

Optimal Allocation And Placement Of Faster Ev Charging Station Using Machine Learning: A Review And Recent Developments.

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Abstract:

Electric Vehicles (EVs) demand is higher over the years. For addressing the associated fossil fuel automobile issues owing to climate change, the utilization of EVs has become more famous. When more EVs are introduced, concerns about the accessibility as well as convenience of Charging Stations (CSs) for consumers occur. Inadequate CSs are associated with consumers' decisions to buy EVs. The critical component of the EVs' accessibility along with future success is to place CSs in regions with developing charging infrastructure. The distribution system is affected by the charging of a large number of EVs. Therefore, voltage fluctuations, power losses, augmented transformer overloads, et cetera may occur. Since ML approaches like Random Forest (RF), K-Nearest Neighbours (KNN), Deep Neural Networks (DNN), Decision Tree (DT), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) can create accurate future decisions grounded on historical data, they are contrasted concerning their performances in optimization. Therefore, this paper explores the overview of the Electric Vehicle Charging Station (EVCS) infrastructure, optimal allocation, and placement of fast EVCS in distribution and hybrid energy sources using ML. By analyzing the outcomes, the reliability of the usage of ML for the management of EVCS could be verified.

Keywords: *Electric Vehicle Charging Stations, Allocation, Placement, Distribution grid and Hybrid energy sources*

1. INTRODUCTION

All sectors, namely aircraft, ships, trains, et cetera have shown constant variation grounded on petroleum to electric-based transportation for the past 20 years. The utilization of EVs among these sectors is encouraged by the authorities from different evolving countries to decline the focus on air pollutants, CO₂, and other greenhouse gases [1]. EVCSs are becoming a significant recharging source for EVs owing to the enhancing penetration of EVs and the growth of charging infrastructure [2]. The equipment that links an EV to an electricity source for recharging electric cars, neighborhood EVs, and plug-in hybrids is named EVCS [3]. New EV sales are expected to evolve exponentially by the next 10 years. Also, substantial investments are required to build charging infrastructures to allow longer

driving distances and contribute to fast charging services. The schematic diagram of EVCS with a grid ensuring optimal as well as quality power exchange is explicated in Figure 1. The research interest has developed in growing fast CSs [4]. Charging time is considered as a significant barrier for EVs; thus, fast charging of EVs is required [5]. For the EVCS infrastructure, the batteries should be recharged. CS cannot be just placed at any location. To moderate the destructive effect activated by EVs, optimal planning for sizing and placement must be done [6]. For the quality power transfer and also to predict the power utilized in EVCSs, Machine Learning (ML) has been utilized. ML also plays an important role owing to its capability to utilize historical data for learning and identifying patterns to develop future decisions with lesser user intervention [7].

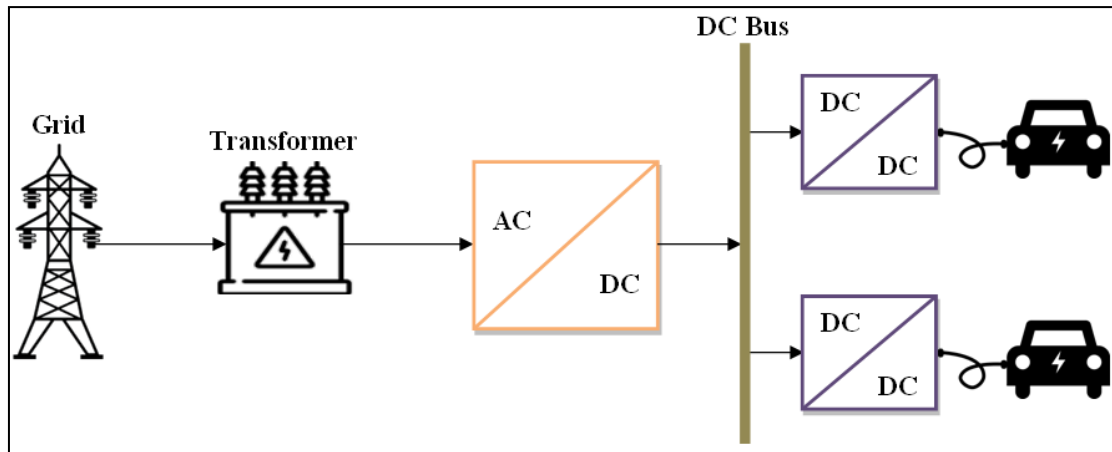


Figure 1: Schematic diagram of EVCS with a grid ensuring optimal as well as quality power exchange

ML algorithms have been developed by researchers that could help decrease charging times and prolong battery life in EVs by predicting how different driving patterns influence battery performance, thus optimizing safety and reliability [8]. Some ways in which ML is fixed to make a positive impact in the EV industry are [9, 10]:

- Battery performance and charging efficiency
- Enhancing Battery Life Prediction Accuracy
- Decreasing battery costs
- Better battery management
- Selecting the optimal location for EVCS

Even though ML has a major role in the optimal allocation and placement of fast EVCS, it has some issues. ML is a probabilistic [11]. It means the ML techniques run randomly. Therefore, the accuracy of utilizing the model will be unpredictable most of the time, so there will be changes in the fallouts [12].

The paper is explained as: Section 2 elucidates the optimal allocation and placement of fast EVCS in the distribution grid and hybrid sources using ML, Section 3 indicates the analysis, and the paper is wrapped up in Section 4.

2. LITERATURE REVIEW

A device that enables charging on EV safely with enhancement in efficiency is named EVCS. It is made of different kinds of equipment. When contrasted with regular vehicles, EVs are often more digitally connected with various EVCSs that give the option to control charging from a smartphone application. ML had been utilized for the outstanding allocation as well as placement of EVCSs in the grid and hybrid sources. Therefore, in this paper, section 2.1 defines the overview of the fast EVCS infrastructure; section 2.2 explains the optimal allocation of fast EVCS in distribution and hybrid energy sources using ML; section 2.3 describes the optimal placement of fast EVCS in distribution and hybrid energy sources using ML.

