An Energy Management System With Renewable Energy and Energy Storage System for Large-scale Electric Vehicle Charging Stations

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***Abstract*—With the increase in the use of electric vehicles (EVs), charging stations are having congestion problems. The grid energy storage system can be used to satisfy the energy demand for charging EV batteries. EV charging/discharging scheduling for vehicle-to-grid (V2G) and grid-to-vehicle (G2V) operations is challenging because customers have different energy requirements. Here, a charging and discharging power scheduling algorithm was applied to an EV charging station. Integrating renewable energies and energy storage systems in charging stations can increase EV charging station's profits and optimize power supply from the grid. With the time-of-use (TOU) electricity tariff, the proposed algorithm can reduce the cost of charging. The optimization problem can be solved through linear programming, which is realized using a data preprocessing procedure for relieving computational burden. The proposed approach can coordinate the charging/discharging power of EVs based on the vehicles' charging/discharging priorities and electricity prices. Thus, the TOU adjustment method can be used to regulate the TOU parameters according to the charging/discharging priorities and electricity prices and ensure the energy usage does not exceed contract capacity. The proposed algorithm was compared with existing methods. The simulation results revealed that the proposed approach effectively satisfied energy demands and reduced charging costs. The proposed approach can considerably increase EV penetration through effective energy scheduling and dispatching.**

***Index Terms*—optimization, energy storage system, large electric vehicle charging station, renewable energies, vehicle-to-grid/grid-to-vehicle (V2G/G2V)**

Nomenclature

A. Indices

i	The EV number.
t	Time instant.

B. Parameters

M	Total number of EVs in the station.
x	EV charging state, binary number, 1 if EV is charging, 0 otherwise.
y	EV discharging state, binary number, 1 if EV is discharging, 0 otherwise.
Δt	Time step size.
α	EV V2G agreement.
$p^{\max}$	EV maximum discharging power (kW).
$p^{\min}$	EV maximum charging power (kW).
w_{ess}	ESS charging state, binary number, 1 if ESS is charging, 0 otherwise.
v_{ess}	ESS discharging state, binary number, 1 if ESS is discharging, 0 otherwise.
$P_{\mathrm{ess}}^{\max}$	ESS maximum charging power (kW).
$SOC_{\mathrm{ess}}^{\max}$	ESS maximum SOC.
P_{T}	Contract capacity (kW).
s	Charging priority order reference.
N	Charging station size in terms of maximum number of EVs.

C. Variables

SOC^{initial}	EV SOC upon arrival.
SOC^{desired}	EV desired SOC at departure time.
$SOC^{\min}$	EV minimum allowed SOC.
$SOC^{\max}$	EV maximum allowed SOC.
SOC^{need}	Energy demand from the user.
SOC^{gain}	Energy accumulated under maximum power.
cap	EV battery capacity (kWh).
E^{sold}	Energy sold to the grid (kWh) from EV.
$BatCost$	EV battery replacement cost ($).
UBC	Unit battery replacement cost ($/kWh).

$Price_{\text{charge}}$	Charging electricity price (\$/kWh).
$Price_{\text{discharge}}$	Discharging electricity price (\$/kWh).
P_{rice}	Daily electricity price (\$/kWh).
t^{a}	Individual EV arrival time.
t^{d}	Individual EV departure time.
t_{start}	First EV arrival time.
t_{end}	Last EV departure time.
p	EV scheduled power (kW).
P_{grid}	Power requested from the grid (kW).
P_{ess}	ESS output power (kW).
η_{ess}	ESS scalability factor.
B_{ess}^{t}	ESS remaining capacity ignoring its minimum SOC.
$B_{\text{ess}}^{\prime t}$	ESS remaining capacity including its minimum SOC.
γ	Fraction of ESS power sold to the grid.
P_{PV}	PV output power (kW).
P_{ess}	ESS output power (kW).
β	Fraction of PV power sold to the grid.
λ	Exterior penalty factor.
$P_{\text{grid\_request}}$	Grid requested power from the station (kW).
$P_{\text{station\_grid}}$	Power delivered to the grid from the station (kW).
$Comp$	Financial compensation for vehicle adhering to V2G (\$).
τ_{charge}	Charging priority index.
$\tau_{\text{discharge}}$	Discharging priority index.
K	Charging priority order.

I. INTRODUCTION

Electric vehicles (EVs) will be widely used in the near future. Emerging technologies such as vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) operations are being developed for balancing the demand and supply in the charging stations. For example, the winter load profile of France shows a peak of energy consumption around afternoon [1]. Thus, a surge in the demand for recharging batteries is expected in the afternoon. This can cause congestion of the distribution system and charging station operators may find it difficult to manage this surge in demand. Several strategies have been studied to prevent the congestion during peak hours [2], [3]. The effect of EV charging on the contract capacity of a charging station has been analyzed [4], [5]. V2G operations of the EVs pose several problems because of the power injection into the electric grid traditionally designed for one-way power flow. Well-designed financial models and transactive energy frameworks that can address technical challenges and contract capacity exigencies are required to make V2G feasible and lucrative [6]–[8].

In practice, the high cost of EVs is a limitation. Additionally, delegating charging control to an operator is undesirable to the customer unless on-demand availability and safety of the vehicle are assured. Therefore, control and scheduling techniques should cater to customer comfort, financially motivate them, and provide incentives for V2G without compromising network or battery health. Several methods have been proposed to overcome the aforementioned problems [9]–[12]. However, EVs, energy storage system (ESS), and renewable energy sources (RESs) have not been considered simultaneously in these linear programming (LP) studies. For instance, in [12], the implementation of 20 EVs scheduling was proposed; however, the ESS and photovoltaic (PV) system were not considered in the problem. RES and EVs have been considered in [13]–[17] by using multiple-objective optimization, Lyapunov optimization, quadratic programming, mixed-integer linear programming, and fuzzy logic to integrate RESs in the charging station for achieving higher profits.

