Machine Learning-Based Strategy for the Regulated Charging of Plug-In Electric Vehicles

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Abstract

Plug-in electric vehicles (PEVs) are a practical and environmentally friendly substitute for conventional automobiles. PEVs have great potential to reduce greenhouse gas emissions by utilizing electricity as their primary energy source, thereby mitigating the negative environmental effects of traditional transportation systems. However, due to the increased and frequently irregular demand for charging, the growing integration of PEVs into the electrical grid raises significant concerns regarding operational dependability and grid stability. In addition to increasing higher charging prices and perhaps causing infrastructure stress, random charging could place further strain on the distribution network. To cope with this issue, this paper proposes a controlled charging approach with centralized control architecture to regulate and schedule the charging process of PEVs powered by machine learning techniques such as neural networks and Naive Bayes, to minimize charging costs. Simulation results demonstrate the efficacy of this strategy, showing cost savings of around 50% and 36% in comparison to the random charging process.

Keywords- Electric vehicles, centralized control, charging cost, machine leaning, charging cost.

I. INTRODUCTION

This Vehicles that run on fossil fuels continue to dominate global sales, and the automotive industry is still expanding quickly. The globe is moving toward electric mobility, nevertheless, because of growing environmental issues like air pollution, the depletion of fossil fuel supplies, and the growing effects of greenhouse gas emissions. Three broad categories of electric vehicles are Plug-in Hybrid Electric Vehicles (PHEVs), Hybrid Electric Vehicles (HEVs), and Battery Electric Vehicles (BEVs) [1]. Furthermore, around 40 million electric vehicles will be on the road globally by the end of 2023, according to the International Energy Agency's (IEA) Global EV Outlook 2024. This sum represents a continuous global trend toward cleaner, more sustainable mobility and includes both BEVs and PHEVs, as shown in Figure 1. PEVs are the most popular kind of electric vehicle at the moment since they can be recharged using an external power source. BEVs are a subclass of PEVs that run solely on electricity and don't have fuel tanks, exhaust systems, or internal combustion engines. They use high-capacity batteries, and in order to prolong battery life, they frequently use regenerative braking. A hybrid HEV, on the other hand, combines an electric motor and an internal combustion engine (ICE). Although the vehicle can be powered by both systems, HEVs cannot be externally charged; instead, they use regenerative brake and gasoline to keep their batteries charged, usually with the electric motor running at low speeds and the ICE running at greater speeds [3]. PHEVs share the dual-drive system of HEVs but include larger batteries that can be recharged both externally and through regenerative braking. PHEVs also allow the ICE to charge the battery or takeover propulsion when battery levels are low, making them technically advanced full hybrids with enhanced charging capabilities [4]. Therefore, the main objective of this study is to develop a centralized control strategy for the regulated charging of PEVs using MLs techniques. The proposed approach aims to reduce electricity charging costs by intelligently scheduling charging times.

The remaining structure of this paper is organized as follows: Section 2 presents a review of related works. Section 3 describes the methodology, including the proposed system architecture, driving patterns, and PEV charging strategies. Section 4 provides the results and discussion of the experimental findings. Finally, Section 5 concludes the study and outlines recommendations for future work.

