DEEP LEARNING MODEL FOR POWER MANAGEMENT TO OPTIMIZE CHARGING OF ELECTRIC VEHICLE

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Abstract --Electric vehicles (EVs) have become a vital component of environmentally friendly and intelligent transportation systems in current smart cities. At the same time, they also offer a huge chance to reduce the amount of greenhouse gas emissions and the dependency on fossil fuels. This is occurring at the same time that EVs have become a key component of these systems. However, the rapid increase in the usage of electric vehicles presents significant issues for the infrastructures of power grids that are already in existence. These grids are already in existence. This is especially true when taking into consideration the fact that events that involve public charges are not only in great demand but also in a state of acute disorganization. If the surge in demand for power is not adequately handled, it can result in grid instability, problems with peak load, and increased operational expenses. These issues can be avoided by effectively managing the surge. There is also the possibility of increasing operational expenses as a consequence. Therefore, the development of intelligent charging techniques has become essential in order to ensure the efficient consumption of energy, maintain the resilience of the grid, and stimulate the widespread integration of electric vehicles and other forms of electric transportation. Within the framework of this discussion, the process of achieving a balance between supply and demand is significantly impacted by the intelligent scheduling of charging sessions for electric vehicles. When it comes to analyzing intricate charging patterns and predicting user behavior, it has been established that data-driven systems, in particular those that make use of machine learning approaches, have demonstrated a great lot of potential. This is especially true for those systems that make use of machine learning. The vast majority of the research that is currently available focuses exclusively on reviewing data from previous billing periods. Among the many criteria that are included in this data are things like prior usage patterns, trends in the time of day, and station occupancy rates.

Despite the fact that these methodologies offer valuable insights, they typically fail to take into account dynamic and context-aware characteristics, which have a substantial influence on charging behavior in situations that occur in the real world. These methods, despite the fact that they provide useful information, are not being utilized. This study aims to establish an improved prediction framework that takes into account additional contextual aspects in order to increase the accuracy of the analysis of charging behavior for electric vehicles. The purpose of this study is to develop this framework. These criteria take into account a variety of factors, including the weather conditions, the patterns of traffic, and the events that are local to the area. A more thorough understanding of charging demand is attempted to be captured by the model by means of the incorporation of these external variables and the utilization of historical data. The primary purpose of this investigation is to arrive at a precise estimation of the amount of time that electric vehicles require to be charged, as well as the quantity of energy that is consumed throughout the charging process. These two significant factors, which have a direct impact on that efficiency, have a direct influence on both the efficiency of scheduling and the balancing of grid load. Both of these aspects are directly influenced by these qualities.

Keywords: Smart, Strains, Charging, Predictions, Optimization

I. INTRODUCTION

Electric vehicles (EVs), which are more popularly known as electronic cars, are a vital component of intelligent transportation networks in the context of smart city environments. Electronic cars are also commonly referred to as electric automobiles. This is because they have the potential to greatly reduce emissions of greenhouse gases, which would in turn reduce reliance on traditional fossil fuels. This is the reason why they are becoming increasingly popular. This is the reason why they are getting a significant level of popularity at the moment. Not only is this the case for a variety of reasons, but one of the most significant ones is that electric vehicles have the capacity to lessen the amount of pollution that is produced. The use of electric vehicles is currently rising at a high speed for a number of reasons, including the fact that urban populations are continuing to rise and the fact that sustainability is becoming an increasingly important concern. Both of these factors are contributing to the rapid acceleration of the adoption of electric vehicles. These two things are both considered to be contributing factors. However, this large-scale integration does provide a number of substantial issues for the infrastructure of the electrical grid that is now in place. These challenges are a necessity. There are a number of particularly significant obstacles that are associated with the management of these concerns. These challenges include the control of the ever-increasing demand for electrical power, the prevention of peak load stress, and the assurance of reliable and consistent energy distribution. To successfully manage the activities that are related with the charging of electric vehicles, it is vital to design solutions that are not only intelligent but also adaptive. This is because the situation is becoming increasingly complex. To fulfill this condition, it is necessary to do so. As a consequence of the constraints that have been described, this is the outcome.

