AI And ML Innovations in EV Charging: Transforming Smart Grids with Vehicle-To-Grid Technologies

Aditya Kumar Sharma

Zūm Services Inc., Redwood City, California.

ABSTRACT

The rapid ascendancy of electric vehicles (EVs) marks a significant pivot towards sustainable transportation, addressing the pressing concerns of energy conservation and environmental degradation. With the global surge in EV adoption, underscored by a 75% sales increase in the early months of 2022 compared to the previous year, the integration of these vehicles into the existing electrical grids emerges as both a challenge and an opportunity. This integration is facilitated by Vehicle-to-Grid (V2G) systems, which leverage EV batteries as dynamic energy storage units, offering ancillary services such as peak shaving and voltage regulation, thereby enhancing grid efficiency and promoting renewable energy utilization. Despite the potential benefits, the practical implementation of V2G technologies is still at a nascent stage, primarily confined to pilot projects with limited scalability. The academic discourse has extensively explored EV charging strategies, yet the operational and economic facets of V2G, especially in discharge scheduling and dynamic pricing strategies, remain underexplored. This paper ventures into this relatively uncharted territory, examining the role of artificial intelligence (AI) in revolutionizing forecasting, scheduling, and dynamic pricing models relevant to EV charging and discharging practices. This research aims to provide a comprehensive analysis of current AI-driven methodologies in EV management, elucidating the synergies between forecasting accuracy, scheduling efficiency, and dynamic pricing efficacy. It identifies significant gaps in existing studies and proposes future research directions to foster the integration of EVs into smart grids. The study underscores the critical need for advanced forecasting models, innovative dynamic pricing strategies, and reinforcement learning-based optimization models to navigate the complexities of EV charging and discharging in a rapidly evolving energy landscape. As the cornerstone of smart city infrastructure, the integration of EVs and the development of intelligent charging systems are imperative for mitigating urbanization pressures and ensuring environmental sustainability. This paper highlights the challenges and opportunities in EV management, emphasizing the importance of machine learning techniques in enhancing charging infrastructure and integrating renewable energy sources into distributed microgrids. It concludes with a call for multidisciplinary research efforts to realize the full potential of EVs in smart grids, paving the way for a sustainable, efficient, and interconnected energy future.

Keywords: Electric Vehicles (EVs), Vehicle-to-Grid (V2G) Technology, Artificial Intelligence (AI) in Energy Management, Dynamic Pricing Strategies, Smart Grid Integration

I. INTRODUCTION

In the landscape of modern transportation, the adoption of electric vehicles (EVs) has been gaining significant momentum across the globe as a pivotal response to the dual challenges of the energy crisis and escalating environmental concerns, notably elevated CO_2 emissions and the overarching threat of climate change. The surge in EV sales, which saw over two million units sold in the early months of 2022—marking a 75% increase compared to the same timeframe the previous year—underscores a growing trend fueled by governmental incentives and policy support aimed at promoting sustainable mobility solutions. This uptick in EV adoption not only presents a unique set of challenges for the existing electrical grids due to the potential strain from uncoordinated charging practices but also offers an innovative opportunity through the utilization of EV batteries. These batteries, as mobile energy storage units, hold the potential for providing critical ancillary services to the power grid, encompassing peak shaving, valley filling, and the regulation of voltage and frequency, thereby facilitating a more efficient and renewable energy-centric grid operation.

The concept of leveraging EV batteries to supply power back to the grid, known as the vehicle-to-grid (V2G) system, was initially proposed over two decades ago. It embodies a transformative approach to align the interests of various stakeholders, including EV owners, grid operators, policymakers, and energy aggregators, by fostering environmental, economic, and socio-technological benefits. Among these, the V2G services offer a promising avenue for reducing EV ownership costs and enhancing grid management through the strategic charging and discharging of EVs, thereby mitigating grid congestion and promoting the use of renewable energy sources. Despite the promising prospects of V2G integration, its penetration into the market and practical implementation remains in nascent stages, primarily confined to pilot projects with limited scope and scale. The academic discourse has predominantly concentrated on EV charging methodologies, with extensive studies dedicated to optimizing charging strategies, scheduling, and the potential economic benefits of dynamic pricing models. Yet, the exploration of V2G's full potential, particularly in operational and economic dimensions such as discharge scheduling and pricing strategies, remains relatively underexplored.

