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Review

Machine Learning-Based Electric Vehicle Charging Demand Forecasting: A Systematized Literature Review

Maher Alaraj [1,*], Mohammed Radi [2], Elaf Alsisi [3], Munir Majdalawieh [1] and Mohamed Darwish [4]

[1] Department of Information Systems and Technology Management, College of Technological Innovation, Zayed University, Dubai 19282, United Arab Emirates
[2] UK Power Networks, London SE1 6NP, UK
[3] Business Informatics Department, Business College, King Khalid University, Abha 3247-61471, Saudi Arabia
[4] Department of Electronic and Electrical Engineering, College of Engineering, Design and Physical Sciences, Brunel University of London, Uxbridge UB8 3PH, UK
* Correspondence: maher.alaraj@zu.ac.ae

Abstract

The transport sector significantly contributes to global greenhouse gas emissions, making electromobility crucial in the race toward the United Nations Sustainable Development Goals. In recent years, the increasing competition among manufacturers, the development of cheaper batteries, the ongoing policy support, and people's greater environmental awareness have consistently increased electric vehicles (EVs) adoption. Nevertheless, EVs charging needs—highly influenced by EV drivers' behavior uncertainty—challenge their integration into the power grid on a massive scale, leading to potential issues, such as overloading and grid instability. Smart charging strategies can mitigate these adverse effects by using information and communication technologies to optimize EV charging schedules in terms of power systems' constraints, electricity prices, and users' preferences, benefiting stakeholders by minimizing network losses, maximizing aggregators' profit, and reducing users' driving range anxiety. To this end, accurately forecasting EV charging demand is paramount. Traditionally used forecasting methods, such as model-driven and statistical ones, often rely on complex mathematical models, simulated data, or simplifying assumptions, failing to accurately represent current real-world EV charging profiles. Machine learning (ML) methods, which leverage real-life historical data to model complex, nonlinear, high-dimensional problems, have demonstrated superiority in this domain, becoming a hot research topic. In a scenario where EV technologies, charging infrastructure, data acquisition, and ML techniques constantly evolve, this paper conducts a systematized literature review (SLR) to understand the current landscape of ML-based EV charging demand forecasting, its emerging trends, and its future perspectives. The proposed SLR provides a well-structured synthesis of a large body of literature, categorizing approaches not only based on their ML-based approach, but also on the EV charging application. In addition, we focus on the most recent technological advances, exploring deep-learning architectures, spatial-temporal challenges, and cross-domain learning strategies. This offers an integrative perspective. On the one hand, it maps the state of the art, identifying a notable shift toward deep-learning approaches and an increasing interest in public EV charging stations. On the other hand, it uncovers underexplored methodological intersections that can be further exploited and research gaps that remain underaddressed, such as real-time data integration, long-term forecasting, and the development of adaptable models to different charging behaviors and locations. In this line, emerging trends combining recurrent and convolutional neural networks, and using relatively new ML techniques, especially transformers, and ML paradigms, such as transfer-, federated-, and meta-learning,

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have shown promising results for addressing spatial-temporality, time-scalability, and geographical-generalizability issues, paving the path for future research directions.

Keywords: electric vehicle (EV); EV charging demand forecasting; EV charging demand forecasting based on machine learning (ML); EV charging session duration; EV charging session power consumption; EV charging station (EVCS)

1. Introduction

The transport sector is one of the major sources of greenhouse gas (GHG) emissions worldwide. In 2021, it accounted for 23% of GHG emissions in the European Union (EU), with passenger cars being responsible for more than 50% [1]. Reducing these emissions is vital for meeting the Paris Agreement goal of limiting the global temperature increase to well below 2 degrees Celsius. In this scenario, electromobility plays a crucial role, since electric vehicles (EVs) significantly reduce GHG emissions throughout their life cycle—including raw materials extraction, production, and usage—compared to internal combustion engine (ICE) ones [2,3]. Moreover, according to EU auditors, despite the different policies that have been implemented to diminish the ICE cars' carbon footprint, electrifying the transportation sector is the only way to achieve an actual reduction in on-the-road CO_2 emissions [4].

In the early 2010s, leading automakers, such as Mitsubishi and Nissan, together with Tesla, produced their first EV models for the mass market. Since then, gas price inflation and people's greater environmental awareness have consistently increased EVs' popularity, as shown in Figure 1. Moreover, in recent years, increasing competition among manufacturers, the development of cheaper batteries, and ongoing policy support have favored EV sales. According to a recent report by the International Energy Agency (IEA), the electric car year-on-year market has steadily grown since 2022, being projected to reach around 17 million in 2024, with China, Europe, and the United States (US) accounting for up to 45%, 25%, and 11% of the market share, respectively [1].

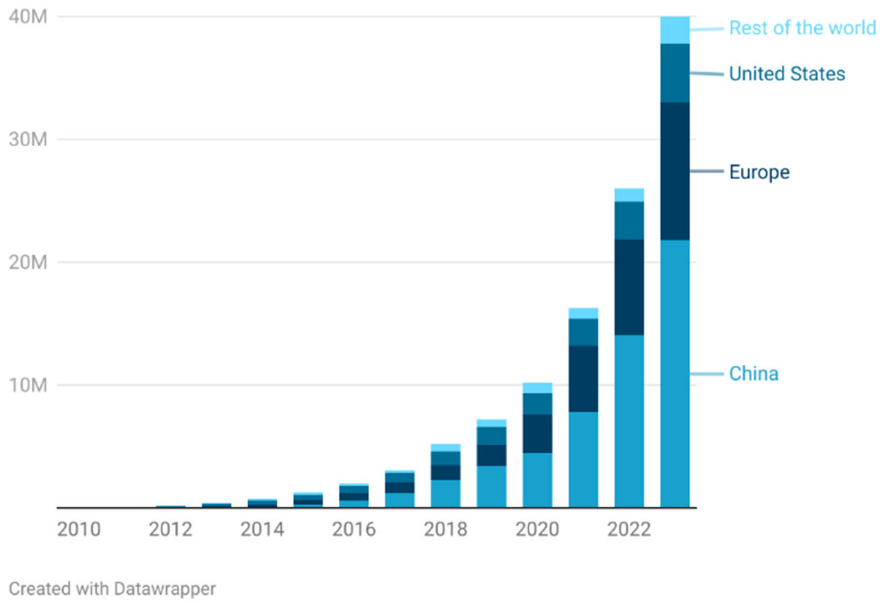


Figure 1. Global EV (BEV and PHEV) stock from 2010 to 2023. Source: International Energy Agency. Global EV Outlook 2024. "Electric car stocks" [dataset] [1].

