# MINIMIZING CHARGING COST OF PLUG-IN ELECTRIC VEHICLE BASED ON ENSEMBLE MACHINE LEARNING TECHNIQUES AND OPTIMAL CONTROL

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FACULTY OF ENGINEERING
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**DISSERTATION SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY**

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**ORIGINAL LITERARY WORK DECLARATION**

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Field of Study: **Control System**

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**MINIMIZING CHARGING COSTS OF PLUG-IN ELECTRIC VEHICLE BASED ON ENSEMBLE MACHINE LEARNING TECHNIQUES AND OPTIMAL CONTROL**


## ABSTRACT

Plug-in Electric Vehicles (PEVs) offer an environmentally friendly alternative to conventional internal combustion engine vehicles, promising reduced greenhouse gas emissions and conservation of oil reserves. However, their increasing integration into the electric grid raises concerns about stability and reliability owing to heightened charging demands. Random or uncoordinated charging within the distribution network can exacerbate these challenges, leading to increased charging costs for PEV owners and potential strain on the grid. In the present study, a smart and coordinated charging approach with centralized control is proposed, aimed at minimizing charging costs and supporting grid stability. This is achieved using the optimal control (OC) technique, considering fixed fluctuations in electricity prices and various driving patterns. Empirical results indicate that, compared to a random charging plan, smart and coordinated charging strategies can reduce charging costs by up to 73% and 21%, respectively. A new hybrid machine learning (ML) model was proposed for electricity price forecasting (EPF) to further optimize charging costs. It integrates the linear automatic relevance determination (ARD) model, addressing trend and seasonality, with the ensemble bagging extra tree regression (ETR) model, capturing interactions. Validated with a Nord Pool market dataset, this approach surpassed other hybrid models, achieving reductions in testing mean absolute error and root mean square error values by 32.1% and 21.5%, respectively. Random PEV charging activities are well-recognized for their potential impacts on both vehicle owners and electric networks, resulting in elevated charging costs and degraded distribution system performance such as power loss, and voltage deviation. To address these challenges, scheduling of PEV charging activities is essential. Coordinated and smart charging strategies incorporated with EPF using ML and OC methods have been devised. These strategies not only lead to cost savings for PEV owners but also benefit electric utilities. To guide PEV charging decisions based on price forecasts, three ML classifiers were employed: neural network, naïve Bayes, and an ensemble approach. Empirical results show that the ensemble ML classifier outperforms its counterparts in various charging strategies. Remarkably, the proposed ensemble smart charging strategy recorded a PEV charging cost of £15, which was significantly lower than the £280 incurred using the random charging strategy. Moreover, compared to the base random charging case, the proposed ensemble-based smart and coordinated approaches reduced the charging cost by approximately 94% and 40%, respectively. To illustrate the impacts of the proposed coordinated and smart charging techniques compared to random charging at various levels of PEV penetration levels (16%, 28%, and 41%), both modified and standard IEEE 69-bus radial distribution systems were employed, smart and coordinated PEV charging showcased better performance in terms of power consumption, voltage drop, and system loss than those of random charging. Overall, this study indicates that an ensemble-based coordinated and smart PEV charging strategy is a promising approach for efficiently managing electricity usage. As PEV adoption increases, smart charging technologies are likely to become more widespread and help drive the transition to a more sustainable energy future.

Keywords: Electric vehicle charging, electricity price forecasting, smart EV charging, optimal control theory, coordinated charging.

**MENGURANGKAN KOS PENCASAN KENDERAAN ELEKTRIK PLUG-IN BERDASARKAN TEKNIK PEMBELAJARAN MESIN ENSEMBLE DAN KAWALAN OPTIMUM**

## ABSTRAK

Kenderaan Elektrik Plug-in (PEV) menawarkan alternatif mesra alam kepada kenderaan enjin pembakaran dalam konvensional, yang menjanjikan pengurangan pelepasan gas rumah hijau dan pemuliharaan rizab minyak. Walau bagaimanapun, penyepaduan yang semakin meningkat ke dalam grid elektrik menimbulkan kebimbangan tentang kestabilan dan kebolehpercayaan disebabkan oleh permintaan pengecasan yang meningkat. Pengecasan rawak atau tidak diselaraskan dalam rangkaian pengedaran boleh memburukkan lagi cabaran ini, membawa kepada peningkatan kos pengecasan untuk pemilik PEV dan potensi ketegangan pada grid. Dalam kajian ini, pendekatan pengecasan pintar dan diselaraskan dengan kawalan berpusat dicadangkan, bertujuan untuk meminimumkan kos pengecasan dan menyokong kestabilan grid. Ini dicapai menggunakan teknik kawalan optimum (OC), dengan mengambil kira turun naik tetap dalam harga elektrik dan pelbagai corak pemanduan.

Keputusan empirikal menunjukkan bahawa, berbanding dengan pelan pengecasan rawak, strategi pengecasan pintar dan terkoordinasi boleh mengurangkan kos pengecasan masing-masing sehingga 73% dan 21%. Model pembelajaran mesin hibrid (ML) baharu telah dicadangkan untuk meramal harga elektrik (KWSP) bagi mengoptimumkan lagi kos pengecasan. Ia menyepadukan model penentuan perkaitan automatik linear (ARD), menangani arah aliran dan bermusim, dengan model regresi pokok tambahan (ETR) ensemble, menangkap interaksi. Disahkan dengan set data pasaran Nord Pool, pendekatan ini mengatasi model hibrid yang lain, mencapai pengurangan dalam ujian ralat mutlak min dan nilai ralat purata kuasa dua akar masing-masing sebanyak 32.1% dan 21.5%.

Aktiviti pengecasan PEV rawak diiktiraf dengan baik kerana potensi kesannya terhadap kedua-dua pemilik kenderaan dan rangkaian elektrik, mengakibatkan kos pengecasan yang tinggi dan prestasi sistem pengedaran yang merosot seperti kehilangan kuasa dan sisihan voltan. Untuk menangani cabaran ini, penjadualan aktiviti pengecasan PEV adalah penting. Strategi pengecasan yang diselaraskan dan pintar yang digabungkan dengan KWSP menggunakan kaedah ML dan OC telah dirangka. Strategi ini bukan sahaja membawa kepada penjimatan kos untuk pemilik PEV tetapi juga memanfaatkan utiliti elektrik. Untuk membimbing keputusan pengecasan PEV berdasarkan ramalan harga, tiga pengelas ML telah digunakan: rangkaian saraf, Bayes naif dan pendekatan ensemble.

Keputusan empirikal menunjukkan bahawa pengelas ML ensemble mengatasi rakan sejawatannya dalam pelbagai strategi pengecasan. Hebatnya, strategi pengecasan pintar ensemble yang dicadangkan merekodkan kos pengecasan PEV sebanyak £15, yang jauh lebih rendah daripada £280 yang ditanggung menggunakan strategi pengecasan rawak. Selain itu, berbanding dengan kes pengecasan rawak asas, pendekatan pintar dan terkoordinasi berasaskan ensemble yang dicadangkan mengurangkan kos pengecasan sebanyak kira-kira 94% dan 40%, masing-masing. Untuk menggambarkan kesan teknik pengecasan yang diselaraskan dan pintar yang dicadangkan berbanding dengan pengecasan rawak pada pelbagai peringkat tahap penembusan PEV (16%, 28%, dan 41%), kedua-dua sistem pengedaran jejari 69-bas IEEE yang diubah suai dan standard telah digunakan. Pengecasan PEV yang diselaraskan dan pintar mempamerkan prestasi yang lebih baik dari segi penggunaan kuasa, penurunan voltan dan kehilangan sistem berbanding pengecasan rawak.

Secara keseluruhan, kajian ini menunjukkan bahawa strategi pengecasan PEV yang diselaraskan dan pintar berasaskan ensemble adalah pendekatan yang menjanjikan untuk menguruskan penggunaan elektrik dengan cekap. Apabila penggunaan PEV meningkat, teknologi pengecasan pintar mungkin akan menjadi lebih meluas dan membantu memacu peralihan kepada masa depan tenaga yang lebih mampan.

Keywords: Pencasan kenderaan elektrik, ramalan harga elektrik, pencasan EV pintar, teori kawalan optimum, pencasan berkoordinasi.

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| | |
|---|---|
| ANFIS | Adaptive neuro-fuzzy inference system |
| ANN | Artificial neural networks |
| ARD | Automatic relevance determination |
| ARIMA | Seasonal autoregressive integrated moving average |
| BDLSTM | Bidirectional long short-term memory |
| BEP | Binary evolutionary programming |
| BEV | Battery electric vehicles |
| BGWO | Binary grey wolf optimization |
| BPSO | Binary particle swarm optimization |
| BVP | Boundary value problem |
| CNN | Convolutional neural networks |
| DBN | Deep belief network |
| DE | Differential evaluation |
| DEP | Daily energy price |
| DL | Deep learning |
| DLP | Daily load profile |
| DNN | Deep neural network |
| DP | Dynamic programming |
| DSM | Demand side management |
| DSP | Dynamic spike pricing |
| EGARCH | Exponential generalized autoregressive conditional heteroscedasticity |
| EPF | Electricity price forecasting |
| ETR | Extra tree regression |

| | |
|---|---|
| EV | Electric vehicle |
| EVCS | Electric vehicle charging stations |
| EWT | Empirical wavelet transform |
| FN | False negative |
| FP | False positive |
| FS | Feature selection |
| FTP | Federal test procedure |
| GA | Genetic algorithm |
| GELM | Generalized extreme learning machine |
| GRU | Gated recurrent unit |
| H | Hamiltonian function |
| HEV | Hybrid electric vehicles |
| HFZ | High forecast zone |
| ICE | Internal combustion engine |
| IEA | International Energy Agency |
| IEMD | Improved empirical mode decomposition |
| IESO | Independent electricity system operator |
| IG | Information gain |
| ILP | Improved linear programming |
| $I$ | Current variable |
| $J$ | Performance index |
| KPCA | Kernel principal component analysis |
| kWh | kilowatt hour |
| LFZ | Low forecast zone |

| | |
|---|---|
| LP | Linear programming |
| LR | Linear regression |
| LSTM | Long short-term memory |
| MA | Moving average |
| MAE | Mean absolute error |
| MDP | Markov decision process |
| MSE | Mean square error |
| MFZ | Medium forecast zone |
| MI | Mutual information |
| MILP | Mixed integer linear programming |
| ML | Machine learning |
| MOPSO | Multi-objective particle swarm optimization |
| MPA | Modified placement algorithm |
| MSS | Maximum sensitivities selection |
| MW | Megawatt |
| Mvar | MegaVar |
| NB | Naïve Bayes |
| NEDC | New European driving cycle |
| NLP | Nonlinear programming |
| NN | Neural networks |
| OC | Optimal control |
| OCST | Optimal charging starting time |
| ODE | Ordinary differential equation |
| OLC | Optimal logical control |

| | |
|---|---|
| OWA | Ordered weighted average |
| PDF | Probability density function |
| PEV | Plug-in electric vehicle |
| PHEV | Plug-in hybrid electric vehicle |
| PJM | Pennsylvania, New Jersey, and Maryland |
| PL | Penetration level |
| PMP | Pontryagin's maximum principle |
| PSO | Particle swarm optimization |
| PU | Per-unit |
| $P_{dr}$ | Power driving |
| $Q_{max}$ | Charge capacity |
| RES | Renewable energy sources |
| RF | Random forest |
| RFR | Random forest regression |
| RL | Reinforcement learning |
| RMSE | Root mean square error |
| RNN | Recurrent neural network |
| $R_{int}$ | Internal resistance |
| SAPSO | Simulated annealing particle swarm optimization |
| SARIMA | Seasonal autoregressive integrated moving average |
| SFLA | Shuffled frog leaping algorithm |
| SOC | State of charge |
| SPSDAE | Stacked pruning sparse denoising autoencoder |
| SSEC | Steady-state equivalent circuit |

| | |
|---|---|
| SVM | Support vector machine |
| TN | True negative |
| TP | True positive |
| $t$ | Time index |
| $t_A$ | Arrival time |
| $t_D$ | Departure time |
| UDDC | Urban dynamometer driving cycle |
| $U$ | Control signal |
| VMD | Variational mode decomposition |
| $V_{oc}$ | Voltage source |
| WLTP | Worldwide harmonized light vehicles test procedure |
| $X_{(t)}$ | State variable |
| $y_t$ | Charging cost |
| $\lambda_t$ | Adjoint variable |
| $\Delta_t$ | Time interval |
| $\eta$ | Efficiency |

## LIST OF APPENDICES

# CHAPTER 1: INTRODUCTION

This chapter briefly discusses the background of electric vehicle (EV) technology and the challenges associated with developing a smart and coordinated system for charging plug-in EVs (PEVs). Additionally, it presents the organization of this research and its novel contributions.

## 1.1 Background

The automotive industry is rapidly expanding, with fossil fuel-powered vehicles accounting for most sales. However, many countries are becoming increasingly concerned about the environmental impact of these vehicles, including the release of harmful contaminants, depletion of fossil fuel reserves, and higher greenhouse gas (GHG) emissions. Consequently, EVs are receiving considerable attention globally as they employ rechargeable batteries and are classified as eco-friendly vehicles. It is widely acknowledged that internal combustion engine (ICE) vehicles consume a significant amount of oil. Hence, EVs have been proposed as a promising technology that can reduce noise, improve efficiency, reduce costs, and have lower or near-zero $CO_2$ emissions and gasoline consumption compared to traditional vehicles comprising ICEs (Lopes et al., 2010). Furthermore, 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. BEVs can be recharged through an external source, and they often employ regenerative braking technology to help recharge their batteries. Despite being powered solely by electricity, BEVs can be considered as plug EVs because they can be charged through an external source. Popular examples of available BEVs include the Tesla Model S, Tesla Model 3, Chevy Bolt, Nissan LEAF, BMW i3, Fiat 500e, and Ford Focus Electric (Simsekoglu & Nayum, 2019). Figure 1.1 shows the key components of a typical BEV.

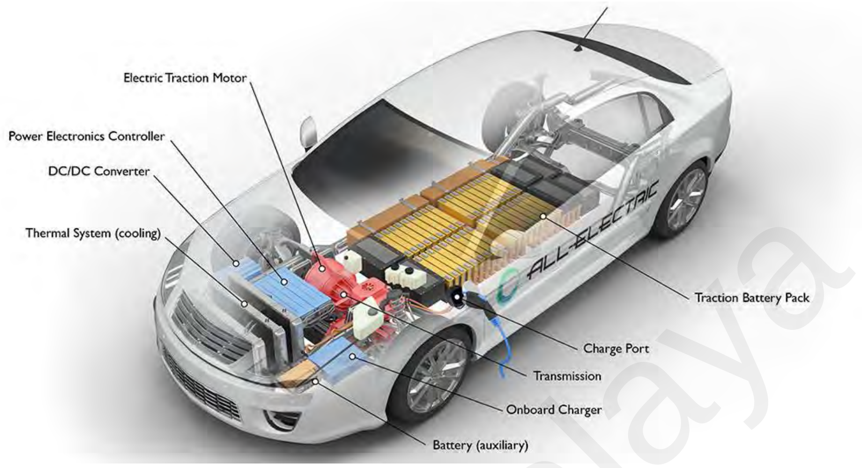


**Figure 1.1: Key components of a BEV** (afdc.energy.gov, 2020)

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. Typically, HEVs use the electric motor at low speeds and switch to the ICE at higher speeds. Figure 1.2 shows the essential components of an HEV. Some examples of HEVs currently in use include the Chevrolet Tahoe Hybrid, Toyota Prius, Toyota Camry Hybrid, Ford C-Max, Honda CR-Z, and Kia Optima Hybrid (Karden et al., 2007).

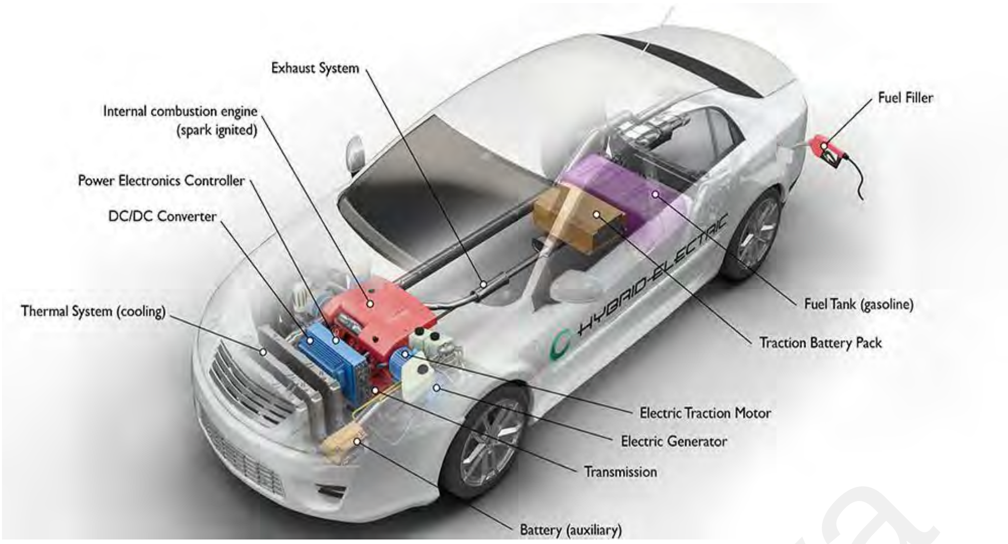


**Figure 1.2: Key components of an HEV** (afdc.energy.gov, 2020)

Similar to HEVs, PHEVs also employ both an electric motor and an ICE; however, the electric motor can be charged through regenerative braking or plugging the vehicle into an external power source, such as an electric vehicle charging station. Additionally, the ICE can charge the battery at lower speeds or serve as the primary power source when the battery is depleted. 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 Figure 1.3. Some examples of PHEVs currently in use are the Toyota Prius Plugin, Porsche Panamera SE, BMW i3, BMW i8, Cadillac ELR, and GM Chevy Volt (Fathabadi, 2018).

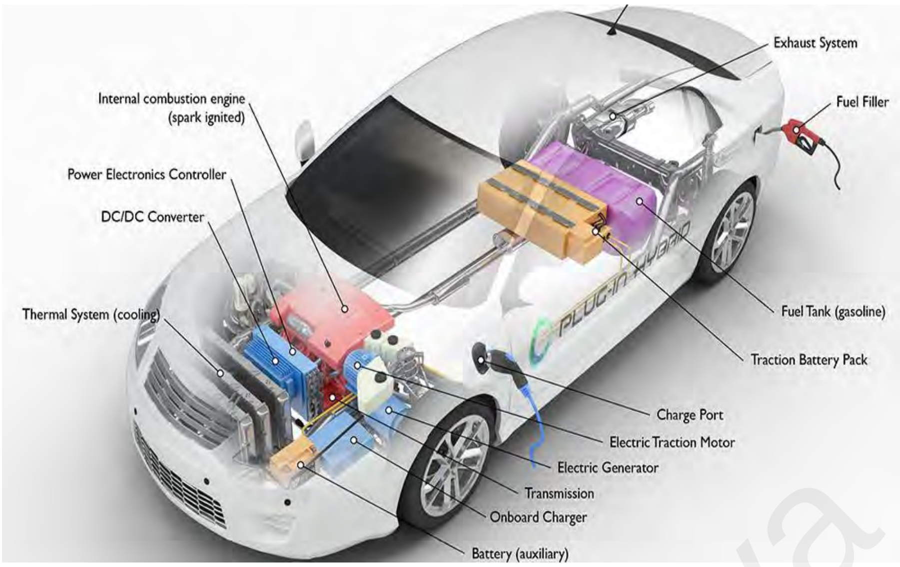


**Figure 1.3: Key components of a PHEV** (afdc.energy.gov, 2020)

However, EVs rely solely on rechargeable batteries to power their electric motors, with lithium-ion batteries being the most commonly employed owing to their high energy density. Lithium-ion batteries comprise cells having a cathode, an anode, and an electrolyte that enables the movement of ions to store or release energy. The battery performance is determined based on its capacity and charging speed, which affects driving range and recharging time, respectively. Additionally, its lifespan depends on various factors such as its chemistry, temperature, and the user's charging habit, and degradation can reduce its capacity, thereby lowering its lower range. Continuous advancements in battery technology are aimed at enhancing the performance and durability of EV batteries (Fan et al., 2018). According to the international energy agency (IEA), there were approximately 3.1 million EVs worldwide in 2017, and this number is expected to increase to 130 million by 2030 (International Energy Agency (IEA), Global EV Outlook, 2022). This growth is owing to the increased environmental and economic concerns regarding GHG emissions from fossil fuels, and the threat of energy crises such as depleting natural oil resources and rising fuel prices. Moreover, various automotive companies, such as Nissan, General Motors, and Chevrolet, have recently launched new PEVs (Chevrolet, Volt Electric Car, 2021; Nissan LEAF Electric Car, 2021; Tesla Motors High-Performance Electric Vehicles. , 2021).

## 1.2 Problem Statement

The widespread adoption of PEVs in the distribution network has resulted in significantly more capital investments in smart grid technologies primarily because EV charging operations demand a substantial amount of electricity owing to their considerable battery capacities and charging durations. Erratic or uncoordinated scheduling of PEV charging sessions can increase charging costs and electricity consumption, which subsequently strain the distribution network and can have various detrimental effects, including distribution network overload. Another concern is voltage quality degradation as voltage fluctuations adversely affect the performance and reliability of electrical equipment. Considering these challenges, a combination of a centralized control framework structure and day-ahead EPF is essential for effectively scheduling PEV charging operations. This approach can allow grid operators to strategically schedule PEV charging during periods of low electricity demand and prices, thereby reducing charging costs and promoting efficient grid utilization. Therefore, implementing a centralized control framework for coordinated and smart charging operations by integrating day-ahead EPF into the scheduling is crucial for reducing charging costs. This dissertation addresses these challenges, with the aim of creating coordinated and smart charging plans to minimize charging expenses of vehicle owners, and overall performance of the power network. Additionally, it addresses the challenges associated with accurate short-term EPF to optimize economic gains and minimize power market risks. The main obstacles for developing reliable machine learning (ML) prediction models for EPF are the complex characteristics of electricity prices, including high volatility, sudden surges, and seasonal variations. By tackling these complexities, this dissertation aims to enhance the efficacy of forecasting models to enable effective scheduling of PEV charging operations. Therefore, coordinated, and smart charging strategies were implemented by integrating them with EPF to mitigate the negative impacts on the distribution network, with an aim to lower charging costs for vehicle owners and improve power grid performance. Furthermore, these strategies can facilitate the integration of RES, thereby supporting the transition toward a more sustainable and resilient energy system.

## 1.3 Research Area

This thesis focuses on proposing efficient strategies for smart and coordinated scheduling of PEV charging and discharging. These strategies aim to minimize the cost associated with charging EVs while also satisfying the requirements of the distribution grid. The proposed techniques employ advanced algorithms and ML models to forecast electricity prices and accordingly optimize PEV charging schedule. By intelligently managing PEV charging, this study aims to reduce the stress on the power grid and ensure that the vehicles are charged in a cost-effective and sustainable manner. Furthermore, owing to the increasing adoption of PEVs, managing their charging has become a critical challenge. A key limitation of PEV charging is the potential strain it can put on the power grid, especially during peak demand periods (Muratori, 2018). However, by optimizing the charging schedule, PEVs can be charged during off-peak hours when electricity is cheaper and demand is lower. In addition to minimizing costs, managing PEV charging and discharging can also help improve the overall stability of the power grid. This is achieved by allowing utility companies to better manage fluctuations in supply and demand that occur owing to various factors such as weather and the deployment of renewable energy sources (RES) (Mohammad et al., 2020). In summary, developing efficient strategies for managing PEV charging operation is an important area of research that can potentially impart substantial benefits to both the PEV owners and the power grid. At the crux of this challenge lies the ingenious creation of a communication bridge that seamlessly connects PEVs and power grids by integrating power supply and data. As smart grid technologies progress, PEVs can be transformed from simple electric loads into distributed energy storage hubs on the power grid. In this context, PEVs serve dual purposes: storing excess energy during low-demand periods, returning the stored energy back to the grid when demand surges. Consequently, it is technically feasible to accommodate a certain PEV penetration level (PL) for energy supply by employing smart and coordinated charging and discharging approaches. The foundation of synchronized PEV charging and discharging relies on building a smart information platform to streamline energy management between PEVs and the grid. Figure 1.4 illustrates the interconnected relationship between information and energy flow when PEVs are integrated into the grid. The power grid is an intricate assembly comprising generation, transmission, and distribution systems, among other components. In such a framework, system operators are essential for integrating the actions of the power consumers and developing a rational strategy for power generation, transmission, and distribution to ensure that the demand and supply are coordinated (Zheng et al., 2019).

Further discussion on smart and coordinated PEV charging and electricity price forecasting (EPF) are presented in Chapter 2.

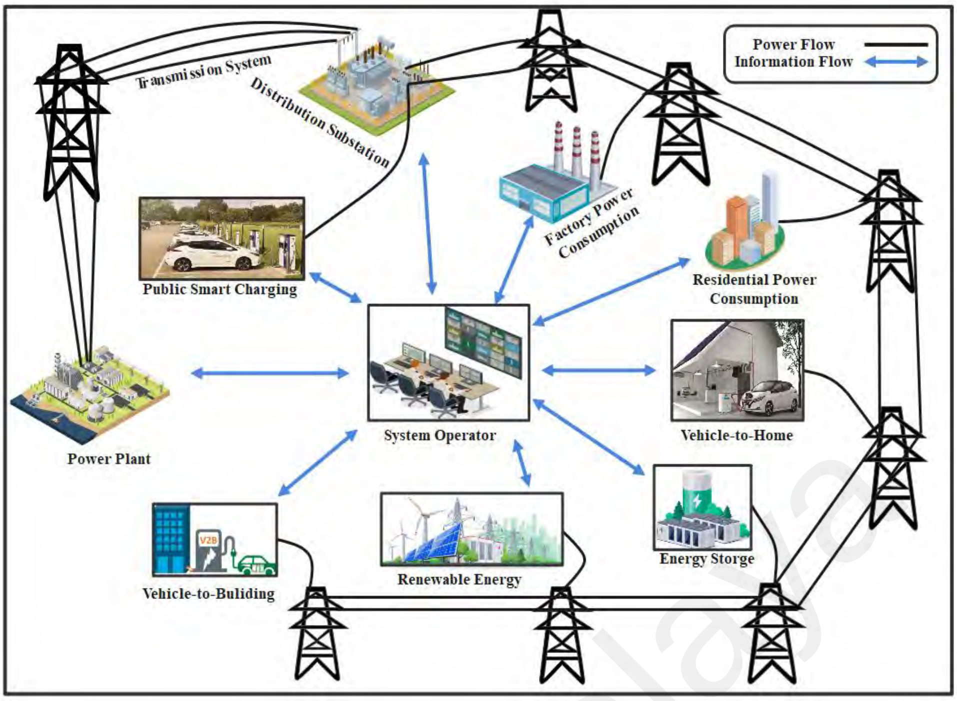


**Figure 1.4: Framework of coordinated PEV charging/discharging**

## 1.4 Aim and Objectives

The broader aim of this study was to develop and evaluate coordinated and smart charging techniques for PEVs to minimize charging costs, thereby maximizing vehicle owners' savings, and enhancing the overall performance of the distribution grid. This research also aimed to tackle the challenges associated with day-ahead EPF, particularly those of time series data, such as volatility and irregular spikes, to schedule PEV charging operations effectively. Additionally, it evaluated the implications of these charging techniques on the distribution grid to demonstrate their effectiveness. Finally, it addresses the issues associated with random (uncoordinated) PEV charging, which can increase charging costs, electricity consumption, and power losses. Accordingly, this study focused on the following four objectives:

1. To develop a smart scheduling system for controlling PEV charging by formulating the EV battery as a differential equation model that incorporates electricity price and optimal control (OC) method. ensuring enhanced performance and efficient energy management.
2. To develop a hybrid ML model for day-ahead EPF by combining both linear and ensemble techniques. This approach adeptly captures and handles complex electricity price fluctuations, ensuring superior accuracy and reliability of EPF.
3. To develop two control techniques for further scheduling PEV charging operations using OC and ML ensemble approaches that incorporate forecasting of electricity price.
4. To evaluate the impact and effectiveness of both random and proposed PEV charging approaches on the distribution grid by examining key performance indicators associated with system losses and power consumption.

## 1.5 Original Contributions

This study presents several significant original contributions in the fields of PEV charging, day-ahead EPF, and centralized charging control methods.

First, it introduces a coordinated and smart scheduling system that formulates the EV battery as a differential equation model, incorporates a typical day of electricity price information, and seamlessly integrates a numerical OC method to minimize PEV charging costs. Second, it proposes an innovative hybrid ML model for day-ahead EPF that combines linear regression (LR), tree-based ensemble techniques, and real electricity market data, resulting in superior accuracy, reliability, and decision-making. Furthermore, two cutting-edge charging control techniques involving OC and ML ensemble approaches, which employ the electricity price information derived from the

EPF, are proposed for scheduling PEV charging operations. Finally, it comprehensively evaluates the effects of both the random and proposed PEV charging techniques on the distribution grid by measuring key performance indicators related to system losses, power consumption, and voltage deviation to provide valuable insights to guide future research and implementation. Thus, this study presents original advancements in PEV charging control approaches and day-ahead EPF that can collectively benefit the EV and power grid industries, as well as EV owners.

## 1.6 Thesis overview

This dissertation is organized into five chapters as follows:

Chapter 1 presents an overview of the mechanisms and principal components of EVs, specifically BEVs, HEVs, and PHEVs. It also briefly highlights the ML techniques employed in this study. This is followed by discussing the research area of this dissertation, focusing on PEV technology and the challenges associated with developing smart and coordinated PEV charging strategies. Finally, the problem statement along with the research aims and objectives are presented.

Chapter 2 provides a brief background of the various PEV charging and discharging techniques. It also cites various studies that have addressed scheduling of PEV charging operations by employing different optimization and control algorithms to minimize PEV charging costs and maintain grid performance. Thereafter, it introduces coordinated and smart charging strategies, considering grid-to-vehicle (G2V) and vehicle-to-grid (V2G) technologies to manage peak loads through load shifting. Additionally, it reviews relevant studies that employed distinct techniques, such as ML, deep learning (DL), and statistical approaches, for modeling and predicting electricity prices, particularly in the global market. Finally, the various scheduling approaches employed for PEV charging and EPF are also analyzed and compared.

Chapter 3 discusses the scheduling of PEV charging and discharging operations using the OC theory and establishes EV battery models based on three types of charging strategies: random (uncoordinated), coordinated (unidirectional), and smart (bidirectional). Additionally, it presents the system architecture assumptions and formulates control tasks. Implementations of the proposed forecasting methods, which were designed to predict electricity prices using both individual and hybrid ML models, are also thoroughly discussed. Subsequently, the importance of smart, coordinated charging techniques implemented using OC and ML classification approaches and integrated with EPF is discussed. Furthermore, the impacts and effectiveness of various charging plans on the power distribution system are analyzed. The primary aim was to evaluate the proposed approach in terms of overall power losses and system power consumption.

Chapter 4 presents the results of optimizing PEV charging cost using OC with various charging strategies under fixed electricity prices. It details the data exploration process, outlines the experimental setup, and elucidates the statistical forecasting measurements of individual and hybrid ML models. Furthermore, it compares the performance of the proposed EPF model with those of several state-of-the-art models to demonstrate its robustness. Moreover, the performances of these models are meticulously compared and analyzed. Finally, the performances of the proposed PEV charging techniques employing OC and ML approaches are evaluated. These techniques encompass all PEV charging behaviors and employ EPF.

Finally, the study contributions, concluding remarks, and directions for future work are summarized in Chapter 5.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Introduction

This chapter comprehensively analyzes existing research related to PEV charging optimization, with a focus on minimizing PEV charging cost, short-term EPF, and deploying various techniques to schedule PEV charging and discharging considering three specific charging strategies: random, coordinated, and smart. This analysis aimed to not only collate and critically evaluate the current state of knowledge in the field but also identify gaps in the existing literature, thereby establishing a robust foundation for the methodologies and analyses employed in this research. First, studies focused on minimizing PEV charging costs are explored, followed by a discussion regarding EPF and the application of ML techniques for scheduling PEV charging. Thereafter, it delves into the optimization of charging costs through EPF, culminating with an evaluation of various PEV charging plans and their impacts on the distribution grid.

## 2.2 Scheduling Techniques for PEV Charging

Scheduling techniques play a crucial role in PEV charging optimization, with a specific emphasis on minimizing charging costs. Moreover, the applications of various scheduling methods have considerably improved the efficiency and cost-effectiveness of PEV charging. A comprehensive classification of the various PEV charging strategies, which are generally classified into non-smart (random) and smart charging, is illustrated in Figure 2.1. In the non-smart or random charging strategy, also referred to as uncoordinated charging, the vehicle begins charging as soon as it is plugged into an external power source. Moreover, this strategy does not allow controlling the charging speed, and charging only stops once the battery is fully charged or the vehicle is disconnected from the charging point (Ahmadian et al., 2020).

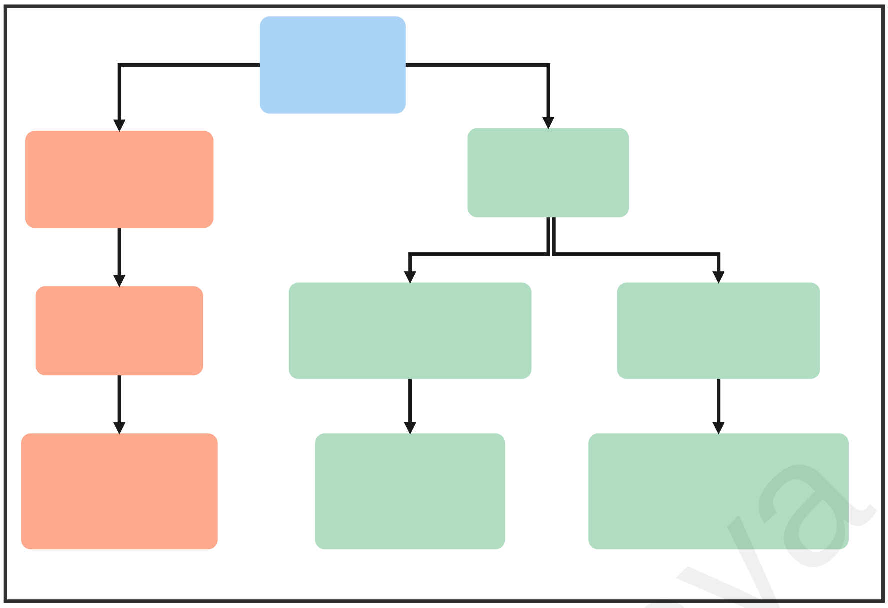

**Figure 2.1: Classification of different PEV charging strategies.**

Smart charging strategies can be further categorized into coordinated (unidirectional) and smart (bidirectional) charging. The coordinated charging strategy optimally determines the timing and rate of PEV charging through an optimization algorithm. However, it necessitates the definition of an objective function and the determination of decision variables (time and power rate) that are subject to technical constraints, which encompasses both the power grid and PEV battery constraints. The objective function can be used to minimize charging costs and losses, or enhance voltage regulation, among other factors. The unidirectional power flow, which is exclusively employed to charge PEV batteries using the G2V technology, has a relatively low implementation cost. This approach avoids additional battery degradation as the battery does not discharge by supplying power back to the grid. This type of flow requires only one electrical connection to the power grid. Notably, the benefits of this technique include the possibility of employing a simple control for coordination, which can mitigate the impacts of charging rate limitations on the network (Saldanha et al., 2016). In the smart (bidirectional) charging strategy, the timings, and rates for charging and/or discharging PEVs are determined optimally. This strategy not only optimizes the charging schedules of PEVs but also allows them to support the grid by sending power back. Although bidirectional power flow incurs higher costs than the unidirectional approach, it enables both charging control and supplying energy to the grid when required. However, owing to the higher number of discharge cycles, the battery may undergo additional degradation. Moreover, implementing such strategies requires the deployment of bidirectional communication and smart metering. This type of power flow allows providing ancillary services to the grid and supports the entry of RES. The performances of the different charging strategies of random (uncoordinated), coordinated (unidirectional), and smart (bidirectional) from various perspectives is outlined in Table 2.1 (Ahmadian et al., 2020; Amjad et al., 2018).