In [18], ESS, EVs, and PV were used. In this study, EVs were charged using PV cells. However, generation of power using PV cells depends on weather conditions, which affects the reliability of the charging station. In the algorithm in [19], the peak consumption and potential overloads of the power infrastructure were reduced by using appropriate loads and 50 EVs. Two concerns should be considered when scheduling EVs, namely the charging station net profit maximization and charging cost minimization for the vehicle owner. However, the study focused on the initial state of charge (SOC) of the vehicles without considering the correlation with the arrival time.

In [20], the net profit of charging stations and vehicle owners' charging cost were considered and multiple objective functions were used for scheduling EVs through dynamic programming. However, problems related to high-dimensional optimization were observed. A scheduling algorithm was proposed in [21] to identify priority levels of vehicles and minimize the waiting time to plug-in at each charging port. The EVs with the highest discharge priority were set for discharging during the peak hours, whereas the EVs with highest charging priority were scheduled to charge during off-peak periods. In [22], the Stackelberg Game approach was used to investigate the V2G process between a charging station operator and EVs considering battery degradation. However, this method requires more computational time, which is a concern.

In this paper, we present the optimization solution for minimizing the cost of charging for EV owners by using PV and ESS to maximize the profits of the charging station. This algorithm can be used for EV charging station management; the connection between vehicles and grid is bidirectional, which allows the vehicles to operate as aggregated loads, distributed storage units, or standalone energy sources. To enhance the optimization performance and reduce the computation burden, a data preprocessing method was used according to the characteristic of the EV power scheduling problem for avoiding unnecessary computation. Data preprocessing determined if the time required for charging the battery of the EV. Two strategies were adopted for vehicles staying for short time and vehicles staying longer. The LP method was used to integrate the proposed data in the preprocessing method to optimization problem.

Furthermore, if the number of EVs simultaneously connected to the distribution grid is too much, then the charging or discharging power may exceed the contract capacity. A regulation method was used to adjust the time-of-use (TOU) tariff, which is based on the charging priority calculated according to the departure urgency and charging energy demand of an EV. The regulated TOU is not used to settle the bill but as a control factor during a shortage of the charging capacity. This considerably reduced the charging cost because we reduced the waiting time of the vehicles, thus avoiding congestion. We investigated the simultaneous consideration of both EVs and ESSs. If the power consumption for charging the vehicle was less than the remaining contract capacity, then ESS is started to schedule after the EVs were scheduled.

The remaining of this paper is organized as follows: Section II presents the system architecture for the EV bidirectional charging station. Section III describes the proposed EV charging optimization approach, followed by extensive computer simulations in Section IV. Section V presents conclusions.

II. System Architecture an Operational Flow

2.1 System Architecture

0 illustrates the schematic of the proposed EV charging station. In addition to EV charging piles, a PV cell and ESS system were incorporated in the system. The related data of the mentioned distributed energy resources and control signals were transmitted through communication interfaces and a supervisory control and data acquisition (SCADA) system. In addition, an aggregator determines the decisions for energy management. The proposed charging and discharging power scheduling algorithm was executed in the aggregator. The charging station was assumed to have the ability to automatically detect the vehicle arrival time, initial SOC, and battery capacity of an EV through a uniform communication protocol between SCADA and EV charging piles. The departure time and the final desired SOC were provided by the EV user through the user–machine interface before charging.

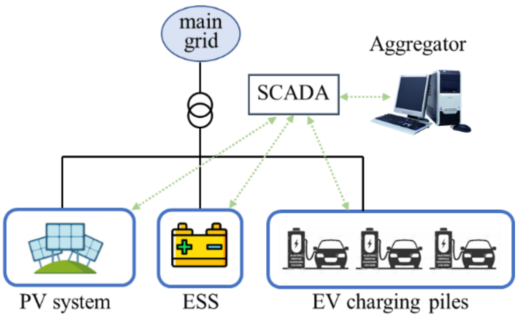


Fig. 1. Schematic of the proposed EV charging station.

The effectiveness of the proposed algorithm was determined by the reduction in the charging cost. Tis can be achieved by charging at the time with lower electricity tariffs. Because electricity tariffs and PV generated power changes with time, PV power and electricity tariffs forecasting systems were used during the scheduling stage. Another key factor to reduce the charging price is to allow the EV to transmit power back to the grid when energy prices are high. In this study, the charging piles were assumed to be bidirectional; that is, the battery in the EV could be charged by the utility grid and discharged to store energy in the grid

2.2 Operational Flow and Data Preprocessing

0 depicts the proposed algorithm. First, when the vehicle enters the station and calculates the required information, namely minimum SOC, maximum SOC, initial SOC, desired SOC, and a smart planning system, reduces the charging cost. Thus, the calculated information can be used to determine if the EV has reached the desired SOC. Assuming we continually provided the maximum power to the vehicle during charging. At the end of the process, the gain in energy is SOC_i^{gain}, as denoted in (1). Then, we compared the energy with SOC needed SOC_i^{need} by the vehicle, as depicted in (2). If SOC_i^{need} exceeds SOC_i^{gain}, the user's

preference would not be preferable. An easier method to solve this problem is charging the given vehicle using the available maximum power even though the final SOC would be less than the desired power.

$$SOC_i^{\text{gain}} = \frac{P_i^{\min} \cdot (t_i^a - t_i^d)}{cap_i} \tag{1}$$

$$SOC_i^{\text{need}} = SOC_i^{\text{desired}} - SOC_i^{\text{initial}} \tag{2}$$

The proposed charging station used the static presence of the vehicle in the station. The longer the time the vehicle spends in the station, the more chance to achieve lower the charging cost, except when the vehicle stays in the period of the same charging price. The consent of the user of the EV is obtained to join the V2G program. The vehicle user may or may not accept, depending on the battery degradation cost compensation proposed by the charging station.