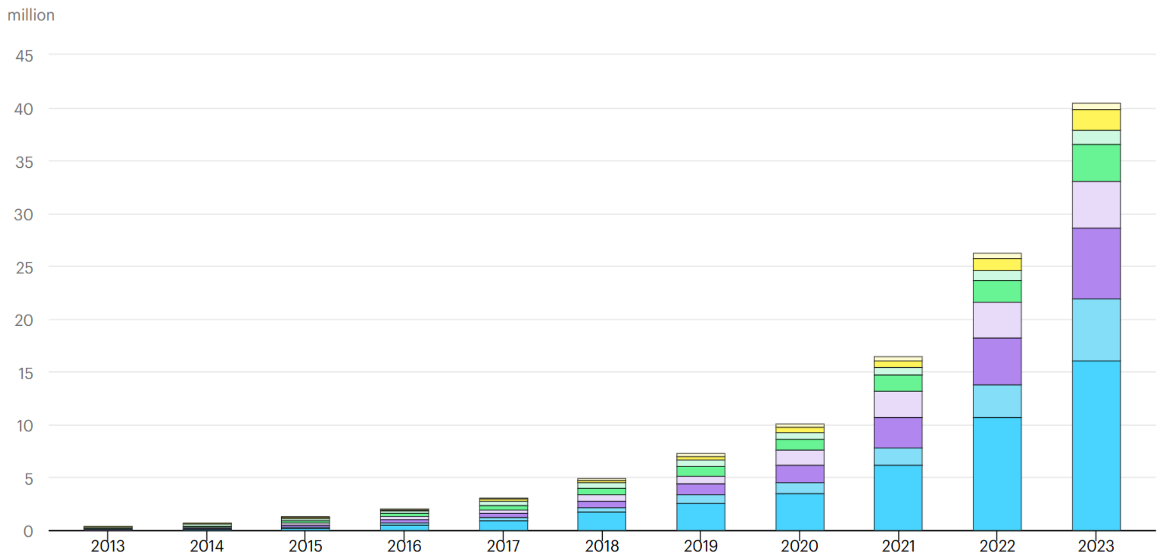

Figure 1 International EV stock, including BEVs and PHEVs, from 2013 to 2023 [2]

II. RELATED WORK

The worldwide EV fleet is expected to reach over 130 million by 2030 as governments throughout the world boost their investments in EVs and charging infrastructure to fight climate change [5]. However, from the standpoint of power providers, this quick growth, especially in PEV, presents difficulties for demand-side management (DSM). When a large number of PEV users begin charging their vehicles at the same time as they get home, which happens during periods of high power demand, there is often cause for concern. Such uncoordinated or random charging behavior can significantly strain the power grid, leading to increased electricity costs for consumers. To mitigate these issues, intelligent and well-coordinated charging strategies between grid operators and EVs are crucial to ensure grid stability and economic efficiency [6]. Recently, various works have explored various approaches to optimize the scheduling of PEV charging operations. For example, heuristic algorithms and linear programming techniques were presented in [7] to solve dynamic and static scheduling difficulties, respectively. Their goal was to include user demand and aggregator earnings into the strategy in order to increase cost reductions for vehicle owners. Using only EV batteries, the study also used Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) technologies to lower residential electricity bills. Similarly, studies [8, 9] suggested techniques including Dynamic Programming (DP), Nonlinear Programming (NLP), and Mixed-Integer Linear Programming (MILP) for scheduling PEV aggregator operations in the face of variable upstream power prices. Even though these techniques produce encouraging results, their computational complexity frequently limits them. Increasing the number of variables and constraints can make these methods extremely complex and time-consuming, making it challenging to find practical options in a fair amount of time. Advanced models for improving EV charging procedures in unpredictable situations have been proposed in a number of research. For instance, the authors [10] created a two-stage stochastic LP model that takes market pricing variations and fleet mobility concerns into account while optimizing EV aggregator profits in both day-ahead and balancing markets. In similar, [11] used stochastic programming approaches to control EV fleet charging, taking into account market bidding, auxiliary service offerings, and the unpredictability of regulation signals. Another study, [12], used a multi-objective particle swarm optimization (MOPSO) framework to simulate electric vehicle charging stations (EVCS) using sequential Monte Carlo simulations to investigate optimal charging and discharging behaviors. Their method used three different battery operation methodologies to regulate the rate and timing of EV energy exchange. In contrast, [13] suggested a dynamic pricing-based charging approach that takes into consideration seasonal variations in EV charging demand and makes use of genetic algorithms (GA) to reduce charging expenses and avoid transformer overloads. Additionally, it was shown by [14] that V2G technology allows EV users to reduce their charging costs by selling electricity back to the grid when demand is at its highest. A decentralized smart charging approach was also presented in this work, which allowed for more scheduling flexibility by treating the dynamic time step as a variable rather than a fixed one. In a similar direction, studies [15, 16] employed a Markov Decision Process (MDP) with uncertain transition probabilities and a constrained MDP to address the challenge of minimizing individual PEV charging costs. Reinforcement Learning (RL) methods were used to create heuristic control strategies for adaptive energy consumption plans. The RL framework allowed for ongoing policy improvement based on observed results by evaluating the efficacy of different charging techniques.