**Table 2.1: Performances of PEV charging strategies from different perspectives.**

| **PEV owner and electric grid perspective** | **Random (uncoordinated)** | **Coordinated (unidirectional)** | **Smart (bidirectional)** |
|---|---|---|---|
| Charging cost | High | Low | Low |
| Full charging assurance | Good | Medium | Poor |
| PEV lifespan | Long | Long | Short |
| Peak load reduction | Poor | Good | Good |
| Power loss | High | Low | Low |
| Voltage regulation | Poor | Good | Good |
| Power grid reliability | Low | Medium | High |
| Component lifetime | Short | Long | Long |
| Component capacity | Low | High | High |
| Poor grid operation cost | High | Low | Low |
| Infrastructure cost | Low | Medium | High |
| Power flow | Unidirectional | Unidirectional | Bidirectional |
| Battery degradation | Low | Low | High |

## 2.3 Charging Control Methods

PEV charging management can be categorized into centralized or decentralized charging control. Centralized charging control allows the power grid operator to manage the PEV charging demand based on the electric grid conditions, such as power loss and voltage constraints. Sometimes, a third party, referred to as an aggregator, is required to coordinate the charging demand between the grid operator and vehicle owners. Depending on the objective functions, aggregators manage PEV demand by considering the constraints of both the grid operator and vehicle owners. They can also participate in electricity markets such as the day-ahead energy and ancillary service markets. In centralized control, either the grid operator or the PEV aggregator directly manages the charging demand to optimize the power usage. However, in decentralized control, charging demands are individually managed by the PEV owners (Amin et al., 2020). The aggregator serves as an intermediary that manages the communication and electricity distribution between the group of electricity users (EV charging customers) and providers, as shown in Figure 2.2. The main role of the aggregator is to establish and monitor market supply and demand between load devices and dispatchers. In a cooperative setup, an aggregator coordinates and schedules PEV charging to minimize the overall charging cost. Thus, the aggregator can manage off-peak loading of the power grid and improve the load curve by consuming the surplus power during off-peak periods (Amin et al., 2020; Jian et al., 2017).

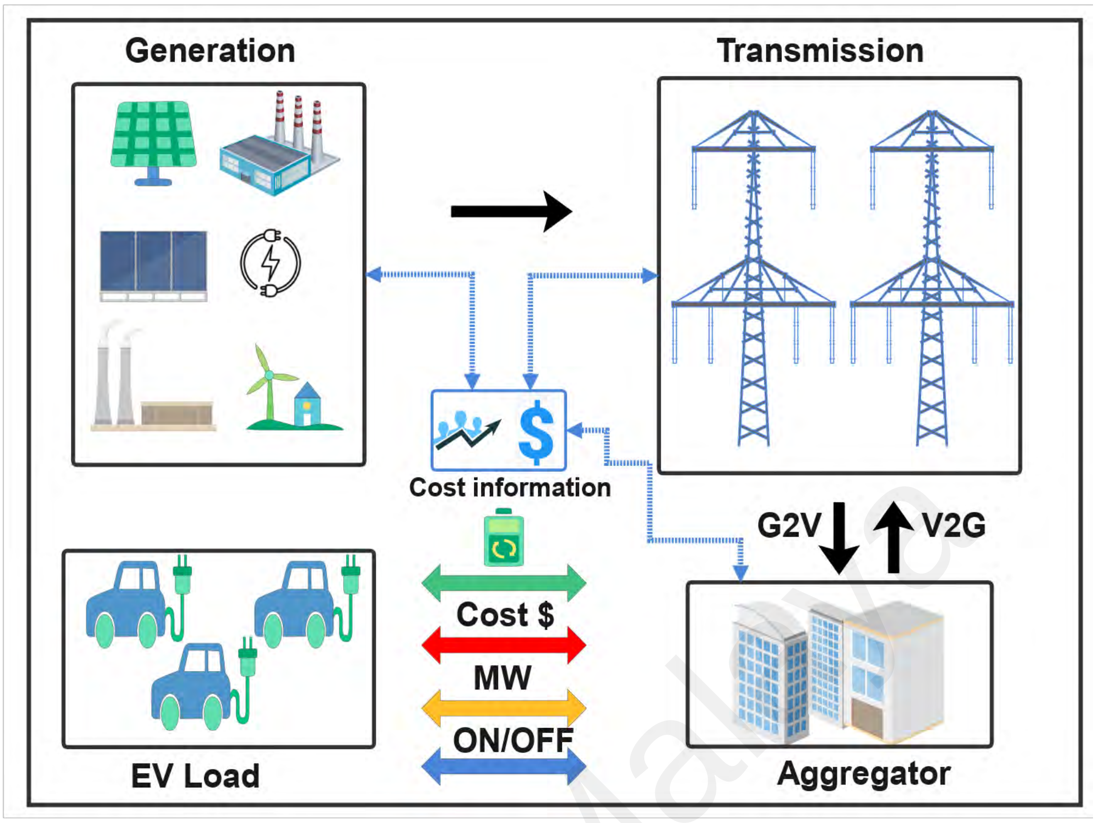


**Figure 2.2: Function of a PEV aggregator in the energy market.**

The significant electric grid penetration of PEVs necessitates substantial investments in smart grid technology owing to the considerable electrical demand associated with charging them. However, improper scheduling of PEV charging can result in increased electricity consumption, potentially leading to higher charging costs and grid overloads. Hence, numerous studies have investigated and proposed various charging strategies employing a power aggregator to optimize and coordinate PEV charging and minimize charging costs (Muratori, 2018). Linear programming (LP) has been proposed to optimize EV charging scheduling from the customer's perspective; it considers aggregator profits, customer demand, and related costs (Jin et al., 2013). Another optimization approach, called the Bat algorithm, has been proposed to provide central control for managing the power unit and charging performance. This method aims to reduce the overall cost of PEVs (Tabatabaee et al., 2017). Likewise, a robust optimization technique, called mixed integer LP (MILP), has been proposed, which considers a model of upstream grid prices instead of the estimated expenses for modeling an undefined restriction (Cao et al., 2020). In contrast, (Ren et al., 2023) introduced a reinforcement learning framework that combined a long short-term memory (LSTM) network and an improved LP algorithm (ILP). This LSTM-ILP framework aims to optimize the V2G control of EVs by considering the overall EV charging demand, discharge potential, large grid electricity price, aggregator, and user interest demands. Heuristic algorithms, such as the genetic algorithm (GA), particle swarm optimization (PSO), differential evaluation (DE), and artificial bee colony (ABC), have been proposed to optimize charging and discharging coordination and reduce the coordination cost, considering the network and EV constraints. However, these methods require a considerable number of variables for time discretization (Dogan et al., 2018). However, (Fernandez et al., 2020; Gong et al., 2020) 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% (Turker & Bacha, 2018). Other studies, such as those conducted by (Cao et al., 2016; Suyono et al., 2019), have focused on reducing both the impacts of PEV charging on the distribution system and PEV charging cost by employing MILP and metaheuristic optimization approaches to minimize customer expenses and improve grid performance. Moreover, (Amamra & Marco, 2019; Dahmane et al., 2021) proposed an optimized bidirectional V2G technique based on a fleet of PEVs connected to a distributed power system. This was achieved by employing a network of charging stations and optimized time steps for EV charging by considering cost and temperature, demonstrating that the cost savings of EVs can be enhanced by adopting V2G technology. Numerous studies have been presented. The details of numerous studies that have presented various methods for optimizing PEV charging are summarized in Table 2.2, including the objectives, methods employed, charging strategies used, and primary outcomes.

**Table 2.2: Details of existing studies on optimizing PEV charging schedule.**

| Authors | Objective | Method employed | PEV charging strategy | Remarks |
|---|---|---|---|---|
| (Mohammed et al., 2022) | Minimize PEV charging costs. | Modified placement algorithm (MPA), heuristic | Unscheduled, scheduled. | This approach successfully reduced PEV charging costs, but its effectiveness may vary in different real-world conditions, and it requires further comparative validation. |
| (Usman et al., 2021) | Make EV charging more cost-effective. | Optimal charging starting time (OCST), binary evolutionary programming (BEP). | Random, coordinated. | Although this method aims to benefit EV customers, its effectiveness may vary based on EV PLs and it may find handling high levels of unexpected EV arrivals challenging. |
| (Ren et al., 2023) | Minimize charging costs of EVs. | LSTM-ILP | Ordered and unordered. | This method successfully reduced charging expenses by up to 42.1%. However, LSTM struggles with longer sequences and ILP potentially oversimplifies complex situations. |
| (Tabatabaee et al., 2017) | Minimize total PEV charging cost. | Stochastic optimization (Bat algorithm) | Smart V2G technology. | This method can effectively manage PEV charging behavior; however, stochastic methods can yield unpredictable results. |
| (Cao et al., 2020) | Maximize EV aggregator profits. | MILP | Various charging and discharging strategies. | Developed robust scheduling for underprice uncertainty. Savings increased by 69.78% using the optimistic strategy, whereas they decreased by 54.94% for pessimistic cases. |
| (Dogan et al., 2018) | Minimize coordination cost. | GA, PSO, DE, ABC | Optimized charge/discharge coordination in V2G. | Achieved efficient charging coordination while satisfying network requirements. GA achieved the best optimization performance; however, heuristic methods may not always guarantee the optimal solution. |

(Table 2.2 continued)

| | | | | |
|---|---|---|---|---|
| (Hou et al., 2023) | Minimize operating costs. | Two-stage stochastic optimization framework. | Not detailed. | The proposed method reduced daily operating costs by up to 27.5%, demonstrated through a case study using real-world data. |
| (Fernandez et al., 2020) | Minimize charging cost. | PSO, SFLA | Not detailed. | Demonstrated that the proposed methods effectively reduced charging costs by up to 29%. However, it did not explicitly detail the PEV charging patterns. |
| (Gong et al., 2020) | Reduce charging cost. | Dynamic spike pricing (DSP) policy, GA | Various charging behaviors. | Implemented a DSP policy for load management, achieving a cost reduction of approximately 19%; however, the model assumes precise forecasting of demand and transformer capacities. |
| (Turker & Bacha, 2018) | Reduce charging costs. | V2G-OLC | Smart unidirectional and bidirectional charging. | Introduced the V2G-OLC algorithm that reduced charging costs by up to 47.94%; however, the effectiveness varies based on the energy billing systems employed in different regions. |
| (Cao et al., 2016) | Reduce PEV charging cost. | MILP | Not detailed. | This optimization algorithm achieved a cost reduction of up to 18%. |
| (Amamra & Marco, 2019) | Minimize charging cost. | NLP | Bidirectional charging. | Demonstrated the potential for grid support and cost reduction by 33%; however, the results may vary for various EV charging strategies. |

Despite the considerable number of studies published on optimizing PEV charging, scheduling PEV charging remains challenging. The OC theory differs from previously applied methods as it adopts a mathematical approach to find the best control or policy for a dynamical system over a given period. It is advantageous over other methods that are complex or require extensive data management as it aims to either minimize or maximize a given function within the set constraints, which may include initial and terminal conditions as well as state and control limitations (Mall et al., 2020; Naidu, 2018), resulting in an adaptable and efficient method. One of the objectives of this study is to minimize PEV charging costs by intelligently scheduling PEV charging. Moreover, the application of the OC theory in the context of PEV charging is particularly promising as it can intelligently adapt to changing market conditions. By continuously optimizing the control policy according to a predefined cost function, such as charging cost, the OC theory can generate a more flexible and efficient charging schedule, which can enhance the savings of PEV owners and improve grid load management, thereby addressing the gaps identified in the literature. Hence, this study addresses the fundamental issue of uncoordinated or nonintelligent EV charging, which can result in higher charging costs owing to the hourly fluctuations in electricity rates, which can burden EV owners. The charging model was developed based on the ordinary differential equation (ODE). Subsequently, the limitations of uncoordinated charging are discussed and thereafter, coordinate charging through the application of OC is proposed. Finally, a discharging model (smart) is embedded into the charging model to further improve charging coordination.

## 2.4 Electricity Price Forecasting

Electricity prices are a critical component of the electricity market. Therefore, an economical and reliable operation of the power grid can be ensured through accurate EPF, which is considered to be a critical component by all participants in the power market competition. Additionally, users may be able to control electricity purchase costs by adjusting their usage based on the EPF. Conversely, producers can use EPF to formulate an accurate bidding plan for increasing revenue (Yang et al., 2017; Zhou et al., 2019). Moreover, the features of electricity prices differ from those of other resources and even commodities owing to characteristics such as balancing supply and demand, oligopolistic market, and unexpected decreases in consumption and generation that may cause grid instability owing to imbalances (Lago et al., 2018; Ugurlu et al., 2018). These characteristics result impart various significant attributes to energy prices, including daily volatility owing to the increasing deployment of RES, irregular fluctuations, and seasonal variations. However, owing to privacy concerns and market competition, information regarding these characteristics could not be accessed by investigators as it is classified and regulated. To generate accurate EPF, it is necessary to evaluate several input combinations, and improving EPF accuracy can help prevent the adverse effects of price instability, improve system stability, and realize economic gains (Hayfavi & Talasli, 2014; Yang et al., 2017). Although EPF has a certain degree of regularity, it comprises several factors that cause electricity price instabilities, such as historical price data, market design, weather conditions, demand and supply balance, and bidding strategies employed by participants. Furthermore, the decision-making in power markets strongly depends on electricity prices, making the EPF an essential factor for ensuring organized and effective market operations. An accurate EPF has many advantages that allow power consumers and producers to make appropriate decisions based on the market environment; for instance, it can be used to optimize electricity storage and reduce energy consumption during peak times. Therefore, developing an accurate model to forecast electricity prices in a time series is challenging (Nowotarski & Weron, 2018; Weron, 2014). Most studies published over the last few years have focused on various techniques such as DL, statistical models, and ML to model and predict electricity prices, particularly for the world market (Ascione et al., 2017; Bissing et al., 2019; Jiang et al., 2016).

### 2.4.1 Deep Learning and Statistical Models

DL is a highly effective ML technique for EPF owing to its ability to learn complex data patterns and relationships. It includes methods such as convolutional neural networks (CNNs) and LSTM. Furthermore, various DL models have been applied for EPF; for instance, (Zhou et al., 2019) proposed an LSTM-based technique for hourly day-ahead EPF using a dataset from the Pennsylvania, New Jersey, and Maryland (PJM) electricity marker. However, they focused on generating a network structure and selecting appropriate hyperparameters for the model by employing a heterogeneous LSTM model. (Sun et al., 2021) executed various EPF phases by employing a deep neural network (DNN) with a stacked pruning sparse denoising autoencoder (SPSDAE) to eliminate the dataset noise with various supplies. The results indicated improvement in terms of the accuracy of electricity price and decrease effectual error criterion. Additionally, (Zhang et al., 2022) proposed a hybrid method based on the Catboost technique with bidirectional LSTM (BDLSTM) to forecast electricity prices using a Nord Pool market dataset. The proposed approach exhibited better performance than conventional models such as support vector machine (SVM), LSTM, and multilayer perceptron. (Darudi et al., 2015) proposed another hybrid approach, called the adaptive neuro-fuzzy inference system (ANFIS) and autoregressive–moving average (ARMA), for EPF in the Spanish market. They employed ordered weighted average (OWA) to construct an individual price forecasting model by combining three models. (Ugurlu, et al., 2018) proposed a novel model that combines the gated recurrent unit (GRU) and LSTM models for day-ahead EPF in the Turkish market; the results indicated that the model outperformed various other neural networks (NN) structures. (Huang et al., 2021) proposed a hybrid model, called SEPNet, comprising a combination of CNN, GRU, and variational mode decomposition (VMD) algorithms, and applied it on the New York electricity dataset. Their results showed that CNN and VMD-CNN outperformed the other models. Similarly, (Zhang et al., 2020) proposed a DL-based hybrid framework for day-ahead EPF of the PJM electricity market by combining four forecasting models deep belief network (DBN), LSTM, recurrent neural network (RNN), and CNN. Empirical results showed that their method offered valuable benefits compared with benchmark techniques. (Pavićević & Popović, 2022) introduced various NN structures for EPF using the Hungarian Power Exchange (HUPX) dataset. Their results demonstrated that combining fully connected layers and RNN is the best approach for predicting electricity prices. Furthermore, (Chang et al., 2019) proposed a hybrid model based on wavelet transform and an Adam-optimized LSTM neural network for EPF. They validated the proposed method under various scenarios using datasets from Australia, New South Wales, and France, and confirmed that it successfully enhanced prediction accuracy. In the same context, (Cheng et al., 2019) employed a hybrid model using SVM, support vector regression, empirical wavelet transform (EWT), and BDLSTM for EPF on European Power Exchange Spot (EPEXSPOT) data. Statistical results showed that their hybrid model performs better than the other models used for comparisons. Furthermore, (Kuo & Huang, 2018) proposed a hybrid approach, called EPNet, using a combination of CNN and LSTM, and employed a PJM dataset to predict hour-ahead electricity prices based on the previous 24-h prices. The results showed that their model outperformed other algorithms in terms of forecast accuracy.

Additionally, statistical techniques have been applied to predict electricity prices using various datasets. (González et al., 2017) proposed a functional version of the autoregressive–moving-average model with exogenous inputs (ARMAX) time series model based on Hilbert operators; however, this approach assesses the moving average (MA) terms of practical time series models. The proposed technique was validated using the German and Spanish electricity price market data. Conversely, (Zhang et al., 2019) introduced day-ahead EPF using new integrated model based on ARMAX, improved empirical mode decomposition (IEMD), ANFIS, and exponential generalized autoregressive conditional heteroscedasticity (EGARCH) and applied it to Australian and Spanish market data. The results showed that the proposed model achieved a better prediction accuracy than other well-known models. Furthermore, (Angamuthu et al., 2018) focused on EPF by combining an ARIMA model with another prediction method to enhance residual errors in hourly price forecasting for the Iberian electricity market. (Zhang et al., 2020) proposed a hybrid model based on VMD, seasonal autoregressive integrated moving average (SARIMA), simulated annealing particle swarm optimization (SAPSO), and (DBN) to predict electricity price using datasets from the PJM, Australian, and Spanish markets; however, SAPSO was employed to optimize DBN and can therefore capture irregular variations in electricity price. The proposed model exhibited better EPF performance than other models.

### 2.4.2 Machine Learning Techniques

ML techniques include a wide range of algorithms and methodologies that allow computers to learn and make predictions or decisions without explicit programming. These techniques involve using statistical models and algorithms that allow computers to analyze and interpret complex data patterns. Some common ML techniques include supervised learning, wherein models are trained using labeled data; unsupervised learning, wherein patterns and structures are identified from unlabeled data; and reinforcement learning, wherein agents learn to make optimal decisions through interactions with environments. Additionally, techniques such as DL employ artificial neural networks (ANNs) with multiple layers to learn hierarchical data representations. These techniques have been instrumental in various fields, such as forecasting analytics and classification, as they empower machines to perform tasks that traditionally required human expertise (Alzubaidi et al., 2021; Esenogho et al., 2022). Numerous studies have employed ML models for EPF; for example, (Albahli et al., 2020) applied extreme gradient boosting (XGBoost) on a dataset provided by an independent electricity system operator (IESO) to forecast electricity prices. Their simulation results indicated that the prediction performance of their model is better than those of benchmark approaches such as SVM and random forest (RF). Similarly, (Rafiei et al., 2016) conducted hourly EPF by applying a new learning method based on the generalized extreme learning machine (GELM) on the Ontario and Australia electricity market data; however, this approach is computationally intensive and provides indeterminate outcomes for large datasets. Another hybrid method proposed by (Wang et al., 2017) combined SVM and kernel principal component analysis (KPCA); however, their model is highly static and location dependent and cannot handle seasonal price variations across different locations.

(Alamaniotis et al., 2015) introduced a hybrid method to forecast electricity prices using historical data of New England. They employed relevance vector machines (RVMs) for individual predictions, which were combined to perform LR; the results showed that their method performed better than those used for comparisons. Furthermore, (Abedinia et al., 2016) employed feature selection (FS) instead of simplistic training for EPF using data from the PJM regulation zone, Spain, and New York electric markets. They employed the information gain (IG) and mutual information (MI) techniques to implement FS; however, their model is limited to online predictions. In contrast, (Zhang et al., 2019) developed a bilevel ML strategy for EPF, wherein LR is employed at the first level to anticipate prices across the wholesale U.S. electricity market. The second level comprises a limited optimal model that receives the price signal and provides feedback regarding the optimal dispatch solutions to the LR model for EPF at the subsequent level.

A summary of the various aspects, such as forecasting models employed, datasets used, and key findings and limitations, of recent EPF studies are listed in Table 2.3.

**Table 2.3: Summary of EPF studies.**

| Authors | Forecasting model | | Dataset used | Key findings and limitations |
|---|---|---|---|---|
| | Single | Hybrid | | |
| (Albahli et al., 2020) | XGboost | N/A | Ontario | ML technique was employed to increase electricity rates to offload data storage and reduce energy consumption at cloud data centers. However, it proposes a single technique to predict EPF using small samples of time series data. |
| (Abedinia et al., 2016) | FS | N/A | PJM, Spain, New York | This study addressed FS instead of simple training. Although they obtained an MAE of 4.09 during tests, the model can only perform offline predictions using a large dataset. |
| (Pavićević & Popović, 2022) | Dense-LSTM | N/A | HUPX | Owing to the increasing number of markets. ANN is becoming essential for performing predictions. However, the dataset employed had a high number of features, which might impact the prediction performance. |

(Table 2.3 continued)

| | | | | |
|---|---|---|---|---|
| (Ugurlu et al., 2018) | N/A | GRU-LSTM | Turkish | Analysis model for EPF with emphasis on the performances of GRU and LSTM. However, experimental results validated only for day-ahead forecasting. Further, the results are inconsistent and can diverge based on season, making the proposed model inadequate for broader applications. |
| (Wang et al., 2017) | N/A | SVM-KPCA | ISO, New England | Extracting new features with minimal redundancy, which improves SVM results. As a large dataset was employed, a significant computation overhead was imposed, contributing to the proposed model's inefficiency. |
| (Kuo & Huang, 2018) | N/A | EPNet | PJM | The model performed better than traditional ML approaches. However, CNN is substantially slower owing to operations such as max pooling. The model outputs prices with large errors during real-time forecasting that involves significant computational complexity. |
| (Sun et al., 2021) | N/A | SDR-MASES-SPSDAE | Australia | The proposed approach analyzes a large amount of input data by separating the essential elements. |
| (Zhang et al., 2020) | N/A | VMD, SAPSO, DBN | Australia, PJM, Spanish | Although the proposed method can enhance forecasting accuracy, it has some limitations in terms of computation time and complexity. |
| (Zhang et al., 2019) | N/A | ANFIS, ARMAX, EGARCH | Australian, Spanish | The proposed model can improve accuracy. However, ANFIS is a highly complex structure and the statistical model has fragile owing to limited capture of nonlinear behavior of electricity fluctuations. |
| (Zhang et al., 2020) | N/A | RNN, LSTM, CNN | PJM | Hybrid DL framework proposed for EPF offers considerable bidding potential. DNNs requires a significant amount of data to obtain better results compared to traditional techniques. |
| (Zhang et al., 2022) | N/A | BDLSTM | Nord Pool | The categorical feature of the proposed model is managed efficiently. However, the proposed method requires a considerable amount of time for training and forecasting. |
| (Darudi et al., 2015) | ANFIS, ANN, ARIMA | N/A | Spanish | Different forecasting models were combined to produce a single framework that conducts accurate EPF. This study employed statistical and DL models using weekly season data (training with limited data). |

Most of these studies employed ML techniques, such as statistical and conventional models, for EPF (Albahli et al., 2020; Pavićević & Popović, 2022). However, a time series electricity price dataset has characteristics such as high volatility, rapid spikes, and seasonality, making it challenging to forecast prices using individual models such as XGBoost and ANN. Moreover, these techniques may produce unsatisfactory results with large forecasting residuals between actual and forecasted values. Additionally, they are inefficient for identifying nonlinear time series behavior and exhibit weak forecasting abilities. Furthermore, several hybrid techniques have also been applied for EPF. However, most researchers have focused on combining linear methods with DL techniques (Kuo & Huang, 2018; Ugurlu et al., 2018; Zhang et al., 2022). DL techniques have complex architectures and consume a significant number of computational resources. Hence, LR with ensemble tree-based models has been proposed to improve EPF performance. Therefore, this study used LR models such as automatic relevance determination (ARD) and ridge in combination with ensemble tree-based models, including extra tree regression (ETR), random forest regression (RFR), and AdaBoost (ADA). Additionally, a real-world Nord Pool electricity market dataset was used to evaluate the methods as it is one of the most volatile and seasonal electricity markets with rapid spikes. Thus, the electricity price dataset adopted in this study could be used to extensively assess the efficiency and applicability of the proposed forecasting model. This allows achieving one of the aforementioned objectives (i.e., Objective 2). Moreover, this study employed supervised learning algorithms, categorized into two distinct phases. The first phase focuses on employing LR techniques, specifically using two models: ridge and ARD. These models serve as solid foundations for predicting continuous target variables. The second phase explores ensemble tree-based models, which have gained significant attention owing to their ability to handle complex data relationships. The prominent models within this category, ETR and RFR, were employed along with ADA. This study aims to comprehensively assess the performances and applicability of these models to various prediction tasks. Figure 2.3 illustrates the classification of the algorithms used in this study.

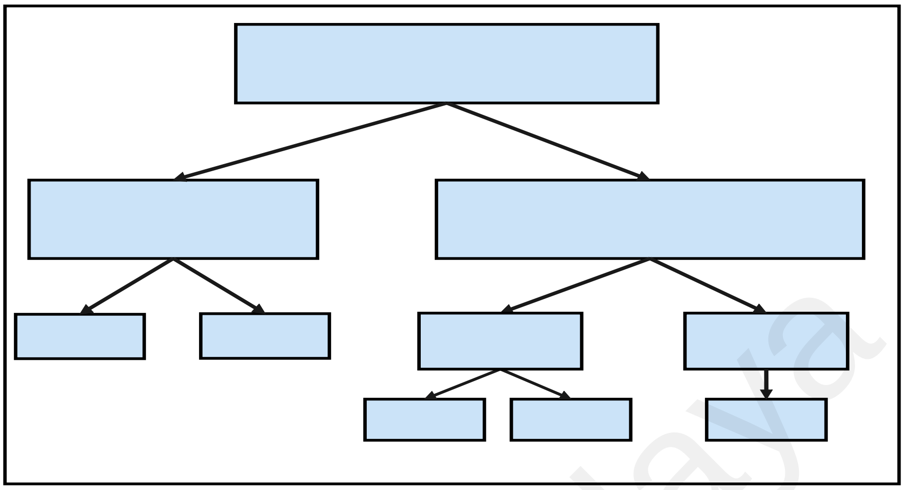

**Figure 2.3: Classification of the ML methods used in this study.**

#### 2.4.2.1 Linear Regression Model

LR is a widely used supervised learning algorithm that aims to predict a continuous target variable based on input features. It assumes a linear relationship between the features and the target variable to determine the best-fitting line that minimizes the difference between the predicted and actual values. Moreover, both ridge regression and ARD are powerful extensions of LR that address different challenges and improve model performance. Ridge regression handles overfitting by adding a regularization term, whereas ARD automatically determines feature relevance, making it particularly useful for scenarios with potentially numerous irrelevant features. These techniques enhance the predictive capabilities of LR and provide valuable tools for modeling and prediction tasks using supervised learning (Carrera & Kim, 2020; Renkens, 2017). The LR analysis model can be formulated as follows:

$$Y = \beta_0 + \beta_1 X_1 \ldots\ldots\ldots + \beta_i X_i + \varepsilon \tag{2.1}$$

where $X_i$ $Y$, $\beta_i$, $\beta_0$, and $i$ denote the independent variable, dependent variable, estimated slope coefficient, intercept, and number of data samples for multiple LR, respectively. The random error component is defined as $\varepsilon$. The unobservable error component accounts for the failure of the data to lie on a straight line and represents the difference between the true and observed values of $Y$.

#### 2.4.2.2 Ensemble Tree-based Model

The ensemble technique is a popular ML approach that combines a collection of learners, instead of employing individual learners, to forecast unidentified targets. Each learner's output values are combined using a voting process to forecast the final class label. The fundamental objective of ensemble learning is to create a more accurate classifier composed of several learners. Moreover, various ensemble techniques such as bagging (ETR and RFR) and boosting (ADA) have been established and implemented. Bagging generates several bootstraps from the training dataset and generates a prediction pattern for each bootstrap, as shown in Figure 2.4. However, ETR employs multiple decision trees trained on different training data subsets, and random FS is performed for each split. The predictions of these trees are combined through averaging or voting, which improves stability, reduces overfitting, and ensures robust predictions. Similarly, RFR builds an ensemble of decision trees by using bootstrapping to create different subsets of the training data and random FS. The predictions of individual trees are combined through voting or averaging, resulting in a robust and accurate regression model (Geurts et al., 2006).

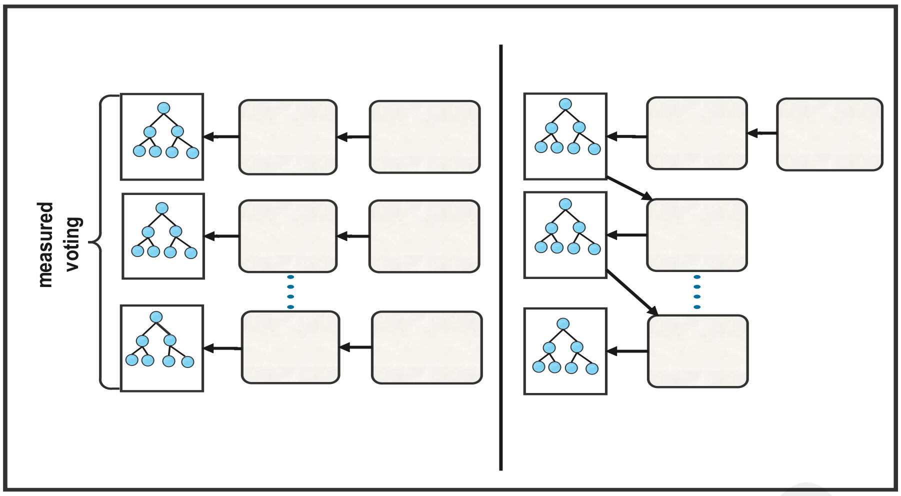


**Figure 2.4: Workflows of boosting and bagging techniques.**

Additionally, the ADA model is a boosting algorithm that iteratively trains weak learners, often decision trees, by assigning higher weights to misclassified examples. The weak learners are then combined to produce a strong ensemble model by leveraging the strengths of each individual learner. However, this increases the risk of selecting misclassified samples as the training data, but a higher proportion of instances are correctly classified. Thus, boosting is a continuous process of constructing classifiers enhanced by the weights of weak classifiers from previous rounds to reduce dataset volatility and variability (Cha et al., 2021; Ribeiro & dos Santos Coelho, 2020).

## 2.5 Coordinated and Smart Plug-in Electric Vehicle Charging Using Machine Learning and Optimal Control

As governments worldwide continue investing in EVs and charging infrastructure to tackle climate change, the number of EVs worldwide is expected to reach 130 million by 2030 (Tirunagari et al., 2022). Hence, PEV penetration of the distribution grids will continue to increase. However, large-scale adoption of PEVs can result in a demand side management (DSM) issue from the supplier's perspective as PEV chargers impart substantial loads on the grid. A possible scenario is that numerous PEV owners begin charging their vehicles as soon as they arrive home from work, which is already a period of high demand. Thus, random (uncoordinated) PEV charging strategies can result in higher charging expenses for PEV owners; this issue can be further intensified under uncoordinated charging demand. Therefore, well-coordinated and smart charging synchronization between grid operators and EVs is essential. Random charging of many PEVs can result in a very serious problem for electric grid operators (Muratori, 2018). Additionally, it can have various negative impacts on the distribution grids, such as transformer overloads, voltage deviations, higher operational costs, and power losses. Consequently, they may pose a significant risk to the safe and reliable operation of the distribution grid, which could result in significant system blackouts due to overloading. Therefore, efficient scheduling of PEV charging with the aim of minimizing charging costs and accounting for the substantial adoption of PEV creates new challenges for the operation of distributed generation and power units within the network (Amin et al., 2020; Deilami et al., 2011; Lyu et al., 2020). To alleviate these impacts, it is recommended that PEVs should be charged during off-peak hours by optimizing their charging schedules, considering hourly variations in electricity price and flexibility of demand load. This will allow charging PEVs during periods of low electricity prices and grid load, thereby minimizing charging costs and enhancing savings of PEV owners by selling energy back to the grid during peak hours. Generally, an aggregator is an essential link between PEVs and the DMS. It is also entirely accountable for ensuring that collaborative PEV charging is employed while benefiting both the grid operator and PEV owners. Thus, an effective communication structure is required to allow real-time information exchange between PEVs and the aggregator for enabling efficient control and monitoring of PEV charging and discharging operations (Liu et al., 2019).

Recently, various studies have addressed scheduling PEV charging operations using different techniques. For instance, (Jin et al., 2013; Turker & Bacha, 2018) proposed linear programming-based optimal schemes and heuristic algorithms for solving static and dynamic problems, respectively, to schedule PEV charging, with an aim to increase the savings of owners by incorporating aggregator profits and customer demand. They exploited both the V2G and V2H techniques to minimize the electricity costs of a household by using only the EV's battery. Although (Amamra & Marco, 2019; Cao et al., 2020; López et al., 2018) proposed various techniques, such as MILP, nonlinear programming (NLP), and dynamic programming (DP), for scheduling PEV aggregators under upstream grid price uncertainty to minimize the overall charging cost. Nevertheless, these techniques have limitations in that they can rapidly become extremely complex and computationally intensive, especially for cases with many variables and constraints. This may pose a challenge for developing an ideal solution within a practical time frame. (Momber et al., 2014) developed a two-stage stochastic LP model to maximize the profits of EV aggregators in both the day-ahead and balancing markets by considering the uncertainties of EV fleet mobility and market prices. (Vagropoulos & Bakirtzis, 2013; Wu et al., 2015) proposed stochastic programming approaches to manage EV fleet charging by considering the randomness of regulation signals, bidding in the market and offering ancillary services. Optimal EV charging and discharging activities were discussed by (Hadian et al., 2020), who modeled electric vehicle charging stations (EVCS) through multi-objective particle swarm optimization (MOPSO) and a sequential Mont Carlo simulation to control the time and rate of EV charging and discharging by employing three different battery operation techniques. (Gong et al., 2020) also proposed a charging strategy based on dynamic spike pricing wherein GA was employed to minimize the EV charging cost and prevent transformer overloads, considering the seasonality of EV charging demand. Additionally, (Dahmane et al., 2021) showed that by employing V2G technology to sell power back to the electric grid during high peak demand, EV owners can reduce their charging costs. Moreover, this study proposed an optimal decentralized smart charging method, wherein the dynamic time step was considered to be a decision variable instead of a fixed time step. Similarly, (Chiş et al., 2016; Li et al., 2019) proposed an approach aimed at reducing the charging cost for an individual PEV. It was modeled as a Markov decision process (MDP) with unknown transition probabilities and a constrained MDP, and reinforcement learning (RL) techniques were employed to create an energy consumption plan for EVs, wherein EV charging was controlled using a heuristic scheme, and the outcomes of the charging policy were obtained via RL. In contrast, (Wan et al., 2018) employed deep RL algorithms to determine the most effective solutions for scheduling EV charging/discharging based on future electricity prices. However, RL has a limitation in that it may require a considerable amount of data to learn effective policies. Moreover, many hyperparameters must tuned to achieve acceptable performance, which can be a time-consuming and computationally expensive process. (Rotering & Ilic, 2010) proposed a method for optimizing smart charging without V2G technology and V2G technology with only power regulation. However, this method does not consider the impact on the state of charge (SOC) owing to bidirectional power regulation with equal upward and downward bidding, as well as battery discharging during periods of high electricity prices. Additionally, (Mehta et al., 2016) proposed two smart charging techniques considering both V2G and G2V technologies to handle peak loads through load shifting. Nevertheless, for all V2G strategies, it must be assumed that users will provide their EVs to allow implementing smart charging strategies and expect longer charging times. Generally, the system operator aims to maintain grid performance, whereas PEV owners aim to charge their vehicles concurrently. Based on this, numerous researchers have explored diverse objectives, such as enhancing voltage profiles, reducing system power losses, and minimizing PEV charging expenses. These objectives can be met using various optimization methods. (Amin et al., 2020) tried to minimize system power losses by optimally managing customer charging requests; they considered a normal driving pattern without any charging preference. (Suyono et al., 2019) proposed coordinated charging approaches, such as binary particle swarm optimization (BPSO), binary grey wolf optimization (BGWO), and metaheuristic techniques, to minimize system losses. They employed different tariff zones and organized customer demand into their preferred tariff slots. Although they considered the fixed charging priorities of customers, their preference flexibility was not considered. Various techniques, such as PSO and BEP, have been proposed to develop optimal EV charging schedules for a distribution network that does not comprise renewable resources. For instance, (Hajforoosh et al., 2016) adopted a variable charging technique with a single objective, whereas (Rahman et al., 2018; Usman et al., 2021) adopted fixed charging with multiple objectives. Their findings revealed that the proposed approach with fixed charging resulted in the lowest power consumption and power losses compared to other algorithms. Although these researchers employed advanced techniques, they did not address the crucial topic of reducing EV charging costs or consider electricity price variations. (Deilami et al., 2011) proposed a load management system that considers market prices that vary with time, time zones preferred by EV owners based on their priority selection, and random plugging in of EVs for coordinated charging in a smart grid system. Thereafter, they employed the maximum sensitivities selection (MSS) optimization method to allow charging EVs as soon as possible based on the priority time zones while maintaining the operational criteria of the grid. Meanwhile, (Clement-Nyns et al., 2009) formulated the power loss problem resulting from extensive grid penetration of EVs as a sequential quadratic optimization algorithm. The charging power obtained through quadratic programming cannot be higher than the maximum power of the charger. The algorithm involves solving a sequence of quadratic programming problems, which is a time-consuming process that requires a significant amount of computing power. Moreover, the performance may be sensitive to the initial conditions of the optimization problem. The distinctive approaches of these related studies are summarized in Table 2.4.