In [23], a linear model describing the unit monetary compensation (UBC) versus the amount of energy provided to the grid by a given vehicle was provided. Equation (3) depicts the UBC using a rigorous linear regression completed [24]. The coefficients were determined to be 0.042 and 312 resulted from the linear regression. Notably, the unit battery compensation cost was strongly associated with the battery replacement cost. For a given EV delivering energy equivalent to E_i^{sold}, the compensation evaluated as (4). After successfully scheduling all the vehicles, we move to schedule ESS if we do not reach the transformer limit.

$$UBC_i = 0.042\left(\frac{BatCost_i}{312}\right) \tag{3}$$

$$Comp_i = UBC \cdot E_i^{\text{sold}} \tag{4}$$

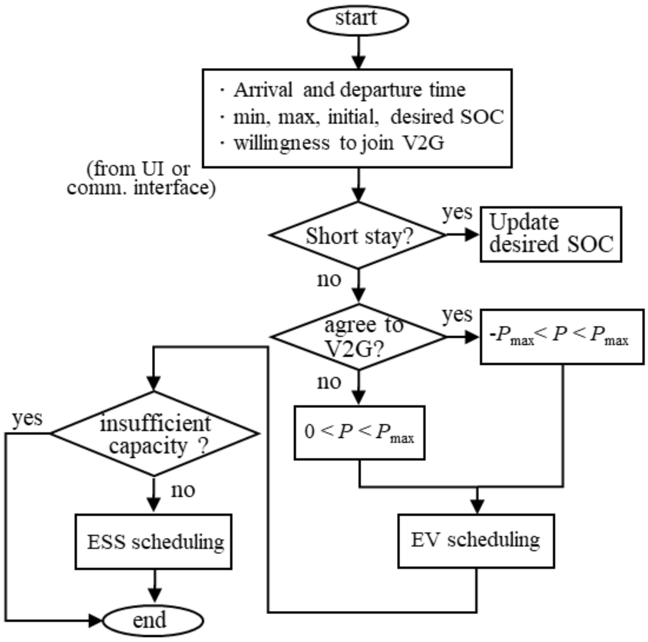


Fig. 2. Proposed algorithm

III. PROPOSED EV CHARGING OPTIMIZATION APPROACH

3.1 Objective function

The total cost is defined as the sum of the charging costs over the charging horizon. The total cost is then calculated using (5). The scheduling optimization problem comprises minimization of the total cost of charging and discharging the EVs during their stay. The optimization involves the relationship between the ESS in an interval and the charging power of an individual EV, instant energy constraints, final energy constraints, lower bound and the upper bound of the charging power. Mathematically, the optimization problem can be formulated as (6).

$$\begin{aligned} \text{cost}(t) = {} & Price_{\text{charge}}^t \Delta t \left[\sum_{i=1}^{M} (-x_i^t \cdot p_i^t) + \eta_{\text{ess}}^t \cdot w_{\text{ess}}^t \cdot P_{\text{ess}}^{\max} \right] - \\ & Price_{\text{discharge}}^t \Delta t \left[\sum_{i=1}^{M} (\alpha_i^t \cdot y_i^t \cdot p_i^t) + \beta \cdot P_{\text{PV}}^t + \gamma \cdot v_{\text{ess}}^t \cdot P_{\text{ess}}^t \right] \end{aligned} \tag{5}$$

$$\min \sum_{t=t_{\text{start}}}^{t_{\text{end}}} \text{cost}(t) \tag{6}$$

The decision variables x_i^t, y_i^t, v_i^t, w_i^t, and p_i^t denote the EV charging status, EV discharging status, ESS charging status, ESS discharging status, and power drawn of each EV in every time slots during its stay in the station, respectively. The objective function is to minimize the total net cost of charging vehicles, maximize V2G, PV cells, and ESS usage. The formulation has four components:

- The cost of buying energy from the grid based on energy price. Energy is purchased preferably when grid offering price is low. Assuming the EV stays in the station and electricity price remains the same, the EV is charged according to the pricing. A similar operation can be performed for EV not having sufficient time.
- ESSs are charged only when the energy price is low, and it is the only method to generate profit.
- V2G essentially considers the EV owner's consent to join the V2G service (α_i^t).
- The amount of PV and ESS to be sold to the grid is decided by the aggregator through parameters β and γ. The remaining 1-β, 1-γ of PV and ESS, respectively, are given to the local load. In this paper, the load constituted the lighting of the station. The energy required by the load can then be easily satisfied by using ESS and PV cells.

In the optimization problem, the objective function is convex, and all the constraints functions are linear. Therefore, the optimization problem can be solved efficiently with the interior point method. Specifically, LP is one of the ramifications of linear programming used. The solution to the optimization problem provides the optimal scheduling scheme for EV charging and discharging during the day.

3.2 Constraints

1) SOC Constraints

a) Generic SOC constraints

The SOC is defined as the electrical energy in an EV battery at that instant. The inverter rating power of the battery and its permissible SOC are commonly used constraints. Regardless of the algorithm to be adopted, the charging power of the battery should not exceed the threshold, $p_i^{\min}$. Bidirectional flow allows discharge for a certain limit $p_i^{\max}$. The minimum power naming is just a sign convention because the charging power is negative and the discharging power is positive in this paper.

$$p_i^{\min} \le p_i^t \le p_i^{\max} \tag{7}$$

The charging of the EV is expected to start as soon as it arrives at the station and stop just before the EV leaves the station (8). This feature turns the proposed algorithm to LP.

$$x_i^t = y_i^t = 0, \text{ if } \left[t \le t_i^a \text{ or } t \ge t_i^d \right] \tag{8}$$

During its stay, EV (9) as well as ESS (10) cannot charge and discharge simultaneously.

