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# Reducing Electric Vehicles Charging Costs Utilizing Optimal Control Method Based on Diverse Charging Patterns

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***Abstract***— *Plug-in electric vehicles (PEVs) present a promising solution for decreasing greenhouse gas emissions and conserving natural oil reserves. However, the growing number of PEVs connected to the electric grid raises concerns regarding the reliable and safe operation of the network. This concern stems from the fact that the charging operation of electric vehicles (EVs) involves a significantly high level of electricity consumption due to the size of EVs' battery charging period. Unscheduled charging activities can lead to increased electricity consumption, increase in PEV charging costs and overload on the distribution grid. To address this issue, this paper proposes a coordinated charging schedule for PEVs, utilizing an optimized EV battery charging model with an optimal control method that deals with finding the best possible control signal for a dynamic system over period of time aiming to optimize a particular performance index, while satisfying various constraints such as boundary condition, state, and control path. The results demonstrate that the proposed optimized charging schedule reduces charging costs by up to 21% compared to an unscheduled charging pattern.*

***Index Terms***— *Charging cost, coordinated charging, optimal control, plug-in electric vehicle, penetration level, unscheduled charging*.

## I. INTRODUCTION

Electric Vehicles (EVs) have earned substantial attention over the past few years as an environmentally friendly alternative to conventional fossil fuel-powered Internal Combustion Engine (ICE) vehicles. This marks a significant shift toward electrification in the transportation sector [1-3]. By reducing the consumption of fossil fuels, EVs offer a compelling economic solution while simultaneously mitigating greenhouse gas emissions, including $CO_2$, $SO_2$, and $NO_x$, which are major contributors to global warming [4]. According to the International Energy Agency (IEA), the global number of EVs reached approximately 3.1 million in 2017. By 2030, it is anticipated that the number of EVs will expand to 125 million [5]. This is due to increased environmental and economic concerns and energy crises such as reducing natural oil resources and rising petrol costs. Moreover, various automotive companies, i.e., Nissan, General Motors, and Chevrolet, have recently launched their product line into the Plug-in Electric vehicles (PEVs) market [6-8]. EVs are classified into three main categories: Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), and Plug-in Hybrid Electric Vehicles (PHEVs). The most common type of EV used currently is the PEV, which refers to any EV that can be charged by plugging into an external power source. BEVs rely solely on electric motors for power and do not have a fuel tank, gasoline engine, or exhaust pipe, and high-capacity batteries are used to power the motor and all electronic systems. As shown in *Fig. 1*, BEVs can be

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recharged through an external source therefore, it is considered as plug EVs. Popular examples of available BEVs include the Tesla Model S, Chevy Bolt, Nissan LEAF, and BMW i3 [9].

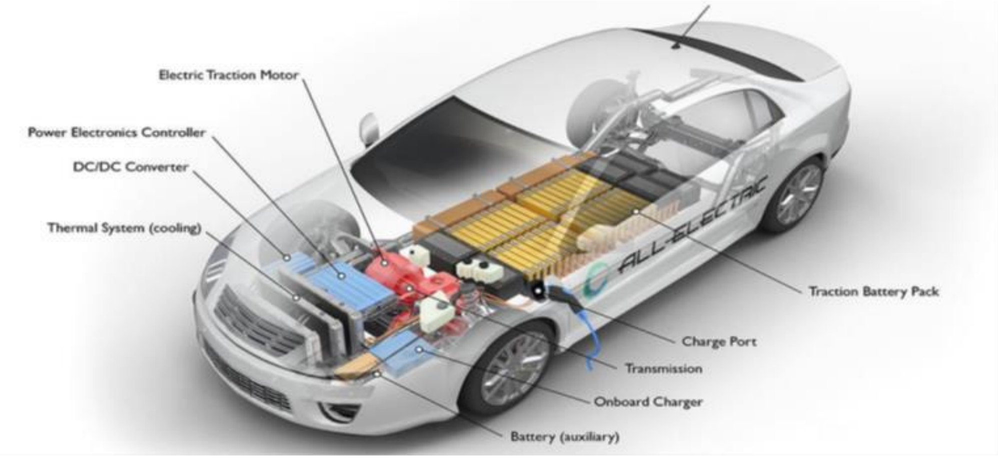


FIG. 1. KEY COMPONENTS OF A BEV [10].

HEVs employ two complementary drive systems: an ICE with a fuel tank and an electric motor with a battery. Both systems can control the transmission simultaneously, which in turn powers the wheels. Unlike BEVs, HEVs cannot be recharged through the electric grid; instead, they use gasoline to power the ICE and regenerative braking to charge the batteries that power the electric motor. *Fig. 2* demonstrates the essential components of an HEV. Some examples of HEVs currently in use include the Chevrolet Tahoe Hybrid, Ford C-Max, Honda CR-Z, and Kia Optima Hybrid [11].