2.1. OVERVIEW OF THE EVCS INFRASTRUCTURE

EVCS is a power supply device, which supplies electrical power to recharge plug-in EVs like plug-in hybrid vehicles, neighborhood EVs, electric buses, electric trucks, and battery EVs [13]. EVCS is also known as an Electric Vehicle Supply Equipment (EVSE) or charge point. Special connectors that ensure a variety of electric charging connector standards are contributed by these stations, which comprise a network operating center, software platform, energy controller, facility meter, power grid, EV charger, and other significant components [14, 15].

Akhtar, et al. [16] explicated the stationary energy storage system for fast EVCSs with the concurrent sizing of battery as well as converter. Sequential sizing might lead to oversizing of ESS; thus, the set targets failed to be attained. To solve this problem, concurrent sizing of the converter and battery was applied. From the simulation outcomes, it was identified that concerning the CS's total annual cost and the amount of power buying during peak load intervals, the applied method performed better than the prevailing sizing techniques.

Yantao, et al. [17] examined the EVCS locations with network equilibrium, station congestion, along with elastic demand. As per the outcomes from the Boston, Massachusetts region network, EVCSs must be located almost 6 along major highways. For a 30-minute charging session, a user fee of \$6 wouldn't be enough for station profitability under a 5-year time horizon if 10% of present PEV owners attempt to charge en route every single day.

Phap, et al. [18] elucidated the PV-powered EVCS's technical economic assessment under various solar irradiation conditions in Vietnam. The optimal configuration of PV-powered EVCS was analyzed technically and economically. From the outcomes, it was found that the rooftop solar power's Feed-In Tariff (FIT) price and solar irradiation value highly

influenced this system’s investment efficacy and optimal configuration in every single urban area.

2.1.1. Key factors influencing the optimal allocation and placement of EVCS

Electric Vehicle Station (EVS) requires wide deployment of the charging infrastructure in the automotive sector. For determining optimal fresh locations, researchers consider and rate various factors by which the charging demand at candidate sites is affected [19, 20]. Various analyses indicated that there are a few important factors like the charging point’s quality and availability, and the placement and optimal allocation are affected by the activities connected to the location [21, 22].

Kris, et al. [23] described the quality of power analysis in the EVCS as a case study in the location of Malta. This system aimed to examine the power quality challenges. The analysis indicated that the maximal harmonic percentage was attained at $h = 5$ with 1.34%; this was less compared to the maximal value permitted in IEEE 519-2014 (5%) and the specific harmonic level in Engineering Recommendation G5/4-1 at $h = 5$ (2%).

Ashish, et al. [24] examined the analysis of the EVCS effect on power quality problems. Regarding transformer power loss, Voltage sag & swelling, harmonics, and power demand, the impact of EVCS in Bangladesh was examined. Outcomes indicated that for acquiring energy security & efficiency in the power sector, power quality disturbances must be reduced. For the power sector’s sustainable development, the power quality issues must be controlled correctly although EVCS has various advantages.

Mikołaj, et al. [25] presented different criteria on the basis of EVCS infrastructure design and power problems. To design the EVCS network, a 5-stage Multicriteria And GIS-centric EVCS location (5MAGISEV) technique was implemented. The results identified that the major factors that affect the allocation of EVCS were activity issues and charging point availability.

Vignesh, et al. [26] analyzed the reliability, charging point availability issues, and cost that influence the EVCS. If the power quality dropped below a certain value, the technique was applied for the calculation of penalties to be paid by the utility; thus, a need to maintain power quality is established. As per the outcomes, from 12 AM until 8 AM corresponding to the closed hours of the EVCS, there was no real power consumption. Among the lines considered for study L1 (19, 20, 21, 22), L2 (23, 24, 25), and L3 (26, 27, 28, 29, 30, 31, 32, 33), the loads were uniformly distributed.

D. Selvabharathi, et al. [27] described the power quality problems’ inspection in EVCS and its mitigation. The charging points for these EVs possess certain problems, which could influence the power quality, decrease the vehicle’s life, and damage the vehicles. The outcomes indicated that these issues were mostly related to power quality, such as losses, voltage lag, noises, harmonics, et cetera. Among these, noises and harmonics were the most important problems owing to which the battery’s life was reduced and led to a huge impact on cost.

2.1.2. EVCS in the distribution grid and hybrid energy source

A technology that enables energy to be pushed back to the power grid from the battery of an EV is named the distribution grid in EVCS. Centered on various signals like consumption and energy production nearby, an EV battery can be discharged with V2G technology [28, 29]. Phase unbalance at the distribution network was improved by the single-phase EV chargers; thus, unnecessary negative effects on connected loads and distribution network operation were improved [30]. For optimizing the quality of power, a hybrid charging and efficient energy conversion stage was applied [31]. The studies of EVCS in the distribution grid and hybrid energy sources with their achieved findings and limitations are explained in Table 1.

Table 1: Studies of EVCS in the distribution grid as well as hybrid energy source with its attained findings and limitations

| Author name | Source | Findings | Limitations |
|---------------------------|----------------------|--|---|
| Kalid, et al. [32] | Distribution grid | As per the results, the fast EVCS stations influence the quality of supply as well as needful activities, namely deploying static var compensators and energy storage needed to keep the fast CS in the distribution grid. | When only one EV has a sufficient state of charge to provide energy, the grid provides power. |
| Fuad, et al. [33] | Hybrid energy source | The outcomes indicated that the capacity of direct powering of EVCS was proved by wind energy sources | Even though more wind turbine sources were used for analysis, only 9 turbines |