Recent advancements in artificial intelligence (AI) have ushered in a new era of research and application possibilities, particularly in forecasting, scheduling, and dynamic pricing models relevant to EV charging and discharging practices. The superior predictive and optimization capabilities of AI algorithms, devoid of the need for intricate system knowledge, present a promising frontier for enhancing the efficiency and integration of EVs into the energy ecosystem. This paper seeks to delve into the existing body of AI-based studies focusing on the EV landscape, aiming to illuminate the synergies between forecasting, scheduling, and dynamic pricing, identify prevailing research gaps, and outline prospective avenues for future investigation. Our primary objective is to furnish a comprehensive analysis of current AI-driven methodologies in the realm of EV charging and discharging, highlighting their contributions to forecasting accuracy, scheduling efficiency, and the efficacy of dynamic pricing mechanisms. In doing so, this research endeavors to pinpoint critical gaps in the literature and propose directions for future studies that could further the integration of EVs into smart grids, thereby contributing to the overarching goals of sustainable transportation and energy systems.

II. ADAPTING EVS TO SMART GRIDS

The auto industry's evolution has recently taken a significant turn with the increased prominence of electric vehicles (EVs), marking a pivotal shift towards more sustainable transportation solutions. In 2019 alone, EV sales surged to 2.1 million, representing a 40% growth compared to previous years, underscoring the rapidly growing acceptance and demand for electric mobility. This surge has not only elevated the importance of EVs but has also brought EV chargers to the forefront as an indispensable component of global infrastructure. With a recorded 7.3 million chargers installed worldwide in 2019 and a notable 60% increase in the installation of public charging stations, the infrastructure to support EVs is expanding at an unprecedented rate. Predictions suggest that by 2030, electric vehicles will constitute 30% of all vehicle sales, amounting to 43 million EVs sold globally, further amplifying the need for robust charging infrastructure and advanced technological solutions to manage the expected increase in electrical load on distribution grids.

The burgeoning number of EVs introduces significant challenges to the existing power distribution networks, primarily due to the substantial energy demands for vehicle charging. This rising tide of electric mobility necessitates the development of efficient and reliable management systems for the distribution grid to ensure stability and sustainability. The adoption of advanced driving technologies aimed at reducing operating costs is anticipated to further boost the demand for electric vehicles, thereby increasing the electricity requirements for charging stations. Consequently, the escalating presence of EVs amplifies the load curve, putting additional stress on transformers and the distribution grid at large, which calls for an effective and resilient management strategy. In response to these challenges, innovative solutions are being explored within the realm of Information and Communication Technology (ICT), particularly in the context of smart cities. Smart cities, defined by their integration of ICT frameworks, aim to address urban challenges through sustainable practices, enhancing the quality of life for their inhabitants. At the heart of a smart city lies the intelligent network of interconnected devices and objects, facilitated by cloud and wireless technologies, which manage and analyze data in real time. This ecosystem not only promotes improved mobility and convenience but also contributes to significant reductions in living costs, energy consumption, and environmental pollution. Specifically, the integration of electric vehicles and renewable energy sources into the smart grid represents a critical step towards achieving these goals. Moreover, smart city technologies allow government agencies to engage with the public more effectively, develop infrastructure, and monitor progress, thereby offering a comprehensive solution to urbanization pressures and improving citizen-government interactions.

This paper delves into the intricacies of integrating electric vehicles into the smart grid, highlighting the essential role of electric vehicle chargers in this transition. It also examines the impact of electric vehicles on the distribution grid and explores the potential of smart cities as a holistic approach to managing the increasing demands placed on urban infrastructure by electric mobility. Furthermore, the review evaluates the performance of various machine learning techniques in optimizing the distribution grid and reducing charging costs, thereby offering insights into the development of intelligent management systems capable of navigating the complexities of a rapidly evolving electric vehicle landscape. Through this exploration, the paper aims to inform policymakers and smart city planners on the strategic integration of EVs into the energy infrastructure, ensuring the well-being and sustainability of urban communities in the face of growing electric vehicle adoption.

III. INNOVATIONS IN EV CHARGING/DISCHARGING

The realm of electric vehicles (EVs) is on the cusp of transformation with the introduction and refinement of various charging and discharging techniques. These methodologies, crucial for the integration of EVs into the power grid and the broader energy system, include uncontrolled charging-discharging, controlled charging-discharging, smart charging, and indirectly controlled charging. Each technique offers its unique set of advantages and challenges, fundamentally shaping the interaction between EVs and the electrical grid. Uncontrolled charging-discharging stands out for its simplicity and convenience, allowing EVs to charge or discharge at their rated power upon connection until reaching the battery's maximum state of charge or until the vehicle is unplugged. Despite its ease of implementation and the autonomy it provides to EV owners, this approach poses significant drawbacks, including potential harm to local distribution networks through power losses, demand-supply imbalances, decreased transformer lifespan, and harmonic distortion.