Installation of intelligent charging scheduling algorithms is one of the many potential solutions that might be adopted to address these difficulties. There are many more potential solutions as well. There are a great number of additional conceivable responses there as well. In addition to this, it is one of the most promising strategies that may be utilized in accordance with the circumstances. By distributing the load in a manner that is appropriate across time and the infrastructure that is available, the purpose of these algorithms is to increase the efficiency of charging operations. This is accomplished by enhancing the effectiveness of charging operations. It is the distribution of the load in a manner that is fair and equitable that makes it possible for this to be accomplished. Additionally, as a result of this, customers will enjoy a reduction in the amount of grid congestion that they encounter, in addition to an increase in the convenience of their consumption. On the other hand, data-driven approaches, in particular those that are based on machine learning, have emerged as tools that are practicable for the purpose of evaluating complex charging patterns of electric vehicles and enabling predictive decision-making. The reason for this is that these methodological methods are the fundamental building blocks of machine learning. Specifically, this is because these methods are based on the knowledge that is provided by machine learning. This is the reason why this is the case. The ability of these models to uncover patterns that are related with user behaviors, charging durations, and energy requirements is made possible by the process of learning from previous charging data. The process of learning from the data can lead to the discovery of certain patterns as a consequence of the process. Through the process of learning, which enables identification, these patterns can be detected and recognized when they occur.

Additionally, the vast majority of the research that has been conducted up until this point is mostly dependent on historical datasets, and it frequently disregards the impact of dynamic external stimuli. This is the case since the study has been carried out up until this point. Despite the fact that there has been progress made in this area, this is the situation the situation is in. Despite the fact that there have been breakthroughs made in this particular field, the situation has not changed throughout the course of time. Prior usage does not completely describe the behavior of charging electric cars in situations that take place in the real world; rather, it is also heavily influenced by contextual aspects such as the weather, the flow of traffic, and local social or commercial activities. In other words, the behavior of charging electric cars is not completely defined by historical usage. To put it another way, the behavior of charging electric automobiles is not totally governed by the usage that has occurred in the past. When it comes to charging electric automobiles, the behavior of the charging process is not entirely dependent on the amount of time that has passed since the past time the vehicle was utilized. Another way of putting this is to say that the amount of time that an electric car has been driven in the past does not totally impact the manner that it is charged with. If these characteristics are incorporated into predictive models, it is probable that the models will become more accurate and long-lasting as a result of the adoption of these traits. This is because the models will begin to incorporate these characteristics. There is also the possibility that the models will become more accurate in the future. The creation of scheduling systems that are more dependable will be the result of this, in turn.

The prediction of the charging behavior of electric vehicles encompasses a wide range of aspects, such as the determination of whether or not a vehicle will be charged on the following day, the determination of preferences for rapid charging, the estimation of the amount of time that will pass before the next plug-in, and the prediction of charging profiles, speeds, as well as daily charging capacity and frequency. All of these aspects are included in the prediction of charging behavior. In order to accurately predict charging behavior, each of these aspects is taken into consideration. Every single one of these characteristics is taken into consideration in order to provide an accurate prediction regarding charging behavior. This study's primary objective is to make an estimate of the amount of energy that is actually consumed, as well as the amount of time that is required for charging sessions. Despite the fact that each of these dimensions provides substantial insights into user behavior and system improvement, this is the situation that has presented itself. Additionally, each of these aspects provides valuable insights. An vital step that must be taken in order to ensure that the system is operating at its maximum capacity is this one. Due to the fact that they have a direct influence on the distribution of demand throughout the grid, the availability of charging stations, and the distribution of resources, these two criteria are considered to be essential for effective scheduling. One of the reasons why they are considered to be essential is because of this particular reason.

The goal of the research that is being offered is to improve the effectiveness of charging management systems for electric vehicles and to provide assistance in the development of urban energy infrastructures that are more intelligent and conscious of their impact on the environment. According to the presentation, these are the two objectives. To ensure that we are successful in achieving this objective, we will be putting an emphasis on three distinguishing features. In addition to making it possible for smart grid and transportation systems to make judgments that are more thoroughly informed after taking into consideration all of the essential information, it is projected that the findings will contribute to the improvement of forecasting accuracy.