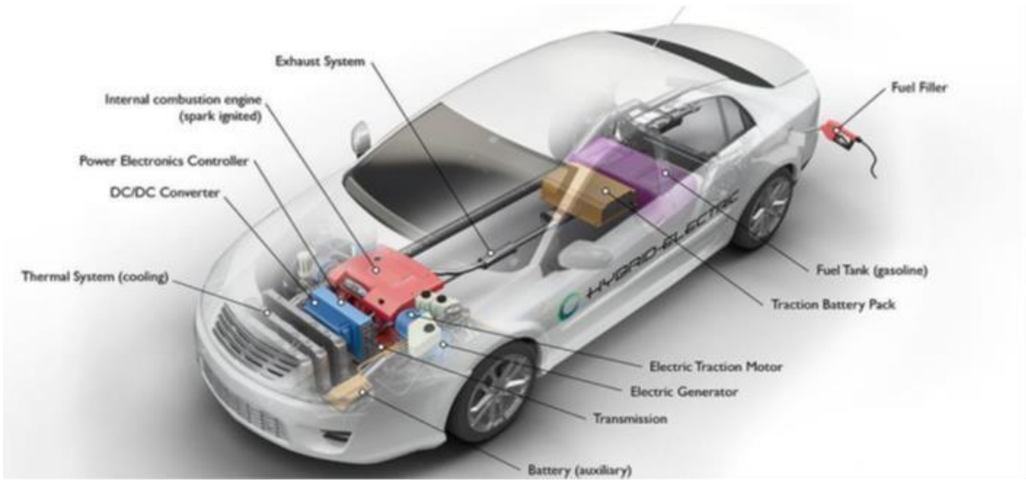


FIG. 2. BASIC ELEMENTS OF A HEV [10].

Unlike HEVs, PHEVs employ an ICE and an electric motor. Nevertheless, the electric motor in PHEVs can be recharged through regenerative braking or by connecting the vehicle to an external power supply, like an electric vehicle charging station [10]. From a technical perspective, PHEVs are full hybrids with additional technology. The main difference between PHEVs and full hybrids is that PHEVs have a larger traction battery that can also be recharged through an auxiliary external power source, whereas full hybrids can only recharge through regenerative braking. The essential components of a PHEV are illustrated in *Fig. 3*. Some patterns of PHEVs currently in use are the Toyota Prius Plugin, Porsche Panamera SE, BMW i8, and GM Chevy Volt [12].

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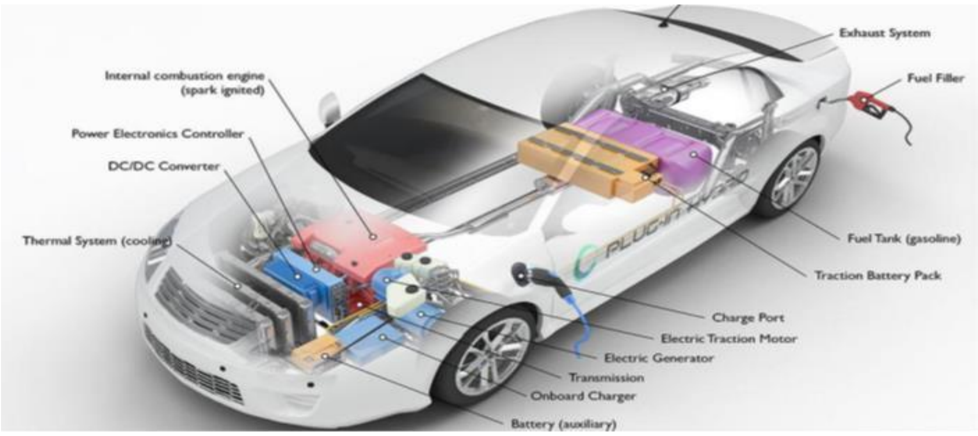


FIG. 3. KEY SECTIONS OF A PHEV [10].

EVs can be charged either using a home-based plug-in system or by accessing a public charging station. Advances in EV technology and charging infrastructure contribute to the widespread adoption of EVs worldwide. Consequently, the Penetration Level (PL) of PEVs integrating further into distribution grids is expected to increase. However, large-scale adoption of PEVs into the power grids will severely challenge the Demand Side Management (DSM) issue from the utility's perspective since PEV battery chargers represent substantial loads in electrical consumption. A frequent scenario is that various PEV owners will tend to immediately plug in their vehicles to charge as soon as they arrive home during high peak demand. These unscheduled PEV charging activities can significantly lead to increased charging costs for the PEV owner and can provoke very serious issues for electricity system operators such as transformer overloading, voltage deviations, and power losses [13]. As a result, there may be a sizeable risk to the distribution grid's ability to operate safely and reliably. Consequently, optimizing the scheduling of PEVs at charging stations to reduce charging expenses, coupled with the extensive embrace of PEVs within the electric grid, may introduce a new challenge for managing distributed generations and power units within the network [14-17]. Typically, an aggregator serves as a crucial intermediary connecting the PEV fleet with the Distribution Management System (DMS). It is responsibility extends to establishing a cooperative procedure for PEV charging, ensuring the alignment of grid operator benefits with PEV charging activities. Consequently, a robust communication framework is imperative to facilitate the real-time exchange of information between PEVs and the aggregator, enabling effective control and monitoring of PEV charging operations [18]. Furthermore, PEVs offer environmental benefits through reduced emissions and potential reliance on renewable energy sources. Advancements in PEV technology are leading to improved efficiency, performance, and decreasing costs. However, PEVs still face limitations such as range anxiety, charging infrastructure needs, and potentially higher purchase costs. Long-term environmental impact depends on battery life-cycles and electricity production methods
[13].