Electric vehicle owners can charge their cars at home, at their workplace, or at public charging points. On the one hand, policymakers and the industry have long encouraged EV users to charge their EVs at home, arguing that residential chargers are not only easy to use but also cheaper and more convenient than public ones. In fact, early adopters have resorted to them, and they are currently the most widespread charging strategy [1,5]. Nevertheless, residential EV charging is usually carried out uncoordinated and uncontrolled, depending on people's working schedules, which can disproportionately raise the already existing evening peak-power demand. On the other hand, the demand for public chargers, which drain a huge amount of electrical energy from the grid, has significantly increased in recent years [6]. According to [1], by 2030, the number of public charging points will be up to four-fold compared to the number in 2023.

Regardless of their type, EV charging stations (EVCSs) are usually powered either by a utility grid or by local energy systems that support multiple energy sources. In this line, EVs can be charged through different infrastructures, including distribution networks, microgrids, energy hubs, and virtual power plants (VPPs), among others [7]. In this context, the growing adoption of EVs and their consequent charging needs stress the electricity infrastructure. In particular, the EV charging demand, which is highly influenced by the uncertain EV drivers' behavior and charging profile, makes EV integration into the power grid on a massive scale challenging. Several issues arise, including overloading, network congestion, voltage and frequency imbalance, harmonic injection, power losses, and grid instability [8–11], which affect the quality of the electricity supply.

Researchers have demonstrated that a coordinated and controlled EV charging strategy can mitigate these adverse effects, reducing or deferring the need for grid upgrades and their corresponding high investments [7,12–15]. Smart charging uses information and communication technologies (ICT) to optimize EV charging schedules in terms of the power systems' constraints, electricity prices, and users' preferences, benefiting the different EV stakeholders by minimizing distribution networks' losses, maximizing aggregators' profit, and reducing users' driving range anxiety [14]. In addition, it enables real-time remote monitoring and control, as well as bidirectional charging, where EVs can discharge energy back to the grid (vehicle-to-grid [V2G]) or to homes (vehicle-to-home [V2H]). This allows for ancillary services provision and participation in electricity markets via strategic bidding [15]. In this way, EVs can contribute to adding flexibility, supporting grid stability, facilitating renewable energy integration, and generating economic value [14,15]. Moreover, coupling these activities with carbon markets offers unique opportunities for carbon emission reduction and trading, thus reinforcing the decarbonization pathway [15].

Smart grids can provide the necessary infrastructure to support smart charging strategies by integrating advanced management, control technologies, and real-time communication to ensure both technical and cost-efficient operations toward grid stability, reliability, and resilience. To this end, local energy systems, including Transmission System Operators (TSOs) and Distribution System Operators (DSOs), should interact efficiently with EVs to coordinate the optimal utilization of their flexibility, determining EV charging schedules, ancillary service capacity, and the operational boundaries of EV aggregators, while guaranteeing safe and reliable power network operation [16]. In this scenario, EVs could benefit TSOs by providing control reserve to the energy market and assist DSOs in terms of voltage regulation and congestion management [16,17]. In [18], the current strategies for the smart management of the coupled system integrated by EVs, the transportation network, and the power grid are reviewed. Different optimization approaches proposed in the literature in terms of system planning and EV charging scheduling are discussed, highlighting the need for multi-dimensional modeling, multi-aspect joint optimization, and collaborative cloud-side-end technologies.

Accurately forecasting EV charging demand is paramount to providing the main EV stakeholders with quality information for efficient energy management in the context of smart charging strategies [18]. On the one hand, grid operators rely on aggregated EV charging load forecasts to identify potential bottlenecks in the distribution network and control its operation [17]. On the other hand, aggregators who consolidate a large number of EVs depend on them to efficiently market EV flexibilities for ancillary services, improving EVCSs' efficiency [17]. Unlike traditional loads, such as normal industrial and household ones, which are relatively stable and predictable, EV loads greatly depend on user behavior, making them uncertain and highly variable. Traditionally, EV charging demand has been forecasted based on model-driven methods [19–22]. These methods usually model travel patterns mathematically and perform a small-scale simulation—using techniques like Monte Carlo (MC)—to evaluate their impact on the power network [21,23,24]. Nevertheless, as they mainly rely on assumptions or simulated data, they may not always accurately represent current real-world EV charging profiles, which are influenced by an increasing number of factors, including weather, special days, electricity prices, user habits, and traffic motifs, among others.

In recent years, the advances in ICT have enabled numerous cloud-based EV services and data integration platforms [25–29], favoring charging data accessibility, collection, and storage. In this scenario, data-driven models' popularity has been catapulted [18,20,22,23], making data-driven management approaches based on big data and cloud-computing platforms play a crucial role in the efficient integration of EVs into the power grid [18,30]. These methods use real-life historical data to forecast EV charging demand. On the one hand, they avoid the need for in-depth knowledge of EV dynamics, travel patterns, and user behavior. On the other hand, they avoid the use of simulated data. In this sense, data-driven models allow for improving the forecasting accuracy in complex and rapidly changing environments such as EV charging demand applications [24].

Among the data-driven methods used for EV charging demand forecasting, statistical models, and machine learning (ML) models can be mentioned [18]. The former includes regression models, such as the linear and logistic ones [31,32]; autoregressive models, such as the well-known autoregressive integrated moving average (ARIMA) model [33,34]; and Bayesian models, among others. These methods are naturally static and suffer from limited flexibility, struggling to capture complex relationships and interactions in the data. In addition, they usually resort to assumptions of linearity that may not hold true in practice, leading to suboptimal forecasting performance in certain scenarios. ML techniques overcome these issues, being able to model complex nonlinear high-dimensional data relationships, providing better adaptability to new data from which they can learn. In this line, they have demonstrated to be well-suited to EV charging demand forecasting applications, a highly variable environment, where user behavior and charging patterns evolve over time, achieving high accuracy [30,35]. In [36], a comparison between statistical and ML models applied to predict EV charging demand confirms the superiority of the latter.

