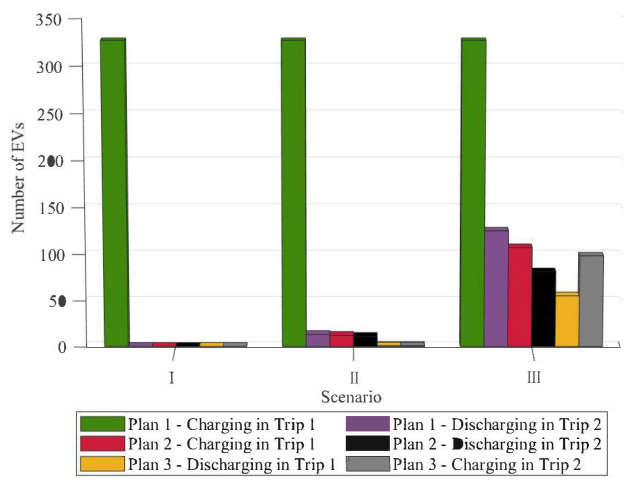


Figure 8: Total number of EVs for **Plan 1**, **Plan 2**, and **Plan 3** in each scenario.

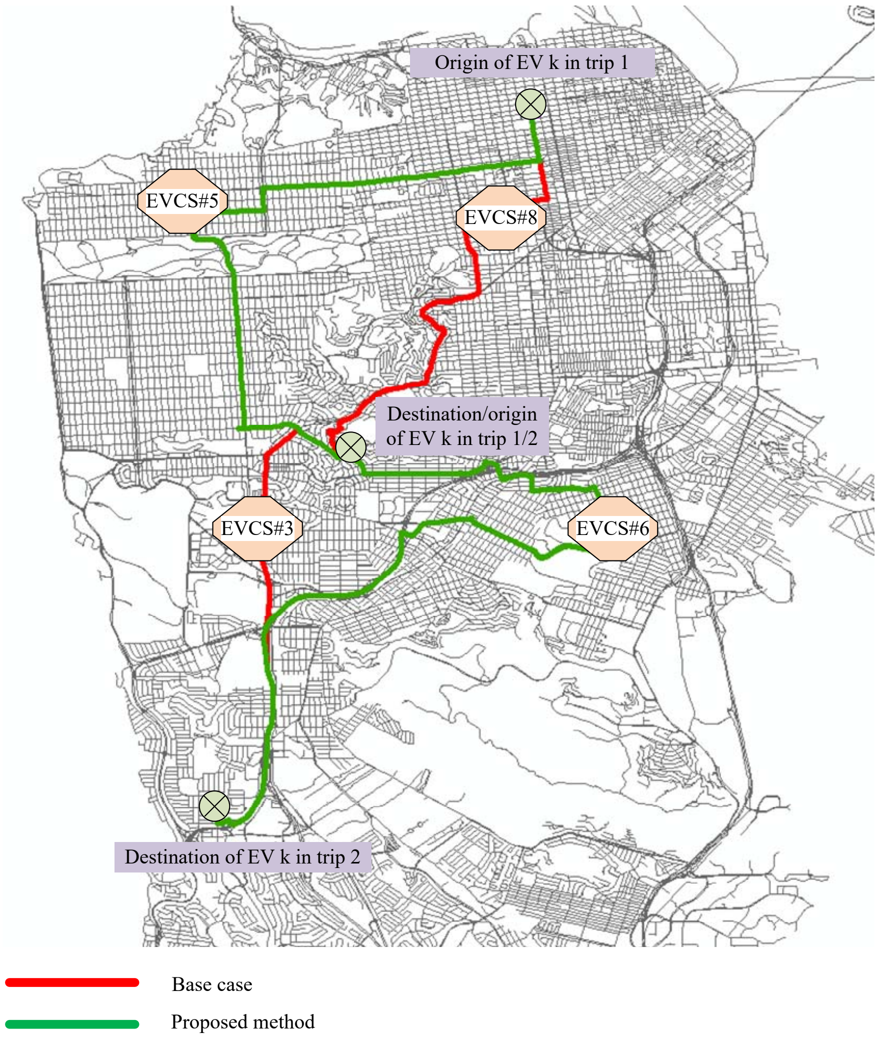


Figure 9: Scheduling results for a sample EV in the base case (red line) and the proposed strategy (green line).

6.2. CS and retailers operation

In Table 3, optimal day-ahead electricity prices offered by three retailers to CSs are reported. The cheapest retailer is selected in each hour, which are specified in the Table. Off-peak and peak periods with minimum and maximum electricity prices occur in hours 10 and 19, respectively, and Retailer#1 is selected by CSs in both off-peak and peak periods.

