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Review

Machine Learning for Solving Charging Infrastructure Planning Problems: A Comprehensive Review

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Abstract: As a result of environmental pollution and the ever-growing demand for energy, there has been a shift from conventional vehicles towards electric vehicles (EVs). Public acceptance of EVs and their large-scale deployment raises requires a fully operational charging infrastructure. Charging infrastructure planning is an intricate process involving various activities, such as charging station placement, charging demand prediction, and charging scheduling. This planning process involves interactions between power distribution and the road network. The advent of machine learning has made data-driven approaches a viable means for solving charging infrastructure planning problems. Consequently, researchers have started using machine learning techniques to solve the aforementioned problems associated with charging infrastructure planning. This work aims to provide a comprehensive review of the machine learning applications used to solve charging infrastructure planning problems. Furthermore, three case studies on charging station placement and charging demand prediction are presented. This paper is an extension of: Deb, S. (2021, June). Machine Learning for Solving Charging Infrastructure Planning: A Comprehensive Review. In the *2021 5th International Conference on Smart Grid and Smart Cities (ICSGSC)* (pp. 16–22). IEEE. I would like to confirm that the paper has been extended by more than 50%.

Keywords: charging; electric vehicle; machine learning; review

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1. Introduction

Global energy consumption is increasing at an alarming rate, and the transportation sector is one of the largest consumers [1]. It was found that, in 2019, in the US, approximately 28% of the net energy consumption was involved in moving people and goods [2]. Furthermore, it was reported that the transport sector is one of the major agents of air pollution [3–5]. The paradigm shift from internal combustion engine (ICE)-driven vehicles to EVs is a viable way to mitigate the serious concerns regarding the energy crisis and air pollution. The large-scale adoption of EVs requires fully operational charging infrastructure. Charging infrastructure planning involves interactions between both the road and power distribution network. Charger placement at weak points in the power distribution network and uncoordinated charging can result in voltage instability, increased power losses, harmonic distortions, and degraded reliability indices [6–12]. Furthermore, charging infrastructure planning must also take into account the convenience of EV drivers, for example, the accessibility of the charging stations, and the waiting time in the charging stations [13]. Moreover, smart coordinated charging is preferred over uncoordinated charging to tackle the detrimental impact of EV charging on the grid [14]. Charging infrastructure planning is a multifaceted problem involving a number of decision variables, objective functions, and constraints. Researchers have used heuristics [15,16], metaheuristics [17], machine learning [18], and game theory [19,20] for solving these problems.

In recent years, the advent of machine learning has made data-driven approaches popular for solving charging infrastructure planning problems. Consequently, researchers started using machine learning techniques to solve the problems associated with charging infrastructure planning, such as charging station placement, charging demand prediction, and charging scheduling. This work aims to provide a comprehensive review of machine learning applications for solving charging infrastructure planning problems. Table 1 lists prominent studies that meticulously review different aspects of charging infrastructure planning. From Table 1, it can be seen that researchers have reviewed various aspects of e-mobility, such as charging station placement, drivers of EV adoption, policies for promoting EVs, charging technologies, and charge scheduling. However, there is lack of comprehensive reviews focused on machine learning applications for solving charging infrastructure planning problems. Hence, this work aims to provide a comprehensive review of the machine learning applications used for solving different aspects of charging infrastructure planning, such as placement, charging demand prediction, and charging scheduling. Furthermore, case studies on charging infrastructure planning are also presented in this work. However, this paper contains more detailed descriptions of machine learning algorithms, more quantitative analyses of the reported literature, and three case studies on charging infrastructure planning. The main contributions of this work as compared to the reviews reported in Table 1 are as follows:

- A comprehensive review of the applications of machine learning algorithms for charging infrastructure planning;
- Qualitative and quantitative analyses of the reported literature;
- Recommendations regarding the suitability of machine learning algorithms for solving charging infrastructure planning problems;
- Case studies on charging hotspot identification and charging demand prediction.

Table 1. Reviews of charging infrastructure planning.

Ref	Author	Journal/Conference	Year	Diligence
[21]	Hardman et al.	Transportation Research Part D: Transport and Environment	2018	Review of consumer preferences towards and interactions with the EV charging infrastructure.
[22]	Pagany et al.	International Journal of Sustainable Transportation	2019	Review of spatial localization methodologies for the electric vehicle charging infrastructure.
[23]	Zhang et al.	Renewable and Sustainable Energy Reviews	2018	Review of the economics of charging infrastructure planning.
[24]	Khan et al.	Smart Science	2018	Review of fast charging infrastructure for EVs.
[25]	Das et al.	Renewable and Sustainable Energy Reviews	2020	Review of EV charging standards and grid impacts of EV charging.
[26]	Ji et al.	Renewable and Sustainable Energy Reviews	2018	Review of policies, methodologies, and challenges for charging infrastructure deployment in China.
[27]	Coffman et al.	Transport Reviews	2017	Review of factors affecting the adoption of EVs.
[28]	Rahman et al.	Renewable and Sustainable Energy Reviews	2016	Review of recent trends in optimization techniques for plug-in hybrid and electric vehicle charging infrastructures.
[29]	Yang et al.	Journal of Cleaner Production	2018	Suggestion on tax policy for promoting the PPP projects of the charging infrastructure in China.
[30]	Rietmann et al.	Journal of Cleaner Production	2019	Review of worldwide policy measures to promote e-mobility.
[31]	Ahmad et al.	Smart Science	2018	Review of electric vehicle charging techniques and standards, and the progression and evolution of EV technologies in Germany.

