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Electric Vehicle Charging System in the Smart Grid Using Different Machine Learning Methods

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Abstract: Smart cities require the development of information and communication technology to become a reality (ICT). A "smart city" is built on top of a "smart grid". The implementation of numerous smart systems that are advantageous to the environment and improve the quality of life for the residents is one of the main goals of the new smart cities. In order to improve the reliability and sustainability of the transportation system, changes are being made to the way electric vehicles (EVs) are used. As EV use has increased, several problems have arisen, including the requirement to build a charging infrastructure, and forecast peak loads. Management must consider how challenging the situation is. There have been many original solutions to these problems. These heavily rely on automata models, machine learning, and the Internet of Things. Over time, there have been more EV drivers. Electric vehicle charging at a large scale negatively impacts the power grid. Transformers may face additional voltage fluctuations, power loss, and heat if already operating at full capacity. Without EV management, these challenges cannot be solved. A machine-learning (ML)-based charge management system considers conventional charging, rapid charging, and vehicle-to-grid (V2G) technologies while guiding electric cars (EVs) to charging stations. This operation reduces the expenses associated with charging, high voltages, load fluctuation, and power loss. The effectiveness of various machine learning (ML) approaches is evaluated and compared. These techniques include Deep Neural Networks (DNN), K-Nearest Neighbors (KNN), Long Short-Term Memory (LSTM), Random Forest (RF), Support Vector Machine (SVM), and Decision Tree (DT) (DNN). According to the results, LSTM might be used to give EV control in certain circumstances. The LSTM model's peak voltage, power losses, and voltage stability may all be improved by compressing the load curve. In addition, we keep our billing costs to a minimum, as well.

Keywords: electric vehicles; smart grid; load forecasting; signal processing; machine learning

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Citation: Mazhar, T.; Asif, R.N.; Malik, M.A.; Nadeem, M.A.; Haq, I.; Iqbal, M.; Kamran, M.; Ashraf, S. Electric Vehicle Charging System in the Smart Grid Using Different Machine Learning Methods. *Sustainability* **2023**, *15*, 2603. https://doi.org/10.3390/su15032603

Academic Editors: Francesco Calise, Maria Vicidomini and Francesco Liberato Cappiello

Received: 9 December 2022
Revised: 9 January 2023
Accepted: 10 January 2023
Published: 1 February 2023

1. Introduction

Electric vehicles (EVs) have grown in importance as the auto industry has developed. EV sales will reach 2.1 million in 2019, a 40% annual growth rate [1]. Electric vehicle (EV) chargers are now an essential part of the world's infrastructure, with 7.3 million chargers installed globally in 2019 and a 60% increase in the number of public charging stations installed in 2019 compared to [1]. Additionally, 43 million electric vehicles are expected to have been sold globally by 2030, accounting for 30% of all vehicles [2]. Fast-changing technologies, like DC-DC converters with improved performance, have greatly contributed to this [3]. EVs must be managed properly as soon as possible. Due to the high amount of energy required to charge these vehicles, the high number of EVs on the road places significant stress on the distribution grid. As new driving techniques are developed to help drivers lower their operating costs, demand for these vehicles is also anticipated to rise. More electricity is needed to power their charging stations as more electric vehicles are on the road. When more EVs are on the road, the load curve rises, which increases the stress on the transformer and the rest of the distribution grid. A strong and reliable management system is necessary for the distribution grid to run efficiently and dependably. For electric vehicles, Apple Inc. has developed a method that only considers the amount of battery charge needed to locate the closest charging station [4]. However, neither the demands on the distribution grid nor the drawbacks of charging the EV are considered. The development of ICT greatly helps the achievement of smart cities. A framework made up of ICT is referred to as a "smart city." It is used to promote and develop sustainable practices to handle the many problems that urban environments present. A smart city is made up of an intelligent network of machines and objects that are linked together using cloud and wireless technology. The Internet of Things manages and analyzes the data they receive in real time to assist citizens, towns, and businesses in making the best decisions to improve living standards [5]. Integrating devices and data with a city's physical infrastructure can lower living expenses and promote sustainability. Electric vehicle (EV) charging stations and parking meters can easily be reached by connected cars. A smart city combines the physical infrastructure with ICT to provide benefits such as improved mobility, convenience, air and water quality, and energy conservation. Sensors, motors, centralized units, networks, interfaces, and intelligent metering infrastructure will all be used in smart buildings in a smart city [6]. Governmental organizations are attempting to utilize cellular and Low Power Wide Area technologies linked to the infrastructure to increase visitor and resident convenience and efficiency. To minimize energy consumption, smart cities must implement a smart grid concept into their energy infrastructure. An intelligent metering infrastructure creates two-way communication in all grid nodes [7]. Customers can take active or passive actions to increase the grid's reliability and energy efficiency. The smart grid can also lessen environmental pollution by facilitating the efficient integration of EVs and renewable energy sources into the grid. Government agencies could interact with the public, create infrastructure, and track operations and development thanks to smart city technologies. IoT devices are used in smart cities to enhance operations, service delivery, and citizen involvement. According to recent research, smart cities are the best solution to population pressure in developing and developed nations. Congestion, housing, pollution, administration, availability of power, etc. ICT is utilized to boost productivity, interact with municipal or urban services, and enhance the products and services provided by city authorities. Better citizen-government relationships save expenses and resource use. They are intended to respond to issues in a realistic, proactive manner [8]. This literature review aims to inform policymakers and smart city planners about how to take the needs and well-being of the community into account when making plans or decisions. The need for eco-friendly vehicle technologies is explained by the decline in global CO_2 emissions and the rising price of carbon fuels. In contrast to conventional vehicles, modern electrical vehicles (EVs) will improve air quality by reducing carbon emissions. The main issues brought on by using traditional vehicles will be solved if electric vehicles are successfully integrated. At this time, the penetration of electric vehicles has not shown a significant effect on the grid's demand for electricity. Electric vehicles will eventually become more widely used and more affordable. As a result, they will have a big impact on how the smart grid operates and how much energy is needed. To lower the failures related to power allocation and electricity flow across the smart grid, intelligent management systems are required. The performance and dependability of various ML techniques were compared to optimize the distribution grid and reduce charging costs.

Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Deep Neural Networks (DNN), and Long Short-Term Memory are the machine learning (ML) techniques used in this paper (LSTM). An ML-based solution for managing and routing an EV fleet is also provided in this paper. The following are the paper's main contributions:

We offer a management system for managing electric vehicle (EV) charging adaptable to the load data uncertainty that can arise with the ML system's input data. This is carried out to ensure the dependability and functionality of the system. This system combines V2G technology with both standard and rapid charging.

The subject of our second analysis is the effectiveness of various machine learning (ML) techniques in managing the charging and reconfiguring of an electric vehicle fleet. Then, to reduce load changes, power losses, voltage fluctuations, and charging costs, we optimize using the best machine learning algorithm.

1.1. Intelligent Information Management in Smart Cities Promotes Energy and Governance Sustainability

City and urban planners and the government should think carefully about how to produce, acquire, and sustainably use the power before making any major decisions. Robotic computing and artificial agencies are two new technologies for solving these problems [9]. Cities and urban areas consume significantly more energy than rural areas. As a result, it will be very challenging to stop environmental pollution and global warming. The most efficient way to reduce pollution is to generate and manage urban electricity using circuit technology. Engineers can better understand human behavior, energy consumption, machine learning, and the Internet of Things. The need for standardized data on smart energy, the integration of energy across smart grids, and behavioral analytics are just a few risks.

The power efficiency art grid will be maximized by smart metering. This is especially important given the complicated sustainability issues that cities and urban areas are currently dealing with. It seems that using smart technology ideas and knowledge may be a good idea based on the findings of this analysis. They facilitate carrier machine multiple kernel learning in NILM energy breakdown using SVMs and a genetic algorithm [5]. The urban use of digital technology has helped the developing world's growing population and lack of services. Due to the expense of ensuring that infrastructure will last for a long time, a sizable informal economy, and numerous social and political pressures in the modern world, the idea of smart citieshas not taken off quickly. They are considering that smart cities are political for many developing countries to support social and economic development.

In the early 1800s, the idea of "smart growth", which emphasizes infrastructure like public transportation and well-planned cities, first appeared. Emerging economies can have technologically advanced smart cities if economic, human resource, policy-making, and legal reforms are fully integrated into development plans [10]. Asserts that for this to happen, government priorities and spending priorities must also change, in addition to the general public becoming aware of and understanding technological advancements. This area of study has become more well-known recently as people have realized how closely related economic and political issues are to the idea of a smart city. In developing nations around the world, building smart cities is challenging due to education and literacy issues. People in cities must learn how to use new technologies to avoid being left out of society because they cannot use information. IT experts and information managers must consider how the data they collect will be used. Smart services, like smart cards, necessitate people to learn, understand, and view things from various angles. These problems will be resolved, and smart cities will become sustainable [5]. The challenges presented by the growth of smart cities and the movement of people from rural to urban areas are strongly intertwined with the well-being of the respective populations. Safety, open government, high-quality education, and creative problem-solving are all crucial [5]. These elements will determine whether smart cities are successful or unsuccessful, as well as the direction of research in all areas, ultimately resulting in comprehensive solutions for the issues that plague these urban areas. To understand user groups and preferences, you must examine data from all academic disciplines. The happiness and well-being of the inhabitants may at first seem simple and unimportant, but it is crucial to consider these when designing smart cities, smart services, and smart technology [11]. Figure 1 shows the Type of Electric Vehicles and their power source.

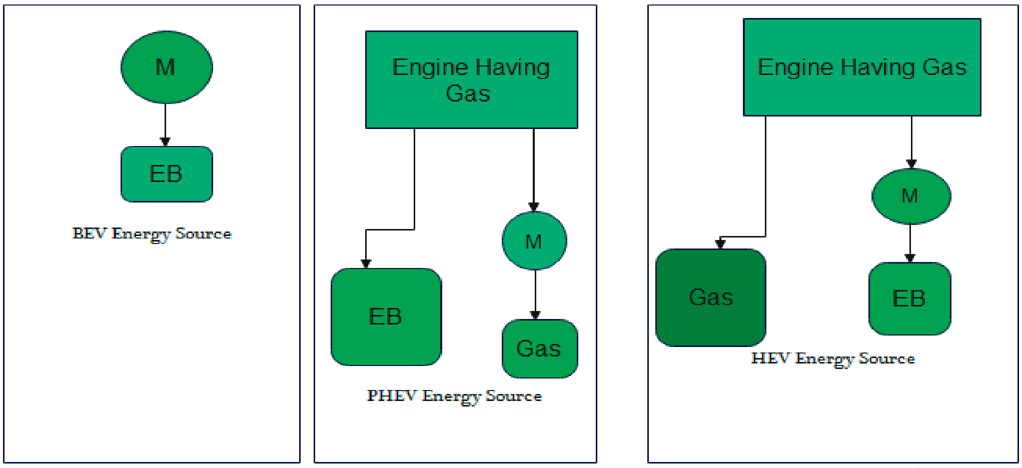

Figure 1. The type of Electric Vehicles [12].