As reported in Table 4, by increasing the number of EVs participating in V2G program from scenario I to III, the net cost of EVs decreases and the net revenue of CS operators and retailers increases. However, in Scenario III, while more EVs participated in the V2G program, the net revenue of retailers and CS operators as well as the net cost of EVs decreased compared to Scenario II. The main reason is that the cost of electricity purchased by CS operators from EVs participating in V2G services increased while the electricity purchased from retailers by CS operators decreased. Based on the results presented in Table 4, the most

Table 3: Optimal day-ahead electricity prices offered by retailers and the selected retailer in each hour (cents/kWh)

Time (Hour)	Retailer#1	Retailer#2	Retailer#3	Selected retailer
t=1	18.74	19.35	21.12	Retailer#1
t=2	18.66	17.48	19.96	Retailer#2
t=3	16.74	17.46	16.43	Retailer#3
t=4	16.73	17.39	16.33	Retailer#3
t=5	17.73	18.24	18.13	Retailer#1
t=6	20.62	18.75	19.25	Retailer#2
t=7	24.34	24.42	22.51	Retailer#3
t=8	20.03	19.49	22.31	Retailer#2
t=9	16.58	15.16	16.72	Retailer#2
t=10	14.25	15.11	16.03	Retailer#1
t=11	16.52	15.55	16.12	Retailer#2
t=12	16.60	18.53	16.20	Retailer#3
t=13	18.06	18.62	17.38	Retailer#3
t=14	18.78	21.16	19.68	Retailer#1
t=15	19.93	21.16	19.96	Retailer#1
t=16	21.56	22.1	21.00	Retailer#3
t=17	22.73	22.19	21.94	Retailer#3
t=18	25.16	27.39	27.81	Retailer#1
t=19	35.64	38.03	39.52	Retailer#1
t=20	32.75	35.15	33.59	Retailer#1
t=21	28.69	29.07	25.67	Retailer#3
t=22	25.22	22.96	25.27	Retailer#2
t=23	22.48	21.57	21.51	Retailer#3
t=24	21.74	19.45	19.00	Retailer#3

Table 4: Objective function values in three layers and the number of EVs discharged in all scenarios

Scenario	Total net cost of EVs ($)	Total net revenue of CSs ($)	Total net revenue of retailers ($)	No. of EVs discharged
Scenario I	1835.1	291.7	643.9	0
Scenario II	1800.4	453	654.7	25
Scenario III	1219.3	378.1	639.7	261

profitable operation is achieved in Scenario II for all three agents, i.e., EV, CS, and retailer.

6.3. The proposed algorithm performance and convergence

To verify the simulation results obtained by SSA, the three-layer optimisation problem is also solved by PSO approach. The optimisation algorithms convergence rates of prices for both optimisation techniques are shown in Figure 10 for each scenario in the three layers, where optimal results are reached after about 70 and 75 iterations in most cases using SSA and PSO, respectively. The optimal values are obtained by SSA and PSO in 1683 and 1829 seconds, respectively. Therefore, it shows that SSA is outperforming PSO in terms of computational time. All computations are executed on a laptop with Intel Core i7 CPU with 1.80GHz processor and 8GB RAM.

