Scheduling of Electric Vehicle's Power in V2G and G2V Modes Using an Improved Charge–Discharge Opportunity-Based Approach

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***Abstract*— With rise in the popularity of electric vehicles (EVs), challenges related to its charging infrastructure are also soaring. In the upcoming smart grid scenario with significant renewable energy sources and distributed generation, EVs have been identified as a key element for grid stability and its optimal operation, primarily due to energy storage capacity. With a large number of EVs in parking, it has huge potential with optimal scheduling. However, EV owners should have the motivation to participate in vehicle-to-grid (V2G). This article proposes a scheduling mechanism using a novel forward–backward energy allocation, based on an improved charge–discharge opportunity approach. The proposed method (PM) addresses the scheduling of power flow in EVs to operate in V2G and grid-to-vehicle (G2V) modes considering EV owners' preferences, optimal cost, and low battery degradation. The implementation of the PM is facile and flexible with the vehicle's time of arrival and departure. A 40- and 60 kWh battery capacity EVs with multiple real-life scenarios have been considered in this study to demonstrate the effectiveness of the PM. The performance and features of the PM have been compared with the existing methods to distinguish its benefits.**

***Index Terms*— Buffer energy, electricity price, energy demand, semi-controlled charging (SCC), uncontrolled charging (UCC), vehicle-to-grid (V2G) services.**

NOMENCLATURE

CO	Charging opportunity.
L_c	Battery life cycle.
CBD	Total cost of battery degradation.
N_{slots}	Total number of slots.
C-DP	Charging–discharging power.
nc/nd	Number of CO/DO for an EV.
DO	Discharging opportunity.
N_n	nth slot number.
DOD	Depth of discharge.
P_{charging}	Charging power [kW].
IEX	Indian energy exchange.
$P_{\text{Discharging}}$	Discharging power [kW].
L	Length of EV vector.
$\text{Pch}_{\text{on-board}}$	On-board charger power [kW].
SOC	State of charge.
$\text{Price}_{\text{average}}$	Average price in range from T_a till T_d slots.
SCE	Shopping complex employee.
P_l	Total number of charging power levels in a set.
TC	Total cost.
Q_{TCF}	Total generated battery capacity fading.
UCC	Uncontrolled charging.
Rth	Thermal resistance of a battery cell.
SOC_{max}	Maximum SOC set by the manufacturer.
SOC_{min}	Minimum SOC set by the manufacturer.
B_{capacity}	Battery capacity [kWh].
$\text{SOC}_{\text{initial}}$	Initial SOC.
B_{eff}	Battery efficiency [kWh/km].
$\text{SOC}_{\text{desired}}$	Desired SOC required at the time of departure.
CBD_{DOD}	DOD related to average battery degradation cost per unit of energy.
T_A	Time of arrival.
T_D	Time of departure.
CBD_{BAC}	Level degradation cost.
T_a	Arrival slot.
$\text{CBat}_{\text{replacement}}$	Battery replacement cost [INR or \$].
T_d	Departure slot.
$\text{CFR}_{\text{power}}$	Capacity fading rate.
$T_{\text{available}}$	Number of slots of stay.
C_{BI}	Battery investment cost [INR or \$].
Td_{slot}	Slot for discharging.
D_{min}	Minimum distance, after the first CO [km].
$\underline{\Delta t}$	Step time [minute].
E_{max}	Maximum energy limit to charge [kWh].
T_{ambient}	Ambient temperature [K].
$E_{\text{requirement}}$	Required energy [kWh].
x_{ch}	Charging duration [slots].
$E_{\text{maxDischarge}}$	Maximum energy limit to discharge [kWh].
x_{dis}	Discharging duration [slots].
$E_{\text{dischargingSlot}}$	Energy for distribution in DO slots [kWh].
$\text{EV}_{\text{vector}}$	Vector that stores energy values of CO and DO.
n	Index of slot counts.
$\text{Ed}_{\text{vector}}$	Demand vector.
k	Index of charging power levels.
E_{DOn}	nth DO maximum discharging energy.
x	Column of CO/DO matrix.
$E_{\text{discharging}}$	Remaining energy for discharging [kWh].
y	Indication of charging(1)/discharging(−1).
E_{buffer}	Buffer energy [kWh].

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I. Introduction

TODAY, the alarming level of greenhouse gas emissions and decreasing traditional energy resources have prompted researchers to focus their attention on the transition from conventional to electric-powered vehicles. Governments are making policies and providing incentives to promote electric vehicles (EVs). Nowadays, countries are adopting EVs as prime means of transportation either two or four wheelers and even buses [1]. Consequently, global sales of EVs doubled in 2021 with respect to the previous year to set a new record of 6.6 million [2]. EV sales have continued to grow substantially in 2022, with 2 million units sold in the first quarter, up to 75% over the same period in 2021. This rapid growth has put considerable pressure on electricity supply infrastructure.

The bulk availability of EVs creates an opportunity for both service providers and customers, but charging/refueling of EVs in such a large quantity is turning into a serious issue [3], [4], [5], [6], [7]. New standards have been developed [8], [9], [10], [11] and separate guidelines and instructions have been released regarding the charging of EVs and associated infrastructure [12]. As EVs involve large number of series and parallel connected cells, reliability, safety, and efficiency are very important. Accordingly, aging assessment [13], abnormality diagnostic [14], and many other such issues have been explored by the researchers in the recent time. Due to the significant time required in charging and adverse effect of rapid charging on battery health, battery swapping has emerged as a crucial alternative; however, siting, sizing, and operation mechanism of battery swapping stations are some of the serious hindrances in its speedy implementation [15]. As a result, with limited roadside charging infrastructure, parking has emerged as the potential charging place for the majority of EVs on road. EVs stay in the parking lot longer than the charging time required by the vehicle to reach a desired SOC. Therefore, it can also act as an energy reserve, and with volatile electricity rates, proper scheduling of charging and discharging at the parking may be fruitful for the grid, economical for the consumer, and beneficial for the parking owner.

This is the reason why parking lots are an attractive place for researchers to schedule EV charging–discharging and has gotten a lot of attention in research works [16], [17], [18], [19], [20]. EV scheduling is a crucial part of driving an EV daily, which should consider the expected drive, battery health, and charging cost. Additionally, it may support the grid if operates in vehicle-to-grid (V2G) mode. Accordingly, the planning of EV's charge–discharge pattern may have several objectives, such as minimizing the charging cost [21], [22], flattening the demand profile [23], [24], [25], [26], supporting renewable energy integration [27], [28], providing ancillary services, frequency and voltage regulations [29], [30], and so on.

Scheduling should honor the EV owner's expectations from the parking owner, which are to fulfill the vehicle's desired charging requirements and in minimum time or as per their time convenience with low impact on battery health. The charging cost impacts the aggregator's profit as well as customer satisfaction. Apart from minimizing the cost, minimum complexity in scheduling and customer emergency exit from the scheduled period needs significant attention in the scheduling process. Several attempts have been made to accomplish these objectives, but none of them fulfills the expectations completely. Selected works are discussed in the following in brief with their key features and limitations.

An approach based on average pricing in [31] is used to model a system, which claims to have maximum profit to the EV owner after including V2G services. However, the effects of V2G and customer travel convenience (emergency departure) have not been taken into consideration. A novel method of profit maximization based on an encouragement and punishment policy, also aiming to minimize charging costs (including V2G), has been discussed in [19], but it does not consider the battery degradation. Apart from this, the control becomes complex as it includes two limits, which are the maximum price to charge and the minimum price to discharge. In the method proposed by Wei et al. [32], battery degradation has been taken into consideration by reducing the charging power; however, this not only increases the required charging slots but also requires highly efficient power electronic devices to detect the changes in charging power, which is very small in this case.

