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ARTIFICIAL INTELLIGENCE ROLE IN OPTIMIZING ELECTRIC VEHICLE CHARGING PATTERNS, REDUCE COSTS, AND IMPROVE OVERALL EFFICIENCY: A REVIEW

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A B S T R A C T

The global popularity of electric cars (EVs) as a sustainable means of transportation, reliable and efficient charging infrastructure is essential. Traditional electric vehicle charging involves connecting the car to a power source and waiting for the battery to charge. However, AI has allowed us to improve charging patterns, reduce costs, and boost efficiency. This article examines how AI algorithms are changing electric car charging. If electric vehicle (EV) charging and discharging are not coordinated, the power supply infrastructure will be overrun. Demand response like dynamic pricing might encourage electric vehicle owners to participate in scheduling initiatives. Thus, EV charging and discharging scheduling and dynamic pricing model research are crucial. Artificial intelligence-based models for EV charging predictions and scheduling have been the focus of researchers. These models outperform linear, exponential, and multinomial logit optimization approaches. Due to the novelty and ongoing development of EVs returning electricity to the power grid, vehicle-to-grid (V2G) systems have received little attention. Thus, a complete analysis of EV charging and discharging research is needed to identify gaps and improve future studies. This study categorizes EV charging and discharging studies into forecasting, scheduling, and pricing techniques. The work links forecasting, scheduling, and pricing processes and identifies research gaps in EV discharge scheduling and dynamic pricing models.

1. INTRODUCTION

Many governments have expedited the implementation of electric vehicles (EVs) in order to address the energy crisis and environmental issues, including elevated CO2 emissions and climate change (Wang, et al., 2016, Wang et al., 2021). In the first quarter of 2022, approximately two million electric vehicles (EVs) were sold, marking a 75% surge compared to the corresponding period in 2021 (Goswami & Shende, 2018). The global proliferation of electric vehicles (EVs) will persist due to the implementation of various governmental incentives and policies. One consequence of the growing and disorganized electric vehicle (EV) charging is that it will place a heavy load on the current power infrastructure. Conversely, electric vehicles (EVs) utilize portable energy storage devices in the form of batteries. These batteries can be employed to offer additional services to power grids, including reducing peak demand and filling in low-demand periods, as well as regulating voltage and frequency (Mohammad et al., 2020, Lee & Choi, 2021). Furthermore, the batteries of electric vehicles (EVs) can be utilized as adaptable sources of power consumption

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and generation in order to optimize the utilization of renewable energy. This can be achieved by effectively coordinating the charging and discharging of EVs to closely align with the profiles of renewable energy generation (Wang & Wang, 2013, Limmer, 2019; Bukya et al., 2020). Vehicle-to-grid (V2G) refers to the concept of utilizing electric vehicle (EV) batteries to provide electricity to the power grid. The concept was initially proposed by Kempton and Letendre in 1997 (Bukya et al., 2020). The utilization of electric vehicles (EVs) as energy storage in the Vehicle-to-Grid (V2G) program can provide numerous environmental, economic, and socio-technological advantages for program participants, including EV owners, grid operators, government entities, and aggregators (Rotering & Ilic, 2011). For instance, V2G services enable EV owners to sell stored energy back to power networks during peak hours, hence reducing the overall cost of owning an EV (Kempton & Tomic, 2005). In addition, the V2G program has the capability to alleviate power grid congestion, decrease emissions, and enhance the utilization of renewable energy for grid operators. This is achieved by scheduling electric vehicle charging during periods of high renewable energy generation and discharging back to the power grids during periods of low renewable energy generation and high demand for electricity (Kempton & Letendre, 1996; Ravi & Aziz, 2022).