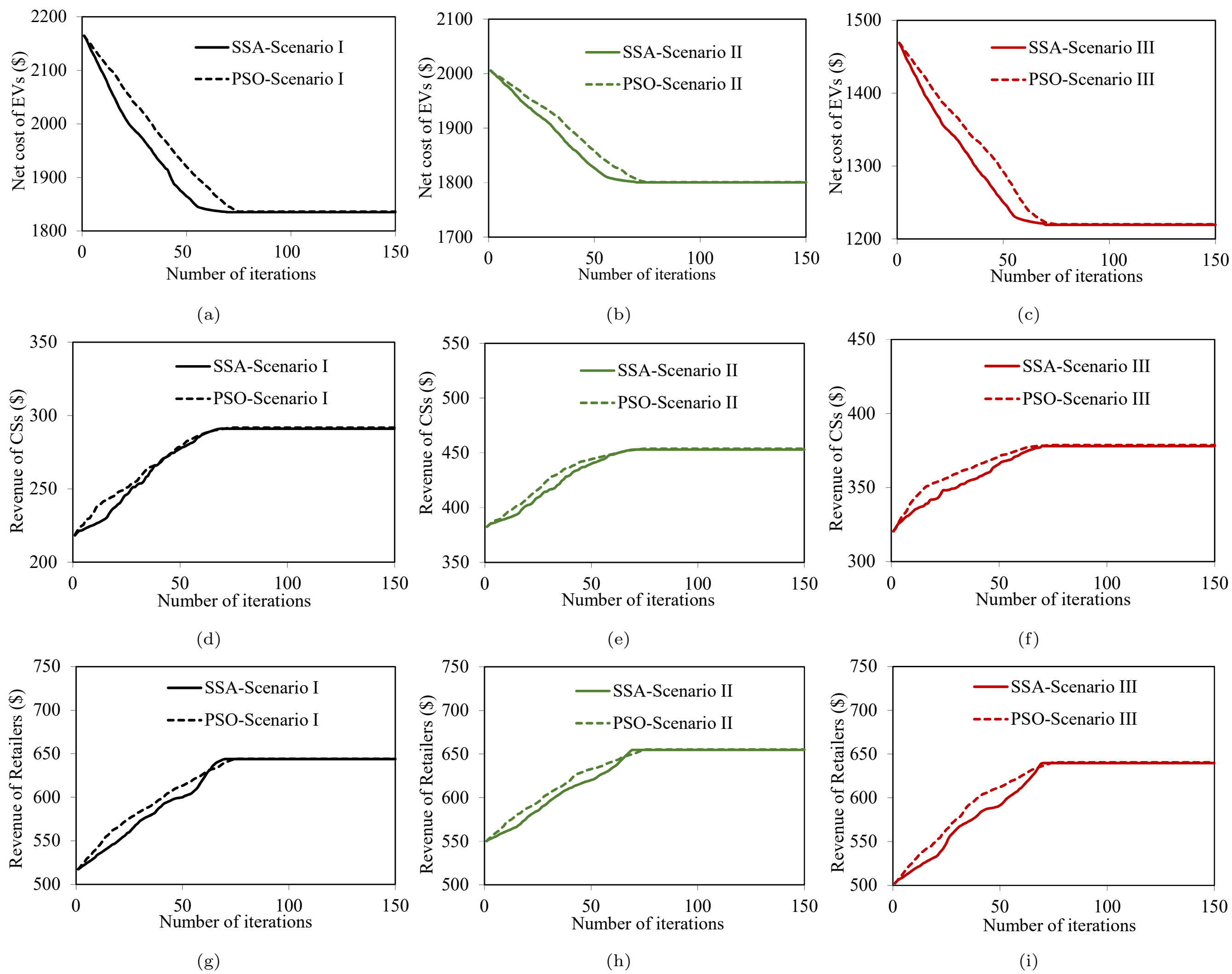


Figure 10: Convergence of the optimisation problems in (a-c) EV layer, (d-f) CS layer, and (g-i) Retailer layer for all scenarios.

In Table 5, the cost/revenue of EVs, CS operators, and retailers are reported for the base case and the proposed three-layer optimisation problem in scenario II , obtained by SSA and PSO. It can be seen that the cost of EVs decreased by 17.6%, and the revenue of CS operators and retailers raised by 21.1% and 22.6%, respectively, in the proposed method solved by SSA in comparison with the base case. The results obtained by SSA and PSO are quite close, with SSA performing slightly better in most instances. It shows the effectiveness of SSA in solving these complex optimisation problems in a reasonable time. To better show the effectiveness of the proposed method, another simulation study is performed, called "Individual optimisation problem", in which the optimisation problem of each stakeholder is solved individually without iterative process. It can be seen from Table 5 that if the our proposed method yields 10.2% reduction in EVs operation cost and 18.4% and 19% increase in revenue of CSs and retailers, respectively, compared to "Individual optimisation problem" in scenario II.

Table 5: Comparing the simulation results for the base case, the proposed three-layer optimisation problem and the individual optimisation problems in Scenario II

Parameters		Optimal Value	
		SSA	PSO
$\mathbb{C}^{EV}$ (\$)	Three-layer optimisation problem	1800.4	1801.3
	Base case	2185.7	2185.7
	Individual optimisation problem	2005.7	2006.2
$\mathbb{R}^{CS}$ (\$)	Three-layer optimisation problem	453	453.7
	Base case	374.1	374.1
	Individual optimisation problem	382.6	382.9
$\mathbb{R}^{Re}$ (\$)	Three-layer optimisation problem	654.7	655.2
	Base case	534.1	534.1
	Individual optimisation problem	550.2	550.8

7. Conclusions and Recommendations

In this study, a day-ahead scheduling framework is presented to guarantee economic and energy-efficient routing of electric vehicles. Based on the proposed strategy, each electric vehicle and charging station finds optimal charging stations and retailers, respectively, for vehicle-2-grid and grid-2-vehicle services by solving an equilibrium problem. The proposed method can be offered as a cloud service to all stakeholders, which facilitates day-ahead electric vehicle scheduling considering objectives and preferences of all stakeholders. In this method, electric vehicles independently plan their charging/discharging depending on the minimum driving routes and cost/benefit analysis based on the prices offered by charging stations. Also, charging stations select optimal retailers to purchase energy while utilising onsite generation and stationary storage in the most economic way. In addition, charging stations are able to facilitate vehicle-2-grid operation by purchasing energy from electric vehicles and selling back to the wholesale market through aggregators.

Comprehensive simulations are conducted on a real test system. Simulation results confirm that the cost-effective operation is achieved for all agents, and it is highly dependant on the level of participation of electric vehicles in the vehicle-2-grid program and the cost of energy in the wholesale market. The optimal solutions are obtained for all stakeholders by respecting physical limits of the network, avoiding queuing at the charging stations, and preserving electric vehicle owners comfort and preferences during the scheduling.

In our future works, we are planning to improve the proposed model by incorporating electric vehicle owners' preferences, and unpredictable and economically-irrational behavior. Also, various sources of uncertainty will be added to the model and stochastic/robust optimisation will be used to deal with the uncertainties. Furthermore, it is recommended to study the cooperative and non-cooperative game theory in order to model the interaction between different agents.