## II. RELATED STUDY

A variety of works have been proposed for scheduling PEV charging activities by employing various algorithms to reduce PEV charging cost for instance, an optimization technique called Mixed Integer Linear Programming (MILP), has been proposed, which considers a model of upstream grid prices instead of the estimated expenses for modeling an undefined restriction [19]. In contrast, [20] introduced a reinforcement learning framework that combined a Long Short-Term Memory (LSTM)

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network and an Improved LP algorithm (ILP). This LSTM-ILP framework aims to optimize the Vehicle to Grid (V2G) control of EVs by considering the overall EV charging demand, discharge potential, large grid electricity price, aggregator, and user interest demands. Heuristic algorithms, for instance, Particle Swarm Optimization (PSO), genetic algorithm (GA), Artificial Bee Colony (ABC), and Differential Evaluation (DE), have been proposed to optimize charging and discharging activities and reduce the charging cost, considering the network and EV constraints. Nevertheless, these methods require a considerable number of variables for time discretization [21]. However, [22, 23] studied GA and PSO coupled with the shuffled frog leaping algorithm (SFLA) to minimize PEV charging costs. Although GA and PSO have achieved noteworthy results, reducing costs by up to 29% and 19%, respectively, they also have certain limitations, such as computational intensity, tendency to converge on local minima, and their applicability in dynamic real-world environments. Another technique has investigated the problem of PEV charging costs in the housing sector by proposing a new V2G algorithm, called the V2G-Optimal Logical Control (OLC) that sells electricity back to the grid during peak hours. The results showed that V2G-OLC is significantly more efficient than traditional OC strategies, with an average cost reduction of 47% [24]. Additionally, [25] explores diverse beamforming objectives for wireless massive MIMO systems, aiming to boost spectral and energy efficiency in modern wireless communication. Analyzing both uplink and downlink scenarios, it seeks optimal beamforming weight matrices. Results show that massive MIMO enhances spectral efficiency through multiplexing and beamforming gain while improving uplink energy efficiency. The distinctive approaches of related works that have presented various methods for optimizing PEV charging are summarized in Table I.

TABLE I. SUMMARY OF EXISTING STUDIES ON OPTIMIZING PEV CHARGING SCHEDULE

| **Works** | **Objective** | **Method applied** | **PEV charging pattern** | **Remarks** |
|---|---|---|---|---|
| [20] | Minimize charging costs of EVs. | LSTM-ILP | Ordered and unordered. | This method successfully reduced charging expenses. However, LSTM struggles with longer sequences and large computing time. |
| [26] | Minimize charging cost. | NLP | Bidirectional charging. | Demonstrated reduction charging cost, the results may vary for various EV charging strategies. |
| [21] | Reduce coordination costs. | GA,PSO, DE, ABC | Charging coordination | Achieved efficient charging coordination however, heuristic methods may not always guarantee the optimal solution. |
| [22] | Minimize charging cost. | PSO, SFLA | Not detailed. | Results revealed that the proposed methods effectively reduced charging costs. However, it did not explicitly detail the PEV charging patterns. |
| [24] | Decrease charging costs. | V2G-OLC | Unidirectional and bidirectional | Introduced the V2G-OLC algorithm that reduced charging costs. Nonetheless, the effectiveness varies based on the energy billing systems employed in different regions. |
| The proposed work | Reduce PEV charging cost | OC | Unscheduled and coordinated | By intelligently scheduling charging time, the OC method can take advantage of pricing structures, periodizing charging during off- peak periods when electricity rates are lower. This can lead to significant savings on PEV charging costs. |

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Hence, it can be comprehended from the literature works, that the selection of scheduling objectives is essential. Among the various methods adopted to address this issue, the optimal control theory stands out owing to its unique mathematical approach, wherein it aims to identify the optimal control for a dynamic system over a given period. Yet, providing plug-in electric vehicle (PEV) customers with the flexibility to charge their vehicles at preferred times, while concurrently upholding network performance and diminishing PEV charging costs, poses more challenges in seamlessly integrating PEVs into the distribution grid. To the author's knowledge, this particular aspect has not been explored in existing literature. Consequently, this paper addresses the fundamental issue of unscheduled PEV charging, which can lead to increased charging expenses and affect the distribution grid. The PEV charging was developed based on the Ordinary Differential Equation (ODE). Afterwards, the limitations of unscheduled charging are discussed and thereafter, coordinated charging through the application of optimal control is proposed.

## III. METHODOLOGY

This section presents an optimized EV battery charging scheduling model utilizing OC theory, along with system assumptions. To evaluate the various PEV charging behaviors, it employs the electricity prices on a typical day, along various charging patterns including unscheduled and coordinated.