**Table 2.4: Summary of related studies on various PEV charging strategies.**

| Authors | Study focus | Key methodology | PEV charging behavior | Datasets | Assessment algorithm system test | Remarks |
|---|---|---|---|---|---|---|
| (Deilami et al., 2011) | Minimize energy cost | MSS | Coordinated, uncoordinated | Western Australia | IEEE 31-bus distribution network | The RT-SLM strategy aims to minimize total energy generation costs and grid losses by considering time-varying market. |
| (Cao et al., 2020) | Minimize charging cost | MILP | Coordinated (charging and discharging) | Not detailed | Not detailed | An optimization technique is employed under uncertain electricity prices by using upper and lower price constraints instead of forecasted prices. |
| (Amamra & Marco, 2019) | minimize charging cost | NLP | Bidirectional charging | UK National Grid regulation data | Standardized IEEE 33-bus system | This study proposes an optimized V2G system using a fleet of EVs for cost-effective. |
| (López et al., 2018) | Decrease EV charging cost | DP, DNN, KNN, SNN | Always charging behavior | Winnipeg, Manitoba, Canada | Not detailed | The aim was to minimize vehicle charging costs. The approach employs to find solutions for historical connection sessions, which then train ML models to make effective decisions. |
| (Mohammed et al., 2022) | Minimize PEV charging costs | Heuristic algorithm | Unscheduled, scheduled charging | Beijing | Not detailed | The method minimized PEV charging costs. However, it requires further validation against unscheduled and using diverse scenarios. |
| (Hou et al., 2023) | Minimize operating costs | Two-stage stochastic optimization. | Not detailed | Vancouver | Not detailed | The proposed method effectively reduced daily operating costs by up to 27.5% in real-world scenarios. However, the performance can vary based on RES and energy demand. |
| (Turker & Bacha, 2018) | Minimize PEV charging costs in the housing sector | V2G-OLC | unidirectional and bidirectional charging | French energy billing system | Not detailed | Various algorithms exploiting V2G and V2H techniques. The results of the proposed method indicated that reduction of 47.94% of average charging costs, compared to other methods. |

(Table 2.4 continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| (Hadian et al., 2020) | Management (EVCS) within a distribution network | MOPSO and sequential Montecarlo | Not detailed | Not detailed | Standard network IEEE 69 buses system | This study proposed an optimal EV charging/discharging plan designed for peak shaving and valley filling considering various objectives. |
| (Gong et al., 2020) | Reduce the charging cost of EVs | GA | Not detailed | NHTS | Not detailed | An optimal charging strategy based on a DSP is proposed. Simulation results demonstrate the effectiveness for peak shaving and reducing charging costs. |
| (Dahmane et al., 2021) | Minimize the vehicle's charging cost | Dynamic time step | G2V, V2G | A real French energy price | Not detailed | The charging strategy is a model-based optimized time step and although it shows promising results, it may not perform as effectively when implemented in real-world. |
| (Chiş et al., 2016) | Reduce electricity cost of PEV owner | MDP, LP | Not detailed | ISO New England | Not detailed | This study presents a demand response method aimed at minimizing the long-term battery charging costs for individual PEVs. Simulations using real-world pricing data show potential cost savings ranging from 10–50%. |
| (Li et al., 2019) | Eliminate PEV charging cost | CMDP | Not detailed | USA, retail-energy | Not detailed | The problem is formulated as a constrained MDP with the objective of minimizing charging costs. Although this study focuses on minimizing charging costs, other metrics such as charging time and grid load impact are not considered. |
| (Suyono et al., 2019) | Minimize system losses and PEV charging cost | BPSO, BGWO | Uncoordinated, coordinated | Western Australia | Modified of IEEE 31 bus system | Minimize power losses and voltage deviations by integrating capacitor switching and an on-load tap changer. The performances of BPSO and BGWO may not guaranteed to always provide the best solution. |

Based on the aforementioned studies, it is evident that selecting the right scheduling objective is crucial. Objectives such as reducing system loss and improving voltage profiles focus on network performance, whereas minimizing PEV charging costs and maximizing owner savings are aimed toward customer care. Most of the cited studies primarily focused on either customer benefits or grid performance. However, allowing PEV customers the flexibility to charge their vehicles during their preferred periods while optimizing network performance and minimizing charging costs is a more complex approach for integrating PEVs into the distribution grid. To the best of the author's knowledge, this aspect has not been extensively explored in previous studies. Therefore, this study proposes a smart and coordinated charging technique that schedules PEV charging with an aim to reduce long-term electricity charging costs and maintain distribution grid stability. Although distinct techniques with the same aims have been proposed in literature, they were tested under various conditions and assumptions, e.g., PEV battery size, daily load profile (DLP), daily energy price (DEP), charging and driving patterns, etc. However, each study was performed in its own context; therefore, comparing the performances of all strategies is challenging. However, this study aims to minimize PEV charging costs using OC and ML techniques, which include NNs, naïve Bayes (NB), and ensemble classifiers. These methods were selected by considering the designated charging zone, EPF, and various PEV charging strategies, such as random, coordinated, and smart. The approaches were selected based on their individual and complementary strengths, along with their proven capabilities for handling complex predictive tasks. By combining these techniques, a balance between computational efficiency, prediction accuracy, and model interpretability could be achieved, which is essential for developing a sustainable and cost-effective plug-in charging system. The charging signals obtained using the proposed methods were evaluated using the standard and a modified IEEE 69-bus distribution grid system to assess the performance indicators associated with system losses, power consumption, and voltage deviations.

## 2.6 Research Gap

While OC theory offers a promising mathematical approach to identify optimal charging strategies for dynamic systems, existing methods lack specific consideration for minimizing PEV charging costs. This gap is particularly relevant when accounting for diverse PEV charging behaviors and designated charging times. Addressing this need for cost-effective solutions requires further research into comprehensive PEV charging systems. Existing techniques for EPF often struggle with capturing the non-linear aspects of electricity prices, hindering their accuracy. This limitation highlights the need for more advanced models that can effectively handle complex price patterns and improve prediction efficiency. While previous research has addressed customer care and grid performance independently, there's a lack of investigation into how to optimize both simultaneously, particularly regarding cost-effective charging. This gap highlights the need for further studies that address both grid performance and reduced charging costs.

## 2.7 Summary

A substantial number of studies have been conducted for reducing PEV charging costs and optimizing PEV charging, signifying the crucial significance of this topic. However, optimal scheduling of PEV charging is still considerably challenging. Among the various methods adopted to address this issue, the OC theory stands out owing to its unique mathematical approach, wherein it aims to identify the OC for a dynamic system over a given period. However, a noticeable research gap exists in that no strategies are specifically aimed at minimizing PEV charging costs by considering factors such as different PEV charging behaviors and designated charging times. This highlights the need for further research to explore comprehensive solutions for developing a more efficient and cost-effective PEV charging system.

Additionally, recent studies on EPF have employed techniques such as DL, statistical models, and ML to model and predict electricity prices, particularly for the global market. However, the inherent characteristics of time series electricity price datasets, such as high volatility, rapid spikes, and seasonality, complicate the prediction process. Moreover, popular traditional models, such as ANN and XGboost, can yield unsatisfactory results, with considerable discrepancies between the forecasted and actual values. Furthermore, they exhibit limited efficacy for identifying nonlinear time series behavior, thereby limiting their predictive capabilities. This research gap emphasizes the urgent need for developing more advanced models to predict electricity prices accurately and efficiently.

Finally, a comprehensive review of the extant literature has emphasized the pivotal role of selecting appropriate scheduling objectives for integrating PEVs into the distribution grid. The significant objectives include minimizing PEV charging costs, system losses, improving voltage profiles, and thereby maximizing PEV owner revenue. Some of these objectives are focused more toward improving network performance, whereas others aim to enhance customer benefits. Generally, studies have tended to focus on either enhancing customer benefits or improving grid performance, and rarely achieved a balance between the two. However, a more inclusive approach should provide PEV customers with the flexibility to charge and discharge their vehicles during low and high-demand times, respectively, optimize network performance, and minimize charging costs. To the best of the author's knowledge, existing studies have not adequately explored an approach that integrates customer benefits (reduces PEV charging cost based on price forecasting) with grid performance optimization. This research gap validates the need for additional investigations and a comprehensive study in this field.

# CHAPTER 3: METHODOLOGY

## 3.1 Introduction

This chapter elucidates the methods and procedures employed to achieve the objectives outlined in Chapter 1. It is divided into several subsections. First, intelligent charging control by a power aggregator for PEVs by employing OC to minimize charging cost using a fixed electricity price is presented. Moreover, the assumptions and system architecture, along with control task formulation, are also presented. The implementation steps for EPF employed in individual and hybrid ML models are also thoroughly explained. Thereafter, it discusses the methodologies of smart and coordinated charging techniques employing these OC and ML classification approaches that consider EPF. Finally, various PEV charging techniques and radial distribution systems with different PEV PLs are used to evaluate the impacts and effectiveness of the proposed charging techniques.

## 3.2 Plug-in Electric Vehicle Charging Control by Power Aggregator through Optimal Control

This section presents an optimized EV battery charging and discharging scheduling model employing the OC theory, along with the system assumptions. To evaluate the various PEV charging behaviors, it employs the electricity prices on a typical day, along with three different charging strategies: random (uncoordinated), coordinated (unidirectional), and smart (bidirectional).

### 3.2.1 Assumptions and System Architecture

Two types of control architectures can be employed for optimal PEV charging: centralized and decentralized. In a decentralized control framework, the decision-making power for PEV charging is distributed among the PEVs, and each PEV owner determines their own charging schedule based on their preferences and requirements. Although this framework allows the customers to make individual charging decisions, it may not guarantee an optimal solution for the distribution grid as the aggregators cannot directly regulate the charging activities. In contrast, in a centralized control framework, the aggregator is entirely responsible for ensuring that the charging process for PEVs is effectively coordinated, considering advantages to both the customers and grid operator. Furthermore, this approach enables better optimization and coordination of charging schedules, considering factors such as grid load, price, and peak demand periods. By considering real-time information and employing advanced algorithms, this system can determine the most cost-effective periods for charging vehicles by taking advantage of lower electricity prices. It can also effectively balance the grid load by distributing the charging demand across different periods. Moreover, strategic scheduling of charging sessions can help avoid periods of peak demand when electricity prices are higher and the grid is strained. This can reduce the overall charging costs for PEV owners and ensure that the grid infrastructure is used efficiently (Amin et al., 2020; Ma et al., 2011). Both centralized and decentralized control architectures for PEV charging are illustrated in Figure 3.1.

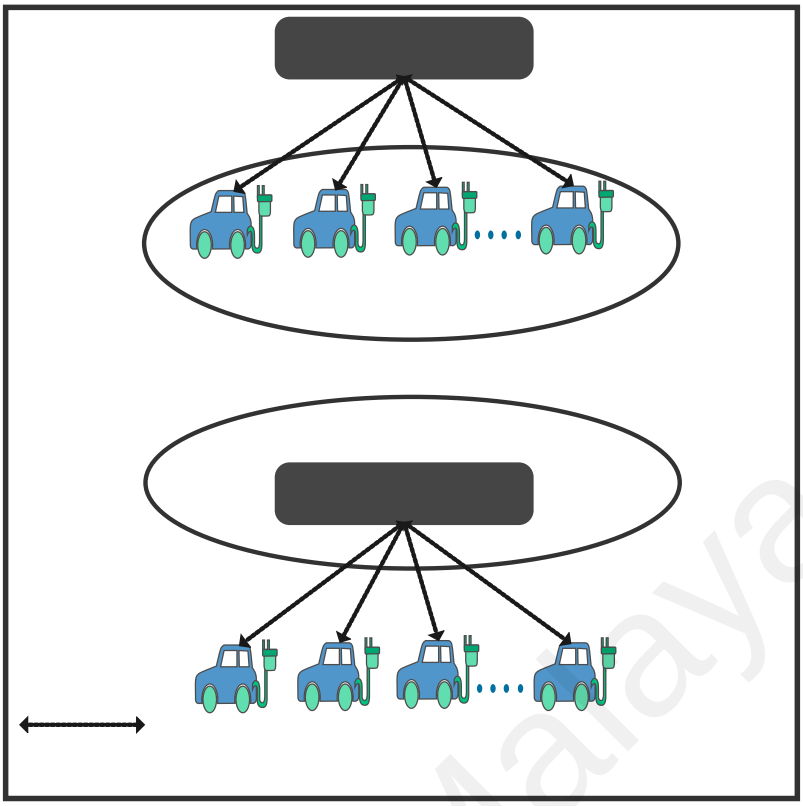

**Figure 3.1: PEV charging control architectures: (a) decentralized and (b) centralized**

Owing to its advantages and the need for optimally controlled PEV charging, the centralized control architecture was employed in this study. It includes an aggregator that streamlines PEV charging activities by directly managing the charging strategy for each vehicle, which indirectly accesses the electricity market through this aggregator, benefiting from the smart interface it provides between the PEVs and the market. The aggregator efficiently schedules charging operations for multiple vehicles, ensuring that the charging process is effective and coordinated. The information flow of the selected centralized control architecture is depicted in Figure 3.2.

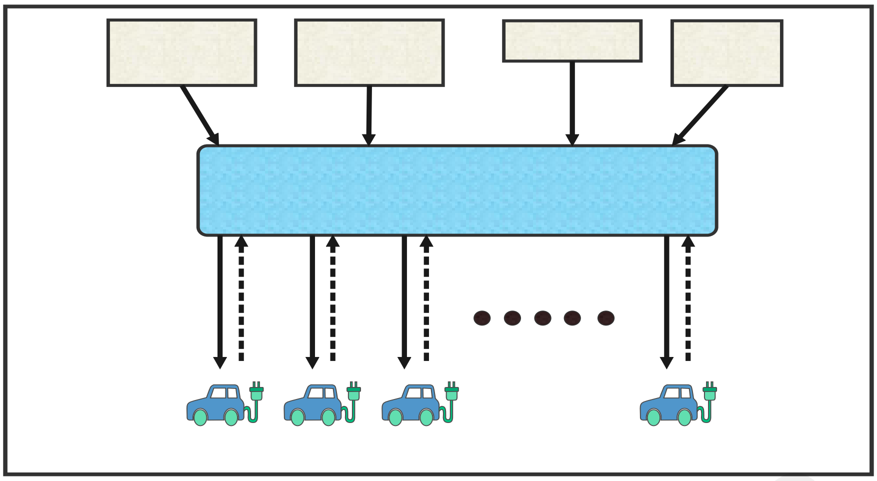

**Figure 3.2: Information flow in a centralized control architecture.**

To implement the centralized control architecture, this study made the following assumptions:

- The aggregator is set as a price taker, indicating that it does not have a sufficiently large market share to affect electricity prices.
- The aggregator is assumed to have knowledge of the electricity price, although in reality, it must be forecasted.
- Automated communication technology is available to facilitate smart charging. For instance, all information regarding PEVs can be promptly communicated to the aggregator, and the control signal generated by the aggregator can be transmitted to the PEVs.
- To establish an effective charging strategy, a representative driving pattern must be adopted. Generally, intracity or short-term driving patterns exhibit higher levels of predictability owing to fixed working hours and established routes of users. Consequently, it was presumed that these driving patterns are known in advance. Moreover, it is imperative to determine the energy required for each trip.

### 3.2.2 Optimal Control Theory

The OC theory is a branch of mathematical optimization that deals with finding the best possible control for a dynamical system over a period of time. However, it involves calculating the time history of the control variables associated with a system, with the aim of optimizing a particular performance index, while satisfying various constraints such as boundary condition, state, and control path. The two main types of methods in the OC theory are direct and indirect. Direct methods discretize the control problem by dividing the time horizon into discrete intervals. The control inputs are parameterized over each interval and directly optimized to minimize a given cost function, considering the constraints and system dynamics. In contrast, indirect methods, also known as variational methods, focus on deriving the conditions required to achieve the optimal solution. The most prominent indirect method is the Pontryagin's maximum principle (PMP). It formulates the necessary conditions for an OC solution by minimizing the Hamiltonian function, which is the sum of the system dynamics and cost function, multiplied by the adjoint variables (costate variables). By solving a two-point boundary value problem derived using the PMP, the OC and state trajectories can be determined. Furthermore, indirect methods, such as PMP, are more advantageous for minimization problems as they guarantee global optimality and handle constraints naturally. In contrast, direct methods suffer from discretization errors, require control input parameterization, and may converge to local optima. Therefore, indirect methods, such as the PMP, are preferable for minimization problems owing to their global optimality, constraint handling, and sensitivity analysis capabilities (Kirk, 2004; Mall et al., 2020).

The general formulation of the OC problem using indirect methods, including the PMP, is expressed as follows:

1. Specify the dynamic behavior of the system using ODEs:

$$\dot{X}(t) = f(X(t), U(t), t) \tag{3.1}$$

where $X(t)$ denotes the state variables, $U(t)$ denotes the control inputs (a vector or multiple control variables), and $f$ denotes the system dynamics function.

2. Define a cost function $J$ that quantifies the objective or performance index to be minimized:

$$J = \int_{t_0}^{t_f} L(X(t), U(t), t)dt \tag{3.2}$$

where $L$ is the instantaneous cost function, $t_0$ is the initial time, and $t_f$ is the final time.

3. Construct the Hamiltonian function $H$, which combines the system dynamics and cost function by introducing adjoint variables $(\lambda(t))$:

$$H(X(t), U(t), \lambda(t), t) = L(X(t), U(t), t) + \lambda(t)^T f(X(t), U(t), t) \tag{3.3}$$

where $\lambda(t)$ denotes the adjoint variables (also known as a costate variables).

4. Derive the necessary conditions for optimality using PMP. These conditions involve the minimization or maximization of the Hamiltonian function with respect to the control inputs. In the case of multiple control options or bang–bang control strategy, control $U$ can have two values, e.g., $U_1$ and $U_2$; the OC $U$ is then determined based on the sign of the partial Hamiltonian derivative with respect to $U$ ($dH/dU$) as follows:

$$U^*(t) = \begin{cases} U_1 & if \quad dH/dU(t) < 0 \\ U_2 & if \quad dH/dU(t) > 0 \end{cases} \tag{3.4}$$

where $U_1$ and $U_2$ represent the two possible control states. The control switches to the minimum value of $U_1$ when the derivative of the Hamiltonian function with respect to $U$ is negative, where $U_2$ has the maximum value when this derivative is positive.

5. Obtain the adjoint equation by considering the Hamiltonian derivative with respect to the state variables, as well as boundary conditions for the state and adjoint variables at the initial and final time points:

$$\dot{\lambda} = -\frac{\partial H}{\partial X} \tag{3.5}$$

$$X(t_0) = X_0, \qquad \lambda(t_f) = 0 \tag{3.6}$$

6. Formulate the OC problem as a two-point boundary value problem (BVP) using the system dynamics, adjoint equation, and boundary conditions. Thereafter, numerically solve this BVP using appropriate techniques, such as shooting or collocation methods, to determine the OC and state trajectories, considering the constraints and the switching behavior of the bang–bang control strategy.

By following these steps and solving the resulting two-point BVP, the indirect approach with PMP offers a solution that satisfies the necessary conditions for optimality in the OC problem, even with multiple control options or a bang–bang control strategy.

### 3.2.3 Electric Vehicle Battery Model

The PEV charging strategies can be categorized into random (uncoordinated), coordinated (unidirectional), and smart (bidirectional). In the random strategy, charging begins when the EV is plugged into a charging point and stops only when the battery is fully charged or the EV is disconnected. In contrast, smart and coordinated processes employ a scheduling technique to monitor the charging process. Coordinated (unidirectional) PEV charging involves one-way flow of electricity, from an external power source to the vehicle's battery, and does not allow the vehicle to supply electricity back into the grid. In contrast, smart (bidirectional) charging, also known as V2G charging, allows the EV to not only receive electricity from the grid but also send it back when required. Moreover, bidirectional PEV charging offers several benefits, such as allowing EV users to monetize their idle EVs by buying and storing electricity when prices are low and selling it when prices are high, thereby allowing them to profit from these transactions. Additionally, in case of emergencies, the bidirectional feature can be used to power other EVs, thereby acting as a backup power source. By leveraging this technology, EVs can serve as a substitute energy resource to help alleviate the strain on the electric grid during peak hours and high-demand periods (Un-Noor et al., 2017). In this research, EVs are considered as battery packs to implement planned charging. Moreover, each battery is modeled as a steady-state equivalent circuit (SSEC), represented by the ideal voltage source $V_{oc}$ and internal resistance $R_{int}$ of a Li-ion battery, as illustrated in Figure 3.3. Each $V_{oc}$ and the $R_{int}$ depend on the SOC of the battery. Power is obtained from the SSEC using Ohm's low: $P = (V_{OC} - R_{\text{int}} I)I$ . Additionally, the circuit current can be obtained by determining the value $I$ through a quadratic equation as follows:

$$I = (soc, V_{oc}, P) = \frac{V_{oc}(soc) - \sqrt{(V_{oc}(soc))^2 - 4R_{\text{int}}P}}{2R_{\text{int}}} \tag{3.7}$$

where $P$ is set to cover all possible values obtained using either $P_{BT} = -\eta_t.U_t.P_{\max-plug}$ when $t \in T_{plug}$ or $P_{BT} = P_{dr}$ when $t \in T_{drive}$ , where $P_{dr}$ denotes the required available power when the EV is being driven, $U_t$ denotes the control variable, and $\eta_t$ denotes the efficiency. In modern batteries, this efficiency is usually close to 100% (Rotering & Ilic, 2010).

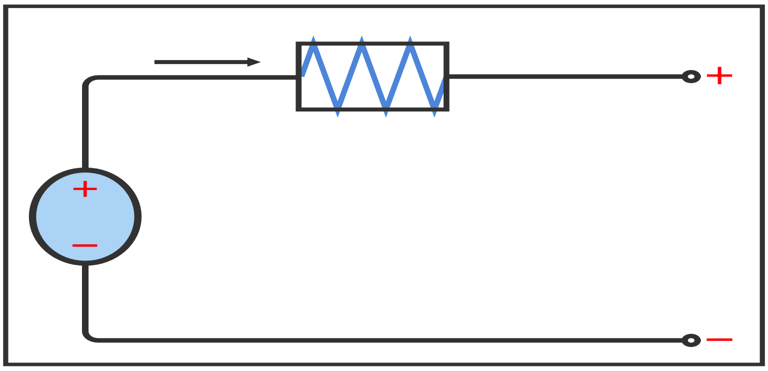

**Figure 3.3: Circuit configuration of a Lithium-ion battery.**

#### 3.2.3.1 Plug-in Electric Vehicle Charging Model

As the electricity price of a typical day was considered, the charging operation involved an entire day.

For instant operation, the entire time day is represented as [*0, N*], which is discretized into $[t, t+1]$, where, $t = 0,1,2,3\ldots N$, and time interval $\Delta_t$. This problem is addressed by considering the following discrete first-order system that describes the battery state:

$$X_{t+1} = f(X_t, U_t, t) \tag{3.8}$$

where the SOC is denoted by state variable $X_t$ at time index $t$, which is described as the set of allowable decisions that indicate the possible SOC of the battery spanning (0%, 1%, 2%, … 99%, 100%). Typically, battery operation is limited to a specific SOC range, whose minimum is set to 10%, constraining the SOC between 10 and 100%. $U_t$ is a set of permissible states for random (uncoordinated), coordinated (unidirectional), and smart (bidirectional) charging processes that indicate the possible control signals. In the preset $X$, any state value that can be obtained as a function of battery charge $Q_t$ and total battery charge capacity $Q_{\max}$ is included, and it is defined as:

$$X_t = \frac{Q_t}{Q_{\max}} \tag{3.9}$$

Furthermore, the Nissan LEAF EV was considered in this study owing to its bidirectional charging capability (Nissan LEAF Electric Car, 2021). As the Nissan LEAF EV does not comprise an ICE to provide power for propulsion, the battery must be charged through an external power source. Hence, the value of $U_t$ is restricted to 0 when the EV is being driven, whereas it changes to either 0 or 1 when the EV is plugged-in. The EV cannot be charged and discharged simultaneously; hence, the value of $U_{plug}$ was set such that it covered all possible values of $U_t$, which is computed as follows:

$$U_t = \begin{cases} U_t \in U_{plug} & t \in T_{plug} \\ U_t = 0 & t \in T_{drive} \end{cases} \tag{3.10}$$

where $U_{plug}$ and $T_{plug}$ are sets of indices $T$ for the period wherein the EV is plugged-in, whereas $T_{dive}$ denotes the period wherein it is being driven. The total number of time intervals $N$ is equal to the number of elements in $T_{plug}$ and $T_{dive}$, which is a predefined set $t \in T = [T_{plug}, T_{dive}]$. The state equation of the problem can be obtained by deriving the time of state variable $X_t$ presented in Equation (3.9) as follows:

$$\frac{dX_t}{dt} = \frac{I(X_t, t)}{Q_{\max}} \tag{3.11}$$

#### 3.2.3.2 Optimal Control of Plug-in Electric Vehicle Model

*(a) **Minimization of Objective Function***

To minimize charging costs, OC can be employed without affecting the daily drive profile of the owner, which can maximize their profits. Hence, the objective function of OC is defined as:

$$\text{Minimize} \int_0^N y_t(X_t, U_t, t)dt \tag{3.12}$$

$$\text{Subject to: } \dot{X}_t = \frac{I(X_t, t)}{Q_{\max}}$$

where $y_t$ denotes the charging cost which has two possible values The general equation of the cost is expressed as

$$y_t(X_t, U_t, t) = \begin{cases} y_{plug}(X_t, U_t, t) & t \in T_{plug} \\ y_{drive}(t) & t \in T_{drive} \end{cases} \quad (3.13)$$

where $y_{plug} = \eta_t.\ U_t.\ P_{max\text{-}plug}.\ C_{el(t)}.\ \Delta_t$ and $y_{\mathrm{drive(t)}} = 0$ to indicate the driving state. To simplify the simulation, the value of $\eta_t$ was assumed to be 100%. $C_{el}$ denotes the electricity price on a typical day and $\Delta_t$ denotes the time interval. In OC, the necessary optimality conditions are employed by minimizing a specific Hamiltonian function $H$:[$0,t$], which is constructed as follows:

$$H = y_t(X_t, U_t, t) + \lambda \cdot \left[\frac{dX_t}{dt}\right] \quad t \in T = [T_{plug},\ T_{drive}] \quad (3.14)$$

By replacing $dX_t/dt$ and $y_t$ with Equations (3.11) and (3.13), respectively, the Hamiltonian function can be expressed as follows:

$$H = \begin{cases} y_{plug} + \dfrac{\lambda}{Q_{\max}} \cdot \left[\dfrac{V_{oc}(X_t) - \sqrt{(V_{oc}{}^2 - 4 \cdot R_{\mathrm{int}} \cdot (\dfrac{\eta_t \cdot U_t \cdot P_{\max-plug}}{n_{cells}})}}{2 \cdot R_{\mathrm{int}}}\right] & t \in T_{plug} \\ y_{drive} + \dfrac{\lambda}{Q_{\max}} \cdot \left[\dfrac{V_{oc}(X_t) - \sqrt{(V_{oc}{}^2 - 4 \cdot R_{\mathrm{int}} \cdot (\dfrac{P_{dr}}{n_{cells}})}}{2 \cdot R_{\mathrm{int}}}\right] & t \in T_{drive} \end{cases} \quad (3.15)$$

The stationary equation $dH/dU_t$ and costate equation $dH/dX_t$ are obtained by deriving the Hamiltonian equation using $U_t$ and $X_t$, respectively. The charging or no charging control is determined based on the value of the derived Hamiltonian with respect to the control variable $U_t$, which is also called the switching function:

$$\frac{dH}{dU_t} = \eta_t \cdot \mathrm{U}_t \cdot P_{\max-plug} \cdot C_{el}(t) \cdot \Delta_t - \frac{\lambda \cdot \eta_t \cdot P_{\max-plug}}{Q_{\max} \cdot n_{cells} \cdot \sqrt{(V_{oc}{}^2 + 4R_{\mathrm{int}} \cdot \frac{\eta_t \cdot U_t \cdot P_{\max-plug}}{n_{cells}}}} \tag{3.16}$$

where $U_t$ is used as a bang–bang input control variable and is expressed as

$$U_t = \begin{cases} 1 \quad \mathrm{PEV}_{[\text{with charge}]} & \frac{dH}{dU} < 0 \\ 0 \quad \mathrm{PEV}_{[\text{with nocharge}]} & \frac{dH}{dU} > 0 \end{cases} \tag{3.17}$$

The costate λ in Equation (3.14) is set to cover all possible values and can be defined by deriving the Hamiltonian function against the state variable $X_t$ as follows:

$$\dot{\lambda} = -\frac{dH}{dX_t} = \begin{cases} \dfrac{-\lambda \cdot V_{oc}}{Q_{\max} \cdot 2R_{\mathrm{int}}} + \dfrac{\lambda \cdot V_{oc} \cdot x_t}{Q_{\max} \cdot n_{cells} \cdot \sqrt{V_{oc}{}^2 + 4R_{\mathrm{int}} \cdot [\frac{\eta_t \cdot U_t \cdot P_{\max-plug}}{n_{cells}}]}} & t \in T_{plug} \\ \dfrac{-\lambda \cdot V_{oc}}{Q_{\max} \cdot 2R_{\mathrm{int}}} + \dfrac{\lambda .\, V_{oc} \cdot X_t}{Q_{\max} \cdot n_{cells} \cdot \sqrt{V_{oc}{}^2 + 4R_{\mathrm{int}} \cdot [\frac{P_{dr}}{n_{cells}}]}} & t \in T_{drive} \end{cases} \tag{3.18}$$

*(b)* ***Optimal Control Parameters of Plug-in Electric Vehicles***

The optimization objective is to schedule a charging plan for each PEV such that the charging costs are minimized and owners can profit by selling electricity back to the grid during peak hours. This study compares the results of OC-based coordinated and smart charging with those of random (uncoordinated) strategies to illustrate the advantages of employing an optimization approach. The plugged-in time of an EV begins as the vehicle owner finishes their drive; however, the charging schedule is divided into 288 intervals of 5 min each, representing a total of 24 h. The structure of an EV battery pack is illustrated in Figure 3.4. To create a battery module, two cells are linked in series and then in parallel with another pair of cells. Thereafter, 48 battery modules are linked together in a series to create a battery pack. Table 3.1 lists the electrical characteristics of the battery pack of Nissan LEAF (Braco et al., 2020; Du et al., 2018; Nissan LEAF Electric Car, 2021).

**Table 3.1: Electrical characteristics of the Nissan LEAF battery pack**

| | |
|---|---|
| Type, Exterior dimensions of cells | Lithium-ion, 290 × 216 mm (L × W) |
| Capacity, Charging rate | 24 kWh, 6.6 kW |
| Battery cell voltage, Nominal voltage | 3.7–3.8 V, 360–400 V |
| Internal resistance of cells | 0.0025 Ω |

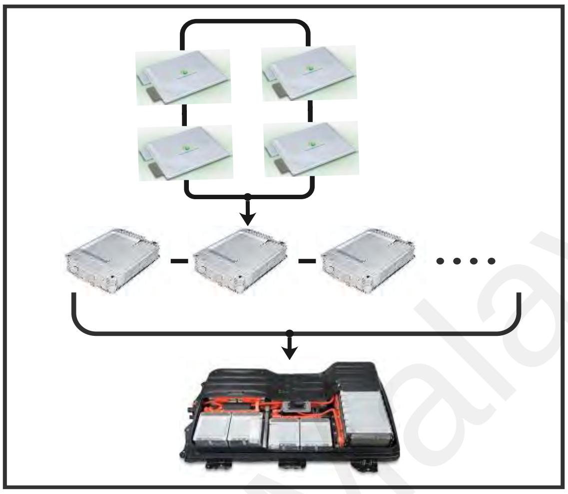

**Figure 3.4: Structure of an EV battery pack.**

Furthermore, it is crucial to understand the driving behavior of EV owners throughout the day by considering factors such as battery SOC, driving pattern, and energy requirements for each trip. 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 type, (Driving Cycle (Simulink Block), 2022) as well as a permanent magnet DC motor was considered as the electric motor (Usman et al., 2019). The specific details regarding each trip, according to the vehicle parameters, are presented in Table 3.2 (Nissan LEAF Electric Car, 2021). Another crucial component was electricity prices, which were selected based on a fixed typical workday and collected from the UK data of Nord Pool market (Nord Pool Historical Market Data, 2020).

**Table 3.2: Driving pattern for each daily trip.**

| Trips | Driving pattern used | Energy required | SOC requirement of each trip |
|---|---|---|---|
| Morning | FTP | 5.738 kWh | 23.908 % |
| Afternoon | NEDC | 2.826 kWh | 11.775 % |
| Night | UDDC | 3.975 kWh | 16.574 % |

#### 3.2.3.3 Plug-in Electric Vehicle Charging Strategies

This section introduces the three different charging strategies considered in this research: random (uncoordinated), coordinated (unidirectional), and smart (bidirectional). In random 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. Furthermore, a PEV using the random charging technique can be one of the following three states:

$$U_{\text{Random}} = \begin{cases} 1 & \text{PEV in charging state} \\ 0 & \text{PEV in idle state} \\ \text{-}1 & \text{PEV in driving state} \end{cases} \tag{3.21}$$

Figure 3.5 presents a flow chart of the processes involved in an uncoordinated charging system. During driving, the SOC of the battery decreases, whereas the vehicle remains idle (no-charging) when the SOC reaches 100%. Thus, the battery is recharged without considering the daily electricity price.