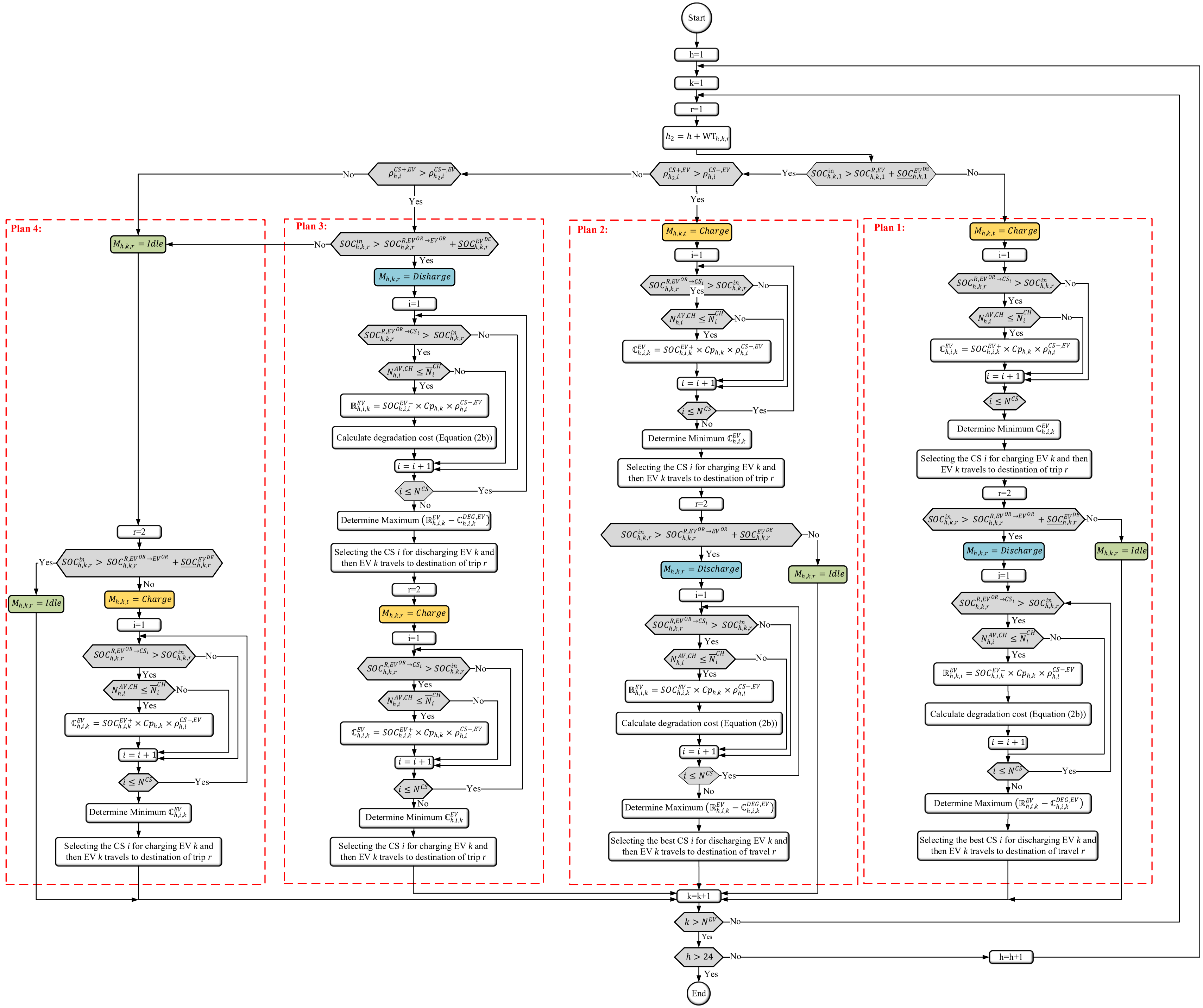


Figure 5: Flowchart of the rule-based process to determine the charging/discharging modes at the end of each trip.

493 ## Nomenclature

Indices

a, b	Index of buses in the distribution network
h	Index of number of cycles of EV's battery
h	Index of hours of a day
i	Index of CS
it	Number of iterations
j	Index of chargers
k	Index of EV
m	Branch of the distribution network
n	Dimension of search space
r	Index of trip
s	Index of retailer

Parameters

494

A_i^{PV}	Area of PV in CS i (m^2)
B_{ba}	Susceptance of overhead line between bus b and a (mho)
$c_{p.u}^{\mathrm{BAT}}$	Per-unit capacity cost of battery
$c_{p.u,i}^{\mathrm{PQ}}$	Per-unit capacity cost of the active power filtering and reactive power compensation in CS i
$Cp_{h,i,j}^{\mathrm{AV,CH}}$	Capacity of available charger j in CS i (kWh)
$Cp_{h,i,j}^{\mathrm{CH}}$	Capacity of charger j in CS i at time h (kWh)
Cp_i^{ESS}	Capacity of ESS of CS i (kWh)
Cp_k^{EV}	Capacity of EV's battery k (kWh)
Cp_i^{GU}	Capacity of CGU of CS i (kWh)
Cp_k^{nom}	Nominal capacity of EV k (kWh)
Cp_k^{re}	Real capacity of EV k (kWh)
Cp^{TR}	Substation transformer capacity (kWh)

$D_{h,k,r}^{\mathrm{EV^{OR}}\rightarrow\mathrm{CS^{SE}}}$	Shortest driving distance of EV k between its origin and the selected CS in trip r at time h (km)
$D_{h,k,r}^{\mathrm{CS^{SE}}\rightarrow\mathrm{EV^{DE}}}$	Shortest driving distance of EV k between the selected CS and its destination in trip r at time h (km)
$D_{h,k,r}^{\mathrm{EV^{OR}}\rightarrow\mathrm{EV^{DE}}}$	Shortest driving distance of EV k between its origin and destination in trip r at time h (km)
G_{ba}	Conductance of overhead line between bus b and a (mho)
HV	Heat value fuel on the operation of gas turbine-generator (kWh/m^3)
$\overline{it}$	Maximum number of iterations
N^b	Number of distribution network nodes
N^{CS}	Number of charging stations
N^{CYC}	Number of cycles of EV's battery
N^{EV}	Number of electric vehicles
N^{Re}	Number of retailers
N^T	Number of trips
$P_i^{\mathrm{PV,nom}}$	Nominal power of PV system of CS i
$PF_{i,j}^{\mathrm{CH}}$	Power factor of charger j in CS i
R_m	Resistance of overhead line (Ω)
Ra_h	Solar radiation at time h (W/m^2)
$S_{D_0,b}$	Nominal apparent electrical load of the distribution network (kVA)
$SOC_{h,k,1}^{in}$	Initial SOC of EV k at the beginning of first trip (%)
$\overline{SOC}_i^{\mathrm{ESS}}/\underline{SOC}_i^{\mathrm{ESS}}$	Maximum/Minimum SOC of ESS in CS i (%)
$\overline{SOC}_k^{\mathrm{EV}}$ / $\underline{SOC}_k^{\mathrm{EV}}$	Maximum/ Minimum SOC of EV k (%)
$\underline{SOC}_{h,k,r}^{EV^{DE}}$	Minimum SOC of EV k at the destination of trip r (%)
Tm_h^{am}	Ambient temperature at time h (°C)
Δt	Time step (s)
ub_n/lb_n	Upper/Lower bound of variables in SSA