The issues of energy scheduling in office buildings with renewable energy and workplace EV charging are discussed in [33] aiming to minimize the operation cost. It contains day-ahead scheduling (to determine how much power was acquired from a day-ahead power market) and real-time operation. Battery degradation cost is also included in the operation cost, but its model without considering temperature effect is not reliable. Apart from this, the work in [33] is limited to office-building scenarios only. Zhou et al. [22] have considered inconvenience cost, battery degradation cost, and parking fee. The inconvenience coefficient is defined as the EVs sensitivity to time in the situation of an early departure, which is not genuine and difficult to formulate. In [31], different modes (charging, discharging, and standby modes) are decided based on an average electricity price and the energy flow is controlled using electricity price, power demand, battery SOC, and EV parking time. Battery degradation and customer travel convenience are not explored in [31]; also, limited maximum power to charge and discharge has been taken.

In this study, a forward–backward energy allocation-based mechanism has been proposed that uses an improved CO–DO approach. The proposed method (PM) considers the total charging cost that includes charging cost, discharging rewards, and battery degradation cost. In forward and backward iterations, with simple formulation, it achieves near optimal cost. Although, the PM attempts achieving the same objectives as the other approaches (minimizing cost, efficient participation in V2G, ensuring desired charging levels, etc.), but implementation of the proposed approach is very simple as compared to other approaches; hence, it requires less computational resources than optimization-based methods. The main contribution of this work is a simplified approach that inherently considers the interests of EV owners and parking operators (POs). For example, the PO may decide to allow the parking with or without charging, participation of the EV in demand-response (allowing discharging), selecting the power levels (having more vehicles at reduced power levels or using high power levels when number of vehicles in the parking are less), and so on. In general, EV owners' choices are influenced by several parameters, including charging time, minimum waiting time, frequency of visits, service fee, and so on. EV owners have been observed to be price sensitive. So, the minimum charging cost and customer time convenience should be the pillars of any work. Accordingly, in the proposed work, charging cost, discharging rewards, battery degradation cost, buffer energy (E_{buffer}), iterative way of charging power allocation, and charging within the allotted time duration have been included and implemented. The average electricity price between vehicle arrival and departure slots has been used to decide opportunities. To make the approach more realistic, buffer energy, which helps in emergency exit anytime (under certain constraints) in between scheduled periods, has been added.

For validating the usefulness and effectiveness of the PM, different scenarios have been considered, which coincide with real-life, day-to-day situations. The PM has been demonstrated to suggest a charging–discharging schedule with minimum TC. TC includes charging cost, battery degradation cost, and discharging rewards. The idea is to charge a vehicle when the price is low and discharge it when the price is at its peak within the stay time at the parked location.

The salient features and contribution of the proposed work are as follows.

1) A novel forward–backward energy allocation mechanism is proposed that uses an improved charge–discharge opportunity approach.
2) Due to simple formulation, its implementation is easy as compared to other optimization-based approaches.
3) Different charging power levels are considered to meet EV owners' charging requirements in a minimum to maximum power charging fashion. Discharging rewards are also included in the proposed approach.
4) Opportunities are decided by comparing the average price for stay period with the price at that instant. The slots with an average price less than the instantaneous price are termed as DO; otherwise, it will be a CO.
5) The vehicle always has buffer energy to handle emergency exit before the scheduled departure time after the first CO.
6) To the possible extent, data from actual EVs have been considered for simulation purposes.
7) The performance of the proposed approach has been compared with UCC [34], [35], i.e., the vehicle is charged on its arrival irrespective of price value, and semi-controlled charging (SCC) [31], i.e., the vehicle is charged with minimum price value first. Apart from that, the proposed work has also been compared with the approach given in [22].

The remainder of this article is organized as follows. The proposed methodology is discussed in Section II. In Section III, simulation results and scenario studies are described, followed by the conclusion and future scope in Section IV.

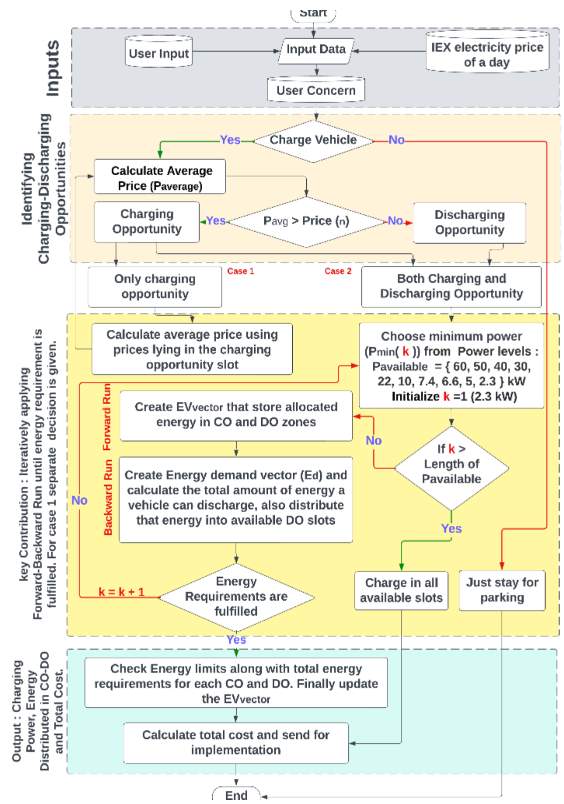

Fig. 1. Overview of the proposed scheduling algorithm.

II. Proposed Methodology

This section discusses the PM including the model adopted in the study, assumptions and constraints of the proposed approach, and key features. The complete algorithm for scheduling and its various modules have been represented in Fig. 1. The possible modes in scheduling are charging [grid-to-vehicle (G2V)] mode, discharging (V2G) mode, and no operation mode (just parking). The algorithm has been illustrated by dividing it into three parts. In the first part, it receives inputs in the form of EV details, such as, SOC, time of stay, and so on, and operational details, such as electricity price forecast and so on. The opportunities (time slots) for charging and discharging are identified, which is illustrated in Section II-B. The identified opportunities provide a general solution for charging and discharging; however, the electricity price within each opportunity may vary significantly; hence, it is necessary to further improve the solution with the selection of better slots with specific power in such a way that the energy requirement for the desired SOC level is met with a near optimal cost. This is achieved in the subsequent parts of the algorithm, which are termed as forward and backward run.

In the forward run, the energy allocation is started from the first slot after the arrival of an EV at the lowest power level; then, energy in each CO and DO along with overall energy is evaluated. It is possible at the end of forward run that either final SOC is not achieved or energy at intermediate CO/DO levels is not properly utilized for V2G operations or operational constraints are not met. Therefore, in the backward run, energy allocation for charging and discharging is further improved in the backward direction, i.e., starting from the last slot before departure to the first slot after arrival of the EV.

The final output of the algorithm is the energy distribution in CO/DO and corresponding charging power that provides near optimal TC of charging.

A. Model Description

In this work, only electrical (charging/discharging) behavior of an EV has been modeled due to simplicity. Although constant current constant voltage (CCCV) charging is most popular for Li-ion batteries, constant current charging model has been adopted in this work, as constant voltage charging is very slow. Accordingly, an EV can be expressed in the form of its SOC status corresponding to charging/discharging in each time slot $\underline{\Delta}t$ as

$$\text{SOC}_n = \text{SOC}_{n-1} + P_{\text{ch}} * \underline{\Delta}t / B_{\text{capacity}} \tag{1}$$

where SOC_{n-1} represents the battery SOC at the beginning of the nth time slot, P_{ch} is the charging/discharging power in the nth slot, and SOC_n is the updated SOC at the end of the nth time slot of the battery having rated energy capacity of B_{capacity} in kWh. In case of discharging mode, charging power P_{ch} is considered as negative.