Table 1. *Cont.*

Ref	Author	Journal/Conference	Year	Diligence
[32]	Gnann et al.	Renewable and Sustainable Energy Reviews	2018	Review of the global EV diffusion model.
[33]	Ding et al.	IEEE transaction on Industry Applications	2020	Review on approaches for EV charging demand management.
[34]	Zhang et al.	Renewable and Sustainable Energy Reviews	2017	Review of EV policies in China.
[35]	Youssef et al.	Materials Science and Engineering Conference Series	2018	Review of EV DC charging stations using photovoltaic sources.
[36]	Du et al.	Applied Energy	2017	Review of EV industrialization in China.
[37]	Hardman	Transportation Research Part A: Policy and Practice	2019	Review of financial incentives for EV adoption.
[38]	García et al.	Applied Soft Computing	2018	Review of metaheuristics for solving charging scheduling problems.
[39]	Zheng et al.	Renewable and Sustainable Energy Reviews	2019	Review of the power interaction mode, scheduling methodology, and mathematical foundation for EV integration with the power grid.
[40]	Jawad et al.	Energies	2020	Review of the current scenario of EV charging service planning and operation considering transport and the power network.
[41]	Solanke et al.	Journal of Energy Storage	2020	Review of strategic charging–discharging control of grid-connected electric vehicles.
[42]	Amjad et al.	Transportation Research Part D: Transport and Environment	2018	Review of EVs charging from the perspective of energy optimization, optimization approaches, and charging techniques.
[43]	Limmer	Energies	2019	Review of dynamic pricing for EVs in charging stations.
[44]	Ahmadi et al.	IET Electrical Systems in Transportation	2019	Review of power quality improvement in smart grids by EVs.
[45]	Ma	Energies	2019	Review of planning of grid-connected charging stations.
[46]	Jia et al.	Control Theory and Technology	2020	Review of charging behavior of data, model, and control in EV charging stations.
[47]	Panchal et al.	Engineering Science and Technology	2018	Review of static and dynamic wireless electric vehicle charging systems.
[48]	Khan et al.	Smart Science	2018	Review of solar EV charging stations.
[49]	Triviño-Cabrera et al.	Transportation and Power Grid in Smart Cities: Communication Networks and Services	2018	Review of wireless charging for smart cities.
[50]	Khan et al.	Smart Science	2018	Review of Level 2 charging systems for EVs.

2. Overview of Charging Infrastructure Planning

Charging infrastructure planning is a prerequisite for the large-scale adoption of EVs. The different activities associated with charging infrastructure planning are shown in Figure 1. Charging demand prediction involves the prediction of the demand of charging services at different times of the day and in different locations. Charging station placement is a typical planning problem centered on the optimal allocation and sizing of charging stations, which takes into consideration the economic factors, the operating parameters of the distribution network, and EV drivers' convenience. Charger utilization computation involves computing how much a charger is utilized or how many charging events a charger has served. Charging scheduling involves managing the charging activities based on the charging demand and load profile, while keeping in mind that the power grid must not be overloaded.

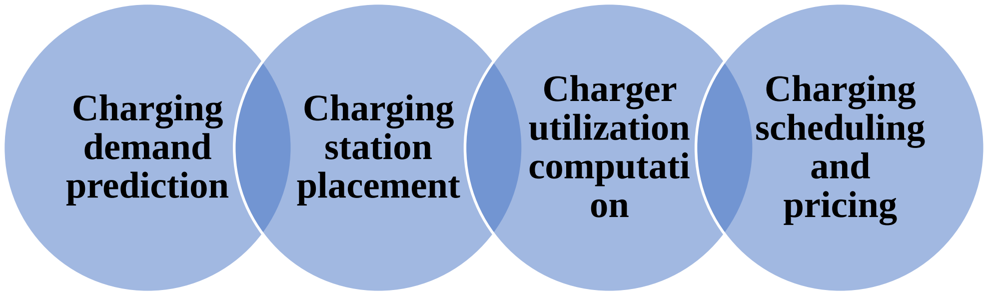

Figure 1. An overview of charging infrastructure planning.

3. Machine Learning Techniques

In machine learning, the computer learns from previous experience without any explicit programming [51]. In this context, experience refers to the dataset that the algorithm uses to train itself [52]. With time and learning experience, the models can accurately predict trends, thereby providing predictive analysis [51]. Typically, machine learning algorithms are categorized into supervised and unsupervised learning algorithms [51,53,54]. Furthermore, depending on the type of variable, the problems that machine learning algorithms approach can be divided into regression problems and the classification problems [51]. If the response variable is continuous, it is called a regression problem [51]; if the response variable is categorical, it is called a classification problem [51]. In the context of charging infrastructure planning, charging demand prediction is a regression problem, as the response variable is continuous. On the other hand, the identification of charging hotspots is a classification problem because the response variable is categorical.

Data partitioning in machine learning is the division of all data available into two or three nonoverlapping sets: the training set, the validation set, and the test set. The parameters of the model were fitted to the available data, and the model demonstrated high prediction accuracy on these data. Partitioning can be performed by different techniques, such as harsh partitioning, list partitioning, and composite partitioning [18].

The classification of machine learning algorithms is shown in Figure 2. Detailed descriptions of these groups are provided in the subsequent subsections.

3.1. Supervised Learning

As the name indicates, supervised machine learning models are trained by labeled datasets [51,55,56]. The dataset contains the input variable and target variable. Model learning is iterative in nature and works by mapping between the input and target output assisted by optimization [51]. As shown in Figure 2, supervised learning can be divided into five types. In the linear regression model, there is a linear relationship between the input variable and the target variable [51]. Linear regression can be used for regression problems and for linearly separable datasets [54]. Decision trees can be used for both regression and classification problems [54]. Decision trees separate complex decisions into simpler decisions using split points [54,57,58]. In the random forest technique, several decision trees are aggregated for the purpose of prediction [59,60]. A support vector machine (SVM) is mainly used for classification problems, but can also be utilized for regression problems [61,62]. An SVM separates the classes with the best hyperplane, which maximizes the marginal difference between the classes [18,62]. The training time for an

SVM is long, and therefore, it is not suitable for large datasets [61,62]. K-nearest neighbors (KNN) can be used for both regression and classification problems [18,63,64]. However, it is mostly used for classification problems [18]. KNN does not require a dedicated training phase and it is associated with a lazy learning phase [18,63,64].