$\underline{V}_b/\overline{V}_b$	Minimum/Maximum nodal voltage of the distribution network (V)
$WT_{h,k,r}$	Waiting time of EV k for trip r at time h (s)
X_i^{CS}	Longitude of CS i
$X_{h,k,r}^{EV^{DE}}$	Longitude of destination of EV k in trip r at time h
$X_{h,k,r}^{\mathrm{EV^{OR}}}$	Longitude of origin of EV k in trip r at time h
Y_i^{CS}	Latitude of CS i
$Y_{h,k,r}^{\mathrm{EV^{OR}}}$	Latitude of origin of EV k in trip r at time h
$\alpha_{i,j}$	Harmonic current containing rate in the AC power input terminal of the charger j of CS i
$\beta_{i,j}$	Reliability coefficient of the charger j of CS i
γ_k	Power consumed by EV k per km (kWh/km)
η_i^{PV}	Efficiency of PV system of CS i at time h
$\eta_{i,j}^{\mathrm{CH}}$	Efficiency of charger j of CS i
$\eta_{h,i}^{\mathrm{GU}}$	Efficiency of CGU of CS i at time h
$\eta^{\mathrm{ESS+}}$	Efficiency of ESS in charging period
$\eta^{\mathrm{ESS-}}$	Efficiency of ESS in discharging period
$\eta^{\mathrm{Bat+}}$	Efficiency of EV's battery in G2V operation
$\eta^{\mathrm{Bat-}}$	Efficiency of EV's battery in V2G operation
κ_i	Overall correction coefficient of CS i
λ_i	Simultaneity coefficient of the chargers of CS i
ρ_h^{gas}	Natural gas price at time h
$\rho_{h,s}^{\mathrm{Re+,WM}}$	Electricity price purchased from wholesale market by retailer s at time h (\$/kWh)
$\overline{\rho}^{\mathrm{Re-,CS}}/\underline{\rho}^{\mathrm{Re-,CS}}$	Maximum/Minimum electricity price sold to CSs by retailers (\$/kWh)
σ_1,σ_2,σ_3	Fitting parameters for cycling degradation related to DOD
ϕ_1,ϕ_2,ϕ_3, ϕ_4	Fitting parameters for cycling degradation related to discharge rate

Variables

$c_{1,it}$	Coefficient for balancing exploration in SSA for iteration it
$c_{2,it}, c_{3,it}$	Random number generated uniformly between 0 and 1 in SSA for iteration it
$\mathbb{C}^{\mathrm{CS+,EV}}$	Cost of energy purchased from EVs (\$)
$\mathbb{C}^{\mathrm{CS+,Re}}$	Cost of energy purchased from retailers (\$)
$\mathbb{C}^{\mathrm{D}}$	Battery degradation cost (\$)
$\mathbb{C}^{\mathrm{EV}}$	The net cost of EVs operation (\$)
$\mathbb{C}^{\mathrm{EV+,CS}}$	The cost of electricity purchased from CSs by EVs (\$)
$\mathbb{C}^{\mathrm{Op,CS}}$	Operation cost of CSs (\$)
$\mathbb{C}^{\mathrm{Re+,WM}}$	Cost of electricity purchased from the wholesale market by retailers (\$)
$\mathbb{D}^{\mathrm{EV}}_{h,k,r}$	Battery degradation of EV k in trip r at time h
$DOD^{\mathrm{EV}}_{h,k,r}(T)$	Depth of charge of EV's battery k in trip r
$DR^{\mathrm{EV}}_{h,k}(T)$	Discharging rate of EV's battery k in trip r
$F_{n,it}$	Position of food source in SSA for iteration it
$I_{h,m}$	Current of overhead line m at time h (A)
it	Number of iterations
$it^{\mathrm{EV}}/it^{\mathrm{CS}}/it^{\mathrm{Re}}$	Number of iterations in EV/CS/Retailer layer
$M_{h,k,r}$	Mode of electric vehicle k in trip r at time h
$N^{\mathrm{AV,CH}}_{h,i}$	The number of available chargers in CS i
$P^{\mathrm{CS+,EV}}_{h,i,k,r}$	Power purchased from EV k by CS i in trip r at time h (kW)
$P^{\mathrm{CS-,EV}}_{h,i,k,r}$	Power sold to EV k by CS i in trip r at time h (kW)
$P_{D_b,h}$	Calculated active electrical load at bus b of the distribution network at time h (kW)
$P^{\mathrm{DN}}_{L_h}$	Power loss of distribution network at time h (kW)
$P^{ESS+}_{h,i}$	Charging power of ESS of CS i at time h (kW)
$P^{ESS-}_{h,i}$	discharging power of ESS of CS i at time h (kW)
$P_{G_b,h}$	Power generation at bus b of the distribution network at time h (kW)