Recent studies show a remarkable trend of using ML approaches for EV charging demand forecasting [30,37]. The ML landscape has been largely led by artificial neural networks (ANNs) [38] due to their strong adaptability and generalization capacity [38,39]. Support vector machines (SVMs) [40] and ensemble methods [41]—especially bagging and boosting of decision trees (DTs), with random forest (RF) [42] being the most popular one—have also been widely used in many applications, whereas deep learning (DL) methods ([39,43]) have become a hot topic in the last decade [39,41,43]. Different ML-based approaches have been proposed in the literature to forecast different aspects of the EV charging demand [35,37]. Accuracy being a crucial aspect of the forecasting models, several research studies have been conducted to compare their performance. In [44], DL-based models based on long-short term memory (LSTM) and gate recurrent units (GRUs) for EV charging demand forecasting were evaluated, showing that a multivariate version of them outperforms their classical implementation. In [45], a comparison between recurrent neural networks (RNNs), LSTMs, bidirectional LSTMs (Bi-LSTMs), GRUs, convolutional neural networks (CNNs), and transformers was conducted, obtaining the latter the best results in terms of EV charging demand forecasting. In [31], the probabilistic forecast of EV charging demand was performed based on linear regressors (LinRs), ANNs, LSTMs, CNNs, and DT-ensemble methods—gradient boosting (GB), adaptable boosting (AdaBoost), bagging, and RF—with AdaBoost, bagging, and RF being the most accurate ones in multiple charging scenarios. In [46], different variants of federated learning (FL) were employed to predict energy demand. Their comparison with traditional ML methods, including K-nearest neighbor (KNN), multi-layer perceptron (MLP), support vector regressor (SVR), and RF, showed their superiority. In [47], the impact of climate factors on the EV charging capacity was evaluated, and the accuracy of MLP, extreme GB (XGBoost), LSTM, CNN-LSTM, Bi-LSTM, GRU, and transformers to predict it was studied, with XGBoost obtaining the best results. In [48], MLP, LSTM, and Bi-LSTM were used to forecast an EV fleet charging demand based on multiple decomposition and swarm decomposition strategies, resulting in Bi-LSTM being the best forecasting method. In [49], a case study conducted in Morocco compared the performance of ANNs, GRUs, LSTMs, and RNNs to predict EVCS power demand, with GRUs achieving the best results.

In this scenario, where a vast corpus of research exists and results are diverse, the need for a comprehensive state-of-the-art review to identify relevant current trends and research gaps in the field of ML methods applied to EV charging demand forecasting arises. A previous work in [35] provides a review of ML-based approaches for modeling EV charging behavior. Nevertheless, it dates back to 2020. Not only has the global EV market share grown almost four times since then (Figure 1), but also EV technologies, EV charging infrastructure, EV charging data acquisition, and ML techniques have evolved. This has raised the need for revisiting the state of the art and further exploring the literature to evaluate the technological advances, the consolidated strategies, the promising emerging trends, the remaining issues, the new challenges, and the future perspectives in the field. To this end, this paper conducts a systematized literature review (SLR).

Our main contribution consists of providing a well-structured synthesis of a large body of literature, categorizing approaches not only based on their ML-based approach, but also on the EV charging application. In the case of the former, we focus on the most recent technological advances, exploring especially deep-learning architectures, spatial-temporal (ST) challenges, and cross-domain learning strategies. For the latter, we analyze the charging scenario, aggregation level, data sources, and forecasting horizons. This offers an integrative perspective that not only maps the state of the art, but also uncovers underexplored methodological intersections that can be further exploited.

In general, EV charging demand refers to the overall EV charging needs, including not only the electrical power drawn from the grid during the charging sessions, but also their duration, where and when they will take place, and the number of EVs that will be charged. According to [50], it is essential to know the charging duration time and the total energy consumption for each session to prioritize and optimize the session charging power, subject to the infrastructure and economic constraints. In this line, accurately forecasting EV charging sessions' demand in energy management applications is critical to control the distribution grid operation and efficiently market EV flexibilities for ancillary services. Then, the proposed SLR is focused on its main characteristics: the electrical energy consumed during the charging sessions (measured in kWh) and the sessions' duration (measured in h) [51]. The main aim of the SLR is to identify the most popular ML techniques used to forecast EV charging sessions' demand in terms of the electrical energy drawn from the grid during the sessions and their duration, synthesize them, evaluate their strengths and weaknesses, and understand for which EV charging scenarios and applications these approaches are better suited. A comprehensive discussion is held to highlight the consolidated strategies, the emerging trends, and the remaining research gaps. Finally, based on the results of the SLR, promising future research directions are defined to help EV stakeholders in developing novel, robust, and accurate ML-based EV charging sessions' demand forecasting approaches toward efficiently integrating EVs into the power grid via smart charging strategies.

The remainder of the paper is organized as follows. Section 2 provides a brief background of EV charging and ML techniques. Section 3 introduces the methodology used in the paper. Section 4 presents the SLR results, and Section 5 analyzes them. Section 6 discusses the SLR results, highlighting the main research findings, the current trends, and the identified research gaps. In addition, it suggests promising future research lines. Finally, the concluding remarks are given in Section 7.

2. Background

Section 2.1 describes the main aspects of the EV charging process, including the different types of EVs, the existing charging infrastructure, and the parameters involved in the EV charging demand. Section 2.2 briefly introduces ML techniques.

2.1. Electric Vehicle Charging

Depending on their propulsion mechanism, EVs can be classified into three main categories: hybrid EVs (HEVs), battery EVs (BEVs), and fuel cell EVs (FCEVs) [52,53]. HEVs, including plug-in HEVs (PHEVs), combine an electric motor with an ICE, whereas BEVs and FCEVs only have an electric motor. Table 1 shows the different types of EVs, describing their propulsion system, electricity source, charging method, operational advantages and disadvantages, and their environmental aspects [52,53].

Plug-in EVs, including PHEVs and BEVs, can be charged at three levels [53]. Level 1 utilizes a standard 120/230-volt AC outlet (US/EU). Being the slowest charging option, it is well suited for residential charging that can take place overnight. Level 2 is faster than level 1, and requires a 240/400-volt AC connection (US/UE). Although it can be found at home, it is commonly used for commercial and public charging. Finally, level 3, also known as DC fast charging, uses DC and high current to charge EVs quickly. DC fast chargers are available for highway services, fleets, and logistics hubs.

An EV charging session can be characterized by the electrical energy consumed during the session (measured in kWh) and its duration (measured in h). The latter consists of the time the EV stays at the charging station, including the time needed to charge, which depends on the initial and final state of charge (SOC) and the power being supplied to the EV, as well as the time it remains parked after charging, usually referred to as idle time. The charging session duration can then be calculated as the time elapsed between the start or arrival time and the end or departure time of an EV as follows:

$$EVChargSess_{duration} = t_{end} - t_{start},$$

where t_{start} and t_{end} are the times when the EV is connected and disconnected to the charger, respectively, and $t_{end} = t_{full} + t_{idle}$, where t_{full} is the time when the EV is fully charged, and t_{idle} is the idle time.

Table 1. Types of EVs.