An electric vehicle's battery can account for 25 to 50% of the overall cost. According to predictions, batteries for electric vehicles are expected to cost about 225 Euros per kilowatt-hour by 2025. The cost of manufacturing Li-Ion batteries for electric vehicles decreased by about 50% between 2007 and 2014. These significant price drops mean that buying an EV will soon be comparable to purchasing a gas-powered car. Currently, three types of electric vehicles are available: battery, plug-in, and hybrid (HEVs). The launch system of the vehicle determines these classifications. The energy needed for power production is stored and released by batteries in BEVs. Plug-in hybrids (PHEVs) have an internal combustion unit that can run on gasoline and other fuels and a battery pack that powers the electric motor (ICE). The battery pack in an HEV can be charged without electricity. The batteries are continuously charged due largely to the internal combustion engine and brake system. BEVs do not emit greenhouse gases, so they help to keep the air clean. The electric motor works with the gasoline engine in PHEVs and HEVs to minimize size and emissions. The electric battery, the power source for the different EVs shown in Figure 1, is denoted by the letter EB.

1.2. The Vehicle to Grid (V2G) Network Is a Crucial Development for the Smart Grid

Enhancing the smart grid network's capacity to balance power supply and demand and enabling mobile batteries to store energy reduces the negative impacts of using non-renewable energy sources [13]. EVs are harder to integrate without an EDMS to control energy consumption. EDMS is looking for user feedback to make charging electric vehicles as quick and easy as possible. By taking into account a range of technical and financial variables, such as the location and charging status of electric vehicles (EVs), user preferences, predicted energy demand, and the state of the distribution network at the time, the Energy Distribution Management System (EDMS) will choose the best answer to this question. Predicting EV demand and impact is one of EDMS's strongest features. Achieve the highest Quality of Service (quality of service) levels possible; this is crucial [14]. The EVs Intelligent Charging (EVIC) specification includes the EDMS concept, as shown in Figure 2.

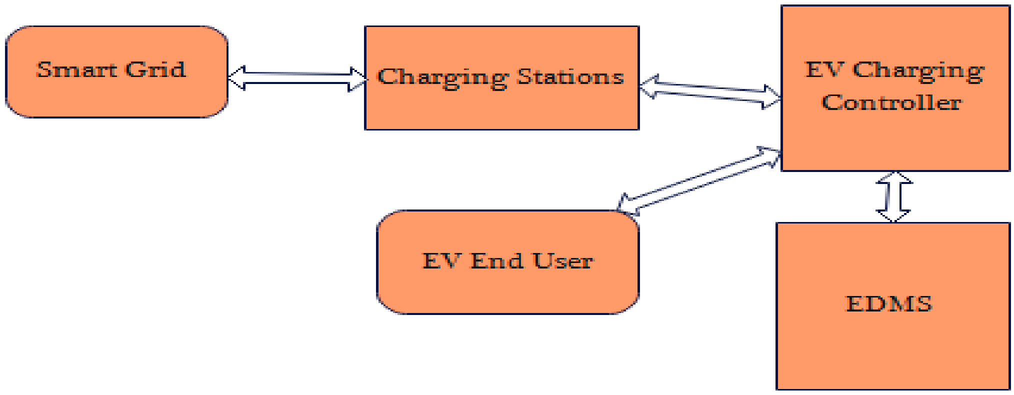

Figure 2. Electric Vehicle powertrain energy management [15].

For the electric vehicle management system (EDMS) to operate as designed, each electric automobile of the future will need to be equipped with an EB that is synchronized with a data-gathering device. The onboard computer will be provided with a GNSS receiver, an inertial measurement unit (IMU), and a Wi-Fi wireless LAN interface. All three of these components have the potential to be used in the process of determining the location of the vehicle [16]. The EV's Onboard Unit has a localization unit that can constantly accurately identify its exact location. A built-in phone modem that can send data to the internet is present in the vehicle. The smart city's communications network will be grounded. Wi-Fi roadside units that can be installed anywhere in the city and are compatible with electric vehicle charging stations will make up this infrastructure. The EDMS will process the location and charging method of electric vehicles.

1.3. Integration of EVs in Smart Grids

Because electric cars utilize power in so many ways, systems that rely on them are prone to problems. After it has been determined that the electrical grid has been built appropriately to minimize larger penetration strains, the load profile for electric vehicles may be forecast. The amount of energy that can be used to power the load on an electric vehicle depends on the battery's capacity. The Nissan Leaf's built-in battery has a 30-kilowatt-hour energy storage capacity. These batteries can hold four full days' worth of lights for the average house. Several approaches may be used to create accurate estimations regarding EV load profiles. To make more precise estimates of the load needs for EVs, probabilistic models for plug-in electric cars make use of the fact that the charging of batteries does not follow a linear pattern. The object principle is the cornerstone of the Markov chain approach, often known as a Markov or hybrid grey model, which forecasts EV demand. This strategy considers both predicted deviations and recurring trends. Artificial neural networks, support vector machines, and decision trees, among other machine learning techniques, may be used to estimate the number of EVs presently in use on the roadways at any time [17]. The initial dataset is split during the data configuration stage into training and test datasets. One uses a training dataset to train the model and find "hidden" correlations and patterns between the target values and attribute values. The effectiveness of the data mining strategy is assessed using the test dataset. Information from the training dataset is used during the testing and grading phases. The training and evaluation process is repeated about 20 times to find the ideal set of parameters. A model's performance can be assessed using r-correlation, root-mean-squared error (RMSE), and root-mean-square absolute error (MAPE). Time and training metrics were used to evaluate the performance. According to the study, SVM offers the most accurate forecasts (r = 98.09). SVM training takes longer than other training approaches. In such a short period, ANN achieved amazing results. The MAPE criterion was the most effective method for evaluating the precision of load forecasts. Values are most effective when they are less than 5%. Applying the RMSE index severely wants to punish large absolute errors. It is possible to develop a model of the requirements and routines of EV drivers using the Markov model. The existing prediction charging model was initially designed to support a single EV, but it has since been changed to support charging multiple EVs simultaneously. Studies on origin-destination (OD) and traffic have also made it possible to predict the load profile for electric vehicles. Integration models for Electric Vehicles (EVs) into the smart grid, both centralized and decentralized is presented in Figure 3.

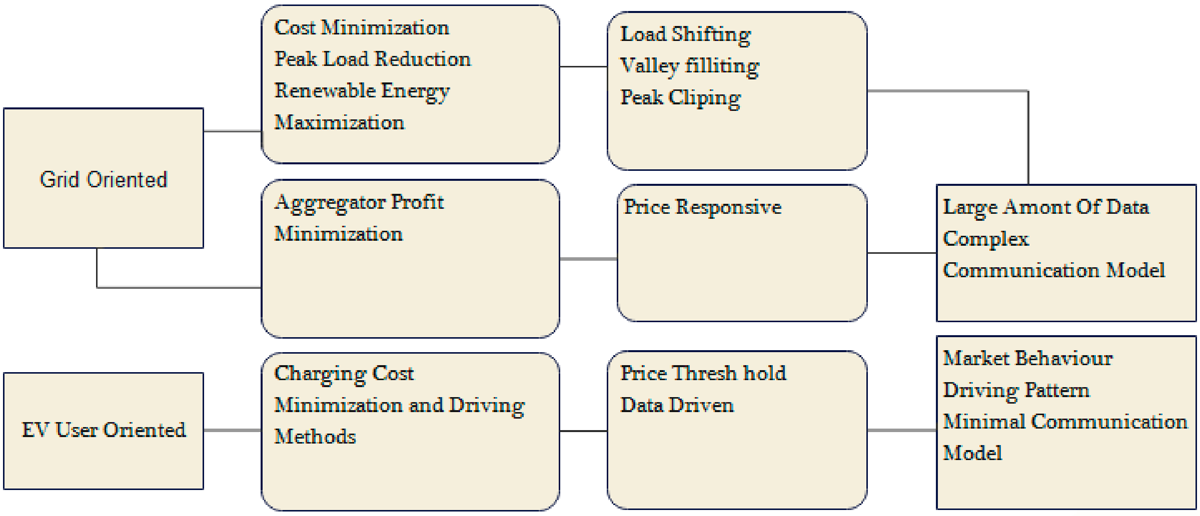

Figure 3. Integration models for Electric Vehicles (EVs) into the smart grid, both centralized and decentralized [18].

The cheap automated decision making is crucial for saving money on maintenance and energy. Authors in [19] were able to increase discharge rates and lower charging costs by utilizing cyber insurance. The short-term price, coverage, and insurance options can be determined by combining the proposed cost function with a Cartesian product. When an elevation is viewed as an idealized cost function with parameters, a learning algorithm can decide the best course of action. The authors in [20] looked at how to forecast the load on the distribution grid from electric vehicles in the upcoming years using an enhanced grey theory prediction model. An intelligent, machine learning-based technique for charging electric automobiles is presented by [21]. In the presence of renewable energy sources, [22] looked at how charging electric vehicles changed the demand profile of the smart grid. They came up with solutions to the problems. According to [23], using artificial intelligence and smart grids have been used to operate electric cars (EVs). The prediction method of [24] was used to project the demand for electric vehicles shortly (2012). To forecast the variable need for charging electric vehicles and the overall number of vehicles on the road [22] created a cellular agent automaton. The use of machine learning in this approach was crucial. Smart city development can reduce population pressures, but overall population growth is predictable, especially in developing countries. Because it would lead to new political, economic, and social problems, including technological exclusion and discrimination, it is not possible. It involves extensive research and consideration from all parties involved, and the best chance of success comes from a plan that looks at the situation from a variety of angles [25]. Research on smart cities suggests incorporating attempts to reduce computer processes into the provision of social services, with an emphasis on boosting end-user comprehension. Infrastructure like the Global Positioning System (GPS), Galileo, and the European Geostationary Navigation Overlay Service is necessary for electric vehicle compatibility with the smart grid (EGNOS). Instead of satellites, Wi-Fi will be used to identify our location [26]. The various ways that EVs can be integrated into smart grids and smart cities are shown in Figure 4. Electric vehicles are introduced in a smart city using Wi-Fi and GPS positioning systems.

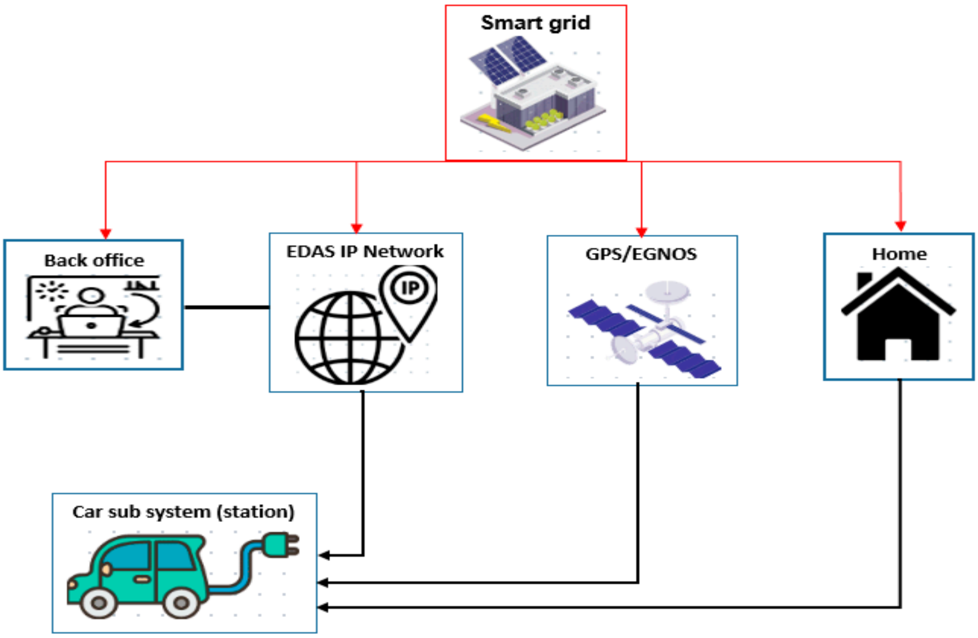

Figure 4. EVs integration with smart grid and smart houses [27].