Nevertheless, the adoption of electric vehicles (EVs) remains limited at present, while the idea of vehicle-to-grid (V2G) technology is still in its early stages and undergoing continuous development. Several V2G projects are still in the first stages of development, specifically as pilot projects (Lund & Kempton 2008; Scott et al., 2021). Table 1 provides a summary of many V2G pilot programs that serve different purposes and offer diverse services. For a comprehensive compilation of V2G pilot programs worldwide, go to (Lund & Kempton, 2008). Table 1 demonstrates that the majority of V2G pilot projects have only been started in the past few years, and these programs are of a limited scale. Furthermore, the majority of the current literature solely concentrates on the subject of electric vehicle charging. The papers (Al-Awami & Sortomme, 2011; Sovacool et al., 2017). discusses the categorization of EVs' charging methods. Researchers in the age range of 17 to 30 developed electric vehicle (EV) charging systems with the aim of reducing charging expenses. In their study, Al-Ogaili et al. (2019) conducted a comprehensive analysis of the current literature on strategies for scheduling, clustering, and forecasting the charging of electric vehicles (EVs). The review conducted in Amin et al. (2020) examined the most effective approach of charging electric vehicles in the presence of dynamic pricing schemes such as Real-Time Pricing (RTP), Time of Use (ToU), Peak Time Rebates (PTR), and Critical Peak Pricing (CPP). Several studies have examined various aspects of Vehicle-to-Grid (V2G) technology. These include investigating customer acceptance of V2G (Kester et al., 2019), exploring the integration of renewable energy into transportation systems through V2G (Shi et al., 2020), assessing the economic viability of implementing V2G on a university campus (Schetinger et al., 2020), examining the coordination of V2G with energy trading (Al-Awami & Sortomme, 2011), and developing optimal energy management systems (Ma et al., 2018). It is challenging to motivate EV owners to take part in the V2G program without financial incentives due to the energy and time required to supply electricity back to power networks. Hence, the economic and operational factors of Vehicle-to-Grid (V2G) technology will assume great significance as the adoption of electric vehicles (EVs) equipped with V2G capabilities increases. Several EV charging scheduling methods have successfully adhered to Time of Use (ToU) and Real-Time Pricing (RTP) signals to reduce peak demand (Widergren et al., 2012), mitigate the effects of load fluctuations (Chen et al., 2014), and lower EV charging expenses (Tushar et al., 2015; Amamra & Marco, 2019; Lee et al., 2020). Nevertheless, the literature has provided limited discussion on the extent to which these pricing systems accurately represent power system conditions. Furthermore, the economic and operational components of the V2G program, including discharge schedule and pricing mechanism, have only been suggested in a limited number of articles (Karfopoulos & Hatziargyriou, 2015; Farzin et al., 2016, Shokouhmand & Ghasemi, 2022). Al-Ogaili et al. (2019) proposed that artificial intelligence models outperform probabilistic models. Due to the accessibility of datasets and the growing processing capabilities, artificial intelligence techniques like neural networks and reinforcement learning have gained significant popularity and proven to be highly effective in various applications, such as forecasting and optimization problems. Artificial intelligence models surpass conventional optimization models, such linear and exponential optimization models, due to their capacity to learn from datasets. Furthermore, artificial intelligence models typically do not necessitate expertise in intricate systems, which might be difficult to acquire. Consequently, artificial intelligence models have been employed in several research linked to electric vehicles, encompassing areas such as EV battery design and management, as well as vehicle-to-grid (V2G) applications (Mojumder et al., 2022). For an in-depth analysis of the various functions that artificial intelligence serves in facilitating the widespread use of electric vehicles, refer to reference Mo et al. 2022. In their study, Shahriar et al. (2020) conducted a comprehensive analysis of machine learning techniques used for predicting and classifying EV charging behavior. They specifically highlighted the promising application of reinforcement learning in EV scheduling. Moreover, numerous artificial intelligence models have been utilized to address tasks associated with EV charging scheduling. These tasks include forecasting EV charging electricity price (Jin et al., 2013; Al-Ogaili et al., 2019; Zhu et al., 2019), predicting EV driving patterns (Zhou et al., 2019), estimating the combined capacity of batteries (Farmann et al., 2015), determining charging load demand (Qian et al., 2010), analyzing charging patterns (Chen et al., 2020), and optimizing EV charging and discharging schedules (He et al., 2012, Jin et al., 2013, Hadian et al., 2020). Nevertheless, the existing literature has not thoroughly addressed the connections and discrepancies among each study. This review seeks to examine artificial intelligence-driven forecasting, scheduling, and dynamic pricing models. Furthermore, this article also examines the correlation between forecasting, scheduling, and dynamic pricing. Additionally, the study identifies the areas of research that have not been well addressed in the current literature, and provides insights into potential future research directions pertaining to the charging and discharging of electric vehicles. The primary focus of this study is to assess, condense, and evaluate the current artificial intelligence-driven algorithms for three essential components of electric vehicle charging and discharging: forecasting, scheduling, and dynamic pricing. This paper also identifies the research deficiencies in the efficient scheduling of electric vehicle discharge and the development of pricing policies, as revealed by the current body of literature.