### A. Assumptions and System Architecture

Two types of control architectures can be employed for optimal PEV charging: centralized and decentralized. In a decentralized, the decision-making power for PEV charging is distributed among the PEVs. In contrast, in a centralized framework, the aggregator is completely accountable for confirming that the charging manage for PEVs has effectively coordinated, considering advantages to both the customers and grid operator [27]. Owing to its advantages and the need for optimally controlled PEV charging, the centralized control architecture was employed in this study. To implement the centralized control architecture, this study made some assumptions such as, the aggregator is set as a price taker, indicating that it does not have a sufficiently large market share to affect electricity prices. Additionally, automated communication technology is available to facilitate control charging. Finally, the driving patterns and energy requirements for each trip are assumed to be known in advance. This study assumed three daily trips: morning, afternoon, and night. To determine the SOC for all trips during the driving state, the Federal Test Procedure (FTP), New European Driving Cycle (NEDC), and Urban Dynamometer Driving Cycle (UDDC) were employed as driving patterns for each trip [28]. Another important component was electricity prices, which were selected based on a fixed typical workday and collected from the Nord Pool electricity market [29].

### B. Optimal Control of an PEV Model

Optimal control (OC) stands out as a contemporary dynamic optimization technique that operates without the constraint of being limited to the interior [30]. Nevertheless, OC involves the determination of the time history of control variables linked to a system, aiming to optimize a specific Performance Index (PI) while simultaneously adhering to Boundary Conditions (BC) and constraints imposed by the state and control paths. In this study, EVs are considered as battery packs for the purpose of charging planning. Moreover, each battery is modeled as Steady-State Equivalent Circuit (SSEC) which is characterized by ideal voltage source $V_{oc}$ and internal resistance $R_{\text{int}}$ of Li-ion battery, as illustrated in *Fig. 4*. Each $V_{oc}$ and $R_{\text{int}}$ are depended on the State of Charge (SOC) of the battery [31]. From the SSEC it can be obtained the circuit current by solving the quadratic equation $P = (Voc - R\text{int}I\ I)$ . The circuit current formula $I$ is defined as follows:

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$$I = \frac{V_{oc} - \sqrt{(V_{oc}^{2} - 4 \cdot R_{\text{int}} \cdot P}}{2 \cdot R_{\text{int}}} \tag{1}$$

Where, $P$ is set to cover all possible values that are given by $P_{BT} = \eta_t \cdot u_t \cdot P_{\max-plug}$ when $T \in T_{plug}$ or $P_{BT} = P_{dr}$ when $T \in T_{drive}$ where $P_{dr}$ represents the required available power when driving. $\eta_t$ denotes efficiency. In modern batteries, this efficiency is usually close to 100%denotes efficiency. In modern batteries, this efficiency is usually close to 100%, and The electrical characteristics of battery is provided from [32].

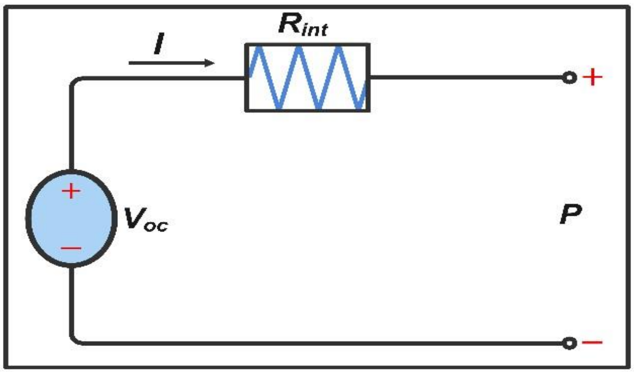


FIG. 4. STEADY STATE LI-ION BATTERY EQUIVALENT CIRCUIT MODEL.

The electricity price for a typical day is considered, thus, charging operation includes a whole time day which is denoted by [$0$, $N$] that discretized into $t$ $t$, $+1$ where, $t=0,1,2,3\ldots N$, and time interval □$_t$ . This issue is tackled by incorporating the following discrete first-order system, which characterizes the behavior of the battery:

$$x_{t+1} = f(x_t, u_t, t) \tag{2}$$

State variable $x_t$ represents the SOC of the battery at time index $t$. Every value has to be element of the predefined set $X$, which can be taken a function of charge $Q_t$ and the total capacity $Q_{\max}$ which are defined as [33]:

$$x_t = \frac{Q_t}{Q_{\max}} \tag{3}$$

Where $u_t$ denotes control variable which is a dimensionless and discrete representation of charge power when plugged in ( $P_t$ ). However, $u_t$ is multiplied with the available charge power when plugged in ( $P_{\max-plug}$ ) in order to obtain $P_t$ . Nevertheless, the EV utilized does not have an ICE to provide power for propulsion. Thus, the battery must be charged from an external electric grid. Because of this, the values of $u_t$ are restricted to 0 when driving, while they may range from 0 for no charge to 1 for charging. Thus, $U_{plug}$ is set that covers all possible values of $u_t$ , its discretization may be expressed as follows:

$$u_t = \begin{cases} u_t \in U_{[charge]} & t \in T_{plug} \\ u_t = 0_{[nocharge/drive]} & t \in T_{drive} \end{cases} \tag{4}$$

Where, $T_{plug}$ represents the set of indices $t$ within time period when the EV is plugged in, while $T_{drive}$ denotes to the driving intervals. The overall number of the time interval is $N$ that equals the calculation number of elements in $T_{plug}$ and $T_{drive}$ which predefined set $T$.