Parking is considered to be operational for entire day; however, any specific time can be easily incorporated in the model. A day/operational period is divided into time slots with $\underline{\Delta}t = 5$-min intervals, with total number of slots N_{slots}. On the arrival of a vehicle at the parking, status information, such as $\text{SOC}_{\text{initial}}$, $\text{SOC}_{\text{desired}}$, time of arrival ($T_A$), time of departure ($T_D$), and battery capacity (B_{capacity}), are recorded in the system. Based on this information, energy demand ($E_{\text{requirement}}$) and available slots ($T_{\text{available}}$) are computed using (2) and (3), respectively. The price of electricity can be obtained from the utility/energy exchange or price forecasting system. In this study, the price of electricity (in INR/kWh) has been taken from the IEX dated February 6, 2022 of the W1 region of Madhya Pradesh, India [36] for the simulation of various scenarios, whereas, for the last case, electricity price (in \$/kWh) used in [22] has been considered. Many existing algorithms result in optimal power values, which requires a charger with continuously variable output power. Such chargers have complex control and are expensive. The proposed algorithm recommends to use standard discrete power levels, as per the recommendation of the manufacturers/standards/government guidelines [12]. For example, the discrete power levels considered in this work, {60, 50, 40, 30, 22, 10, 7.4, 6.6, 5, 2.3} kW, are adopted from the guidelines by the Ministry of Power, Government of India [12]. Similarly, on-board discrete charging power levels $\text{Pch}_{\text{on-board}}$ for Nissan Leaf 2018 are {2.3, 6.6, 7.4, 50}. The use of discrete power levels significantly reduces the complexity of the charging infrastructure and simplifies the implementation of the proposed algorithm. The total number of charging/discharging power levels available in a set is denoted by P_l

$$E_{\text{requirement}} = (\text{SOC}_{\text{desired}} - \text{SOC}_{\text{intial}}) * B_{\text{capacity}} \tag{2}$$

$$T_{\text{available}} = T_d - T_a + 1. \tag{3}$$

The manufacturer specifies the allowable minimum and maximum SOC values; accordingly, maximum energy of an EV available for charging/discharging holds a fixed value for an EV, which can be defined as

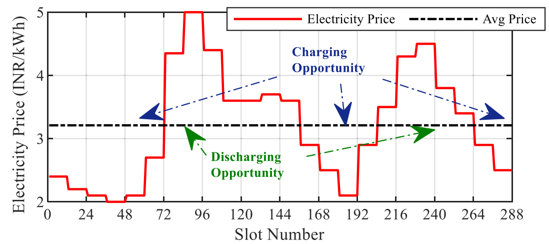

Fig. 2. Opportunities representation.

$$E_{\max} = (\text{SOC}_{\max} - \text{SOC}_{\min}) * B_{\text{capacity}} \tag{4}$$

where $\text{SOC}_{\min}$ and $\text{SOC}_{\max}$ are the minimum and maximum values of SOC for a particular EV. In this study, the maximum energy has been considered the same as the capacity of the EV's battery. The proposed algorithm also has the provision of buffer energy, which ensures the emergency exit before the scheduled departure time of the vehicle. If a vehicle needs to move minimum $D_{\min}$ kilometers (km) at any time in emergency, the desired buffer energy can be computed as

$$E_{\text{buffer}} = B_{\text{eff}} * D_{\min} \tag{5}$$

where B_{eff} is the battery efficiency, which is defined as the energy required by the vehicle to move per unit distance. For Nissan Leaf 2018 model, the specified battery efficiency by the manufacturer is 0.205053 kWh/km (330Wh/mile) [37]. Accordingly, the maximum energy available for discharging is also fixed for a particular EV, which can be defined as

$$E_{\text{maxDischarge}} = (E_{\max} - E_{\text{buffer}}). \tag{6}$$

B. CO and DO

To identify the CO and DO, it is necessary to have electricity prices for each slot of the day/period, which may be provided by the utility, energy exchange, or may be obtained from an electricity price forecast system. In this study, the electricity price (INR/kWh) is obtained from IEX [36] and distributed in slots with $\underline{\Delta}t = 5$ min. The average price of the day is computed first. When the instantaneous electricity price in any slot is more than the average electricity price, it is denoted as a DO, i.e., it is economically better to feed the power to the grid from the battery reserves. On the other hand, it is economical to charge the vehicle when the electricity price in a particular slot is lower than the average price. This is denoted as a CO. These are represented as follows:

$$\begin{cases} \text{CO}, \text{Price}_{\text{average}} > \text{Price}(n), & \text{within } T_a \text{ and } T_d \\ \text{DO}, \text{Price}_{\text{average}} < \text{Price}(n), & \text{within } T_a \text{ and } T_d \end{cases} \tag{7}$$

where T_a and T_d represent the vehicle's arrival and departure slot, respectively. $\text{Price}_{\text{average}}$ denotes the average price of the prices in between T_a and T_d slot. $\text{Price}(n)$ represents the instantaneous price, where n denotes the respective slot number.

CO's slots and DO's slots are used for G2V and V2G mode operations, respectively, with minimum possible charging power among the available set of powers. Fig. 2 illustrates the opportunities distribution as per the criteria given in (7). The CO/DO can be represented by a vector *CD* as

$$\mathrm{CD}(n) = \begin{cases} 1, & \text{for CO} \\ -1, & \text{for DO} \end{cases} \quad \text{for } n = T_a, T_{a+1}, \ldots, T_d. \quad (8)$$

C. Assumptions and Constraints

In this work, assumptions have been made, which are: 1) discard opportunity if a vehicle arrives in DO; 2) no loss in SOC has been considered in the "no operation mode" during parking, i.e., self-discharge is negligible; 3) vehicles arrive at the beginning of a time slot and depart at the end of a time slot; and 4) it is assumed that enough power is available in the parking lot according to its capacity to charge EVs, i.e., there is no constraint on maximum power limit from the supply side. The first assumption means when a vehicle arrives at the parking, it does not have sufficient energy (SOC) to exploit any discharge opportunity; hence, if any vehicle arrives in DO slots, then that DO will be ignored and the algorithm starts from the next CO slots.

For estimating, the degradation cost Arrhenius equation [38] has been used, which provides temperature-dependent battery degradation. Equations (4) and (6) represent constraints related to maximum charging in the CO and maximum discharging in the DO, respectively.

D. Probable Cases

The proposed algorithm considers all possible scenarios to schedule the EV charging/discharging with near optimal solution. The scenarios may fall under the following two cases.

Case 1: Only COs is/are available.

There may be a condition when only a CO and a DO are present, and DO occurs first on the arrival of the vehicle. Then, it needs to be discarded because a vehicle on arrival at the parking is assumed to have insufficient SOC for participating in V2G operation. Now, the best slots for charging from the only CO are identified by calculating the new average for the CO duration and new opportunities are identified. This may change the new scenario into case 2.

Case 2: Both COs and DOs are available.

A vehicle with a long parking time will follow case 2, in which both COs and DOs are available for scheduling. There is no such case possible, in which only DO is available. Algorithm 1, presented in the following, describes the initial steps to identify CO and DOs.