In contrast, the controlled charging-discharging method, or unidirectional V2G, grants system operators greater discretion in determining the timing for EV charging and discharging. This strategy, however, requires EV owners to relinquish control over their vehicles' charging schedules to operators or aggregators, potentially complicating its adoption. Smart charging emerges as a solution aimed at balancing energy demand with supply, optimizing charging schedules based on real-time grid conditions and requirements. Although smart charging seeks to maximize the efficiency of power systems and potentially reduce charging costs, its success hinges on effectively motivating EV owners to participate, often necessitating clear incentives. The indirectly controlled charging technique leverages economic incentives, utilizing dynamic pricing schemes like Time of Use (ToU) and Real-Time Pricing (RTP), to encourage EV owners to adjust their charging and discharging behaviors in response to financial benefits. Despite its potential to streamline the integration of EVs into smart grid operations, the effectiveness of this approach depends on the precision of electricity pricing signals and the clarity of the incentives offered to EV users.

Amidst these developments, the Vehicle-to-Grid (V2G) concept represents a pivotal innovation, enabling the use of EV batteries not only for mobility but also as flexible energy storage solutions for the power grid. V2G technology offers the promise of enhancing renewable energy utilization, reducing emissions, and providing ancillary services to the grid, all while potentially lowering charging costs for EV owners. Notably, the implementation of V2G can circumvent the need for additional investment in battery storage systems, capitalizing on the high availability of parked vehicles. However, the path to widespread V2G adoption is fraught with challenges, including concerns over battery degradation, the efficiency of charging and discharging processes, and the necessity for significant upfront investments. Despite these obstacles, the potential benefits of V2G for both power systems and EV owners are considerable, suggesting that overcoming these challenges could significantly advance the sustainability and resilience of energy systems.

As the electric vehicle market continues to evolve, the development and refinement of charging and discharging techniques, alongside the strategic implementation of V2G technology, stand as critical milestones in the journey toward more sustainable and efficient energy systems. This exploration underscores the need for continued innovation, research, and policy support to harness the full potential of electric vehicles as integral components of the future energy landscape.

Aspect	Details
Battery Degradation Factors	Charging and discharging rates, Depth of Discharge (DOD), temperature, voltage, cycle number, storage State of Charge (SOC).
Types of Aging	Calendar aging (occurs during storage, influenced by battery temperature and SOC) and Cycle aging (happens during charging/discharging, affected by cycle number, charging rate, and DOD).
Monitoring and Prediction	- Meng et al.: Extended equivalent circuit model for battery monitoring. - Kalman filter and Gaussian process regression for End-of-Life (EOL) prediction. - Recurrent Neural Networks (RNNs) for SOC and SOH estimation without the need for battery modeling.
V2G Impact	- Additional cycling accelerates degradation. - Different impacts on NCA and LFP battery types. - High SOC increases capacity loss during storage. - Overcharging/over-discharging degradation occurs outside specified voltage range.
Charging Efficiency	- Power losses mostly in power electronics for AC-DC conversion. - Higher efficiency in charging than discharging due to higher voltage and lower current, reducing internal resistance losses. - Importance of optimal rate, temperature, and SOC for charging/discharging.

Figure 1 : Variables affecting battery life and Efficiency.

IV. OPTIMIZING SMART GRID PERFORMANCE THROUGH V2G INTEGRATION

The Vehicle to Grid (V2G) network stands as a pivotal advancement in the evolution of smart grids, enhancing the ability to balance power supply and demand effectively. This innovative network transforms electric vehicles (EVs) into mobile energy storage units, reducing the reliance on non-renewable energy sources and mitigating the adverse environmental impacts associated with their use. The integration of EVs into smart grids, however, presents challenges that necessitate sophisticated management systems like the Energy Distribution Management System (EDMS) to optimize energy consumption and distribution.

EDMS plays a critical role in refining the charging experience for electric vehicle users by analyzing a myriad of factors, including the location, charging status of EVs, user preferences, forecasted energy demand, and the condition of the distribution network. This system's capability to predict EV demand and its impact on the grid is instrumental in achieving unparalleled Quality of Service (QoS) levels, ensuring that the smart grid operates efficiently and sustainably. For effective EDMS operation, future electric vehicles will be equipped with an Energy Balancing (EB) unit synchronized with data-gathering devices. These include GNSS receivers, inertial measurement units (IMU), and Wi-Fi wireless LAN interfaces, essential for determining the vehicle's precise location. This accurate localization, combined with the ability to communicate data to the internet through built-in phone modems, lays the foundation for a robust communication network essential for smart city ecosystems.