Type of EV	Propulsion System	Electricity Source	Charging Method	Operational Advantages	Operational Disadvantages	Environmental Aspects
HEV	Combines an electric motor with an ICE.	Battery	All energy for the battery is gained through regenerative braking.	- Improved fuel efficiency compared to ICE cars. - Longer driving range than BEVs.	- Depends on gasoline. - More expensive operation than BEVs. - Complex system.	Zero tailpipe emissions are not achieved.
PHEV	Combines an electric motor with an ICE.	Battery (larger than HEVs).	Plugged into the grid.	Extended range due to ICE.	Less efficient than BEVs.	Zero tailpipe emissions are not achieved.
BEV	Electric motor	Rechargeable battery packs.	- Plugged into the grid. - Regenerative braking.	- High efficiency. - Overall low cost of operation.	Driving range anxiety.	Zero tailpipe emissions.
FCEV	Electric motor	Fuel cell	Specialized hydrogen stations provide hydrogen gas to generate electricity through the fuel cell.	Quick refueling.	- Lack of infrastructure. - High costs.	Zero tailpipe emissions.

Note. BEV: Fully battery electric vehicle; HEV: hybrid electric vehicle; PHEV: plug-in hybrid electric vehicle; FCEV: fuel cell electric vehicle.

2.2. Machine Learning Methods

Machine learning aims to construct computer programs that automatically improve (learn) with experience (data). Figure 2 shows a typical ML process. The first step involves data collection. This usually includes exploratory data analysis and data cleaning. In addition, for the data to be interpreted by ML algorithms, appropriate preprocessing, including data normalization, should be carried out. The second step, feature engineering, is crucial for the success of the ML-based approach. It consists of a feature extraction phase, where a suitable representation of the data is built, and a feature selection phase, where the most relevant features are selected based on some importance criteria to enhance the model's performance. In the modeling step, the ML model is chosen and its hyperparameters are optimized. The latter is critical for the model's performance, influencing its complexity, behavior, speed, and accuracy. It aims at finding the values of the parameters that are intrinsic to the ML model that obtain the best prediction results on a validation dataset. This hyperparameter setting will then govern the model's training phase [54]. Once the model is trained on the training data, the final step consists of evaluating its performance. This is conducted on a subset of unknown data (usually called testing data), based on different classification and regression error measurements.

Traditionally, ML techniques have been broadly classified into supervised, unsupervised, semi-supervised, and reinforcement learning (RL) [39,41,55,56]. Supervised ML learns an output based on labeled training samples in the form of input-output pairs [41]. They can perform classification tasks, separating data into different categories or "classes", or regression tasks, fitting the data. Unsupervised ML learns patterns from unlabeled data. It is typically used for clustering purposes [41]. Semi-supervised ML is useful for cases where labeled data is scarce, incorporating unlabeled data into the model to improve its performance [56]. Finally, RL is a more sophisticated approach based on trial-and-error learning that uses agents and machines to automatically evaluate the optimal action to take in a particular scenario toward increasing the reward and minimizing the penalty [57]. It is well suited to solve sequential decision-making problems. Table 2 summarizes the main characteristics of these ML paradigms, including the most popular algorithms used in the literature to implement them [41].

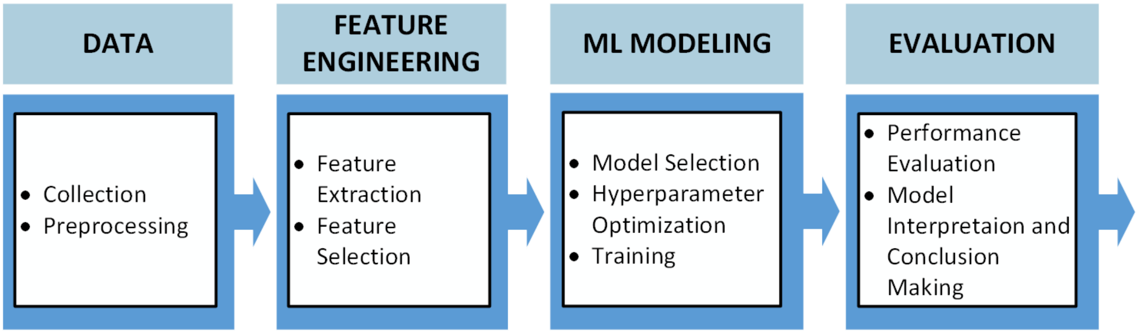


Figure 2. Typical ML process. Note. ML: machine learning.

Table 2. ML types.

Learning Paradigm	Data	Approach	Popular Algorithms
Supervised	Labeled	Task-driven	LinR, DT, KNN, SVM/SVR, ANN-based methods, DT ensembles, such as RF and XGBoost
Unsupervised	Unlabeled	Data-driven	K-means
Semi-supervised	Labeled and unlabeled	Hybrid	Generative models
Reinforcement	Unlabeled	Environment-driven	Q-learning, SARSA

Note. ANN: artificial neural network; DNN: deep neural network; DT: decision tree; LinR: linear regression; KNN: k-nearest neighbors; SVM/SVR: support vector machine/regressor; RF: random forest; SARSA: state action reward state action; XGBoost: extreme gradient boosting.

According to [55], supervised learning is the most widely considered in the literature. Nevertheless, in recent decades, new learning paradigms have gained momentum [55]. Among them, transfer learning (TL) can be mentioned, which uses the information from a source task to improve the learning of a target task. In TL-based approaches, the knowledge transfer can be conducted via features, hyperparameters, etc.

Since the 2000s, DL—a branch of ML based on ANNs—has become a core technology in the field of ML, being applied to a wide variety of problems, including visual recognition, natural language processing, text analysis, etc. [39,43]. DL can address learning tasks within the different learning paradigms. They extend the functionality of a typical neural network. A neural network consists primarily of a series of interconnected processing units known as neurons. Each neuron produces a sequence of real-valued activations that contribute to the outcome. A shallow neural network includes an input layer, a hidden layer, and an output layer [39]. The feedforward neural network (FFNN) is the simplest neural network architecture. DL adds hidden layers to the neural network structure, with the multilayer perceptron (MLP) being the basic unit of deep neural networks (DNNs) [39,43]. Based on a multilayered architecture, DNNs can extract low- and high-level features through the first and last layers, respectively, without the need for time-consuming and expert-based feature extraction, providing more robust and customizable solutions. This is one of the main advantages of DL with respect to conventional ML approaches. In addition, they are highly adaptable to updating data, being well-suited for applications like weather and price prediction, and are scalable [43]. Typical architectures of DNNs include CNNs, RNNs—such as LSTM and GRU—autoencoders (AEs), and graph adversarial networks (GANs).

3. Methodology

An SLR was conducted to explore the ML-based approaches that have been used in the literature to forecast EV charging sessions' demand. We focused on the main characteristics of the EV charging sessions' demand: the electrical energy consumed during the sessions (measured in kWh) and their duration (measured in h). As introduced in Section 2.1, the EV charging duration can be calculated based on different times, including the arrival and departure times, the time required to fully charge the EV, and the idle time. In this line, these time-related parameters were also considered in the SLR.