Algorithm 1 Part 1: Taking Inputs, Identifying Opportunities, and Deciding the Cases

Input to Part 1 algorithm: T_a, T_d, $SOC_{initial}$, $SOC_{desired}$, *Electricity Price.*

Step 1 Calculate the average electricity price ($Price_{average}$) of price values lying between $< T_a$, -$T_d >$
$Price_{average}$ = sum(Electricity Price) / (T_d-T_a)

Step 2 Identifying opportunities
CO if $Price_{average} > Price(n)$ and DO if $Price_{average} < Price(n)$ where n is the slot number corresponding to time (in second).

Step 3 Identifying cases
If **Case 1**: GOTO Step 1, calculate $Price_{average}$ for available CO slots.
If **Case 2**: GOTO Algorithm part 2
Output: CO/DO vector and number of CO nc and number of DO nd

E. Forward Run

Forward run is used to allocate energies in all COs and DOs following constraints (4) and (6). An $\mathrm{EV_{vector}}$ is created to store energies in all available CO and DO slots as

$$\mathrm{EV_{vector}} = \left[E_{\mathrm{CO1}}, -E_{\mathrm{DO1}}, E_{\mathrm{CO2}}, -E_{\mathrm{DO2}} \ldots E_{\mathrm{CO}n}/-E_{\mathrm{DO}n}\right] \quad (9)$$

where the negative sign indicates the discharging energy and $E_{\mathrm{CO}n}$ is energy in the nth CO, which is defined as

$$E_{\mathrm{CO}n} = P_{\min} * \mathrm{Slots}_n * \underline{\Delta} t \quad (10)$$

where Slots_n is the number of slots in the nth CO. Discharging energy is calculated in a similar way. The $\mathrm{EV_{vector}}$ entries may change after every update.

The power used to calculate the allotted energies in various COs and DOs is fixed for an iteration; however, it iteratively changes in increasing order, until the vehicle's charging requirements are fulfilled. Algorithm 2 describes forward run steps of energy allocation.

F. Backward Run

It is possible after the energy allocation in the forward run that either energy demand is not met or it is not optimal. The backward run is used to estimate energy demand in each CO/DOs and then optimizes the energy allocation at minimum charging power, which also ensures reduced battery degradation. Energy allotted during forward run and energy requirement by the EV is added up if at the time of departure DO is present and subtracted if CO is present at the time of departure. In this fashion, an *energy demand vector* is created as

$$\mathrm{Ed_{vector}} = \left[Ed_1, Ed_2, Ed_3, \ldots, Ed_{L-1}\right] \quad (11)$$

where

$$Ed_{L-1} = E_{\mathrm{requirement}} \pm E_{\mathrm{CO}n/\mathrm{DO}n} \quad (12)$$

where L represents the length of $\mathrm{EV_{vector}}$. The length of energy demand vector is always one less than the length of $\mathrm{EV_{vector}}$. The key steps of the backward run are briefly described in Algorithm 3 as follows.

G. Cost Calculation

The TC of charging includes energy cost and battery degradation cost. The energy cost is computed as the product of energy price in a slot and energy consumption/supply in that slot. The TC, which includes charging cost and discharging

Algorithm 2 Part 2: Forward run (Allocation of energy in all COs and DOs)

Input to Part 2 algorithm: Output of part 1 algorithm and set of charging power levels.

Step 1 Initialize variable: $k = 1$ and choose minimum charging power from a set of charging power levels.
Pmin = min(set of charging power levels).

Step 2 if $k > P_l$
True: Charge vehicle in all available slots.
False: GOTO step 3.

Step 3 Store maximum energy a CO and DO can have in a vector termed as EV_{vector}
$EV_{vector} = [E_{CO1}, -E_{DO1}, E_{CO2}, -E_{DO2} \ldots . E_{COe}/-E_{DOe}]$
where $E_{COe}/-E_{DOe}$ represents energy in e^{th} CO/DO respectively.

Step 4 Update EV_{vector}
Stage 1: Using SOC_{max} for CO and SOC_{min} for DO.
Stage 2: To avoid over charging/discharge after CO/DO, ensure that the sum of CO energy and DO energy is equal to $E_{requirement}$. If at time, the condition of E_{max} or $E_{maxDischarge}$ are violated, update energy values to these boundary limits in EV_{vector}.

Output: EV_{vector}

Explanation

Charging power level set:{60, 50, 40, 30, 22, 10, 7.4, 6.6, 5, 2.3} kW, $P_{\min}$ =2.3 kW
Total number of power levels in a set (P_l) : 10
Step 2 ensures whether all charging powers are checked or not.
Step 3: Considering the case shown in Fig. 2, there are 3 COs and 2 DOs. EV_{vector} entries will be formed as: E_{CO1}= *2.3∗72∗5 and* E_{DO1} = *2.3∗84∗5,* and so on.
Once the EV_{vector} has been created in Step 4, it gets updated based on E_{max} and $E_{maxDischarge}$.

- The value of k is incremented by 1 in case the charging requirements have not been fulfilled after the backward run (Algorithm part 3).
- If $k > P_l$, represents that the charging power levels have not been enough to charge the vehicle, this is possible in cases when the charging requirement would be more with a short stay time. In that case, the vehicle is charged with maximum allowed power for entire stay period.

rewards, can be defined as

$$\text{TC} = \sum_{\text{Ta}}^{\text{Td}} (\text{Price} * y * \text{Energy} + \text{CBD}) \tag{13}$$

where $y = 1$ and -1 indicates charging and discharging, respectively, and CBD is the cost of battery degradation.

Battery degradation cost includes two components, one component that is dependent on temperature and the other based on the DOD. Arrhenius equation is used to calculate battery degradation cost, which gives temperature-dependent degradation. According to Arrhenius, the capacity fading rate increases in an exponential manner as the temperature rises. The charging or discharging power rate affects the temperature rise. According to the approach given in [39], the temperature varies linearly as a function of charging or discharging power $P_{\text{charging/discharging}}$, which can be computed as

$$T_{\text{power}} = T_{\text{ambient}} + R_{\text{th}} * P_{\text{charging/discharging}} \tag{14}$$

Algorithm 3 Part 3: Backward Run (Calculation of Energy Demands & Distribution of Energy in DO slots)

Input to Part 3 algorithm: EV_{vector}, $E_{requirement}$, *Pmin.*

Step 1 Create a Ed_{vector} using EV_{vector}, and $E_{requirement}$
$Ed_{vector} = [Ed_1, Ed_2, Ed_3 \ldots \ldots Ed_{L-1}]$ where Ed_1 represents demand in the last opportunity area which needs to be fulfilled.
$Ed_{L-1} = E_{requirement} \pm E_{COn/DOn}$

Step 2 Update EV_{vector} concerning Ed_{vector}.

Step 3 Update EV_{vector} using Part 2 algorithm, Step 4, Stage 2.

Step 4 Check if the sum(EV_{vector}) $\geq E_{requirement}$
True: Distribute discharging energy ($E_{dischargingSlot}$) in all DOs present in EV_{vector}.
$E_{dischargingSlot} = sum(EV_{vector}) - E_{requirement}$
False: Charging power does not fulfill the charging requirement: GOTO part 2 algorithm with $k = k+1$.

Step 5 Finally, update the EV_{vector} using part 3 algorithm.

Output: *Energy Scheduling of a vehicle and the required charging power*

Explanation

Suppose the EV_{vector} from the Algorithm Part 2 would be [15, -5, 10, -10] kWh, length of the EV_{vector} (L)= 4 and $E_{requirement} = 32$ kWh (using (2) with $B_{capacity} = 40$ kWh, $SOC_{desired} = 0.9$ and $SOC_{intial} = 0.10$).
Now, $Ed_{vector} = [Ed_1, Ed_2, Ed_3]$ where $Ed_3 = E_{requirement} + E_{DO2} = 42$ kWh, $Ed_2 = Ed_3$-E_{CO2} = 32 kWh and $Ed_1 = Ed_2 + E_{DO1}$ =37 kWh.
Check whether $E_{d1} < E_{CO1}$ or not.