The integration of EVs into smart grids is a multifaceted process, with electric vehicles' varying power usage patterns posing potential system challenges. Successfully integrating these vehicles into the grid

requires accurate forecasting of EV load profiles, taking into consideration the battery capacity and the nonlinear nature of battery charging. Probabilistic models, artificial neural networks, support vector machines, and decision trees are among the machine learning techniques employed to predict the presence and demand of EVs on the road. Automated decision-making systems are vital for minimizing maintenance and energy costs, with research demonstrating how cyber insurance can optimize discharge rates and reduce charging costs. Such systems utilize advanced models to make informed decisions regarding short-term pricing, coverage, and insurance options, leading to more efficient and cost-effective smart grid operations.
The integration of EVs into smart grids, both through centralized and decentralized models, represents a significant step towards realizing the full potential of smart cities. By harnessing machine learning and artificial intelligence, smart grids can efficiently manage electric vehicles' charging and discharging, contributing to enhanced grid reliability and reduced energy costs. These technological advancements underscore the critical importance of V2G networks in optimizing smart grid performance, offering a sustainable pathway towards mitigating population pressures and advancing global smart city initiatives.

Feature	Description
Magnetic Coupling Coefficients	Measure the efficiency of power transfer between the primary and secondary coils. High values are essential for efficient power transmission.
Static Wireless Fast Chargers	Can deliver power exceeding 20 kW, indicating progress in the standardization of high-power WPT systems.
Notable Projects	OLEV (Online Electric Vehicle) achieved 83% efficiency with an air gap up to 20 cm and 20 kHz frequency for 60 kW power transfer. DWC (Dynamic Wireless Charging) showed the feasibility of transmitting 22 kW across air gaps and lateral deviations.
Frequency Control	Frequency droop control is crucial for integrating EVs into the smart grid, allowing EVs to adjust charging or discharging in response to frequency deviations.
Research & Development Focus	Focuses on optimizing the power transmitted and the efficiency of the transfer process, highlighting the importance of improving air gap efficiency and system compactness.
Optimal System Quest	Involves navigating trade-offs between efficiency, frequency, and coupling coefficients. Standardization of frequencies is vital for optimal performance.
Innovative Control Strategies	Leverage distributed algorithms for cost-effective energy utilization through decentralized decision-making. The 'water filling' technique illustrates the potential for managing the charging of multiple EVs.

Figure 2 : Contactless EV charging Systems.

V. MACHINE LEARNING OPTIMIZED CHARGING EFFICIENCY AND ENERGY STORAGE

In the realm of electric vehicle (EV) management systems, the evolution of machine learning (ML) techniques offers significant potential to enhance charging efficiency and energy storage. This paper delves into the comparative analysis of various ML algorithms, including decision trees, random forests, support vector machines, k-nearest neighbors, deep neural networks, and long short-term memory (LSTM), to determine the most effective model for EV control and charging station classification. Utilizing a comprehensive dataset, these algorithms were assessed to identify which yields the highest accuracy in predicting and managing EV charging behaviors and hybrid energy storage systems.
The study revealed that LSTM models, in particular, hold promising capabilities in optimizing EV charging strategies. By accurately predicting incoming data, these models facilitate the flattening of load curves, thereby enhancing peak voltage management, reducing power losses, and ensuring voltage stability. This optimization leads to lower electricity billing costs for consumers, underpinning the