II. LITERATURE REVIEW

Roslan (2024), This paper investigates that the techno-economic impacts analysis of renewable energy-based hybrid energy storage system integrated grid electric vehicles charging station (EVCS). Additionally, the optimized EVCS-based hybrid energy storage system contributes to reducing carbon dioxide (CO2) emissions, promoting a cleaner environment and an eco-friendly energy ecosystem.
Elalfy (2024), This paper states that energy storage is one of the hot points of research in electrical power engineering as it is essential in power systems. It can improve power system stability, shorten energy generation environmental influence, enhance system efficiency, and also raise renewable energy source penetrations. This paper presents a comprehensive review of the most popular energy storage systems including electrical energy storage systems, electrochemical energy storage systems, mechanical energy storage systems, thermal energy storage systems, and chemical energy storage systems.
Zand (2024), This paper proposes that a novel energy management structure for electric vehicles, consisting of a supercapacitor and two types of batteries, to improve efficiency and navigable distance. The key features of a suitable energy storage system include high power and energy density, low cost and weight, minimal maintenance, and long life. Although batteries are the primary power storage source in electric vehicles, they have power limitations. Therefore, a high-power-density supercapacitor is added to the battery to create a hybrid energy storage system, reducing stress on the battery and increasing its lifespan.
Carne (2024), This paper states that the way to produce and use energy is undergoing deep changes with the fast-pace introduction of renewables and the electrification of transportation and heating systems. As a consequence, the electrical grid sees much higher power variability than in the past, challenging its frequency and voltage regulation. Energy storage systems will be fundamental for ensuring the energy supply and the voltage power quality to customers. This survey paper offers an overview on potential energy storage solutions for addressing grid challenges following a "system-component-system" approach.
Wang (2024), This paper states that with the increasing penetration of distributed energy resources (DER) in the electric power system, Peer-to-Peer (P2P) energy trading has become a promising paradigm for future electric power systems. Building thermal load, which is an important demand side resource, should be considered carefully in the design of a P2P trading method. In this paper, we investigate the application of building thermal energy storage capability in P2P energy trading.
Barakat (2024) , This paper optimizes and evaluates a Photovoltaic-Wind-Battery/Electric Vehicle Charging Station (PVWB/ EVCS) system using four Multi-Objective Optimization (MOO) techniques: MOPSO, NSGAII, NSGAIII, and MOEA/D. The main goals are to minimize the Total Net Present Cost (TNPC) and Loss of Power Supply Probability (LPSP) of the system, which are crucial for sustainable electric vehicle charging. The study analyzes the economic, operational, and sustainability aspects of the optimized system and compares it with HOMER software.
Fachrizal (2024), Renewable energy and electric vehicles (EVs) are crucial technologies for achieving sustainable cities. However, intermittent power generation from renewable energy sources and increased peak load due to EV charging can pose technical challenges for the power systems. Improved load matching through energy system optimization can minimize these challenges. This paper assesses the optimal urban-scale energy matching potentials in a net-zero energy city powered by wind and solar energy, considering three EV charging scenarios: opportunistic charging, smart charging, and vehicle-to-grid (V2G). A city on the west coast of Sweden is used as a case study.
Singh (2024), This paper states that the transport sector is experiencing a notable transition towards sustainability, propelled by technological progress, innovative materials, and a dedication to environmental preservation. This study explicitly examines the incorporation of electric vehicles (EVs) into the power grid, with a particular emphasis on passenger automobiles. Our analysis emphasises the vital importance of updated transport infrastructure in decreasing greenhouse gas emissions and aiding carbon reduction efforts in electricity networks. The analysis uncovers that adopting electric vehicles offers significant advantages, including enhanced grid efficiency and decreased emissions.
Sarmokadam (2024), This paper states that the domestic Photovoltaic (DPV) installation along with Domestic Energy Storage System (DESS) can play effective role in AC Ring Main Residential Distribution Network (ACRMRDN) to address the impact of Electric Vehicle (EV) charging on residential distribution network. This paper proposed two different architectures with structural changes for effective energy management in AC ring main system connected to electric charging station. The main aim of this research is to design the electric vehicle charging infrastructure in support of DPV and DESS. The effective implementation of such charging infrastructure motivate domestic consumer to play a role of prosumer