- If not, then update the EV_{vector} entries by removing the discharging opportunity one by one in a loop after every check.
- If yes then follow step 3, step 4 and step 5 as per algorithm part 3.

where Rth is the thermal resistance of a battery pack and T_{ambient} is the ambient temperature. According to this computed temperature (in K), a capacity fading rate can be defined as

$$\text{CFR}_{\text{power}} = A * e\hat{}\left[(-E_a/R) * \left(1/T_{\text{power}}\right)\right] \tag{15}$$

where A is the proportionality constant, E_a is the activation energy, and R is the universal gas constant. Accordingly, a cumulative capacity fading can be computed by adding the same for the entire number of slots N_{slot}. It can be expressed as

$$Q_{\text{TCF}} = \sum_{\text{slot}=1}^{N_{\text{slot}}} \text{CFR}_{\text{power}}(\text{slot}) * \underline{\Delta} t. \tag{16}$$

The temperature-dependent degradation cost of the battery can be obtained as

$$\text{CBD}_{\text{temp}} = \left(Q_{\text{TCF}}/B_{\text{capacity}}\right) * \text{CBat}_{\text{replacement}} \tag{17}$$

where $\text{CBat}_{\text{replacement}}$ is a battery replacement cost that depends upon EV's battery capacity. Table I presents the typical values of $\text{CBat}_{\text{replacement}}$ of different vehicles, which are subject to change as per market conditions.

The second battery degradation cost depends on the DOD [40]. It can be expressed as

$$\text{CBD}_{\text{DOD}} = \text{CBD}_{\text{BAC}} * \left(x_{\text{ch}} * P_{\text{charging}} + x_{\text{dis}} * P_{\text{Discharging}}\right) \tag{18}$$

TABLE I

BATTERY REPLACEMENT COSTS [41], [42]

EV name	Battery Capacity	Battery Replacement Cost (in \$ and INR)
Nissan Leaf	30 kWh 40 kWh 62 kWh	\$4500 (349265.25 INR) \$7500 (582108.75 INR) \$9500 (737337.75 INR)
Chevrolet Bolt	66 kWh	\$16000 (1241832 INR)
BMW i3	21.6 kWh	\$13725 (1065259 INR)
Tesla Model 3	75 kWh	\$15799.27 (1226252.44 INR)

where x_{ch} and x_{dis} represent the charging and discharging duration, respectively. CBD_{BAC} is a level degradation cost [22], which depends on the battery life cycle L_C, battery investment cost C_{BI}, battery capacity B_{capacity}, and DOD d_{DOD}. It is expressed as

$$\text{CBD}_{\text{BAC}} = C_{\text{BI}}/\left(2 * L_C * B_{\text{capacity}} * d_{\text{DOD}}\right). \tag{19}$$

The total battery degradation cost is computed by adding two components obtained in (17) and (18) and can be expressed as

$$\text{CBD} = \text{CBD}_{\text{temp}} + \text{CBD}_{\text{DOD}}. \tag{20}$$

III. SIMULATIONS AND PERFORMANCE INVESTIGATION

To demonstrate the effectiveness of the PM, several simulation studies on practical EV data and a variety of possible real-life scenarios (Table II) have been carried out. The results have been compared with base cases (UCC and SCC methods), and a separate comparative study with an existing approach [22] has been presented. Simulations have been performed in MATLAB with Intel[1] Core[2] i3-5005U CPU at 2 GHz, 64-bit Windows, and 4-GB RAM.

A. Simulation Settings

This work considers scheduling for a parking system that operates round the clock. Accordingly, six different possible scenarios are considered, which are summarized in Table II. A day is divided into 288 equal slots of 5-min intervals. Two types of battery capacities, 40 kWh (Nissan Leaf 2018) and 60 kWh, have been used for simulation studies. Nissan Leaf 2018, 330 Wh/mi capacity has been used for buffer energy calculation. Fixed charging power levels with {60, 50, 40, 30, 22, 10, 7.4, 6.6, 5, 2.3} kW and on-board charger power with {2.3, 6.6, 7.4, 50} kW of capacity are taken for simulation. The range of $\text{SOC}_{\text{initial}}$ is 0.10–0.50 and for $\text{SOC}_{\text{desired}}$, 0.70–0.95. For E_{buffer} calculation, the minimum distance ($D_{\min}$) is taken as 10 km for simulation. For simplicity and ease of comparison, in all scenarios with a 40 kWh EV battery capacity, a fixed value of $\text{SOC}_{\text{initial}}$, i.e., 0.10 and $\text{SOC}_{\text{desired}}$, i.e., 0.90, is taken.

B. Simulation Results

In this section, the evaluations of different scenarios are given. The proposed approach scheduling results in different

[1]Registered trademark.

[2]Trademarked.

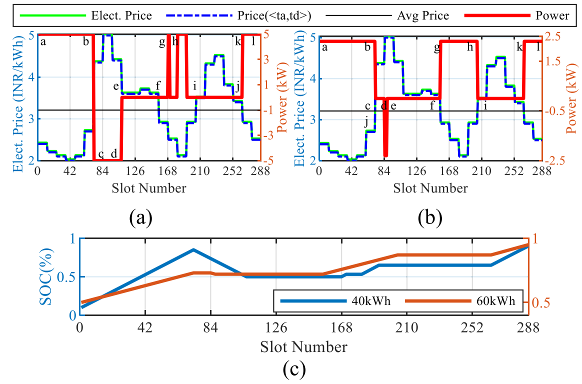

Fig. 3. Scheduling results for Scenario-1 with (a) 40 kWh battery capacity, (b) with a 60 kWh battery capacity, and (c) SOC.

scenarios are investigated and TC has been compared with UCC and SCC methods. The results for the first scenario have been described in complete detail, and a similar approach shall be adopted to analyze the remaining results.

1) Scenario-1: Weekend/Holiday: The first case study considers a day when the vehicle is parked for the whole day and its participation in charge schedule is expected to be for the whole day, such as a weekend or holiday. Two different cases of battery capacity 60 and 40 kWh have been considered with different initial SOCs in the two cases. The scheduling results of the PM for these cases are presented in Fig. 3(a) and (b). It is interesting to observe here that the vehicles have been scheduled with a minimum charging power, which ensures lower battery degradation. Fig. 3(c) represents the SOC variations of the vehicle with B_{capacity} 40 and 60 kWh. Table III shows the energy charging/discharging and SOC variation in the marked region of Fig. 3(a) and (b).

As shown in Fig. 3(a) from a to b, the EV is scheduled for charging with 5 kW power, the energy demand in this section is 30 kWh, and SOC changes from 0.10 to 0.85. In the next operation, from c to d, a maximum of 14 kWh is scheduled to discharge as the section falls under DO, and the SOC reduces from 0.85 to 0.50. Discharging takes place in the slots of decreasing order of their electricity prices to get maximum reward. In regions from e to f and from i to j, there will be no operation. From g to h and finally from k to l, EV demands to charge by 6 and 10 kWh, respectively. Finally, the SOC reaches the desired SOC level, and the TC will be INR 44.0671. Similarly, for Fig. 3(b), Table III represents the energy allocation and stages of SOC in CO and DO, and accordingly, the TC, in this case, is found to be INR 64.7491.