| | | | |
|-----------------------------|----------------------|---|--|
| | | with various merits, and the results exhibited higher power availability. | exhibited continuous power. |
| Sherif, et al. [34] | Distribution grid | It is exhibited that a better service was contributed to EVs by the grid-unaware controllers on the basis of desired energy levels at the expense of severely violating the grid security along with power quality constraints. | It was significant to include the prediction in EVCS problems; however, it was not added. |
| Fulin, et al. [35] | Hybrid energy source | Outcomes indicated that the employed fast EVCS with the price of \$39800 was utilized as an alternative for battery banks while analogizing with the other CSs; in addition, it could be utilized in the electric grids' absence. | The lifetime had been limited by the EVC system in the battery banks. |
| C. Bala, et al. [36] | Distribution grid | The results indicated that protection against EV batteries' overcharging was successfully supplied by the implemented multi-step constant current control technique, which improved the number of EVCS infrastructures. | In the infrastructure, the quality of the EVCS has to be still improved. |
| Wajahat, et al. [37] | Distribution grid | According to the outcomes, the net energy rendered by the grid was decreased by the merged system with the power output of EV fleet batteries available at the CS; hence, the conversion loss was decreased. | Still, there are multilevel uncertainties to deal with; thus, the analysis required an additional framework. |
| Shakti, et al. [38] | Hybrid energy source | The analysis showed that at 0.038 \$/kWh, the Levelized Cost Of Electricity (LCOE) and Loss Of Power Supply Probability (LPSP) for the applied EVCS were measured, and the system was reliable and cost-efficient. | Significant economic analysis was not included. |
| Abdul, et al. [39] | Hybrid energy source | According to the results, via the grid and vehicle-to-grid, the EV power demand was primarily satisfied while there was no solar power and energy cost was low. | A CS's operational decisions were affected because of human-induced events like cyber attacks. |

Abdulla, et al. [40] described the growth of an off-grid EVCS hybridized with renewable, including multiple energy storage units and a battery cooling system. Centered on writing the balance equations for exergy, entropy, energy, and mass for the system's components along with their energy efficiency equations, the thermodynamics analysis was implemented. The outcomes signified that the presented integrated system's overall exergy efficiencies and energy were 19% and 45%.

Prasanna, et al. [41] analyzed the smart EVCS utilizing a hybrid power generation system. This system developed EVCS, which incorporates BESS (Battery Energy Storage System), grid, wind energy, and solar energy. According to the outcomes, to create a pollution-free environment and charge electric cars, the EVCS and the renewable charging mechanism were found to be more appropriate.

However, for minimizing the CS's dimensions, an alternative technique was required.

2.2. OPTIMAL ALLOCATION OF FAST EVCS IN DISTRIBUTION AND HYBRID ENERGY SOURCES USING ML

Recently, the advent of ML has made information-driven techniques popular in solving charging infrastructure planning issues [42]. As a result, for solving the problem of allocation, researchers started utilizing ML techniques [43, 44]. Deep Learning (DL) also plays a major part in solving the allocation issue of fast EVCS in the distribution grid and hybrid energy sources since DL is a subset of ML [45, 46]. In Table 2, the studies of optimal allocation of fast EVCS in the distribution of hybrid energy sources utilizing ML with its findings and limitations are described.

Table 2: Studies of optimal allocation of fast EVCS in the distribution of hybrid energy sources using ML with its findings and limitations

| Author name | Techniques | Findings | Limitations |
|-------------------------------|---|---|---|
| Yuanzheng, et al. [47] | LSTM [DL] | According to the analysis, when analogized with other conventional approaches, the applied LSTM-Adaptive Exploration Proximal Policy Optimization (AEPPPO)'s performance was superior for fast EVCS's optimal allocation. | Parameters have uncertainties in the approach and data. |
| Mostafa, et al. [48] | DT, RF, SVM, Naïve Bayes (NB), K-Nearest Neighbors (KNN), DNN, and LSTM | Outcomes exhibited that LSTM was found to be the best out of all mentioned ML approaches, with an error rate of $\pm 0.71\%$ and an accuracy of 95.3%. For EVCS's optimal allocation and power rating, LSTM contributed the best results. | LSTM experienced gradient problems even though it performed well. |
| Jin, et al. [49] | Genetic Algorithm-Particle Swarm Optimization (GA-PSO) | As per the outcomes, for multi-objective optimization problems, GA-PSO was found to be best suitable and also suited for evaluating the EVCS's proper allocation number. | There would be complications in selecting the parameters. |
| A. S. Monikandan, et al. [50] | Convolutional Neural Network (CNN) [DL] | The applied CNN-Dynamic Capacity Expansion (CNN-DCE) method revealed that for the short-term planning horizon, the resources reduced the planning cost to 26%, and the long-term plan has 150% of the expansion. | Still, for training efficiently, more data was needed. |
| Jiawei, et al. [51] | Multivariable Residual Correction Grey Model (EMGM) and the LLSTM | According to the outcomes, the applied method completely optimized the accuracy of EVCSs' load forecasting and optimal allocation. | More time had been taken for the analysis in LSTM. |
| B. Rajani, et al. [52] | Fertile Field algorithm (FFA) and Gradient Boost (GBDT) | As per the simulation outcomes, the applied FFA-GBDT technique was more efficient in the performance of optimal allocation of EVCS, and the applied technique's energy consumption was 720.34 KJ. | The applied approaches were computationally expensive. |
| Silvester, et al. [53] | Logistic Regression (LR), KNN, Neural Network and SVM | Analysis displayed that the allocation's optimal value was identified to be 3, resulting in an accuracy rate of 86.67%, and for EVCS, this contributed to the successful allocation. | Need higher memory for storing all data. |
| Sayeed, et al. [54] | Fuzzy logic and RNN-LSTM | As per the outcomes, the applied fuzzy logic method displayed superior results in optimal allocation, and the estimated profit was computed to be \$0.22 M/year. | Handling imprecise data was challenging. |

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|----------------------------|-------------------------------|---|---|
| <p>Ashish, et al. [55]</p> | <p>Fuzzy inference system</p> | <p>Analysis showed that the applied methodology reduced energy costs by 74.67%, suited for allocation when analogized to prevailing flat rate tariffs, and also, delivers low charging costs.</p> | <p>The computational cost was higher.</p> |
|----------------------------|-------------------------------|---|---|

Rawan, et al. [56] described the EVCS allocation for a network utilizing stochastic modeling and Grey Wolf Optimization (GWO). For choosing the superior CS locations, the GWO algorithm was utilized. According to the outcomes, the applied procedure was applied to transportation infrastructure and showed superior performance in allocation. CS's different types and sizes were important to be considered for charging rates. Yet, it was not covered.