$P_{h,i}^{\mathrm{PV}}$	PV generation of CS i at time h (kW)
$P_{h,i}^{\mathrm{CS-,AG}}$	Power sold to the aggregator by CS i at time h (kW)
$P_{h,s,i}^{\mathrm{CS+,Re}}$	Power purchased from retailer s by CS i at time h (kW)
$P_{h,i,k,r}^{\mathrm{EV+,CS}}$	Power purchased from CS i by EV k in trip r in trip r at time h (kW)
$P_{h,i,k,r}^{\mathrm{EV-,CS}}$	Power sold to CS i by EV k in trip r at time h (kW)
$P_{h,i}^{\mathrm{GU}}$	Power produced by CGU of CS i at time h (kW)
$P_{h,s,i}^{\mathrm{Re-,CS}}$	Power sold to CS i by retailer s at time h
$P_{h,s}^{\mathrm{Re+,WM}}$	Power purchased from wholesale market by retailer s at time h (kW)
$PF_{h,b}$	Power factor at bus b and time h
$Q_{D_b,h}$	Calculated reactive electrical load at bus b of the distribution network at time h (kVar)
$Q_{L_h}^{\mathrm{DN}}$	Reactive power loss of distribution network at time h (kVar)
$\mathbb{R}^{\mathrm{CS}}$	Net revenue of CS operators (\$)
$\mathbb{R}^{\mathrm{CS-,AG}}$	Revenues of CSs from selling energy to the aggregators (\$)
$\mathbb{R}^{\mathrm{CS-,EV}}$	Revenues CSs from selling energy to EVs (\$)
$\mathbb{R}^{\mathrm{EV-,CS}}$	Revenue of EVs from selling electricity to CSs (\$)
$\mathbb{R}^{\mathrm{Re}}$	Net revenue of retailers (\$)
$\mathbb{R}^{\mathrm{Re-,CS}}$	Revenue of retailers obtained by selling electricity to CSs (\$)
$S_{D_b,h}$	Calculated apparent electrical load at bus b of the distribution network at time h (kVA)
$SOC_{h,k,r}^{\mathrm{DP,EV}}$	SOC of EV k in trip r at time h (%)
$SOC_{h,i}^{ESS}$	SOC of ESS of CS i at time h (%)
$SOC_{h,k,r}^{\mathrm{EV}}$	SOC of EV k in trip r at time h (%)
$SOC_{h,k,r}^{\mathrm{EV^{DE}}}$	SOC of EV k at its destination in trip r at time h (%)
$SOC_{h,k,r}^{\mathrm{in}}$	Initial SOC of EV k at the beginning of trip r and time h (%)
$SOC_{h,k,r}^{\mathrm{R,EV+}}$	Required SOC of EV k in trip r at time h during charging period (%)

$SOC_{h,k,r}^{\mathrm{R,EV^{OR}\rightarrow CS^{SE}}}$	Required SOC of EV k in order to reach the selected CS from its origin in trip r at time h (%)
$SOC_{h,k,r}^{R,EV^{\mathrm{OR}}\rightarrow EV^{\mathrm{DE}}}$	Required SOC of EV k in order to reach its destination from its origin in trip r at time h (%)
$SOC_{h,k,r}^{R,CS^{\mathrm{SE}}\rightarrow EV^{\mathrm{DE}}}$	Required SOC of EV k in order to reach its destination from the selected CS in trip r at time h (%)
T^{CYC}	Period of cycle
$V_{h,b}$	Voltage at bus b and time h (V)
$x_{n,it}^{\mathrm{f}}$	Position of the follower f in the dimension n in SSA
$\theta_{b,h}$	Voltage angle of the bus b at time h
$\rho_{h,i}^{\mathrm{CS-,AG}}$	Electricity price sold to the aggregator by CS i at time h ($/kWh)
$\rho_{h,i}^{\mathrm{CS+,EV}}$	Electricity price purchased from EVs by CS i at time h ($/kWh)
$\rho_{h,s}^{\mathrm{Re-,CS}}$	Electricity price sold to CSs by retailer s at time h ($/kWh)
$\rho_{h,i}^{\mathrm{CS-,EV}}$	Electricity price sold to EVs by CS i at time h ($/kWh)
$\rho_{h,s}^{\mathrm{CS+,Re}}$	Electricity price purchased from retailer s by CS i at time h ($/kWh)
$\rho_{h,i}^{\mathrm{EV+,CS}}$	Electricity price purchased from CS i by EVs at time h ($/kWh)
$\rho_{h,i}^{\mathrm{EV-,CS}}$	Electricity price sold to charging station i by EVs at time h ($/kWh)

Acknowledgment

The work is funded by PGR scholarship at Northumbria University and supported by a project funded by the British Council under grant contract No: IND/CONT/GA/18-19/22.

References

[1] Z. Ding, Y. Lu, K. Lai, M. Yang, W. J. Lee, Optimal coordinated operation scheduling for electric vehicle aggregator and charging stations in an integrated electricity-transportation system, International Journal of Electrical Power & Energy Systems 121 (2020) 1–11.

[2] M. Moradijoz, M. P. Moghaddam, M. Haghifam, E. Alishahi, A multi-objective optimization problem for allocating parking lots in a distribution network, International Journal of Electrical Power & Energy Systems 46 (2013) 115–122.

[3] C. G. Hoehne, M. V. Chester, Optimizing plug-in electric vehicle and vehicle-to-grid charge scheduling to minimize carbon emissions, Energy 115 (2016) 646–657.