2) Scenarios-2–6: The results for the remaining five different scenarios are discussed in this section. The second scenario is similar to a case of school parking, the half-day shift of an employee. In this scenario, the vehicle is considered to arrive at the 96th slot and depart at the 168th slot. The scheduling for 40- and 60 kWh battery capacity vehicle is shown in Fig. 4(a) and (b) and their respective SOC variations are shown in Fig. 4(c). It can be observed that because the vehicle is staying at the parking for a shorter duration and the required energy is more to obtain the desired SOC, the battery charging power has increased to the next higher levels. The first few slots after arrival have no operation mode because

TABLE II
TIMING OF EV'S ARRIVAL AND DEPARTURE

Scenario	Activity	Activity coinciding with real-life cases	T_A	T_a	T_D	T_d
S1	Whole Day	Weekends / Holidays	12 am	1st	12 am	288th
S2	First Half of a Day	School Parking / Half Day shifts of employee	08 am	96th	02 pm	168th
S3	Second Half of a Day	Second shift employee scenario	12 pm	144th	07 pm	228th
S4	Random 1	Office / Metro Parking / SCE	10am	120th	10 pm	264th
S5	Random 2	Hotel / Restaurants Employee	12 am	144th	12 am	288th
S6	Random 3	Office / General Parking	05 am	60th	05 pm	204th

TABLE III
ENERGY AND SOC VARIATION FOR SCENARIO-1

Case	Section in Fig. 3	Description
40 kWh	a – b	E_ch = 30 kWh , SOC = 0.10 – 0.85
	c – d	E_dis = 14 kWh , SOC = 0.85 – 0.50
	e – f	No Operation
	g – h	E_ch = 06 kWh , SOC = 0.50 – 0.65
	i – j	No Operation
	k – l	E_ch = 10 kWh , SOC = 0.65 – 0.90
60 kWh	a – b	E_ch = 13.8 kWh , SOC = 0.50 – 0.73
	c – d	No Operation
	d – e	E_dis = 0.60 kWh , SOC = 0.73 – 0.72
	e – f	No Operation
	g – h	E_ch = 9.20 kWh , SOC = 0.72 – 0.87
	i – j	No Operation
	k – l	E_ch = 4.60 kWh , SOC = 0.87 – 0.95

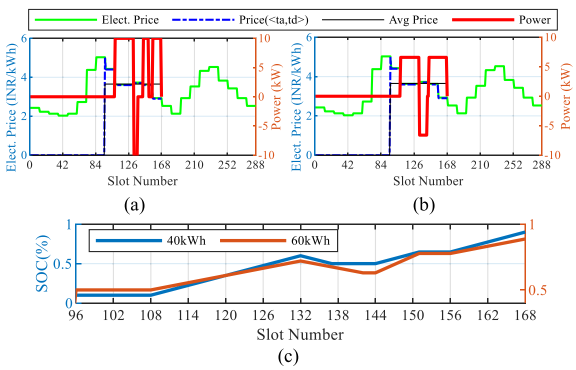

Fig. 4. Scheduling results for Scenario-2 with (a) 40 kWh battery capacity, (b) with a 60 kWh battery capacity, and (c) SOC.

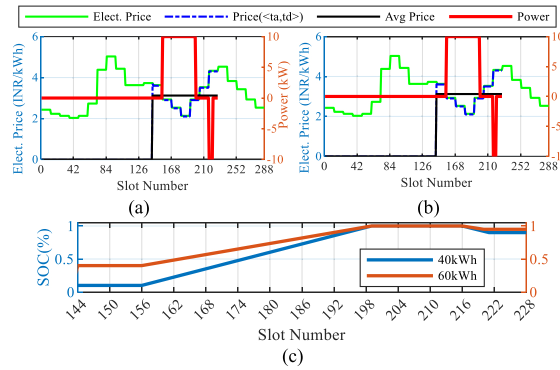

Fig. 5. Scheduling results for Scenario-3 with (a) 40 kWh battery capacity, (b) with a 60 kWh battery capacity, and (c) SOC.

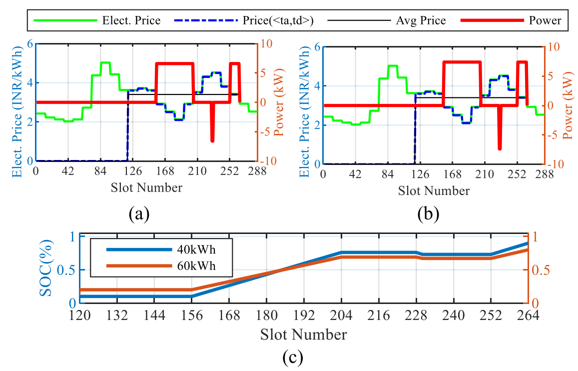

Fig. 6. Scheduling results for Scenario-4 with (a) 40 kWh battery capacity, (b) with a 60 kWh battery capacity, and (c) SOC.

the price is high; also, sufficient initial SOC is not there to operate in V2G mode and the vehicle arrives in DO, so that opportunity has been discarded.

In third scenario, afternoon shift parking timing is considered for scheduling. T_a = 144th slot and T_d = 228th slot. Fig. 5(a) and (b) represents the scheduling curve for scenario 3, and their SOC variations are shown in Fig. 5(c). The fourth to sixth scenarios are under random parking timings, which include office, metro, shopping complex, restaurant customers, and general parking, and their scheduling and SOC variations curves are shown in Figs. 6–8 respectively. The 40 kWh capacity battery with $SOC_{initial} = 0.1$ and $SOC_{desired} = 0.9$ is the same for all scenarios. In the fourth scenario , T_a = 120th slot and T_d = 264th slot. The 60 kWh battery capacity vehicle scheduled with $SOC_{initial} = 0.2$ and $SOC_{desired} = 0.8$. For the fourth scenario, the charging power versus price versus slot number curve is shown in Fig. 6(a) and (b). The fifth scenario with T_a =144th slot and T_d = 288th slot. The 60 kWh battery capacity vehicle scheduled with $SOC_{initial} = 0.3$ and $SOC_{desired} = 0.85$.

Fig. 7(a) and (b) represents the schedule corresponding to the fifth scenario. For the sixth scenario with T_a =60th slot and T_d = 204th slot, the scheduling output of the PM has been shown in Fig. 8. In this case, discharging happens for a very short duration, because of the energy limits and the SOC level. In the second CO, the desired SOC level needs to be achieved with the same power, so as per the algorithm, a set amount of discharging is allowed only in DO; otherwise, the charging requirements are not fulfilled with minimum power.

3) Comparative Study: To investigate the relative performance of the proposed approach, a comparative study with the recommendation model proposed in [22] has been carried out. The TC in the given model includes charging cost, discharging rewards, battery degradation cost, inconvenience cost, and parking fee. As parking fee is constant, the comparison has been done by considering only charging cost, discharging rewards, and battery degradation cost. The referred model suggests that EVs leave before the scheduled time to save money, which is not a general practical case when parking lots are considered. Still, a case of an early departure in an emergency has been considered in the proposed approach.

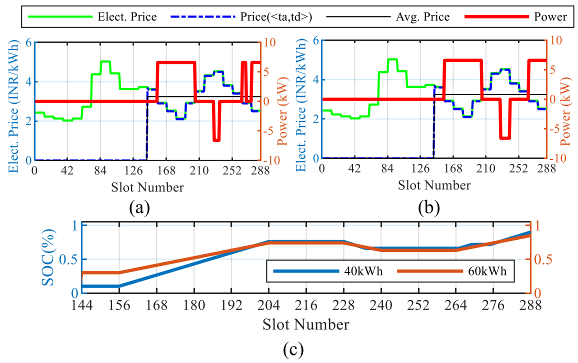

Fig. 7. Scheduling results for Scenario-5 with (a) 40 kWh battery capacity, (b) with a 60 kWh battery capacity, and (c) SOC.