The research question is defined as follows: What ML-based approaches have been used in the literature to forecast EV charging sessions' demand in terms of sessions' electrical energy consumption (kWh) and duration (h)? Figure 3 shows the methodology followed in this paper to identify the consolidated and emerging trends in ML-based forecasting of EV charging sessions' demand and the main remaining research gaps toward proposing solid and promising future research directions. First, a literature search was conducted based on the strategy described in Section 3.1. The results of the SLR (described in Section 4) were then synthesized, and a descriptive analysis was performed (see Section 5). Finally, the main research findings and gaps were identified to suggest areas where research should be deepened to help EV stakeholders in developing novel, robust, and accurate ML-based EV charging session demand forecasting approaches that allow the efficient integration of EVs to the power grid via smart charging strategies (see Section 6).

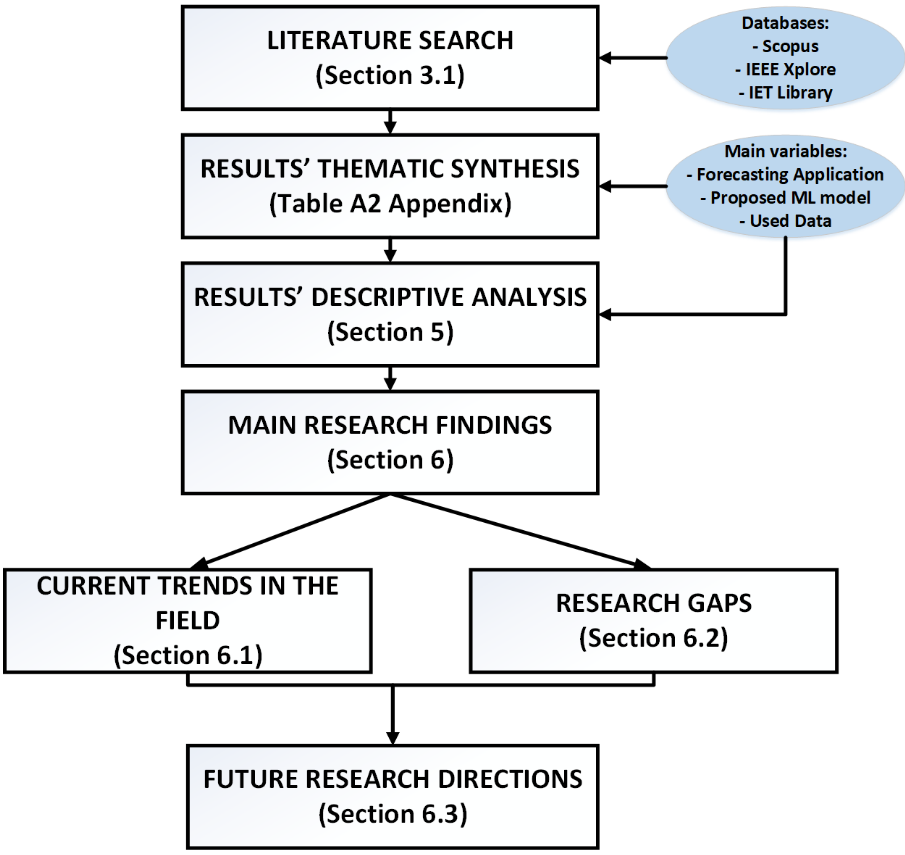


Figure 3. Methodology followed in this paper.

3.1. Literature Search Strategy

3.1.1. Database Search

A database search methodology was used. String-based searches were conducted in three databases, one multidisciplinary and two specialized, to cover as much evidence as possible. The bibliographical search was undertaken on 6 May 2024, in Scopus, the source-neutral multidisciplinary abstract and citation database owned by Elsevier; the IEEE Xplore digital library, which allows access to scientific and technical content published by the IEEE and its publishing partners; and the IET Library, which provides content produced by the IET.

3.1.2. Search Equation

Table 3 shows the search equation used in each of the three databases.

Table 3. Search equation.

Database	Search Fields	Search Equation
Scopus	TITLE-ABS-KEY	(TITLE-ABS-KEY((“electric vehicle” OR “electric vehicles” OR “EV” OR “EVs” OR “electric car” OR “electric cars”)) AND TITLE-ABS-KEY((“charging demand” OR “kWh demand” OR “kW-h demand” OR “kW h demand” OR “kilowatt hour demand” OR “kilowatt-hour demand” OR “charging consumption” OR “kWh consumption” OR “kW-h consumption” OR “kW h consumption” OR “kilowatt hour consumption” OR “kilowatt-hour consumption” OR “charging load” OR “charging behavior” OR “charging behavior” OR “charging pattern” OR “charging profile” OR “charging time” OR “demand profile”)) AND TITLE-ABS-KEY((forecast * OR predict * OR estimate * OR model *)) AND TITLE-ABS-KEY((“machine learning” OR “deep learning” OR “artificial intelligence” OR “artificial intelligent” OR AI OR “neural network” OR “neural networks” OR “artificial neural network” OR “artificial neural networks” OR “NN” OR “NNs” OR “ANN” OR “ANNs”)))
IEEE Xplore	All metadata + full text	All metadata + full text ((((“electric vehicle” OR “electric vehicles” OR “EV” OR “EVs” OR “electric car” OR “electric cars”)) AND ((“charging demand” OR “kWh demand” OR “kW-h demand” OR “kW h demand” OR “kilowatt hour demand” OR “kilowatt-hour demand” OR “charging consumption” OR “kWh consumption” OR “kW-h consumption” OR “kW h consumption” OR “kilowatt hour consumption” OR “kilowatt-hour consumption” OR “charging load” OR “charging behavior” OR “charging behavior” OR “charging pattern” OR “charging profile” OR “charging time” OR “demand profile”)) AND ((forecast * OR predict * OR estimate * OR model *)) AND ((“machine learning” OR “deep learning” OR “artificial intelligence” OR “artificial intelligent” OR ai OR “neural network” OR “neural networks” OR “artificial neural network” OR “artificial neural networks” OR “NN” OR “NNs” OR “ANN” OR “ANNs”))))
IET Library	All fields including full text	All fields including full text ‘(((“electric vehicle” OR “electric vehicles” OR “EV” OR “EVs” OR “electric car” OR “electric cars”)) AND ((“charging demand” OR “kWh demand” OR “kW-h demand” OR “kW h demand” OR “kilowatt hour demand” OR “kilowatt-hour demand” OR “charging consumption” OR “kWh consumption” OR “kW-h consumption” OR “kW h consumption” OR “kilowatt hour consumption” OR “kilowatt-hour consumption” OR “charging load” OR “charging behavior” OR “charging behavior” OR “charging pattern” OR “charging profile” OR “charging time” OR “demand profile”)) AND ((forecast * OR predict * OR estimate * OR model *)) AND ((“machine learning” OR “deep learning” OR “artificial intelligence” OR “artificial intelligent” OR AI OR “neural network” OR “neural networks” OR “artificial neural network” OR “artificial neural networks” OR “NN” OR “NNs” OR “ANN” OR “ANNs”)))’

Note. ANN/s: artificial neural network/s; NN/s: neural network/s; EV/s: electric vehicle/s. The * tells the database to match any possible ending of the root word.