2. LITERATURE REVIEW

Mohammad et al. (2020) conducted aParametric on reviewing the state-of-the-art literature on the modelling of grid-connected EV-PV (photovoltaics) system.

The review is concluded with a summary of potential research directions in this area. The paper presents an evaluation of different modelling components of grid-connected EV-PV system to facilitate readers in modelling such system for researching EV-PV integration in the distribution network.

(Wang et al., 2021), did a comparative study of an EV cluster scheduling strategy considering real-time electricity prices based on deep reinforcement learning. Firstly, we establish a distributed real-time optimal scheduling structure according to the real-time price signals of distribution system operators (DSO). Furthermore, to alleviate the curse of dimensionality, we propose a C–D model of a single EV according to the C–D characteristics of EV, and we establish the C–D control model of EVs as a Markov decision process (MDP). Finally, to adapt to the uncertainty of the learning environment, we propose a model-based deep reinforcement learning to optimize the C–D behavior of EVs. After day-ahead training and parameter saving of the proposed model, the C–D scheduling strategy is generated for the real-time system state at each moment of the day. The simulation results of the C–D scheduling strategy for cost-oriented EV charging show that the proposed scheduling strategy effectively reduces the user charging cost by 133.7 dollars and the load peak–valley difference, stabilizes the load fluctuation, and achieves the win–win situation between the power grid and EV users.

(Mohammad et al., 2020), conducted Profit maximization of electric vehicle charging station (EVCS) operation yields an increasing investment for the deployment of EVCSs, thereby increasing the penetration of electric vehicles (EVs) and supporting high-quality charging service to EV users. However, existing model-based approaches for profit maximization of EVCSs may exhibit poor performance owing to the underutilization of massive data and inaccurate modeling of EVCS operation in a dynamic environment. Furthermore, the existing approaches can be vulnerable to adversaries that abuse private EVCS operation data for malicious purposes. To resolve these limitations, we propose a privacy-preserving distributed deep reinforcement learning (DRL) framework that maximizes the profits of multiple smart EVCSs integrated with photovoltaic and energy storage systems under a dynamic pricing strategy.

(Mohammad et al., 2020), conducted Plug-in hybrid electric vehicles are a midterm solution to reduce the transportation sector's dependency on oil. However, if implemented in a large scale without control, peak load increases significantly and the grid may be overloaded. Two algorithms to address this problem are proposed and analyzed. Both are based on a forecast of future electricity prices and use dynamic programming to find the economically optimal solution for the vehicle owner. The first optimizes the charging time and energy flows. It reduces daily electricity cost substantially without increasing battery degradation. The latter also takes into account vehicle to grid support as a means of generating additional profits by participating in ancillary service markets.

3. ELECTRIC VEHICLE CHARGING PATTERNS

Understanding Electric Vehicle Charging: In order to fully understand the importance of AI in electric car charging, it is essential to realize the difficulties that are connected to traditional charging methods. The growing need for effective charging solutions has prompted the creation of sophisticated AI-driven technologies that address these difficulties directly.

Leveraging AI for Charging Optimization:Real-Time Data Collection and Analysis: Charging stations enabled by artificial intelligence utilize sensors and communication capabilities to collect up-to-the-minute information on vehicle charging habits, grid demand, and energy costs. This information serves as the foundation for optimizing the charging process.

Vehicle-to-Grid (V2G) technology facilitates the exchange of energy between electric vehicles (EVs) and the power grid in both directions. Artificial intelligence algorithms employ vehicle-to-grid (V2G) capabilities to regulate electric vehicle (EV) charging in response to fluctuations in grid demand and supply, effectively maintaining a harmonized energy usage.

Predictive Analytics for Charging Optimization: AI systems, especially those related to machine learning, demonstrate exceptional proficiency in recognizing patterns and generating predictions by leveraging past data. When utilized for electric vehicle charging, these algorithms can assess variables such as user conduct, charging station accessibility, and energy costs to generate precise forecasts regarding charging needs. Through the application of predictive analytics, AI algorithms can suggest the most advantageous times and durations for charging to customers, guaranteeing the efficient use of charging infrastructure while minimizing expenses and strain on the power grid.