Various elements, such as energy storage technologies, electric cars, and renewable energy sources, were considered while studying the ideal energy management framework. To estimate the activity for the next day that would result in the lowest overall cost for the energy that was bought, the authors solved a linear programming problem. Using a case study encompassing three separate buildings, it was shown that the suggested method reduced energy costs while simultaneously boosting grid dependability. They developed a domestic energy consumption management system that [28] identified the ideal procedure for scheduling various loads and supplies across different price levels using a multi-objective optimization problem. Results showed that the system could decrease transformer losses for the utility provider while still meeting customer demand. Various techniques have been used to study optimization, like dynamic and quadratic programming. Sequential and probabilistic reasoning techniques for lowering distribution system losses were studied by [29]. Based on the outcomes, the developed method showed that minimizing load variation is more advantageous than minimizing losses because it produces the same overall result in a shorter time. In addition, it works with any configuration of the distribution grid, regardless of type. [29] investigated how improving the voltage profile of a real-time coordination system could be achieved by lowering the total cost of energy production and power losses. Assuming that EVs are randomly plugged in, the algorithm uses the maximum sensitivities selection optimization method. With the help of a real-time system, the distribution grid can be more effective, and its load can be decreased [30] investigated load variance optimization for a single-home micro grid. Quadratic programming is used in a micro grid that serves a single house to minimize load variation. The system lowers the variance in individual loads, which reduces the conflict in loads on the distribution grid. This shows that the system benefits the entire grid, according to the data. However, because some parameters, like the load curve, were taken as givens, the system is not as effective as it could be. In the real world, this might not be accurate. A coordinated charging method for EVs based on power factor correction was developed by [31] to decrease power losses and enhance the voltage profile. Users' favorite charging methods were considered using a priority selection algorithm. The system reduced peak demand and improved the performance of the electrical grid. Researchers in [32] proposed charging many electric vehicles simultaneously using a decentralized topology system. The suggested approach employs collectively pointless games. The system decreases the peak-to-valley gap by filling the valley of the load curve—costs for producing power decrease as a result. Less two-way communication is needed between command centers and EVs. Regardless of power loss or voltage variations, the optimization challenge ensures that EVs can be completely charged using the least amount of energy. The approach assumes that all loads, not just those from EVs, are predictable.

In the design of power architectures, energy storage methods, micro-grid control systems, and energy management optimization, key problems and limitations are covered in the article. A summary of current research on EV charging stations is also provided. An added benefit is that the infrastructure was built to support various degrees of micro grids for charging electric automobiles. In order to make EV charging stations as efficient as possible, a lot of research is done on the coordinated control systems, energy management plans, and machine learning methods utilized by these stations. To analyze and compare the system's performance, many machine learning techniques were used. In the end, this approach is extensively used, and it found how to add and remove constraints and obstacles in the most reliable way possible

2. Literature Review

2.1. Managed Charging of Electric Vehicle

Unplanned EV charging harms the distribution grid, as shown by several studies. Researchers [33,34] examined how electric vehicles are charged. Without proper coordination, it has been seen that charging EVs causes significant voltage disturbances and energy loss.

One of the most popular methods of frequency control frequency droop control is currently being successfully applied to electric cars. The major technique for controlling the frequency now is to regulate the output of generators connected to the main power grid. As conventional power plants are phased out, electric vehicles are a great alternative since their batteries may be charged or discharged in response to frequency deviation alarms. As a result, we investigate frequency regulation in a power grid model with loads, traditional producers, and a sizable amount of EVs. By providing grid-related services, these last devices, in particular the FDC, autonomously optimize the grid. Two new control algorithms that may be used to manage electric car batteries in the best possible way during frequency regulation service. The control processes, on the one hand, make sure that the power balance and frequency management of the main grid are stable. On the other hand, these approaches can meet a range of EV charging needs. The available methods are designed to reduce the failure rates of battery-powered devices. This contrasts with the EV literature, which frequently concentrates on determining the ideal charge level. The performance of the solutions is then contrasted with that of other state-of-the-art V2G control systems. The results of numerical experiments carried out using an accurate representation of the power grid show that the suggested methods perform well in actual operational circumstances. According to [33], these detrimental effects might become more noticeable as more EVs are on the road. Renewable energy may be able to solve these problems, but [34] analysis shows that power quality regulation is still a problem. Authors in [35] investigated the dangers of using the distribution grid to charge EVs. It follows that V2G technologies can enhance the grid's functionality. V2G technologies, according to [36], have many benefits, such as power regulation, load balancing, and current harmonics filtering. V2G technologies, however, might lead to EVs discharging deeply. In order to charge an electric vehicle fleet as efficiently as possible while the total capacity of the power grid is constrained, a new distributed control technique is proposed in this study. The most economical way to charge for a profile of total energy use can be found by solving a scheduling problem. As a result, the optimization issue that arises is a quadratic programming issue with choice variables linked to both the objective function and the constraint. In our model, people only interact with their immediate neighbors and reach out to higher-ups when making decisions. The answer was discovered using a distributed iterative approach that takes into account duality, proximity, and consensus theory. An illustration case study shows how the tactic can result in the best solution for everyone [37]. This work proposes a new distributed control technique for optimally charging an electric vehicle (EV) fleet when the overall capacity of the power grid is constrained. By resolving a scheduling issue, the most cost-effective method of charging for a profile of total energy use can be determined. Consequently, the resulting optimization problem is expressed as a quadratic programming problem with choice variables that are connected to both the objective function and the constraint. In our concept, individuals just communicate with their close neighbors and make decisions without contacting anyone above them. A distributed iterative method that considers duality, proximity, and consensus theory was utilized to obtain the solution. An example case study demonstrates that the strategy can lead to the optimal answer for everyone.

The batteries in electric vehicles (EVs) degrade over time, shortening their life cycle and lowering customer satisfaction, so this comes at a cost. Because it only considers the power grid's needs and ignores those of the end users, it is not thought to be the best option. The impact of various charging techniques on the price of charging and the rate of battery decrease was also studied by [38]; the effectiveness of non-coordinated, one-way, and two-way charging was examined. Battery life can be significantly increased at a lower cost when intelligent charging techniques and time-of-use electricity prices are combined. Most of the research on coordinated charging of electric vehicles conducted by [39] was user-focused. Within the limitations of the power grid, an optimization model that reduces costs has been created. The benefits of the system become clearer as the number of EVs rises. The system can cut costs by up to 50% compared to uncoordinated billing. The system requires smart meters to gather real-time data on how electric vehicles are being charged and does not consider fast charging. It can be challenging to charge electric vehicles (EVs) because they consume a lot of energy, and renewable energy generation is not always reliable, according to [39], who also looked into this issue. Significant cost savings of up to 8% were found when comparing the results of the charging scheme to those of uncoordinated charging. Recharging an electric vehicle reduces the amount of carbon dioxide released into the atmosphere and is better for the environment. In agreement with [39], smart charging infrastructure is crucial for deploying EVs. Inductive and conductive charging is used for electric and plug-in hybrid vehicles. Conducted charging systems demand a power station that is physically connected to an electric vehicle compared to inductive charging systems. A scheme for electrical conversion may also include a high-to-low-frequency converter and power factor correction (PFC). Either an internal or external charging system can be used to charge the device. The battery and inverter current regulators and their power supplies are built to house inside the vehicle in onboard chargers. Off-board chargers are located outside the car. Conductive chargers need not be able to transfer power in order to be considered such. We might also add more standards. The AC level 1 charger is one of many different charger types. Figure 5 shows the Static WCS for EVs.

Power grids are experiencing a loss of transmission and a decrease in their ability to perform main frequency control as traditional generators are being phased out in favor of renewable energy sources. The issue is made significantly more challenging by the steadily increasing number of electric vehicles (EVs), which necessitates the creation of trying to cut methods for the management of grid operations. Rather than being an issue, the growth of electric vehicles could end up being a solution to a number of issues that have arisen with the electricity grid. In this context, the so-called vehicle-to-grid (V2G) mode of operation is crucial and is one of the main operating modes for electric vehicles. This mode can offer auxiliary services to the power grid such peak clipping, load shifting, and frequency management. To be more precise, frequency droop management, one of the more traditional techniques for frequency regulation, has just lately begun to be successfully applied to electric vehicles. This is the primary frequency regulation, which is done by controlling the current active power of the largest grid generators. Due to the decommissioning of conventional power plants, electric vehicles are viewed as particularly advantageous alternatives. This is because electric vehicles (EVs) have the ability to respond to alarms about frequency deviations by either charging or discharging their batteries.

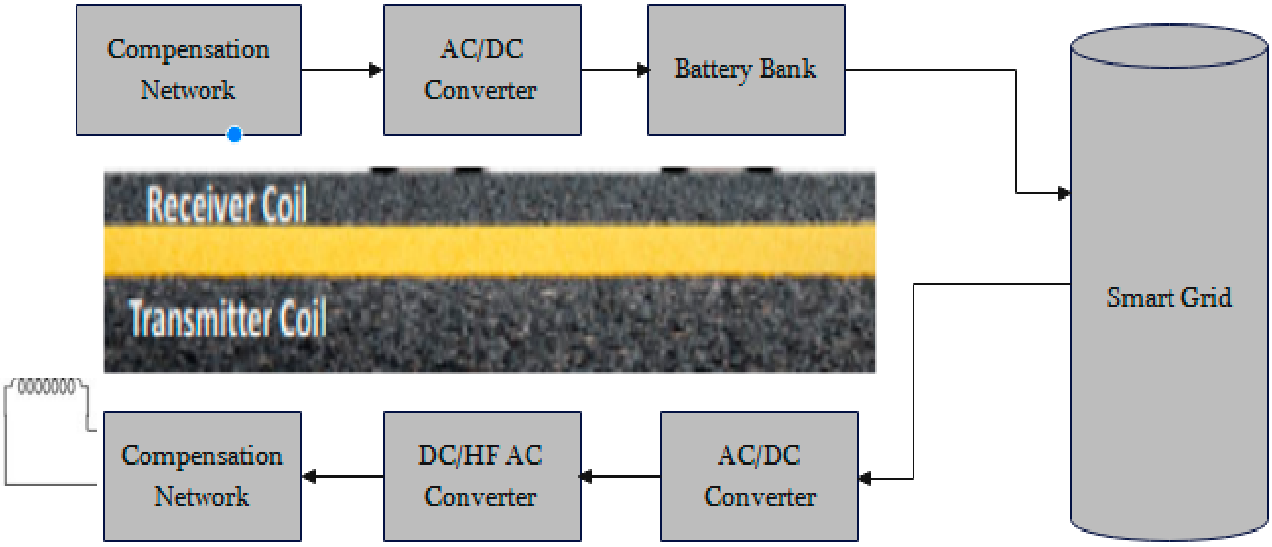

Figure 5. Static WCS for EVs [40].