Ebrahimi (2024), This paper states that with the increase in the penetration of electric vehicles (EVs), there is a substantial need for a proper solution to meet the EVs' charging demand. Due to the high investment cost of charging stations, the efficient operation of EV chargers is crucial. In this regard, in this paper, charger-sharing charging has been proposed to charge multiple EVs with a single EV charger. However, the existing models cannot model uncertain EV parking lots (EVPLs) with charger-sharing charging. In addition, most presented methods for uncertainty modelling of EVPLs are hard to implement in planning and large-scale system-level studies due to their complicated process and high computational burden.

III. OBJECTIVES

Following are the objectives in which the work will be achieved

1. To evaluate accurate values for prediction of EV charging demand at different times to maintain balance across the grid and prevent overload.
2. To identify and minimize the cost of electricity usage during EV charging by analysing distribution of electric sources with renewable energy sources.
3. To examine wait times and provide convenient charging solutions that align with users' schedules and preferences.
4. To execute some machine learning algorithm to simulate the energy storage mechanisms.

IV. RESEARCH METHODOLOGY

Dataset of various issues was collected and training/testing of those dataset was done using machine learning algorithms (lstm,cnn or which is related with the parameters) and one unique model for created which then used as an ideal source for comparing various issues in EV charging

A. Data Collection and Preprocessing

- Collect data on EV charging sessions, historical grid loads, electricity prices, and renewable energy generation patterns.
- Collection can be done from charging station and service point from a recognised service provider.
- Preprocess data by handling missing values, scaling features, and converting time-series data into a suitable format.
- Engineer features such as weather conditions, traffic data, and user preferences to provide additional predictive value.

B. Model Selection and Development

- Evaluate various deep learning architectures, such as Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and hybrid models, for time-series forecasting and optimization tasks.

Implement models for predicting demand, optimizing charging schedules, and load balancing, possibly using reinforcement learning for dynamic scheduling.

C. Model Training and Tuning

- Evaluating various models in the past to figure out the gap related to storage mechanism.
- Split the dataset into training, validation, and test sets.
- Train models using deep learning frameworks (e.g., TensorFlow or PyTorch), adjusting parameters like learning rates, batch sizes, and model architectures.
- Use techniques like cross-validation and grid search for hyperparameter tuning.

D. Evaluation Metrics and Performance Testing (Previous and Current systems)

- Select evaluation metrics such as Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), and Mean Squared Error (MSE) for demand prediction.
- For optimization, evaluate metrics like total cost reduction, peak load reduction, and user satisfaction scores.
- Test model performance on unseen test data to ensure generalizability.

E. Simulation and Scenario Testing

- Simulate different EV adoption levels, varying renewable energy availability, and peak demand scenarios.
- Test models under these conditions to analyse performance under diverse situations, such as high user demand or limited grid capacity.

F. Implementation of an Integrated System

- Develop an integrated architecture that coordinates predictions and optimizations for power management and charging scheduling.
- Incorporate user interfaces for EV owners and control interfaces for grid operators.

G. Validation and Comparison with Baselines

- Compare the integrated model's performance against baseline approaches, such as rule-based scheduling or traditional optimization algorithms.
- Conduct statistical analysis to verify performance improvements.