proposed system's economic viability. To conduct this analysis, a detailed examination of dataset characteristics was undertaken, encompassing various parameters critical to EV charging and management. The dataset included information on session IDs, total kWh, cost implications, and temporal charging data, among others. This granular data allowed for a nuanced understanding of charging behaviors and station efficiency. In evaluating the performance of ML models for charging station classification, the research found that random forests and LSTM algorithms outperformed others with a 94% accuracy rate. Decision trees followed closely with 93% accuracy, while deep neural networks also demonstrated considerable efficacy with 77% accuracy. This finding underscores the potential of ML in directing EVs to the most suitable charging stations, thereby optimizing the distribution network's performance and reducing charging costs.
The analysis further explored the classification of charging speeds into three categories: fast charging, conventional charging, and vehicle-to-grid (V2G) capabilities. Here again, LSTM models excelled, proving 4% more accurate than random forests in identifying optimal charging rates. This superiority of LSTM in handling multiclass classification problems highlights its potential as a strategic tool for managing an EV fleet, particularly given its prowess in recognizing temporal patterns in power consumption data. However, the incorporation of uncertain load data introduced through Gaussian white noise presented a challenge to the accuracy of these models. Despite this, LSTM maintained its robust performance, indicating its adaptability and effectiveness even under conditions of uncertainty. This resilience is crucial for the reliable management of EV charging and distribution systems in the face of unpredictable energy demands.
Given the significance of machine learning in enhancing EV charging infrastructure and hybrid energy storage management, further research is imperative. Advancements in deep learning, reinforcement learning, and federated learning could centralize and streamline EV utilization regulation, addressing the limitations of current systems. Moreover, expanding the dataset to include more parameters and embracing more dynamic charging and discharging strategies could further optimize energy usage and cost-efficiency for EV owners and grid operators alike. Hence, the integration of advanced ML algorithms into EV management systems represents a transformative step towards more sustainable and efficient energy usage. With continued innovation and refinement, these technologies hold the promise of revolutionizing how we manage electric vehicles and their interaction with the smart grid, paving the way for a more energy-efficient future.

Algorithm	Advantages	Disadvantages
Decision Tree (DT)	Data does not need to be sized or normalized. Benefits regression and classification analyses—highly accurate predictions and understanding.	Training can be time-consuming as even minor changes to the dataset could significantly affect the final structure.
Random Forest (RF)	Capable of processing large datasets with high dimensionality and handling uncertainty while outputting the mean or mode of several decision trees.	Complexity increases with the number of trees created. Training typically requires a considerable amount of time.
Support Vector Machine (SVM)	Useful for both classification and regression; minimizes the classifier's performance error.	Training process is slow with large datasets. Performs poorly when the number of features exceeds the number of training samples.
K-Nearest Neighbors (KNN)	Useful for both classification and regression analysis. Short training times. Clear and straightforward implementation.	Performs poorly with large datasets and a high number of input features. Struggles with unbalanced datasets.

Deep Neural Network (DNN)	Versatile model for various tasks, such as classification and regression. Capable of complex pattern recognition.	Requires large datasets and is highly susceptible to overfitting. Determining the optimal model structure can be challenging.
Long Short-Term Memory (LSTM)	Effective for time series analysis, accurate forecasting, and adaptable to different applications (classification and regression).	Lacks a standardized method for determining the optimal model structure. Selecting the best hyperparameters can be challenging.

Figure 3: Machine Learning Techniques with Advantages and Disadvantages

VI. CHALLENGES AND INNOVATIONS IN EV MANAGEMENT

The journey of Vehicle-to-Grid (V2G) technology is unfolding through distinct developmental phases, each characterized by
its unique challenges and advancements in electric vehicle (EV) charging and discharging strategies. Currently, V2G finds itself in an embryonic stage where EV charging constitutes a minor fraction of the overall load on power grids. Predominantly, uncontrolled and controlled charging techniques are employed, reflecting the nascent state of V2G integration. This phase is also marked by numerous pilot projects that are either in the conceptual or initial testing stages, highlighting a gradual yet promising start toward a comprehensive V2G ecosystem.

As we anticipate moving into the second developmental phase, the landscape begins to shift significantly. With an expected surge in EV adoption, charging loads are projected to form a substantial portion of the grid's demand. This influx of EVs introduces the potential for increased strain on the grid during peak times, underscoring the need for meticulous coordination. Herein, the role of aggregators becomes crucial, tasked with harnessing smart charging and discharging strategies to facilitate demand-side management services. This period will likely witness a deeper exploration into smart charging/discharging approaches, emphasizing the importance of accurate forecasting and scheduling models to mitigate the challenges of high EV penetration. The accuracy of forecasting models, primarily reliant on supervised learning techniques, is pivotal for optimizing EV charging/discharging schedules. These models, enriched by advancements in artificial intelligence, play a vital role in predicting future electricity prices, EV load demands, and the availability of battery State of Charge (SOC) for V2G services. However, the stochastic nature of EV charging and discharging patterns introduces a layer of complexity and unpredictability, challenging the forecasting process. To combat this, hybrid and ensemble methods, alongside online-based forecasting and prediction confidence interval techniques, offer promising avenues to refine forecasting accuracy and manage inherent uncertainties.