This study focuses on modifying individual loads to conform to system constraints. This research was conducted because it is challenging to charge a significant number of electric vehicles with our current infrastructure. Since distributed methods may extend and communicate more efficiently than earlier approaches, they are being evaluated as a potential solution. We show that distributed linear optimization and communication networks can be used to ensure relative average fairness while maximizing utilization. Here, we outline these techniques. The outcomes of our research and simulation are presented to show how highly useful these techniques are. When used in test scenarios, the algorithm often performs within 5% of the ideal centralized configuration. Scaling up, however, is easier and requires less communication than in the perfect situation. The end user, in this case, the owner of the vehicle, is the one who is looking at battery charging in this article. We describe a number of distributed algorithms to accomplish specific policy goals due to the fact that vehicle owners' priorities can change over time. Our main focus is on the many types of distributed charges. Dispersed systems stand out in terms of recharging electric vehicles for a number of reasons. First, when individual components fail, decentralized algorithms are often more stable. Second, it is anticipated that in charging conditions, the number of electric vehicles competing for the same amount of energy will vary quickly, indicating a random quality. It would be nice to have self-managing distributed optimization approaches in this kind of circumstance. In conclusion, a distributed approach makes it possible to implement a set of rules with little risk of data loss [41].

As a result, we investigate frequency regulation in a power grid model that includes loads, traditional generators, and lots of EVs. By offering auxiliary services to the grid, the latter, most notably the FDC, can take an independent part in the process of grid optimization. For the purpose of optimizing the control of electric vehicle batteries while the service is being provided to regulate frequency, we provide two unique control algorithms. On the one hand, the control strategies make sure that the main grid's power balance and frequency stability are upheld. On the other hand, the techniques are adaptable enough to meet a variety of electric vehicle charging requirements (EVs). The suggested approaches' main goal is to prevent battery device degradation, which is in contrast to the pertinent literature's frequent discussion of obtaining the ideal charge level in relation to electric vehicles. The proposed solutions are last evaluated in comparison to various cutting V2G control systems and their outcomes are contrasted. The solutions proposed are successful when used in real operational settings, as shown by the outcomes of numerical tests performed using a realistic model of a power grid.

Because batteries lose power while linked to the grid, it is difficult to determine the cost of an Energy Storage System for frequency management. As a result, researchers are looking at how real-world conditions affect Li-ion batteries' capacity to store energy. Both a control method for Li-ion ESS that helps with frequency management and a cost accounting model for frequency regulation that takes the impact of shorter battery life into account are created. We estimate the expected lifetime and the average annual cost of the Li-ion ESS for different dead bands and SOC set-points. Case studies show that the Li-ion ESS's estimated operating life under standard and full discharge settings is much shorter than the manufacturer's reported nominal life. In this paper, a precise method for calculating the cost of ESS that take part in grid frequency regulation is presented. This is carried out to aid ESS's growth in the auxiliary services sector [42].

Because batteries degrade while the system is linked to the grid, it is challenging to estimate the cost of an Energy Storage System (ESS) for frequency regulation. Researchers are examining how the stresses of practical use affect the Li-ion cells in the battery energy storage system to find a solution to this issue. We construct a control method for Li-ion ESS that can take part in grid frequency management, and we develop a cost accounting model for frequency regulation that takes the effect of battery life loss into account. We determine the anticipated working life and annual average cost of the Li-ion ESS for various dead bands and SOC thresholds. Case studies demonstrate that the nominal lifetime specified by the manufacturer for standard and full discharge settings for the Li-ion ESS is significantly shorter than the predicted lifetime under practical working conditions. This study offers an accurate costing method for ESS participating in grid frequency regulation, which will aid in the expansion of ESS participation in the market for peripheral services.

The controller's charging cost can be reduced numerically and repeatedly due to the model's efficiency and simplicity. The developed EV charge features indicate a balance between the following four trends: (1) charging during times of low electricity prices; (2) charging slowly; (3) charging near the end of the authorized charge period; and (4) preventing vehicles from sending power back to the grid. The result shows that batteries charged using optimized methods exceed those charged using standard methods by a significant margin, using data from real hybrid electric vehicles. This suggests that smaller batteries could be used to satisfy the needs of vehicle life. It has been shown that identical patterns hold true for batteries of different sizes, allowing them to be used in both plug-in hybrids and pure electric vehicles [43].

Next, we go over a distributed water filling technique that can be applied to networked control systems where nodes communicate data with distant nodes. Water filling is a well-known method of communication system optimization. It has assisted in solving real-world control engineering and decision-making problems. In a system with multiple control points, the decentralized approach of filling water tanks is described in this study. To do this, we take into account the water levels of a number of users who only interact with their immediate neighbors and decide as a group. We create two versions of a new distributed algorithm that combines consensus, proximity, and fixed-point mapping theory (exact and approximation), and we show that both converge. A charging station for a fleet of electric vehicles is used as an example to show how it works.

This study shows how to charge a car's battery in the most economical way possible, taking into consideration the cost of power and the predicted cost as the battery ages. It does this by using a simplified lithium-ion battery lifetime model. The fundamental battery life model shown below takes temperature, battery charge level, and daily power loss into account. This model's correctness was demonstrated by comparing it to a precise model developed at the National Renewable Energy Laboratory. Comparing this model to experimental results proved its validity. The charger controller can use iterative numerical charge cost minimization because the basic model runs quickly. Electric car charging profiles strike a compromise between four trends: quick charging, charging at the end of the permitted charge period, charging at low-cost intervals, and prohibiting vehicles from sending electricity back to the grid. Simulations using data from actual Prius plug-in hybrid EV show that fully charged batteries may be used for a lot longer than batteries that have only been partially charged. This suggests that the requisite vehicle lifespan could be met with smaller batteries. These patterns have been shown to hold true across a range of battery sizes. They therefore apply to both plug-in hybrid and pure electric vehicles.

2.2. Types of Contactless EVS

Magnetic coupling coefficients measure the effectiveness of the connection between the secondary and primary coils. Coupling coefficients with high values are necessary to move a lot of power. The static wireless fast charger, which uses more than 20 kW of power, is standardized. The OLEV and DWC initiatives' main goals were to make the technology more efficient and commercially viable. The OLEV project raised the air gap to 20 cm and retained an efficiency of 83% while achieving the needed high frequency of 20 kHz for 60 kW.

Additionally, the horizontal sensitivity was around 24 cm. The fifth-generation diesel water heater (DWC) OLEV got its fuel supply from an S-type power station rail. Despite only having a 20 cm air gap tolerance and a side-to-side deviation tolerance of 30 cm, it was nevertheless able to transmit 22 kW of electricity.

A dynamic WPT can move the 820 kW MPT for the high-speed train being built in Korea through the 5 cm air gap, with an efficiency of 83%. The roughly 16-km-long Bus Route 16 in Malaga, Spain has been overseen by a WPT since December 2014.

One of the most popular methods of frequency control frequency droop control is currently being successfully applied to electric cars. The major technique for controlling the frequency now is to regulate the output of generators connected to the main power grid. As conventional power plants are phased out, electric vehicles are a great alternative since their batteries may be charged or discharged in response to frequency deviation alarms. As a result, we investigate frequency regulation in a power grid model with loads, traditional producers, and a sizable amount of EVs. By providing grid-related services, these last devices, in particular the FDC, autonomously optimize the grid. Two new control algorithms that may be used to manage electric car batteries in the best possible way during frequency regulation service. The control processes, on the one hand, make sure that the power balance and frequency management of the main grid are stable. On the other hand, these approaches can meet a range of EV charging needs. The available methods are designed to reduce the failure rates of battery-powered devices. This contrasts with the EV literature, which frequently concentrates on determining the ideal charge level. The performance of the solutions is then contrasted with that of other state-of-the-art V2G control systems. The results of numerical experiments carried out using an accurate representation of the power grid show that the suggested methods perform well in actual operational circumstances [44].

Researchers are working to create integrated infrastructure solutions that calculate the amount of power transmitted through the system using a U-shaped power station rail and a frequency of 35 kHz. The near field, where there is no radiation, and the far field, where there is radiation, are two separate areas in the electromagnetic fields created by the antenna of a moving electric charge. The area surrounding the transmitter (T x) where the energy level is constant is referred to as the "close field." If there is no receiver to receive the energy, T x cannot transmit it. The size and shape of the transmitter and receiver have an impact on the near-field ranges. Magnetic and electric fields exist separately in non-radiating areas. Electrodes and coils can transmit power through electric and magnetic fields. The force decreases at a rate of 1/r3 as the distance r between the transmitter and receiver grows, but the energy does not change. The rapid power loss rate results in the WPT electric field's shorter range. The WPT magnetic field can transmit power over greater distances than alternative methods because magnetic fields can easily pass through solid objects like furniture, people, and walls. An electric vehicle's air gap and efficiency must be increased to improve WCS. The system's size and surface area can be reduced by altering its operating frequency. The WPT's efficiency at a specific power level rises as its frequency does as well. Businesses, academic institutions, and research institutions come in a wide variety.

We now have some responses after looking into wireless charging. In reality, the WPT system rises by about 1 MHz before reaching a high frequency. One option is a system that runs between 100 and 200 kHz. The final expression is T0 = M/R0. The mutual inductance (M) between the receiver and transmitter (T-to-T) and equivalent resistance make up T0 (R-to-zero). To get the mouse a high TQ. The ideal conditions for maximizing TQ are high driving frequency, high mutual inductance, and low equivalent resistance. The inductance L and capacitance C are needed to determine the resonant frequency, which equals 1/LC. The resonant frequency will drop if L or C is increased. When the frequency is raised to such a high level, the conversion encounters the switching problem. The WPT system is limited in its ability to operate at high frequencies by a low coupling coefficient. Because it is more practical, the frequency is fixed. When frequency standardization is used, the frequencies are chosen to ensure that the system performs at its best. To promote wireless electric car charging systems, additional study is required on efficiency requirements, operation frequency, power level, electromagnetic interference (EMI), safety, and testing technology (WEVCSs).

A novel distributed control approach to charge a fleet of electric vehicles (EVs) as effectively as feasible when the overall capacity of the power grid is limited. By resolving a scheduling issue, the ideal charging can be discovered. Obtaining a cost-effective profile of the entire quantity of energy utilized is the objective. In the resulting optimization problem, the decision variables are connected to both the objective function and the constraint variables. In our approach, people just communicate with their near neighbors and take decisions without seeking advice from those in positions of authority. To find a solution, a distributed iterative algorithm founded on the ideas of duality, closeness, and consensus is employed. The global optimum can be reached using this strategy, as demonstrated by a simulated case study.

The water filling technique can be used in networked control systems with node-to-node communication that is independent. Water filling is a well-known method of communication system optimization. It has assisted in solving real-world control engineering and decision-making problems. In a system with multiple control points, the decentralized approach of filling water tanks may be used. A study of interconnected water levels among users who do not involve a central authority structure and simply use them to communicate with their immediate neighbors was conducted. In this study, we develop a unique distributed algorithm that combines fixed point mapping theory, proximity theory, and consensus theory. The algorithms' exact and approximation implementations provide the same outcome. The charging of a fleet of electric vehicles is used to illustrate how the system functions [45].

The difficulty of charging a large number of electric vehicles with infrastructure that has a limited capacity led to the need for this study, which examines the issue of individual load adjustment under overall capacity limits. Distributed solutions to this challenge are being looked into for scalability and communication ease. We discuss a number of distributed algorithms for maximizing utilization and relative average fairness using concepts from communication networks (AIMD algorithms) and distributed convex optimization. We give analytical and simulation findings to demonstrate the effectiveness of these algorithms. The algorithm's performance in the analyzed circumstances is often within 5% of the ideal centralized case's performance, but with substantially better scalability and fewer communication requirements.

2.3. Machine Learning Techniques

The many uses of ML algorithms have been widely covered in writing. The authors in [4] investigated how SVM could be used to solve problems with more than two classes. The algorithm was developed so that it could be used to solve problems involving multiple categories by using various normalization techniques. The algorithm passed thorough testing and discovered that it was effective with a wide range of normalization techniques. Its multiclass classification accuracy was also quite impressive.