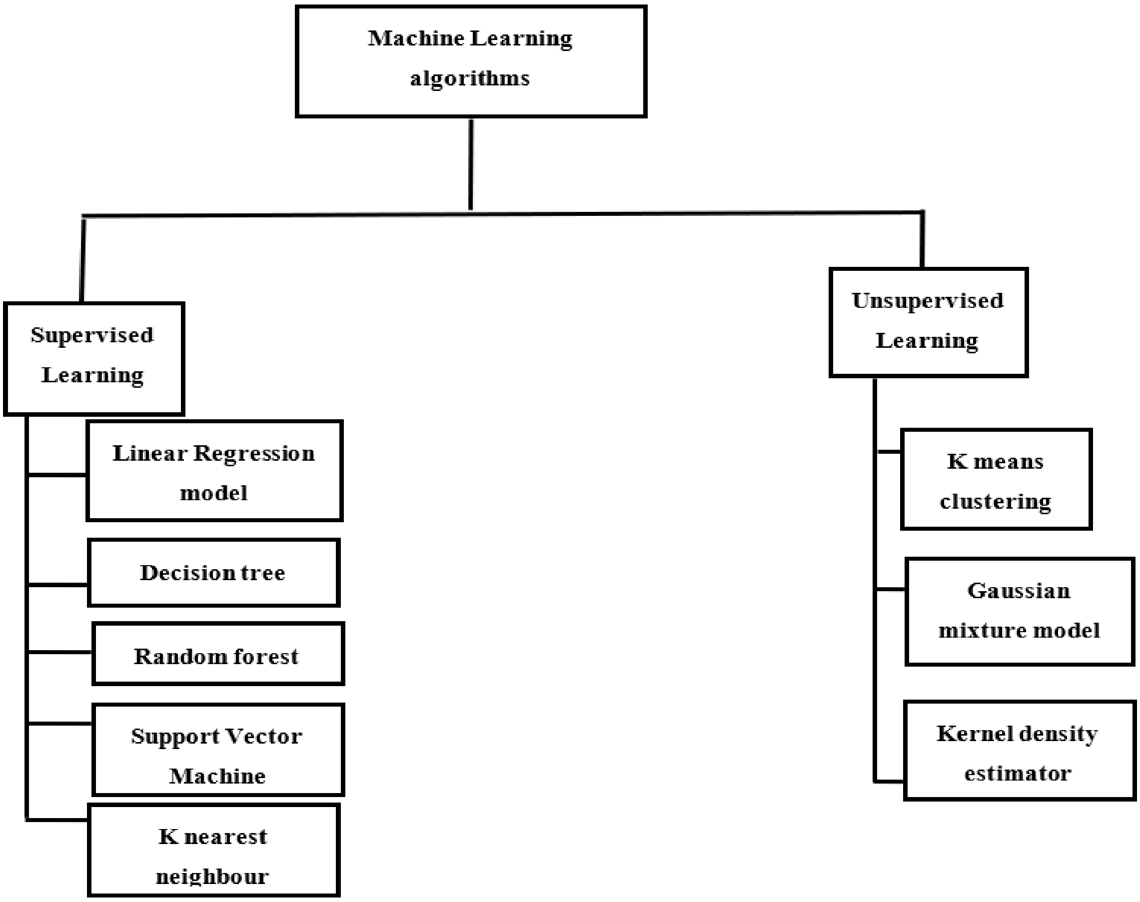

Figure 2. Classification of machine learning algorithms.

There is also another class known as semi-supervised learning. Semi-supervised learning is an innovative approach to machine learning that combines a small amount of labeled data and a large amount of unlabeled data during training. Semi-supervised learning falls between unsupervised learning (with no labeled training data) and supervised learning (with only labeled training data) [52].

3.2. Unsupervised Learning

In the case of unsupervised learning, the training dataset comprises the input variable only [18,65,66]. The key goal of this model is to find patterns within the dataset using clustering [18,65,66]. The subdivisions of unsupervised learning are as illustrated in Figure 2. In k clustering, individual datapoints form k clusters, wherein each and every point is assigned to k center points at the beginning in a random fashion [18,67], and later datapoints are assigned to the nearest centers based on new datapoint calculations. The Gaussian mixture model (GMM) is a probabilistic learning model that has the capacity to represent subpopulations of normal distribution by considering multiple normal distributions of the dataset in use [18]. The kernel density estimator (KDE) is used in the case of a nonparametric probability density function [18].

4. Performances of Machine Learning Algorithms

The performances of different machine learning algorithms can be compared on the basis of some metrices. For regression models, root mean square error (*RMSE*), mean absolute error (MAE), and mean absolute percentage error ($MAPE$) are some of the metrices for performance evaluation [18].

Equations (1)–(3) represent these indices mathematically.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - y_i'\right)}{n}} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - y_i' \quad (2)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{y_i - y_i'}{y_i'}\right] \times 100 \quad (3)$$

Ideally, the difference between the predicted value y_i', and the target value y_i, should be small.

For the classification problem, the evaluation metrices are *accuracy*, *precision*, and *F*1 *score* [18], as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$F1\ score = \frac{2 \times Precision \times TPR}{Precision + TPR} \quad (6)$$

A true positive (*TP*) represents a case in which the predicted positive class value and the real value belong to the positive class. Moreover, a true negative (*TN*) represents a case in which the predicted negative class value and the real value belong to the negative class. False positives (*FP*) are cases in which the model falsely predicts the positive class for actual values belonging to the negative class. False negatives (*FN*) are cases in which the model falsely predicts the negative class for actual values belonging to the positive class.

5. Machine Learning for Charging Infrastructure Planning

Applications of machine learning techniques for solving different charging infrastructure planning problems are shown in Figure 1.

5.1. Machine Learning for Charging Station Placement

The charging station problem involves determining the locations and sizes of chargers. In [68], the authors provided an optimal wireless charging station placement scheme for electric trams by applying an algorithm that hybridizes the genetic algorithm (GA) and reinforcement learning (RL). The integration of GA with reinforcement learning improved the performance of GA by preventing it from becoming stuck in local optima. The superior performance of the hybrid GA RL algorithm as compared with the standalone algorithms is illustrated in Table 2.

Table 2. A performance comparison of GA RL with standalone GA and RL algorithms [68].