On the other hand, [17] optimized EV charging and discharging schedules based on anticipated electricity prices using RL algorithms. Despite its promise, RL techniques frequently need large datasets to develop efficient policies and require adjusting a large number of hyperparameters, which can be computationally and time-intensive. A review of existing literature highlights the critical importance of selecting appropriate scheduling objectives. Among the various methods explored, ML stands out for its robust mathematical foundations and adaptability. Nonetheless, integrating PEVs into the power distribution network remains challenging, particularly when aiming to balance grid performance with user flexibility, allowing customers to charge their vehicles during preferred time windows while minimizing associated costs. To the best of the authors' knowledge, this balance between consumer autonomy and network optimization has not been comprehensively addressed in prior research. Consequently, this study focuses on the core issue of uncoordinated PEV charging, which can lead to increased electricity costs and inefficiencies.

III. METHODOLOGY

Now This section outlines the system architecture and underlying assumptions, alongside an optimized charging schedule model that leverages ML techniques. To assess different PEV charging behaviors, the study incorporates typical daily electricity pricing and examines various charging strategies, including both random and controlled charging scenarios.

A. System Architecture and Underlying Assumptions

There are two main control systems that can be used to get the best PEV charging schedule: centralized and decentralized. Individual PEVs share decision-making power in a decentralized control structure, enabling each owner to choose their charging schedule according to their own tastes and energy needs. In a centralized control structure, a central aggregator manages the entire billing process with the goal of maximizing system performance and striking a balance between grid operators' and consumers' incentives. By taking into account variables like grid load, electricity prices, and periods of peak demand, this method also makes it possible to optimize and coordinate charging plans more effectively. Utilizing real-time data and sophisticated optimization algorithms, the system can take advantage of changes in electricity prices to determine the most economical charging times [1, 18]. Both centralized and decentralized control structures for EV charging are conceptually represented graphically in Figure 2.

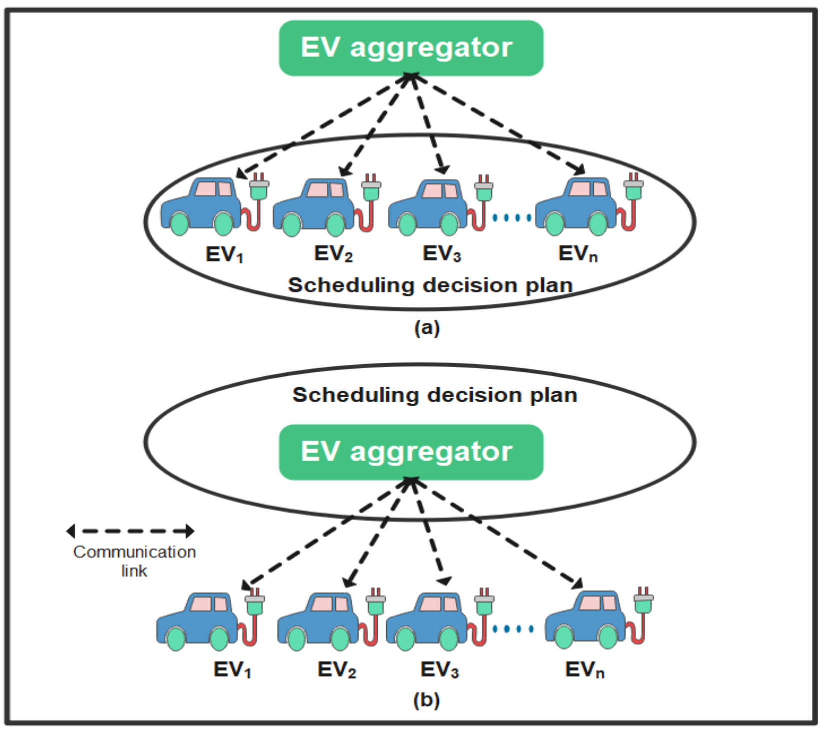

Figure 2 Architecture for PEV charging control (a) decentralized (b) centralized [1]

This study uses centralized control architecture because of its benefits and the increasing demand for charging that is optimally handled. As an intermediary that indirectly engages with the energy market on behalf of the vehicles, an aggregator plays a crucial role in this structure by actively controlling the charging strategies of individual PEVs. This method is predicated on a number of assumptions. First, it is believed that the aggregator acts as a price taker, meaning it lacks the market power to change the price of electricity. Second, it is believed that the availability of automated communication technology will allow for real-time charging process coordination and control.