Smart Grid Integration: Artificial intelligence (AI) is crucial in the process of integrating electric vehicle charging with smart grids. Smart grids utilize artificial intelligence algorithms to effectively handle demand response, maintain grid load equilibrium, and improve energy distribution.

Demand response management entails modifying electric vehicle (EV) charging schedules in response to current grid conditions and fluctuations in energy demand. This strategy helps mitigate peak load scenarios and alleviates stress on the power system during moments of high demand.

Load balancing systems guarantee the equitable distribution of electricity among charging stations, hence reducing the likelihood of overload and optimizing the utilization of resources.

Benefits of AI-Optimized Charging (Cao et al., 2012, Ding et al., 2020): Cost Reduction and Energy Efficiency: AI-optimized charging algorithms utilize time-of-use (TOU) pricing data to plan charging sessions during periods of low demand, when energy expenses are reduced. This decreases the total expense of charging for electric vehicle (EV) owners and promotes the acceptance of environmentally friendly transportation. Load shifting and peak demand management strategies optimize the timing of charging activities in order to alleviate stress on the power grid during periods of high demand. This ensures the efficient utilization of the available energy resources.

Enhanced User Experience: AI algorithms facilitate the creation of customized charging schedules by taking into account customer preferences, historical data, and real-time grid circumstances. AI-powered solutions provide EV owners with ease and flexibility, enabling optimal management of their charging requirements.

AI-integrated mobile applications offer up-to-date data on the availability of charging stations, energy costs, and the status of charging. This enables electric vehicle (EV) users to make well-informed choices and improves their overall charging experience.

Environmental Sustainability: By incorporating artificial intelligence algorithms with renewable energy sources, the process of charging electric vehicles can be synchronized with the production of clean energy. AI algorithms can optimize charging schedules to favor charging during periods of abundant renewable energy generation, hence decreasing dependence on fossil fuels. In addition, AI-optimized charging aids in grid stabilization by equilibrating energy demand and supply, thereby diminishing greenhouse gas emissions and promoting a more environmentally friendly and sustainable future.

Challenges and Considerations: Although the potential of artificial intelligence (AI) in optimizing the charging of electric cars is vast, there are specific obstacles and issues that must be dealt with Infrastructure and Compatibility, In order to widely implement AI-powered charging solutions, it is necessary to create infrastructure that is compatible with these solutions. This includes the creation of smart charging stations and communication networks. Standardization and interoperability are crucial to guarantee smooth integration and functioning across different charging systems.

Data Privacy and Security: AI algorithms depend on comprehensive data gathering and analysis. Safeguarding user privacy and ensuring the protection of sensitive charging data is of paramount importance. It is crucial to implement strong data protection procedures and comply with strict privacy requirements.

Standardization and Interoperability: To ensure interoperability and promote the widespread use of AI-optimized charging systems, it is essential to standardize charging protocols, communication standards, and data formats across various charging networks and vehicle manufacturers.

Future Outlook and Conclusion: Integrating AI algorithms into electric vehicle charging systems has significant potential for optimizing charging patterns, minimizing expenses, and enhancing overall efficiency. With the progression of technology and ongoing collaboration among industry participants, we can anticipate the development of an intelligent, environmentally friendly, and enduring charging infrastructure. AI has the capacity to greatly improve the user experience, reduce expenses, and promote environmental sustainability. It is poised to transform the charging process for electric vehicles and lay the foundation for a future of efficient and sustainable transportation

4. THE ROLE OF ARTIFICIAL INTELLIGE NCE IN SMART CHARGING SYSTEMS

Smart charging systems have become crucial in the age of electric cars (EVs) to guarantee efficient, dependable, and environmentally-friendly charging infrastructure. Artificial intelligence (AI) is one of the key technologies propelling the progress of these systems. Artificial intelligence (AI) enhances electric vehicle (EV) charging by streamlining charging procedures, improving integration with the power grid, and enhancing consumer satisfaction. This blog article will examine the function of artificial intelligence (AI) in smart charging systems and investigate its capacity to transform the electric vehicle (EV) charging industry.