Parameter	GA	RL	GA + RL
Investment cost ($)	106.230	104.561	103.891
Battery capacity (kWh)	15.06	13.14	12.60

In [69], the authors provided a novel scheme for placing new charging stations that utilizes the maximization utilization rate of chargers as the objective function. The problem was solved by hierarchal clustering [70]. In [71], the authors categorized charging stations as top ranked and bottom ranked using the linear regression model and decision trees. The simulation results established the superiority of the linear regression model over decision trees. In [72], a cellular automaton agent-based model was proposed to study different EV deployment scenarios.

5.2. Machine Learning for Charging Demand Prediction

Accurately predicting the charging load is crucial for charging infrastructure planning and the large-scale adoption of EVs. In [73], the authors presented a novel scheme for predicting the aggregated load demand of buildings in the presence of EVs that utilizes a methodology based on feature selection and an enhanced SVM. In [74], the authors predicted the charging load of the UCLA campus by applying a modified pattern sequence-based technique. In [75], the authors used a deep learning approach to estimate multiscale EV charging demand. Moreover, in [76,77], an enhanced deep learning-based approach was used for charging load prediction. In [78], the authors used a hybrid ant lion algorithm and deep learning for charging demand prediction. In [79], the authors proposed a hybrid KDE using both Gaussian and diffusion-based KDE (GKDE and DKDE) to predict the stay duration and charging demand of EVs. In [80], authors employed a generalized regression neural network (GRNN) model to predict the charging load. In [81], the authors predicted the charging demands of electric bus charging stations using an SVM and the wolf pack algorithm. In [82], the authors compared the performances of different deep learning approaches as applied to the charging demand prediction problem, and concluded that the long short-term memory (LSTM) method performed best, as it reduced the forecasting error by over 30%. In [83], the authors used a regression model to predict the charging load. In [84], the authors compared the time series approach with machine learning techniques, such as the random forest technique and the regression model, as applied to the charging demand prediction problem. The simulation results established the superiority of machine learning techniques over the time series approach. In [85], the authors used ensemble learning to predict household EV charging demand. Ensemble learning is a machine learning technique that leans by evaluating the results from different machine learning models. In the aforementioned work, the ensemble learning model was based on the results of the random forest, gradient boosting, adaptive boosting, and regression techniques. In [86], the authors used the k-nearest neighbors method for charging demand prediction. In [87], the authors applied a neural network to predict the charger occupancy for an EV charging station in an urban area.

5.3. Machine Learning for Charging Scheduling

The management of charging activities at charging stations is important to avoid sudden increases in the peak load demand. In [88], the authors considered the operational benefit of EVs by focusing on vehicle-to-grid (V2G) technology and scheduled EV charging at charging stations using reinforcement learning. In [89], the authors proposed a demand response method for long-term charging cost reduction and provided a charging schedule for EVs. The solution was based on reinforcement learning. In [90], the authors proposed a constrained EV charge scheduling strategy and utilized reinforcement learning for this. In [91], the authors formulated charging scheduling as a NP-hard problem and found a solution using reinforcement learning. In [90], the authors proposed an artificial neural network (ANN) for solving charging scheduling and suggested adopting a smart pricing strategy at charging stations. In [92], the authors identified the best charging time for EVs in a fast-charging station integrated with a smart grid using the Q-learning method. In [93,94], the authors solved the charging scheduling problem using reinforcement learning. In [95,96], the authors used multiagent reinforcement learning for charging scheduling and proposed a dynamic pricing strategy. In [97], the authors proposed a reinforcement learning-based approach for optimizing the charging scheduling and pricing strategies of a public EV charging station. In [98], the authors used reinforcement learning to regulate charging scheduling for electric buses in a charging station in a smart grid environment.

5.4. Machine Learning for Charger Utilization Prediction

Estimating the charger utilization rate is essential for the expansion of the charging infrastructure. In [99], the authors predicted EV charging station usage using an ANN. In [100], the authors used the linear regression model to compute the charger idle time for a dataset in the Netherlands. In [101], the authors used the linear regression model to predict the charger utilization rate, assuming a nonlinear charging profile.

6. Literature Review Summary

A summary of the research reported in the previous section is presented in Table 3. Furthermore, a quantitative analysis of the reported literature is presented in Figure 3. From Figure 3, it is clear that machine learning techniques can be successfully applied to charging demand prediction problems.

Table 3. Summary of the research concerning the use of machine learning for charging infrastructure planning.

Ref	Author	Journal	Year	Problem	Technique
[68]	Ko	Computers and Industrial Engineering	2019	Charging station placement	Hybrid GA RL
[69]	Pevec et al.	International Journal of Energy Research	2018	Charging station placement.	Hierarchal clustering
[70]	Cohen-Addad et al.	Journal of the ACM (JACM)	2019	Charging station placement	Linear regression model and decision trees
[71]	Straka	Preprint	2018	Charging demand prediction	SVM
[73]	Duan et al.	Sustainable Cities and Society	2014	Charging Demand prediction	Modified pattern sequence
[74]	Majidpour et al.	2014 IEEE International Conference on Smart Grid Communications	2019	Charging Demand prediction	Deep learning
[75]	Zhu et al.	IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)	2017	Charging Demand prediction	Deep learning
[76]	Li et al.	4th International Conference on Information Science and Control Engineering (ICISCE)	2019	Charging Demand prediction	Deep learning
[77]	Zhu et al.	Applied Science	2018	Charging Demand prediction	Hybrid ant lion and deep learning
[78]	Li et al.	Energies	2018	Charging Demand prediction	Hybrid KDE
[79]	Chung et al.	IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)	2020	Charging Demand prediction	GRNN
[80]	Mansour et al.	Electronics	2018	Charging Demand prediction	SVM
[81]	Zhang	Energies	2019	Charging Demand prediction	Deep learning
[82]	Zhu et al.	Energies	2020	Charging Demand prediction	Regression model
[83]	Almaghrebi et al.	Energies	2019	Charging Demand prediction	Random forest and regression model
[84]	Buzna et al.	1st International Conference on Energy Transition in the Mediterranean Area (SyNERGY MED)	2018	Charging Demand prediction	Ensemble learning
[85]	Ai eta al.	IEEE International Conference on Energy Internet (ICEI)	2014	Charging Demand prediction	KNN