3.1.3. Inclusion/Exclusion Criteria

Studies published in any language and without exclusion due to publication date were retrieved. As introduced in Section 1, the SLR is focused on the main aspects that characterize the EV charging session demand defined in Section 2.1: the electric energy consumed during the session and its duration. The latter can be computed based on the start or arrival time, the time after which no charge is delivered, the idle time, and the end or departure time. Thus, studies forecasting these times were included in the SLR corpus. Table 4 details the inclusion and exclusion criteria used.

Table 4. Inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Geographical origin	No limitations	No exclusion
Language	No limitations	No exclusion
Timeframe	No limitations	No exclusion
Type of publication	No limitations	No exclusion
Type of document	Journal articles, reviews, conference proceedings, books, book chapters	Retracted documents
Type of electric vehicle	PEV: BEV, PHEV	HEV, FCEV
Forecasted variable	EV charging session demand: electrical energy consumption (kWh), duration (h)	EV travel/on-road electrical energy consumption
Forecasting technique	ML-based approach	Non-ML-based approach

Note. BEV: battery electric vehicle; EV: electric vehicle; FCEV: fuel cell electric vehicle; ML: machine learning; PEV: plug-in electric vehicle; PHEV: plug-in hybrid electric vehicle.

4. Literature Search Results

Figure 4 shows the results of the literature search described in Section 3.1. In particular, 1248 records were identified: 425 from Scopus, 437 from IEEE Xplore, and 386 from the IET Library. After duplicate removal, the title and abstract of each record were screened independently based on the inclusion/exclusion criteria defined in Table 4. For those who passed the screening phase, their full-text versions were acquired. In this stage, 282 studies were evaluated for quality assessment and eligibility. After careful review, 120 studies were excluded. The rationale for excluding them comprised little to no contribution toward the research question and poor quality in terms of methodology, clarity, and relevance of the results. Finally, 162 records were included in the SLR corpus. Table A1 in Appendix A lists them. The remaining records were considered supporting material for the SLR.

Figure 5 shows the distribution of the studies included in the SLR in terms of publication year and type. Although no restrictions were applied regarding the searching period, the first studies in the field retrieved in the SLR were published in 2012. This is in line with the plethora of research regarding EVs that can be found since the 2010s, when leading automakers began to massively produce EVs. In addition, the central role electromobility plays in limiting global climate change in terms of the sustainable goals set by the Paris Agreement has made EV adoption a crucial task for many countries around the world. Consequently, the EV market has consolidated in recent years, as shown in Figure 1. As the adoption of EVs grows, the need for more research regarding EV charging demand management arises. Figure 5 shows a clear increase in ML-based approaches addressing EV charging sessions' demand forecasting since 2019. The annual growth rate accelerated in 2022, when researchers published 60% more studies than in 2021, reaching 87.5% in 2023. Finally, only in the first four months of 2024, included in the literature search performed on May 6 (see Section 3.1), 16 studies were published, confirming the hot-topic nature of the SLR subject, as well as the need for complementing the results published in 2020 by [35]. Regarding the type of publications, although publishing in conference proceedings is a common practice in many engineering-related disciplines, there has been an increasing number of journal articles since 2019.

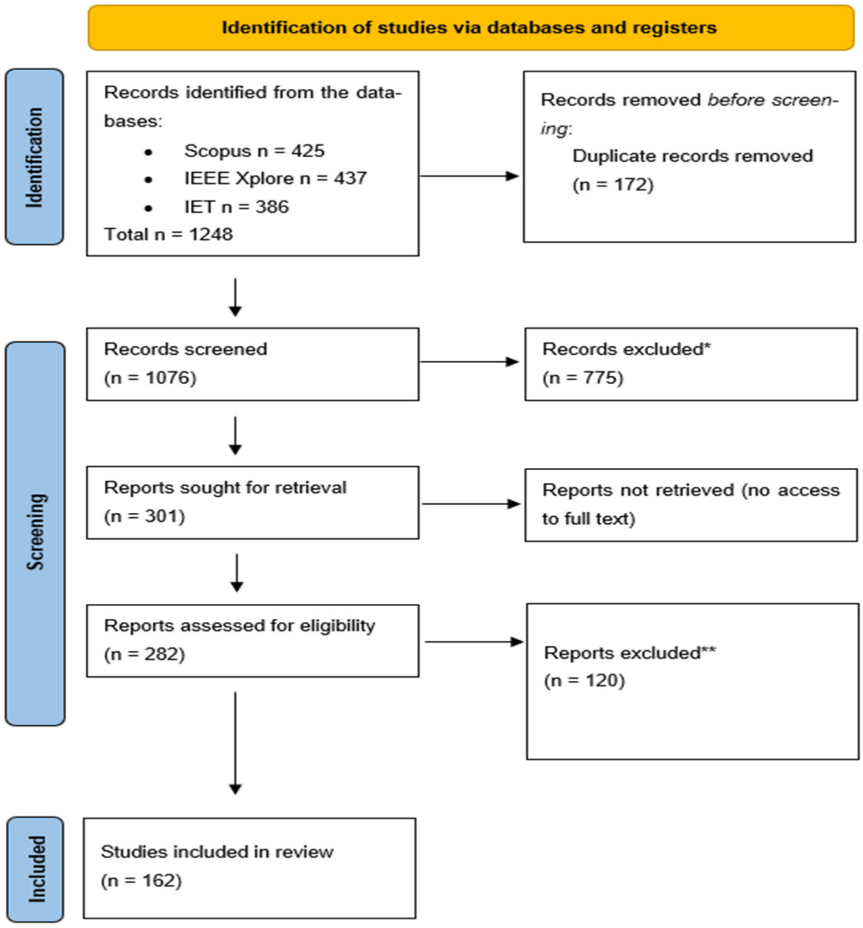


Figure 4. Literature search results. * According to the inclusion/exclusion criteria. ** Poor quality records, records that are out of the LR scope. **Note.** Scheme adapted from [58].