DNN was also examined by [46] for classifying multi-type images. As a result, the proposed algorithm has a wide range of applications, even for famously challenging to-label classes that are frequently misclassified by other ML techniques using a DNN-improved class identification. The capacity of the algorithm to forecast travel times was also investigated by [47]. Its regressive predictions were the most accurate and reliable of all the tested algorithms. One of the best regression algorithms, especially for time series, is LSTM. Additionally, LSTM helps classify issues because it can be used to create classes based on number intervals. Authors in [48] looked into using radio waves to estimate the required energy and power (RF). RF was easy to use and produced accurate results. The energy consumption model had a mean absolute percentage error of only 16%, making it more accurate than the autoregressive model. Creating a multiclass classification problem was necessary for managing EV fleets. As a result, many ML techniques previously shown to be the most successful for classification problems were used. We assessed each model's accuracy before contrasting and comparing its performance to see if there were any viable options for increasing the effectiveness of the distribution network. The ML algorithm summary is presented in Table 1.

Table 1. ML algorithm summary.

Algorithm	Advantages	Disadvantages
Decision Tree (DT)	Data does not need to be sized or normalized. Regression and classification analyses benefit from it—highly accurate predictions and understanding.	Training takes a while since even little changes to the dataset could greatly impact the final structure.
Random Forest (RF)	Capable of processing large datasets with various factors and handling uncertainty while putting out the mean or mode of several decision trees.	The problem is made harder by how many trees are created. Training typically requires a sizable amount of time.
Support Vector Machine (SVM)	Classification and regression are possible uses; the classifier's performance is minimized.	The training procedure takes longer with large datasets—poor performance when there are more features than training samples.
K-Nearest Neighbors (KNN)	Both classification and regression analysis can benefit from its use. Shorter training sessions. Clear use of ideas.	We are having poor performance when dealing with huge datasets. Poor performance when dealing with a large number of inputs. Poor performance when dealing with datasets that are not balanced
Deep Neural Network (DNN)	A model that may be utilized for various tasks, like classification and regression.	Need enormous data sets very prone to over fitting. The ideal width and depth cannot be determined using a general principle.
Long Short-Term Memory (LSTM)	Time series detection, accurate forecasting and adaptability to various applications (classification and regression).	There is no established methodology for determining the optimum breadth and depth. There is no theory for selecting optimal hyper parameters.

3. Methodology

3.1. Machine Learning

Machine learning studies focus on building automatons that can learn new skills through observation and exposure to new data. This area of research aims to create algorithms that allow machines to remember and operate independently without human intervention. Data is provided to a generic algorithm in machine learning, which builds its logic based on the data rather than being preprogrammed. Supervised learning, unsupervised learning, and reinforcement learning are a few machine learning techniques [49] Computers are used to make predictions in computational statistics. It is closely related to machine learning and frequently crosses over with it. Mathematical optimization is known to study how to make optimization processes, theories, and applications better. Mathematical optimization is related to machine learning, as well. Unsupervised learning, also known as exploratory data analysis, is frequently highlighted when combining machine learning and data mining [50]. Unsupervised machine learning is a powerful tool for understanding the typical behavior of many organisms and observing constant movement from these patterns. Predictive analytics, or machine learning, is a method for developing complicated algorithms and models that can be used to forecast outcomes based on data analysis. Even then, AI falls far short of machine learning's capabilities. When artificial intelligence (AI) was first developed, some scientists programmed computers to learn from their mistakes. They looked for a solution using symbolic techniques like neural networks. But as rational and knowledge-based approaches gain more attention, there is a clear distinction between AI and machine learning. Data collection and presentation in probability systems had theoretical and practical problems. Statistics lost their value after 1980 when cyber systems had already exceeded artificial intelligence. However, the statistical focus of other research was seen outside of AI in pattern recognition and information retrieval. In contrast, work on knowledge-based learning continued inside AI and resulted in inductive logic programming. Academics in AI and CS started to ignore neural network research simultaneously. Under the umbrella of "connectionism", researchers outside AI/CS, like Hopfield [51], made comparable attempts. They had great success with backpropagation, which they used in the middle of the 1980s [52]. Data mining and machine learning are very similar and use many methods. Machine learning entails making predictions based on previously discovered properties from training data. On the other hand, data mining entails identifying novel properties (the step of analyzing knowledge extraction in the database). Machine learning frequently uses data mining techniques for "unsupervised learning" or as a step before learning to increase accuracy. Except for the ECML PKDD, most of the distinctions between the two fields, which frequently have separate conferences and journals, are founded on those assumptions. Discovering new information is typically how knowledge extraction and data mining (KDD) is judged effective. The effectiveness of machine learning is generally assessed by how well it can replicate existing data. Due to a lack of training data, supervised methods cannot be used in a typical KDD task. Still, an unsupervised manner, also known as an "uninformed method", can relatively easily outperform other monitored methods. Machine learning techniques that divide data into training and test sets, such as the holdout method, enable extremely precise estimation of classification models (usually two-thirds of the data in the training set and one-third). It also assesses how successfully the model was trained using real test data. The N-fold cross-validation method, in contrast, randomly selects k subsets from the data, of which k1 is used to train the model, and k1 is used to assess the model's predictive capability. The bootstrap technique, which uses a copy-and-paste method to choose n random samples from the data set, can be used in addition to the holdout and cross-validation techniques [52] to evaluate the model accurately

3.2. Learning Algorithms

The Q-learning algorithm was used by [53] in 2012 to improve the power management system of electric and hybrid bicycles. In terms of power management, these researchers aimed to increase rider comfort and safety and utilize battery power more effectively. Simulated results from this study showed that the proposed power management system could increase riding comfort by 24% and energy efficiency by 50%. Since then, reinforcement learning algorithms have been used in several studies to replace control optimization theory for HESS energy management. To find the best way to maintain an HEV's battery at the ideal charge level. The author in [53] used the Q-learning algorithm. By combining this strategy with a long-term plan, you can strike a balance between maximum effectiveness and the capacity to act now. Atheros in [54] employs "reverse reinforcement learning" to develop a probabilistic driving path prediction system that determines the ideal engine-to-battery power ratio based on the expected behavior of the driver. Several papers on the application of reinforcement learning to control the power flow in hybrid transmission systems have recently been published [54]. First, the adjustment, effectiveness, and learning capacity of a Q-learning-based energy management strategy for a hybrid tracked vehicle was assessed [55]. The researchers then developed online Q-learning-based recursive algorithms to allow real-time updates to control methods for hybrid transmission systems. When the driver's actions, location, and conditions on the road all vary, these algorithms' effectiveness may likely decline.

3.3. Proposed Methods

Driving cycle data could be used to find flexible energy management strategies using advanced reinforcement learning. A comparison of rule-based energy management strategies and those learned through DRL and online learning was done. The examples show both transactional and ad hoc neural networks. Machine learning can be used to overcome this issue in five different ways. A block diagram of an electric vehicle's static wireless charging system is shown in Figure 6. The receiver coil and transmitter coil are placed on top of one another to show how well the EVs work. Over time, using this approach will lessen pollution and conserve our finite supply of conventional energy. Figure 7 shows proposed methodology.

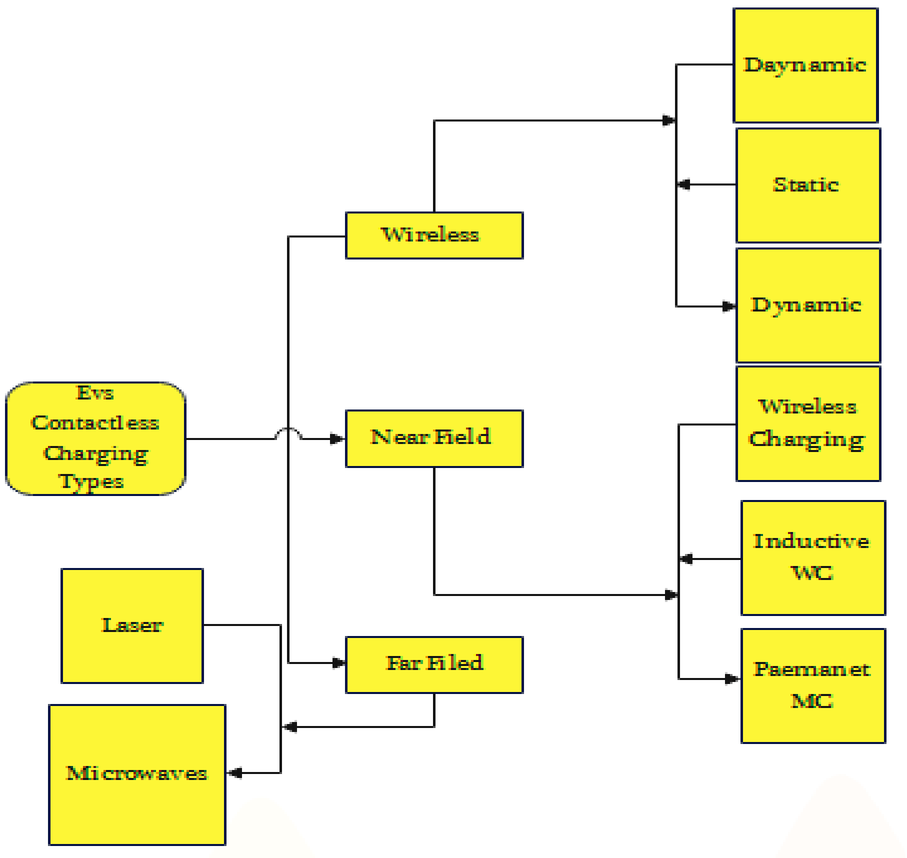

Figure 6. Contactless charging types [56].