Furthermore, it is assumed that the energy needs and driving habits for every vehicle journey are known beforehand. A crucial element in the model is the electricity price, which is derived from the Nord Pool electricity market and is based on an average workday [19]. Figure 3 depicts how information moves through the centralized control system.

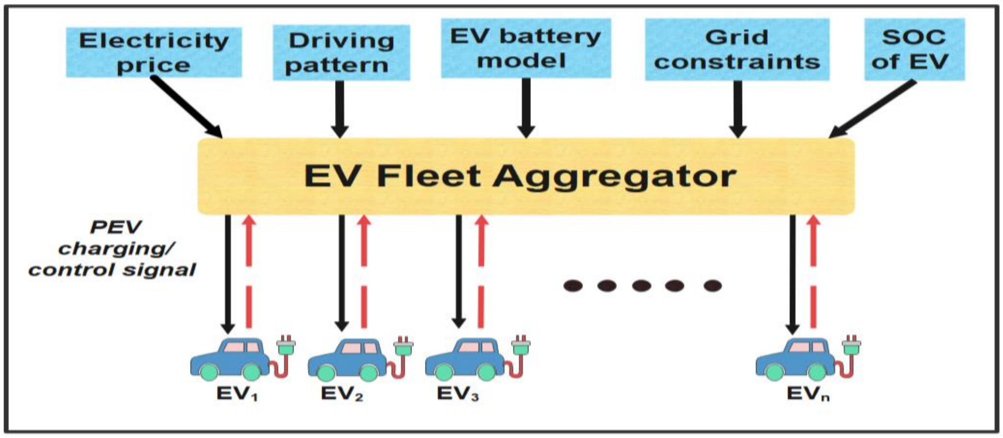

Figure 3 Diagram of the centralized control architecture's information flow [20]

B. Driving Pattern Behavior

Developing an efficient charging strategy requires an understanding of how EV owners drive on a regular basis. This entails taking into consideration important variables such as the battery's State of Charge (SOC), normal driving habits, and the energy needed for each journey. Three daily tours morning, afternoon, and night were considered for this study. The Federal Test Procedure (FTP), New European Driving Cycle (NEDC), and Urban Dynamometer Driving Cycle (UDDC), which correspond to various trip types, were the standard driving cycles used to estimate the SOC throughout each driving phase. The Driving Cycle Simulink Block (2025) served as the source for these driving patterns. Based on the technical specifications of the vehicle, Table I offers comprehensive details on every possible trip situation.

TABLE I. DRIVING PATTERNS ASSOCIATED WITH DAILY TRAVEL PERIODS [20]

Tours	***Driving configuration used***	***Energy demanded***	***SOC necessity of each trip***
Morning	FTP	5.738 kwh	23.908 %
Afternoon	NEDC	2.826 kwh	11.775 %
Night	UDDC	3.975 kwh	16.574 %

C. Dataset

In this study, a supervised ML approach was used to optimize the charging schedules of PEVs. The dataset consists of numerical time-series with 24 hourly records covering a full day. The primary source of the electricity price data is collected from [19], which reflects real-time variations in electricity cost throughout the day. Each record represents one hour and includes variables such as electricity price, vehicle availability, and battery state. Time series data is essential in this context because both electricity prices and charging decisions are inherently time-dependent charging during peak hours incur higher costs, while off-peak periods offer economic advantages. Modeling this temporal behavior allows ML algorithms to learn patterns in electricity pricing, enabling it to make accurate charging decisions at specific times. The input features include hour of the day, electricity price, initial SOC, vehicle arrival/departure times, and maximum charging power, while the output is a binary or probabilistic signal indicating whether charging should occur during that hour.

D. PEV Charging Strategies

This section explores two distinct charging strategies: random, and controlled charging. In the random charging scenario, EVs start charging as soon as they’re plugged in, with no regard for changes in electricity prices throughout the day. Figure 4 illustrates the flowchart detailing the steps involved in random EV charging scenario. At each iteration, the simulation first evaluates whether the vehicle is currently in a driving state.

If the vehicle is in motion, its SOC is reduced to reflect energy consumption due to driving activity. Following this, the model checks whether the battery SOC has reached 100%. If the SOC is below full capacity, the vehicle enters a charging phase during which the SOC incrementally increases based on the selected charging strategy and rate. Once charging is completed, or if the SOC was already at 100%, the simulation proceeds to verify whether the Max_iter has been met. If so, the cycle is terminated for the day. Conversely, if the vehicle is not being driven during a given time step, it remains idle and the SOC remains unchanged. In this idle state, the model includes a cost computation step that estimates the charging cost incurred during the most recent charging event. This cost is typically determined based on dynamic electricity pricing. After the cost calculation, the Max_iter condition is again evaluated to decide whether to continue or terminate the simulation cycle.