[4] Y. R. Rorigues, A. C. Z. de Souza, P. F. Ribeiro, An inclusive methodology for Plug-in electrical vehicle operation with G2V and V2G in smart microgrid environments, International Journal of Electrical Power & Energy Systems 102 (2018) 312–323.

[5] P. Jain, A. Das, T. Jain, Aggregated electric vehicle resource modelling for regulation services commitment in power grid, Sustainable Cities and Society 45 (2019) 439–450.

[6] L. Wang, S. Sharkh, A. Chipperfield, Optimal decentralized coordination of electric vehicles and renewable generators in a distribution network using A^* search, International Journal of Electrical Power & Energy Systems 98 (2018) 474–487.

[7] M. R. Mozafar, M. H. Amini, M. H. Moradi, Innovative appraisement of smart grid operation considering large-scale integration of electric vehicles enabling V2G and G2V systems, Electric Power Systems Research 154 (2018) 245–256.

[8] S. Pirouzi, J. Aghaei, T. Niknam, H. Farahmand, M. Korpås, Exploring prospective benefits of electric vehicles for optimal energy conditioning in distribution networks, Energy 157 (2018) 679–689.

[9] J. Zhao, J. Wang, Z. Xu, C. Wang, C. Wan, C. Chen, Distribution network electric vehicle hosting capacity maximization: A chargeable region optimization model, IEEE Transactions on Power Systems 32 (2017) 4119–4130.

[10] F. Manríquez, E. Sauma, J. Aguado, S. de la Torre, J. Contreras, The impact of electric vehicle charging schemes in power system expansion planning, Applied Energy 262 (2020) 1–15.

[11] Y. Zhao, X. He, Y. Yao, J. Huang, Plug-in electric vehicle charging management via a distributed neurodynamic algorithm, Applied Soft Computing 80 (2019) 557–566.

[12] K. Clement-Nyns, E. Haesen, J. Driesen, The impact of vehicle-to-grid on the distribution grid, Electric Power Systems Research 81 (2011) 185–192.

[13] N. Neyestani, M. Y. Damavandi, M. Shafie-Khah, J. Contreras, J. P. S. Catalao, Allocation of plug-in vehicles' parking lots in distribution systems considering network-constrained objectives, IEEE Transactions on Power Systems 30 (2015) 2643–2656.

[14] D. Wu, N. Radhakrishnan, S. Huang, A hierarchical charging control of plug-in electric vehicles with simple flexibility model, Applied Energy 253 (2019) 1–9.

[15] W. Su, M.-Y. Chow, Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm, IEEE Transactions on Smart Grid 3 (2011) 308–315.

[16] M. Honarmand, A. Zakariazadeh, S. Jadid, Optimal scheduling of electric vehicles in an intelligent parking lot considering vehicle-to-grid concept and battery condition, Energy 65 (2014) 572–579.

[17] M. Shafie-Khah, M. Moghaddam, M. Sheikh-El-Eslami, J. Catalão, Optimised performance of a plug-in electric vehicle aggregator in energy and reserve markets, Energy Conversion and Management 97 (2015) 393–408.

[18] Farnaz Safdarian and Logan Lamonte and Amin Kargarian and Mehdi Farasat, Distributed optimization-based hourly coordination for V2G and G2V, in: 2019 IEEE Texas Power and Energy Conference (TPEC), 2019, pp. 1–6.

[19] Ahmed Abdulaal and Mehmet H Cintuglu and Shihab Asfour and Osama A Mohammed, Solving the multivariant EV routing problem incorporating V2G and G2V options, IEEE Transactions on Transportation Electrification 3 (2016) 238–248.

[20] A. G. Anastasiadis, G. P. Kondylis, A. Polyzakis, G. Vokas, Effects of increased electric vehicles into a distribution network, Energy Procedia 157 (2019) 586–593.

[21] A. Triviño-Cabrera, J. A. Aguado, S. de la Torre, Joint routing and scheduling for electric vehicles in smart grids with v2g, Energy 175 (2019) 113–122.

[22] S. S. Barhagh, B. Mohammadi-Ivatloo, A. Anvari-Moghaddam, S. Asadi, Risk-involved participation of electric vehicle aggregator in energy markets with robust decision-making approach, Journal of Cleaner Production 239 (2019) 118076.

[23] Shafiee, Mehdi and Ghazi, Reza and Moeini-Aghtaie, Moein, Day-ahead Resource Scheduling in Distribution Networks with Presence of Electric Vehicles and Distributed Generation Units, Electric Power Components and Systems 47 (2019) 1450–1463.

[24] A. Moradipari, N. Tucker, M. Alizadeh, Mobility-aware electric vehicle fast charging load models with geographical price variations, IEEE Transactions on Transportation Electrification (2020).

[25] W. Wei, S. Mei, L. Wu, M. Shahidehpour, Y. Fang, Optimal traffic-power flow in urban electrified transportation networks, IEEE Transactions on Smart Grid 8 (2016) 84–95.

[26] J. Tan, L. Wang, Real-time charging navigation of electric vehicles to fast charging stations: A hierarchical game approach, IEEE Transactions on Smart Grid 8 (2015) 846–856.

[27] Das, Ridoy and Wang, Yue and Putrus, Ghanim and Kotter, Richard and Marzband, Mousa and Herteleer, Bert and Warmerdam, Jos, Multi-objective techno-economic-environmental optimisation of electric vehicle for energy services, Applied Energy 257 (2020) 113965.