4.1 AI-Driven Charging Optimization

Artificial intelligence empowers intelligent charging systems to improve the charging process by considering multiple aspects, including electricity consumption, energy prices, and grid conditions. AI algorithms possess the capability to assess data in real-time and make informed decisions in order to effectively handle the charging load, prioritize charging according to user preferences, and maintain a balance in the energy requirements of the grid. AI-powered smart charging systems can optimize cost reduction, alleviate peak load strain, and enhance the utilization of renewable energy sources by taking into account aspects such as time-of-use tariffs, availability of renewable energy, and individual charging profiles.

4.2 Predictive Analytics and Demand Forecasting

AI systems are highly proficient in processing vast amounts of data, a critical factor in accurately estimating charging demand and optimizing charging infrastructure. AI can estimate charging requirements and allocate resources accurately by analyzing historical data, weather patterns, and individual driving histories. This functionality enables the prevention of grid congestion, the anticipation of periods of high demand, and the enhancement of overall grid stability. Furthermore, predictive analytics can be utilized to forecast the accessibility of charging stations, thereby diminishing the ambiguity linked to electric vehicle charging.

4.3 Enhanced User Experience

Artificial intelligence technology enables intelligent charging systems to deliver a customized and smooth user experience. Machine learning algorithms enable charging stations to acquire knowledge about individual preferences, charging habits, and driver behavior. This knowledge may be applied to customize charging sessions, recommend the best charging times, and adjust to user preferences as time goes on. AI can enhance smart charging systems by providing intuitive mobile applications, real-time charging notifications, and remote charging management features. This enables electric vehicle owners to easily monitor and control their charging process.

4.4 Grid Integration and Load Balancing

The integration of electric vehicle (EV) charging infrastructure with the current power system poses a significant issue. Artificial intelligence (AI) is crucial in facilitating the optimization of workload distribution and the efficient management of power grids. AI algorithms can optimize charging rates, prioritize charging according to grid requirements, and reduce potential grid imbalances by assessing grid conditions, energy supply, and demand forecasts. Additionally, AI has the capability to enable vehicle-to-grid (V2G) technologies, in which electric vehicle (EV) batteries can function as decentralized energy storage units. This allows them to assist the grid during times of high demand and improve the overall resilience of the system.

4.5 Continuous Improvement and Adaptability

An outstanding characteristic of AI is its capacity for ongoing learning and enhancement. AI algorithms can enhance and improve their charge optimization tactics by utilizing the increasing amount of data gathered by electric vehicles (EVs) and charging infrastructure. The iterative learning approach enables ongoing improvements in charging efficiency, load control, and grid integration. Moreover, AI has the capability to recognize deviations from the norm, diagnose malfunctions, and issue advance notifications for repair, thereby guaranteeing the dependability and durability of charging infrastructure.

The utilization of artificial intelligence is transforming the approach to electric vehicle charging by optimizing charging procedures, improving the integration with the power grid, and enhancing the overall user experience. AI-powered smart charging systems provide substantial advantages, including cost reductions, grid stability, and seamless user interactions, by utilizing predictive analytics, machine learning, and intelligent decision-making. The expanding electric vehicle (EV) market will rely heavily on artificial intelligence (AI) to shape the future of smart charging infrastructure. AI will play a crucial role in driving us towards a sustainable and efficient electric transportation ecosystem.

5. AI PLAYS KEY ROLE IN EV CHARGER DEPLOYMENT

5.1 Charger Deployment

Michigan is utilizing artificial intelligence (AI) to assist transportation planners in determining optimal locations for electric vehicle (EV) charging stations. The AI engine relies on the prevailing EV adoption rates in particular regions, the demand for EVs, and the projected usage of chargers to provide its suggestions. According to Michigan state officials, the software has already suggested the installation of eight additional chargers at various Kroger grocery store locations. Furthermore, numerous scientific research exist that explore the potential applications of AI and machine learning in aiding planners in determining optimal locations for EV chargers and selecting appropriate charger types.

In the United Kingdom, several local governments have collaborated with artificial intelligence (AI) companies to determine optimal locations for electric vehicle (EV) charging stations. This strategic partnership aims to promote the adoption of EVs and enhance the overall welfare of the community. Oxfordshire City Council is collaborating with Mind Foundry to employ geospatial modeling and diverse data sources in order to determine the optimal locations for Level 2 and Level 3 electric vehicle (EV) charging stations inside the city.

Mind Foundry stated in a techUK case study that the workflows are driven by scalable probabilistic machine learning and are connected to both real-time and historical data sources, enabling advanced scenario modeling and rollout planning capabilities.