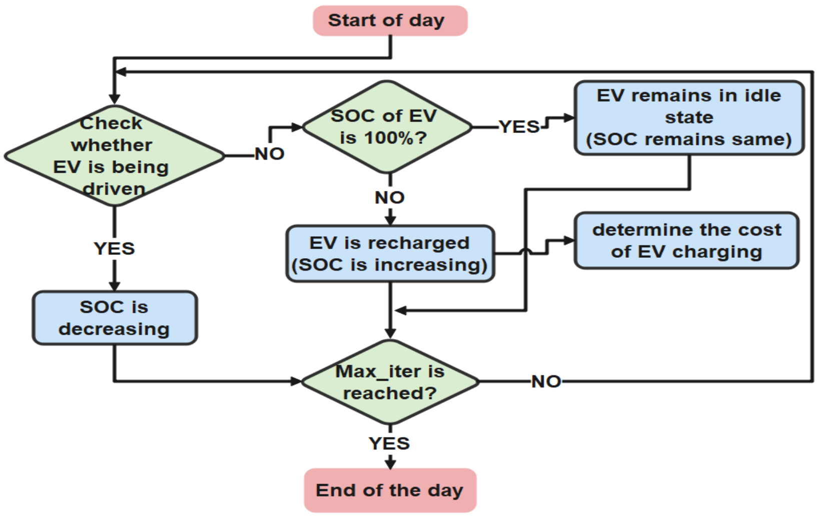

Figure 4 Flow chart of a random PEV charging scenario

E. PEV Charging based on ML Techniques

Supervised ML classifiers, including Neural Networks (NNs) and Naive Bayes (NB) methods, were employed to develop a controlled charging schedule based on electricity price data. Neural Networks, widely used for both classification and regression tasks [21], were implemented using a network architecture comprising an input layer, a single hidden layer with 100 neurons, and an output layer with neurons corresponding to the number of target classes. A hyperbolic tangent sigmoid activation function was utilized in both the hidden and output layers. For the classification output, the NN generated the label [1, 0]T to indicate a controlled charging plan. In parallel, the Naive Bayes classifier, a probabilistic model grounded in Bayes' theorem, was also applied. Despite its simplicity, the NB classifier is known for its effectiveness and computational efficiency. It is referred to as "naïve" due to its strong assumption that all features are conditionally independent given the class label, which often does not hold in practice but can still yield robust performance. The EV's arrival time was taken into consideration in order to determine if the PEV was charging or not. Based on threshold values connected to the SOC at the time of the EV's arrival, electricity prices were divided into two zones: the High Price Zone (HPZ) and the Low Price Zone (LPZ) to enable a regulated charging strategy. A low SOC suggests a longer charging time is required, whereas a high SOC suggests the vehicle needs a limited recharging time. A time-series electricity pricing dataset with hourly intervals was acquired to support this classification. Two separate classes were established in order to categorize the dataset under the regulated charge scenario. The LPZ was represented by the label "1" for price values over a predefined threshold, whereas values below. Values below or equal to the threshold were designated as "0," which corresponded to the HPZ, while price values beyond a predefined threshold were designated as "1," which represented the LPZ as demonstrated in Figure 5.