The application of reinforcement learning-based models, particularly those overcoming the limitations of conventional Q-learning through Deep-Q networks (DQN), has shown promise in managing the dynamic and complex environment of EV charging/discharging scheduling. These models, including DQN, Double DQN, Deep Deterministic Policy Gradient (DDPG), and Soft Actor-Critic (SAC), enhance the capability to handle high-dimensional problems, albeit with considerable training time. As the field progresses, exploring faster convergence methods like Asynchronous Advantage Actor-Critic (A3C) and incorporating episodic memory and meta-reinforcement learning could offer breakthroughs in training speed and policy optimization. Looking forward, the third phase of V2G development envisions a scenario where EVs not only support the grid through ancillary services but also engage in sophisticated interaction with the power system operators. This ideal state of smart grids will necessitate robust communication mechanisms and innovative artificial intelligence-based battery design and management strategies to mitigate battery degradation and minimize charging/discharging losses. The implementation of dynamic pricing, inspired by models from various industries, emerges as a critical strategy to navigate the high penetration of EVs and their charging/discharging preferences. A well-designed dynamic pricing model that accurately reflects the power grid's conditions could significantly influence EV charging and discharging behaviors, optimizing energy utilization. However, the design of such dynamic pricing schemes remains underexplored, with current research primarily focused on scheduling models that aim to minimize charging costs without fully considering EV penetration impacts and owners' preferences. In conclusion, the evolution of V2G technology, from its preliminary phase through to a future of integrated smart grids, underscores the need for continued innovation in charging/discharging strategies, forecasting accuracy, reinforcement learning applications, and dynamic pricing models. As V2G transitions through these phases, the focus will increasingly shift towards creating a resilient, efficient, and user-centric ecosystem that supports the widespread adoption of EVs and their active participation in enhancing grid stability and sustainability.

VII. CONCLUSION

This study delves into the critical components of electric vehicle (EV) management systems, focusing on forecasting, scheduling, and dynamic pricing mechanisms. Their intertwined nature is evident as the success of scheduling models hinges on precise forecasting and effective dynamic pricing strategies. Conversely, the utility of dynamic pricing is significantly influenced by the precision in forecasting and the efficacy of scheduling.

In the domain of forecasting, the study highlights the dominance of supervised learning models, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). These models are lauded for their proficiency in navigating nonlinear dynamics and long-term dependencies inherent in EV charging and discharging data. Yet, the challenge of inherent uncertainty in forecasting demands ongoing enhancements in model accuracy. Solutions such as hybrid and ensemble methods, real-time data updates, and the incorporation of uncertainty intervals emerge as promising strategies to bolster decision-making processes.

The application of reinforcement learning (RL) for optimizing EV charging and discharging operations underscores the complexity of managing numerous variables within state spaces. Popular RL models including Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), and Soft Actor-Critic (SAC) each present unique benefits and drawbacks, such as DQN's resolution of dimensionality issues and the common challenges of action value overestimation and extensive training durations. Innovations like Double-DQN and Asynchronous Advantage Actor-Critic (A3C) are noted for their potential in addressing these challenges.

Scheduling effectiveness is contingent upon utilizing data that accurately mirrors the power grid’s real-time state. This underscores the importance of both forecasting precision and dynamic pricing signals. Despite extensive exploration into forecasting and scheduling, literature on EV discharging and dynamic pricing remains sparse. Current dynamic pricing models often overlook EV owners' preferences and fail to consider all relevant charging/discharging factors, highlighting a gap in research.

The study calls for a balanced approach to dynamic pricing scheme design, one that can adapt to real-time power system conditions while accommodating both system operators and EV owners. Furthermore, it advocates for research into the social and economic dimensions of EV management, including stakeholder responses to dynamic pricing and the viability of such models.

In the broader context of smart cities and grid integration, the proliferation of EVs presents both challenges and opportunities in energy management, charging standardization, and the integration of machine learning for seamless grid integration. The exploration extends to charging technologies, assessing conductive and inductive methods, and the compatibility of current wireless charging standards across various frequencies.

This paper reviews the landscape of smart grid applications and the integration of EVs, underscoring the need for comprehensive strategies that consider community well-being, infrastructure robustness, and environmental sustainability. It anticipates discussions on wireless power transmission systems and their critical role in linking vehicles with the grid. By examining mobile energy storage and the incorporation of renewable sources into distributed microgrids, this research contributes to the understanding of future infrastructure developments essential for the widespread adoption of EVs.