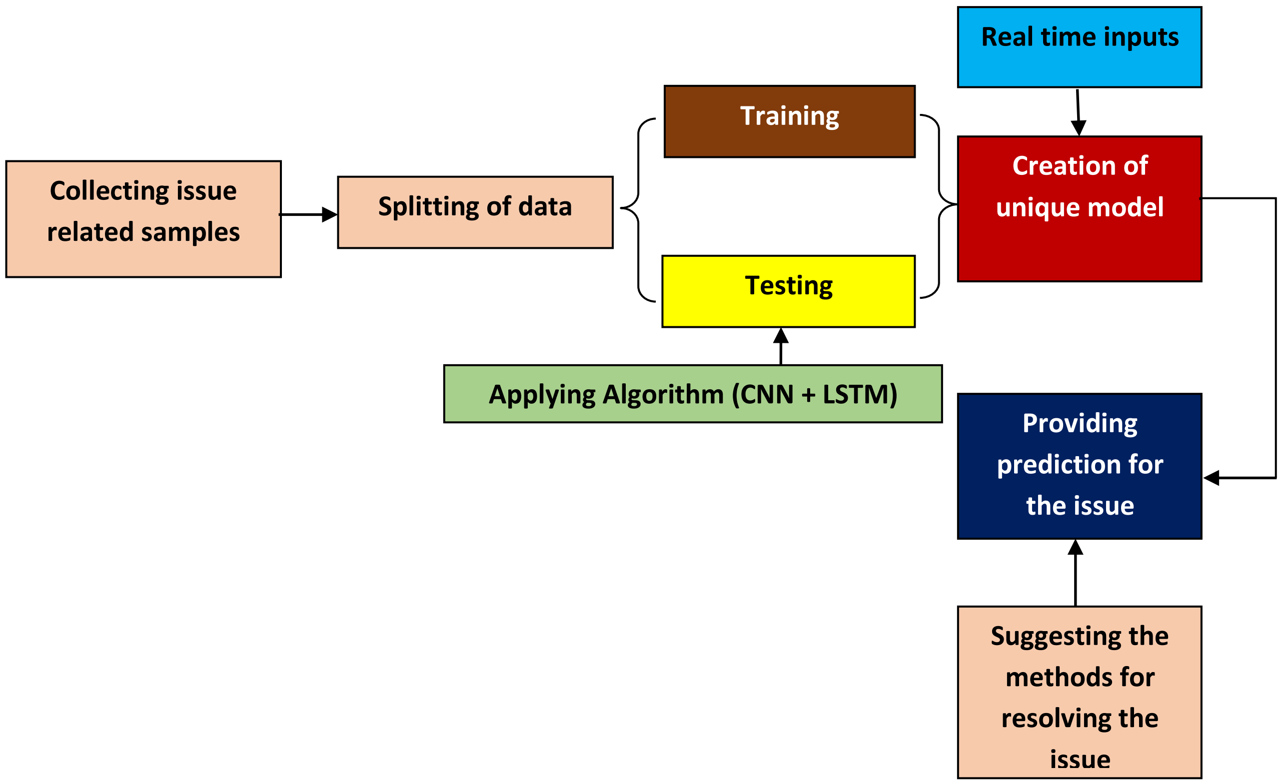

Fig. 1 Flow of the proposed system

V. RESULT AND DISCUSSION

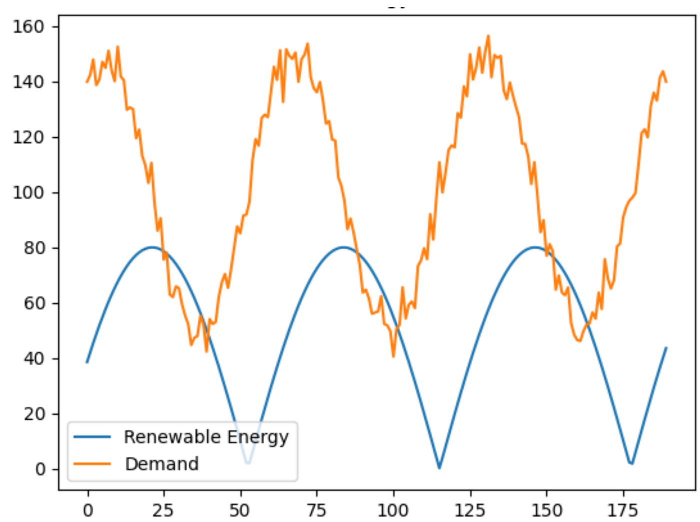

Fig. 2 Renewable energy vs demand

The graph compares renewable energy generation (blue curve) with electricity demand (orange curve) over time. Renewable energy follows a smooth, cyclical pattern with regular peaks and drops, indicating predictable generation (likely from sources like solar or wind). In contrast, demand fluctuates more irregularly and generally remains higher than renewable supply. There are several periods where demand significantly exceeds renewable generation, highlighting a gap that must be met by other energy sources or storage systems. Overall, the graph emphasizes the challenge of balancing variable renewable energy with dynamic consumer demand, underscoring the need for efficient energy management and storage solutions.