$$x_i^t = \begin{cases} 1 \\ 0 \Rightarrow y_i^t = \begin{cases} 1 \\ 0 \end{cases} \end{cases} \text{For EV} \tag{9}$$

$$w_{\text{ess}}^t = \begin{cases} 1 \\ 0 \Rightarrow v_{\text{ess}}^t = \begin{cases} 1 \\ 0 \end{cases} \end{cases} \text{For ESS} \tag{10}$$

Giving that the maximum of the inverter may not be possible if the battery is almost full, the maximum allowable SOC should be known in advance. The same can be said about the minimum SOC. Therefore, we obtain the following equation:

$$SOC_i^{\min} \le SOC_i^t \le SOC_i^{\max} \tag{11}$$

At departure, the EV is expected to have its desired SOC, fulfilling user demand as follows:

$$\Delta t \sum_{t=t_{\text{start}}}^{t_{\text{end}}} (x_i^t \cdot p_i^t + \alpha_i^t \cdot y_i^t \cdot p_i^t) = Cap_i (SOC_i^{\text{initial}} - SOC_i^{\text{desired}}) \tag{12}$$

b) SOC constraint linearization

Numerical optimization of general nonlinear multivariable objective functions requires efficient and robust techniques. Efficiency is essential because these problems require an iterative solution procedure, trial and error is impractical for more than three or four variables. Robustness (the ability to determine an optimal solution) is desirable because a general nonlinear function is unpredictable in its behavior; several relative minima may occur. In some regions, the optimization algorithm can evolve very slowly toward the optimum, requiring excessive computation time. A reliable charging station is expected to perform scheduling within 5 min of the arrival of the EV and account for the owner's random behavior until the departure time. Constraints exhibited by evolutionary techniques such as genetic algorithm, differential evolution (DE), particle swarm optimization, and bee colony are time consuming [25]-[27].

The aforementioned problem can be solved by linearizing the SOC of the EV battery. Linear programming [12] can be used to accurately determine the minimum cost. In this paper, instead of just describing linear programming [28], a well-structured linearization approach was proposed. By definition, the SOC is defined as follows:

$$SOC_i^t = SOC_i^{t-1} - \frac{p_i^t \Delta t}{cap_i} \text{ , at time } t \tag{13}$$

$$SOC_i^{t+1} = SOC_i^t - \frac{p_i^{t+1} \Delta t}{cap_i} \text{ , at time } t+1 \tag{14}$$

Replacing SOC_i^t from (13) by its expression in (14), we obtain the following expression:

$$SOC_i^{t+1} = SOC_i^{t-1} - \frac{p_i^t \Delta t}{cap_i} - \frac{p_i^{t+1} \Delta t}{cap_i} \tag{15}$$

We present the generalized equation of the SOC constraint in a compact form using the aforementioned deductions. The generalization considers the cumulative constrained power exchanged between the grid and a given vehicle within a specified interval of time. By an immediate recurrence, we obtain the following expression:

$$SOC_i^t = SOC_i^{\text{initial}} - \frac{\Delta t}{cap_i}(p_i^{t_0} + \ldots + p_i^{t-1} + p_i^t) \tag{16}$$

The relationship between the SOC and the cumulative power developed in (16) is a used to impose some constraints to the cumulative power to avoid battery capacity violation. Recalling inequality (11) and inserting (16) in (11):

$$SOC_i^{\min} \le SOC_i^{\text{initial}} - \frac{\Delta t}{cap_i}(p_i^{t_0} + \ldots + p_i^{t-1} + p_i^t) \le SOC_i^{\max} \tag{17}$$

Thus, the following useful constraint is obtained for writing the format $Ax \le b$ of LP.

$$\frac{cap_i(SOC_i^{\text{initial}} - SOC_i^{\max})}{\Delta t} \le p_i^{t_0} + \ldots + p_i^{t-1} + p_i^t \le \frac{cap_i(SOC_i^{\text{initial}} - SOC_i^{\min})}{\Delta t} \tag{18}$$

The aforementioned constraints are only applicable to ESS because it is not expected to have a specific SOC. Profit maximization is the main target. In addition to these constraints, the cumulative energies stored in the EV battery must be equal to the desired SOC of the customer when leaving the station. The equality constraint $A_{\text{eq}}x = b_{\text{eq}}$ of LP is devised as follows:

$$SOC_i^{\text{d}} = SOC_i^{\text{a}} - \frac{\Delta t}{cap_i}(p_i^{t_{\text{a}}} + \ldots + p_i^{t_{\text{d}}-1} + p_i^{t_{\text{d}}}) \tag{19}$$

$$(p_i^{t_{\text{a}}} + \ldots + p_i^{t_{\text{d}}-1} + p_i^{t_{\text{d}}}) = \frac{cap_i}{\Delta t}(SOC_i^{\text{a}} - SOC_i^{\text{d}}) \tag{20}$$

2) ESS Charging Feasibility

a) Transformer acknowledging

A major constraint of a charging station is its contract capacity, namely the maximum charging power. An ideal charging station operates within 1%–90% of its capacity and still charge the ESS. Beyond a certain threshold, an estimate of the amount of power from the grid to be purveyed to ESS makes the charging station the subject of smart scheduling. The coefficient C_p established in (21) denotes the proportion of the maximum power to be supplied to the ESS by considering the transformer remaining capacity. The expression for C_p is

$$C_\mathrm{p} = \frac{P_T - \sum_{i=1}^{M} p_i^t}{P_T}\,. \tag{21}$$

b) ESS capacity limits

Another non-negligible and straightforward parameter to consider in ESS scheduling is its previous SOC. A full ESS need not need be charged. Furthermore, a nearly full ESS requires very little power depending on the constraint imposed by the contract capacity. For an empty battery, the maximum power would be the desired charging. With respect to the aforementioned context, fraction B_ess^t is calculated to adjust the maximum power of ESS.