Guangyou, et al. [57] explained the location and allocation optimization of EVCS centered on a cost model and genetic algorithm. The minimization issue of operating cost under the constraints of the depreciation period of the CS, allocation issues, and CS's power consumption per unit distance was solved by the applied models. Analysis displayed that charging vehicle flow was reduced by 5% and the CS's overall construction cost was decreased by 4%. The charging vehicle flow was not a sensitive factor to the cost.

Tai, et al. [58] described the multistep EVCS occupancy prediction utilizing hybrid LSTM neural networks. Grounded on the EV charging data, the model was analogized to a number of ML and DL approaches. As per the outcomes, very accurate predictions of 99.99% and 81.87% were generated for 1 step (10 min) and 6 steps (1 h) ahead by the applied approach, which also considerably outperformed the benchmark techniques (+22.4% for one-step-ahead prediction and +6.2% for 6 steps ahead).

2.3. OPTIMAL PLACEMENT OF FAST EVCS IN DISTRIBUTION AND HYBRID ENERGY SOURCES USING ML

In the analysis, enhancing the placement of fast EVCS in distribution and hybrid energy sources is necessary [59, 60]. ML approaches were used correctly to improve the placement of EVCS and are best suited for the placement of fast EVCS [61, 62]. Not only ML but also DL studies have achieved superior results for the optimal placement of fast EVCS infrastructure [63].

Kulsomsup, et al. [64] explained the optimal placement of distributed PV systems and EVCS by

utilizing metaheuristic optimization techniques, such as GA, Cuckoo Search Algorithm (CSA), and Simulated Annealing Algorithm (SAA). As per the results, the implemented technique SAA had less mean computation time and GA secured 2nd position in achieving less mean computation time. Bus no. 6 was the possible location of Distributed Photovoltaic (DPV), and the GA identified the best Fast-CS (FCSS) locations with the better percentage on buses number 2, 3, 13, 14, 28, 15, and 27.

Faisal, et al. [65] presented the energy demand load forecasting for EVCS networks centered on BiConvLSTM and ConvLSTM architectures. For these models, energy demand data from EVCS located in 4 various cities were wielded. The analysis indicated that while analogized with considered traditional models like CNN-LSTM, BiLSTM-BiLSTM, and LSTM-LSTM for optimizing the performance, the error was minimized by a good percentage through changing the number of layers.

Mohammad, et al. [66] described the agent-centric online learning technique for power flow control of fast EVCS incorporated with a smart microgrid. A DNN was used by the RL-centric online controller. The findings indicated that during EV (dis)charging, better control over the traditional offline controller was provided by the implemented online controller, which also proved a superior result for optimal placement. However, it did not calculate the considerable charging saturation point.

3. RESULTS AND DISCUSSION

This section describes the supervised demand prediction model's results with respect to performance (R-squared score) for the optimal placement of public EVCS using ML techniques and EVCS allocation of occupancy prediction using various models. For producing EVCS placements' predictive maps, ML algorithms are utilized. These maps are analogized with various levels of spatial inequity for quantifying the accessibility problems associated with these EVCS placements [67, 68]. The graphical representation of the supervised demand prediction model's results of performance for the optimal placement of public EVCS using ML techniques is explained in Figure 2.

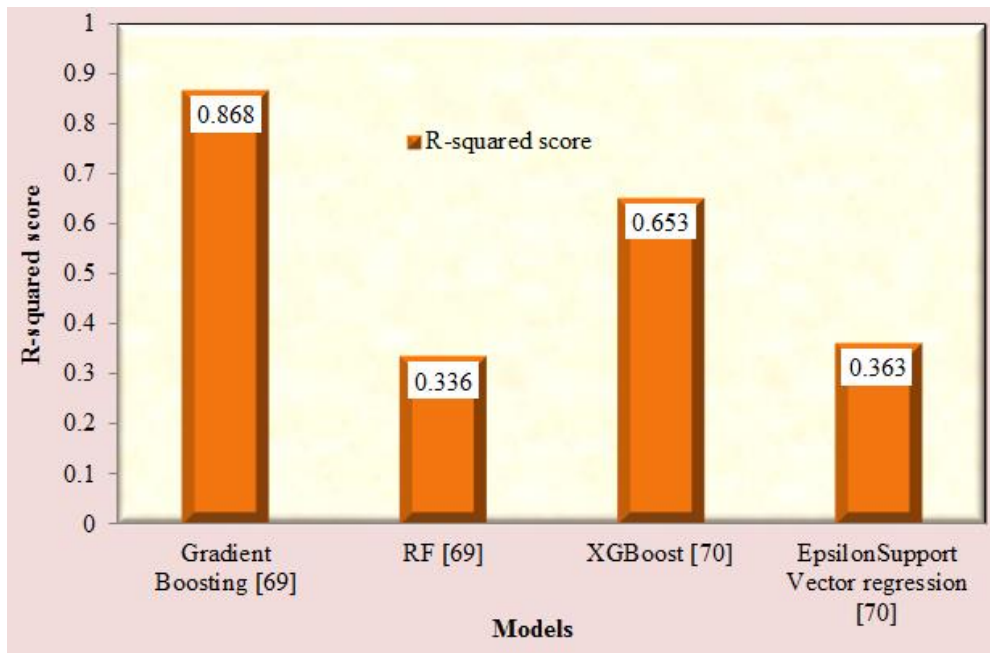


Figure 2: Graphical representation of supervised demand prediction model’s outcomes of performance (R-squared score) for the optimal placement of public EVCS by utilizing ML methods.

Figure 2 indicates that for the analysis, models like Gradient Boosting [69], RF [69], XG Boost [70], and Epsilon Support Vector regression [70] were utilized. The comparison showed that the Gradient boosting [69] model performed better with an R-squared score (0.87) than other models. Hence, using the supervised gradient boosting approaches, the complex problem of improving the placement of EVCS is solved.

Moreover, EVCS allocation of occupancy prediction using various models has been examined. By estimating resources and optimal locations for CSs, AI algorithms make it simpler to manage power-generation interactions and EVs; thus, congestion in CSs is minimized [71]. The graphical representation of EVCS allocation of occupancy prediction using various models is described in Figure 3.