In essence, Mind Foundry is utilizing artificial intelligence to analyze various data points, such as population density, existing electric vehicle (EV) charging infrastructure, projected EV adoption rates, and other relevant factors. Based on this analysis, the AI system determines the optimal locations for installing EV charging stations in the city, as well as the specific types of stations that should be implemented.

To gain a comprehensive understanding of the process and application of artificial intelligence in this context, I recommend reading an article titled "Optimal Locations for EV Charging Stations in Manchester" by Obed Sims, available on Towards Data Science. The paper delves into the creation and utilization of a computer model for this purpose.

5.2 Planning tools

Several innovative methods have been developed to assist transportation planners in efficiently implementing electric vehicle (EV) chargers. Street Light Data has created a novel data-driven dashboard that enables planners to determine optimal locations for installing new EV charging stations in their area.

The Oak Ridge National Laboratory has created an open-source modeling tool called REVISE, which assists regional infrastructure planners in determining the optimal locations for charging stations along interstate highways, thereby facilitating inter-city travel using electric vehicles. AI is employed for more than merely determining optimal locations for installing EV charging stations.

5.3 Grid Management

AI is utilized not only for the deployment of charging stations but also for the management of the electrical grid. In Ottawa, Ontario, the Ontario Energy Board (OEB) has collaborated with BluWave-ai and Hydro Ottawa to employ artificial intelligence (AI) for the purpose of regulating electric vehicle (EV) charging during periods of high demand.

The anticipated surge in electricity demand due to the growing prevalence of electric vehicles in Ontario is projected to reach 20% every year. In order to address this annual rise, a pioneering initiative named EV Everywhere will employ artificial intelligence to develop a web-based platform catering to electric vehicle owners. This service aims to aggregate the storage and charging capacities of electric vehicle (EV) batteries to mitigate fluctuations in electricity demand and enable drivers to benefit from cheaper energy rates during non-peak hours, typically in the evenings, nights, and on weekends.

The platform intends to alleviate pressure on the local grid and enable electric vehicles (EVs) to offer services to the wider provincial power market by incorporating consumer feedback, optimizing charging times, and strategically locating battery storage, according to a news release from the OEB.

5.4 Trip Planning

In January 2021, Google unveiled a novel AI tool that assists drivers in devising travel routes by considering the accessibility of public charging stations along their journey from the origin to the destination.

The AI algorithm included into the native Android Automotive operating system, which is present in some electric vehicles (EVs), provides recommendations for charging stops along a driver's journey. These suggestions are determined by considering the driver's current location, the remaining battery capacity, and the specific plug type required by their car.

Google, in a blog post unveiling the AI algorithm, stated that the Maps algorithms can now swiftly scan and filter through a large number of public charging stations, ranging from tens to thousands, to identify the most efficient route when a destination necessitates two or more recharge stops. This entire process takes less than 10 seconds. By providing information on the duration of each charge and the updated overall travel time, you will always have a clear understanding of how long it will take for each charge and your final estimated time of arrival (ETA) will no longer be unknown.

5.5 Fast Charging Battery Development

Scientists at the Idaho National Laboratory are employing artificial intelligence and machine learning techniques to accelerate the process of electric vehicle battery charging while ensuring the integrity of the vehicle's battery remains intact (Figure 1).

Figure 1. Map of centers in USA

ttempting to accelerate the charging process of a lithium-ion battery with present-day technology might result in the accumulation of lithium metal on the battery, leading to a decrease in its lifespan and range. Additionally, it may cause the cathode of the battery to deteriorate and develop cracks. In order to prevent this issue, scientists are currently endeavoring to develop novel charging protocols for electric vehicle (EV) batteries. These protocols aim to rapidly charge the battery of a car within a mere 10 minutes. This is achieved by inputting data from various types of lithium-ion batteries into a machine learning algorithm.

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"We have substantially augmented the energy capacity that can be stored in a battery cell within a brief duration," stated Dr. Eric Dufek, a researcher. At now, batteries are capable of reaching a charge level of more than 90 percent during a duration of 10 minutes, without experiencing issues such as lithium plating or cathode breaking.

The team aims to leverage their knowledge of extremely fast charging in current batteries to facilitate the development of newer batteries that can be fully charged in a matter of minutes. This would enable electric car charging to be nearly as expeditious as refueling a vehicle with liquid fuels such as gasoline or diesel.