$$B_\mathrm{ess}^t = \frac{SOC_\mathrm{ess}^\mathrm{max} - SOC_\mathrm{ess}^{t\text{-}1}}{SOC_\mathrm{ess}^\mathrm{max}} \tag{22}$$

A flat battery compared with a battery discharged to a certain tolerance, namely $SOC_\mathrm{ess}^\mathrm{min}$, lasts the least [29]–[31]. Given this additional factor, B'^t_ess is derived from B_ess^t to include $SOC_\mathrm{ess}^\mathrm{min}$ as follows:

$$B'^t_\mathrm{ess} = \frac{SOC_\mathrm{ess}^\mathrm{max} - SOC_\mathrm{ess}^{t\text{-}1}}{SOC_\mathrm{ess}^\mathrm{max} - SOC_\mathrm{ess}^\mathrm{min}} \tag{23}$$

The two previously mentioned proportional coefficients together constitute the scalability factor of ESS, as depicted in (24). The scalability factor is a value between 0 and 1. The incapacity to charge ESS is denoted by $\eta_\mathrm{ess}^t = 0$. For a nonzero value of η_ess^t, ESS is settled to receive energy from the grid depending on the current grid offering energy price. In case we exceed the contract capacity, η_ess^t becomes 1, which shows that ESS is able to take in its maximum charging power.

Thus, if the maximum capacity is reached, the first term C_p is equal to zero, the second term need not be checked. We infer that ESS cannot be charged, too many vehicles are present in the station. If the number of EVs in the station is less, then the first term C_p is evaluated to a value close to 1 exempting the charging of the ESS from the capacity constraint. The second term B'_p expresses the constraints emanating from the battery minimum SOC and its maximum SOC, allowing permissble energy flow between the ESS and grid. Thus, the scalability factor η_ess^t adjusts the amount of ESS maximum charging power available for its charging by considering both the contract capacity constraint and the battery inherent limits simultaneously.

$$\eta_\mathrm{ess}^t = C_p^t \cdot B'^t_\mathrm{ess} \tag{24}$$

3) Capacity Constraint Exemption

a) Charging priority

EVs are expected to be widely used in the near future. Therefore, EV charging stations can charge hundreds of EVs. Contract capacity is a contraint. At peak time, with the high penetration of EV, the transformer is likely to be overloaded if all electrical vehicles have same behavior, either charging or discharging, simultaneously.

Smart scheduling necessary to manage the EVs at the charging stations. Modified electricity price patterns were used to shift the charging periods for the same charging cost. Those patterns were assigned according to a fair and concise method, unlike [32], in which the priority of the EV is determined two ambiguous steps. An EV that is nearly full is set to have low priority, engendering its charging delay. By contrast, EVs leaving soon should be charge as soon as possible by keeping it in a high priority group. The charging priority is defined in (25). The smaller the index, the higher is the priority.

$$\tau^t_{\mathrm{charge}_i} = \frac{t_i^d - t}{SOC_i^\mathrm{desired} - SOC_i^{t-1}} \tag{25}$$

b) TOU patterns assignment

The charging priority index τ_{charge} was used to classify EVs. The smallest priority index was assigned order 1. Then, priority index is from 1 to M. Equation (26) is an arithmetic progression with common difference of d, set to 1 for preference. The priority order table is computed in Fig.3 (a).

$$k_n^t = k_m^t + (n-m)\cdot d \ , \tag{26}$$

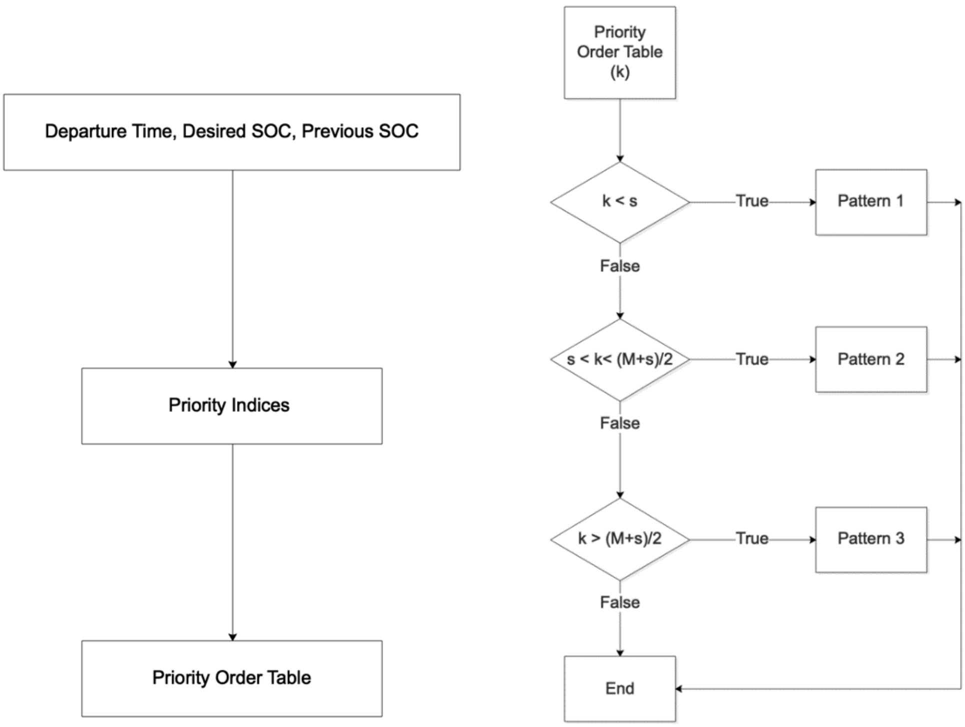
where m is the starting index, n is any index ($n \geq m$), k_m is the first term of the arithmetic progression, and s is defined as the number of vehicles leading to the transformer overloading.

$$\sum_{i=1}^{S} P_i^t = P_T \quad , \quad s \leq N \tag{27}$$

For simplicity, we considered the extreme situation in which vehicles are at their maximum charging power. Here, s is computed as follows:

$$s = \left| \frac{P_T}{P^{\min}} \right| \tag{28}$$

Here, s is triggered when the number of vehicles exceeds the number at the station can assign the maximum power to each vehicle. Vehicles whose priority order is more than the threshold are assigned patterns 2 and 3. The vehicles less than the threshold are assigned pattern 1 (Fig.3(b)).