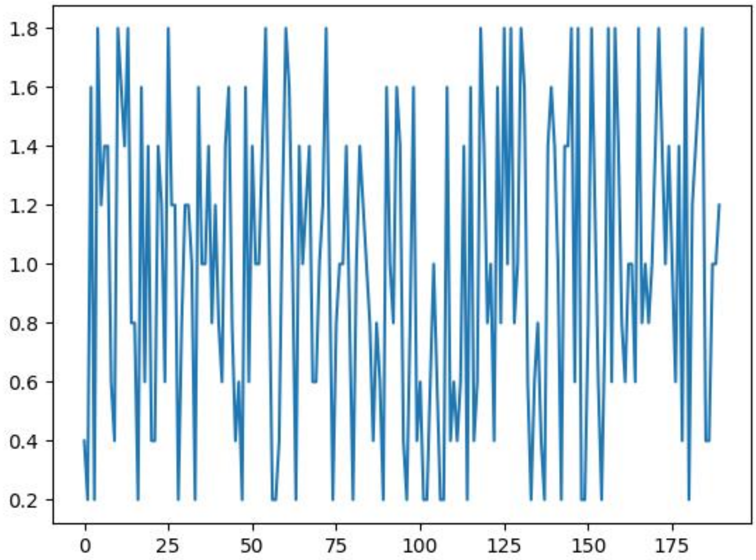

Fig. 3 EV charging waiting time

The graph shows the variation in EV charging waiting time over a period. The waiting time fluctuates significantly, ranging roughly from 0.2 to 1.8 units, indicating an inconsistent and unpredictable charging experience for users. These frequent ups and downs suggest that charging station availability and demand are highly dynamic, likely influenced by factors such as time of day, user arrival patterns, and station capacity. Periods of higher waiting times indicate congestion at charging stations, while lower values reflect smoother access with minimal delays. Overall, the graph highlights the need for efficient scheduling and load management strategies to reduce waiting times and improve user convenience in EV charging systems.

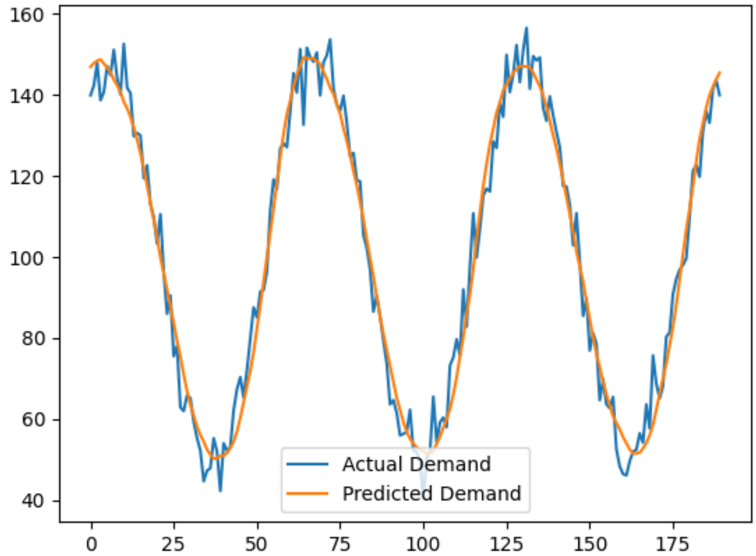

Fig. 4 EV Charging demand prediction

The graph illustrates the comparison between actual EV charging demand (blue line) and predicted demand (orange line) over time. Both curves follow a similar cyclical pattern, indicating that the prediction model effectively captures the overall trend and seasonality of the demand. The predicted values closely align with the actual demand, with only minor deviations at certain points, showing good accuracy of the model. Slight differences between the two lines occur during sudden fluctuations, where the model smooths out sharp variations. Overall, the graph demonstrates that the prediction approach is reliable and can be used for efficient scheduling and energy management in EV charging systems.