Then it can be obtaining the state equation of the problem by time derivation of the state variable $x_t$ given in (3) is defined as:

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$$\frac{dx_t}{dt} = \frac{I(x_t,t)}{Q_{\max}} \tag{5}$$

In order to reduce charging costs, OC is utilized, which may maximize the EV owner's profit. Hence, the objective function in OC is defined as:

$$\textit{minimize} \int_0^N y_t(x_t,u_t,t)dt$$

$$\textit{subject to:} \quad \dot{X}_t = \frac{I(x_t,t)}{Q_{\max}} \tag{6}$$

Where, $y_t$ represents charging cost. The general expression of the cost is defined as:

$$y_t(x_t,u_t,t) = \begin{cases} y_{[charge]} & t \in T_{plug} \\ y_{[nocharge/drive]} & t \in T_{drive} \end{cases} \tag{7}$$

Where, $y_{t[charge]} = \eta_t \cdot u_t \cdot P_{\max-plug} \cdot C_{el} \cdot \Delta_t$ , $C_{el}$ *and* $\Delta_t$ represent the electricity price and time interval respectively. Meanwhile, $y_{t[nocharge/drive]}$ sets to 0 during the driving or non-charged status. Within OC, the essential optimality conditions take the form of minimizing a designated Hamiltonian function H:[0,t], outlined as follows:

$$H = y_t(x_t,u_t,t) + \lambda \cdot \left[\frac{dx_t}{dt}\right] \tag{8}$$

By replacing the terms of $dx_t/dt$ and $y_t$ in (8) with (5) and (7) respectively. Hence, the Hamiltonian function can be described as follows:

$$H = \begin{cases} y_{[charge]} + \dfrac{\lambda}{Q_{\max}} \cdot \left[\dfrac{V_{oc}(x_t) - \sqrt{(V_{oc}{}^2 - 4 \cdot R_{\text{int}} \cdot (\frac{\eta_t \cdot u_t \cdot P_{\max-plug}}{n_{cells}})}}{2 \cdot R_{\text{int}}}\right] & t \in T_{plug} \\ y_{[drive/nocharge]} + \dfrac{\lambda}{Q_{\max}} \cdot \left[\dfrac{V_{oc}(x_t) - \sqrt{(V_{oc}{}^2 - 4 \cdot R_{\text{int}} \cdot (\frac{P_{dr}}{n_{cells}})}}{2 \cdot R_{\text{int}}}\right] & t \in T_{drive} \end{cases} \tag{9}$$

The stationary equation $dH/du_t$ and co-state equation $dH/dx_t$ are attained by deriving Hamiltonian equation (9) with respect to both $u_t$ and $x_t$, where $u_t$ utilized as a bang-bang control which expressed as:

$$u_t = \begin{cases} 1 \;\; EV_{[charge]} & \frac{dH}{du} < 0 \\ 0 \;\; EV_{[nocharge]} & \frac{dH}{du} > 0 \end{cases} \tag{10}$$

Where the control signal $u_t$ is labelled as the set of a permitted state for charging or no charge that covers two controlled values [0,1] determined by the value of Hamiltonian derivation which is defined as:

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$$\frac{dH}{du_t} = \eta_t \cdot u_t \cdot P_{max-plug} \cdot C_{el}(t).\Delta_t - \frac{\lambda \cdot \eta_t \cdot P_{max-plug}}{Q_{max} \cdot n_{cells} \cdot \sqrt{(V_{oc}{}^2 + 4R_{int} \cdot \frac{\eta_t \cdot u_t \cdot P_{max-plug}}{n_{cells}}}} \quad (11)$$

The co-state, λ in (8) or (9), is set that covers all possible values and can be defined by derivation of Hamiltonian function against the state, $x_t$ which can be expressed as:

$$\dot{\lambda} = \frac{dH}{dx_t} = \begin{cases} \dfrac{-\lambda \cdot V_{oc}}{Q_{max} \cdot 2 \cdot R_{int}} + \dfrac{\lambda \cdot V_{oc} \cdot x_t}{Q_{max} \cdot n_{cells} \cdot \sqrt{V_{oc}{}^2 + 4 \cdot R_{int} \cdot [\frac{\eta_t \cdot u_t \cdot P_{max-plug}}{n_{cells}}]}} & t \in T_{plug} \\ \dfrac{-\lambda \cdot V_{oc}}{Q_{max} \cdot 2R_{int}} + \dfrac{\lambda.V_{oc}.x_t}{Q_{max} \cdot n_{cells} * \sqrt{V_{oc}{}^2 + 4 \cdot R_{int} \cdot [\frac{P_{dr}}{n_{cells}}]}} & t \in T_{drive} \end{cases} \quad (12)$$

The Euler method is employed to solve the state and co-state equations, with the costate being determined in reverse from the final to the initial time interval. The Hamiltonian equation, expressed in (8), presents a set of ordinary differential equations (ODEs) that can be addressed through a numerical approach or any alternative method. In unscheduled charging, EVs begin charging immediately when they are plugged into an external power source, without considering the daily fluctuations in electric prices, and stops when the batteries are full. In coordinated charging, OC is applied to decide whether charging should be initiated. This approach differs from the uncoordinated charging strategy, wherein the charging process initiates whenever the SOC is below 100% and the EV is in the idle state. OC considers market prices and aims to minimize daily charging expenses of PEV owners. The flowchart in *Fig. 5* illustrates the charging power control, denoted by a dashed square, which represents the coordinated unidirectional charging processes.