[28] Madahi, Seyed Soroush Karimi and Nafisi, Hamed and Abyaneh, Hossein Askarian and Marzband, Mousa, Co-Optimization of Energy Losses and Transformer Operating Costs Based on Smart Charging Algorithm for Plug-in Electric Vehicle Parking Lots, IEEE Transactions on Transportation Electrification (2020).

[29] A. Zakariazadeh, S. Jadid, P. Siano, Multi-objective scheduling of electric vehicles in smart distribution system, Energy Conversion and Management 79 (2014) 43–53.

[30] Y. Luo, G. Feng, S. Wan, S. Zhang, V. Li, W. Kong, Charging scheduling strategy for different electric vehicles with optimization for convenience of drivers, performance of transport system and distribution network, Energy 194 (2020) 116807.

[31] Shafiee, Mehdi and Ghazi, Reza and Moeini-Aghtaie, Moein, A multi-objective framework for energy resource scheduling in active distribution networks, International Journal of Ambient Energy 40 (2019) 504–516.

[32] A. Moradipari, M. Alizadeh, Pricing and routing mechanisms for differentiated services in an electric vehicle public charging station network, IEEE Transactions on Smart Grid 11 (2019).

[33] Z. Moghaddam, I. Ahmad, D. Habibi, Q. V. Phung, Smart charging strategy for electric vehicle charging stations, IEEE Transactions on Transportation Electrification 4 (2017) 76–88.

[34] V. Dvorkin, J. Kazempour, P. Pinson, Chance-constrained equilibrium in electricity markets with asymmetric forecasts, arXiv preprint arXiv:2005.11749 (2020).

[35] H. Uzawa, Walras' tatonnement in the theory of exchange, The Review of Economic Studies 27 (3) (1960) 182–194.

[36] "ArcGIS 10.5.1 desktop." Available: https://desktop.arcgis.com/en/. [Accessed: 01-oct-2018]. (2019).

[37] A. Ahmadian, M. Sedghi, B. Mohammadi-ivatloo, A. Elkamel, M. A. Golkar, M. Fowler, Cost-benefit analysis of V2G implementation in distribution networks considering pevs battery degradation, IEEE Transactions on Sustainable Energy 9 (2017) 961–970.

[38] X. Chen, H. Lei, R. Xiong, W. Shen, R. Yang, A novel approach to reconstruct open circuit voltage for state of charge estimation of lithium ion batteries in electric vehicles, Applied Energy 255 (2019) 113758.

[39] Z. Liu, F. Wen, G. Ledwich, Optimal planning of electric-vehicle charging stations in distribution systems, IEEE Transactions on Power Delivery 28 (2013) 102–110.

[40] S.G.Tichi, M.M.Ardehali, M.E.Nazari, Examination of energy price policies in iran for optimal configuration of chp and cchp systems based on particle swarm optimization algorithm, Energy Policy 38 (2010) 6240–6250.

[41] A. Algarni, K. Bhattacharya, A generic operations framework for discos in retail electricity markets, IEEE Transactions on Power Systems 24 (2009) 356–367.

[42] J. Zhang, Y. Wu, Y. Guo, B. Wang, H. Wang, H. Liu, A hybrid harmony search algorithm with differential evolution for day-ahead scheduling problem of a microgrid with consideration of power flow constraints, Applied Energy 183 (2016) 791–804.

[43] S. P. Simon, N. P. Padhy, R. Anand, An ant colony system approach for unit commitment problem, International Journal of Electrical Power & Energy Systems 28 (2006) 315–323.

[44] Z. Chen, R. Xiong, J. Cao, Particle swarm optimization-based optimal power management of plug-in hybrid electric vehicles considering uncertain driving conditions, Energy 96 (2016) 197–208.

[45] B. Amirhosseini, S. H. Hosseini, Scheduling charging of hybrid-electric vehicles according to supply and demand based on particle swarm optimization, imperialist competitive and teaching-learning algorithms, Sustainable cities and society 43 (2018) 339–349.

[46] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, M. Mirjalili, Salp swarm algorithm: A bio-inspired optimizer for engineering design problems, Advances in Engineering Software 114 (2017) 163–191.

[47] R. A. El Sehiemy, F. Selim, B. Bentouati, M. Abido, A novel multi-objective hybrid particle swarm and salp optimization algorithm for technical-economical-environmental operation in power systems, Energy 193 (2019) 116817.

[48] H. Faris, M. M. Mafarja, A. A. Heidari, I. Aljarah, A. M.Al-Zoubi, S. ali Mirjalili, H. Fujita, An efficient binary salp swarm algorithm with crossover scheme for feature selection problems, Knowledge-Based Systems 154 (2018) 43–67.

[49] San francisco map, available at:
https://www.arcgis.com/home/...
item.html?id=e66bb5dac376457b9f721b083572712c.

[50] K. Shaloudegi, N. Madinehi, S. H. Hosseinian, H. A. Abyaneh, A novel policy for locational marginal price calculation in distribution systems based on loss reduction allocation using game theory, IEEE Transactions on Power Systems 27 (2012) 811–20.

[51] California ISO, available at: http://www.oasis.caiso.com (2019).

[52] U.s. environmental protection agency combined heat and power partnership, catalog of chp technologies section 5. technology characterization - microturbines (2015).

[53] J. Jannati, D. Nazarpour, Optimal performance of electric vehicles parking lot considering environmental issue, Journal of cleaner production 206 (2019) 1073–1088.