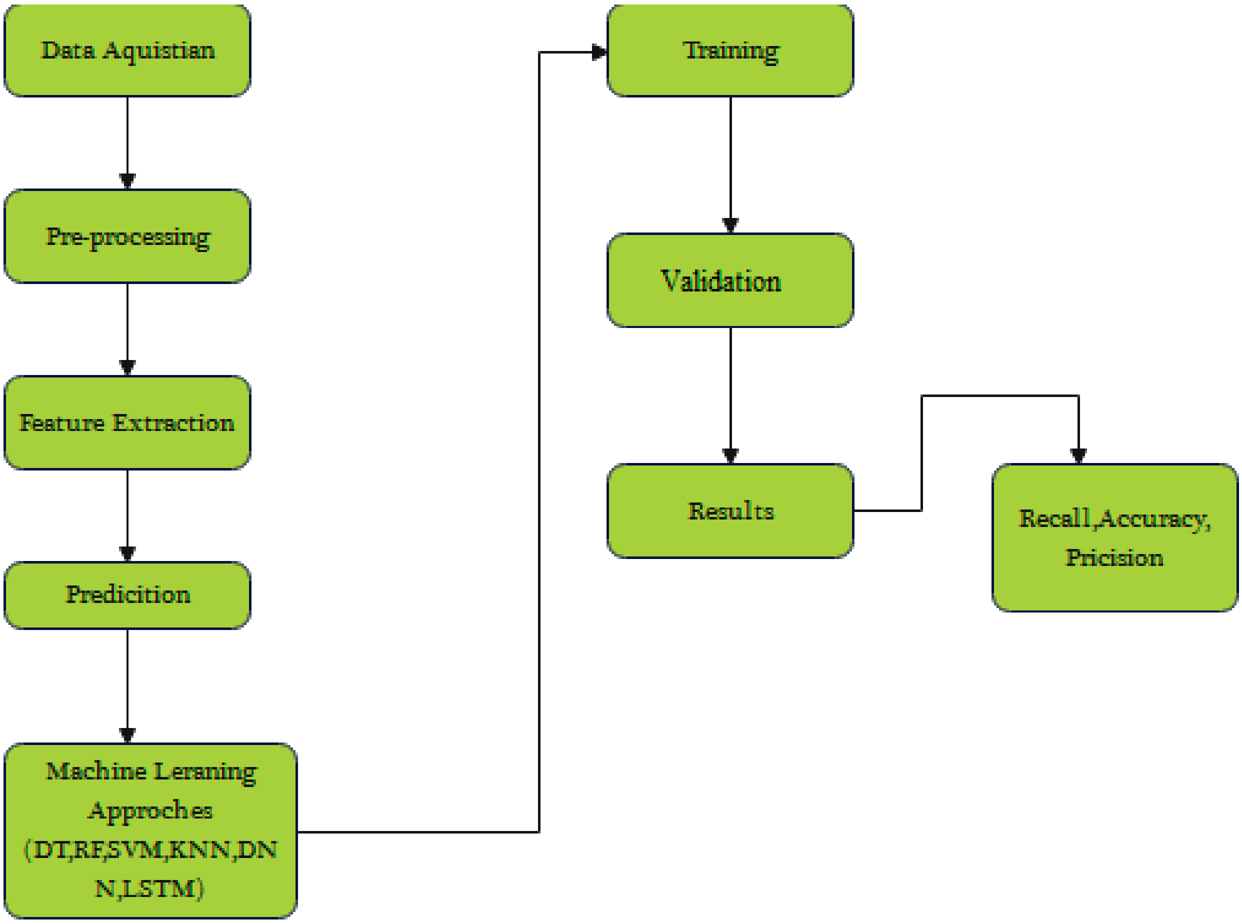

Figure 7. Proposed methodology.

4. Data Acquisition

We discovered a dataset about charging electric vehicles after searching for it on Kaggle. Details include the overall cost of the energy utilized, the date, and the length of each session. In this dataset, 3395 EV charging sessions are covered in great. A workplace charging initiative involved 85 distinct EV drivers who used 105 station sessions spread over 25 different sites. There are 24 resources and 3395 specifics on the car. The effectiveness of various machine learning techniques is assessed and contrasted. The techniques used include deep neural networks, k-nearest neighbors, long short-term memory, random forest, support vector machines, and decision trees. All machine learning methods were compared using the same dataset to see which produced the most accurate results. According to the results, it seemed that LSTM could help with EV control in some circumstances. The peak voltage, power losses, and voltage stability of the LSTM model can all be improved by flattening the load curve. We can lower our billing costs by predicting incoming data. The proposed Smart Grid Electric Vehicle Charging and Hybrid Energy Storage Management System's dataset is described in Table 2.

A decision was made regarding how much data should be shared between Train and Test (80–20%) for each neural network after considering the findings for DNN, KNN, SVM, RF, DT and LSTM. Tests and simulations are performed using Mat lab 2021a. It has an 8.00 GB RAM, a hard drive, and an 11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40 GHz high-performance PC CPU.

Table 2. Summary of data set (Electric Vehicle Charging Dataset Kaggle).

1.	Session ID	13.	station Id
2.	KWH Total	14.	location Id
3.	Dollars	15.	manager Vehicle
4.	Created	16.	facility Type
5.	Ended	17.	Mon
6.	Start Time	18.	tues
7.	End Time	19.	wed
8.	Charge Time Hrs	20.	Thurs
9.	Week Day	21.	Fri
10.	Platform	22.	sat
11.	Distance	23.	sun
12.	User ID	24.	reported zip

5. Results

5.1. Machine Learning Models:

5.1.1. Charging Station Classification Results

According to the charging station classification, the network has twelve different types of charging stations. Table 3 shows how well other models direct EVs to the most effective charging locations, maximizing the effectiveness of the distribution network and lowering the cost of charging.

Table 3. Accuracies of ML classifier for charging station classification.

Machine Learning Model	Accuracy
Decision Tree	93%
Random Forest	94%
SVM	29%
KNN	41%
DNN	77%
LSTM	94%

SVM and KNN cannot be used for EV routing, as shown in Table 3 by their incredibly low precision. The most accurate models, with a 94% accuracy rate, are RF and LSTM. The 93% precision of DT is identical to that of RF and LSTM. DNN has a remarkable 77% accuracy rate. Expanding the datasets and changing the hyper parameters, such as the number of layers and nodes in each layer, can improve the system's performance. These results explain that RF and LSTM perform better at multiclass classification problems than algorithms like SVM and KNN.

Figure 8 shows the accuracies of ML classifier for charging station classification.

5.1.2. Classification Based on Charging

Three categories of charging speeds have been created to reflect the range of uses for charging stations (fast charging, conventional charging, and V2G). How well ML models could see the ideal charging rate is shown in Table 4.

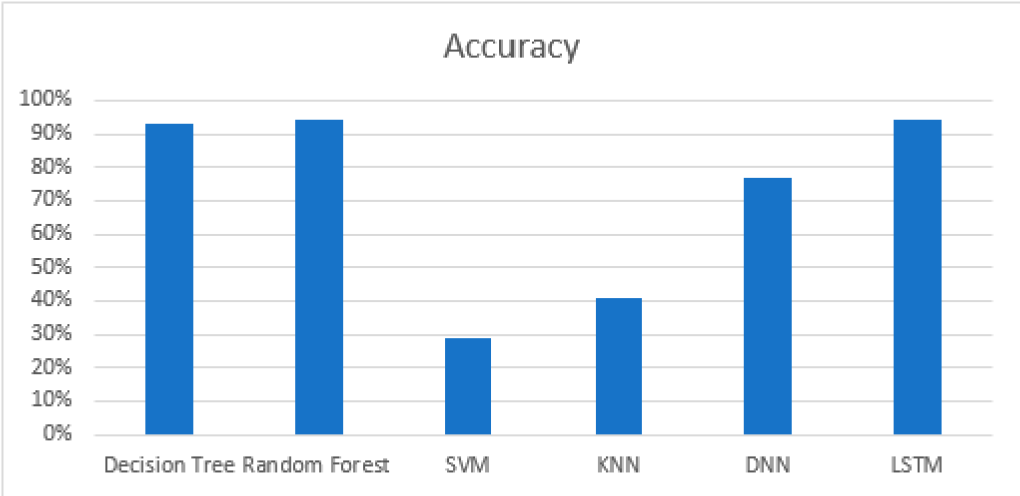

Figure 8. Accuracies of ML classifier for charging station classification.

Table 4. Accuracies of ML classifier for charging speed classification.

Machine Learning Model	Accuracy
Decision Tree	83%
Random Forest	89%
SVM	56%
KNN	83%
DNN	84%
LSTM	93%

Table 4 demonstrates that only SVM has a low level of precision. DT, KNN, and DNN have accuracy rates of about 83%, 83%, and 84%, respectively. The most accurate results are produced by RF and LSTM models. LSTM is 4% more precise in determining the ideal charging rates than RF. The best ML model for classifying charging stations and vehicle speeds is LSTM. Because it addresses both classification issues, it is the best strategy for managing an EV fleet. Its ability to recognize temporal patterns in data about power consumption is one of the reasons it is so accurate.

Figure 9 shows the accuracies of ML classifier for charging speed classification.

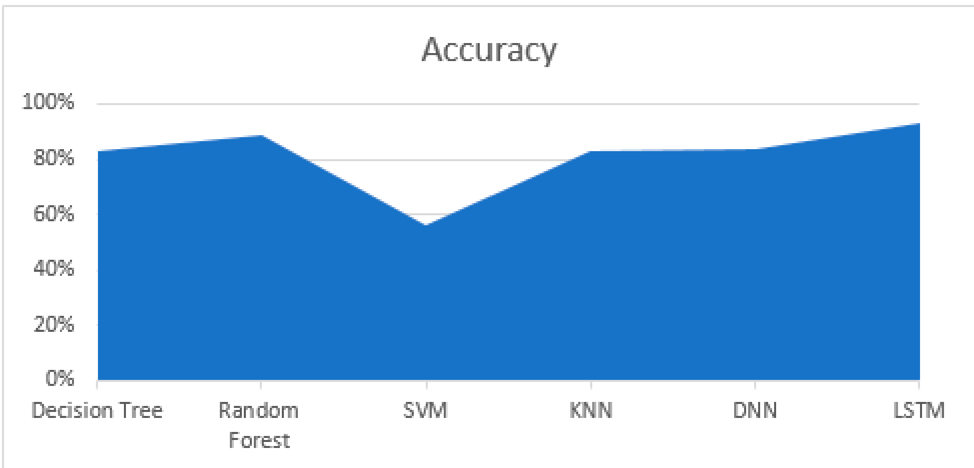

Figure 9. Accuracies of ML classifier for charging speed classification.

5.2. The Impact of Uncertain Load Data on the EV Management System

The load data is augmented with various concentrations of Gaussian white noise (GWN) to simulate the data's unpredictability and add different degrees of uncertainty. We evaluate previously successful ML methods to see how well they can handle new types of luck. Thus, the impact of tension on the system is researched, especially how it affects power losses and load curves.

Variation in Load Data and Its Impact on Machine Learning Accuracy

The results of including uncertainty to the load data used to group charging stations are shown in Table 5. By contrasting precision before and after adding delay, we can identify the change in precision. When there is uncertainty, DT's accuracy drops to 77%. Although still not as good as DT's, RF's accuracy drops to 86%. The best model, LSTM, remained accurate 95% of the time and was unaffected by uncertainty.

Table 5. Classification accuracy of a machine learning classifier using a 10% global weighted network for Electric Vehicles charging stations.

Machine Learning Model	Accuracy	Accuracy Change
DT	76%	−17%
RF	85%	−9%
LSTM	94%	0

The impact of adding uncertainty to load data on the effectiveness of the machine learning algorithms used to categorize charging speeds is shown in Table 3. In RF and DNN, accuracy has fallen by 1% and 2%, respectively. The accuracy of DT, KNN, and LSTM remained unchanged when GWN was added. The outcomes show that LSTM is adaptable even in the presence of GWN in the load data and performs excellently both before and after the introduction of uncertainty. Machine Learning Classification of Pricing Structures: Accuracy of Prediction: 10% Standardization of Weights around the World is presented in Table 6.

Table 6. Machine learning classification of pricing structures: Accuracy of prediction: 10% standardization of weights around the world.

Machine Learning Model	Accuracy	Accuracy Change
DT	83%	0%
RF	88%	−1%
KNN	84%	0
DNN	82%	−2%
LSTM	93%	0%

ML implementation Results for EV-HESMS is presented in Table 6. In the proposed EV-HESMS model, 80% for training and 20% data for testing taken to find the Gradient Loss, Action Error and MSE.

Table 7 shows how the EV-HESMS Model behaves in terms of gradient Loss, MSE, training, and testing. Efficiency by itself is insufficient. The system's loss and error for each machine learning technique using Gradient loss and Event error must also be determined. The dataset and the capabilities of the system can be considered to a great extent as the gradient loss, action error, and MSE are taken into account. Additionally, LSTM is already thought to be more effective than other methods. In reality, LSTM also considerably reduces errors in this situation.

Table 7. ML implementation Results for Proposed EV-HESMS Model.