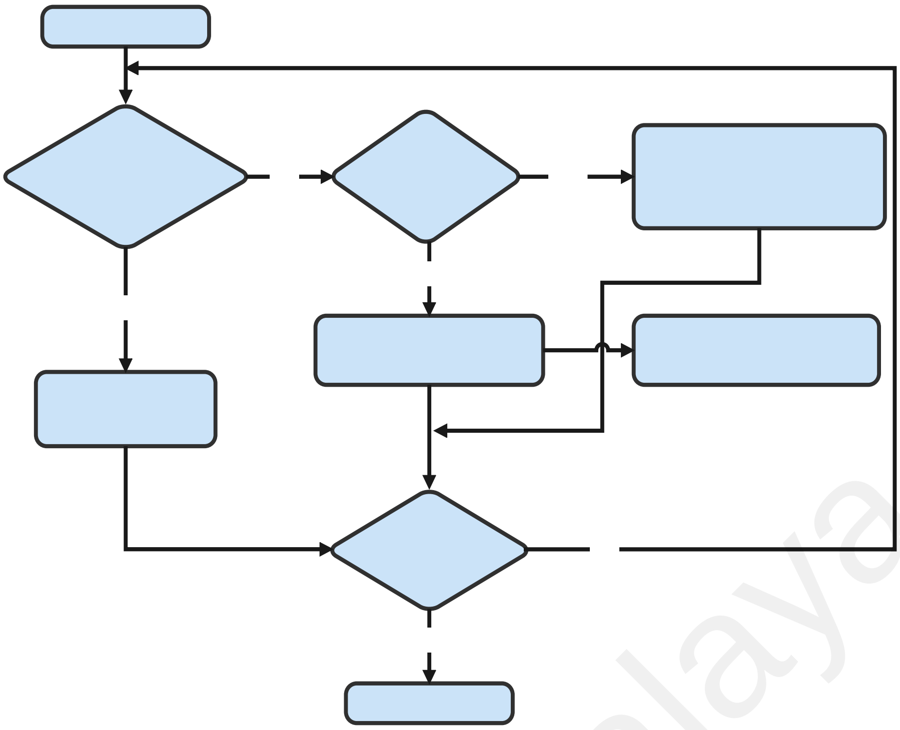

**Figure 3.5: Flow chart of a random (uncoordinated) PEV charging plan.**

In coordinated unidirectional 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. Moreover, the coordinated unidirectional charging system can be in one of the following three control states:

$$U_{\text{Coordinated}} = \begin{cases} 1 & \text{PEV in charging state} \\ 0 & \text{PEV in idle state} \\ -1 & \text{PEV in driving state} \end{cases} \tag{3.22}$$

In smart bidirectional charging, the decision to charge or discharge is based on the outcome of OC. Additionally, the decision to discharge is based on the energy required for the next trip, SOC, and electricity price. The flowchart in Figure 3.6 illustrates the charging power control, denoted by a dashed square, which represents the coordinated unidirectional charging processes. At the beginning of the day, the system checks whether the EV is being used, and if it is, the SOC decreases. However, if the EV is idle, the stationary equation dH/dU is used to determine whether the EV should be charged, based on the values obtained using Equation (3.16). If dH/dU < 0, the EV is charged; else, it remains in the idle state. If the result of the dH/dU evaluation suggests that the EV should not be charged, the coordinated unidirectional charging switches to the smart bidirectional mode. In this mode, the scheduling system charges the PEV only if certain constraints, such as the minimum SOC or energy requirement for the next trip, are violated. However, if these constraints are not violated, the PEV is allowed to discharge the excess energy back into the grid. Consequently, the optimized plan for PEV smart bidirectional charging is obtained, represented by a bold line in the flow chart illustrated in Figure 3.6. Moreover, in the smart bidirectional charging plan, the EV is in one of the following four control states:

$$U_{\text{Smart}} = \begin{cases} 1 & \text{PEV in charging state} \\ 0 & \text{PEV in idle state} \\ -1 & \text{PEV in driving state} \\ -2 & \text{PEV in discharging state} \end{cases} \tag{3.23}$$

where $U$ denotes the control input that is determined based on values obtained using Equation (3.16). Furthermore, the smart charging feature is only activated if the EV is in the idle state and the SOC exceeds the minimum threshold. For simplicity, the charging and discharging states are defined in Equation (3.23).

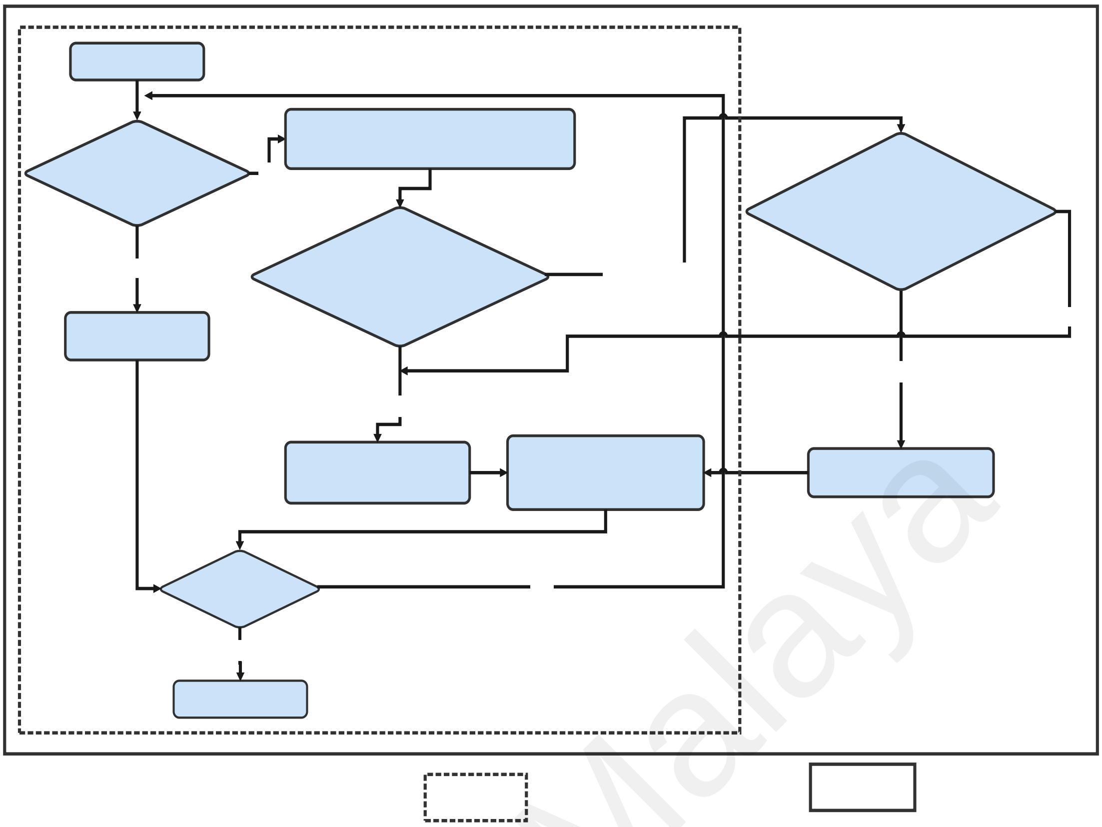

**Figure 3.6: Flowchart of the optimized, smart, and coordinated PEV charging control.**

## 3.3 Electricity Price Forecasting Using a Hybrid Regression Model

This section describes the implementations of the proposed forecasting methods to predict day-ahead electricity prices using individual and hybrid ML models, as shown in Figure 3.7. First, hourly time series data were collected from the UK data of Nord Pool spot market, which is a pan-European power exchange (Nord Pool Historical Market Data, 2020). Thereafter, the data were split into train and test sets. For training, several ML models, including single and hybrid, were applied and their performances were compared using the test set. Subsequently, the final predication model was obtained.

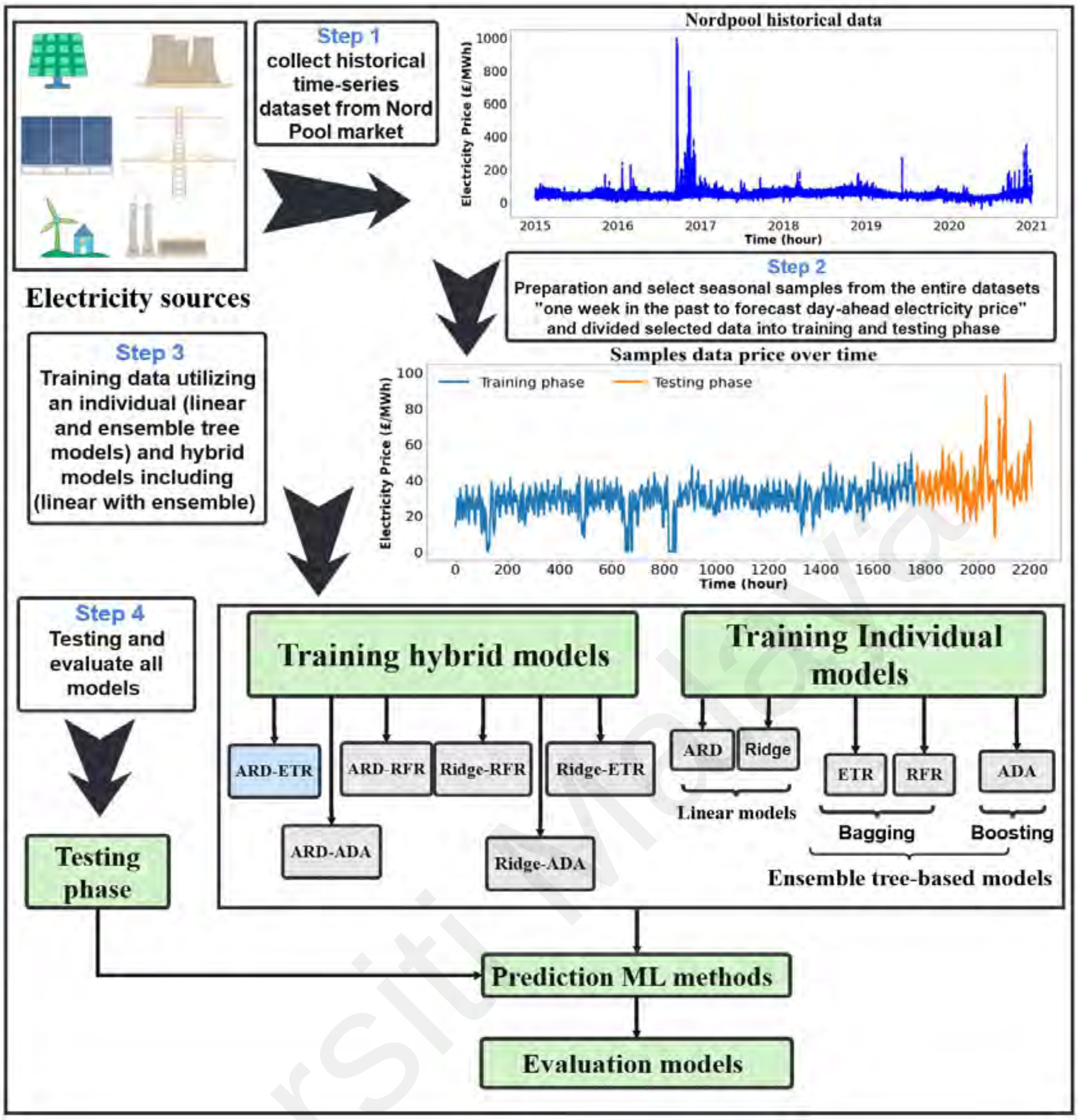


**Figure 3.7: Overall framework of the day-ahead EPF employed in this study.**

### 3.3.1 Performance Indices for Evaluating Model Effectiveness

The performance of the proposed regression model was evaluated using various criteria, as discussed by (Botchkarev, 2019). Moreover, three statistical indices were employed to evaluate EPF performance: mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE). These indices were computed as follows:

$$MAE = \tfrac{1}{N}\int_{i=1}^{N}\left|X_i - y_i\right| \tag{3.24}$$

$$MSE = \frac{1}{N}\int_{i=1}^{N}(X_i - \mathrm{y}_i)^2 \tag{3.25}$$

$$RMSE = \sqrt{\tfrac{1}{N}\int_{i=1}^{N}(X_i - \mathrm{y}_i)^2} \tag{3.26}$$

where $X_i$ denotes the actual value, $y_i$ denotes the predicted electricity price at time $i$, and $N$ is the number of testing samples. Generally, lower MSE, MAE, and RMSE scores indicate higher prediction accuracy, which occurs when the predicted value $y_i$ is close to the actual value $X_i$.

### 3.3.2 Time Series Data

A time series is a collection or sequence of observable data organized chronologically using equally spaced periods, such as days or hours. Time series analyses are primarily employed to generate suitable models for predicting future events based on known past events using an observed time series. Subsequently, these models are used for accurate time series forecasting. Furthermore, time series data can be visualized and analyzed to find the most effective component, such as a trend that elucidates the observation of downwards or upwards patterns over an extended period. Additionally, seasonal variations are regular; for example, electricity consumption is high throughout the day and low at night. The cyclical component is considered over the long-term (Mudelsee, 2019). These time series data components are illustrated in Figure 3.8. The historical time series dataset used in this study only contained the measured price information and approximately 2200 instances, collected every 1 h. The characteristics of the dataset, including periods and data preparation, are discussed in Chapter four.

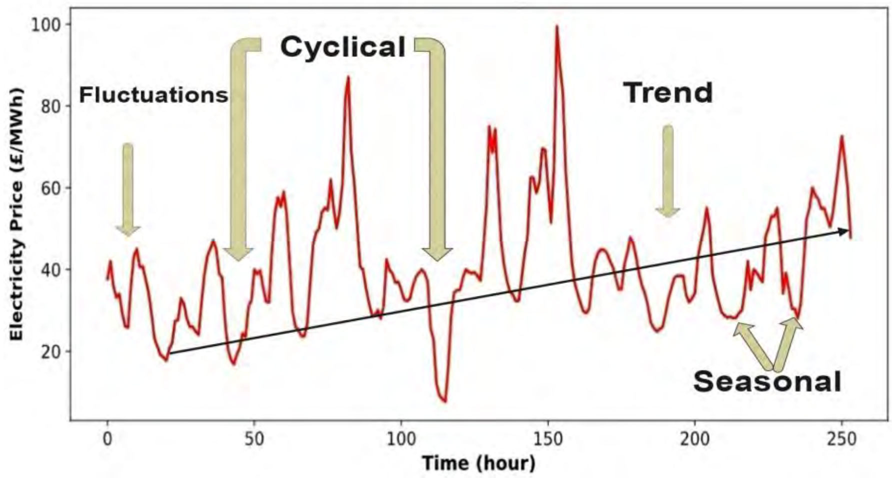


**Figure 3.8: Components of time series data.**

### 3.3.3 Proposed Hybrid Forecasting Method

ARD is a linear model that is highly comparable to Bayesian ridge regression. However, the ARD regression model outputs a sparser coefficient; it also replaces the spherical Gaussian distribution with a centered elliptic one. This means that each coefficient can be drawn from a Gaussian distribution, centered on zero. Conversely, Bayesian ridge regression has its standard deviation. ARD allows selecting relevant features, which can prevent overfitting. Thus, using the benefits of ARD, it is theoretically possible to enhance the prediction accuracy for a short-term EPF time series (Wipf & Nagarajan, 2007). The ensemble bagging method ETR is an ML technique that extends the RF algorithm and is less prone to overfitting. It employs a framework similar to RF and randomly selects features for training each base estimator. However, it also randomly selects the optimal feature and value for splitting the node. ETR trains each regression tree during the entire training set. In contrast, RF trains the model on a bootstrap replica (Geurts et al., 2006). Moreover, ETR enhances model functionality, reduces errors, and forecasts spikes by learning from interactions to generate accurate predictions. The structure of an ETR model is shown in Figure 3.9. Moreover, the ML-based linear model, ARD, and tree-based bagging model, ETR, were combined into a single model, called the ARD-ETR, for day-ahead EPF. This was done because ARD captures the general trends and seasonality, whereas the ETR improves performance by reducing errors and predicting spikes by learning from interactions to produce accurate forecasts. Hence, combining LR with the ensemble tree model, ARD-ETR, can produce more accurate forecasts and overcome the shortcomings of each model.

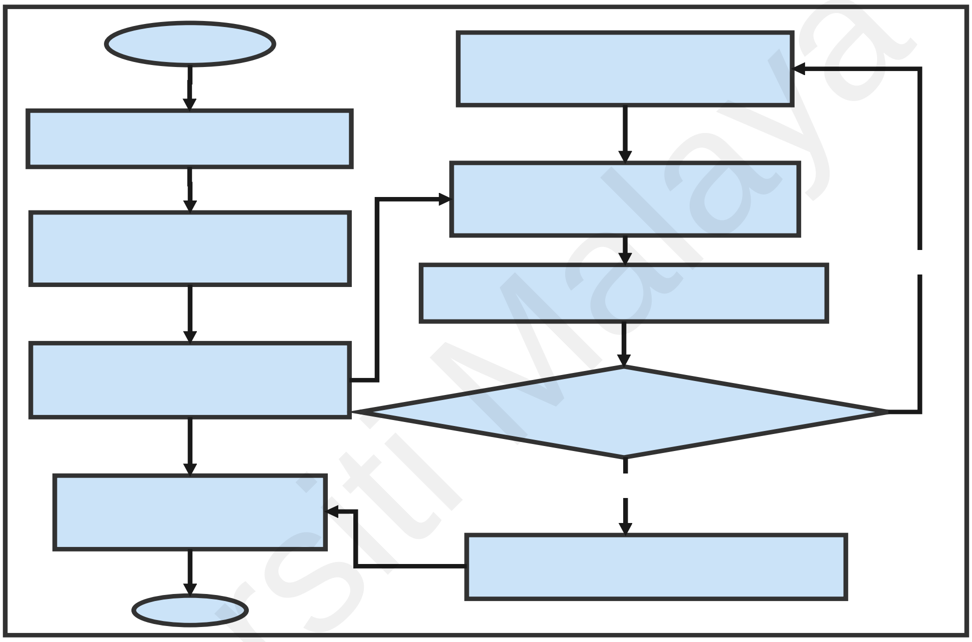

**Figure 3.9: Framework of the ETR model.**

During the training phase, the parameters of model $i$ were optimized to minimize the loss function $L_i$ as follows:

$$L_i = (X_i - y_i)^2 \tag{3.27}$$

where $X_i$ and $y_i$ denote the actual and predicted outcomes of model $i$, respectively. However, ML models are not ideal because, for instance, the value predicted by ARD deviates from the actual value $ARD_{predict} = X_i + \varepsilon_1$.Therefore, an ETR model was trained to forecast residuals $\varepsilon_1$ by reducing the loss to decrease the deviation $\varepsilon_1$. The loss is defined as follows:

$$L_2 = (ETR_{predict} - \varepsilon_1)^2 \tag{3.28}$$

where $\varepsilon_1 = ARD_{predict} - X_1$. The final EPF of the hybrid model is expressed as

$$EPF = ARD_{predict} - ETR_{predict} = (X_1 + \varepsilon_1) - (\varepsilon_1 + \varepsilon_2) = X_1 + \varepsilon_2 \tag{3.29}$$

The experimental results were in agreement with those of ensemble learning and showed that hybrid error $\varepsilon_2 < \varepsilon_1$. Hence, the challenges of time series data for EPF were eliminated owing to the robustness of these models. The proposed hybrid method is illustrated in Figure 3.10 using a comprehensive flowchart. This approach includes the following steps:

1. Samples of historical time series datasets with hourly time steps were collected from the Nord Pool spot electricity market price.
2. The values of past weeks were used to forecast day-ahead electricity prices by dividing the samples into a train: test ratio of 80:20.
3. Final EPF is predicted using the trained hybrid ARD-ETR model.
4. The hybrid model developed in Step (3) was trained. The final trained model was used to generate predictions, and its accuracy was assessed using MSE, RMSE and MAE values.

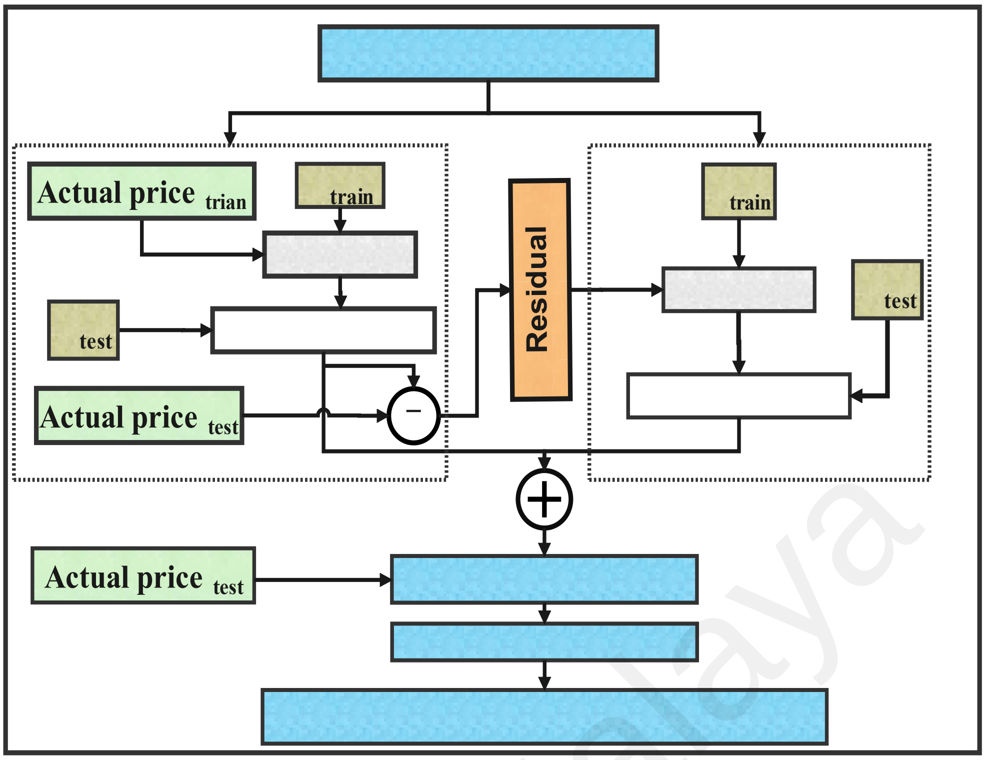


**Figure 3.10: Flowchart of the proposed hybrid approach for EPF.**

## 3.4 Smart Plug-in Electric Vehicle Charging Control Using Ensemble Machine Learning Approach with Electricity Price Forecasting

This section introduces smart and coordinated PEV charging techniques incorporating EPF to establish the most cost-effective charging schedule that benefits vehicle owners and enhances network performance. Additionally, it provides an overview of the PEV charging assumptions and approaches employed.

### 3.4.1 System Control and Assumptions

This study considered a fluctuating electricity market price, which is significant because the price is immediately given weight in the scarcity signal of electricity. A market that includes day-ahead and spot electricity prices is appropriate for employing OC charging. To provide grid support, prices of ancillary services based on capacity, rather than energy production, should also be made available. To employ these market signals, vehicle charging must be based on forecasted rather than fixed rates. As mentioned earlier, this study employed a centralized control architecture, providing automated communication infrastructure exists. In this architecture, all information is sent to a charge controller, which sends a dispatch plan for a given period to the system operator. These modules are linked through the Internet, a wireless network, or any other communication network. The other important piece of information is the driving pattern, which is assumed to be known and in reality, may be estimated based on past trip information or route planning made available by an on-board system or the vehicle owner. Additionally, in the centralized control approach, the aggregator directly manages the charging strategy for each vehicle. However, every vehicle indirectly interacts with the electricity market via this aggregator, which serves as an intelligent intermediary between the EVs and the market and coordinates the charging and discharging of numerous vehicles. By consolidating several EVs, the aggregator increases its proficiency in the electricity market, and may potentially have the opportunity to purchase electricity at lower rates and provide steady ancillary services to the grid. After gathering all information, the aggregator is fed with data to generate a PEV charging plan, as illustrated in Figure 3.11. It should be noted that certain underlying assumptions exist for centralized control, such as the aggregator is the price taker, implying that it lacks sufficient market share to impact electricity prices. Additionally, automated connection technology facilitates smart and coordinated charging by allowing instant transmission of EV-related information to the aggregator, which can then send the generated control signals back to the vehicles.

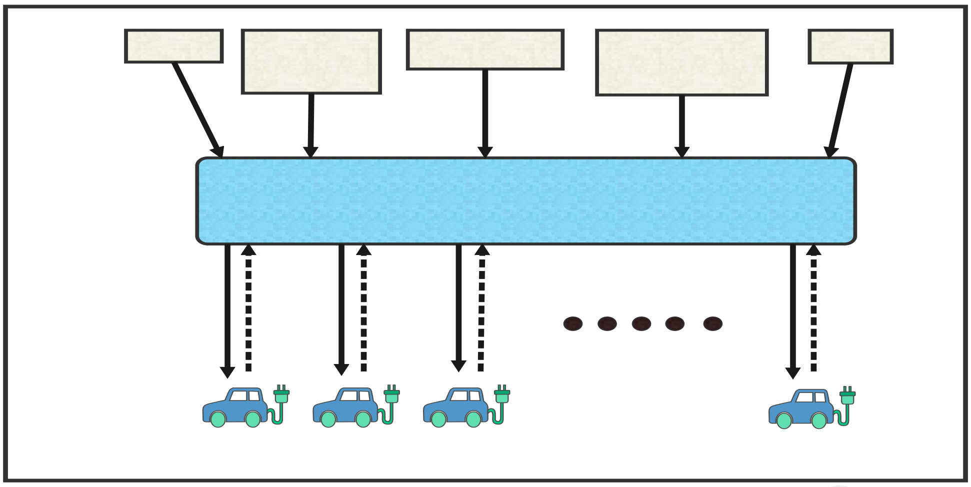

**Figure 3.11: General PEV control flow in a centralized control architecture.**

### 3.4.2 Control Task Formulation

This section presents the formulation of the PEV charging and discharging scheduling problem from the user's perspective, with an aim to minimize charging costs and meet the EV charging demand, while considering the SOC, a narrow arrival time range, and EPF. The problem formulation uses OC and ensemble ML techniques for scheduling PEV charging.

### 3.4.3 Plug-in Electric Vehicle Charging with Optimal Control

The OC theory can play a significant role in optimizing the PEV charging process by employing it to minimize the overall charging cost, thereby enhancing savings of PEV owners. In this regard, the EV battery model and OC parameters described in Section 3.2.3 were adopted, which precisely outlines the objective function and associated components. By employing OC, the PEV charging process can be strategically managed to enhance savings while ensuring efficient energy utilization, ultimately benefiting PEV owners in terms of charging costs and sustainability. The general equation of the cost function is defined as

$$y_t(X_t, U_t, t) = \begin{cases} y_{t\,[\text{Charge/discharge}]} & t \in T_{plug} \\ y_{t\,[\text{nocharge/drive}]} & t \in T_{drive} \end{cases} \tag{3.30}$$

where $y_t$ denotes the charging/discharging cost when the EV is plugged-in and no-charging/drive when EV is in the driving mode. $U_t$ denotes the generated control signal, which is defined in Equation (3.10). The control action of charging, discharging, and no-charging is based on the Hamiltonian function defined in Equations (3.15) and (3.16). However, instead of fixed electricity price, the EPF obtained using the hybrid regression model was employed using various driving patterns. It is assumed that owners depart their homes during morning hours, when the EVs are in a drivable state, and return in the evening. Based on this assumption, most owner's plug-in their EVs for charging upon arriving home. To determine the SOC of the battery during the driving state, the worldwide harmonized light vehicles test procedure (WLTP) was employed as the driving pattern (Driving Cycle (Simulink Block), 2022). A simulation and vehicle parameters were used to determine that the SOC required for the entire trip was approximately 45.4% and the energy requirement for the entire trip was approximately 10.89 kWh (Nissan LEAF Electric Car, 2021). Hence, the control signal is restricted to 0 when the EV is in the driving state, whereas it has a value of 0 or 1 when the EV is plugged into the charging point. Here, 0 denotes not charging, whereas 1 denotes either charging or discharging. Thereafter, OC verifies PEV in all possible charging plans, including smart and coordinated.

### 3.4.4 Machine Learning-based Plug-in Electric Vehicle Charging

Supervised ML classifiers, such as NN, NB, and ensemble approaches, were employed for coordinated and smart PEV charge scheduling problems using the best EPF model. To determine whether the PEV was in the charging, no charging (coordinated scenario), or charging and discharging (smart scenario) state, the arrival time of the EV was included. The best EPF models based on the time of arrival ($t_A$) to departure time ($t_D$)

were classified into high forecast zone (HFZ) and low forecast zone (LFZ) in the coordinated charging architecture, and HFZ, medium forecast zone (MFZ), and LFZ in the smart charging architecture, based on the threshold values of the battery SOC at the time of arrival. A high SOC indicates that the EV requires less time to recharge; thus, the charging region is smaller than the discharging region. Conversely, a low SOC indicates that the EV requires more time to recharge; hence, the charging region will be larger than the discharging one. The MFZ denotes hours of medium prices, which lie between the HFZ and LFZ that denote peak and off-peak price hours, respectively. A time series electricity price dataset with hourly time intervals, collected from the Nord Pool market, was used for classification. To label datasets, two and three values for coordinated and smart charging plans, respectively, were employed. Any value in coordinated charging plan more than the threshold 1 was set to 0 (HFZ), and the others were set to 1 (LFZ), while the smart charging plan comprised three values based on two thresholds, where, any value more than the threshold 1 was set to -1 (HFZ), and the others were set to 1 (LFZ) . However, any values between threshold 1 and threshold 2 were set to 0 (MFZ), and there was no charging plan for this region, as shown in Figure 3.12. Subsequently, three supervised ML algorithms (i.e., NN, NB, and ensemble) were employed to classify the charging regions based on EPF.

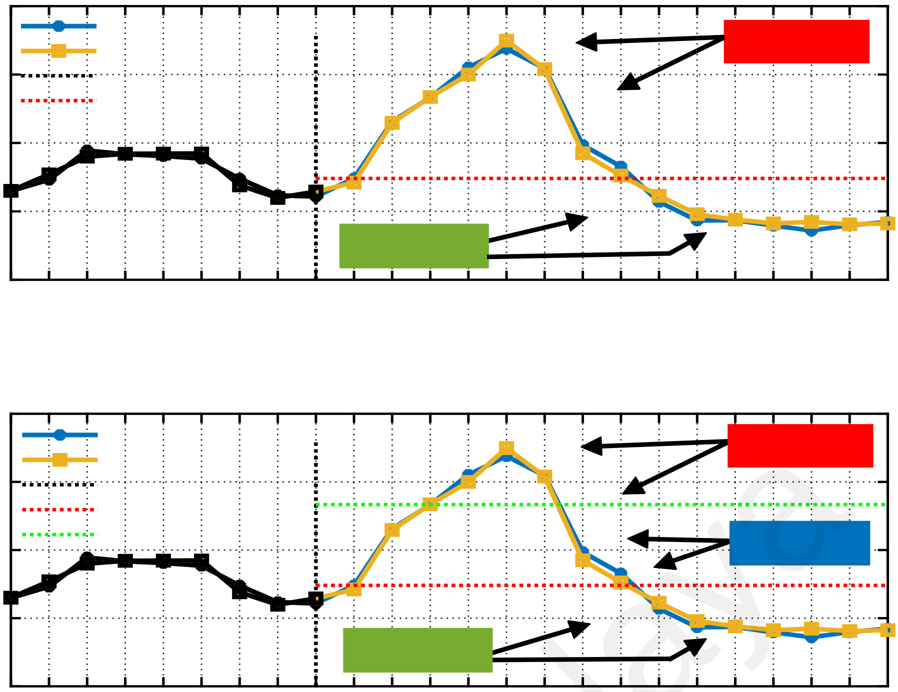

**Figure 3.12: Charging time zones for PEVs based on forecasted electricity prices: (a) coordinated and (b) smart charging.**

#### 3.4.4.1 Neural Networks

NNs are commonly used in classification and regression tasks. Consequently, numerous designs, training algorithms, and activation functions for NNs have been proposed (Alzubaidi et al., 2021). The network architecture selected in this study comprised an input layer, a single hidden layer with 100 neurons, and an output layer comprising neurons corresponding to the number of classes. A hyperbolic tangent sigmoid activation function was applied to the hidden and output layers. The NN labeling produced $[1, 0]^T$ and $[1, 0, -1]^T$ labels for the coordinated and smart charging plans, respectively. Thus, the connection weights between nodes were adjusted by employing the resilient backpropagation algorithm in the MATLAB environment. Each class in the coordinated charge strategy represents LFZ and HFZ, whereas those in the smart strategy represent LFZ, MFZ, and HFZ.

#### 3.4.4.2 Naive Bayes

The NB classifier is a probabilistic ML model based on Bayes' theorem. It is called ”*naïve*” because it makes a powerful assumption regarding feature independence. The NB classifier takes in a set of features as input for a classification problem and employs Bayes' theorem to calculate the probability that a sample belongs to each class based on the features. Thereafter, the class with the highest probability is selected as the prediction. A *fitcnb* function from the ML Toolbox in MATLAB was adopted because it allows training a multiclass classifier on a dataset and using it to make predictions for new data (MathWorks. Fit Naive Bayes Classifier, 2022).

#### 3.4.4.3 Ensemble Approach

An ensemble classifier is an ML model that combines the predictions of multiple smaller classifiers to improve accuracy. The idea behind ensemble models is that they can harness the strengths of different models to improve overall performance. This technique is often applied to enhance the performance of ML models as it can make more robust and accurate predictions than a single classifier. The statistics ML Toolbox from MATLAB was employed to create an ensemble of learners for a classification task using the “*fitcensemble*” function, which can improve the model performance by reducing overfitting and increasing its generalizability, followed by the function “*predict*” to predict the test data classification (MathWorks. Fit Ensemble Classifier, 2022). The “*fitcensemble*” function trains each classifier on a subset of the data, and the final prediction is obtained by taking the weighted average of the forecasts provided by the individual classifiers. The weights are selected such that the individual classifiers that show good performance for the training data are assigned higher weights. The main advantage of employing “*fitcensemble*” is that the model performance is improved by reducing overfitting and its generalizability is increased as each classifier is trained on a different subset, which helps minimize model variance and enhance its robustness.

Furthermore, "*RUSBoost*" was used as the ensemble classification method, wherein individual classifiers are trained using random subspace sampling, i.e., each classifier is trained on a different, randomly selected subset of predictor variables. This helps in reducing the correlation between the classifiers, which can improve the overall model performance (Seiffert et al., 2009). Algorithm 1 illustrates PEV charge scheduling through ML approaches. The inputs of Algorithm 1 are the battery SOC after driving, best EPF model, and dataset collection ($\psi$). The output is provided through trained classifiers. At Line 1, a time series dataset with hourly time steps is created. Thereafter, based on the charging plan, threshold value $\lambda_1$ is set for coordinated charging, whereas $\lambda_1$, and $\lambda_2$ are set for smart charging. The training and testing phases of all ML classifiers begin at the inner loop of Line 19, whereas the results are obtained at Line 24.

**Table 3.3: ML-based PEV Charging Schedule.**

**Algorithm 1** PEV charging scheduling through ML approaches

**Input:** SOC of the battery, arrival time, best model of EPF (ARD-ETR), and historical datasets.
**Output:** Trained classifiers.
1: Create an hourly dataset ($\psi$) using the data from the Nord Pool spot market.
2: Assign one or two threshold values ($\lambda_1, \lambda_2$) for coordinated or smart charging plans, respectively.
3: **while** $i = 1{:}\ length\ (\psi)$ **do**
4: Set charging plan (coordinated)
5: **if** Any value of $\psi > \lambda_1$ **then**
6: Assign class 1 = 0;
7: **else**
8: Assign class 2 = 1;
9: **end if**
10: Set a charging plan (smart)
11: **if** Any value of $\psi > \lambda_1$ && $\psi > \lambda_2$ **then**
12: Assign class 1 = -1;
13: **else if** $\psi < \lambda_1$ && $\psi < \lambda_2$
14: Assign class 2 = 1;
15: **else**
16: Assign class 3 = 0;
17: **end if**
18: **end while**
19: **for** (*trail =1,…10*) **do**
20: Randomly use 80% data for training and remaining 20% for testing.
21: Train the NNs, NBs, and ensemble methods using the training dataset.
22: Implement equations of matrices according to test data labels and classification outcomes.
23: **end for**
24: Determine the accuracy, precision, recall, and F-score for each ML approach.

## 3.5 Plug-in Electric Vehicle Charging Techniques and Radial Distribution System

### 3.5.1 Plug-in Electric Vehicle Charging Behavior

Various factors, including charging strategy, SOC, start time, and charging duration, influence the PEV charging process. In this context, this study examines three distinct PEV charging strategies: random (uncoordinated), coordinated (unidirectional), and smart (bidirectional). As stated earlier, random charging refers to charging without any coordination or optimization. However, if many vehicles in a specific area are plugged-in simultaneously without coordination, the electric grid can be strained, causing voltage fluctuations or power outages. This can be particularly problematic during periods of high demand, such as hot summer days or cold winter nights when the electricity grid is already under stress. Therefore, coordinated, and smart PEV charging strategies have been proposed to minimize charging costs and reduce system power losses by employing algorithms to manage the PEV charging activities and shifting some of the charging demand to off-peak hours when electricity prices are lower. Additionally, smart charging strategy allows PEVs to sell electricity back to the grid during periods of high demand when prices are higher, resulting in cost savings for both the PEV owners and the electric utility. Furthermore, the decision to charge or discharge the PEV is determined by applying OC and ensemble ML strategies, considering EPF and system constraints to ensure that the charging session is well-organized and cost-effective.

### 3.5.2 Radial Distribution System Topology

To demonstrate the impact and effectiveness of the proposed coordinated and smart charging strategies compared to the random (uncoordinated) charging strategy for various PEV PLs, a radial distribution system based on the topology of an IEEE 69-bus system, as shown in Figure 3.13, was employed (Badr et al., 2022a; Baran & Wu, 1989).