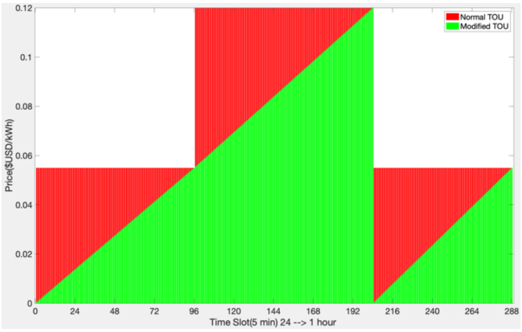


(a) (b)

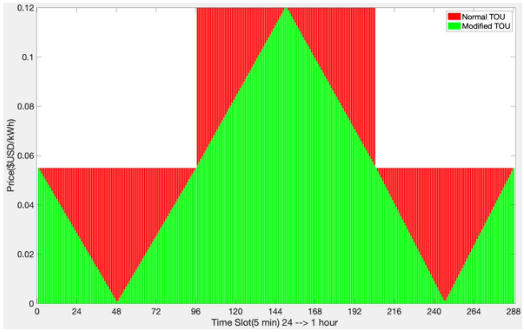
Fig. 3. (a) Priority order table. (b) TOU pattern assignment.

The TOU rate plan was used in determining the charging EV electricity consumption. TOU is a sliding rate scale, structured according to the peak and off-peak times of the day. Under such a plan, the EV bill was determined by amount of energy the EV charges/discharges with the grid and the time of the charge/discharge. The standard TOU was modified for the following reasons. From Fig.4(a), pattern 1 is the most profitable and is assigned to the first vehicle entering the charging station. This pattern allows charging at the beginning of the low electricity price periods. Notably, unless the number of vehicles exceeds the number that threshold of the transformer, these three patterns will not be used.

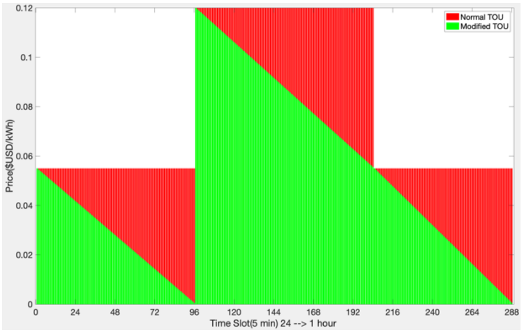
Then, pattern 2 (Fig.4 (b)) is the next profitable pattern. This pattern allows charging at the middle of the low electricity period. The least profitable among these three patterns is pattern 3 (Fig.4(c)). Vehicles in this pattern are served the last. The modified TOU is used for the scheduling. It does not influence the charging cost and only allows us to have control over the charging and discharging period.



(a)



(b)



(c)

Fig. 4. Revised TOU: Patterns (a) 1, (b) 2, and (c) 3.

3.3 Energy exchange with Grid

PV and ESS were installed to support the local load demand, reducing dependency on the grid. A sunny day may result in high generation of solar power. The surplus power is distributed on the grid or stored in the ESS. The charging station aggregator is responsible for setting β of PV. The grid energy requirement depends on the time its request exceeds the aggregated PV and ESS power ($P_{\text{ESS}}^t + P_{\text{PV}}^t$). When PV and ESS could not provide the power requested, the power from EV adherent to V2G (α) is dispatched to address the shortage (29) following a priority. The EV with high SOC and not close to their departure time is assigned high priority, as expressed in (31). Notably, the lowest grid requested power is no longer defined when the requested power exceeds the available aggregated PV and ESS power by 50%. The margin 50% was imposed for providing energy to the charging station's other demand, such as lighting. H(.) is the heaviside function. The higher the index, the higher is the priority.

$$p_{\text{station\_grid}}^t = \gamma \cdot P_{\text{ess}}^t + \beta \cdot P_{\text{PV}}^t + H\left(p_{\text{grid\_request}}^t - \frac{P_{\text{ess}}^t + P_{\text{PV}}^t}{2} \right) \cdot \sum_{i=1}^{M} \alpha_i^t \cdot y_i^t \cdot p_i^t \tag{29}$$

$$H(z) = \begin{cases} 0, & \text{if } z < 0 \\ \dfrac{1}{2}, & \text{if } z = 0 \\ 1, & \text{if } z > 0 \end{cases} \tag{30}$$

$$\tau_{\text{discharge}_i}^t = (SOC_i^{t-1} - SOC_i^{\min}) \cdot (t_t^d - t) \tag{31}$$

IV. Computational Results

4.1 Simulation Setup

To validate the effectiveness of the proposed algorithm, various numbers of fleet size of EV were investigated. A time window of 1440 min was considered in the charging scheduling triggered by the first vehicle entering the station. Scheduling stops eventually when all vehicles leave the station. The scheduling time horizon is divided equally into T = 288 time slots of length Δt = 5 min.