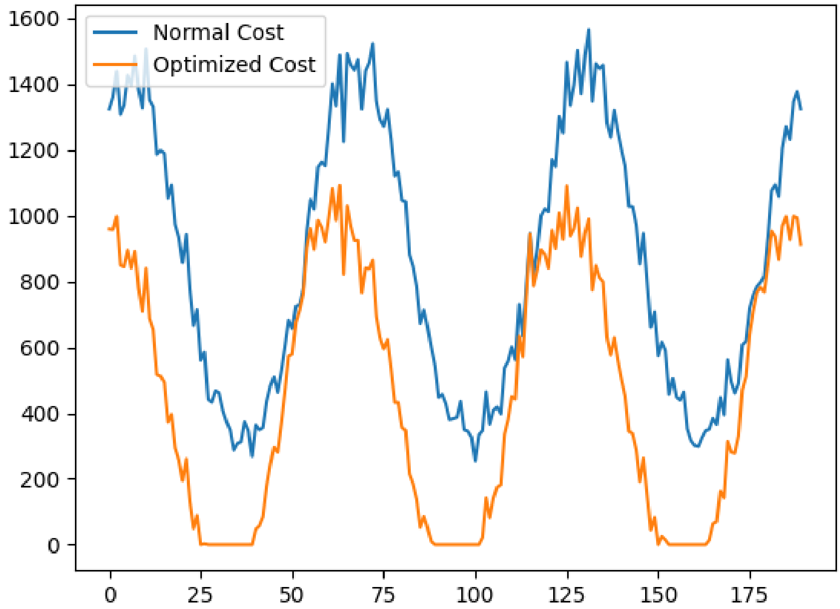

Fig. 5 Cost optimization using renewable energy

The graph compares normal charging cost (blue line) with optimized cost using renewable energy (orange line) over time. The optimized cost is consistently lower than the normal cost, clearly demonstrating the effectiveness of renewable energy integration in reducing overall expenses. While both curves follow a similar trend, the optimized cost shows sharper drops, even reaching near-zero values at certain intervals, indicating periods where renewable energy fully satisfies the demand. In contrast, the normal cost remains significantly higher due to reliance on conventional energy sources. This highlights that smart utilization of renewable energy not only reduces operational costs but also improves efficiency and sustainability in EV charging systems.

VI. LIMITATIONS

Despite the significant advantages offered by these advanced techniques, several limitations must be considered. Reinforcement Learning (RL) models often require extensive training time and large volumes of interaction data, making real-time deployment challenging in dynamic environments. Demand prediction models such as LSTMs and GRUs heavily depend on the quality and availability of historical data, and their performance may degrade under sudden or unforeseen changes in user behavior or external conditions. Smart charging algorithms and multi-agent systems can become computationally complex and may face scalability issues when applied to large networks of EVs. Similarly, renewable energy alignment relies on accurate forecasting, which is inherently uncertain due to weather variability. Load balancing techniques, including CNN-based approaches, may require high computational resources and sophisticated infrastructure for real-time analysis. Multi-objective optimization introduces trade-offs that can complicate decision-making, as improving one objective (e.g., cost) may negatively impact others (e.g., battery health). Lastly, federated learning, while beneficial for privacy preservation, faces challenges such as communication overhead, model heterogeneity, and synchronization issues across decentralized systems.