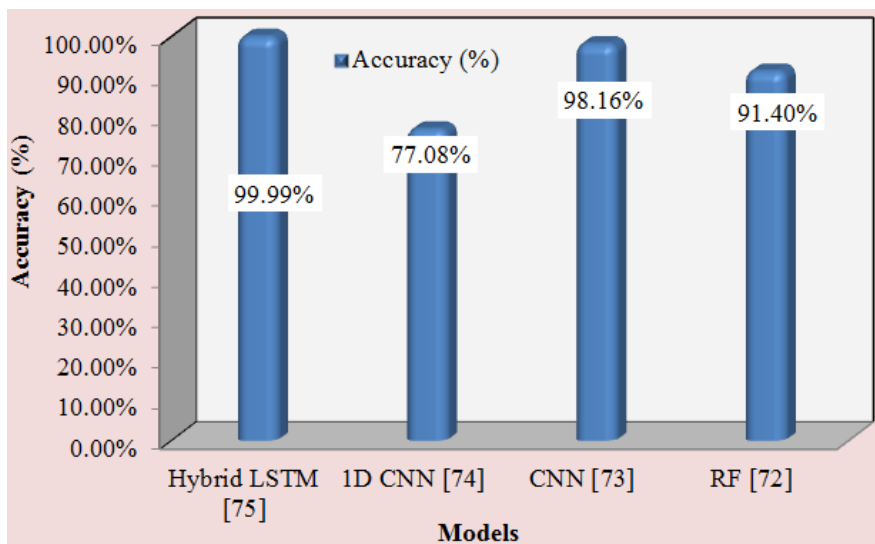


Figure 3: Graphical representation of the accuracy of EVCS allocation of occupancy prediction by utilizing different models

Hybrid LSTM [75], 1D CNN [74], CNN [73], and RF [72] models are considered for the analysis. Figure 3 exhibits that with a higher accuracy (99.99%), Hybrid LSTM [75] dominates the other models. Thus, it was concluded that a hybrid LSTM neural network, which merges both LSTM and forward neural networks, displayed superior prediction of EV charging occupancy over a planning horizon.

Summary:

Recently, the optimal location and the placement of EVCS on the distribution grid and renewable energy sources have become the most important research topics. As an outcome, the researchers have examined different techniques in various studies for

quality power transfer. The techniques of various studies are less accurate in consideration. For optimal allocation and placement, studies of EVCS related to ML have exhibited accurate results. Even though numerous researchers analyzed optimal allocation and placement separately, fewer researchers concentrated on combined studies. Examining the improvement of the allocation as well as placement for EVCS in the distribution grid and hybrid energy source utilizing ML is the survey's major goal. EVCS has been discussed deeply in this review to identify the pros and cons. The researchers can further move broadly to the objective by considering the limitations identified in this survey. Thus, the limitations identified in the survey can be solved.

4. CONCLUSION

For meeting future demand and solving vehicle charging availability and compatibility problems, EVCS is necessary. Using ML approaches, the objective associated with EVCS, such as optimal allocation and placement for quality power transfer is completely achieved. In addition, it is found that ML algorithms could be effectively implemented in charging scheduling and charging demand prediction. The findings analyzed the supervised demand prediction model's results of performance (R-squared score) for the optimal placement of public EVCS using ML techniques and the EVCS allocation of occupancy prediction using various models. In the EVCS placement infrastructure, gradient boost performed better, and the other models are completely dominated by hybrid LSTM with superior accuracy in allocating the occupancy of EVCS. In numerous research studies, only limited EVCS data was provided with ML models, which is the limitation of this survey paper. Future researchers should consider this limitation and utilize more EVCS data while examining ML models.

REFERENCES

1. George Crabtree, "The coming electric vehicle transformation a future electric transportation market will depend on battery innovation", *Science*, vol. 366, no. 6464, pp. 422-424, 2019.
2. Omer Kaya, Ahmet Tortum, Kadir Diler Alemdar and Yasin Codur M, "Site selection for EVCS in Istanbul by GIS and multi-criteria decision-making", *Transportation Research Part D*, vol. 80, pp. 1-16, 2020.
3. Aashish Joshi, Vishall Somaiya K. M, Arni Tharakaram Hariram and Mubashir Hussain, "Electric vehicle charging station", *International Journal of Scientific Research in Science, Engineering and Technology*, vol. 8, no. 4, pp. 122-128, 2021.
4. Gert Berckmans, Maarten Messagie, Jelle Smekens, Noshin Omar, Lieslot Vanhaverbeke and Joeri Van Mierlo, "Cost projection of state of the art lithium-ion batteries for electric vehicles Up to 2030", *Energies*, vol. 10, no. 9, pp. 1-20, 2017.
5. Xiaohong Huang, Cheng Xu, Pengfei Wang and Hongzhe Liu, "LNSC: A security model for electric vehicle and charging pile management based on blockchain ecosystem", *IEEE Access*, vol. 6, pp. 13565-13574, 2018.
6. Omar Hafez and Kankar Bhattacharya, "Optimal design of electric vehicle charging stations considering various energy resources", *Renewable Energy*, vol. 107, pp. 576-589, 2017.
7. Weijia Zhang, Hao Liu, Fan Wang, Tong Xu, Haoran Xin, Dejing Dou and Hui Xiong, "Intelligent electric vehicle charging recommendation based on multi-agent reinforcement learning", *The Web Conference 2021*, 19-23 April 2019, New York, United States, 2021.
8. Irfan Ullah, Kai Liu, Toshiyuki Yamamoto, Muhammad Zahid and Arshad Jamal, "Prediction of electric vehicle charging duration time using ensemble machine learning algorithm and Shapley additive explanations", *International Journal of Energy Research*, vol. 46, no. 1, pp. 15211-15230, 2022.
9. Frederik Boe Hüttel, Filipe Rodrigues and Francisco Camara Pereira, "Mind the gap: Modelling difference between censored and uncensored electric vehicle charging demand", *Transportation Research Part C*, vol. 153, pp. 1-19, 2023.
10. Morteza Dabbaghjamesh, Amirhossein Moeini and Abdollah Kavousi-Fard, "Reinforcement learning-based load forecasting of electric vehicle charging station using Q-Learning technique", *IEEE Transactions on Industrial Informatics*, vol. 17, no. 6, pp. 4229-4237, 2021.
11. Baojun Sun, "A multi-objective optimization model for fast electric vehicle charging stations with wind, PV power and energy storage", *Journal of Cleaner Production*, vol. 288, pp. 1-43, 2021.
12. Sheik Mohammed S, Femin Titus, Sudhakar Babu Thanikanti, Sulaiman S. M, Sanchari Deb and Nallapaneni Manoj Kumar, "Charge Scheduling Optimization of Plug-In Electric Vehicle in a PV Powered Grid-Connected Charging Station Based on Day-Ahead Solar Energy Forecasting in Australia", *Sustainability*, vol. 14, no. 6, pp. 1-20, 2022.
13. Hasan Mehrjerdi and Reza Hemmati, "Electric vehicle charging station with multilevel charging infrastructure and hybrid solar-battery-diesel generation incorporating comfort of drivers", *Journal of Energy Storage*, vol. 26, pp. 1-9, 2019.
14. Jing Liang, Yueming (Lucy) Qiu, Pengfei Liu, Pan He and Denise L Mauzerall, "Effects of expanding