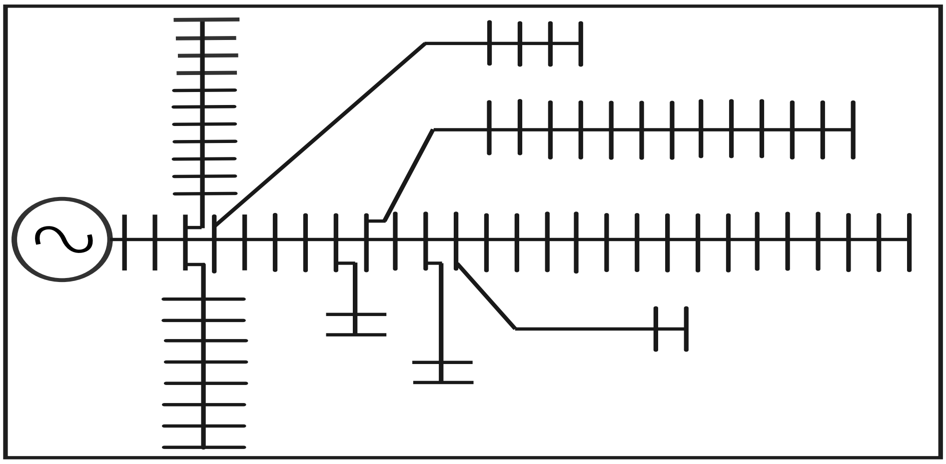

**Figure 3.13: IEEE 69-bus distribution system.**

Moreover, the challenge involves controlling PEV charging under various PLs, minimizing the overall charging expense, and examining the effects of different charging plans on the distribution grid. To assess the impact and effectiveness of the proposed PEV charging system, two case studies were conducted: one using a modified IEEE 69-bus distribution system with active and reactive powers of 456.2 kw and 323.232 kVar, respectively, and the other using an original system with 3.8 MW and 2.69 MVar, respectively (Badr et al., 2022b). The modified IEEE 69-bus distribution system aimed to replicate real-world conditions by introducing voltage drops and congestion issues that can arise owing to the integration of PEVs into the power grid, thereby providing a suitable environment for evaluating the performances of the proposed charging techniques. The second case study employed the original system without any modifications, providing a baseline to evaluate the improvements and benefits of the proposed PEV charging system. In the first case study, the modified IEEE 69-bus distribution system was structured such that each node represented a low-voltage residential feeder, which was designed to simulate power distribution to one or two households under various PEV PLs. This setup allowed analyzing the impact of PEVs on voltage drops and congestion issues at the household level. In contrast, the second case study employed the original system, wherein each feeder represented approximately ten customer households on average with different PEV PLs. By considering a larger group of customer households within each feeder, this case study provided insights into the effects of PEVs on the overall performance of the power grid, including voltage stability and power consumption. All residential feeders are supplied through main buses using 12.66 kV/ 400 V, 100 MVA distribution transformers. The residential load applied on the IEEE 69-bus distribution system was based on the residential load profile over 24 h using a one-hour time basis, collected from the Nord Pool market, as shown in Figure 3.14.

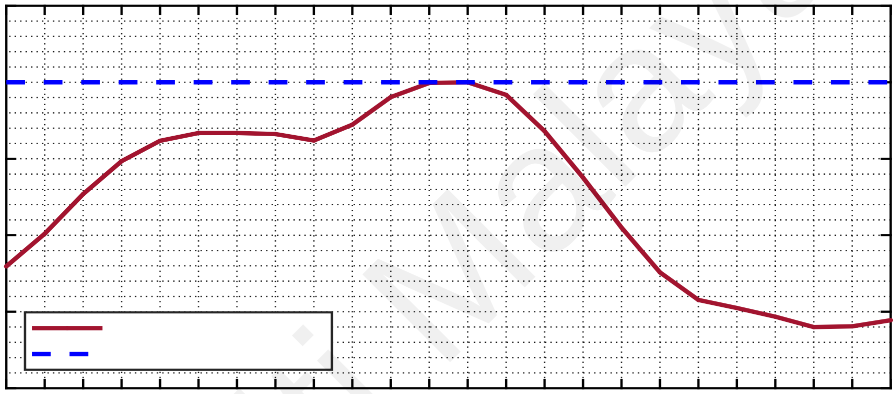

**Figure 3.14: Daily residential load curve of the radial distribution system.**

To cover a broad range of potential PEV charging scenarios, three PEV penetration levels (16%, 28%, and 41%) were simulated for each charging strategy, wherein PEVs were randomly distributed across low voltage levels. PL is defined as the ratio of PEV nodes to the total number of low-voltage residential nodes. The number of PEVs connected to the selected node for each PL in case one is illustrated in Figure 3.15. The total power loss was computed using Equation (3.31), and the voltage constraints of the distribution system were considered by setting the upper and lower limits to correspond to the typical voltage regulation limits set by utilities. The voltage limits were set to ($\pm$10 %), which is typical of most distribution systems (Badr et al., 2022a; Deilami et al., 2011).

$$\sum_{i=1}^{T=24} P_{total\ loss} = \sum_{j=1}^{N-1} P_{\Delta t,\ (j,j+1)}^{loss} \tag{3.31}$$

$$V_{\min} \leq V_{i,(\Delta t)} \leq V_{\max} \quad for\ i\ =\ 1,...N_{node} \tag{3.32}$$

where the $P_{\Delta t,\ (j,j+1)}^{loss}$ denotes the real power loss between line sections $i$ and $i + 1$. The voltage limits of $V_{i,(\Delta t)}$ denote the voltage of node $i$ at any time interval $\Delta_t$, whereas $V_{min}$ and $V_{max}$ denote the minimum and maximum voltage limits, respectively. The load flow in the modified IEEE 69-bus distribution system under nominal load, before the introduction of PEVs, was 2.804 kW and the total power loss over 24 h was 49.374 kW, with a minimum node voltage of 0.9899 PU. Furthermore, selecting 100 MVA and 12.66 kV as the base power and voltage, respectively, allowed for relative comparisons of power and voltage values across the system. By expressing power and voltage in per-unit (PU) values relative to these base values, the real power, and voltages at different buses within the system can be determined. Therefore, the base values of 100 MVA and 12.66 kV for power and voltage, respectively, were considered appropriate for analyzing the IEEE 69-bus distribution system and conducting power system calculations.

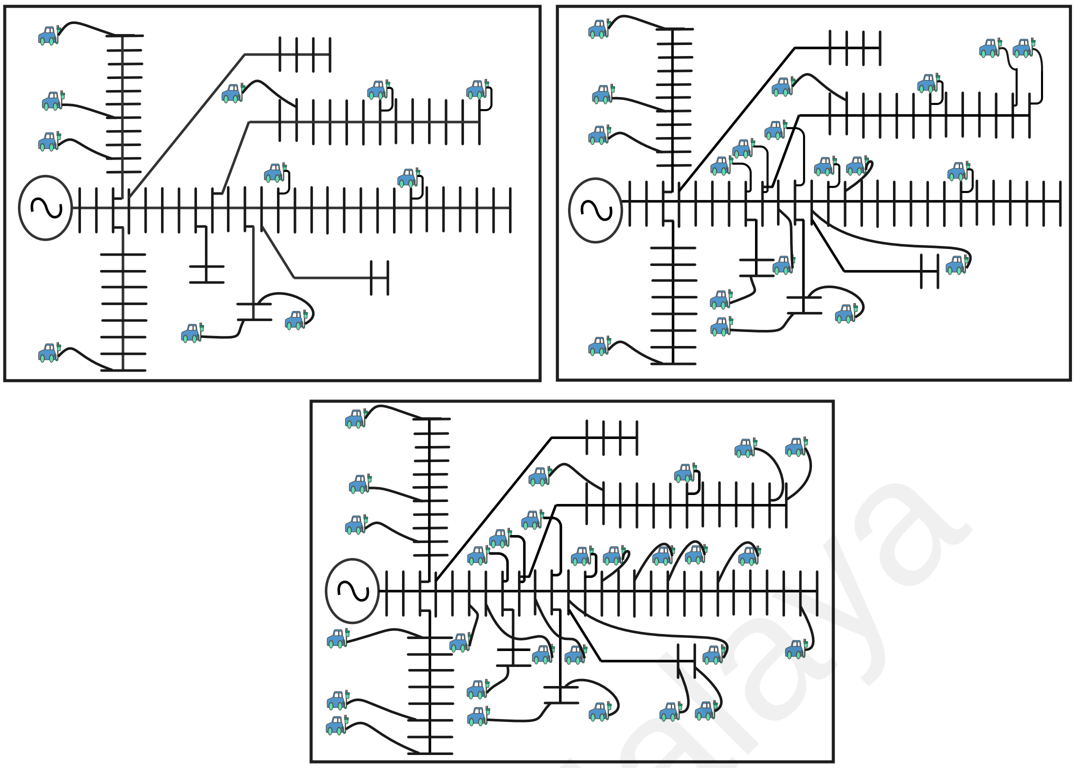

**Figure 3.15: PEV connections at the selected nodes for different PEV PLs: (a) 16%, (b) 28%, and (c) 41%.**

## 3.6 Summary

This chapter described intelligent PEV charging control by a power aggregator in detail. First, OC techniques and their applications for managing PEV charging were discussed. Thereafter, the system architecture and assumptions were presented, which laid the foundation for subsequent discussions, including centralized and decentralized framework controls, and the factors that must be considered for implementing intelligent PEV charging strategies were discussed. EV battery packs were considered for various charging plans by modeling the EV battery as an SSEC. Subsequently, the control task was formulated, emphasizing the importance of OC for establishing an efficient and coordinated PEV charging system. Next, the implementation of day-ahead EPF using both hybrid and individual ML models was discussed; these forecasting techniques are essential for optimizing the charging process.

Thereafter, the methodologies of smart and coordinated charging techniques employing OC and ML classification approaches integrated with EPF were presented. This integration can enable the development of efficient charging strategies that consider the predicted electricity prices.

Finally, it discussed various PEV charging techniques and radial distribution bus systems under different PLs, with the aim to showcase the benefits and impacts of random, coordinated, and smart charging plans on the distribution grid in terms of factors such as charging costs, power losses, and power consumption. The analytical results are collated under Chapter 4.

# CHAPTER 4: RESULTS AND DISCUSSION

## 4.1 Introduction

This chapter presents and discusses the results of the advanced modeling and simulations conducted in this study. First, the validation results for optimizing PEV charging cost through OC using a fixed electricity price with various PEV charging strategies are presented. Second, the data exploration and experimental setup of the proposed EPF method, including statistical forecast measurements of hybrid and individual models, are discussed. Third, the performance evaluation and simulation analysis of PEV charging, which incorporates ML classification and OC approaches integrated with price forecasting, are presented. Finally, the impact and effectiveness of the random and proposed charging techniques on the distribution grid for various PEV PLs are presented.

The results presented in this chapter are obtained using the methods described in Chapter 3.

## 4.2 Intelligent Plug-in Electric Vehicle Charging Using Optimal Control

This section evaluates the three different PEV charging strategies: random (uncoordinated), coordinated (unidirectional), and smart (bidirectional). Each strategy is analyzed using an OC framework with the aim of minimizing daily charging costs, and thereby benefiting vehicle owners. Additionally, the charging costs associated with each charging method are also compared.

### 4.2.1 Plug-in Electric Vehicle Charging Behavior

The charging behavior of PEVs is influenced by various factors such as the charging strategy employed, battery SOC, battery capacity, and charging duration. However, these factors become uncertain when all PEVs plugged into a charging station are considered. To better understand this variability, three distinct charging plans were considered:

random, coordinated, and smart charging. As stated previously, the random (uncoordinated) 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. Figure 4.1 illustrates the SOC of an EV battery throughout the day, divided into different regions indicating trips and charging periods, under a random charging strategy. Regions R1, R3, and R5 correspond to morning, afternoon, and night trips, respectively, and indicate EV usage. 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 fully charged and ready to be used the next day.

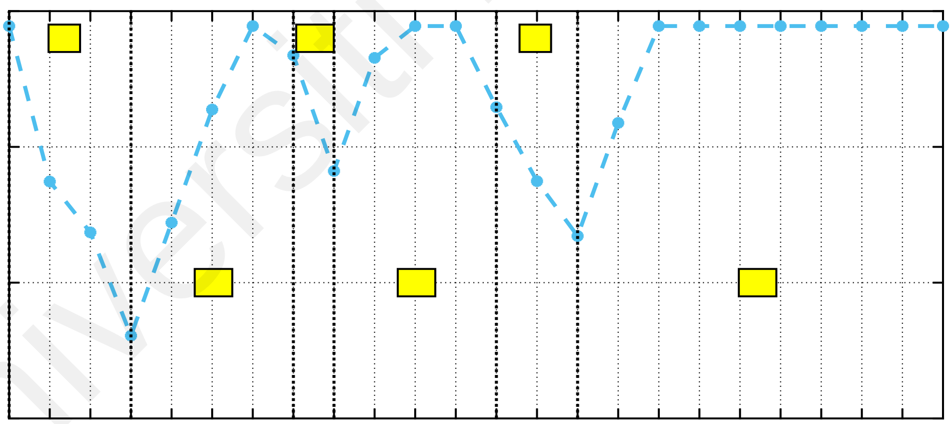

**Figure 4.1: SOC of EV for an entire day under a random (uncoordinated) charging strategy.**

Additionally, four subplots indicating electricity price, charging state, SOC with battery capacity, and charging cost are shown in Figure 4.2, which illustrate the consequences of random PEV charging. The "Electricity Price" subplot shows the daily electricity price fluctuations, whereas the "Charging State" subplot depicts the uncoordinated PEV charging instances. The "SOC" and "Battery Capacity" subplots show the SOC and battery capacity of the PEV over time, indicating periods of charging and idling, wherein the battery is fully charged. Moreover, the “Charging Cost” subplot highlights the financial impact of random charging, which does not consider electricity price variations. This uncoordinated approach results in a considerable charging cost, amounting to approximately £882, indicating the potential for cost optimization through more strategic charging plans.

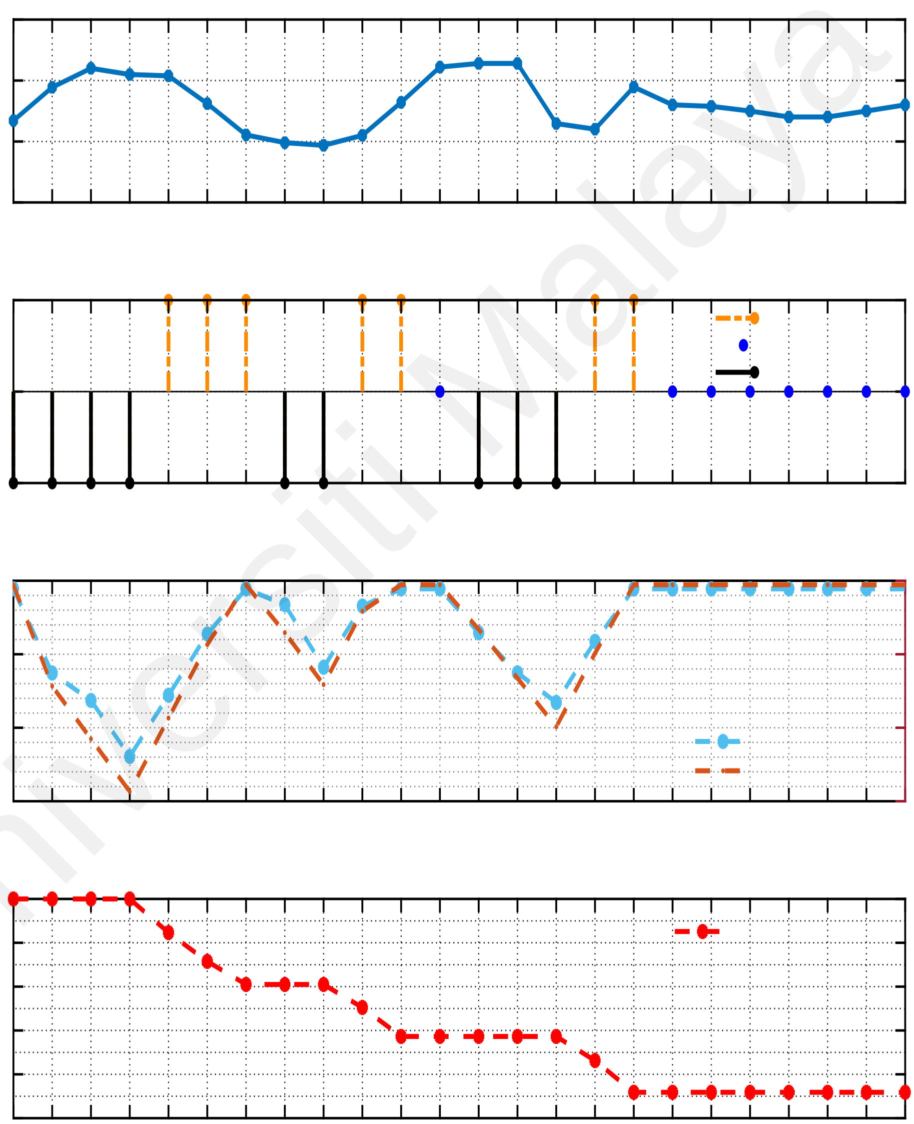

**Figure 4.2: Random (uncoordinated) charging plan profile: (a) electricity price, (b) charging state, (c) SOC (%) with battery capacity, and (d) charging cost (£).**

The coordinated (unidirectional) charging strategy employs OC, which is based on the stationary equation discussed in Chapter 3, to strategically schedule PEV charging during periods of low electricity prices. This approach significantly minimizes charging costs, thereby enhancing savings of vehicle owners. Thus, it offers substantial improvements compared to random charging and highlights the importance of strategic PEV charging coordination. Furthermore, Figure 4.3 presents a visual representation of the SOC of an EV battery over a day, considering both trips and charging periods, under the coordinated (unidirectional) charging strategy. Regions R1, R3, and R5 correspond to the morning, afternoon, and night trips respectively, indicating periods when the EV is in the driving state. Additionally, regions R2, R4, and R6 depict charging periods, wherein the EV is plugged-in and charged at strategic intervals by exploiting lower electricity prices. 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. This is followed by the night trip (R5), which again decreases the SOC; however, after the night trip concludes, the SOC increases again as charging resumes, capitalizing on periods of low electricity prices.

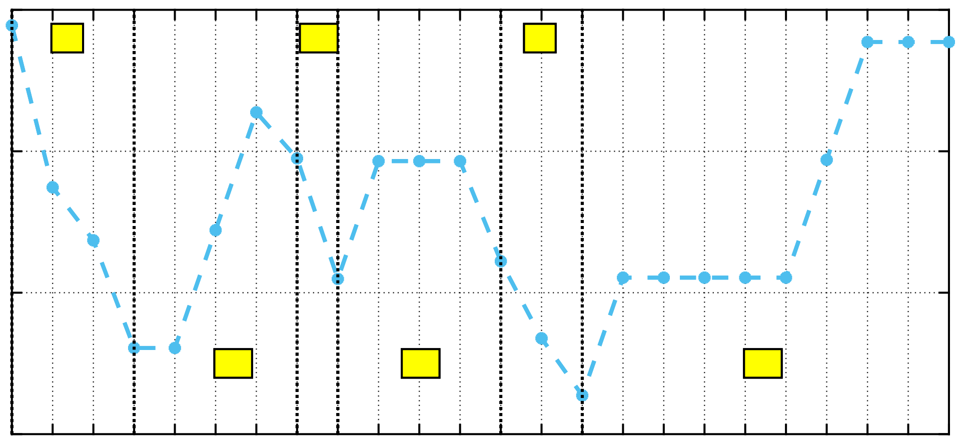

**Figure 4.3: SOC of an EV for an entire day under the coordinated (unidirectional) charging strategy.**

The planned, unidirectional coordinated charging system is illustrated in Figure 4.4. It is evident that the PEV is charged during periods of considerably low electricity prices, as indicated by the “charging state” subplot, wherein periods of PEV charging and no-charging are indicated in orange and blue, respectively, whereas periods of driving are indicated in black. This is accomplished by implementing an OC technique that accounts for electricity price fluctuations, allowing the aggregator to make data-driven decisions for each PEV by sending the control signal obtained using the OC technique to either initiate or suspend charging. To minimize charging costs, some charging demand is shifted to off-peak hours to align with periods of low electricity prices. However, it is crucial to guarantee that the battery’s SOC has sufficient capacity for the upcoming trip. In this charging plan, PEV owner’s plug-in their vehicles for charging immediately after trip completion. However, the actual charging process is postponed until off-peak hours based on the control signal received through OC. Compared to the random approach, the coordinated charging plan notably reduced charging expenses, resulting in savings of approximately £690. This number emphasizes the considerable potential for reducing PEV charging costs by employing a well-coordinated charging strategy.

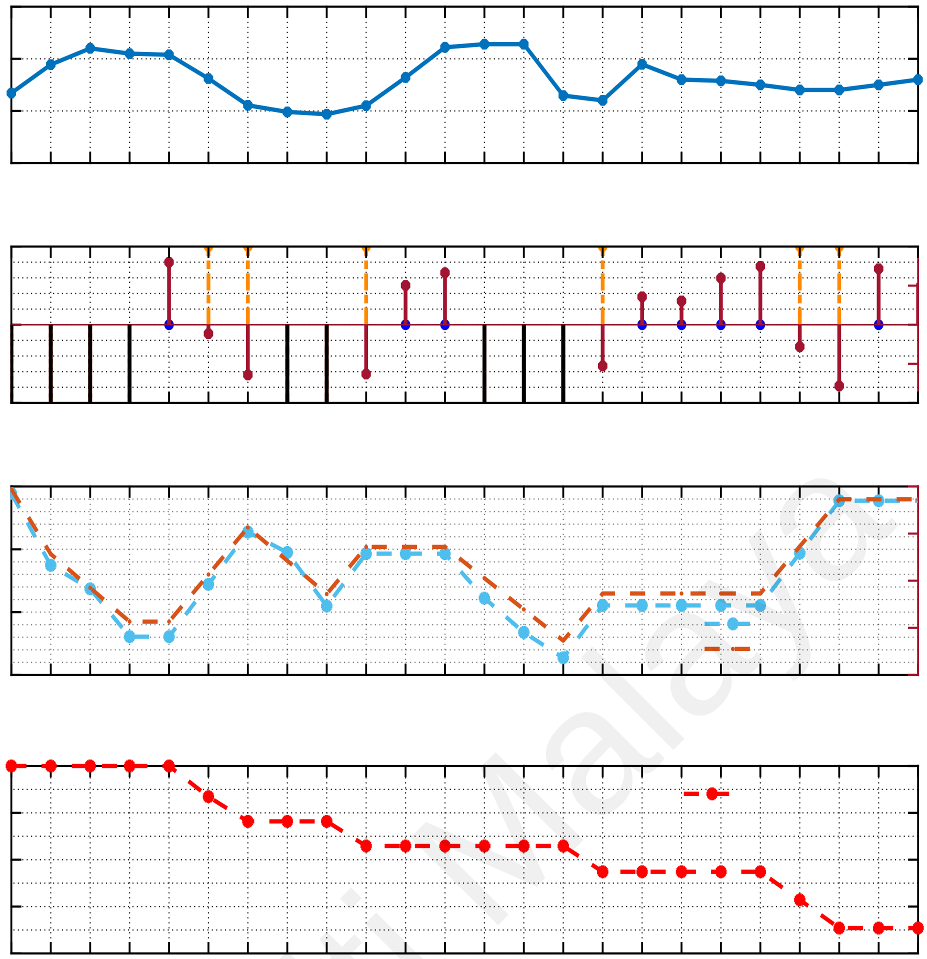

**Figure 4.4: Coordinated (unidirectional) charging plan profile: (a) electricity price, (b) charging state with dH/dU, (c) SOC (%) with battery capacity, and (d) charging cost (£).**

Smart (bidirectional) charging is an advanced V2G technology that enables two-way energy transfer between the PEV and the power grid. It not only permits charging PEVs during periods of low electricity demand, but also allows them to return excess energy from their batteries back into the grid when it is under strain or during peak price periods. This allows balancing the grid load, optimize energy usage, and potentially generate revenue for vehicle owners. The SOC of an EV battery across a 24-h period, including charging, discharging, and driving instances, is shown in Figure 4.5. It is evident that regions R1, R3, and R5 correspond to morning, afternoon, and evening trips, respectively, indicating periods of driving. Conversely, regions R2, R4, and R6 represent periods of charging and discharging. During these intervals, the EV is plugged-in and is either charging or discharging, depending on the electricity prices. This is particularly evident at the start of region R2, where the EV is discharged owing to high electricity prices, resulting in a progressive decrease of SOC. Subsequently, after the afternoon trip (R3) is completed, the PEV is charged for 1 h by capitalizing on lower electricity prices, thereby increasing the SOC. Additionally, the PEV discharges power when electricity prices are high, decreasing the battery SOC, as depicted at region R4. This is followed by the night trip (R5), which again reduces the SOC based on the trip requirements. However, after the night trip concludes, the SOC surges again as the charging process recommences to capitalize on periods of lower electricity prices. Thereafter, energy is discharged back into the grid at the midnight hour, especially when no charging activity is occurring, or the EV remains idle. However, the discharging process is restricted when the SOC reaches the minimum threshold value that indicates whether it is sufficient for the next day's trip. Consequently, despite high electricity prices, the SOC remains constant. Subsequently, the PEV recommences charging primarily during periods of low electricity prices, as indicated at region R6.

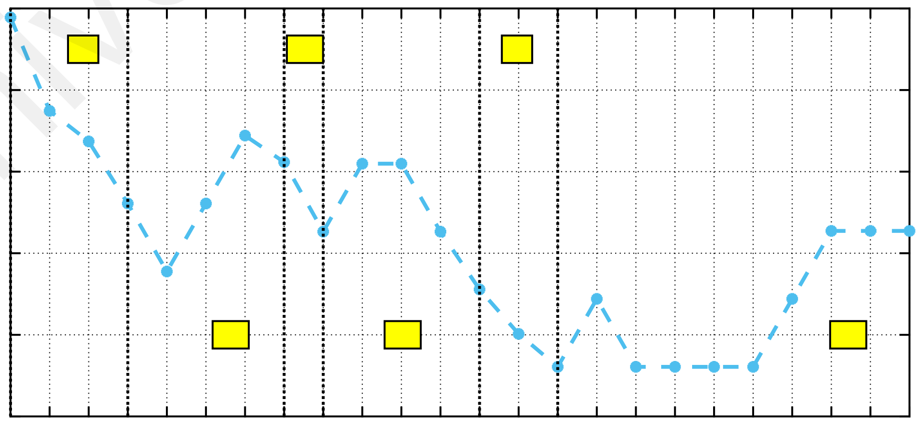

**Figure 4.5: SOC of an EV over a 24 h period under a smart (bidirectional) charging plan.**

Moreover, Figure 4.6 shows the charging states, SOC, battery capacity, and charging costs of the EV, providing insights into the implications of the smart PEV charging strategy. The “Charging State” graph represents the smart charging and discharging of the PEV, indicating intervals of charging (orange), idling (blue), and discharging (green). The “SOC” and “Battery Capacity” subplots show the changes in the SOC and battery capacity over time. Furthermore, the “Charging Cost” graph exhibits the financial implications of employing smart charging by considering electricity price fluctuations. The advantages of this intelligent approach are exemplified by the charging cost of approximately £232, which demonstrates its significant potential for reducing charging costs compared to other charging strategies, as shown in Figure 4.7. It is evident that the coordinated charging plan has a considerable advantage over random (uncoordinated) charging, with approximately 21.6% lower charging costs. However, the most significant cost reduction can be observed using the smart charging and discharging plan, which offers cost reduction of up to 73.7% compared to random charging. This remarkable cost disparity highlights the effectiveness of the smart PEV charging strategy.

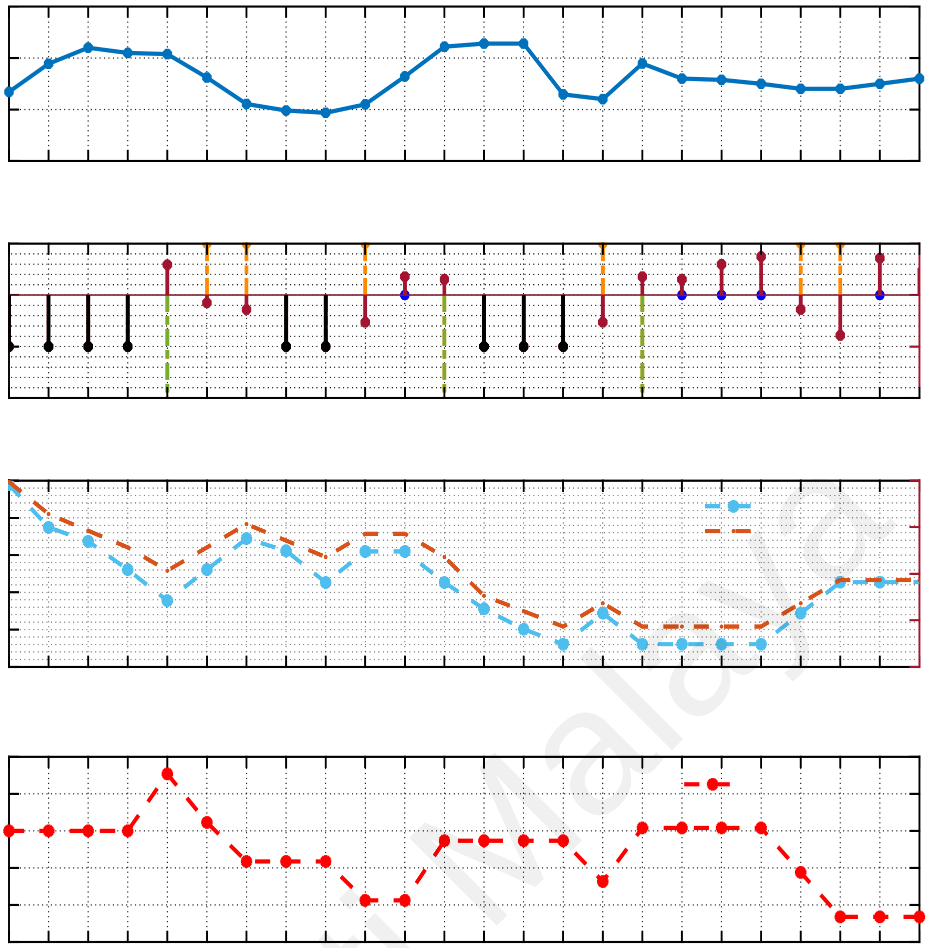

Figure 4.6: Smart (bidirectional) charging plan profile: (a) electricity price, (b) charging state with dH/dU, (c) SOC (%) with battery capacity, and (d) charging cost (£).

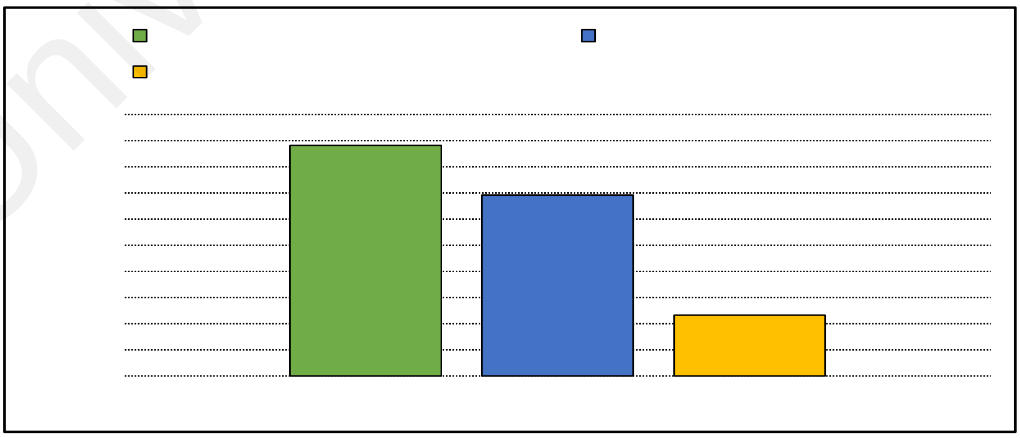

Figure 4.7: Minimum PEV charging costs under various strategies.

### 4.2.2 Comparative Studies of Plug-in Electric Vehicle Charging Cost

As illustrated in Figure 4.8, the methods proposed in this study demonstrate a notable superiority for reducing the cost of charging PEV compared to previous studies. Notably, the charging cost was reduced by up to 73%, which was considerably higher than other methods. In comparison, (Turker & Bacha, 2018) achieved a cost reduction of approximately 47%, whereas (Cao et al., 2016; Gong et al., 2020) achieved comparatively lower cost reductions of 18% and 19% respectively. This indicates that the proposed strategy can effectively optimize the PEV charging process. However, it must be validated under various conditions, such as EPF and diverse driving patterns, to confirm its widespread applicability.

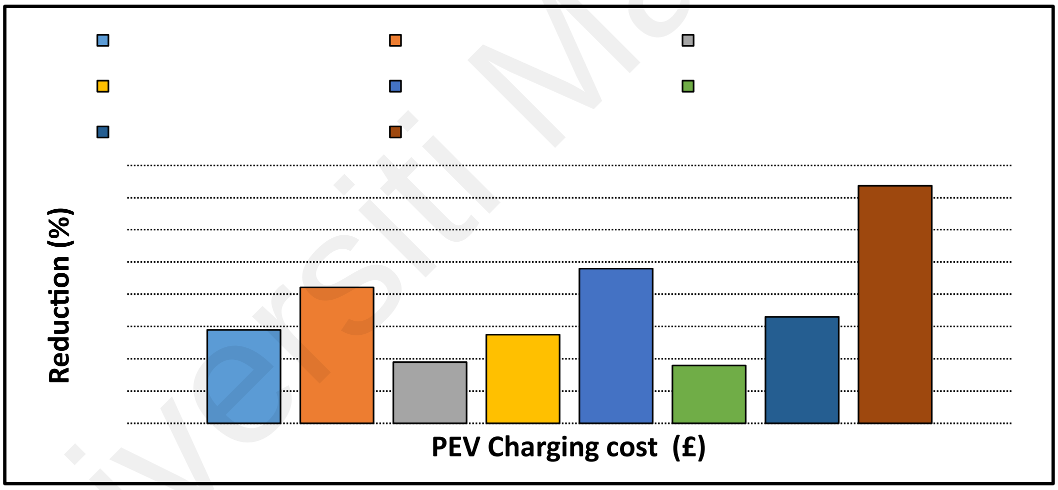


**Figure 4.8: PEV charging cost reductions achieved in various studies.**

## 4.3 Electricity Price Forecasting Using Hybrid Regression Technique

This section discusses the data preparation techniques employed and experimental results obtained in this study. Additionally, the proposed model is benchmarked against several state-of-the-art models to demonstrate its robustness. A concise comparative analysis is also included at the end.

### 4.3.1 Experimental Setup and Data Preparation

The proposed forecasting model employed a real electricity price dataset collected from the UK data of Nord Pool spot electricity market (Nord Pool Historical Market Data, 2020). Furthermore, historical time series data from 2015–2020 were included in a single CSV file with 24 h observations divided into hours. The overview of the entire dataset as a time series is presented in Figure 4.8. Moreover, the essential statistical characteristics indicate mean, maximum, minimum, and standard deviation values of 43.6502, 999, -38.8, and 18.95, respectively. As illustrated in Figure 4.9, the dataset comprised irregular price fluctuations, as well as trend and seasonality variations. Additionally, the price fluctuated significantly and exhibited random spikes. Moreover, the dataset included some negative values, which generally occur if supply exceeds demand; this usually happens in the middle of the day, when various utilities (i.e., wind, large-scale solar, and coal-fired) compete for energy dispatch. To comprehensively assess the performance, samples from different seasons were selected and used for price forecasting. Additionally, a time series dataset comprises a chronological sequence of observations recorded at regular intervals. Supervised learning takes (x) patterns as input and outputs (y) patterns; hence, the algorithm can learn how to forecast (y) using (x). Thus, a time series dataset requires reframing into supervised learning by shifting data into the past to predict future values. In this study, the past weeks' values were used for one day-ahead EPF by employing lag features, also known as time-lag or time-shifted features, which are variables derived from previous observations of a time series analysis. They involve using past values of a variable to predict or analyze its current or future behavior.