Table 3. *Cont.*

Ref	Author	Journal	Year	Problem	Technique
[86]	Majidpour et al.	IEEE Transactions on Industrial Informatics	2019	Charging Demand prediction	Reinforcement learning
[87]	Dang et al.	IEEE Transportation Electrification Conference and Expo (ITEC)	2020	Charging Demand prediction	Reinforcement learning
[88]	Wang et al.	IEEE Transactions on Vehicular Technology	2019	Charging scheduling	Reinforcement learning
[89]	Li et al.	IEEE Transactions on Smart Grid	2019	Charging scheduling	Reinforcement learning
[90]	Zhang et al.	IEEE Transactions on Intelligent Transportation Systems	2020	Charging scheduling	ANN
[91]	Dang et al.	IEEE Transportation Electrification Conference and Expo (ITEC)	2018	Charging scheduling	Reinforcement learning
[92]	Sharbaaf et al.	2018 Electrical Power Distribution Conference (EPDC)	2018	Charging scheduling	Reinforcement learning
[93]	Liang et al.	IEEE Transactions on Smart Grid	2018	Charging scheduling	Reinforcement learning
[94]	Wan et al.	IEEE Transactions on Smart Grid	2020	Charging scheduling	Reinforcement learning
[95]	Han et al.	IEEE Global Communications Conference (GLOBECOM)	2019	Charging scheduling	Reinforcement learning
[96]	Shin et al.	IEEE Transaction on Industrial Informatics	2019	Charging scheduling	Reinforcement learning
[97]	Wang et al.	IEEE Transaction on Industrial Informatics	2019	Charging scheduling	Reinforcement learning
[98]	Chen et al.	IEEE Global Communications Conference (GLOBECOM)	2018	Charger utilization	ANN
[99]	Ramachandran et al.	Preprint	2019	Charger utilization	Linear regression model
[100]	Lucas et al.	Energies	2019	Charger utilization	Linear regression model
[101]	Frendo et al.	Energy and AI	2021	Charging station placement	Supervised learning
[102]	Ma et al.	Preprint	2021	Charging demand prediction	ANN

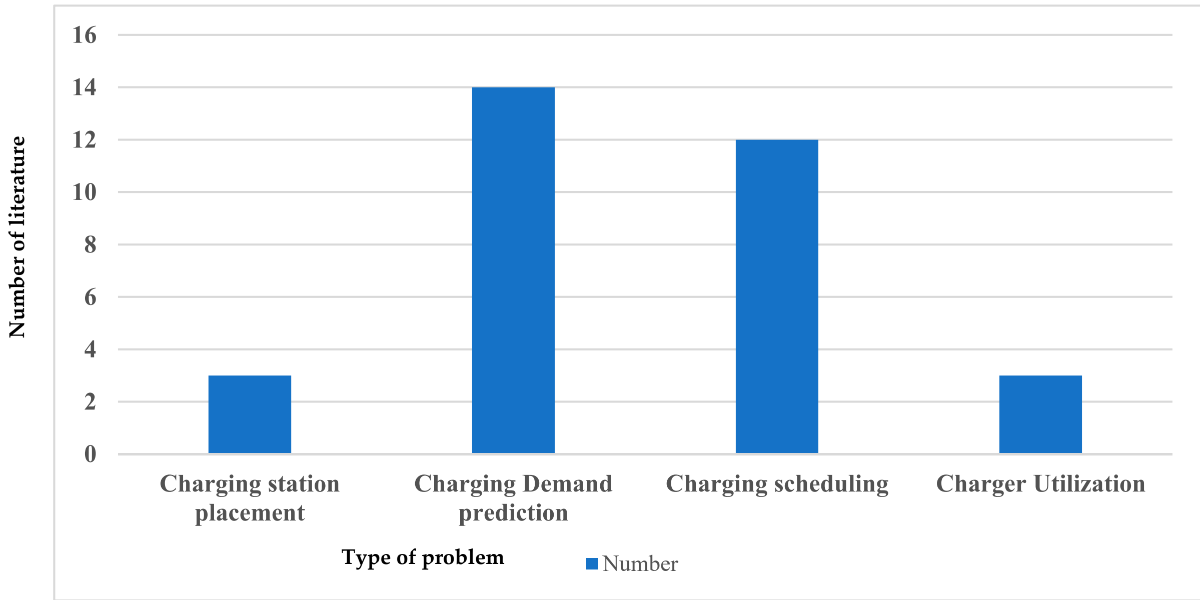

Figure 3. Quantitative analysis of the reported literature.

7. Case Studies

7.1. Home Charging Hotspot Prediction for Helsinki, Finland

Charging hotspots are points with relatively high charging demand throughout the day. It is expected that, during the initial stages of EV deployment, the majority of charging activity will take place at home. Hence, identifying home charging hotspots is necessary. In this work, we identified home charging hotspots for the city of Helsinki. The charging behavior and schedule of EV drivers in Helsinki specifically concerning home charging was modeled using the Activity-Based Transport Model (ABTM) [103,104]. A data-driven approach was adopted to identify the charging hotspots. The output of the ABTM model was utilized as an input with which to evaluate the charging hotspots. In this scenario, it was considered that the EV drivers charged their vehicles at home at the end of their journeys. The data-driven approach used for the identification of home charging hotspots is shown in Figure 4. Moreover, the home charging hotspots computed using the methodology shown in Figure 4 are presented in Table 4.