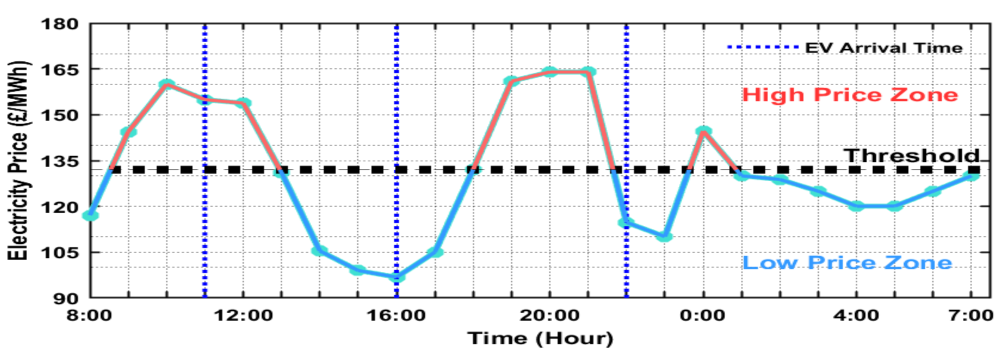

Figure 5 Controlled charging time zones for PEV

The mathematical formulations underpinning the PEV charging optimization are crucial for defining the input features and evaluating the model's performance. The electricity price at any given hour h, denoted as P_h, serves as a primary time-series input feature, directly obtained from real-time data. The evolution of the PEV's SOC is governed by the charging decisions made by the ML model; specifically, $SOC_{h+1} = SOC_h + \delta_h \cdot \frac{\eta_{charg} \cdot P_{charg,max} \cdot \Delta_t}{C_{max}}$ where, $\delta_h$is the binary charging decision (1 for charging, 0 for no charging), η_{charg} is the charge efficiency, $P_{charg,max}$ is the is the maximum charging power, Δ_t is the time step duration, and C_{max} is the battery's capacity. This formulation ensures that the remain within defined limits $SOC_{min} \leq SOC_h \leq SOC_{max}$ Finally, the charging cost for an hour h, $cost_h$is calculated as $cost_h = \delta_h \cdot P_{charg,max} \cdot P_h \cdot \Delta_t$ directly linking the model's decision with the prevailing electricity price. The total charging cost over the 24-hour period is then the summation of these hourly costs: $cost_{total} = \int_{h=1}^{24} (\delta_h \cdot P_{charg,max} \cdot P_h \cdot \Delta_t)$. These equations collectively provide a quantitative framework for the supervised ML approach, enabling the model to learn optimal charging strategies that minimize cost while adhering to operational constraints.

IV. RESULTS AND DISCUSSION

This section presents and critically analyzes the results derived from the study's advanced modeling and simulation processes. A range of PEV charging scenarios is also explored to capture the variability in charging behavior, which is influenced by several factors, including the selected charging strategy, the battery's SOC, battery capacity, and required charging duration. To investigate these dynamics, two distinct charging patterns were analyzed: random charging and controlled charging. The random charging approach operates without coordination electricity price signals, which can lead to increased charging costs, particularly during peak demand periods. In contrast, the controlled charging strategy aims to align vehicle charging with lower electricity prices, thereby enhancing cost-efficiency. Moreover, four subplots indicating electricity price, charging state, SOC of battery, and charging cost are shown in Figure 6, which illustrates the consequences of random PEV charging. It demonstrated distinct regions indicating trips and charging periods. Regions R1, R3, and R5 correspond to trips, and indicate EV driving. Conversely, regions R2, R4, and R6 represent charging intervals during which the EV is connected to the charger and begins charging immediately, without accounting for fluctuations in the daily electricity price. This uncoordinated charging strategy leads to a substantial cost, approximately £882, highlighting a clear opportunity for cost reduction through more deliberate and optimized charging schedules. Once the SOC reaches full capacity, the EV transitions to an idle state where no further charging occurs, maintaining a stable SOC throughout this phase, as observed during certain hours within R4 and R6. By the conclusion of the day, the EV battery is fully charged and prepared for use on the following day.