The researchers want to develop EV batteries with the capability to communicate with EV charging stations, providing optimal charging instructions for efficient and safe charging.

If you are utilizing AI to determine optimal locations for placing electric vehicle (EV) chargers in your area, or if you are a business owner seeking to support the shift towards a more environmentally friendly future, Blink Charging can assist you in selecting the most suitable EV charging solutions to meet your requirements.

6. CONCLUSIONS

Analysis and design in this study yielded the following conclusions:

This study examines three essential elements of electric vehicle (EV) charging and discharging: prediction, arrangement, and flexible pricing. The interdependence between forecasting, scheduling, and dynamic pricing is recognized. The performance of scheduling models mostly relies on the precision of anticipating outcomes and pricing tactics. However, the accuracy of forecasting and the performance of scheduling greatly impact the success of dynamic pricing schemes in accurately reflecting the current conditions of the power system.

The majority of forecasting models discussed in this work are supervised models that rely on learning-based approaches. LSTM and GRU are widely favored approaches because of their capacity to effectively manage nonlinear relationships and long-term dependencies. Nevertheless, uncertainty is an inherent characteristic of predicting models. Hence, it is imperative to enhance the efficacy of forecasting models. In addition to hybrid and ensemble techniques, including the most recent data to update forecasting models and incorporating uncertainty intervals are alternative strategies to support decision-making.

Many researchers have utilized reinforcement learning-based optimization models to make optimal decisions regarding EV charging and discharging. These models are capable of considering numerous variables as state spaces and rely on projected results, such as charging and discharging prices. DQN, DDPG, and SAC are among the most widely recognized reinforcement learning models. Each of them possesses distinct benefits and drawbacks. DQN can effectively address the challenge of dimensionality that standard Q-learning encounters. Nevertheless, these systems often encounter the challenges of overestimating action values and demanding extensive training time.

Double-DQN and A3C address the issue of action value overestimation and expedite the training process, respectively. Enhancing the performance of reinforcement learning is a crucial area of investigation.

If the information used by scheduling models to make decisions does not precisely reflect the real-time conditions of the power grid, they are unable to make efficient charging/discharging decisions to optimize power grids. Hence, it is crucial to have both accurate forecasting outcomes and dynamic price signals that accurately represent the current state of the power grid.

Several research papers have investigated the prediction and arrangement components of electric vehicle (EV) charging.

Nevertheless, there is a scarcity of literature that specifically addresses the topics of EV discharging and dynamic price design. The majority of current dynamic pricing models are developed by system operators without taking into account the preferences of electric vehicle (EV) owners. Furthermore, dynamic pricing models do not incorporate all the crucial elements associated with EV charging and discharging. Dynamic pricing techniques play a crucial role in the process of indirectly controlling charging and discharging. Furthermore, the implementation of dynamic pricing can serve as a motivating factor for a greater number of electric vehicle (EV) owners to engage in vehicle-to-grid (V2G) programs. Hence, it is imperative for academics to prioritize the development of dynamic pricing schemes that accurately capture real-time power system conditions and effectively strike a compromise between system operators and electric vehicle (EV) owners. Furthermore, this article emphasizes the necessity of investigating the social and economic dimensions of EV charging/discharge scheduling and dynamic pricing, in addition to the technical components. A survey and analysis of the response of EV owners and system operators to dynamic pricing is required to understand the social element.

The perspectives of all the parties involved can be utilized to improve the design of the dynamic pricing strategy. It is necessary to examine the economic feasibility and profitability of the dynamic pricing model for the entire system, which includes individual electric vehicle owners, system operators, and power systems.

The structure designed in this research introduce the AI role optimizing the Artificial Intelligence Role in Optimizing Electric Vehicle Charging Patterns, Reduce Costs, and Improve Overall Efficiency conducted literature survey and concluded the survey by review apart in the section third discuss the different pattern of EV charging Real-Time Data Collection and Analysis, Predictive Analytics for Charging Optimization, Smart Grid Integration, Cost Reduction and Energy Efficiency, Enhanced User Experience, In addition, AI-optimized charging aids in grid stabilization by equilibrating energy demand and supply, thereby diminishing greenhouse gas emissions and promoting a more environmentally friendly and sustainable future the firth section discussion about AI key roles in EV Charger deployment in different strategies finally concluded about AI role into EV charger with conflict of depletion.

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