Based on [35]–[37], the distributions of plug-in and departure times of EVs follow the normal distributions. Table I summarizes EVs' status. The plug-in time of an EV is generated based on a normal distribution with the mean at 05:00 and a standard deviation of 3 h. Similarly, the plug-out (departure) time of an EV is assumed to follow a normal distribution with the mean at 16:00 and a standard deviation of 5 h. The SOC of EV upon arrival is generated using a normal distribution with a mean of 36% and a standard deviation of 15% using the Switch EV project [38]. The charging requirement of an EV is generated using a normal distribution with a mean of 86% and a standard deviation of 14%.

Additional details on the battery specification are presented in Table II. To illustrate the EV's high penetration could be manageable, we use different fleet size. Table III depicts each fleet size with its imposed contract capacity. The simulation is conducted in MATLAB Release 2018b, using the LP optimization solver. The specifications of the computer used for simulation were as follows: Intel i7 8700 CPU and 16 GB RAM.

4.2 Comparing Different Methods

The effectiveness of the presented algorithm was verified according to the methods presented in [33]. The performance of the propped algorithm was compared with those of others. In the uncoordinated charging algorithm (UCA), the vehicle is charged upon arrival until it reaches the desired SOC (0). This approach is called first come, first served because the temporal price variation is not considered. The objective is to minimize the charging period of a given vehicle [34]. The objective function is formulated using external penalty function (32) and easily can be solved both by linear as well as nonlinear optimizer.

$$\sum_{t=t_{\text{start}}}^{t_{\text{end}}} t\left(\sum_{i=1}^{M} x_i + \lambda_t \cdot \left(-\sum_{i=1}^{M} x_i^t \cdot p_i^t + P_T\right)^2\right) \tag{32}$$

The decision variables x_i^t, p_i^t, and t denote the charging status, power drawn of each EV in every time slots during its stay in the station, and charging duration, respectively. In the brute charging algorithm (BCA), the temporal price variation is used (0). In contrast to the uncoordinated charging, its effectiveness relies on long charging times, and the charging period is not. This method differs from that of the proposed method mainly in the absence of V2G technology and three TOU patterns. The contract capacity power constraint is included directly into the objective function. Priority was not set in this BCA, which is expressed by (33). The decision variables x_i^t and p_i^t denote the charging status and the power drawn of each EV in every time slots, respectively, during the vehicles stay in the station.

$$\sum_{t=t_{\text{start}}}^{t_{\text{end}}} P_{\text{price}}^t \cdot \Delta t \cdot \left(\left(\sum_{i=1}^{M} -x_i^t \cdot p_i^t\right) + \lambda_t \cdot \left(-\sum_{i=1}^{M} x_i^t \cdot p_i^t + P_T\right)^2\right) \tag{33}$$

The evolutionary algorithm is the third algorithm to be studied. Evolutionary algorithms have been used widely to implement electrical vehicles charging scheduling. DE was used for comparison in this paper (Fig. 7). The objective is the same as the proposed method (Fig. 8). The V2G feature was disabled on both testing algorithms for fair assessment. In practice, DE did not allow us to implement the aforementioned constraint once the V2G feature is enabled. However, we successfully performed G2V because the minimum, maximum, and needed SOC are maintained after the mutation and crossover stage. The proposed method was compared with DE by looking at both the cost achieved and the simulation time by each method.

TABLE I
STATUS OF EVS

Parameters	Distribution	Mean	Standard deviation
Arrival Time	Normal	05:00	3 h
Departure Time	Normal	16:00	5 h
Minimum SOC	Normal	12%	8%
Maximum SOC	Normal	94%	5%
Initial SOC	Normal	36%	15%
Desired SOC	Normal	86%	14%

TABLE II
BATTERY SPECS

Specs	Values
Capacity(kWh)	44
Minimum charging power(kW)	−7
Maximum charging power(kW)	7
Battery Cost ($)	8800
Unit Battery replacement cost($/kWh)	1.18

TABLE III
CHARGING STATION SPECIFICATION

Fleet Size	200	400	500
Contract Capacity(kW)	1000	1900	2500

4.3 Simulation Results

The uncoordinated method presented in [32] is set as the benchmark. The charging cost and algorithm speed were compared. The first two algorithms, namely the UCA and BCA were tested over their final total charging cost. Table IV lists the cost reduction achieved by the BCA. Owing to its V2G feature, the proposed method could achieve considerable cost reduction if the user adhered to the V2G program. On average, BCA achieved 19.2% of cost reduction while G2V/V2G with the proposed method cost reduction reached 29.6%.

In terms of the algorithm speed, all algorithms converged within the threshold of 5 min (Table V), with the exception of the DE method. UCA was the fastest (30 s for 500 EVs) because it does not perform any scheduling. Then, BCA (44.9s for 500 EVs), which attempts to locate charging period mostly during low charging price periods, was next. This additional feature makes it slower than UCA method. Thus, LP with several intelligent features was the slowest but its computation time was acceptable because it was less than the time limit (5 min) imposed.

TABLE IV
COST OF CHARGING USING DIFFERENT ALGORITHMS

Parameters		Fleet size			Average
Performance	Method	200	400	500	-
cost ($)	UCA	336.1	643.2	833.9	604.4
	BCA	261.8	533.3	669.1	488
	DE	281.2	555.9	688.5	508.5
	G2V only (proposed)	258.5	517.1	659.4	478.3
	G2V/V2G (proposed)	229.5	459	588.3	425
Cost Reduction (%)	BCA	-22.1	-17	-19.6	-19.2
	DE	-16.3	-13.5	-17.4	-15.8
	G2V only (proposed)	-23	-19.6	-20.9	-20.8
	G2V/V2G (proposed)	-31.7	-28.6	-29.4	-29.6

Thus, the random search–based optimization algorithms such as DE can considerably reduce the cost compared with traditional methods such as UCA or BCA. This is because the random search results in longer convergence time in the BCA and UCA, especially with large number of EVs. Table V indicates that if the number of EVs is 500, the convergence time almost reaches the preset time slot, 5 min, thus resulting in no further execution of the commands by the EMS because the scheduling of the next turn is starts. By contrast, the proposed method can not only improve the cost but also save approximately 85% CPU time, which is a pivotal for real-world application.