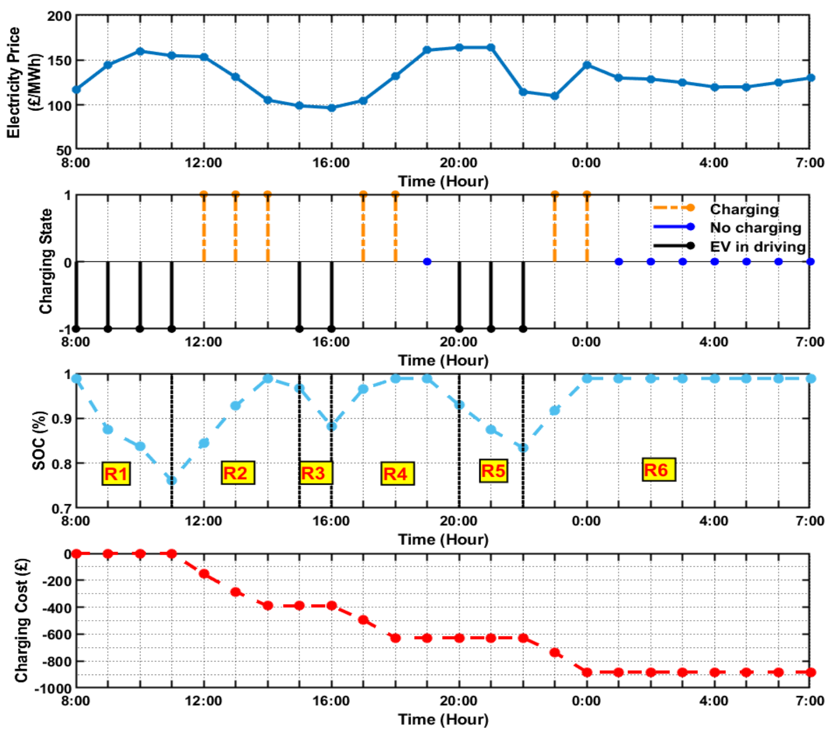

Figure 6 Random charging plan

Furthermore, the control signal obtained using ML approach is based on employing NN and NB classifier, which divides charging times into low and high charging zones. Additionally, the controlled PEV charging strategy with the ML (NN) approach is illustrated in Figure 7.

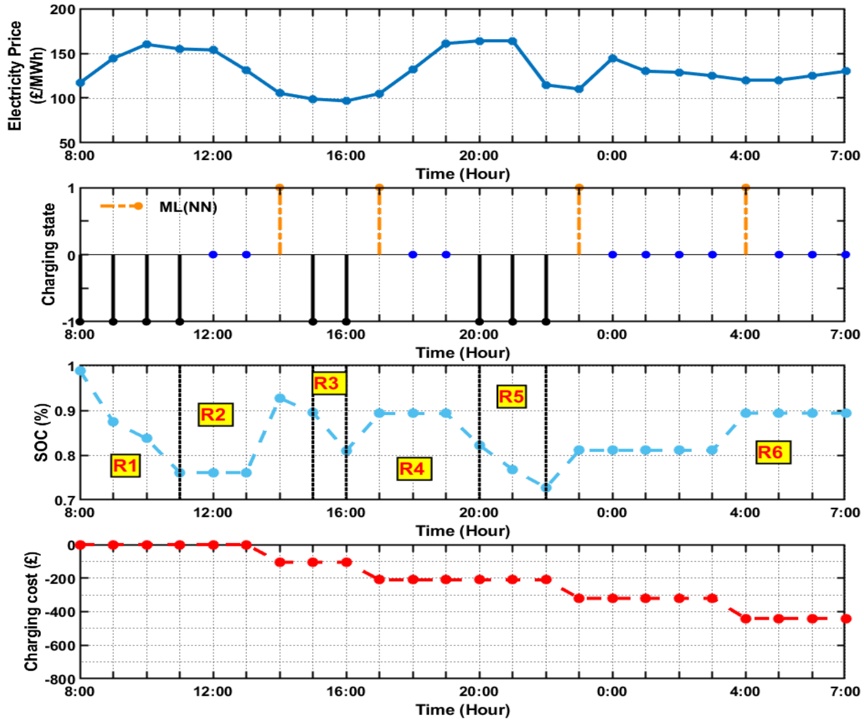

Figure 7 Controlled charging plan using ML (NN)

As illustrated in Figure 7, the PEV charging control signal derived from the ML approaches is activated exclusively within the LPZ. This implies that the EV's SOC remains unchanged until the charging signal is triggered, coinciding with periods when the forecasted electricity price is significantly low. Consequently, this results in a marked increase in the SOC during these intervals. Additionally, this charging scenario results in a PEV charging cost of ML(NN) of approximately £440, with SOC at the end of the day is 89.3%. Moreover, the controlled charging scenario based on ML (NB), has been illustrated in Figure 8, which indicates more efficient compared to other controlled charging techniques due to the outcomes of charging cost and SOC at the end of the day with £560, and SOC of 99%. These numbers highlight the significant potential for reducing PEV charging costs by employing a well-coordinated charging strategy.