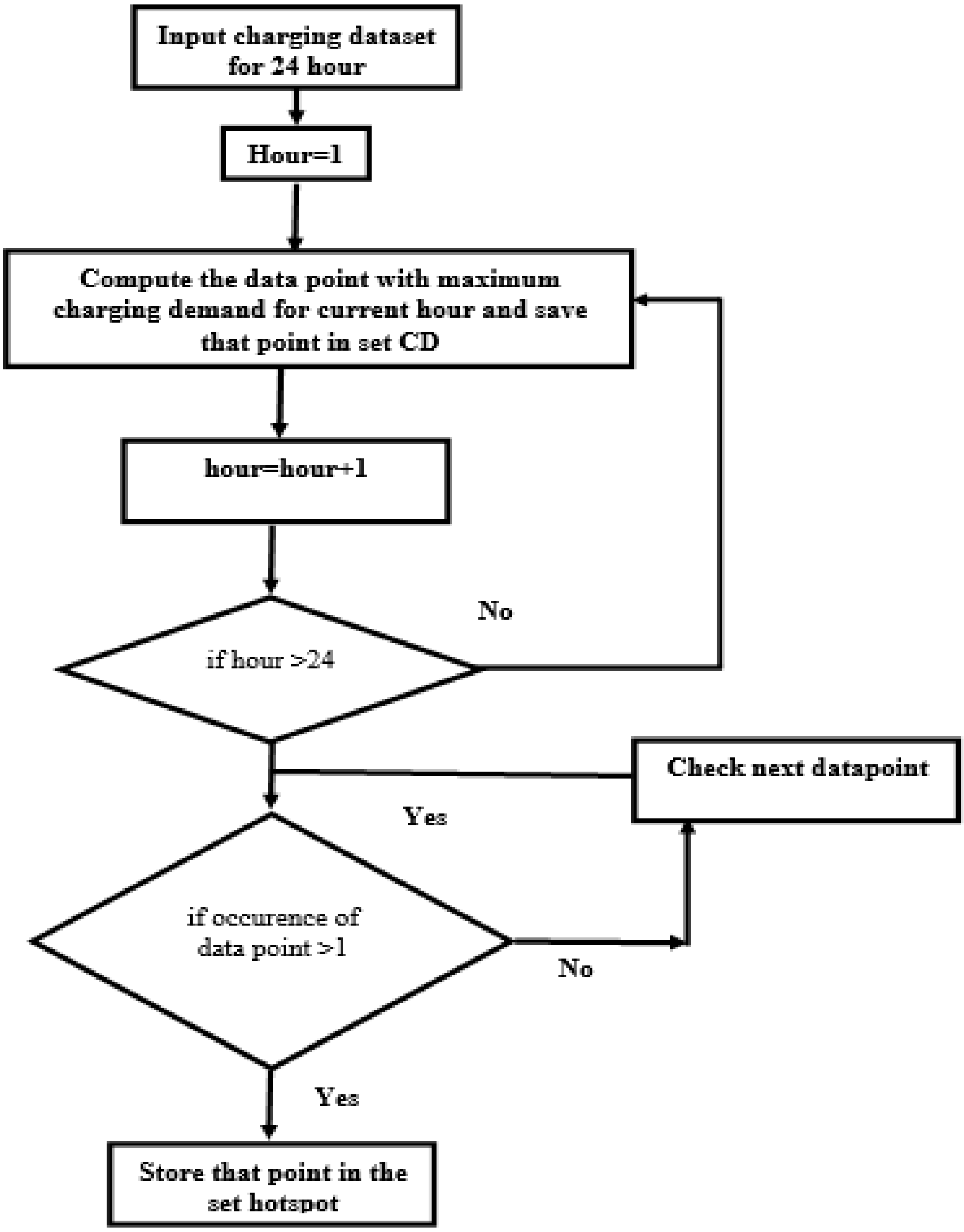

Figure 4. Flowchart for the computation of home charging hotspots [105].

Table 4. Home charging hotspots for Helsinki [105].

Latitude	Longitude	Location	Region	Pin
60.16088	24.92796	Hietalahdenranta 14	Helsinki	00180
60.17884	24.945945	Säästöpankinranta 10	Helsinki	00530
60.349377	25.05433	Kuhankeittäjäntie 5	Vantaa	01450
60.14246	24.640027	Ristiniementie 5	Espoo	02320
60.197788	24.92788	Pasilankatu 8b	Helsinki	00240

7.2. Commercial Charging Hotspot Prediction for Dundee City Council, United Kingdom

In addition to home charging, commercial public charging stations will be required for the large-scale adoption of EVs. Therefore, the identification of commercial public charging hotspots is also essential. A data-driven methodology was used for the identification of charging hotspots for Dundee city council, as shown in Figure 5. The identified charging hotspots are presented in Table 5.

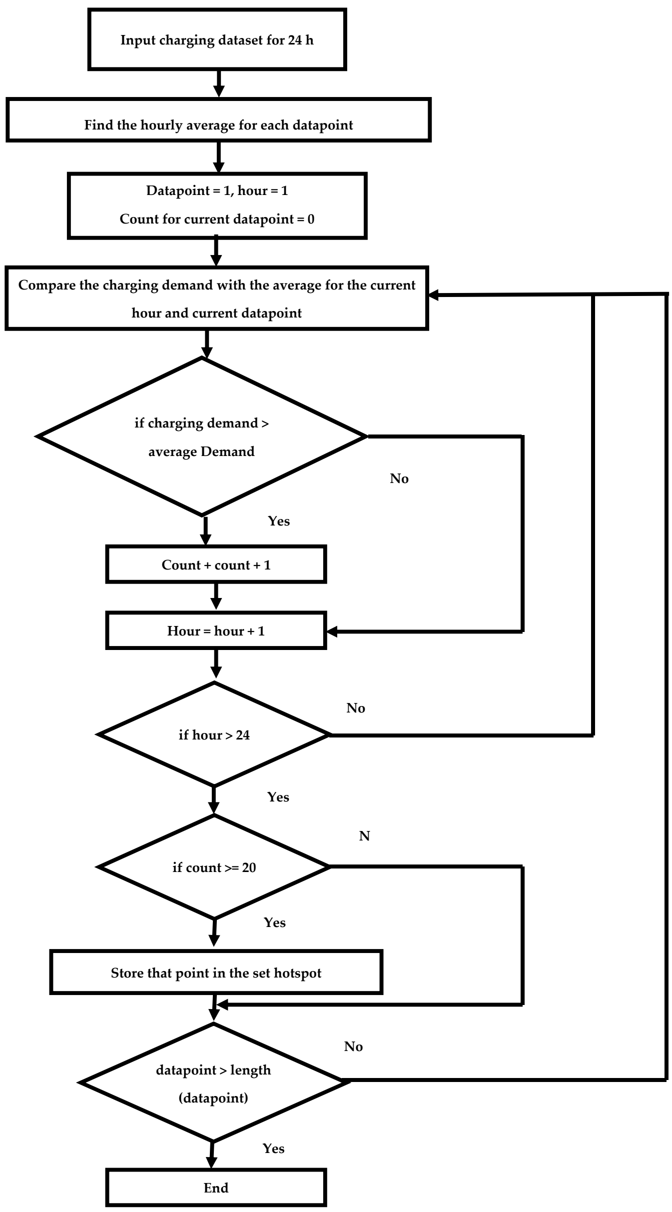

Figure 5. Flowchart for the computation of public commercial charging hotspots [105].