Methods	Train (80%)	Test (20%)	Gradient Loss	Action Error	MSE
1. Random Forest	2716	679	0.366	0.304	0.342
2. SVM	2716	679	0.359	0.449	0.303
3. KNN	2716	679	0.426	0.402	0.333
4. DNN	2716	679	0.390	0.329	0.475
5. LSTM	2716	679	0.386	0.310	0.258

5.3. Mathematically Model to Different Calculated Parameters:

Controlling parameters can be changed in real-time in a system with real-time control [34]. The method's practicality was shown by simulated experiments on a hardware operating system based on rechargeable batteries and super capacitors. b_{min} is added to the estimate to get the minimum battery load (w). The following defines the cost function: The edge is deleted as unneeded if the sum of the values $b_{min}(v) = b_{min}(w) + cost(e)$ is more than M.

$$C_e^+(b_w) = \begin{cases} Cos(e)bw \leq M - Cost(e) \\ \infty Otherwise \end{cases} \tag{1}$$

If the original edge, $e = (v, m)$, has negative costs, we subtract the value of the price from b_{min} (w). We obtain $b_{min}(v)$. The cost function is given by:

$$C_e^-(b_w) = \begin{cases} -bwbw < -Cost(e) \\ Cost(e)Otherwise \end{cases} \tag{2}$$

$$MAPE = \frac{\sqrt{\sum_{i=1}^{N} \frac{(|xi-yi|)^1}{xi}}}{N} \times 100\% \tag{3}$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(xi-yi)^2}{N}} \tag{4}$$

$$r = \frac{\sum_{i=1}^{N}(Xi - X')(Yi - Y')^1}{\sqrt{\sum_{i=1}^{N}(Xi - X')^1}\ \sqrt{\sum_{i=1}^{N}(Yi - Y')^2}} \tag{5}$$

Numerous solutions must be developed to deal with problems like excesses and overload when electric vehicles are connected to a smart grid. This does not happen until the most economical energy has been acquired. Using the defined criteria, electric vehicles can compete for reduced electricity rates in a given area. They are using price signals to discourage the charging of vehicles in crowded places and make money through electric car sharing. EV software uses a variety of machine-learning techniques. Some of the most popular methods for analyzing data and identifying its relevance include decision trees, ANNs, SVMs, GRNNs, and k-nearest neighbors (KNN). Usually, MAPE, r, and RMSE are used to evaluate a forecast's degree of accuracy. R is a common abbreviation for the correlation coefficient. Measures of how far off an estimate is from reality include the root-mean-square error and mean absolute percentage error (MAPE). You can find the tools RMSE, r, and MAPE in EQU. In the first case, the true value is represented by Xi, while YI represents the close approximation. There are intriguing differences between the means of the true value vector's X and the projected value vector's Y. The letter N stands for the whole cast set of values. Figure 10 show the classification accuracy of a machine learning classifier.

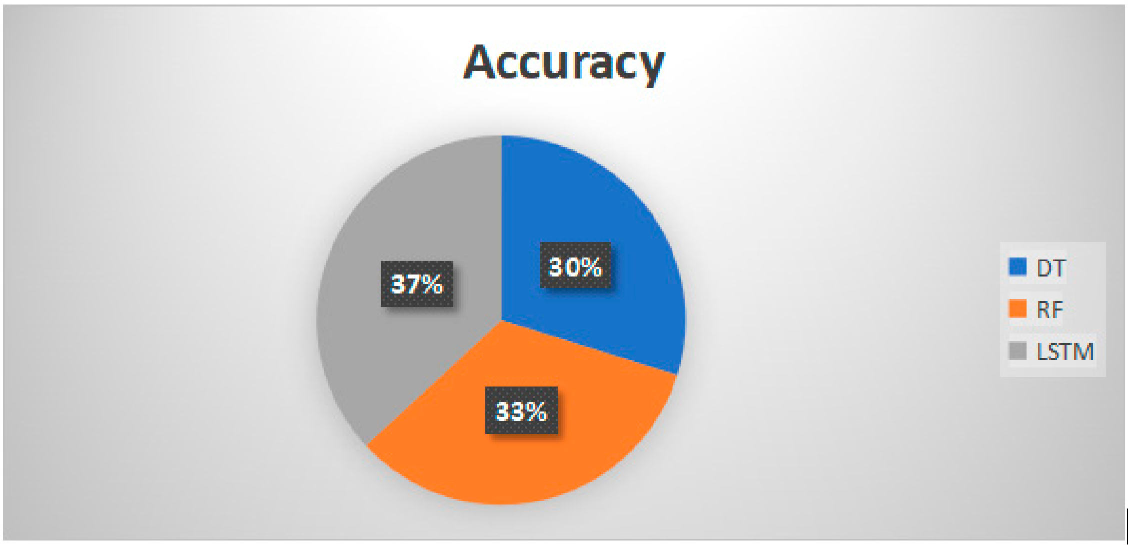

Figure 10. Classification accuracy of a machine learning classifier.

Figure 11 shows the accuracy of prediction: 10% standardization of weights around the world.

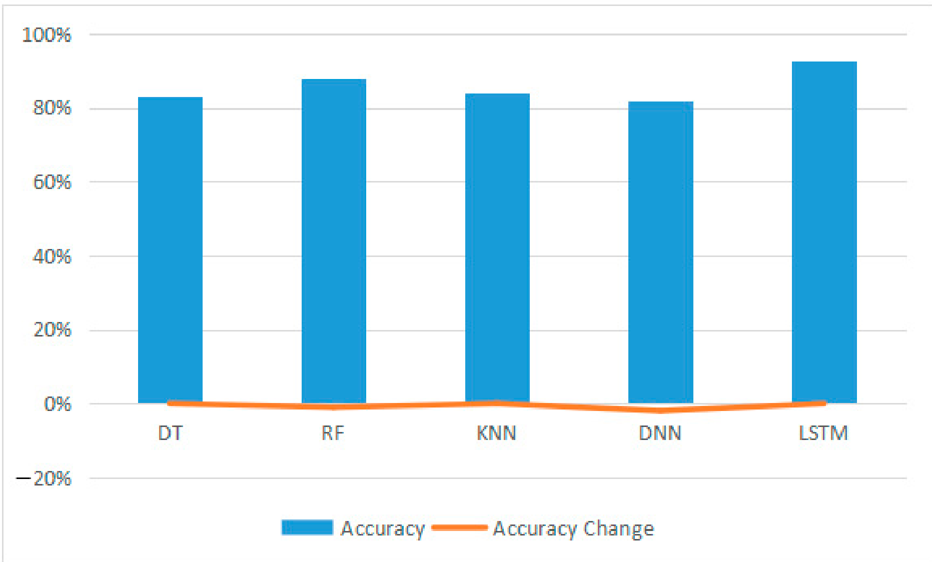

Figure 11. Accuracy of prediction: 10% standardization of weights around the world.

Figure 12 shows the ML implementation results for proposed EV-HESMS model.

5.4. Limitations of the Proposed System

(1) More advanced deep learning, reinforcement learning, and federated learning techniques can be used to centralize this system, enabling more effective vehicle utilization regulation. Obviously, if there are more providers vying for fewer stations, the problem will improve.

(2) The dataset should contain more parameters. Electric vehicle (EV) sales have been increasing, and this trend is likely to continue as prices fall and ranges increase. Currently, the percentage of electric cars (EVs) in use is quite modest. Any company that has a parking lot for clients or staff will be impacted by this. Therefore, it is crucial for businesses to consider how their energy policy will change as a result of planned changes to EVs and EV charging. Particularly for businesses, having multiple chargers or fast-charging equipment on hand is essential.

(3) As automakers work to reduce the amount of time needed to charge an EV so that the "refueling" process is more equivalent to that of a normal vehicle, chargers need more power.

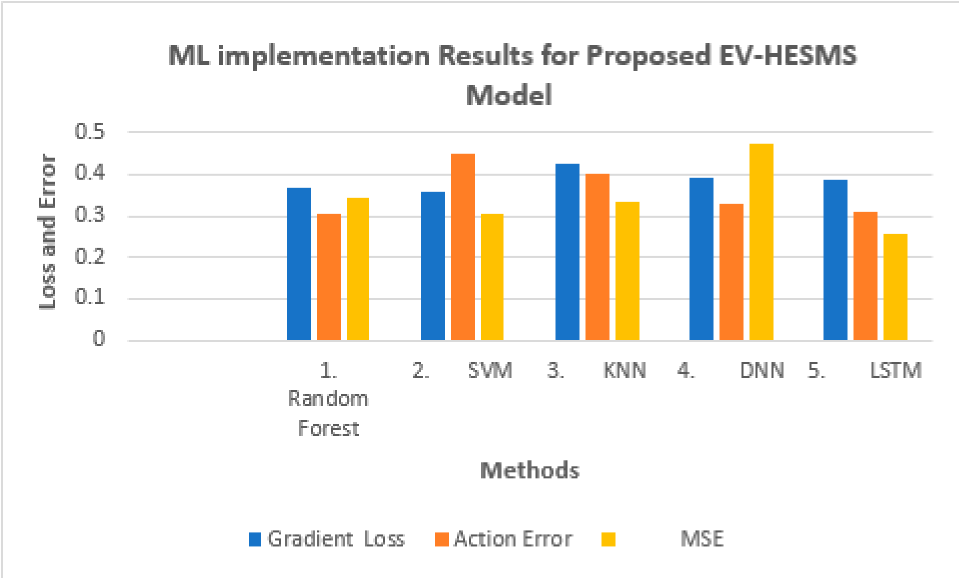

Figure 12. ML implementation results for proposed EV-HESMS model.

6. Conclusions

Information and communication technology development is crucial to the worldwide spread of smart cities (ICT). Every developing city needs a smart grid. Government and corporate organizations are promoting using electric vehicles (EVs) to reduce greenhouse gas emissions and combat climate change. Electric automobiles have sparked several previously unforeseen problems due to their greater presence in contemporary, sophisticated power networks. Two significant issues are implementing cost-saving technology for controlling energy supply and demand and creating more efficient techniques for invoicing clients. This issue has received various possible solutions that have been put forward. This entails a thorough investigation of charging procedures, industry standards, and different data-driven models and machine-learning techniques to facilitate the seamless integration of electric vehicles into the smart grid. We examine the most recent developments in smart grid-based energy management services and applications and the growing appeal of electric vehicles. This indicates that individuals with a say in infrastructure development must consider the health of communities, public safety, access to electricity and information, the provision of services, and other issues [11]. This kind of smart city and technology development will be effective when all stakeholders and important factors are considered. Hurdles and opportunities have emerged as technology have advanced toward long-term solutions. We talk about conductive and inductive charging for electric cars. The most important studies that have been done on electric vehicles, connector hybrid electric vehicle types, charging rates, and battery capacity, and these topics are reviewed. This paper analyzes current advancements in fixed and portable wireless charging technology. Although there are international standards for wirelessly charging electric vehicles, different wireless charging systems employ a range of frequencies. The efficacy of contemporary machine learning algorithms and robotic models is being assessed to integrate the smart grid. We examine the techniques presently used to calculate the driving range, charging time, and traffic impact of electric vehicles. It is necessary to study the effects of the public infrastructure's energy efficiency, robustness, and dependability on the economy, society, and environment to make widespread usage of electric vehicles feasible. Discussions and analyses will focus on wireless power transmission systems in the future. These systems, which include those that carry energy inside cars and those that do so between autos and the grid, will be of great importance. Research on mobile energy storage and delivery infrastructures based on electric vehicles may help us better understand how to incorporate renewable energy sources into distributed micro grids.