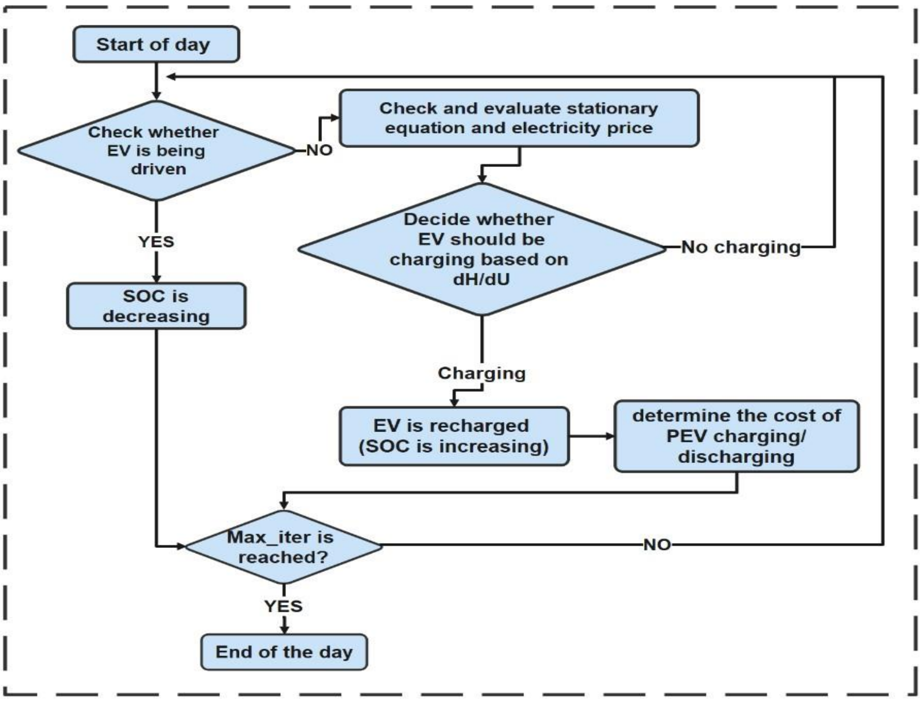


FIG. 5. FLOW CHART OF EV OPTIMIZED COORDINATED CHARGING CONTROL.

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## IV. RESULTS AND DISCUSSION

The charging behavior of PEVs is influenced by various factors such as the charging strategy employed, battery SOC, battery capacity, and charging duration. To better understand this variability, two distinct charging patterns were considered: unscheduled, and coordinated charging. The unscheduled charging strategy lacks coordination with the grid demand and electricity pricing and can potentially result in higher charging costs and grid instability due to potential overloads during peak demand hours. *Fig. 6* illustrates the SOC of an EV battery throughout the day, divided into different regions indicating trips and charging periods, under an unscheduled charging pattern. Regions R1, R3, and R5 correspond to trips, and indicate EV driving. In contrast, regions R2, R4, and R6 correspond to charging periods, wherein the EV is plugged-in and begins charging immediately without considering the daily electricity price fluctuations. After reaching full SOC, the EV state changes to idle with no charging activity, exhibiting a constant SOC during this period, as indicated at regions R4 and R6. By the end of the day, the EV battery is completely charged and ready to be used the next day.

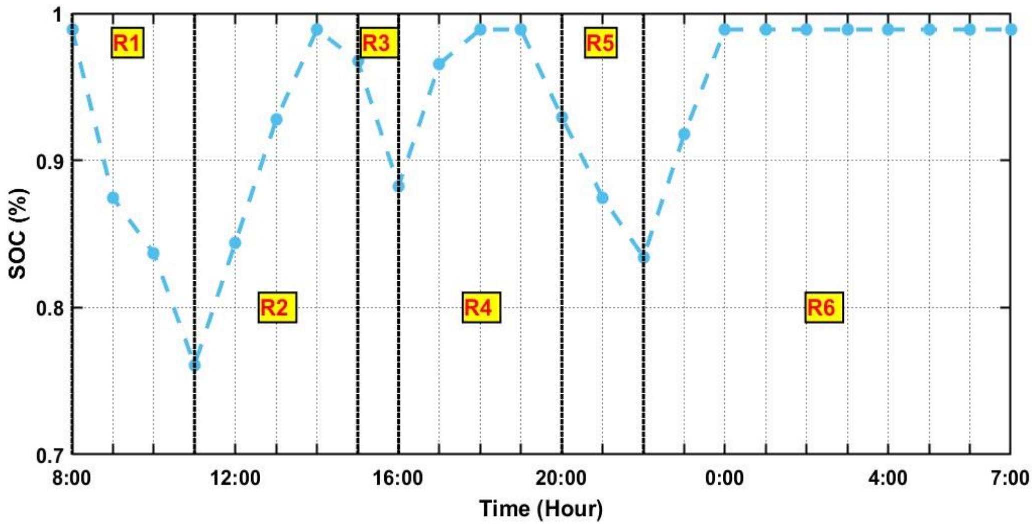


FIG. 6. SOC OF EV FOR AN ENTIRE DAY UNDER UNSCHEDULED CHARGING PATTERN.