TABLE V
SIMULATION TIME

Parameters		Fleet size		
Performance	Method	200	400	500
Time (s)	UCA	15	23	30
	BCA	20	31.5	44.9
	DE	110.8	229.5	280.2
	G2V only (proposed)	19.3	41.7	51.1
	G2V/V2G (proposed)	22	43.1	56.7

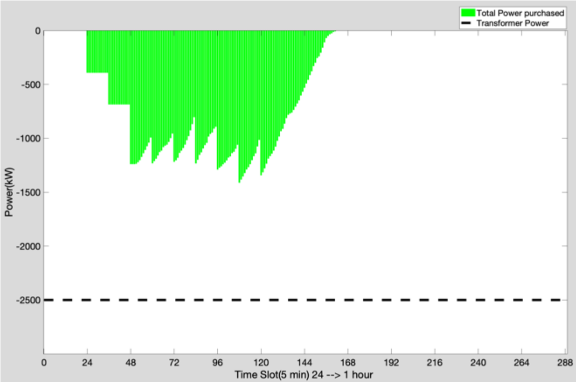


Fig. 5. Scheduled power using UCA.

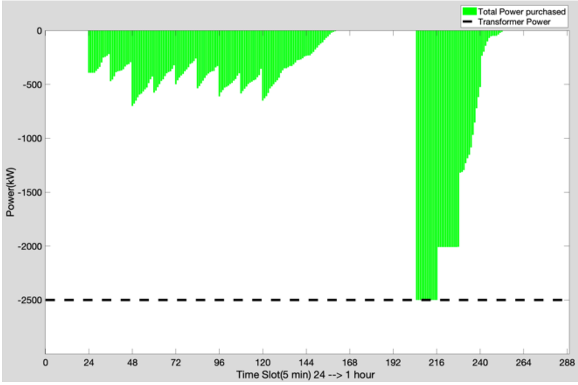


Fig. 6. Scheduled power using BCA.

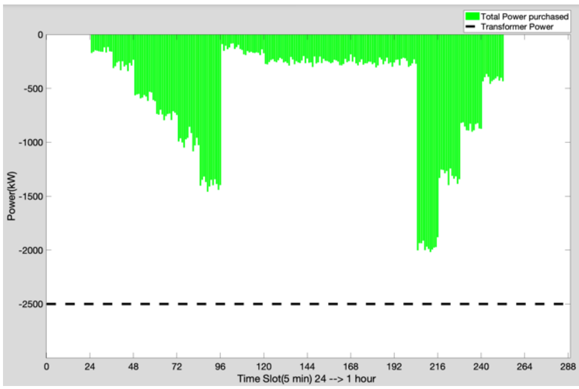


Fig. 7. Scheduled power using DE with G2V function.

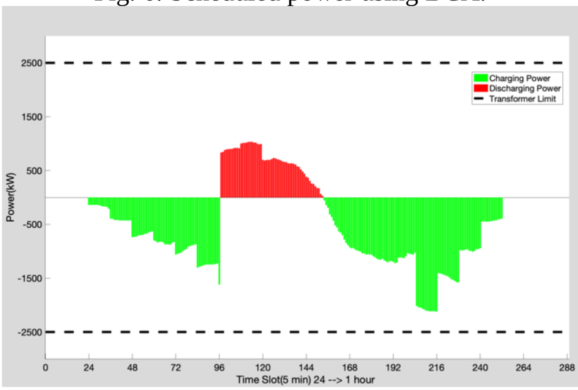


Fig. 8. Scheduled power usng proposed method with the G2V/V2G function.

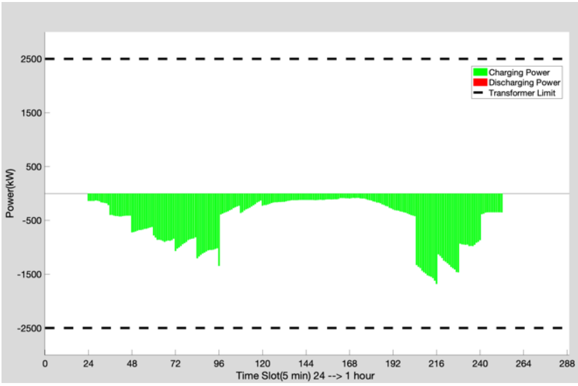


Fig. 9. Scheduled power using the proposed method with the G2V function.

V. CONCLUSION

A novel LP with preprocessed data, integrating EV, ESS, and PV, was proposed within a large-scale EV charging station. A simulated EV charging station with 500 chargers and 2500-kW contract capacity were used for testing the proposed method. We set charging priority for different EVs for charging and discharging to ensure the charging station operated below its contract capacity. The results of this study revealed that the LP algorithm can be adopted for solving such problems. The simulation results indicated that the proposed method reduced computation compared with DE. Our method also reduced the total electricity cost for a single EV user by 29.6% because EV absorbed energy from the grid when the electricity price was low and injected energy into the grid when the price of electricity was high. The proposed algorithm allowed smart charging of all EVs during the entire electricity low period by spreading their charging periods. Compared with BCA, an eventual congestion can result in higher waiting for some vehicles. As a result, they are not able to charge during the low electricity periods.

The net cost was considerably lower than that of UCA, BCA, and DE charging, highlighting the benefits of the proposed smart charging algorithm. Such a reduction in electrical cost may increase EV adoption. With regard to the charging station aggregator, additional studies to optimize the use of RES and ESS are warranted. In the future, we intend to extend our study to propose a reasonable algorithm in determining the size of ESS to be installed as well as the rating power of the PV to be purchased. To generate more revenue price-based and incentive-based demand response programs may help to identify the right size of ESS.

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