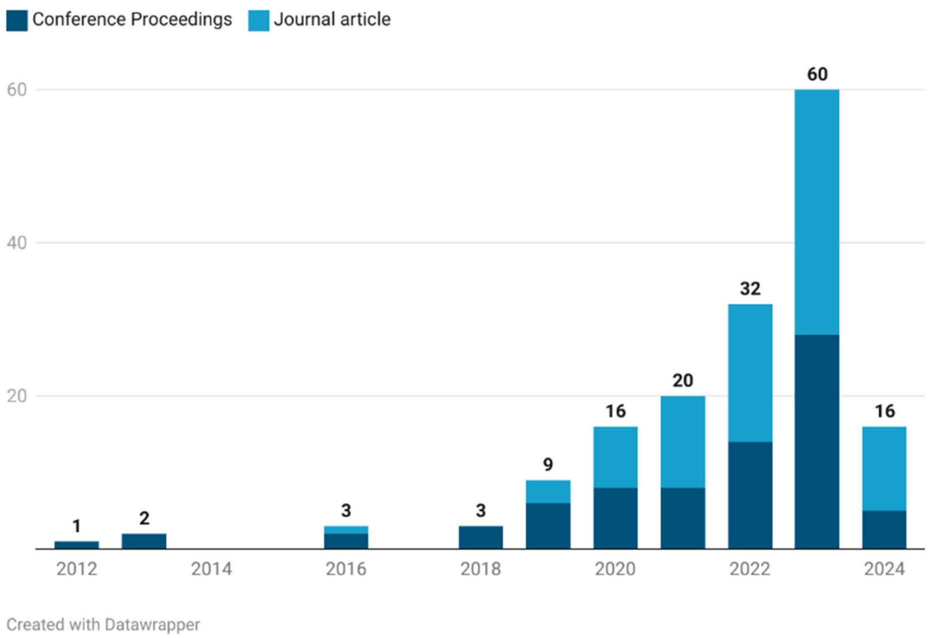


Figure 5. Number of studies included in the SLR per year and document type. Note. SLR: Systematized literature review.

5. Systematized Literature Review Results' Analysis

The SLR results are thematically synthesized in Table A2. Due to space constraints and for the sake of readability, Table A2 is included in Appendix A. To describe the literature regarding ML-based approaches proposed to forecast EV charging session demand, the following variables are considered in Table A2:

- Data: origin, availability, and features used for forecasting.
- Proposed ML-based approach.
- Application: forecasted variable, charging scenario, aggregation level, and time horizon of the forecasting.

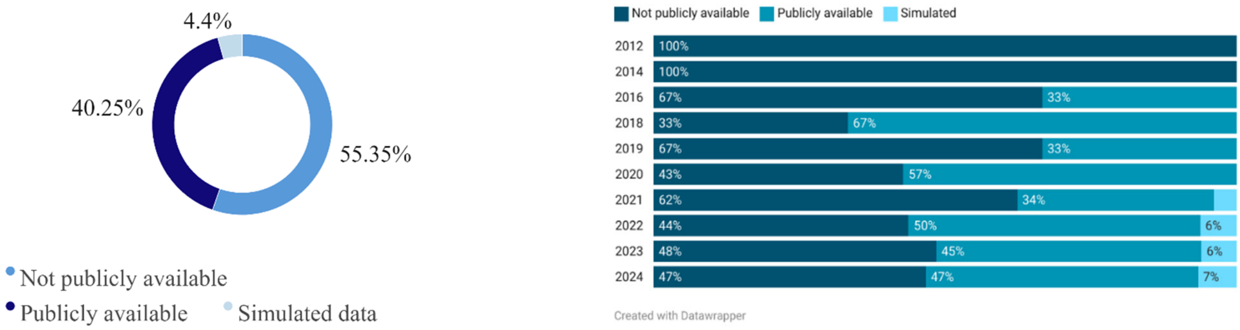
Then, a descriptive analysis of the SLR results is conducted. In Section 5.1, the main characteristics of the EV charging session demand-related data, including their origin, availability, and quality, are introduced, and how the work in the SLR dealt with them is discussed. In addition, the main feature engineering strategies proposed to handle different aspects of the data and adapt them to the diverse EV charging scenarios presented in Section 5.3 are analyzed. In Section 5.2, the reviewed articles are classified based on the main ML-based method they have proposed for EV charging session demand forecasting. In this line, we aim to identify the most used and better suited ML techniques in the field of EV charging session demand, as well as their strengths and weaknesses for this application. Finally, Section 5.3 shows how the ML approaches identified in the SLR (Section 5.2) were used to forecast the EV charging session consumption and duration within the context of different charging scenarios, aggregation levels, and forecasting time horizons.

5.1. Data

In data-driven models like ML-based ones, data availability, accessibility, and quality are critical. These aspects have long been highlighted as one of the main limitations for further developing EV charging management approaches. The previous study reviewing the state of the art of ML techniques applied to EV charging behavior forecasting conducted in 2020 [35] identified two well-known public EV charging datasets: the Adaptive Charging Network (ACN) dataset [59] and the Pecan Street dataset [60]. The ACN dataset collects data from two ACNs located in California: the parking garage of the Caltech campus, which is open to the public, and the NASA Jet Propulsion Laboratory (JPL)'s parking garage, which is restricted to employees. The Pecan Street dataset [60], on its part, contains the measurement of circuit-level household electricity consumption data, including data from major appliances—heating, ventilation, and air conditioning (HVAC), refrigerators, and EVs—from nearly 1000 homes across the US. In this line, some techniques are required to extract EV charging session data. In [61], a factorial hidden Markov model (HMM) was used for the decomposition of charging data from the Pecan Street dataset. Then, an LSTM was trained on these data to forecast the short-term EV charging sessions' consumption, obtaining a Root Mean Squared Error (RMSE) of 8.26%.

In [62], a comprehensive review of open EV charging load datasets was conducted. The authors in [62] found open datasets from Boulder, Colorado (US), Dundee and Perth (UK), and Paris, which contain public EVCS data, and a domestic dataset from the UK, widening the landscape depicted in [35]. The results of the SLR shown in Figure 6a reveal that 95% of the studies use real-life data for their experiments, whereas only 5% resorted to simulated data. The total or some of the real-life data used in the SLR studies is publicly available in 40% of the cases, showing that this tendency began in 2016 (Figure 6b). Among the open datasets, the most popular is the ACN one, used in 44.44% of the studies, whereas the one from Boulder, Colorado, has also been widely used (12.69%). Nevertheless, 55% of the cases still resort to data that are either company-owned or collected specifically for the study (Figure 6a), making it not possible to make them public because of privacy concerns.