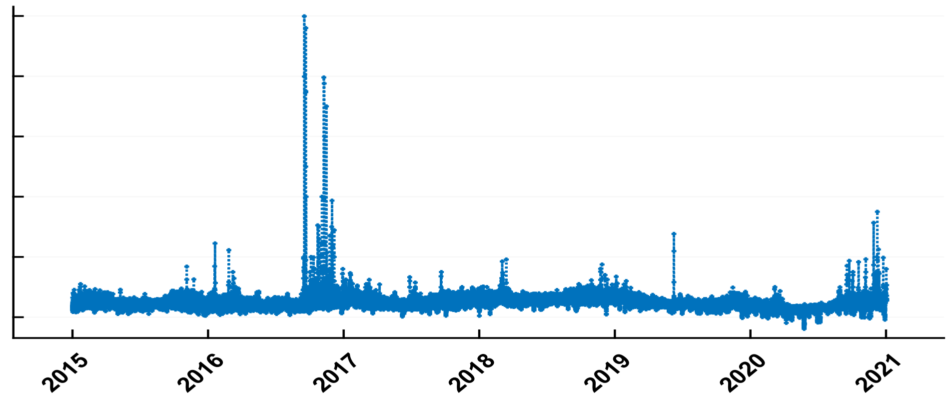


**Figure 4.9: Historical time series data from 2015–2020 collected from Nord Pool.**

The dataset was split into two subsets, 80% for training and 20% for testing, as illustrated in Figure 4.10. However, the time series data comprised irregular fluctuations over some periods, which can be attributed to either or combinations of high energy demand, supply disruptions, and global shortages of oil, gas, and coal that affect global energy prices (Albahli et al., 2020). During training, sliding window validation was employed for the time series data to fine-tune the model, wherein the algorithms were continuously trained K times (Bengio & Grandvalet, 2003). At this instance, a K value of 5 was selected, as indicated in Figure 4.10. As sequential samples in a time series are correlated, a standard train/test split that assumes the samples are independent does not make sense. Instead, sliding window validation allows testing the predictive performance at various correlated time steps, mimicking a model that is retrained as more data is collected, followed by electricity price prediction. The experiments were conducted in a Python 3.8.5 environment on a PC comprising an Intel i7-8565U CPU @1.8 GHz, 8 GB RAM and, NVIDIA GeForce MX150 GPU. Furthermore, effective day-ahead EPF can allow producers and consumers to make appropriate decisions in a market-oriented environment as it can be used to optimize electricity storage and enables demand-side flexibility to reduce consumption during peak demand periods. Finally, it can maximize economic benefits and reduce power market risks.

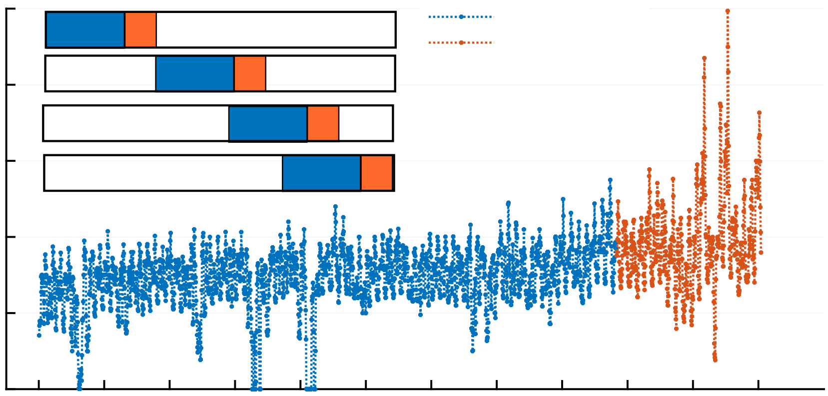

**Figure 4.10: Training and testing phases represented in a time series dataset.**

### 4.3.2 Forecasting Results

To assess the performance of the proposed hybrid ML method, the performances of various ML-based forecasting methods, including individual and hybrid models, were compared. Tables 4.1 and 4.2 list the statistical forecasting results of individual and hybrid regression models. As indicated in Table 4.1, the ensemble bagging ETR regression model exhibited the highest MAE, RMSE, and MSE scores of 2.99, 4.36, and 19.03, respectively, followed by another bagging model, RFR, which exhibited MAE, RMSE, and MSE values of 3.43, 4.94, and 24.37, respectively. Thereafter, linear models such as the ridge obtained a lower MAE of 4.06, compared to RMSE and MSE values of 6.24 and 38.95, respectively, whereas ARD obtained marginally higher MAE, RMSE, and MSE values of 4.1, 6.26, and 39.24, respectively. Additionally, ADA achieved the worst scores among all ML models. These results indicate that the forecasting performance of the LR model is better than that of the ensemble boosting method. This is because the LR model performs remarkably well for linearly separable time series datasets and manages overfitting effectively by using sliding window validation and dimensionality reduction techniques. However, the tree-based bagging models achieved better results than LR owing to their ease of implementation, ability to handle overfitting, and variation reduction by the learning algorithm, which increased their accuracies.

**Table 4.1: Statistical forecasting results of various ML-based forecasting models.**

| Model | MSE (£/MWh) | RMSE (£/MWh) | MAE (£/MWh) |
|---|---|---|---|
| RFR | 24.37 | 4.93 | 3.43 |
| ARD | 39.24 | 6.26 | 4.1 |
| Ridge | 38.95 | 6.24 | 4.06 |
| ETR | 19.03 | 4.36 | 2.99 |
| ADA | 45.67 | 6.76 | 5.16 |

Moreover, Table 4.2 lists the day-ahead EPF accuracy results of the proposed model, ARD-ETR, and other models, such as ARD-RFR, ARD-ADA, Ridge-ETR, Ridge-RFR, and Ridge- ADA, in terms of MSE, MAE, and RMSE, wherein ARD-ETR achieved the best values of 11.7, 2.03, and 3.42, respectively. This linear model with an ensemble bagging tree also obtained the best results because linear models can manage the challenges associated with time series data, such as trend and seasonality. Additionally, it generates extraordinarily linearly separable datasets and adequately handles overfitting. Moreover, the ensemble bagging model handles irregular price fluctuations over time and can effectively learn from interactions with low variance; therefore, integrating ARD with ETR produces the best EPF results, as indicated in Table 4.2.

**Table 4.2: Statistical forecasting performances of various hybrid models.**

| Model | MSE (£/MWh) | RMSE (£/MWh) | MAE (£/MWh) |
|---|---|---|---|
| ARD-RFR | 16.4 | 4.05 | 2.8 |
| Ridge-RFR | 15.8 | 3.98 | 2.4 |
| Ridge-ETR | 17.24 | 4.15 | 2.83 |
| ARD-ADA | 38.32 | 6.19 | 4.85 |
| Ridge-ADA | 37.71 | 6.14 | 4.81 |
| ARD-ETR (Proposed) | 11.7 | 3.42 | 2.03 |

The forecasting accuracies of various ML approaches and the proposed hybrid model are illustrated in Figure 4.11, wherein it is evident that the proposed hybrid method ARD-

ETR achieves significantly better MSE, RMSE, and MAE scores than ML models and other hybrid approaches. Thus, the proposed hybrid method can successfully predict electricity prices.

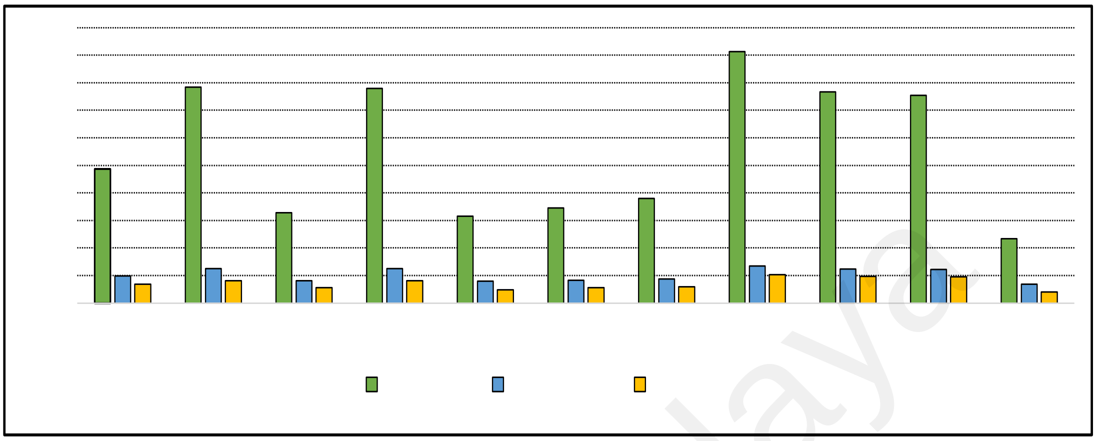

**Figure 4.11: Forecasting results of the proposed and other hybrid models.**

To elucidate the differences between the forecasting curves generated through various hybrid methods, 24 forecasted samples for different days of the forecasted data were plotted to verify the model performance. Figure 4.12 depicts the forecasting results of the individual ETR and other hybrid models. It is evident that the performance of ARD-ADA is inadequate as it cannot determine the actual electricity price, resulting in high predictions. ETR obtained better results than the hybrid ARD-RFR model as it can determine the actual price with fewer errors. However, the forecasts of the proposed hybrid ARD-ETR method are incredibly close to the actual electricity prices, which is in contrast to other ML approaches.

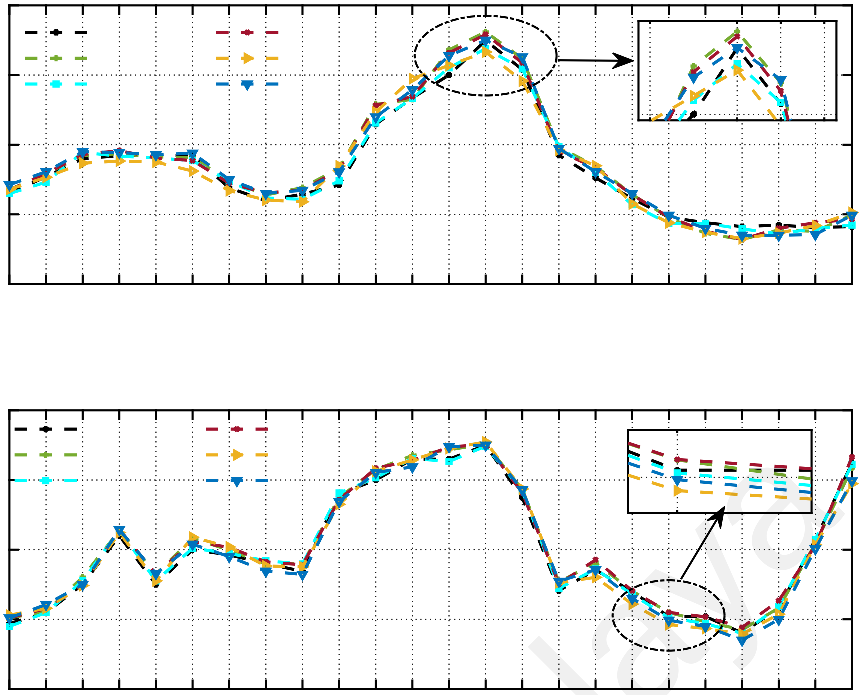

**Figure 4.12: Forecasting results of the proposed and other hybrid models: test data on (a) day 1 and (b) day 2.**

The following index was employed to evaluate the improvements of the proposed method (Zhang et al., 2020):

$$P_{index} = \frac{N_p - N_o}{N_o} \tag{4.1}$$

where $P_{index}$ denotes the assessment index, $N_o$ denotes the error value of other models, and $N_P$ denotes the residual error of the proposed model. Table 4.3 lists the results of various ML approaches, wherein the proposed hybrid model shows significant improvements. Compared to the RFR, ARD, ARD-RFR, Ridge, Ridge-RFR, ETR, Ridge-ETR,ADA, ARD-ADA, and Ridge-ADA models, the proposed method exhibited RMSE reduction of 30.62%, 45.36%, 15.55%, 45.19%, 14.07%, 21.55%, 17.59%, 49.4%, 44.74% and 44.29%, respectively, MAE reduction of 40.8%, 50.48%, 27.5%, 50%, 15.41%, 32.1%, 28.26%, 60.65%, 58.14%, and 57.79%, respectively, and MSE reduction of 51.99%, 70.18%, 28.65%, 69.96%, 25.94 %, 38.51%, 32.13%, 74.38%, 69.46%, and

68.97%. These results demonstrate that the proposed hybrid method can handle the challenges associated with time series price data. Hence, the proposed method produces more accurate EPF.

**Table 4.3: Performance comparison of various ML models with the proposed method**

| Model | $P_{RMSE}$ | $P_{MAE}$ | $P_{MSE}$ |
|---|---|---|---|
| RFR | 30.62 | 40.8 | 51.99 |
| ARD | 45.36 | 50.48 | 70.18 |
| ARD-RFR | 15.55 | 27.5 | 28.65 |
| Ridge | 45.19 | 50 | 69.96 |
| Ridge-RFR | 14.07 | 15.41 | 25.94 |
| ETR | 21.55 | 32.1 | 38.51 |
| Ridge-ETR | 17.59 | 28.26 | 32.13 |
| ADA | 49.4 | 60.65 | 74.38 |
| ARD-ADA | 44.74 | 58.14 | 69.46 |
| Ridge-ADA | 44.29 | 57.79 | 68.97 |

### 4.3.3 Comparative Analysis

Among the various techniques compared in this study, the results showed that the ARD-ETR method is the most suitable for day-ahead EPF. Moreover, empirical results indicated that the proposed hybrid strategy outperforms other methods in terms of MAE, RMSE, and MSE. Figure 4.13 illustrates the reductions in MAE and RMSE values by four hybrids algorithms, including the proposed ensemble ETR model. Additionally, the proposed hybrid approach, ARD-ETR, successfully reduced the MAE and RMSE by 32.1 and 21.5%, respectively, which was significantly higher than the other hybrid methods.

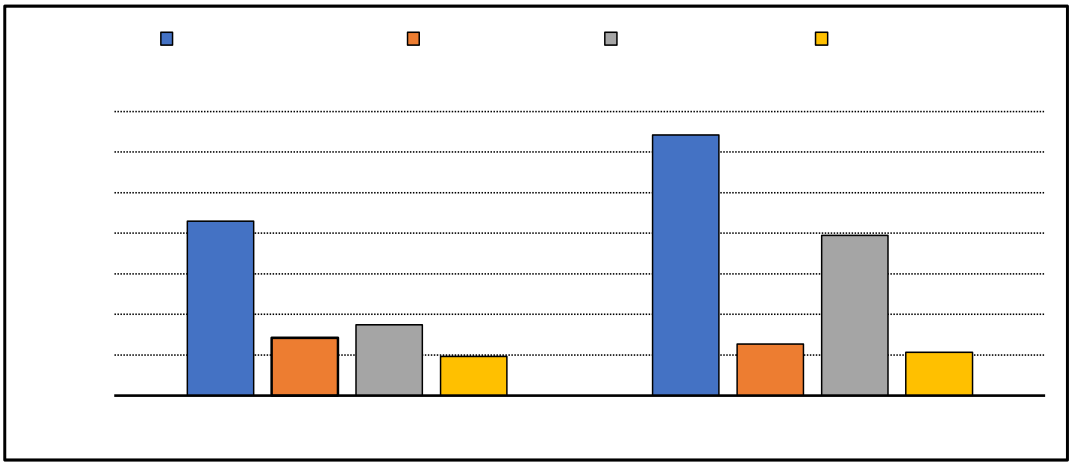

**Figure 4.13: RMSE and MAE reduction using various hybrid models, including the proposed ARD-ETR model.**

The forecasting accuracy results of the proposed hybrid ARD-ETR model and previous studies are listed in Table 4.4, wherein it is evident that the proposed model achieved the lowest MAE and RMSE of 2.03 (£/MWh) and 3.42 (£/MWh), respectively. Additionally, (Albahli et al., 2020) applied the XGboost model on an Ontario electricity market dataset collected between November and December, and achieved and RMSE and MAE of 9.25 (£/MWh) and 3.74 (£/MWh), respectively. In contrast, the EPNet method (Kuo & Huang, 2018) attained and MAE and RMSE of 8.84 (£/MWh) and 14.2 (£/MWh), respectively. In addition, (Zhang et al., 2022) employed BDLSTM on a Nord Pool market dataset and achieved an RMSE of 34.99 (£/MWh) and MAE of 22.186 (£/MWh), were significantly worse than those achieved by the proposed ARD-ETR model. Additionally, the proposed model was slightly superior to that proposed by (Zhang et al., 2020), exhibiting better results with lower testing error values for EPF compared to other approaches.

**Table 4.4: Forecasting results of the proposed hybrid ARD-ETR and previously proposed models.**

| Authors | Forecasting Techniques | Testing Matrices (£/MWh) | Dataset Used |
|---|---|---|---|
| This study | ARD-ETR | RMSE: 3.42 MAE: 2.03 | Nord Pool market |
| (Albahli et al., 2020) | XGboost | RMSE: 9.25 MAE: 3.74 | Ontario |
| (Pavićević & Popović, 2022) | Dense-LSTM | RMSE: N/A MAE: 14.438 | HUPX market |
| (Zhang et al., 2022) | BDLSTM | RMSE: 34.99 MAE: 22.186 | Nord Pool |
| (Abedinia et al., 2016) | FS | RMSE: 18.9 MAE: 4.09 | PJM, Spanish, New York |
| (Ugurlu et al., 2018) | GRU-LSTM | RMSE: 11.99 MAE: 5.71 | Turkish |
| (Wang et al., 2017) | SVM-KPCA | RMSE: 10.21 MAE: 18.97 | ISO, New England |
| (Kuo & Huang, 2018) | EPNet | RMSE: 14.2 MAE: 8.84 | PJM |
| (Zhang et al., 2020) | VMD-DBN | RMSE: 3.28 MAE: 2.07 | Australia, PJM, Spanish |
| (Zhang et al., 2022) | SSA-DELM | RMSE: 4.7 MAE: 3.8 | Nordic market |
| (Sun et al., 2021) | SDR-MASES-SPSDAE | RMSE: 4.12 MAE: 11.76 | Australia |

## 4.4 Coordinated and Smart PEV Charging Techniques Using Machine Learning and Optimal Control with Electricity Price Forecasting

This section evaluates the proposed PEV charging techniques and demonstrates their effectiveness through a simulation analysis. Additionally, it discusses the generation of datasets and experimental results obtained using the random, coordinated unidirectional, and smart bidirectional PEV charging strategies, and their impacts on the distribution grid. Furthermore, all experiments included in this section were executed in MATLAB 2020a on a PC with an Intel Core i7-8565U@1.8 GHz CPU, 8 GB RAM, and NVIDIA GeForce MX150 GPU.

### 4.4.1 Data Collection and Experimental Setup

The performance of the ML classification approaches was evaluated using a dataset composed of an hourly time series of electricity prices across two years, 2020 and 2021, collected from the Nord Pool market. However, datasets used for classification tasks must be labeled (classes); thus, two and three classes were adopted based on the number of threshold values and charging plan employed (coordinated or smart). The commuting behavior from WLTP was employed in this study, wherein the EV customer arrives home in the evening. In this regard, most PEV owners tend to plug-in their vehicles for charging when they return home from work. Therefore, a uniformly distributed probability density function (PDF) with a narrow range around 5:00 PM was considered to be close to the actual conditions. Hence, the charging session was set to commence at 5:00 PM for all charging plans. The Nissan LEAF model with the maximum battery capacity of 24 kWh was employed for the experiments. Various ML classifiers were used to generate optimal charging and discharging schedules, and their performances were evaluated using four performance metrics: accuracy, precision, recall, and F-score. Additionally, a confusion matrix was employed to evaluate the outputs using true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values. These performance metrics were computed as follows (Alzubaidi et al., 2021):

$$Accuracy = \left( \frac{\sum TP + \sum TN}{\sum TP + \sum FP + \sum TN + \sum FN} \right) \times 100\% \tag{4.2}$$

$$Precision = \left( \frac{\sum TP}{\sum TP + \sum FP} \right) \times 100\% \tag{4.3}$$

$$Recall = \left( \frac{\sum TP}{\sum TP + \sum FN} \right) \times 100\% \tag{4.4}$$

$$F\_score = \left( \frac{Recall \times Precision}{Recall + Precision} \times 2 \right) \times 100\% \tag{4.5}$$

The ensemble model was employed for both charging strategies, and it showed significantly improved prediction accuracy compared to other models. For comparison, we selected three distinct ML models (NN, NB, and ensemble) that are widely employed and have proven history of efficiency and accuracy owing to their individual strengths, including simplicity and efficiency with robustness through model diversity, and error reduction capabilities. The performance results of the three ML classifiers for both the coordinated and the smart charging strategies are presented in Table 4.5. It is evident that the ensemble approach performed best for both charging strategies, achieving accuracy, precision, recall, and F-scores of 98.3%, 100%, 92.2%, and 95.9%, respectively, for the coordinated charging strategy, and 99.5%, 98.5%, 100%, and 99.2%, respectively, for the smart charging strategy. This is because the ensemble approach combines the predictions of multiple smaller classifiers to improve accuracy.

**Table 4.5: Performances of the three ML classification approaches employed.**

| Classification approach | Coordinated charging strategy | | | | Smart charging strategy | | | |
|---|---|---|---|---|---|---|---|---|
| | Accuracy (%) | Precision (%) | Recall (%) | F-score (%) | Accuracy (%) | Precision (%) | Recall (%) | F-score (%) |
| NB | 89.338 | 76.827 | 90.91 | 84.917 | 97.78 | 97.121 | 95.815 | 96.463 |
| NN | 94.277 | 100 | 81.9 | 90.006 | 87.951 | 72.417 | 100 | 83.9 |
| Ensemble | 98.324 | 100 | 92.28 | 95.98 | 99.544 | 98.579 | 100 | 99.284 |

### 4.4.2 Plug-in Electric Vehicle Random Charging Base Case

In the random charging strategy, the PEV owner's plug-in their vehicles immediately upon arriving home. Thus, the batteries recharge as quickly as possible without considering electricity price fluctuations, as illustrated in Figure 4.14, ensuring that the EV is fully charged by morning. Hence, the SOC of the EV decreases until the trip ends, and no charging action occurs during this period. However, after the trip ends, the EV begins charging instantaneously despite high electricity prices, resulting in high PEV charging costs, which were estimated to be £280. As depicted in Figure 4.14, the SOC of the battery becomes full at approximately 10:00 PM and remains consistent thereafter in preparation for the next trip. Additionally, the random charging strategy allows owners to recharge their vehicles without considering system constraints. Thus, the distribution system faces increased risks, such as substantial power losses and unacceptable voltage deviations. The effects of this charging strategy are illustrated in Figures. 4.15, 4.16, and 4.17.

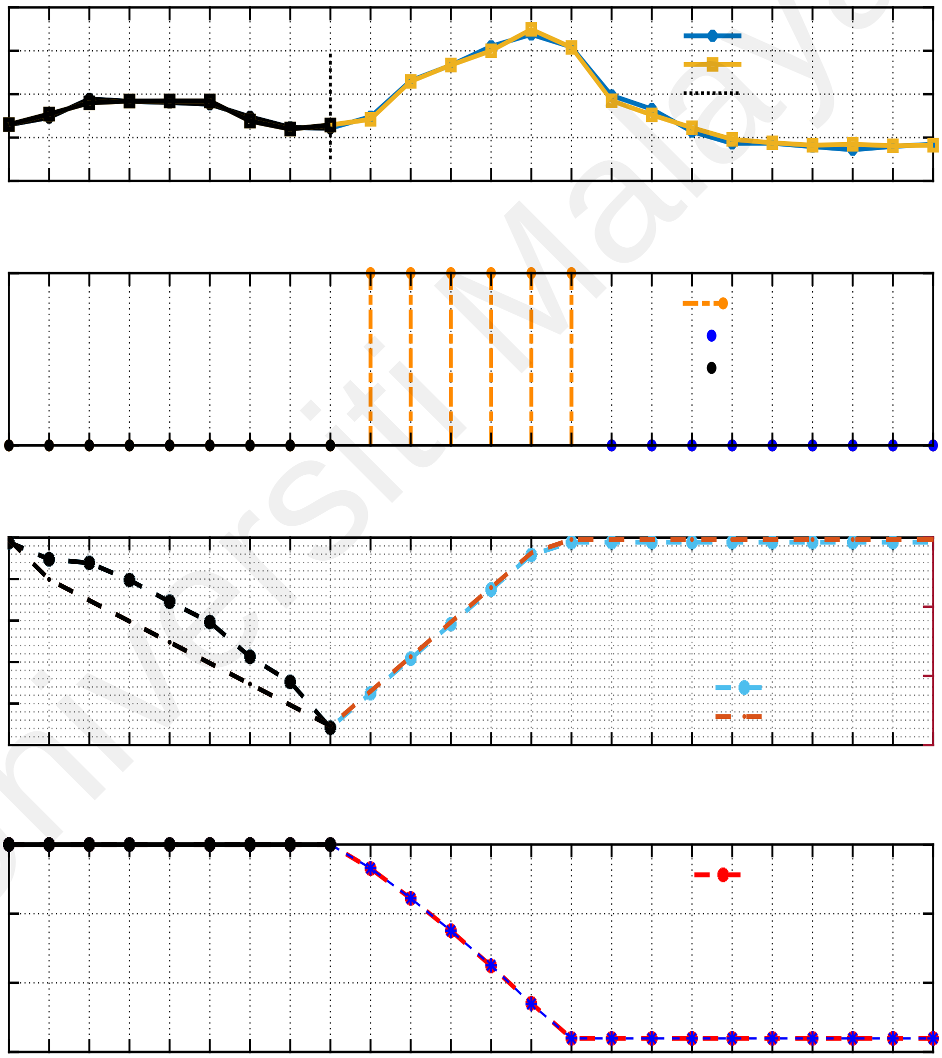

**Figure 4.14: Effects of the random (uncoordinated) PEV charging strategy: (a) EPF, (b) charging state, (c) SOC (%) with battery capacity, and (d) charging cost (£).**

The purple line in Figure 4.15 represents the typical electricity demand profile without the integration of PEVs. The blue, red, and yellow lines represent the additional electricity demand resulting from random PEV charging for PEV PLs of 41%, 28%, and 16%, respectively. Evidently, as multiple PEVs begin charging simultaneously, there are sudden and unpredictable spikes in electricity demand. These spikes can impart a significant amount of stress on the grid, particularly during peak demand hours, resulting in increased electricity prices and power outages. Moreover, high percentages system losses were observed under different PLs and the voltage constraints at the worst node were violated, as illustrated in Figures 4.16 and 4.17.

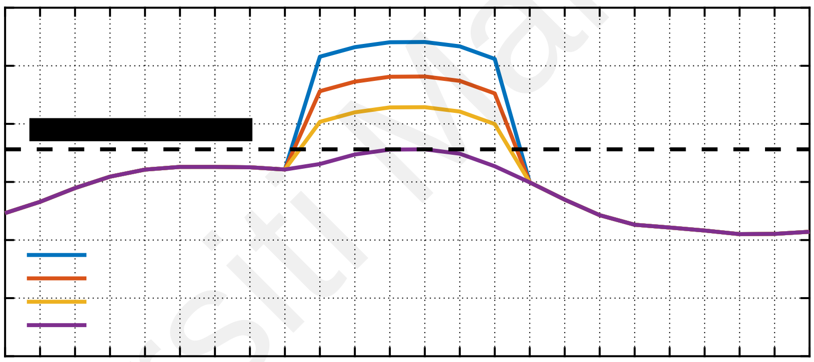

**Figure 4.15: Impact of random (uncoordinated) PEV charging on system demand.**

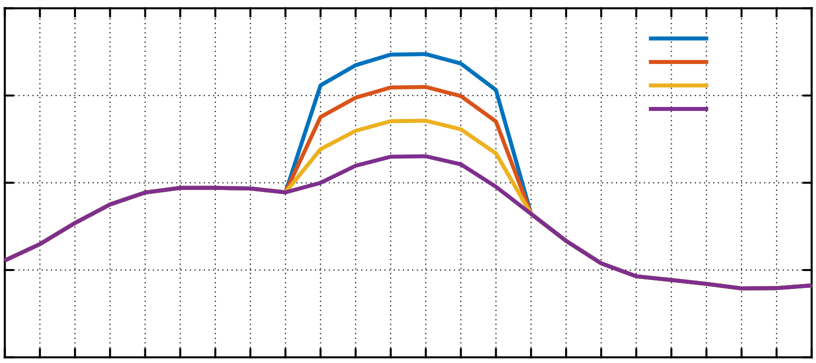

**Figure 4.16: Impact of random (uncoordinated) PEV charging on system power losses.**

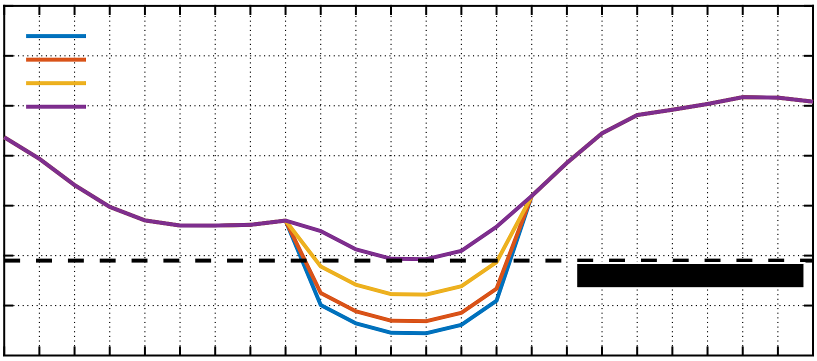

**Figure 4.17: Impact of random (uncoordinated) PEV charging on voltage profile.**

### 4.4.3 Coordinated Plug-in Electric Vehicle Charging

This section discusses the coordinated PEV charging strategy that aims to minimize charging costs and prevent grid overloads. This was achieved by employing OC and ensemble ML techniques with EPF, which allow the aggregator to make informed decisions for each PEV by sending a control signal, which is obtained through the OC and ensemble approach, that instructs it to charge or not. Thus, it shifts some charging demand to off-peak hours when electricity prices are lower and the grid is less likely to be overloaded. In this charging strategy, PEV owner's plug-in their vehicles as soon as they return home; however, charging is delayed until off-peak hours based on the control signal obtained from the aggregator. Furthermore, the control signal in the coordinated PEV charging strategy with OC is adjusted based on the control input and stationary equations provided in Chapter 3. As illustrated in Figure 4.18, the PEVs are charged when electricity prices are comparatively lower. The charging control obtained using the OC method manages all possible values for charging and not charging throughout the charging session, considering period of peak and off-peak electricity prices.

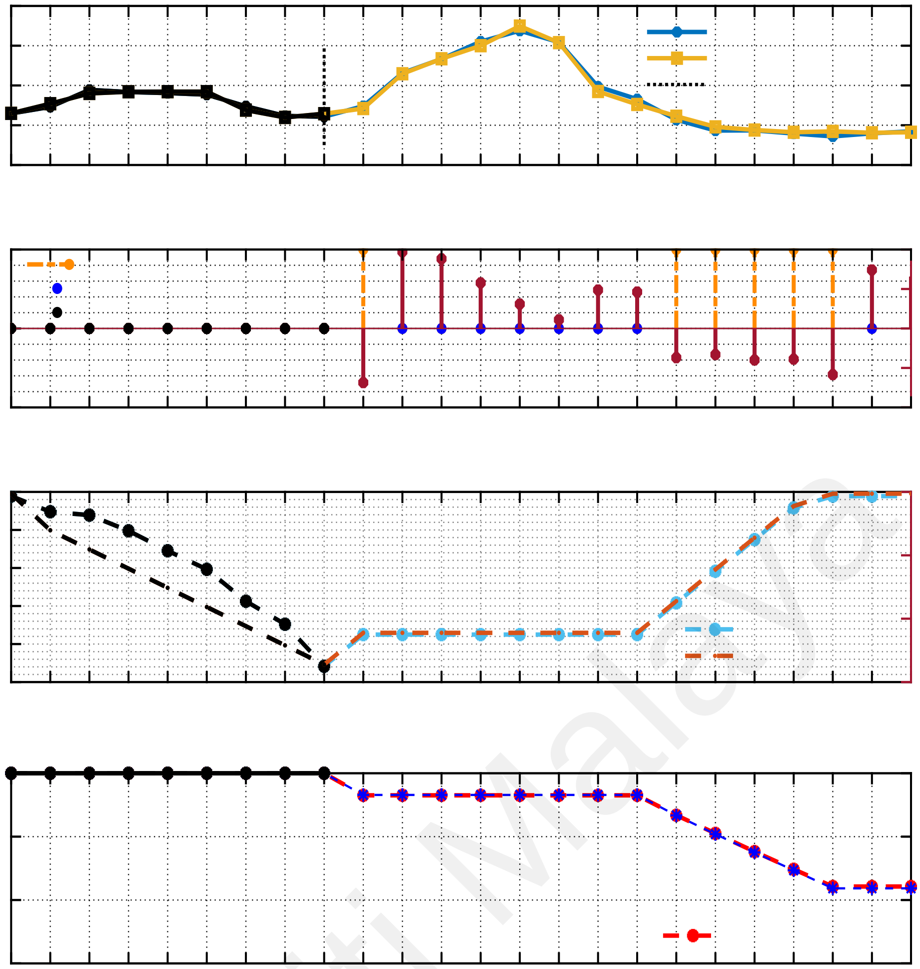

**Figure 4.18: Coordinated PEV charging strategy with OC: (a) EPF, (b) charging state with dH/dU, (c) SOC (%) with battery capacity, and (d) charging cost (£).**

Figure 4.18 shows that the SOC decreases during the day, and upon reaching home, the PEV owner plugs the vehicle into the charging point. The charging session begins as soon as the PEV is plugged-in, as illustrated in the charging state graph, wherein the orange color bars indicate that the EV is in charging mode, whereas the blue indicates periods of no charging. It is evident that the EV initially charges for only 1 h and then stops charging owing to the start of peak hours, resulting in a constant SOC during this period. Thereafter, charging resumes when electricity prices reduce, resulting in a total charging cost of approximately £182. After conducting a simulation study of random PEV charging, the proposed optimal coordinated PEV charging strategy was implemented using PLs of 41%, 28%, and 16% to examine its effects on system load, power loss, and voltage deviation, which are depicted in Figures 4.19, 4.20, and 4.21, respectively. As shown in Figure 4.19, coordinated PEV charging can help manage peak demand on the electric grid at several PEV PLs by charging the PEVs during low demand periods. Additionally, as evident from Figures 4.20 and 4.21, the coordinated charging strategy significantly reduces the total system losses and voltage drops compared to the random charging strategy for various PEV PLs.

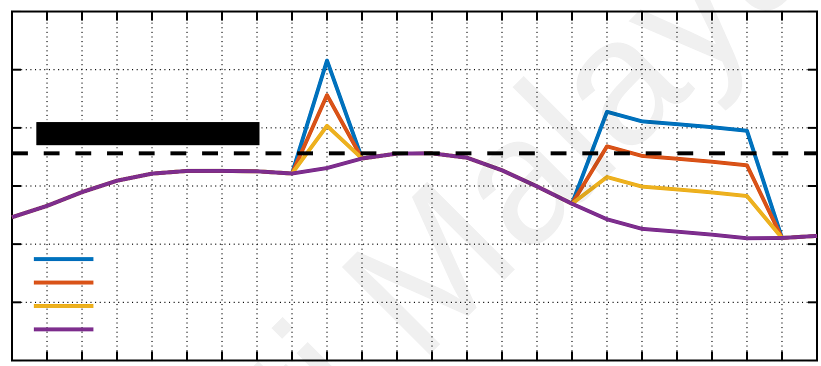

**Figure 4.19: Impact of coordinated PEV charging using OC on system demand.**

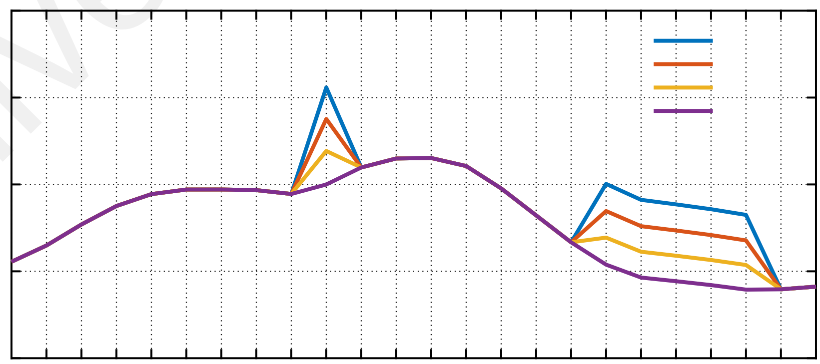

**Figure 4.20: Impact of coordinated PEV charging using OC on system loss.**

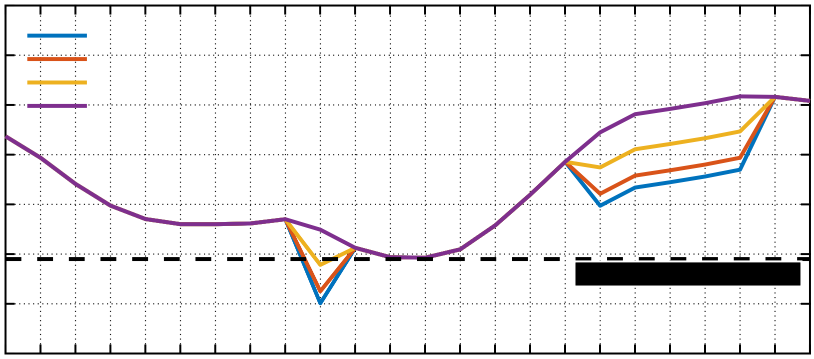

**Figure 4.21: Impact of coordinated PEV charging using OC on voltage profile.**

Additionally, the control signal obtained using the proposed ML approach is based on employing an ensemble classifier, which divides charging times into low and high charging zones, as explained in Chapter 3. Additionally, the coordinated PEV charging strategy with the ensemble approach is illustrated in Figure 4.22.