Additionally, four subplots indicating electricity price, charging state, SOC with battery capacity, and charging cost are shown in *Fig. 7*, which illustrate the consequences of unscheduled PEV charging. This unscheduled method results in a significant charging cost, amounting to approximately £882, indicating the potential for cost optimization through more strategic charging plans.

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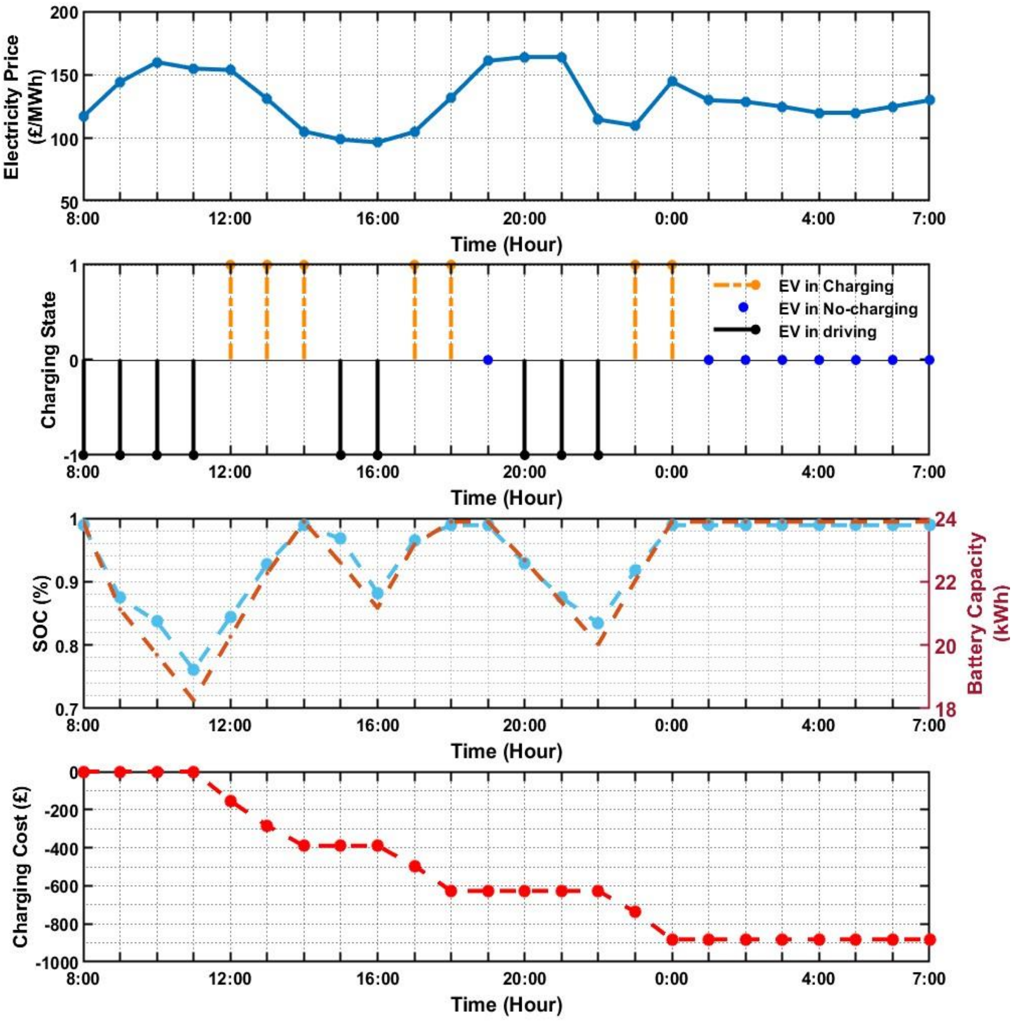


FIG. 7. UNSCHEDULED CHARGING PROFILE.

The coordinated charging strategy employs OC, which is based on the stationary equation to strategically schedule PEV charging during periods of low electricity prices. This approach significantly reduces charging costs, thereby enhancing the savings of vehicle owners. Thus, it offers substantial improvements compared to unscheduled charging and highlights the importance of strategic PEV charging coordination. Furthermore, *Fig. 8* presents a visual representation of the SOC of an EV battery over a day, considering both trips and charging periods, under the coordinated charging strategy. The application of this strategy is particularly evident in region R2, wherein the EV does not charge during the first hour but resumes charging as soon as the electricity price drops. Consequently, the SOC starts increasing. Notably, after the afternoon trip (R3), the EV is charged for only one hour before charging ceases owing to high electricity prices, resulting in a constant SOC during this period.