Author Contributions: Conceptualization, T.M.; methodology, T.M., R.N.A.; software, T.M., R.N.A., M.A.M. and S.A.; validation, T.M., M.I. and M.K.; formal analysis, S.A.; investigation, T.M and I.H.; resources, T.M. and I.H.; data curation, T.M., M.A.N.; writing—original draft preparation, T.M.; writing—review and editing, T.M., M.A.M. and M.A.N.; visualization, T.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. IEA, C. Global EV Outlook 2020. 2020. Available online: https://www.iea.org/reports/global-ev-outlook-2020 (accessed on 1 February 2022).
2. Dhakal, T.; Kangwon National University; Min, K.-S. Macro Study of Global Electric Vehicle Expansion. *Foresight STI Gov.* **2021**, *15*, 67–73. [CrossRef]
3. Elmenshawy, M.; Massoud, A. Modular Isolated DC-DC Converters for Ultra-Fast EV Chargers: A Generalized Modeling and Control Approach. *Energies* **2020**, *13*, 2540. [CrossRef]
4. Shibl, M.; Ismail, L.; Massoud, A. Electric Vehicles Charging Management Using Machine Learning Considering Fast Charging and Vehicle-to-Grid Operation. *Energies* **2021**, *14*, 6199. [CrossRef]
5. Lytras, M.D.; Visvizi, A.; Jussila, J. Social media mining for smart cities and smart villages research. *Soft Comput.* **2020**, *24*, 10983–10987. [CrossRef]
6. Morvaj, B.; Lugaric, L.; Krajcar, S. Demonstrating smart buildings and smart grid features in a smart energy city. In Proceedings of the 2011 3rd International Youth Conference on Energetics (IYCE), Leiria, Portugal, 7–9 July 2011.
7. Qaisar, S.M.; Alyamani, N. A Review of Charging Schemes and Machine Learning Techniques for Intelligent Management of Electric Vehicles in Smart Grid. *Manag. Smart Cities* **2022**, 51–71. [CrossRef]
8. Axelsson, K.; Granath, M. Stakeholders' stake and relation to smartness in smart city development: Insights from a Swedish city planning project. *Gov. Inf. Q.* **2018**, *35*, 693–702. [CrossRef]
9. Lytras, M.D.; Chui, K.T. The Recent Development of Artificial Intelligence for Smart and Sustainable Energy Systems and Applications. *Energies* **2019**, *12*, 3108. [CrossRef]
10. Liu, Z.; Wu, Q.; Huang, S.; Wang, L.; Shahidehpour, M.; Xue, Y. Optimal Day-Ahead Charging Scheduling of Electric Vehicles Through an Aggregative Game Model. *IEEE Trans. Smart Grid* **2017**, *9*, 5173–5184. [CrossRef]
11. Wang, T.; Liang, Y.; Jia, W.; Arif, M.; Liu, A.; Xie, M. Coupling resource management based on fog computing in smart city systems. *J. Netw. Comput. Appl.* **2019**, *135*, 11–19. [CrossRef]
12. Dericioğlu, C.; Yirik, E.; Ünal, E.; Cuma, M.U.; Onur, B.; Tümay, M. A Review of Charging Technologies for Commercial Electric Vehicles. *Int. J. Adv. Automot. Technol.* **2018**, *2*, 61–70. [CrossRef]
13. Wang, S.; Wan, J.; Li, D.; Zhang, C. Implementing smart factory of industrie 4. *0: An outlook. Int. J. Distrib. Sens. Netw.* **2016**, *12*, 3159805.
14. Danish, M.S.S.; Bhattacharya, A.; Stepanova, D.; Mikhaylov, A.; Grilli, M.L.; Khosravy, M.; Senjyu, T. A Systematic Review of Metal Oxide Applications for Energy and Environmental Sustainability. *Metals* **2020**, *10*, 1604. [CrossRef]
15. Ehsani, M.; Gao, Y.; Gay, S.E.; Emadi, A. *Modern Electric, Hybrid Electric, and Fuel Cell Vehicles*; CRC Press: Boca Raton, FL, USA, 2018.
16. Cattaruzza, D.; Absi, N.; Feillet, D.; González-Feliu, J. Vehicle routing problems for city logistics. *EURO J. Transp. Logist.* **2017**, *6*, 51–79. [CrossRef]
17. Xydas, E.S.; Marmaras, C.E.; Cipcigan, L.M.; Hassan, A.S.; Jenkins, N. Forecasting electric vehicle charging demand using support vector machines. In Proceedings of the 2013 48th International Universities' Power Engineering Conference (UPEC), Dublin, Ireland, 2–5 September 2013.
18. Sadeghian, O.; Oshnoei, A.; Mohammadi-Ivatloo, B.; Vahidinasab, V.; Anvari-Moghaddam, A. A comprehensive review on electric vehicles smart charging: Solutions, strategies, technologies, and challenges. *J. Energy Storage* **2022**, *54*, 105241. [CrossRef]
19. Vu, Q.V.; Dinh, A.H.; Van Thien, N.; Tran, H.T.; Le Xuan, H.; Van Hung, P.; Kim, D.T.; Nguyen, L. An Adaptive Hierarchical Sliding Mode Controller for Autonomous Underwater Vehicles. *Electronics* **2021**, *10*, 2316. [CrossRef]

20. Huang, X.; Shi, J.; Gao, B.; Tai, Y.; Chen, Z.; Zhang, J. Forecasting Hourly Solar Irradiance Using Hybrid Wavelet Transformation and Elman Model in Smart Grid. *IEEE Access* **2019**, *7*, 139909–139923. [CrossRef]
21. Quesada, J.A.; Lopez-Pineda, A.; Gil-Guillén, V.F.; Durazo-Arvizu, R.; Orozco-Beltrán, D.; López-Domenech, A.; Carratalá-Munuera, C. Machine learning to predict cardiovascular risk. *Int. J. Clin. Pr.* **2019**, *73*, e13389. [CrossRef]
22. Zhai, Z.; Su, S.; Liu, R.; Yang, C.; Liu, C. Agent–cellular automata model for the dynamic fluctuation of EV traffic and charging demands based on machine learning algorithm. *Neural Comput. Appl.* **2018**, *31*, 4639–4652. [CrossRef]
23. Rigas, E.S.; Ramchurn, S.D.; Bassiliades, N. Managing Electric Vehicles in the Smart Grid Using Artificial Intelligence: A Survey. *IEEE Trans. Intell. Transp. Syst.* **2014**, *16*, 1619–1635. [CrossRef]
24. Sangdehi, S.M.M.; Hamidifar, S.; Kar, N.C. A Novel Bidirectional DC/AC Stacked Matrix Converter Design for Electrified Vehicle Applications. *IEEE Trans. Veh. Technol.* **2014**, *63*, 3038–3050. [CrossRef]
25. Sultana, B.; Mustafa, M. Impact of reconfiguration and demand response program considering electrical vehicles in smart distribution network. In Proceedings of the 3rd International Electrical Engineering Conference (IEEC 2018), Karachi, Pakistan, 9–10 February 2018.
26. 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. [CrossRef] [PubMed]
27. 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.
28. 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. [CrossRef]
29. 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. [CrossRef]
30. 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. [CrossRef]
31. 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. [CrossRef]
32. 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. [CrossRef]
33. 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.
34. 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. [CrossRef]
35. Dileep, G. A survey on smart grid technologies and applications. *Renew. Energy* **2019**, *146*, 2589–2625. [CrossRef]
36. 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. [CrossRef]
37. Carli, R.; Dotoli, M. A Distributed Control Algorithm for Optimal Charging of Electric Vehicle Fleets with Congestion Management. *IFAC-PapersOnLine* **2018**, *51*, 373–378. [CrossRef]
38. 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. [CrossRef]
39. 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. [CrossRef]
40. 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. [CrossRef]
41. 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. [CrossRef]
42. Ashraf, S.; Ahmed, T.; Saleem, S. NRSM: Node redeployment shrewd mechanism for wireless sensor network. *Iran J. Comput. Sci.* **2020**, *4*, 171–183. [CrossRef]
43. Hoke, A.; Brissette, A.; Smith, K.; Pratt, A.; Maksimovic, D. Accounting for Lithium-Ion Battery Degradation in Electric Vehicle Charging Optimization. *IEEE J. Emerg. Sel. Top. Power Electron.* **2014**, *2*, 691–700. [CrossRef]
44. Scarabaggio, P.; Carli, R.; Cavone, G.; Dotoli, M. Smart control strategies for primary frequency regulation through electric vehicles: A battery degradation perspective. *Energies* **2020**, *13*, 4586. [CrossRef]
45. Carli, R.; Dotoli, M. A Distributed Control Algorithm for Waterfilling of Networked Control Systems via Consensus. *IEEE Control Syst. Lett.* **2017**, *1*, 334–339. [CrossRef]
46. Murthy, V.N.; Singh, V.; Chen, T.; Manmatha, R.; Comaniciu, D. Deep decision network for multi-class image classification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–29 June 2016.
47. Ma, X.; Tao, Z.; Wang, Y.; Yu, H.; Wang, Y. Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. *Transp. Res. Part C Emerg. Technol.* **2015**, *54*, 187–197. [CrossRef]

48. Deligiannis, P.; Koutroubinas, S.; Koronias, G. Predicting Energy Consumption Through Machine Learning Using a Smart-Metering Architecture. *IEEE Potentials* **2019**, *38*, 29–34. [CrossRef]
49. Manishimwe, A.; Alexander, H.; Kaluuma, H.; Dida, M.A. Integrated Mobile Application Based on Machine Learning for East Africa Stock Market. *J. Inf. Syst. Eng. Manag.* **2021**, *6*, em0143. [CrossRef]
50. Fernandes, A.; Salazar, L.H.; Dazzi, R.; Garcia, N.; Leithardt, V.R.Q. Using Different Models of Machine Learning to Predict Attendance at Medical Appointments. *J. Inf. Syst. Eng. Manag.* **2020**, *5*, em0122. [CrossRef] [PubMed]
51. Rumelhart, D.E.; Smolensky, P.; McClelland, J.L.; Hinton, G.E. is achieved. Prior to stabilization, neural networks do not jump around between points in activation space. Stabiliza-tion is the process whereby a network first generates a de-terminate activation pattern, and thereby arrives at a point in activation space. *Behav. Brain Sci.* **2004**, *27*, 2.
52. Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Comput. Sci.* **2021**, *2*, 1–21. [CrossRef] [PubMed]
53. Hsu, R.C.; Lin, T.-H.; Su, P.-C. Dynamic Energy Management for Perpetual Operation of Energy Harvesting Wireless Sensor Node Using Fuzzy Q-Learning. *Energies* **2022**, *15*, 3117. [CrossRef]
54. Gui, T.; Liu, P.; Zhang, Q.; Zhu, L.; Peng, M.; Zhou, Y.; Huang, X. Mention recommendation in Twitter with cooperative multi-agent reinforcement learning. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, Paris, France, 21–25 July 2019.
55. Liu, T.; Zou, Y.; Liu, D.; Sun, F. Reinforcement Learning of Adaptive Energy Management with Transition Probability for a Hybrid Electric Tracked Vehicle. *IEEE Trans. Ind. Electron.* **2015**, *62*, 7837–7846. [CrossRef]
56. Alsharif, A.; Wei, T.C.; Ayop, R.; Lau, K.Y.; Bukar, A.L. A Review of the Smart Grid Communication Technologies in Contactless Charging with Vehicle to Grid Integration Technology. *J. Integr. Adv. Eng.* **2021**, *1*, 11–20. [CrossRef]