- electric vehicle charging stations in California on the housing market”, *Nature Sustainability*, vol. 6, no. 5, pp. 549-558, 2023.
15. Jeeyung Kim and Sangjae Bae, “Optimal installation of electric vehicle charging stations using fleet-vehicles data”, *IEEE Power & Energy Society General Meeting*, Montreal, QC, Canada, 2020.
 16. Akhtar Hussain, Van-Hai Bui, Ju-Won Baek and Hak-Man Kim, “Stationary energy storage system for fast EV charging stations: Simultaneous sizing of battery and converter”, *Energies*, vol. 12, no. 23, pp. 1-17, 2019.
 17. Yantao Huang and Kara M Kockelman, “Electric vehicle charging station locations: Elastic demand, station congestion, and network equilibrium”, *Transportation Research Part D: Transport and Environment*, vol. 78, pp. 1-45, 2020.
 18. Phap Vu Minh, Sang Le Quang and Manh-Hai Pham, “Technical economic analysis of photovoltaic-powered electric vehicle charging stations under different solar irradiation conditions in Vietnam”, *Sustainability*, vol. 13, no. 6, pp. 1-20, 2021.
 19. Lennart Adenaw and Sebastian Krapf, “Placing BEV Charging infrastructure: Influencing factors, metrics, and their influence on observed charger utilization”, *World Electric Vehicle Journal*, vol. 13, no. 4, pp. 1-29, 2022.
 20. Rick Wolbertus, Maarten Kroesen, Robert van den Hoed and Caspar Chorus, “Fully charged: An empirical study into the factors that influence connection times at EV-charging stations”, *Energy Policy*, vol. 123, pp. 1-7, 2018.
 21. Han Wu and Dongxiao Niu, “Study on influence factors of electric vehicles charging station location based on ISM and FMICMAC”, *Sustainability*, vol. 9, no. 4, pp. 1-19, 2017.
 22. Fabiano Pallonetto, Marta Galvani, Agostino Torti and Simone Vantini, “A Framework for Analysis and Expansion of Public Charging Infrastructure under Fast Penetration of Electric Vehicles”, *World Electric Vehicle Journal*, vol. 11, no. 1, pp. 1-20, 2020.
 23. Kris Scicluna, Brian Azzopardi and Kurt Spiteri, “Power quality analysis for light-duty electric vehicles: A case study in Malta”, *Energies*, vol. 16, no. 15, pp. 1-13, 2023.
 24. Ashish Kumar Karmaker, Sujit Roy and Raju Ahmed, “Analysis of the impact of electric vehicle charging station on power quality issues”, *International Conference on Electrical, Computer and Communication Engineering*, 7-9 February 2019, Cox's Bazar, Bangladesh, 2019.
 25. Mikołaj Schmidt, Paweł Zmuda-Trzebiatowski, Marcin Kicinski, Piotr Sawicki and Konrad Lasak, “Multiple-criteria-based electric vehicle charging infrastructure design problem”, *Energies*, vol. 14, no. 11, pp. 1-34, 2021.
 26. Vignesh S, Nihith Koundinya S. P. V. S, Narayanan K, Gulshan Sharma and Tomonobu Senjyu, “Investigation on reliability and cost in the presence of electric vehicle charging station”, *International Conference on Smart Grids and Energy Systems*, 23-26 November 2020, Perth, Australia, 2021.
 27. Selvabharathi D, Mrinmay Saha, Rima Haldar, Palanisamy R and Karthikeyan D, “Inspection of power quality issues in electric vehicles and its mitigation”, *International Journal of Electrical Engineering and Technology*, vol. 11, no. 3, pp. 113-21, 2020.
 28. Sanchari Deb, Karuna Kalita and Pinakeshwar Mahanta, “Impact of electric vehicle charging stations on reliability of distribution network”, 21-23 December 2017, Kollam, India, 2018.
 29. Brinkel N. B. G, Schram W. L, AlSkaif T. A, Lampropoulos I and van Sark W. G. J.H. M, “Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits”, *Applied Energy*, vol. 276, pp. 1-13, 2020.
 30. Yue Xiang, Zhuozhen Jiang, Chenghong Gu, Fei Teng, Xiangyu Wei and Yang Wang, “Electric vehicle charging in smart grid: A spatial-temporal simulation method”, *Energy*, vol. 189, pp. 1-23, 2019.
 31. Shailendra Singh, Vijay Babu Pamshetti and Singh S. P, “Time horizon-based model predictive Volt/VAR optimization for smart grid enabled CVR in the presence of electric vehicle charging loads”, *IEEE Transactions on Industry Applications*, vol. 55, no. 6, pp. 5502-5513, 2019.
 32. Kalid Yunus, Hector Zelaya De La Parra and Muhamad Reza, “distribution grid impact of plug-in electric vehicles charging at fast charging stations using stochastic charging model”, *Proceedings of the 2011 14th European Conference on Power Electronics and Applications*, 30 August 2011 – 01, Birmingham, UK, 2011.
 33. Fuad Noman, Ammar Ahmed Alkahtani, Vassilios Agelidis, Kiong Sieh Tiong, Gamal Alkawsian and Janaka Ekanayake, “Wind-energy-powered electric vehicle charging stations: resource availability data analysis”, *Applied Sciences*, vol. 10, no. 16, pp. 1-13.
 34. Sherif Fahmy, Rahul Gupta and Mario Paolone, “Grid-aware distributed control of electric vehicle charging stations in active distribution grids”, *Electric Power Systems Research*, vol. 189, pp. 1-9, 2020.
 35. Fulin He and Hassan Fathabadi, “Novel standalone plug-in hybrid electric vehicle charging station fed by solar energy in presence of a fuel cell system used as supporting power source”, *Renewable Energy*, vol. 156, pp. 964-974, 2020.
 36. Balasundar C, Sundarabalan C. K, Jayant Sharma, Srinath N. S, Josep M Guerrero, “Design of power