VII. ADVANTAGES

These cutting-edge technologies have the potential to produce considerable benefits for a number of different industries, including the control of smart grids and the optimization of charging for electric vehicles. These technological advancements not only provide a great deal of advantages that are essential, but they also provide a great deal of advantages that are significant. To add insult to injury, the optimization of charging electric vehicles is a component of each of these domains. Reward learning (RL), which offers dynamic and flexible decision-making, enables charging systems to continuously learn and change the scheduling tactics that are most successful based on the conditions that are currently present. This is made possible by their ability to learn from their experiences. Taking into account the circumstances that are now in place, this information has been generated. The availability of RL makes this possible because it enables dynamic and flexible decision-making, which is made possible by the fact that is available. It is possible to accomplish this because RL enables decision-making that is not just dynamic but also adaptable. This makes it possible for this to happen. Overload scenarios can be anticipated by the operators of the grid with the assistance of demand prediction models such as LSTMs and GRUs. These models allow the operators to make modifications to prevent overloads from occurring. By doing so, they are able to prevent occurrences of this nature from taking place. Because this is the case, they are able to steer clear of any prospective complications that might present themselves in the future. Through the utilization of these models, it is possible to make forecasts concerning the patterns of energy consumption with an exceptionally high degree of precision. This is made possible by the fact that these models are quite realistic in their representations. The use of smart charging algorithms not only leads to an increase in the degree of satisfaction that users experience, but it also leads to an increase in efficiency and a reduction in expenses. These are all positive outcomes. These algorithms are able to accomplish this goal because they are able to dynamically assign charging intervals and power levels because they are able to take into account pricing indicators, grid conditions, and the preferences of consumers.

Integration with renewable energy sources contributes to the further promotion of sustainability by reducing dependency on fossil fuels, lowering carbon emissions, and making it easier to charge electric vehicles during times of high generation from renewable sources. These are all ways in which the integration of renewable energy sources helps to promote sustainability. All of these are actions that can be made to reduce the amount of carbon emissions that go into the atmosphere. Two methodological strategies that contribute to the equal distribution of energy demand, the reduction of system stress, and the prevention of malfunctions during peak hours are load balancing and peak shaving. Both of these strategies are mentioned in the previous sentence. Both of these strategies are put into place with the intention of improving the effectiveness of the system. In the world of shaving techniques, both of these approaches are considered to be examples of "peak shaving." It is essential to keep in mind that the two methods cannot be substituted for one another to get the desired results. One must make sure that this is not something that is forgotten. To add insult to injury, the implementation of multi-objective optimization not only ensures that a well-balanced approach will be chosen, but it also results in a system performance that is more thorough. For the goal of accomplishing this objective, it is essential to take into consideration a variety of various aspects at the same time. In addition to the cost, the energy efficiency, and the state of the battery, these are some of the other elements to consider. Federated learning has a number of benefits, one of which is that it enables decentralized optimization to be carried out while simultaneously safeguarding the privacy of people. The fact that this is possible makes it possible for many electric vehicles or stations to collaborate in order to enhance the intelligence of the system without exchanging the personal information of customers. Considering that this is something that can be accomplished, this is made attainable. These solutions, when everything is taken into consideration, lead to the construction of an ecosystem for charging electric vehicles that is more cost-effective, dependable, efficient, and environmentally friendly than the current system. Additionally, this habitat is better for the environment than other ecosystems.

VIII. CONCLUSION AND FUTURE SCOPE

A. Conclusion:

The analyzed graphs collectively demonstrate the importance of intelligent energy management in EV charging systems. The renewable energy vs. demand graph highlights the mismatch between generation and consumption, emphasizing the need for effective scheduling and storage solutions. The EV charging waiting time graph shows significant fluctuations, indicating inconsistent user experience and the necessity for better load distribution. The demand prediction graph confirms that machine learning models can accurately forecast charging demand, enabling proactive decision-making. Additionally, the cost optimization graph clearly shows that integrating renewable energy and smart strategies significantly reduces operational costs. Overall, the results validate that combining predictive analytics, smart charging, and renewable energy integration can enhance efficiency, reduce costs, and improve grid stability in EV ecosystems.

B. Future Scope:

Future work can focus on incorporating more real-time and external factors such as weather conditions, traffic patterns, and user behavior to further improve prediction accuracy. Advanced techniques like reinforcement learning can be implemented for fully autonomous and adaptive charging decisions. Integration of vehicle-to-grid (V2G) technology can allow EVs to act as energy storage units, supporting grid stability during peak demand. Moreover, large-scale deployment of federated learning can ensure privacy-preserving optimization across distributed charging networks. The use of digital twins and IoT-enabled smart infrastructure can also enhance monitoring and control. Finally, expanding the system to include multi-objective optimization—balancing cost, energy efficiency, user convenience, and battery health—will lead to more robust and sustainable smart charging solutions for future smart cities.

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