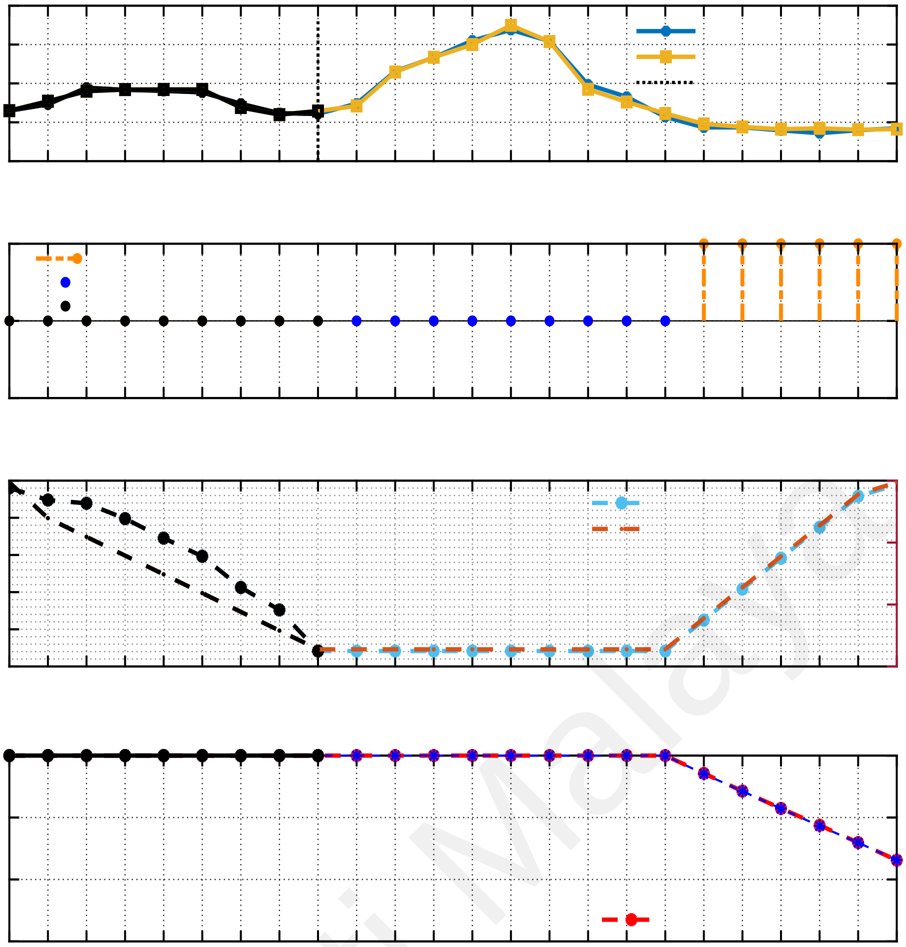

**Figure 4.22: Coordinated PEV charging plan using an ensemble approach: (a) EPF, (b) charging state, (c) SOC (%) with battery capacity, and (d) charging cost (£).**

As depicted in Figure 4.22, the PEV charging control signal obtained using the ensemble approach is only active after midnight, which means that the SOC of the EV remains constant until the charging signal becomes active when the forecasted price is substantially low, resulting in a notable increase in the SOC. Additionally, this strategy results in a PEV charging cost of approximately £168, which is lower than those obtained via previous techniques owing to varying charging periods based on different charging signals. After conducting a simulation analysis of the PEV coordinated charging strategy with OC, another charging technique based on an ensemble approach was implemented using different PEV PLs. This approach considered two designated charging time zones, red (high) and green (low), to assess its impacts on system load, power loss, and voltage deviations, as illustrated in Figures 4.23, 4.24, and 4.25 respectively. The results indicate that the ensemble-based coordinated charging approach not only reduced power consumption and system losses of the electric grid but also enhanced network performance in terms of voltage deviation compared to the previous coordinated and random charging strategies. Additionally, the charging process shifted from red (high zone) to green (low zone) based on the control signal obtained using the proposed ensemble technique considering EPF. This enhanced the cost savings of PEV owners by charging the batteries only in the low zone. Thus, coordination PEV charging can optimize electric grid utilization, minimize charging costs, and enhance grid reliability and efficiency.

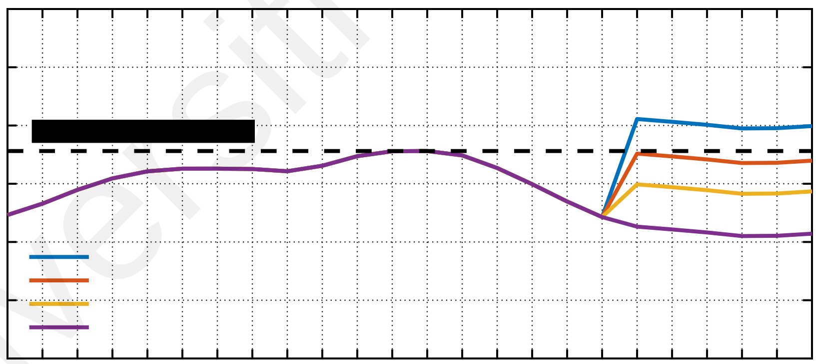

**Figure 4.23: Impact of the ensemble-based coordinated PEV charging approach on system demand.**

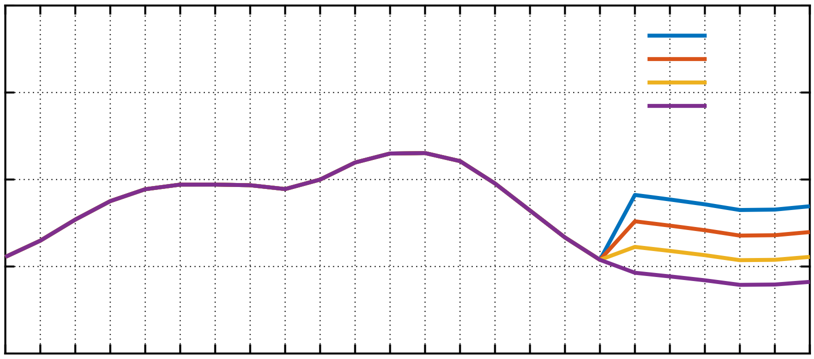

**Figure 4.24: Impact of the ensemble-based coordinated PEV charging approach on system loss.**

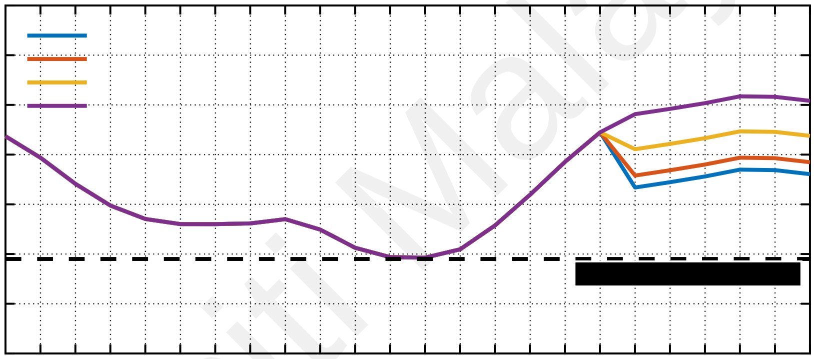

**Figure 4.25: Impact of the ensemble-based coordinated PEV charging approach on voltage profile.**

### 4.4.4 Smart Plug-in Electric Vehicle Charging

Smart charging refers to the use of advanced technologies and strategies to optimize the charging and discharging processes of PEVs such that the efficiency and benefits for both the vehicle owner and the power grid are satisfied. This charging technique allows PEV to discharge the stored energy back into the grid during peak hours, acting as a valuable power source for the grid that can help reduce the electricity bills of vehicle owners. Moreover, when PEV owners plug their vehicles into an external power source to recharge the batteries, the aggregator sends a control signal, obtained using the OC and ensemble ML approaches, to either charge or discharge the battery. The control signal in a smart PEV charging strategy with OC changes based on the switching function; thus, the control input is obtained using the control equation presented in Chapter 3. The performance of the smart PEV charging plan with OC is illustrated in Figure 4.26, which indicates the PEV charging (orange) and discharging (green) states according to the electricity price variations during the charging period. The results show that the PEV begins charging after it is plugged into the charging point in the evening. However, the charging session stops during peak hours (high demand), indicating that these periods are more suitable for discharging, provided that the batteries have sufficient energy. Moreover, the negative SOC slope indicates that the EV batteries are discharging; hence, the PEV charging cost increases gradually, as shown in Figure 4.26. Thereafter, the charging session resumes when electricity demand is comparatively lower and thus, the SOC increases, and the PEV charging cost for the charging session increases, resulting in a total cost of approximately £25.

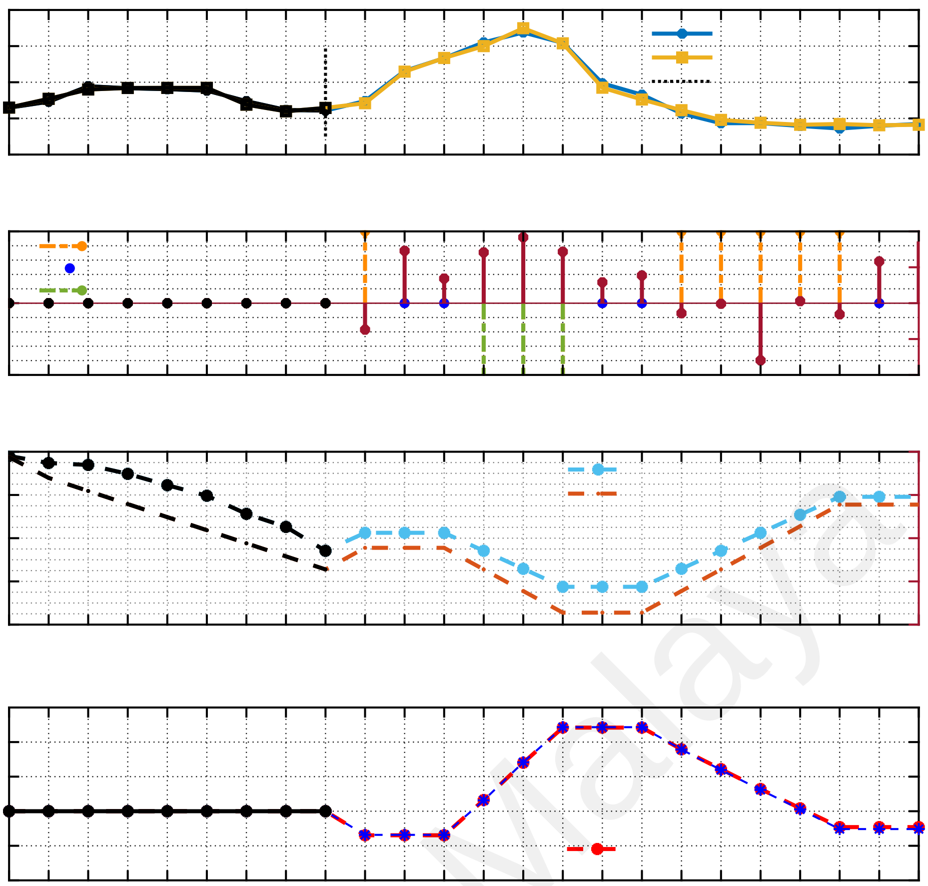

**Figure 4.26: Smart PEV charging strategy with OC: (a) EPF, (b) charging state with dH/dU, (c) SOC (%) with battery capacity, and (d) charging cost (£).**

To observe the impacts of this charging strategy on the power load, total system losses, and voltage deviations on the distribution grid, an IEEE 69-bus distribution system with three PEV PLs of 41%, 28%, and 16%, was employed, as illustrated in Figures 4.27, 4.28, and 4.29. The results indicate that the smart charging strategy helped manage the system demand by shifting PEV charging to off-peak hours and discharging them during high-demand periods. Furthermore, smart charging plans can reduce power losses and mitigate voltage deviations on the power grid, as illustrated in Figures 4.28 and 4.29.

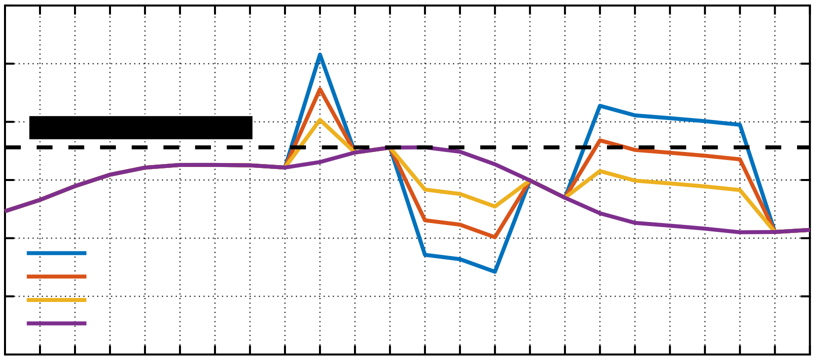

**Figure 4.27: Impact of the smart PEV charging strategy with OC on system demand.**

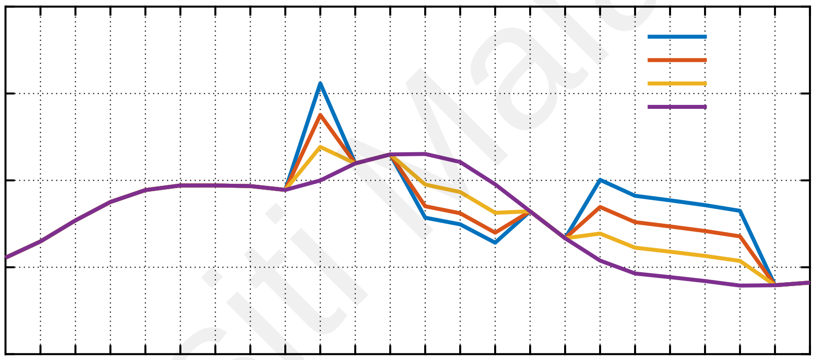

**Figure 4.28: Impact of the smart PEV charging strategy with OC on system loss.**

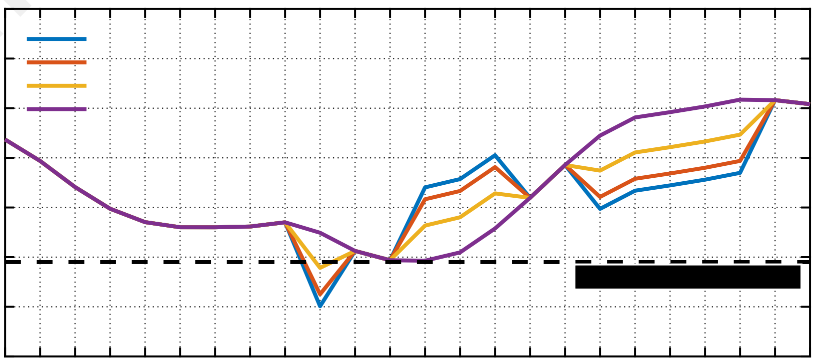

**Figure 4.29: Impact of the smart PEV charging strategy with OC on voltage profile.**

Additionally, the proposed smart charging control signal based on the ensemble approach is obtained by classifying charging hours into three charging zones: green (low), blue (medium), and red (high). The low and high zones represent off-peak and peak demands, respectively, whereas the medium zone denotes neutral demand. The performance of the ensemble-based smart charging strategy in terms of PEV states, SOC, and charging cost are illustrated in Figure 4.30. It evident that there is no charging session at the beginning owing to the gradual increase in prices, the SOC remains constant. However, during peak (high-demand) hours, the EV discharges, lowering the SOC. Subsequently, charging begins again after midnight when demand is low, again increasing the SOC. Moreover, the charging cost for the entire day is approximately £15, which is significantly lower than that of the previously discussed charging strategies. Further, the impacts of ensemble-based PEV smart charging on system power consumption, system losses, and voltage drops are presented in Figures 4.31, 4.32, and 4.33 respectively.

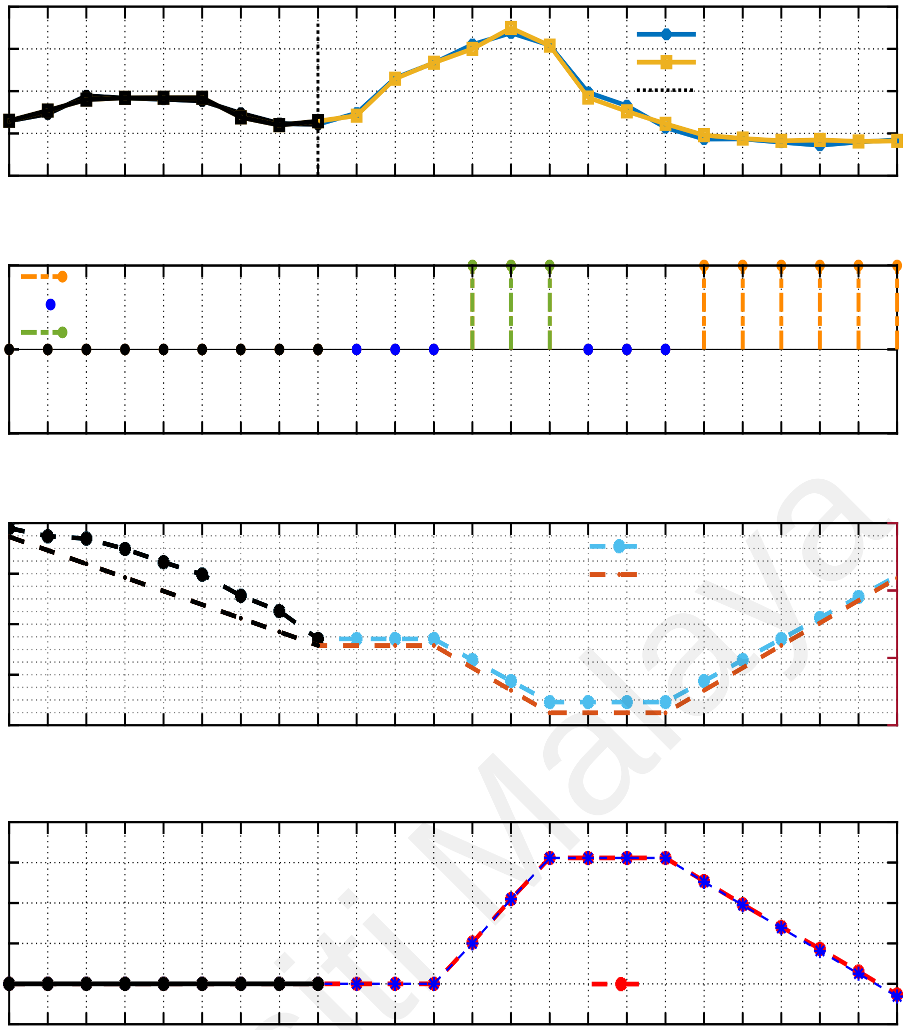

Figure 4.30: Ensemble-based smart PEV charging approach : (a) EPF, (b) charging state, (c) SOC (%) with battery capacity, and (d) charging cost (£).

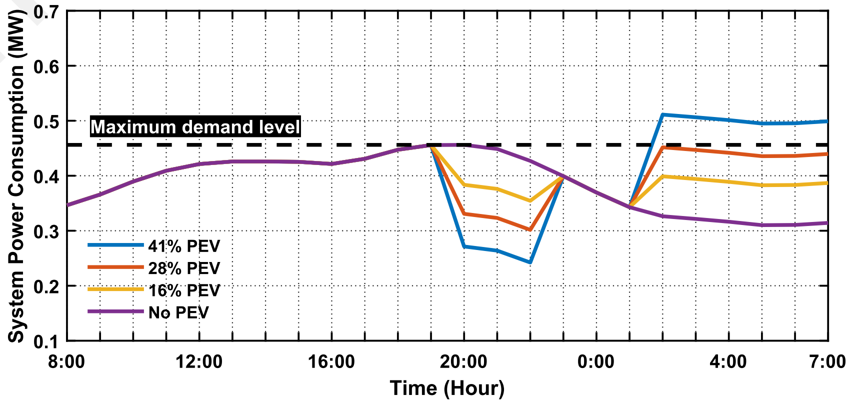


Figure 4.31: Impact of the ensemble-based smart PEV charging approach on system demand.

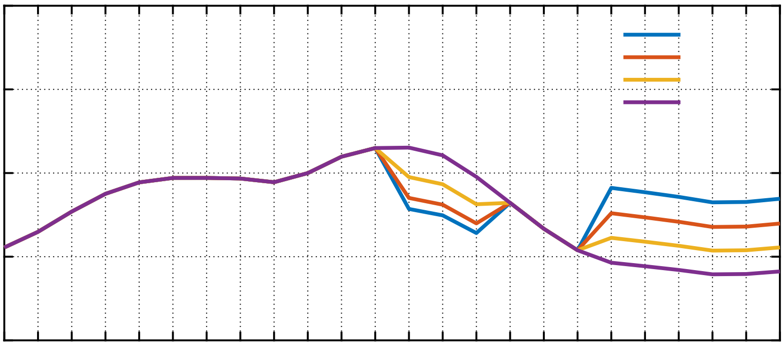

**Figure 4.32: Impact of the ensemble-based smart PEV charging approach on system loss.**

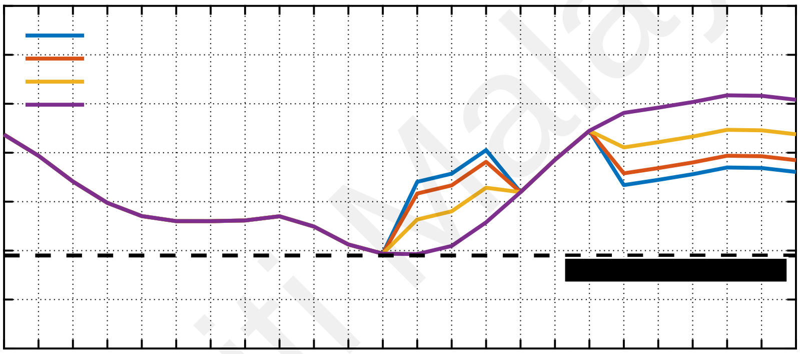

**Figure 4.33: Impact of the ensemble-based smart PEV charging approach on voltage profile.**

The results also show that the ensemble-based smart charging strategy performed better than the previous charging strategies in terms of power consumption, total system losses, and voltage drops. Furthermore, smart PEV charging activities employing the ensemble ML approach may transition from high-demand (red) to low-demand (green) zones based on the control signal obtained using the proposed ensemble technique with EPF. This implies that PEV owners can reduce their charging expenses by charging at lower electricity prices and discharging at higher prices. Overall, the ensemble-based smart PEV charging strategy is a promising approach for efficiently and effectively managing electricity usage. As PEV adoption increases, smart charging technologies are likely to become more widespread and help drive the transition to a more sustainable energy future.

### 4.4.5 Comparison Results of Various Plug-in Electric Vehicle Charging Strategies

This section compares the various random, coordinated, and smart PEV charging strategies in terms of charging cost and impact on the distribution grid for various PEV PLs (41%, 28%, and 16%); the empirical results indicate that the proposed ensemble-based smart charging strategy outperforms the others. Furthermore, Figure 4.34 illustrates the charging costs incurred using various PEV charging strategies with EPF.

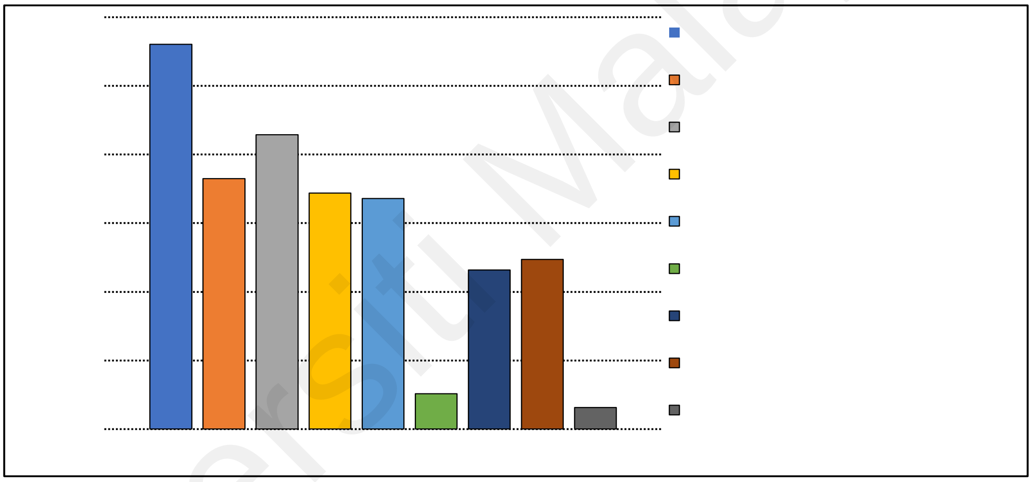

**Figure 4.34: PEV charging costs incurred using various charging approaches with EPF.**

The results show that the proposed smart charging strategy incurred a PEV charging cost of £15, which was significantly lower than £280 incurred using the random charging strategy. However, the ensemble-based coordinated PEV charging strategy incurred a lower PEV charging cost than other coordinated and random charging strategies, with cost reductions of approximately 8% and 40%, respectively. Conversely, the proposed smart ensemble-based smart charging strategy reduced the charging cost by approximately 94% compared to the base random charging strategy. The system losses incurred for all charging strategies are listed in Table 4.6, wherein it is evident that compared to the random charging base case, the proposed ensemble-based smart charging strategy incurred the least amount system power losses, followed by coordinated charging strategies with various PEV PLs. Furthermore, the findings indicate that the smart charging approach offers significant benefits in terms of PEV charging costs and negative impacts on the distribution grid.

**Table 4.6: Power losses incurred by various charging strategies for different PEV PLs.**

| PEV PL (%) | Min_voltage (PU) | Total power loss (kW) | Increase in losses (%) |
|---|---|---|---|
| **Nominal case without PEVs** | | | |
| 0 | 0.9899 | 49.374 | - |
| **Random (uncoordinated) charging base case:** | | | |
| 16 | 0.9892 | 51.758 | 4.828 |
| 28 | 0.9887 | 54.026 | 9.421 |
| 41 | 0.9884 | 56.248 | 13.922 |
| **Coordinated charging using OC:** | | | |
| 16 | 0.9897 | 51.234 | 3.767 |
| 28 | 0.9892 | 53.06 | 7.465 |
| 41 | 0.989 | 54.933 | 11.259 |
| **Ensemble-based coordinated charging:** | | | |
| 16 | 0.9921 | 51.108 | 3.511 |
| 28 | 0.9915 | 52.831 | 7.001 |
| 41 | 0.9913 | 54.617 | 10.618 |
| **Smart charging using OC:** | | | |
| 16 | 0.9897 | 50.2 | 1.672 |
| 28 | 0.9892 | 51.31 | 3.921 |
| 41 | 0.989 | 52.81 | 6.96 |
| **Proposed ensemble-based smart charging:** | | | |
| 16 | 0.9921 | 50.08 | 1.43 |
| 28 | 0.9915 | 51 | 3.29 |
| 41 | 0.9913 | 52.49 | 6.311 |

### 4.4.6 Original System Case Study

This section focuses on the authentication of the proposed smart and coordinated PEV charging scheduling strategies on an original radial distribution test system. Several simulations were conducted to test the smart and coordinated charging strategies. Additionally, a comprehensive analysis was performed to investigate the reduction in system losses and the effects of voltage deviation to verify the proposed techniques. The analysis included three behaviors of charging: the random, coordinated, and proposed ensemble-based smart charging strategies. The effects of the random charging strategy on the original IEEE 69-bus distribution system are illustrated in Figures 4.35, 4.36, and 4.37. As indicated in Figure 4.35, the system overloads during peak hours, surpassing the maximum demand limit. Notably, the voltage constraints at the most affected node are violated, particularly under PEV PLs of 28% and 41%, which exhibit substantial system losses, as evident in Figures 4.36 and 4.37. The peak losses are sustained at the PEV PL of 41%, as it involves more charging load than the other levels.

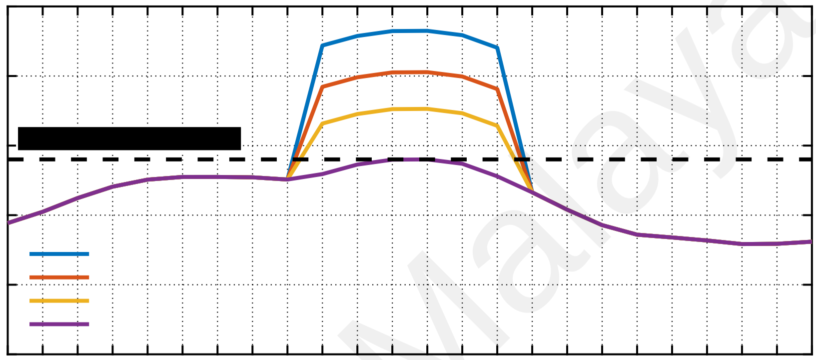

**Figure 4.35: Impact of random PEV charging on system load using the original IEEE 69-bus distribution system.**

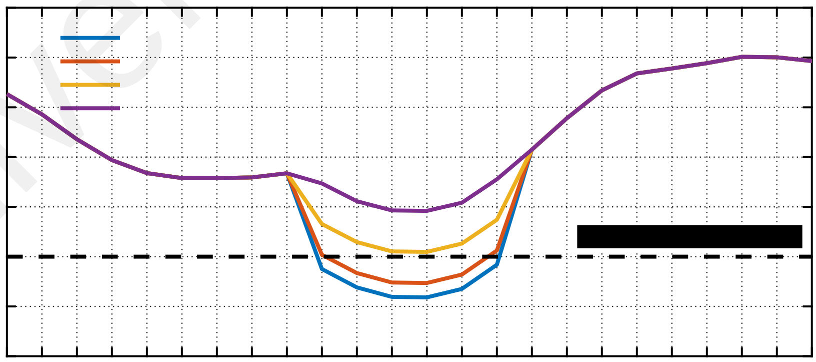

**Figure 4.36: Impact of random PEV charging on system voltage using the original IEEE 69-bus distribution system.**

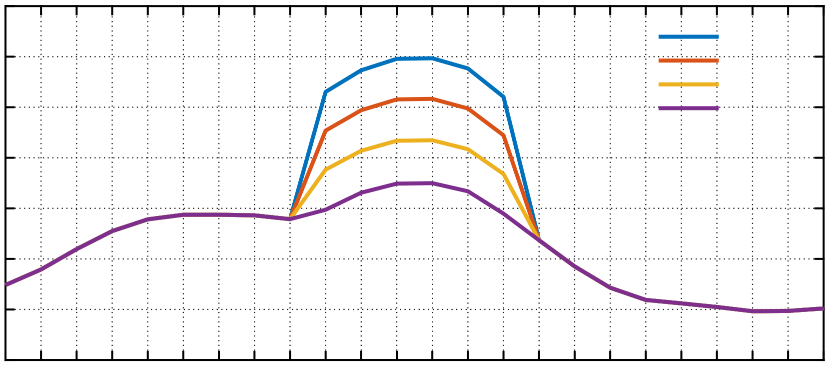

**Figure 4.37: Impact of random PEV charging on system power loss using the original IEEE 69-bus distribution system.**

Following the random charging simulation, the proposed smart and coordinated charging strategies were simulated to examine their impacts on the distribution grid. Initially, the coordinated charging strategy was employed, followed by the smart charging technique, factoring in a control signal derived using an ensemble ML method. Under coordinated charging, the system load remained within the maximum demand level during peak times for PEV PLs of 16% and 28%, as depicted in Figure 4.38. Additionally, the voltage drops at all nodes were within the acceptable utility limits, even at higher PEV PLs, as illustrated in Figure 4.39. Additionally, Figure 4.40 indicates that the total system power losses reduced significantly compared to those shown in Figure 4.37.

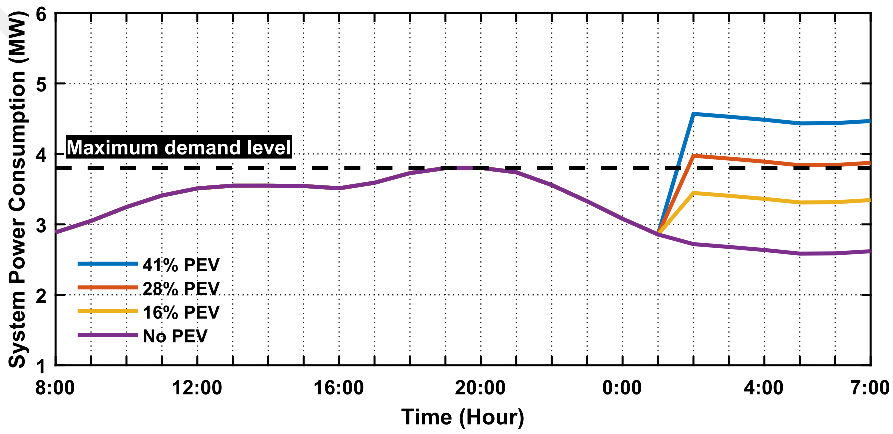


**Figure 4.38: Impact of coordinated PEV charging on power consumption using the original IEEE 69-bus distribution system.**

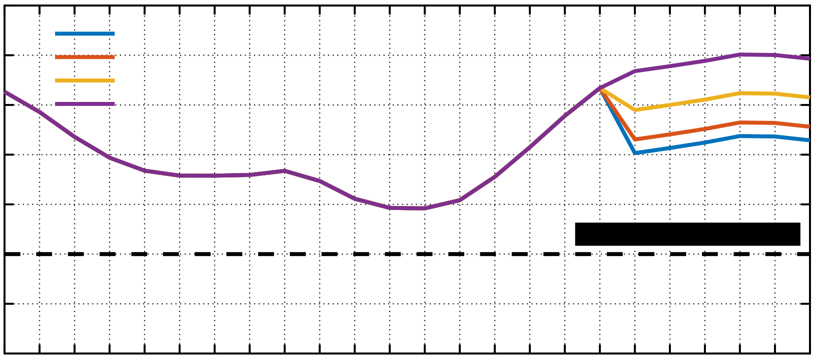

**Figure 4.39: Impact of coordinated PEV charging on system voltage using the original IEEE 69-bus distribution system.**

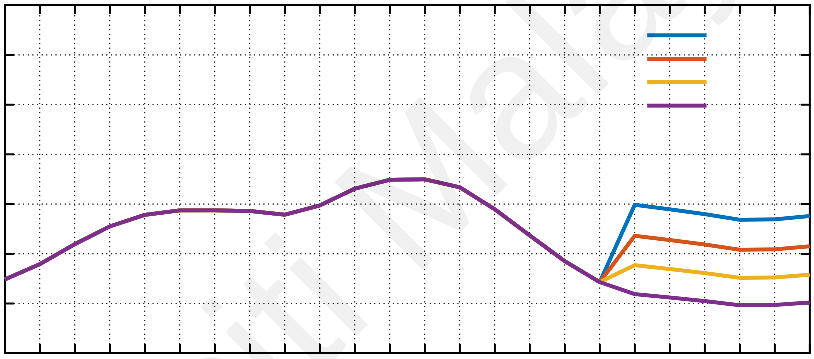

**Figure 4.40: Impact of coordinated PEV charging on power system loss using the original IEEE 69-bus distribution system.**

Moreover, the control signal of the smart charging strategy was employed to assess its effectiveness in terms of system power consumption, system voltage, and total system losses. The power consumption and optimal periods for charging and discharging for various PEV PLs are depicted in Figure 4.41. The results indicate that all EVs were charged during low-demand periods and discharged during high-demand periods. Thus, this strategy effectively minimized charging costs, improved the system voltage profile, and reduced power losses, as illustrated in Figures 4.42 and 4.43. To highlight the effectiveness of the proposed charging strategies, the obtained results are juxtaposed with those of the random charging technique, wherein the total system losses are significantly higher than those using smart and coordinated charging strategies. Additionally, in uncoordinated PEV charging, a substantial number of voltage drops are evident, particularly at high PEV PLs (i.e., 28%, 41%), resulting in poor power quality. In contrast, coordinated and smart PEV charging strategies ensure that the voltage deviations are constrained within the utility limits, resulting in superior power quality and customer satisfaction.