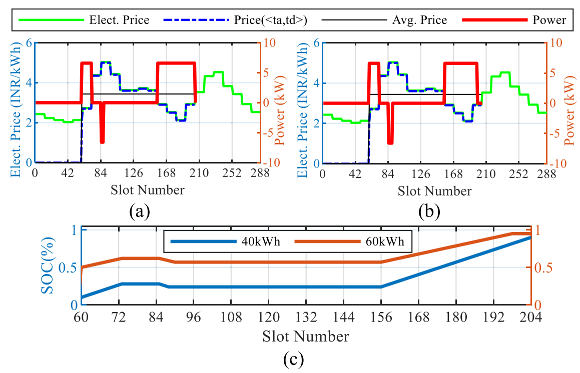

Fig. 8. Scheduling results for Scenario-6 with (a) 40 kWh battery capacity, (b) with a 60 kWh battery capacity, and (c) SOC.

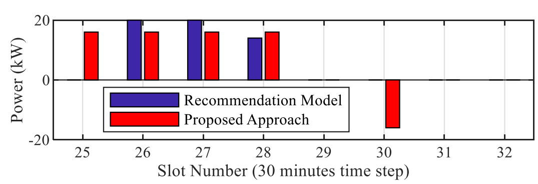

Fig. 9. C-DP for EV-1.

TABLE IV
SIMULATION PARAMETERS VALUES [22]

Parameters	Values
$SOC_{initial}$	EV1: 0.20, EV2: 0.246
$SOC_{desired}$	0.80 (for all EVs)
$B_{capacity}$	40 kWh (for all EVs)
DOD	0.80
L_c	3000
C_{BI}	$ 4000

Wholesale electricity prices of the National Electricity Market of Singapore (NEMS) have been considered [22]. The 30-min time step is converted into 5-min time step to simulate the proposed approach. Charging power levels are [60, 50, 30, 20, 16, 10, 7.4, 6.6, 5, 2.3] kW. Other simulation parameters are the same as the original work [22], which are reproduced in Table IV.

Two different vehicles have been considered. The first EV arrives at 12:30 P.M. and needs to stay there until 4 P.M. The given model suggests leaving at 02:30 P.M. Fig. 9 shows the scheduling with corresponding C-DP. It can be observed that there is no discharging suggested by the recommendation model and it charges at higher power values. Contrary to this, the PM of scheduling is more consistent with charging at the same power level and then utilizing the discharge opportunity before the departure. The TC for the recommendation model comes up to be U.S. $5.129, whereas with the PM, the TC is U.S. $5.125. It is worth mentioning here that the recommendation model does not consider the temperature-dependent term in battery degradation cost, which is included in the proposed model.

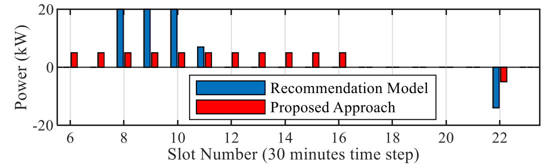

Fig. 10. C-DP for EV-2.

The second EV is considered to arrive at 3 A.M. and has to stay there up to 11:30 A.M. The scheduling with corresponding C-DP for this vehicle from the two methods is shown in Fig. 10. The referred model suggests EV leave at 11 A.M. It can be observed again that the PM utilizes the maximum possible slots for charging/discharging at low power values. The TC for the recommendation model comes up to U.S. $2.703, whereas it is U.S. $2.617 with the PM.

4) Parking Lot Scenario: In the previous results, the effectiveness of the proposed algorithm on single EV for various scenarios has been demonstrated. This case study considers a parking lot scenario with multiple vehicles to demonstrate the comparative benefits to the PO. Many business models are possible for a parking lot operator, considering numerous operating conditions and business preferences [43]. Two simple models have been considered in this case for the parking lot operators: 1) the parking lot operator provides charging facility as per the actual rates by the utility with a service fee and 2) the parking lot operator provides charging at fix rates. Accordingly, the TC for the parking including charging for the first model can be defined as

$$\mathrm{CP1}_{\text{total}} = \sum_{i=1}^{N_v} (\mathrm{TC}_i - \mathrm{CBD}_i + \mathrm{CPO}_i + \mathrm{CSF}_i)$$

where N_v is the total number of vehicles arrived in the parking; TC_i, CBD_i, CPO_i, and CSF_i are the total charging/discharging cost, cost of battery degradation, cost of parking only, and service fee, respectively, for the ith EV. The service fee can be chosen either as a percentage of the TC_i or as a fixed value, depending upon the business strategy of the operator. The parking only cost can be computed from the hourly parking rate. The TC for the parking including charging for the second model can be defined as

$$\mathrm{CP2}_{\text{total}} = \sum_{i=1}^{N_v} \left(E_{\text{requirement\_}i} \times \mathrm{Rate}_{\text{Energy}}\right) + \mathrm{CPO}_i$$

where $E_{\text{requirement\_}i}$ is the total energy consumed by the ith EV for the desired SOC and $\mathrm{Rate}_{\text{Energy}}$ is the per unit price of the energy, which may be the same for entire day or may have 2 and 3 rates for peak/off-peak periods.

For illustration purpose, the six EVs used in Sections III-B1 and III-B2 have been considered with the same operating conditions. Fig. 11 presents the total

TABLE V
PERFORMANCE INVESTIGATION FOR PARKING SYSTEM

(All values are in INR)	Proposed Approach		UCC method		SCC method	
	Model-1	Model-2	Model-1	Model-2	Model-1	Model-2
Total electricity cost to the PO **[A]**	471.71	471.71	641.96	641.96	535.03	535.03
Total Parking Only Cost **[B]**	1460	1460	1460	1460	1460	1460
Total cost recovered from the EVs **[C]**	2001.87	2996	2195.25	2996	2070.29	2996
Net profit in charging/discharging **[D=C-(A+B)]**	70.16	1064.29	93.29	894.04	75.26	1000.97
Net profit in charging/discharging considering competitive (minimum) price	70.16	1064.29	-100.09	894.04	6.84	1000.97