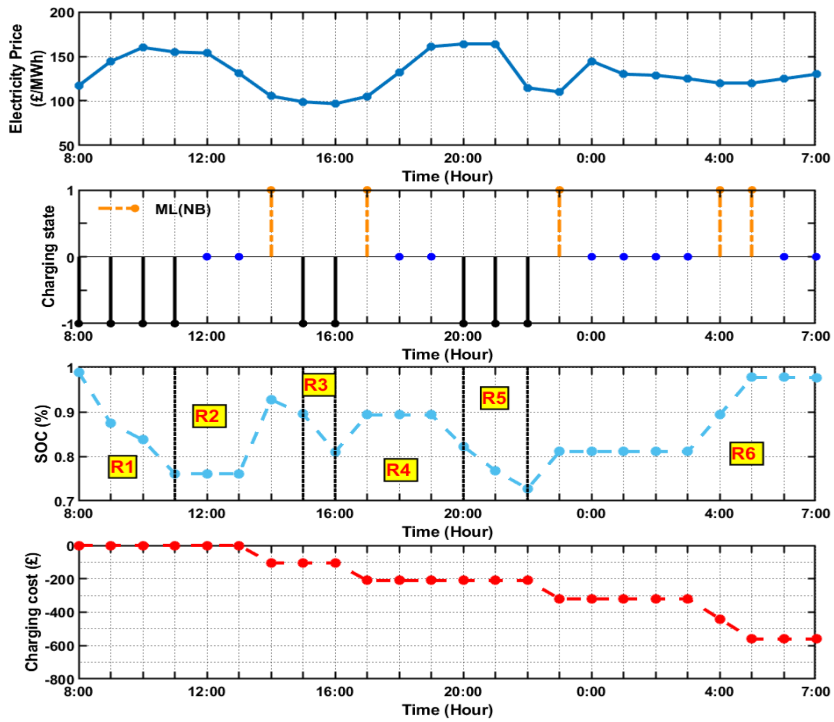

Figure 8 Controlled charging plan using ML (NB)

A detailed comparison of the charging costs under different control strategies is presented in Table II. It can be seen that the base scenario of random (uncontrolled) charging resulted in the highest cost of £882, whereas by applying the proposed centralized control strategy using ML models, the charging costs were significantly reduced. Specifically, using the NN model, the optimized cost dropped to £440, representing a cost saving of approximately 50.1%. Similarly, with the NB model, the total cost was £560, which equates to a 36.5% reduction. These cost savings were achieved by scheduling vehicle charging during off-peak hours and avoiding periods of high electricity tariffs, made possible through effective centralized control and predictive load management by the ML models. The results indicate that the NN model outperforms the NB model in terms of cost efficiency. This can be attributed to the NN's ability to better capture non-linear relationships in the data, resulting in more accurate prediction and scheduling of optimal charging times.

TABLE II. SUMMARY OF COST COMPARISON BETWEEN UNCONTROLLED AND ML-BASED CONTROLLED CHARGING METHODS

Method	***Charging Cost (£)***	***Cost Saving (£)***	***Cost Reduction (%)***	***Control Strategy***	***Remarks***
Base (Uncontrolled Charging)	882	–	–	None	No control, random charging behavior
ML-Based (Neural Network)	440	442	50.1%	Centralized (NN)	Best performance; capturing non-linear demand patterns
ML-Based (Naïve Bayes)	560	322	36.5%	Centralized (NB)	Moderate performance; based on probabilistic classification

V. CONCLUSION AND FUTURE WORK

This paper introduces a ML-based algorithm designed to minimize the daily charging costs of PEVs through controlled charging strategies implemented within a centralized control architecture. The random charging plan represents an uncontrolled charging approach, where PEVs commence charging immediately upon connection to a charging point, without taking electricity price variations into account. Such an uncoordinated strategy not only poses risks of grid instability during peak demand periods but also leads to considerable charging expenses, estimated to be approximately £882. In contrast, controlled charging involves initiating or delaying the charging process based on ML strategies such as NN and NB that take into account dynamic energy pricing to minimize overall charging costs.

Under this approach, although PEVs are connected to the grid immediately after completing a trip, actual charging is strategically postponed to off-peak periods when electricity rates are lower. The results, cost savings are comparatively lower, about 50% and 36% less effective than the savings achieved by the random method, respectively.
This work can be extended to incorporate multiple models of PEVs, accounting for differences in battery capacities and energy consumption profiles. Additionally, it would be valuable to consider a wider range of usage patterns, including scenarios with more than three trips per day or irregular, non-standard usage behaviors.

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