Additionally, coordinated charging increased system losses by approximately 18.6% at high PLs compared to the random charging base case. However, smart charging incurred less system losses by approximately 8.36% for the same PLs. The simulation results for power loss are listed in Table 4.7.

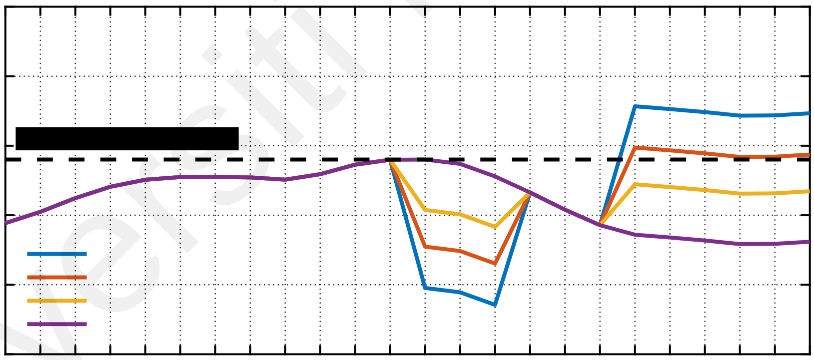

**Figure 4.41: Impact of smart PEV charging on system power load using the original IEEE 69-bus distribution system.**

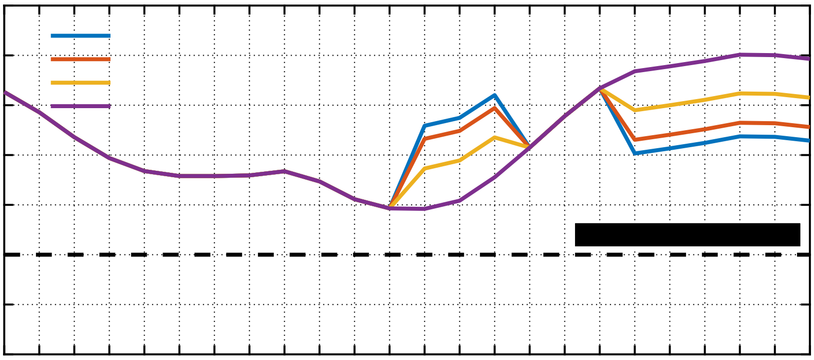

**Figure 4.42: Impact of smart PEV charging on system voltage using the original IEEE 69-bus distribution system.**

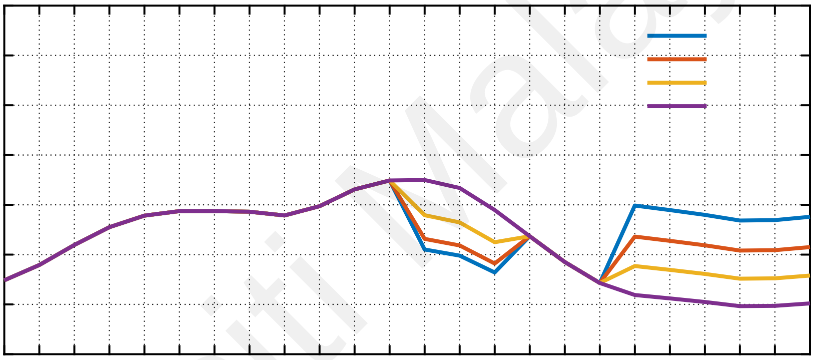

**Figure 4.43: Impact of smart PEV charging on power system loss using the original IEEE 69-bus distribution system.**

**Table 4.7: Results of the various charging strategies for different PEV PLs using the original IEEE 69-bus distribution system.**

| PEV (%) | Min_vlotage (PU) | Total power loss (MW) | Increase in losses (%) |
|---|---|---|---|
| **Nominal case without any PEV** | | | |
| 0 | 0.9092 | 3.883 | - |
| **Random (uncoordinated) charging:** | | | |
| 16 | 0.901 | 4.13 | 6.36 |
| 28 | 0.8947 | 4.369 | 12.51 |
| 41 | 0.8918 | 4.605 | 18.6 |
| **Ensemble-based coordinated charging:** | | | |
| 16 | 0.929 | 4.052 | 4.35 |
| 28 | 0.923 | 4.225 | 8.807 |
| 41 | 0.9203 | 4.408 | 13.52 |
| **Ensemble-based smart charging:** | | | |
| 16 | 0.929 | 3.95 | 1.72 |
| 28 | 0.923 | 4.054 | 4.403 |
| 41 | 0.9203 | 4.208 | 8.37 |

## 4.5 Comparative Studies

This study introduced smart and PEV charging coordinated strategies, with the aim of minimizing charging expenses for PEV owners and ensuring power grid stability. A comprehensive overview of this study and related works is presented in Table 4.8, which presents the study objectives, approaches employed, evaluation systems used, datasets adopted, and performance results obtained, thereby facilitating a direct comparison of the results obtained in each study. Importantly, it is evident that this study achieved superior results than the others, especially in terms of reducing PEV charging costs and minimizing impacts on the distribution grid.

**Table 4.8: Comparative analysis of this and related studies on PEV charging strategies.**

| Authors | Objectives | Method | Evaluation system | Dataset | Performance results (PEV charging cost reduction) |
|---|---|---|---|---|---|
| This study | Minimize charging cost and power losses | ML (ensemble) and OC | Modified and original IEEE 69-bus distribution system | Nord Pool market | Empirical results revealed a 94% reduction in PEV charging expenses and 6.7% reduction of power losses compared to random charging. |
| (Deilami et al., 2011) | Minimize charging cost and losses | MSS | IEEE 31-bus distribution system | Western Australia | Coordinated RT-SLM reduced charging cost by approximately 9.7% compared to the uncoordinated method. |
| (Cao et al., 2020) | Maximize profits and minimize charging cost | MILP | N/A | N/A | Charging cost was reduced by 27.06%. |
| (Amamra & Marco, 2019) | Minimize charging cost | NLP | Standard IEEE 33-node distribution system | N/A | EV charging cost was reduced by 33.3%. |
| (López et al., 2018) | Decrease charging cost | DP | N/A | Winnipeg, Manitoba, Canada | Findings indicated that the proposed method significantly reduced charging costs. |

(Table 4.8 continued)

| | | | | | |
|---|---|---|---|---|---|
| (Ren et al., 2023) | Minimize charging cost | LSTM-ILP | N/A | Data.gov website | The approach effectively decreased charging costs by 42.1%. |
| (Jin et al., 2013) | Reduce PEV charging costs | LP | N/A | Glasgow, UK and NYISO | PEV charging cost was reduced by 17.4% compared to simple charging. |
| (Turker & Bacha, 2018) | Minimize PEV charging costs in the housing sector | Heuristic algorithms | N/A | French energy billing system | Compared to basic charging, the charging cost was reduced by 47.94% on average. |
| (Chiş et al., 2016) | Reduce electricity cost of PEV owner | MDP | N/A | ISO New England | Results from simulations indicated that the charging cost was reduced by 10–50%. |
| (Hou et al., 2023) | Minimize operating expenses | Two-stage stochastic optimization | N/A | Vancouver | The proposed method reduced daily operating expenses by 27.5%. |
| (Li et al., 2019) | Reduce PEV charging cost | MDP | N/A | USA, retail-energy | Simulation results indicated that the proposed method can significantly reducing cost. |
| (Suyono et al., 2019) | Minimize system losses and PEV charging cost | Metaheuristic method (BPSO, BGWO) | Modified of IEEE 31-bus distribution system | Western Australia | Simulation results indicated that the proposed strategy could reduce charging cost by 15.89%. |

## 4.6 Summary

This chapter comprehensively presented and discussed the key results obtained in this study. First, the validation results for optimizing PEV charging cost were presented, demonstrating the application of OC techniques with a fixed electricity price using various PEV charging strategies, such as random (uncoordinated), coordinated (unidirectional), and smart (bidirectional). Subsequently, data exploration and the experimental setup for the proposed EPF were discussed, including statistical forecasting measurements for hybrid and individual ML models. Thereafter, performance evaluation and simulation analysis of the various PEV charging strategies are presented, which incorporate ML classification and OC methods integrated with EPF. Finally, the impact and effectiveness of both the random and proposed charging strategies on the distribution grid under various PEV PLs were reported and discussed. The findings suggest that the ensemble-based smart PEV charging strategy offers substantial benefits as it effectively reduces the PEV charging cost and impact on the distribution grid. Comprehensive performance comparisons indicated that the smart and coordinated charging strategies using ensemble ML algorithms and OC offer notable improvements compared to the random (uncoordinated) PEV charging strategy.

# CHAPTER 5: CONCLUSION AND FUTURE WORK

## 5.1 Conclusion

In this thesis, significant efforts were made to schedule PEV charging with the aim of minimizing charging cost and system losses using various charging strategies. The results of the random charging strategy were compared with those of coordinated and smart strategies. In this study, a new hybrid ML technique was developed to forecast day-ahead electricity prices using real-world electricity data to handle the issues associated with time series data, such as volatility and irregular spikes. It also proposed using ML and OC with EPF to further optimize PEV charging cost. Furthermore, the control charging signals derived using these techniques were evaluated using both the standard and a modified IEEE 69-bus distribution system.

The main findings of this can be summarized as follows:

- The random 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 approximately £882. However, coordinated charging involves initiating or postponing charging based on OC, which considers energy prices. This strategy significantly reduces charging costs compared to the random strategy, resulting in savings of approximately £690. In contrast, in smart bidirectional charging based on OC is significantly cost-effective, incurring a total charging cost of approximately £232. Although coordinated charging decreases the charging cost by approximately 21% compared to random charging, smart bidirectional charging reduces it by approximately 73%.

- Developing robust ML tools for EPF is challenging owing to the complex characteristics of electricity price, such as high volatility, and rapid spikes, which can affect short-term electricity price predictions. Therefore, a new hybrid ML technique, ARD-ETR, based on LR and ensemble tree bagging models was proposed for price prediction. A historical dataset was collected as a time series which was used to validate the efficiency of the proposed method. Empirical results demonstrated that the proposed ARD-ETR model achieved the best performance in terms of MAE, RMSE, and MSE compared to the individual and other hybrid approaches employed in this study. The ARD-ETR model obtained the lowest MAE, RMSE, MSE values of 2.03, 3.42 and 11.7 (£/MWh) respectively.
- Simultaneously charging many PEVs in a specific area without any coordination can put considerable strain on the electric grid, resulting in voltage fluctuations or power outages. Therefore, coordinated, and smart PEV charging strategies were proposed to minimize charging costs and reduce system power losses by employing ML and OC algorithms to manage PEV charging, which can enhance cost savings for both PEV owners and the electric utility. Three distinct ML approaches were employed (i.e., NN, NB, and ensemble) based on designated charging zones. Empirical results showed that the ensemble approach achieved better results for both charging strategies than the other approaches, obtained accuracy, precision, recall, and F-scores of 98.3%, 100%, 92.2%, and 95.9%, respectively, for the coordinated approach, and 99.5%, 98.5%, 100% and 99.2%, respectively, for the smart approach. Additionally, the simulation results indicated that the proposed smart charging approach significantly reduced the PEV charging cost compared to the random charging base case, from £280 and £15. Moreover,

the ensemble-based coordinated PEV charging strategy incurred a lower charging cost than the other coordinated and random charging strategies, reducing the cost by approximately 8% and 40%, respectively. However, compared to the base case, the proposed ensemble-based smart approaches reduced the charging cost by approximately 94%.

- To illustrate the impacts and efficiencies of the proposed coordinated and smart charging techniques compared to random charging at various levels of PEV PLs (16%, 28%, and 41%), both modified and standard IEEE 69-bus radial distribution systems was employed. The modification aimed to create a conducive environment for evaluating the performances of the proposed charging strategies. It was structured such that each node represented a low-voltage residential feeder. These feeders were designed to simulate power distribution to one or two households under different PLs. The results indicated that the impacts of the smart and coordinated charging were lower than those of random charging. By contrast, each feeder in the standard system configuration distributed power to approximately ten households on average, which also exhibited varying PLs. The results showed that the smart and coordinated PEV charging strategies exhibited superior performances than the uncoordinated approach in terms of power consumption, voltage drops, and system losses.

In summary, the results indicated that the proposed charging approach can significantly reduce the charging cost and improve grid reliability and stability compared to uncoordinated charging. Thus, owing to the increasing adoption of PEVs, the prevalence of smart and coordinated charging techniques is expected to increase, thereby aiding the transition toward a more sustainable energy future.

## 5.2 Recommendations for Future Work

This study proposed scheduling PEV charging using various strategies to minimize charging cost and improve grid reliability. Moreover, a new hybrid ARD-ETR method was proposed to forecast electricity prices. Thereafter, various optimized PEV charging approaches were employed using ML and OC with EPF and different charging strategies. To determine the impacts of the proposed charging approaches, a modified and standard IEEE 69-bus radial distribution system grid was adopted. However, the following suggestions can provide directions for future work to further reduce PEV charging costs and improve grid stability:

- This research could be extended to incorporate multiple types and models of EVs, considering the variations in battery capacities and energy consumptions. Moreover, diverse usage patterns, potentially exceeding three trips per day or encompassing irregular usage, can be considered. Additionally, exploring the potential impacts of integrating RES, such as solar panels and wind farms, into the charging infrastructure could provide further insights into changes in charging costs or grid performance.
- The performance of the ARD-ETR hybrid model can be further validated by applying it on more extensive or diverse datasets, from various regions and power markets, to validate its robustness. Additionally, a deeper exploration of parameter optimization for the ARD and ETR models might enhance the overall performance of the hybrid model. Finally, hybrid models can be extended to investigate its potential for long-term EPF, offering additional benefits for future planning in the energy sector.
- Analyses of alternative distribution grids, especially those with large feeders, can present a broader validation scope for the proposed charging model. Integrating this model with smart grid technologies, or exploring its

interactions with RES, may provide valuable insights into its enhancement of grid efficiency and stability. Additionally, prediction accuracy can be enhanced by employing various ML techniques, such as hybrid models. A comprehensive study of V2G strategies, their grid impact, and the effects of different charging schedules on the battery lifespan of PEVs can provide a deeper understanding of the model's practical implications. Finally, evaluating real-time applications of the optimized charging techniques can provide insights into their adaptability to dynamic conditions, such as unexpected trips or fluctuations in electricity prices.

# REFERENCES


Abedinia, O., Amjady, N., & Zareipour, H. (2016). A new feature selection technique for load and price forecast of electrical power systems. *IEEE Transactions on Power Systems*, *32*(1), 62-74.

afdc.energy.gov. (2020). Retrieved 6 June 2022, from https://afdc.energy.gov/vehicles/how-do-all-electric-cars-work.

Ahmadian, A., Mohammadi-Ivatloo, B., & Elkamel, A. (2020). A review on plug-in electric vehicles: Introduction, current status, and load modeling techniques. *Journal of Modern Power Systems and Clean Energy*, *8*(3), 412-425.

Alamaniotis, M., Bargiotas, D., Bourbakis, N. G., & Tsoukalas, L. H. (2015). Genetic optimal regression of relevance vector machines for electricity pricing signal forecasting in smart grids. *IEEE Transactions on Smart Grid*, *6*(6), 2997-3005.

Albahli, S., Shiraz, M., & Ayub, N. (2020). Electricity price forecasting for cloud computing using an enhanced machine learning model. *IEEE Access*, *8*, 200971-200981.

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of big Data*, *8*, 1-74.

Amamra, S.-A., & Marco, J. (2019). Vehicle-to-grid aggregator to support power grid and reduce electric vehicle charging cost. *IEEE Access*, *7*, 178528-178538.

Amin, A., Tareen, W. U. K., Usman, M., Ali, H., Bari, I., Horan, B., Mekhilef, S., Asif, M., Ahmed, S., & Mahmood, A. (2020). A review of optimal charging strategy for electric vehicles under dynamic pricing schemes in the distribution charging network. *Sustainability*, *12*(23), 10160.

Amin, A., Tareen, W. U. K., Usman, M., Memon, K. A., Horan, B., Mahmood, A., & Mekhilef, S. (2020). An integrated approach to optimal charging scheduling of electric vehicles integrated with improved medium-voltage network reconfiguration for power loss minimization. *Sustainability*, *12*(21), 9211.

Amjad, M., Ahmad, A., Rehmani, M. H., & Umer, T. (2018). A review of EVs charging: From the perspective of energy optimization, optimization approaches, and charging techniques. *Transportation Research Part D: Transport and Environment*, *62*, 386-417.

Angamuthu Chinnathambi, R., Mukherjee, A., Campion, M., Salehfar, H., Hansen, T. M., Lin, J., & Ranganathan, P. (2018). A multi-stage price forecasting model for day-ahead electricity markets. *Forecasting*, *1*(1), 26-46.

Ascione, F., Bianco, N., De Stasio, C., Mauro, G. M., & Vanoli, G. P. (2017). Artificial neural networks to predict energy performance and retrofit scenarios for any member of a building category: A novel approach. *Energy*, *118*, 999-1017.

Badr, H. M., Ali, R. S., & Mahmood, J. R. (2022a). Centralised Fuzzy Control Asset Congestion Management in Distribution Networks. 2022 4th Global Power, Energy and Communication Conference (GPECOM),

Badr, H. M., Ali, R. S., & Mahmood, J. R. (2022b). A new approach for optimal photovoltaic resources in distribution networks with reconfiguration based on L_∞. *COMPEL-The international journal for computation and mathematics in electrical and electronic engineering*, *41*(5), 1699-1726.

Baran, M., & Wu, F. F. (1989). Optimal sizing of capacitors placed on a radial distribution system. *IEEE Transactions on power Delivery*, *4*(1), 735-743.

Bengio, Y., & Grandvalet, Y. (2003). No unbiased estimator of the variance of k-fold cross-validation. *Advances in neural information processing systems*, *16*.

Bissing, D., Klein, M. T., Chinnathambi, R. A., Selvaraj, D. F., & Ranganathan, P. (2019). A hybrid regression model for day-ahead energy price forecasting. *IEEE Access*, *7*, 36833-36842.

Botchkarev, A. (2019). A new typology design of performance metrics to measure errors in machine learning regression algorithms. *Interdisciplinary Journal of Information, Knowledge, and Management*, *14*, 045-076.

Braco, E., San Martín, I., Berrueta, A., Sanchis, P., & Ursúa, A. (2020). Experimental assessment of cycling ageing of lithium-ion second-life batteries from electric vehicles. *Journal of Energy Storage*, *32*, 101695.

Cao, C., Cheng, M., & Chen, B. (2016). Optimal scheduling of PEV charging/discharging in microgrids with combined objectives. *Smart Grid and Renewable Energy*, *7*(4), 115.

Cao, Y., Huang, L., Li, Y., Jermsittiparsert, K., Ahmadi-Nezamabad, H., & Nojavan, S. (2020). Optimal scheduling of electric vehicles aggregator under market price uncertainty using robust optimization technique. *International Journal of Electrical Power & Energy Systems*, *117*, 105628.

Carrera, B., & Kim, K. (2020). Comparison analysis of machine learning techniques for photovoltaic prediction using weather sensor data. *Sensors*, *20*(11), 3129.

Cha, G.-W., Moon, H.-J., & Kim, Y.-C. (2021). Comparison of random forest and gradient boosting machine models for predicting demolition waste based on small datasets and categorical variables. *International Journal of Environmental Research and Public Health*, *18*(16), 8530.

Chang, Z., Zhang, Y., & Chen, W. (2019). Electricity price prediction based on hybrid model of adam optimized LSTM neural network and wavelet transform. *Energy*, *187*, 115804.

Cheng, H., Ding, X., Zhou, W., & Ding, R. (2019). A hybrid electricity price forecasting model with Bayesian optimization for German energy exchange. *International Journal of Electrical Power & Energy Systems*, *110*, 653-666.

Chevrolet, Volt Electric Car. (2021). Retrieved 9 November 2022, from http://www.chevrolet.com/electriccar.

Chiş, A., Lundén, J., & Koivunen, V. (2016). Reinforcement learning-based plug-in electric vehicle charging with forecasted price. *IEEE Transactions on vehicular technology*, *66*(5), 3674-3684.

Clement-Nyns, K., Haesen, E., & Driesen, J. (2009). The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Transactions on Power Systems*, *25*(1), 371-380.

Dahmane, Y., Chenouard, R., Ghanes, M., & Alvarado-Ruiz, M. (2021). Optimized time step for electric vehicle charging optimization considering cost and temperature. *Sustainable Energy, Grids and Networks*, *26*, 100468.

Darudi, A., Bashari, M., & Javidi, M. H. (2015). Electricity price forecasting using a new data fusion algorithm. *IET Generation, Transmission & Distribution*, *9*(12), 1382-1390.

Deilami, S., Masoum, A. S., Moses, P. S., & Masoum, M. A. (2011). Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile. *IEEE Transactions on Smart Grid*, *2*(3), 456-467.

Dogan, A., Bahceci, S., Daldaban, F., & Alci, M. (2018). Optimization of charge/discharge coordination to satisfy network requirements using heuristic algorithms in vehicle-to-grid concept. *Advances in Electrical and Computer Engineering*, *18*(1), 121-130.

Driving Cycle (Simulink Block). (2022). Retrieved 8 April 2023, from (https://www.mathworks.com/matlabcentral/fileexchange/46777-driving-cycle-simulink-block), MATLAB Central File Exchange.

Du, G., Cao, W., Hu, S., Lin, Z., & Yuan, T. (2018). Design and assessment of an electric vehicle powertrain model based on real-world driving and charging cycles. *IEEE Transactions on vehicular technology*, *68*(2), 1178-1187.

Esenogho, E., Djouani, K., & Kurien, A. M. (2022). Integrating artificial intelligence Internet of Things and 5G for next-generation smartgrid: A survey of trends challenges and prospect. *IEEE Access*, *10*, 4794-4831.

Fan, L., Wei, S., Li, S., Li, Q., & Lu, Y. (2018). Recent progress of the solid-state electrolytes for high-energy metal-based batteries. *Advanced Energy Materials*, *8*(11), 1702657.

Fathabadi, H. (2018). Plug-in hybrid electric vehicles: Replacing internal combustion engine with clean and renewable energy based auxiliary power sources. *IEEE Transactions on Power Electronics*, *33*(11), 9611-9618.

Fernandez, G. S., Krishnasamy, V., Kuppusamy, S., Ali, J. S., Ali, Z. M., El-Shahat, A., & Abdel Aleem, S. H. (2020). Optimal dynamic scheduling of electric vehicles in a parking lot using particle swarm optimization and shuffled frog leaping algorithm. *Energies*, *13*(23), 6384.

Geurts, P., Ernst, D., & Wehenkel, L. (2006). Extremely randomized trees. *Machine learning*, *63*, 3-42.

Gong, L., Cao, W., Liu, K., & Zhao, J. (2020). Optimal charging strategy for electric vehicles in residential charging station under dynamic spike pricing policy. *Sustainable Cities and Society*, *63*, 102474.

González, J. P., San Roque, A. M. S. M., & Perez, E. A. (2017). Forecasting functional time series with a new Hilbertian ARMAX model: Application to electricity price forecasting. *IEEE Transactions on Power Systems*, *33*(1), 545-556.

Hadian, E., Akbari, H., Farzinfar, M., & Saeed, S. (2020). Optimal allocation of electric vehicle charging stations with adopted smart charging/discharging schedule. *IEEE Access*, *8*, 196908-196919.

Hajforoosh, S., Masoum, M. A., & Islam, S. M. (2016). Online optimal variable charge-rate coordination of plug-in electric vehicles to maximize customer satisfaction and improve grid performance. *Electric Power Systems Research*, *141*, 407-420.

Hayfavi, A., & Talasli, I. (2014). Stochastic multifactor modeling of spot electricity prices. *Journal of Computational and Applied Mathematics*, *259*, 434-442.

Hou, L., Dong, J., Herrera, O. E., & Mérida, W. (2023). Energy management for solar-hydrogen microgrids with vehicle-to-grid and power-to-gas transactions. *International Journal of Hydrogen Energy*, *48*(5), 2013-2029. https://doi.org/https://doi.org/10.1016/j.ijhydene.2022.09.238

Huang, C. J., Shen, Y., Chen, Y. H., & Chen, H. C. (2021). A novel hybrid deep neural network model for short-term electricity price forecasting. *International Journal of Energy Research*, *45*(2), 2511-2532.

International Energy Agency (IEA), Global EV Outlook. (2022). Retrieved 10 January 2023, from https://www.iea.org/reports/global-ev-outlook.

Jian, L., Zheng, Y., & Shao, Z. (2017). High efficient valley-filling strategy for centralized coordinated charging of large-scale electric vehicles. *Applied Energy*, *186*, 46-55.

Jiang, H., Zhang, Y., Muljadi, E., Zhang, J. J., & Gao, D. W. (2016). A short-term and high-resolution distribution system load forecasting approach using support vector regression with hybrid parameters optimization. *IEEE Transactions on Smart Grid*, *9*(4), 3341-3350.

Jin, C., Tang, J., & Ghosh, P. (2013). Optimizing electric vehicle charging: A customer's perspective. *IEEE Transactions on vehicular technology*, *62*(7), 2919-2927.

Karden, E., Ploumen, S., Fricke, B., Miller, T., & Snyder, K. (2007). Energy storage devices for future hybrid electric vehicles. *Journal of Power Sources*, *168*(1), 2-11.

Kirk, D. E. (2004). *Optimal control theory: an introduction*. Courier Corporation.

Kuo, P.-H., & Huang, C.-J. (2018). An electricity price forecasting model by hybrid structured deep neural networks. *Sustainability*, *10*(4), 1280.

Lago, J., De Ridder, F., & De Schutter, B. (2018). Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. *Applied Energy*, *221*, 386-405.

Li, H., Wan, Z., & He, H. (2019). Constrained EV charging scheduling based on safe deep reinforcement learning. *IEEE Transactions on Smart Grid*, *11*(3), 2427-2439.

Liu, G., Kang, L., Luan, Z., Qiu, J., & Zheng, F. (2019). Charging station and power network planning for integrated electric vehicles (EVs). *Energies*, *12*(13), 2595.

Lopes, J. A. P., Soares, F. J., & Almeida, P. M. R. (2010). Integration of electric vehicles in the electric power system. *Proceedings of the IEEE*, *99*(1), 168-183.

López, K. L., Gagné, C., & Gardner, M.-A. (2018). Demand-side management using deep learning for smart charging of electric vehicles. *IEEE Transactions on Smart Grid*, *10*(3), 2683-2691.

Lyu, L., Yang, X., Xiang, Y., Liu, J., Jawad, S., & Deng, R. (2020). Exploring high-penetration electric vehicles impact on urban power grid based on voltage stability analysis. *Energy*, *198*, 117301.

Ma, Z., Callaway, D. S., & Hiskens, I. A. (2011). Decentralized charging control of large populations of plug-in electric vehicles. *IEEE Transactions on control systems technology*, *21*(1), 67-78.

Mall, K., Grant, M. J., & Taheri, E. (2020). Uniform trigonometrization method for optimal control problems with control and state constraints. *Journal of Spacecraft and Rockets*, *57*(5), 995-1007.

MathWorks. Fit Ensemble Classifier. (2022). Retrieved 10 March 2023, from https://www.mathworks.com/help/stats/fitcensemble.html.

MathWorks. Fit Naive Bayes Classifier. (2022). Retrieved 10 March 2023, from https://www.mathworks.com/help/stats/fitcnb.html.

Mehta, R., Srinivasan, D., Khambadkone, A. M., Yang, J., & Trivedi, A. (2016). Smart charging strategies for optimal integration of plug-in electric vehicles within existing distribution system infrastructure. *IEEE Transactions on Smart Grid*, *9*(1), 299-312.

Mohammad, A., Zamora, R., & Lie, T. T. (2020). Integration of electric vehicles in the distribution network: A review of PV based electric vehicle modelling. *Energies*, *13*(17), 4541.

Mohammed, S. S., Ahamed, T. P. I., Aleem, S. H. E. A., & Omar, A. I. (2022). Interruptible charge scheduling of plug-in electric vehicle to minimize charging cost using heuristic algorithm. *Electrical Engineering*, *104*(3), 1425-1440. https://doi.org/10.1007/s00202-021-01398-z

Momber, I., Siddiqui, A., San Roman, T. G., & Söder, L. (2014). Risk averse scheduling by a PEV aggregator under uncertainty. *IEEE Transactions on Power Systems*, *30*(2), 882-891.

Mudelsee, M. (2019). Trend analysis of climate time series: A review of methods. *Earth-science reviews*, *190*, 310-322.

Muratori, M. (2018). Impact of uncoordinated plug-in electric vehicle charging on residential power demand. *Nature Energy*, *3*(3), 193-201.

Naidu, D. S. (2018). Constrained optimal control systems. In *Optimal control systems* (pp. 293-364). CRC press.

Nissan LEAF Electric Car. (2021). Retrieved 9 November 2022, from http://www.nissanusa.com/leaf-electric-car.

Nord Pool Historical Market Data. (2020). Retrieved 15 March 2021, from https://www.nordpoolgroup.com/historical-market-data/.

Nowotarski, J., & Weron, R. (2018). Recent advances in electricity price forecasting: A review of probabilistic forecasting. *Renewable and Sustainable Energy Reviews*, *81*, 1548-1568.

Pavićević, M., & Popović, T. (2022). Forecasting day-ahead electricity metrics with artificial neural networks. *Sensors*, *22*(3), 1051.

Rafiei, M., Niknam, T., & Khooban, M.-H. (2016). Probabilistic forecasting of hourly electricity price by generalization of ELM for usage in improved wavelet neural network. *IEEE Transactions on Industrial Informatics*, *13*(1), 71-79.

Rahman, M. T., Othman, M., Mokhlis, H., Muhammad, M. A., & Bouchekara, H. R. (2018). Optimal fixed charge–rate coordination of plug-in electric vehicle incorporating capacitor and OLTC switching to minimize power loss and voltage deviation. *IEEJ Transactions on Electrical and Electronic Engineering*, *13*(7), 963-970.

Ren, L., Yuan, M., & Jiao, X. (2023). Electric vehicle charging and discharging scheduling strategy based on dynamic electricity price. *Engineering Applications of Artificial Intelligence*, *123*, 106320. https://doi.org/https://doi.org/10.1016/j.engappai.2023.106320

Renkens, V. (2017). Automatic relevance determination for nonnegative dictionary learning in the Gamma-Poisson model. *Signal Processing*, *132*, 121-133.

Ribeiro, M. H. D. M., & dos Santos Coelho, L. (2020). Ensemble approach based on bagging, boosting and stacking for short-term prediction in agribusiness time series. *Applied soft computing*, *86*, 105837.

Rotering, N., & Ilic, M. (2010). Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets. *IEEE Transactions on Power Systems*, *26*(3), 1021-1029.

Saldanha, J. J. A., Dos Santos, E. M., De Mello, A. P. C., & Bernardon, D. P. (2016). Control strategies for smart charging and discharging of plug-in electric vehicles. *Smart Cities Technologies*, *1*, 121-141.

Seiffert, C., Khoshgoftaar, T. M., Van Hulse, J., & Napolitano, A. (2009). RUSBoost: A hybrid approach to alleviating class imbalance. *IEEE transactions on systems, man, and cybernetics-part A: systems and humans*, *40*(1), 185-197.

Simsekoglu, Ö., & Nayum, A. (2019). Predictors of intention to buy a battery electric vehicle among conventional car drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *60*, 1-10.

Sun, L., Li, L., Liu, B., & Saeedi, S. (2021). A novel Day-ahead electricity price forecasting using multi-modal combined integration via stacked pruning sparse denoising auto encoder. *Energy Reports*, *7*, 2201-2213.

Suyono, H., Rahman, M. T., Mokhlis, H., Othman, M., Illias, H. A., & Mohamad, H. (2019). Optimal scheduling of plug-in electric vehicle charging including time-of-use tariff to minimize cost and system stress. *Energies*, *12*(8), 1500.

Tabatabaee, S., Mortazavi, S. S., & Niknam, T. (2017). Stochastic scheduling of local distribution systems considering high penetration of plug-in electric vehicles and renewable energy sources. *Energy*, *121*, 480-490.

Tesla Motors High-Performance Electric Vehicles. (2021). Retrieved 9 November 2022, from http://www.teslamotors.com.

Tirunagari, S., Gu, M., & Meegahapola, L. (2022). Reaping the benefits of smart electric vehicle charging and vehicle-to-grid technologies: Regulatory, policy and technical aspects. *IEEE Access*.

Turker, H., & Bacha, S. (2018). Optimal minimization of plug-in electric vehicle charging cost with vehicle-to-home and vehicle-to-grid concepts. *IEEE Transactions on vehicular technology*, *67*(11), 10281-10292.

Ugurlu, U., Oksuz, I., & Tas, O. (2018). Electricity price forecasting using recurrent neural networks. *Energies*, *11*(5), 1255.

Ugurlu, U., Tas, O., & Gunduz, U. (2018). Performance of electricity price forecasting models: Evidence from Turkey. *Emerging Markets Finance and Trade*, *54*(8), 1720-1739.

Un-Noor, F., Padmanaban, S., Mihet-Popa, L., Mollah, M. N., & Hossain, E. (2017). A comprehensive study of key electric vehicle (EV) components, technologies, challenges, impacts, and future direction of development. *Energies*, *10*(8), 1217.

Usman, H. M., Mukhopadhyay, S., & Rehman, H. (2019). Permanent magnet DC motor parameters estimation via universal adaptive stabilization. *Control Engineering Practice*, *90*, 50-62.

Usman, M., Tareen, W. U. K., Amin, A., Ali, H., Bari, I., Sajid, M., Seyedmahmoudian, M., Stojcevski, A., Mahmood, A., & Mekhilef, S. (2021). A coordinated charging scheduling of electric vehicles considering optimal charging time for network power loss minimization. *Energies*, *14*(17), 5336.

Vagropoulos, S. I., & Bakirtzis, A. G. (2013). Optimal bidding strategy for electric vehicle aggregators in electricity markets. *IEEE Transactions on Power Systems*, *28*(4), 4031-4041.

Wan, Z., Li, H., He, H., & Prokhorov, D. (2018). Model-free real-time EV charging scheduling based on deep reinforcement learning. *IEEE Transactions on Smart Grid*, *10*(5), 5246-5257.

Wang, K., Xu, C., Zhang, Y., Guo, S., & Zomaya, A. Y. (2017). Robust big data analytics for electricity price forecasting in the smart grid. *IEEE Transactions on Big Data*, *5*(1), 34-45.

Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International journal of forecasting*, *30*(4), 1030-1081.

Wipf, D., & Nagarajan, S. (2007). A new view of automatic relevance determination. *Advances in neural information processing systems*, *20*.

Wu, H., Shahidehpour, M., Alabdulwahab, A., & Abusorrah, A. (2015). A game theoretic approach to risk-based optimal bidding strategies for electric vehicle aggregators in electricity markets with variable wind energy resources. *IEEE Transactions on Sustainable Energy*, *7*(1), 374-385.

Yang, Z., Ce, L., & Lian, L. (2017). Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods. *Applied Energy*, *190*, 291-305.

Zhang, F., Fleyeh, H., & Bales, C. (2022). A hybrid model based on bidirectional long short-term memory neural network and Catboost for short-term electricity spot price forecasting. *Journal of the Operational Research Society*, *73*(2), 301-325.

Zhang, J.-L., Zhang, Y.-J., Li, D.-Z., Tan, Z.-F., & Ji, J.-F. (2019). Forecasting day-ahead electricity prices using a new integrated model. *International Journal of Electrical Power & Energy Systems*, *105*, 541-548.

Zhang, J., Tan, Z., & Wei, Y. (2020). An adaptive hybrid model for short term electricity price forecasting. *Applied Energy*, *258*, 114087.

Zhang, Q., Dehghanpour, K., Wang, Z., & Huang, Q. (2019). A learning-based power management method for networked microgrids under incomplete information. *IEEE Transactions on Smart Grid*, *11*(2), 1193-1204.

Zhang, R., Li, G., & Ma, Z. (2020). A deep learning based hybrid framework for day-ahead electricity price forecasting. *IEEE Access*, *8*, 143423-143436.

Zhang, Y., Tao, P., Wu, X., Yang, C., Han, G., Zhou, H., & Hu, Y. (2022). Hourly electricity price prediction for electricity market with high proportion of wind and solar power. *Energies*, *15*(4), 1345.

Zheng, Y., Niu, S., Shang, Y., Shao, Z., & Jian, L. (2019). Integrating plug-in electric vehicles into power grids: A comprehensive review on power interaction mode, scheduling methodology and mathematical foundation. *Renewable and Sustainable Energy Reviews*, *112*, 424-439.

Zhou, S., Zhou, L., Mao, M., Tai, H.-M., & Wan, Y. (2019). An optimized heterogeneous structure LSTM network for electricity price forecasting. *IEEE Access*, *7*, 108161-108173.