TABLE VI
SUMMARY OF THE SIMULATION STUDY AND PERFORMANCE INVESTIGATION

Scenario		Proposed Approach		UCC method		SCC method	
Scenario S1 : $SOC_{initial}$ = 0.10 for 40 kWh and 0.50 for 60 kWh. $SOC_{desired}$ = 0.90 for 40 kWh and 0.95 for 60 kWh		C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)
$B_{capacity}$	40 kWh	5	44.0671	2.3	102.2048	5	70.9537
	60 kWh	2.3	64.7491	2.3	85.6666	2.3	65.7682
Scenario S2 : $SOC_{initial}$ = 0.10 for 40 kWh and 0.50 for 60 kWh. $SOC_{desired}$ = 0.90 for 40 kWh and 0.85 for 60 kWh		C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)
$B_{capacity}$	40 kWh	10	108.1054	6.6	123.5593	10	123.5643
	60 kWh	6.6	70.9842	5	81.0024	6.6	73.0014
Scenario S3 : $SOC_{initial}$ = 0.10 for 40 kWh and 0.40 for 60 kWh. $SOC_{desired}$ = 0.90 for 40 kWh and 0.95 for 60 kWh		C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)
$B_{capacity}$	40 kWh	10	75.6551	5	96.2473	10	82.8593
	60 kWh	10	79.9913	5	103.4108	10	98.3548
Scenario S4 : $SOC_{initial}$ = 0.10 for 40 kWh and 0.20 for 60 kWh. $SOC_{desired}$ = 0.90 for 40 kWh and 0.80 for 60 kWh		C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)
$B_{capacity}$	40 kWh	6.6	86.8968	5	98.3725	6.6	89.2393
	60 kWh	7.4	97.9032	5	110.9554	7.4	100.0561
Scenario S5 : $SOC_{initial}$ = 0.10 for 40 kWh and 0.30 for 60 kWh. $SOC_{desired}$ = 0.90 for 40 kWh and 0.85 for 60 kWh		C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)
$B_{capacity}$	40 kWh	6.6	77.8003	5	96.2473	6.6	83.5743
	60 kWh	6.6	75.2209	5	101.6132	6.6	86.7606
Scenario S6 : $SOC_{initial}$ = 0.10 for 40 kWh and 0.50 for 60 kWh. $SOC_{desired}$ = 0.90 for 40 kWh and 0.95 for 60 kWh		C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)	C-DP (kW)	TC (INR)
$B_{capacity}$	40 kWh	6.6	80.1907	5	125.333	6.6	84.8393
	60 kWh	6.6	62.9893	2.3	93.3346	6.6	70.4760

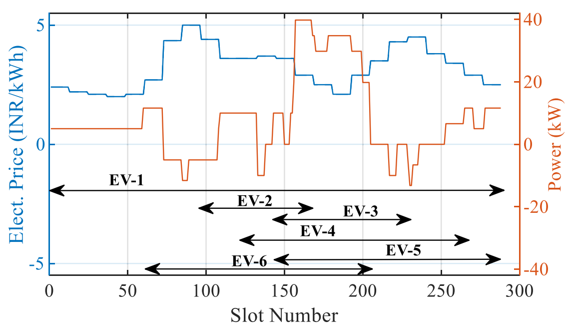

Fig. 11. EVs stay at the parking lot with total power exchange with the utility grid.

power drawl from the utility grid and price of electricity charged by the utility, along with the stay duration of various EVs. The service fee in the first model has been considered as 15% of the TC and $\text{Rate}_{\text{energy}}$ for the second model has been taken as INR 8/kWh. The parking only fee has been fixed at INR 20/h for each hour or its part. The results obtained for the EVs' stay, as shown in Fig. 11, are presented in Table V.

It can be easily observed from the results that the PO has maximum profit in Model-2 from the PM. Because the first model is based on percentage of TC, the profits from the other methods appear more; however, considering a highly competitive market scenario, a high parking rate is not beneficial for the business of the PO; hence, considering the lowest parking price as a benchmark, the PM earns maximum benefit for the PO.

C. Performance Evaluation and Discussion

To evaluate the relative performance of the PM, a comparative cost analysis has been carried out for all the scenarios and cases discussed in Section III-B. Two base cases have been considered for this analysis. The first base case is UCC when EV is charged on arrival at the parking place irrespective of the electricity price at that time. The second base case is SCC, in which a vehicle is charged in the CO only, whenever the average price is less than the price at that instant vehicle is getting charged and those slots are occupied first which is having less price value.

Fig. 12 shows the comparison of the TC of the PM for all the six scenarios discussed above along with the total charging cost for the two base cases. A summary of the simulation study along with the simulation parameters considered for specific scenarios is presented in Table VI. The result shows that the TC (charging cost, discharging rewards, and battery degradation cost) is less for the PM.

TABLE VII
COMPARATIVE FEATURES AMONG SELECTED WORKS

S/No.	Features	[22]	[19]	[31]	[32]	[33]	Proposed Approach
1	Early departure	✓	x	x	✓**	x	✓**
2	Renewable Resources integration	x	x	x	x	✓	x
3	Battery degradation	✓	x	x	✓	✓	✓✓
4	V2G	✓	✓	✓	x	✓***	✓
5	Algorithm Simplicity (S/M/Cx)	M	Cx	M	Cx	M	S
7	Multiple scenarios	x	x*	x*	x*	x*	✓
6	Iterative charging power allocation	x	x	x	x	x	✓*
7	Dynamic Power allocation	✓	✓	✓	✓	✓	x
8	Defining charging opportunity using average electricity price.	x	x	✓	x	x	✓

S/M/Cx = Simple/Moderate/Complex , ✓✓ = two different methods are included , ✓* = Iterate until requirements are not fulfilled using constant power , ** = under certain constraints, x* = multiple EV scenarios, ✓*** = Vehicle-to-Building

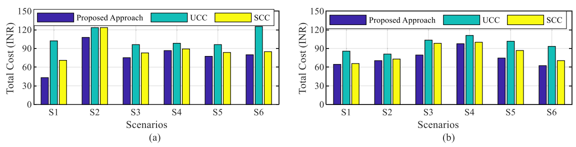

Fig. 12. Comparisons of the TC (a) with 40 kWh battery capacity and (b) with 60 kWh battery capacity.

It can be noticed from Table VI that in some scenarios, the charging power is more for the PM; still, the battery degradation cost is low. This is because the number of slots required to charge the vehicle is less for the PM, and it utilizes the low-price value in those slots.

Due to underdeveloped roadside charging infrastructure and negative impact of rapid charging on battery health, charging at parking station is going to be a better option to an EV owner. POs can exploit maximum benefit out of this opportunity by minimizing electricity consumption cost, electricity demand cost, maintenance and repair cost, and optimally utilizing the time of use tariff with V2G option. Although the PM can provide high-power fast charging, as evident from Fig. 10, it explores charging the EV at lower power levels by forward–backward iterations and thus minimizes electricity demand cost and maintenance cost, as these costs are low for charging at low levels [44]. Figs. 9–12 and Tables V and VI confirm that with low charging cost at low power and using V2G operation in DO, the POs can not only enhance their profit, but by offering low-cost charging plans, may attract more EVs to grow their business.

IV. Conclusion and Future Work

In this article, a novel forward–backward energy allocation-based approach has been presented for scheduling EVs in public parking systems. The proposed approach uses an improved CO-DO to minimize the TC, which includes charging cost, discharging rewards, and battery degradation cost. Along with that EV owner's emergency exit from the charging place has been also considered. Table VII highlights the key features of the proposed work as compared with the other existing methods.

The performance of the PM has been investigated in different real-life scenarios and has been compared with other approaches. The results confirm that the PM utilizes the CO and DO and allocates the charging and discharging power in an iterative manner to ensure the minimum possible degradation of the battery with a low total charging cost. The PM does not involve any optimization algorithm and, hence, is expected to have low computational time and reduced computational burden; also, the consumer will benefit from the decrease in overall cost. The complexity of the algorithm used in the earlier attempts reduces the power equipment's efficiency, which shortens their durability. Therefore, by using the PM, the PO will turn a profit.

In future work, to increase the robustness of the proposed approach, a dynamic power allocation will be used in a forward–backward way to assign energies in CO and DO, so that inaccuracies due to assumption of arrival/departure at the edges of a time slot can be minimized and charging cost can be further reduced with relatively high-power charging/discharging at peak/valley electricity price. Furthermore, the influence of DOD on battery aging is different under different temperatures. Especially at low temperatures, the impact of DOD on battery aging is greatly increased.

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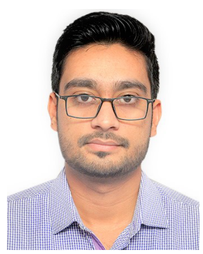

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