VIII. FUTURE SCOPE

The exploration into electric vehicle (EV) charging and discharging mechanisms, as examined in this paper, lays a solid foundation for advancing the integration of EVs into smart grids and enhancing the efficiency of renewable energy utilization. Looking ahead, the future scope of this research is vast and multifaceted, focusing on technological, economic, and social dimensions to address emerging challenges and harness opportunities. Future research should concentrate on advancing forecasting techniques that can accurately predict EV charging demands, renewable energy availability, and power grid conditions. Innovations in machine learning, particularly in dealing with uncertainty and real-time data processing, could significantly improve the precision of forecasts. Exploration into hybrid, ensemble, and online-based forecasting models will be critical to adapting to the dynamic nature of smart grids and EV behaviors.

Developing dynamic pricing models that reflect real-time grid conditions and accommodate both EV owners' preferences and grid stability requirements presents a significant research avenue. Future studies should aim to create more sophisticated models that facilitate greater EV participation in Vehicle-to-Grid (V2G) services, potentially leveraging machine learning to optimize pricing in response to the fluctuating supply and demand. The application of reinforcement learning (RL) in scheduling EV charging and discharging offers a promising approach to optimizing grid operations. Future work could explore advanced RL techniques, such as Asynchronous Advantage Actor-Critic (A3C) and meta-reinforcement learning, to enhance model performance, reduce training times, and ensure that charging schedules contribute positively to grid stability and efficiency.

As EV adoption grows, understanding the societal and economic implications of EV integration into smart grids becomes increasingly important. Future research should investigate the impact of dynamic pricing on EV owners' behavior, the economic viability of V2G services, and how different stakeholder preferences can be balanced in the design of EV charging policies. The evolution of EV charging technologies, including conductive, inductive, and wireless charging systems, warrants further exploration. Research should focus on standardizing these technologies, improving charging efficiency, and reducing infrastructure costs to facilitate broader EV adoption. The synergy between EVs and renewable energy sources is an essential component of future smart grids. Investigating strategies for effectively integrating EV charging and discharging with renewable energy production can enhance grid resilience and sustainability. This includes studying the role of EVs in distributed microgrids and the potential for EVs to serve as mobile energy storage solutions. Developing supportive policy and regulatory frameworks is crucial for the successful implementation of advanced EV charging models and technologies. Future studies should examine the regulatory barriers to V2G implementation, the potential for incentivizing EV owner participation in grid services, and the creation of standards for dynamic pricing and charging technologies. As cities evolve into smarter, more connected ecosystems, the integration of EVs into public infrastructure becomes a pivotal area of research. Future studies could explore the development of smart charging stations, the impact of EVs on urban planning, and the role of ICT in facilitating seamless communication between EVs, charging stations, and grid operators.

IX. REFERENCES

1. Cedillo, M.H.; Sun, H.; Jiang, J.; Cao, Y. Dynamic pricing and control for EV charging stations with solar generation. Appl. Energy 2022, 326, 119920.
2. Mao, T.; Lau, W.H.; Shum, C.; Chung, H.S.H.; Tsang, K.F.; Tse, N.C.F. A regulation policy of EV discharging price for
   demand scheduling. IEEE Trans. Power Syst. 2018, 33, 1275–1288.
3. Erdinc, O.; Paterakis, N.G.; Mendes, T.D.P.; Bakirtzis, A.G.; Catalão, J.P.S. Smart household operation considering bi-directional EV and ESS utilization by real-time pricing-based DR. IEEE Trans. Smart Grid 2015, 6, 1281–1291.
4. Moghaddam, V.; Yazdani, A.; Wang, H.; Parlevliet, D.; Shahnia, F. An online reinforcement learning approach for dynamic pricing of electric vehicle charging stations. IEEE Access 2020, 8, 130305–130313.
5. Dang, Q.; Wu, D.; Boulet, B. EV charging management with ANN-based electricity price forecasting. In Proceedings of the 2020 IEEE Transportation Electrification Conference & Expo (ITEC), Chicago, IL, USA, 23–26 June 2020.
6. Deligiannis, P.; Koutroubinas, S.; Koronias, G. Predicting Energy Consumption Through Machine Learning Using a Smart-Metering Architecture. IEEE Potentials 2019, 38, 29–34.