Table 5. Commercial public charging hotspots for Dundee city council.

Latitude	Longitude	Location	Type
56.47296514	−3.011192798	Housing Office West	Slow
56.46983341	−3.057191231	Hillcrest Housing Association	Fast
56.48982926	−2.917475296	Whitfield Centre	Slow
56.46149716	−2.96647828	Gellatly Street Car Park	Fast
56.4821483	−3.024697396	Dundee Ice Arena	Fast
56.46999414	−2.910300665	Oranges & Lemons	Slow
56.45682527	−2.973600267	Greenmarket Car Park	Fast
56.4575	−2.9785	Dundee University	Slow
56.45563168	−3.024181427	Dundee University Botanic Gardens	Slow
56.4725685	−2.973004185	Taxi Hub, Isla street	Slow and Fast
56.48588707	−2.89249497	Michelin Tyres	Fast
56.46779037	−2.873580046	Queen Street Car Park	Slow
56.47946054	−2.90444341	Douglas Community Centre	Slow
56.47796824	−2.913471531	Janet Brougham House	Slow
56.47016332	−2.920663615	Brington Place Sheltered Housing	Slow
56.47847573	−2.94163689	AutoecosseMitsibushi	Slow
56.48838239	−3.014352526	Ardler Complex	Slow
56.46543565	−3.035060314	Menziehill House	Slow
56.45677168	−3.068633303	James Hutton Institute	Slow
56.46553827	−3.04197669	Ninewells Car Park	Fast
56.46238032	−3.016417028	Royal Victoria Hospital	Fast
56.46826957	−3.005973737	Oakland Centre	Slow
56.47296831	−3.002456461	Marchbanks	Slow
56.46355616	−2.962498196,	Olympia Multi-Storey Car Park	Slow
56.46297438	−2.966068959	Trades Lane	Fast
56.46024694	−2.966793953	Dock Street	Fast
56.4568153	−2.977853701	Perth Road	Fast
56.45907815	−2.977267895	South Tay Street	Fast

7.3. Charging Demand Prediction for Helsinki, Finland

Predicting the charging demand in advance will assist in the smart and effective management of the charging load. In this work, a case study on charging demand prediction using the random forest technique for e-buses and private EVs in Helsinki is presented. The RF model was validated for Leepavara, which is a commercial shopping hub in Espoo, Finland. The e-buses charging dataset was generated using the bus timetables available on the HSL website [106–108]. Moreover, the charging dataset for private EVs was generated using the Bayesian network (BN)-based approach [109–111] proposed in [112]. The congestion levels in the city, as recorded using the Tom application [113] and shown in Figure 6, and the typical traffic conditions in Leepavara, as shown in Figure 7, were also taken into account while generating the charging dataset for private EVs. The charging demand was predicted using the random forest technique. The target and predicted charging demands are shown in Figure 8.

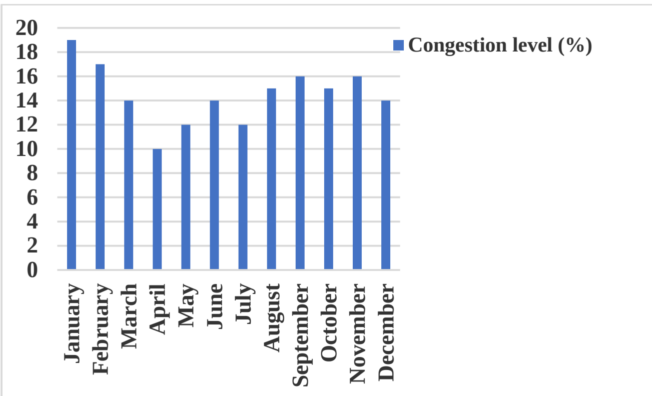

Figure 6. Congestion levels in Helsinki [113].