- quality enhanced sustainable bidirectional electric vehicle charging station in distribution grid", *Sustainable Cities and Society*, vol. 74, pp. 1-16, 2021.
37. Wajahat Khan, Furkan Ahmad and Mohammad Saad Alam, "Fast EV charging station integration with grid ensuring optimal and quality power exchange", *Engineering Science and Technology, an International Journal*, vol. 22, no. 1, pp. 143-152, 2019.
38. Shakti Singh, Prachi Chauhan and Nirbhaw Jap Singh, "Feasibility of grid-connected solar-wind hybrid system with electric vehicle charging station", *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 2, pp. 295-306, 2021.
39. Abdul Quddus, Mohannad Kabli and Mohammad Marufuzzaman, "Modeling electric vehicle charging station expansion with an integration of renewable energy and Vehicle-to-Grid sources", *Transportation Research Part E: Logistics and Transportation Review*, vol. 128, pp. 251-279, 2021.
40. Abdulla Al Wahedi and Yusuf Bicer, "Development of an off-grid electrical vehicle charging station hybridized with renewables including battery cooling system and multiple energy storage units", *Energy Reports*, vol. 6, pp. 2006-2021, 2021.
41. Prasanna Pothi, Prasanna Titarmare, Shital Yende, Swati S Khobragade, Prayas M Dhole, Renuka V Bedarkar, "Smart EV charging station using hybrid power generation system", *International Research Journal of Modernization in Engineering Technology and Science*, vol. 5, no. 1, pp. 520-526, 2023.
42. Yonggang Liu, Jie Li, Jun Gao, Zhenzhen Lei, Yuanjian Zhang and Zheng Chen, "Prediction of vehicle driving conditions with incorporation of stochastic forecasting and machine learning and a case study in energy management of plug-in hybrid electric vehicles", *Mechanical Systems and Signal Processing*, vol. 158, pp. 1-24, 2021.
43. Alexandre Lucas, Ricardo Barranco and Nazir Refa, "EV idle time estimation on charging infrastructure, comparing supervised machine learning regressions", *Energies*, vol. 12, no. 2, pp. 1-17, 2019.
44. Irfan Ullah, Kai Liu, Toshiyuki Yamamoto, Muhammad Zahid and Arshad Jamal, "Modeling of machine learning with SHAP approach for electric vehicle charging station choice behavior prediction", *Travel Behaviour and Society*, vol. 31, pp. 78-92, 2023.
45. Yaofeng Song, Han Zhao, Ruikang Luo, Liping Huang, Member, Yicheng Zhang and Rong Su, "A SUMO framework for deep reinforcement learning experiments solving electric vehicle charging dispatching problem", *arXiv preprint arXiv:2209.02921*, 2022.
46. Tao Qian, Chengcheng Shao, Xiuli Wang and Mohammad Shahidehpour, "Deep reinforcement learning for EV charging navigation by coordinating smart grid and intelligent transportation system", *IEEE transactions on smart grid*, vol. 11, no. 2, pp. 1714-1723, 2019.
47. Yuanzheng Li, Shangyang He, Yang Li, Leijiao Ge, Suhua Lou and Zhigang Zeng, "Probabilistic charging power forecast of EVCS: reinforcement learning assisted deep learning approach", *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 1, pp. 344-357, 2022.
48. Mostafa Shibl, Loay Ismail and Ahmed Massoud, "Machine learning-based management of electric vehicles charging: towards highly-dispersed fast chargers", *Energies*, vol. 13, no. 20, pp. 1-24, 2020.
49. Jin-peng Liu, Teng-xi Zhang, Jiang Zhu and Tian-nan Ma, "Allocation optimization of electric vehicle charging station (EVCS) considering with charging satisfaction and distributed renewables integration", *Energy*, 2018. doi: 10.1016/j.energy.2018.09.028
50. Monikandan A. S, Chellaswamy C, Geetha T. S and Sivaraju S. S, "Optimized convolutional neural network-based capacity expansion framework for electric vehicle charging station", *International Transactions on Electrical Energy Systems*, pp. 1-21, 2022.
51. Jiawei Feng, Junyou Yang, Yunlu Li, Haixin Wang, Huichao Ji, Wanying Yang and Kang Wang, "Load forecasting of electric vehicle charging station based on grey theory and neural network", *Energy Reports*, vol. 7, pp. 487-492, 2021.
52. Rajani B and Chandra Sekhar D, "A hybrid optimization based energy management between electric vehicle and electricity distribution system", *International Transactions on Electrical Energy Systems*, vol. 31, no. 6, pp. 1-30, 2021.
53. Herjuna S. A, Prabowo H. E, Prasetyo T. C and Maluku P. T, "Manyala app machine learning-powered decision support system for hassle-free EV charging station location prediction", *PS2 Innovations in Future Power Grids in Energy Storage, Electric Generation Mix of the Future, Tutorial & Regional Conference on Power System Bali*, 21-23 June, 2023.
54. Sayeed Hasan, Mohammad Zeyad, S. M Masum Ahmed, Dewan Mahnaaz Mahmud, Sadik Tasrif Anubhove and Eftakhar Hossain, "Techno-economic feasibility analysis of an electric vehicle charging station for an International Airport in Chattogram, Bangladesh", *Energy Conversion and Management*, vol. 293, 1-12, 2023.
55. Ashish Kumar Karmaker, Alamgir Hossain, Hemanshu Roy Pota, Ahmet Onen and Jaesung Jung, "Energy management system for hybrid renewable energy-based electric vehicle charging station", *IEEE Access*, vol. 11, pp. 27793-27805, 2023.