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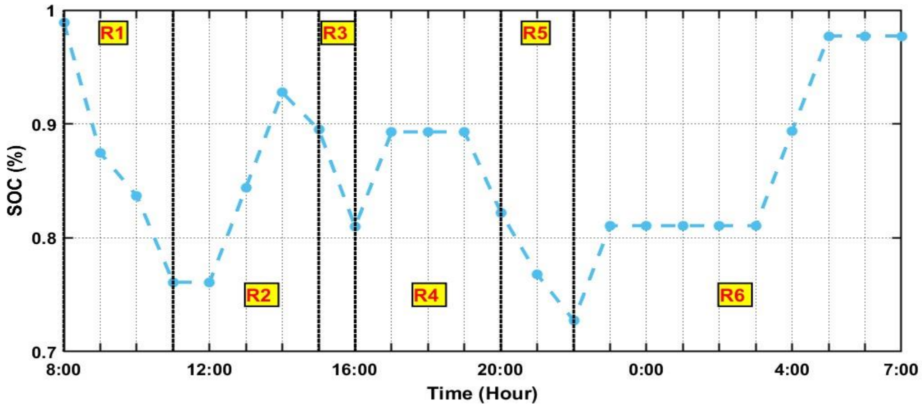


FIG. 8. SOC OF AN EV FOR AN ENTIRE DAY UNDER COORDINATED CHARGING PATTERN.

The planned, unidirectional coordinated charging system is illustrated in *Fig. 9*. It is evident that the PEV is charged during periods of considerably low electricity prices. To reduce charging costs, some charging demand is shifted to off-peak hours to align with periods of low electricity prices. Compared to the unscheduled method, the coordinated charging plan remarkably reduced charging expenses, resulting in savings of about £690. This number underscores the significant potential for reducing PEV charging costs by employing a well-coordinated charging strategy.

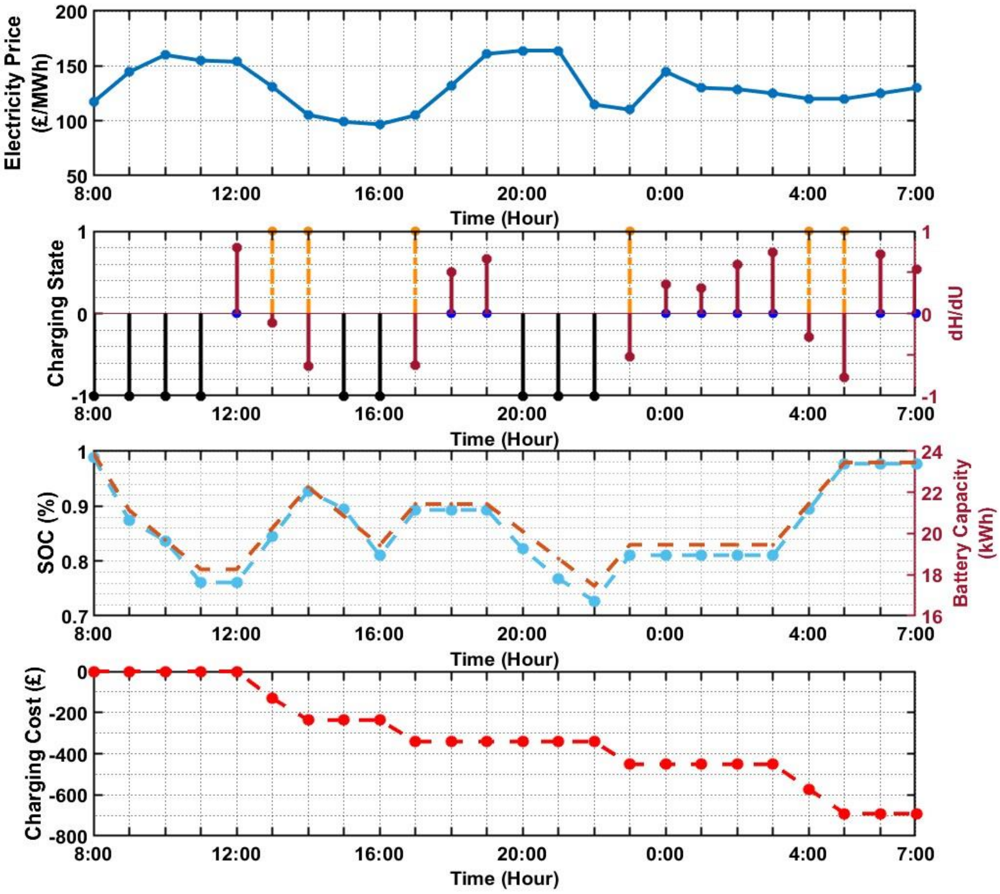


FIG. 9. COORDINATED CHARGING PROFILE.

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## V. CONCLUSIONS

This paper presents a mathematical formulation of an optimal control-based algorithm aimed at reducing daily EV charging cost through coordinated charging. The proposed model optimizes PEV charging using various charging patterns within a centralized control architecture. The unscheduled plan represents an uncoordinated PEV charging strategy wherein the PEVs begin charging immediately when they are plugged into a charging point, without considering electricity prices or grid demand. This approach may not only potentially result in grid instability during peak hours, but also incurred substantial charging costs, estimated at almost £882. However, coordinated charging involves initiating or postponing charging based on OC, which considers energy prices to minimize charging costs. In coordinated charging, although the PEVs are plugged in immediately after a trip, charging is deferred to off-peak hours. This strategy significantly reduces charging costs compared to the random strategy, resulting in savings of approximately £690. This number emphasizes the considerable potential for reducing PEV charging costs by employing a well-coordinated charging strategy. Further investigation is crucial for exploring potential extensions in future work. This includes expanding the optimization model to encompass the provision of regulation services, accommodating diverse types of electric drive vehicles, and incorporating various driving behaviors.

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