7. Ding, T.; Zeng, Z.; Bai, J.; Qin, B.; Yang, Y.; Shahidehpour, M. Optimal electric vehicle charging strategy with markov decision process and reinforcement learning technique. IEEE Trans. Ind. Appl. 2020, 56, 5811–5823.
8. Li, S.; Hu, W.; Cao, D.; Dragiˇcevi´c, T.; Huang, Q.; Chen, Z.; Blaabjerg, F. Electric vehicle charging management based on deep reinforcement learning. J. Mod. Power Syst. Clean Energy 2022, 10, 719–730.
9. Lee, S.; Choi, D.H. Dynamic pricing and energy management for profit maximization in multiple smart electric vehicle charging stations: A privacy-preserving deep reinforcement learning approach. Appl. Energy 2021, 304, 117754.
10. Qiu, D.; Ye, Y.; Papadaskalopoulos, D.; Strbac, G. A deep reinforcement learning method for pricing electric vehicles with discrete charging levels. IEEE Trans. Ind. Appl. 2020, 56, 5901–5912.
11. Ramirez-Vazquez, R.; Gonzalez-Rubio, J.; Escobar, I.; Suarez Rodriguez, C.D.P.; Arribas, E. Personal exposure assessment to Wi-Fi radiofrequency electromagnetic fields in Mexican microenvironments. Int. J. Environ. Res. Public Health 2021, 18, 1857. [PubMed]
12. Lund, P.D.; Byrne, J.; Haas, R.; Flynn, D. (Eds.) The role of electric vehicles in smart grids. In Advances in Energy Systems: The Large-scale Renewable Energy Integration Challenge; John Wiley & Sons: Hoboken, NJ, USA, 2019; pp. 245–264.
13. Amer, A.; Shaban, K.; Gaouda, A.; Massoud, A. Home Energy Management System Embedded with a Multi-Objective Demand Response Optimization Model to Benefit Customers and Operators. Energies 2021, 14, 257.
14. Ashraf, S. Culminate Coverage for Sensor Network Through Bodacious-instance Mechanism. In I-Manager's Journal on Wireless Communication Networks; I-Manager Publications: Nagercoil, India, 2019; Volume 8, p. 1.
15. Jian, L.; Xue, H.; Xu, G.; Zhu, X.; Zhao, D.; Shao, Z.Y. Regulated Charging of Plug-in Hybrid Electric Vehicles for Minimizing Load Variance in Household Smart Microgrid. IEEE Trans. Ind. Electron. 2012, 60, 3218–3226.
16. Moghaddam, Z.; Ahmad, I.; Habibi, D.; Phung, Q.V. Smart Charging Strategy for Electric Vehicle Charging Stations. IEEE Trans. Transp. Electrification 2017, 4, 76–88.
17. Hu, J.; Morais, H.; Sousa, T.; Lind, M. Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects. Renew. Sustain. Energy Rev. 2016, 56, 1207–1226.
18. Karmaker, A.K.; Roy, S.; Ahmed, R. Analysis of the impact of electric vehicle charging station on power quality issues. In Proceedings of the 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE), Chittagong, Bangladesh, 7–9 February 2019.
19. Ashraf, S.; Alfandi, O.; Ahmad, A.; Khattak, A.M.; Hayat, B.; Kim, K.H.; Ullah, A. Bodacious-Instance Coverage Mechanism for Wireless Sensor Network. Wirel. Commun. Mob. Comput. 2020, 2020, 8833767.
20. Dileep, G. A survey on smart grid technologies and applications. Renew. Energy 2019, 146, 2589–2625.
21. Yilmaz, M.; Krein, P.T. Review of the Impact of Vehicle-to-Grid Technologies on Distribution Systems and Utility Interfaces. IEEE Trans. Power Electron. 2012, 28, 5673–5689.
22. Carli, R.; Dotoli, M. A Distributed Control Algorithm for Optimal Charging of Electric Vehicle Fleets with Congestion Management. IFAC-PapersOnLine 2018, 51, 373–378.
23. Yong, J.Y.; Ramachandaramurthy, V.K.; Tan, K.M.; Mithulananthan, N. A review on the state-of-the-art technologies of electric vehicle, its impacts and prospects. Renew. Sustain. Energy Rev. 2015, 49, 365–385.
24. Clairand, J.-M.; Guerra-Terán, P.; Serrano-Guerrero, X.; González-Rodríguez, M.; Escrivá-Escrivá, G. Electric Vehicles for Public Transportation in Power Systems: A Review of Methodologies. Energies 2019, 12, 3114.
25. Panchal, C.; Stegen, S.; Lu, J. Review of static and dynamic wireless electric vehicle charging system. Eng. Sci. Technol. Int. J. 2018, 21, 922–937.
26. Stüdli, S.; Crisostomi, E.; Middleton, R.; Shorten, R. A flexible distributed framework for realising electric and plug-in hybrid vehicle charging policies. Int. J. Control. 2012, 85, 1130–1145.