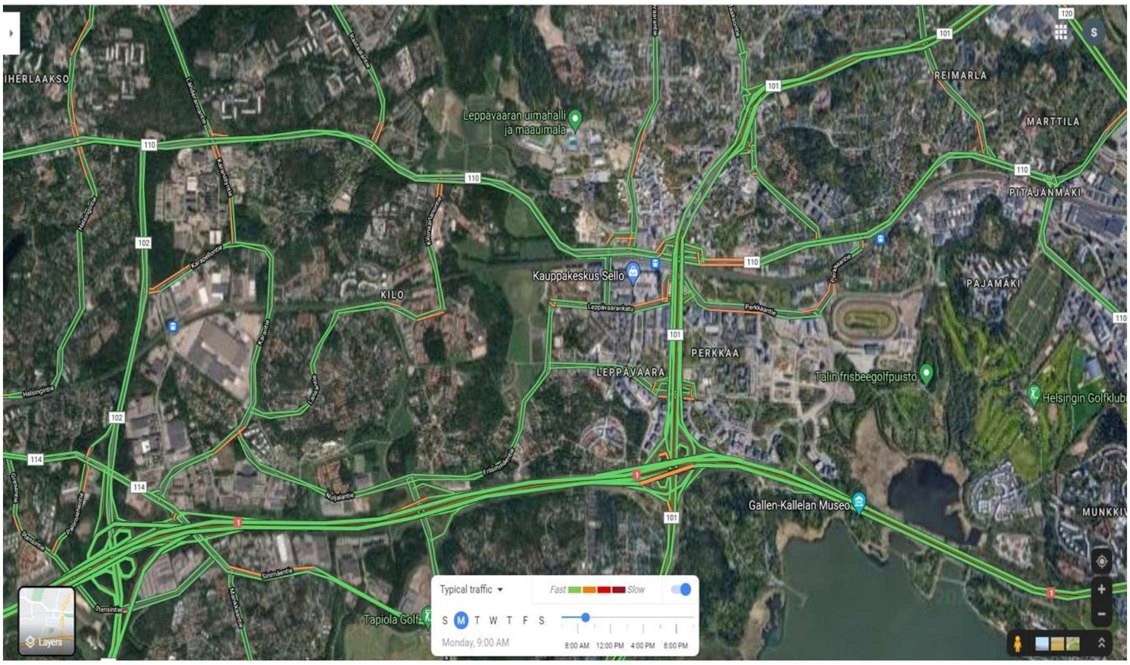

Figure 7. Typical Monday morning traffic in Leepavara (source: Google Maps).

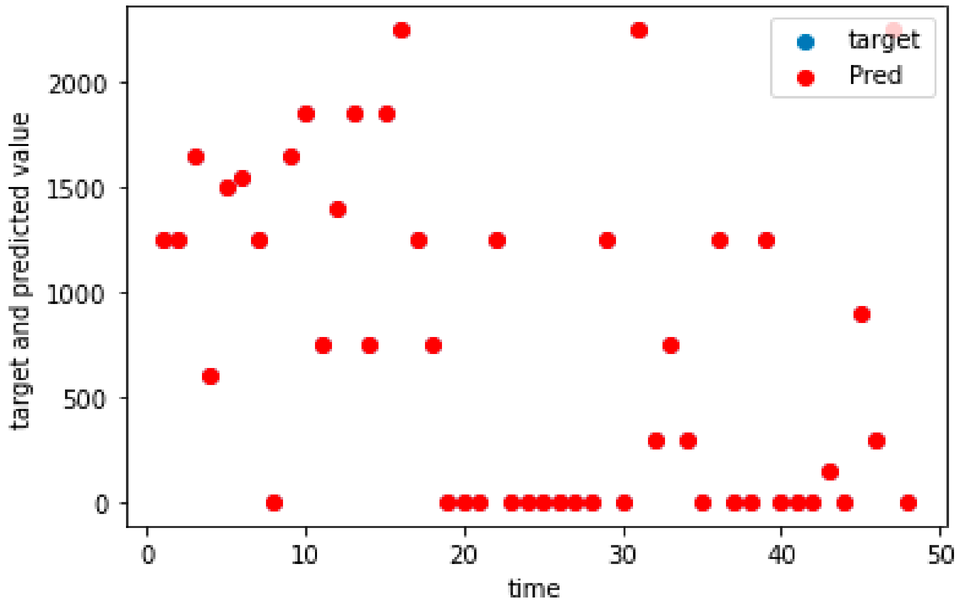

Figure 8. Target and predicted charging demand in kW.

Note: In the above figure, red implies high traffic levels, amber implies moderate traffic levels, and green implies lower traffic levels.

8. Discussions

This work comprehensively reviews the applications of machine learning algorithms for solving charging infrastructure planning problems. An overview of charging infrastructure planning is also provided herein. Charging station placement, charging demand prediction, charger utilization computation, and charging scheduling and pricing are some of the activities involved in charging infrastructure planning. Dedicated chargers serve the scheduled EV operations, which can be derived from GTFS and fleet management (i.e., to provide the combined flow of EVs). Different machine learning algorithms, such as supervised learning, reinforcement learning, and ANN, are used extensively for solving these problems. Qualitative and quantitative analyses of the research in this arena are provided. It can be seen that machine learning algorithms can be successfully applied to charging demand prediction and charging scheduling. SVM, deep learning, and random forest techniques are extensively used in charging demand prediction. Moreover, reinforcement learning is widely used for solving the problem of charging scheduling. Three case studies focused on charging infrastructure planning are also provided in this work in order to provide real-world examples. The first case study was focused on identifying home charging hotspots in the city of Helsinki, Finland, using a data-driven methodology. One of the main contributions of the first case study is the realization that initial EV adopters will mostly rely on home charging. The second case study identified public charging hotspots for Dundee city council. The identification of charging hotspots in advance will help power grid operators check whether grid reinforcement is required to support the increasing EV adoption. The planning model adopted in this case study performed better than the model reported in [114–117]. The third case study predicted the charging demand in Helsinki using a hybrid Bayesian network and RF-based methodology. It was observed that the model used for prediction was efficient as compared with the model proposed in [101,102].

This has been an extensive review of the machine learning algorithms utilized for solving different charging infrastructure planning problems. We hope to provide researchers with an analysis of the suitability of machine learning algorithms for charging infrastructure planning problems. However, this work was limited to the charging infrastructure without vehicle grid integration (VGI).

9. Conclusions

The large-scale deployment of EVs requires sustainable charging infrastructure. This work systematically analyzed the machine learning applications for solving charging infrastructure planning problems. Qualitative and quantitative analyses of the research in this arena are provided herein. It can be seen that machine learning algorithms can be successfully applied in charging demand prediction and charging scheduling. Furthermore, three case studies that focus on charging infrastructure planning are presented. These explored charging station placement and charging demand prediction. We presented an extensive review of the machine learning algorithms utilized in solving different charging infrastructure planning problems. We hope to provide researchers with an analysis of the suitability of machine learning algorithms for charging infrastructure planning problems. However, this work was limited to charging infrastructures without vehicle grid integration (VGI).

We expect this work to attract the attention of researchers working in the areas of e-mobility, optimization, machine learning, power, and energy. Our future research will address some of the following key issues:

- The use of machine learning in localizing charging hotspots;
- A performance comparison of machine learning techniques combined with heuristics and metaheuristics applied to charging infrastructure planning problems;
- Planning V2G-enabled charging facilities.

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