56. Rawan Shabbar, Anemone Kasasbeh and Mohamed M Ahmed, "Charging station allocation for electric vehicle network using stochastic modeling and grey wolf optimization", *Sustainability*, vol. 13, no. 6, pp. 1-20, 2021.
57. Guangyou Zhou, Zhiwei Zhu and Sumei Luo, "Location optimization of electric vehicle charging stations: Based on cost model and genetic algorithm", *Energy*, vol. 247, pp. 1-11, pp. 1-11, 2022.
58. Tony Nasr, Sadegh Torabi, Elias Bou-Harb, Claude Fachkha and Chadi Assi, "Power jacking your station: In-Depth security analysis of electric vehicle charging station management systems", *Computers & Security*, vol. 112, pp. 1-47, 2022.
59. Tao Ding, Ziyu Zeng, Jiawen Bai, Boyu Qin, Yongheng Yang and Mohammad Shahidehpour, "Optimal electric vehicle charging strategy with Markov decision process and reinforcement learning technique", *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5811-5823, 2020.
60. Sakib Shahriar, Al-Ali A. R, Ahmed H Osman, Salam Dhou and Mais Nijim, "Prediction of EV charging behavior using machine learning", *IEEE Access*, vol. 9, pp. 111576-111586, 2021.
61. Gunapriya Balan, Singaravelan Arumugam, Suresh Muthusamy, Hitesh Panchal, Hossam Kotb, Mohit Bajaj, Sherif S. M Ghoneim and Kitmo, "An improved deep learning-based technique for driver detection and driver assistance in electric vehicles with better performance", *International Transactions on Electrical Energy Systems* 2022. <https://doi.org/10.1155/2022/8548172>
62. Irfan Ullah, Kai Liu, Toshiyuki Yamamoto, Rabia Emhamed Al Mamlook and Arshad Jamal, "A comparative performance of machine learning algorithm to predict electric vehicles energy consumption: A path towards sustainability", *Energy & Environment*, vol. 33, no. 8, pp. 1583-1612, 2021.
63. Lulu Wen, Kaile Zhou, Shanlin Yang and Xinhui Lu, "Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting", *Energy*, vol. 171, pp. 1053-1065, 2019.
64. Kulsomsup Yenchanalit, Yuttana Kongjeen, Prakasit Prabpal and Krischonme Bhumkittipich, "Optimal placement of distributed photovoltaic systems and electric vehicle charging stations using metaheuristic optimization techniques", *Symmetry*, vol. 13, no. 12, pp. 1-15, 2021.
65. Faisal Mohammad, Dong-Ki Kang, Mohamed A Ahmed and Young-Chon Kim, "Energy demand load forecasting for electric vehicle charging stations network based on ConvLSTM and BiConvLSTM architectures", *IEEE Access*, vol. 11, pp. 67350-67369, 2023.
66. Mohammad Amir Zaheeruddin, Ahteshamul Haque, Bharath Kurukuru V. S, Farhad Ilahi Bakhsh and Akbar Ahmad, "Agent based online learning approach for power flow control of electric vehicle fast charging station integrated with smart microgrid", *IET Renewable Power Generation*, 2022. <https://doi.org/10.1049/rpg2.12508>
67. SAKIB SHAHRIAR, A. R. AL-ALI, AHMED H. OSMAN, SALAM DHOU AND MAIS NIJIM, "Machine Learning Approaches for EV Charging Behavior: A Review", *IEEE Access*, vol. 8, pp. 168980-168993, 2020.
68. Avipsa Roy and Mankin Law, "Examining spatial disparities in electric vehicle charging station placements using machine learning", *Sustainable cities and society*, vol. 83, pp. 1-13, 2022.
69. Ahmad Almaghrebi, Fares Aljuheshi, Mostafa Rafaie, Kevin James and Mahmoud Alahmad, "Data-Driven Charging Demand Prediction at Public Charging Stations Using Supervised Machine Learning Regression Methods", *Energies*, vol. 13, no. 16, pp. 1-21, 2020.
70. Shankar Padmanabhan, Aidan Petratos, Allen Ting, Kristina Zhou, Dylan Hageman, Jesse R. Pisel and Michael J. Pycrc, "Optimal Placement of Public Electric Vehicle Charging Stations Using Deep Reinforcement Learning", *arXiv preprint arXiv:2108.07772*, 2021.
71. Ivan Grcic, Hrvoje Pandžić and Viktor Sunde, "Electric vehicle charging station fault detection: A machine learning approach", *work shop*, University of Zagreb, pp. 745-749, 2022.
72. Jiwon Lee, Midam An, Yongku Kim and Jung-In Seo, "Optimal Allocation for Electric Vehicle Charging Stations", *Energies*, vol. 14, no. 18, pp. 1-9, 2021.
73. Manoj Basnet, Subash Poudyal, Mohd Hasan Ali and Dipankar Dasgupta, "Ransomware detection using deep learning in the SCADA system of electric vehicle charging station", In *2021 IEEE PES Innovative Smart Grid Technologies Conference-Latin America (ISGT Latin America)*, 15-17 September 2021, Lima, Peru, 2021.
74. Per Harald Barkost, "Detecting EV charging from hourly smart meter data", *thesis*, The Arctic University of Norway, 2020.
75. Tai-Yu Ma and Sebastien Faye, "Multistep electric vehicle charging station occupancy prediction using hybrid LSTM neural networks", *Energy*, vol. 244, pp. 1-20, 2022.