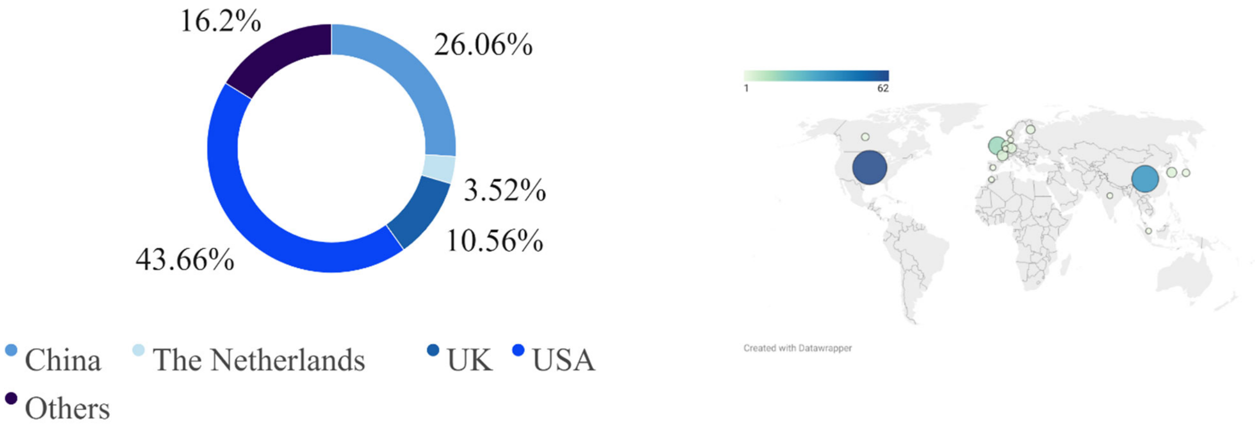
It is important to note that some of these data are accessible for research purposes upon request to the articles' authors.



(**a**) (**b**)

Figure 6. Percentage of the studies that used publicly available data, private data, and simulated data: (**a**) Time period: 2012–May 2024; (**b**) Per year.

Figure 7a shows the percentage of studies that use real-world data acquired from different countries, whereas Figure 7b illustrates their geographical distribution. The US and China dominate the landscape. In this line, they lead not only the EV market, as shown in Figure 1, but also the development of data acquisition infrastructure for EV research purposes. European countries, mainly the UK and the Netherlands, also offer researchers the possibility of using local real-world EV charging sessions' data, but these data have been used to a much lesser extent.



(**a**) (**b**)

Figure 7. Percentage of the studies that used data from different countries: (**a**) Time period: 2012–May 2024; (**b**) Per year.

5.1.1. Feature Engineering

Data availability relates tightly to the features that can be used as input of the ML techniques to build the forecasting model. Figure 8 shows the features used in the SLR articles to forecast EV charging sessions' demand per year. While 39% of the studies resort only to historical EV charging session data, 61% of them include exogenous features in addition to them, showing that ML models have been increasingly adapted to the EV charging forecasting domain. In general, researchers agree that considering weather features, such as temperature, and calendar features—including weekdays, weekends, and holidays—to train the ML model can improve its forecasting accuracy [63]. In this scenario, DL-based methods that are capable of efficiently processing complex multivariate time series can be particularly useful, offering advantages with respect to conventional ML ones.

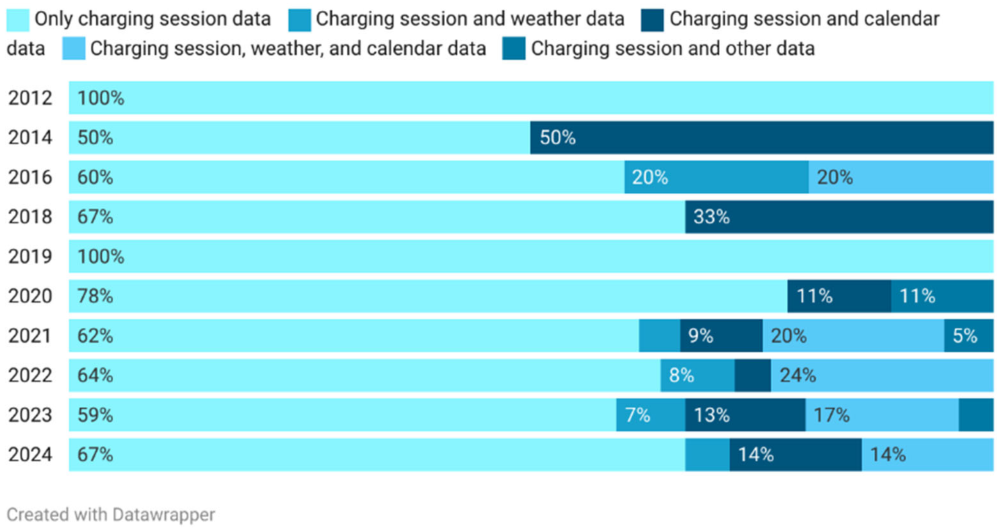


Figure 8. Percentage of studies using different types of features to forecast EV charging sessions' demand per year.

Many SLR studies have shown the benefits of including different variables in the EV charging session demand forecasting process. On the one hand, weather features and seasonality impact EVs' charging demand forecasting accuracy [47,64,65]. In [65], LSTMs, GRUs, and adaptive network-based fuzzy inference systems (ANFIS) were used to forecast the hourly average EV charging demand over the seasonality effect, with ANFIS obtaining the best results, with an accuracy of 99.3% in winter. The results of [65] showed that seasonality has a great impact on the EVs' consumption profile since batteries' charging and draining depend on the use of the air conditioner and the heating. Researchers of [64] agree with these observations and add that, according to their exploratory data analysis, charging time and temperature are inversely correlated. In [64], the seasonality effect on the EV charging session demand consumption prediction was evaluated resorting to different regression methods, reaching RF the best performance (Mean Absolute Percentage Error [MAPE] = 0.08% and an RMSE = 2.27). In particular, date features, including day, weekday, and weekend, and seasonal features, distinguishing between winter, fall, spring, and summer, were used. The results of [64], obtained on the Boulder dataset, showed that the EV consumption reaches its minimum in winter, but the charging time is the maximum, decaying in fall, spring, and summer, accordingly.

On the other hand, calendar features influence the EV users' behavior and charging pattern [44,66]. In [44], the capability of LSTMs and GRUs for EV charging demand forecasting at different time horizons (24, 28, and 72 h) was evaluated. Six different models were trained on the ACN dataset: univariate LSTM and GRU, combined CNN-LSTM and CNN-GRU, and multivariate LSTM and GRU. The multivariate versions considered the time of day and the month of the year, reducing over 60% of RMSE and over 40% of Mean Absolute Error (MAE). In [66], the influence of data types on the driving behavior of private EV owners was evaluated. Four travel destinations—business, working, recreational, and living areas—and two date types—working and resting days—were considered. The EV charging demand was forecasted based on a multiple linear regressor that used the driving time as the dependent variable. Results of [66], obtained from the U.S. Department of Transportation travel data (https://www.bts.gov/ (accessed on 25 November 2024)), suggest that date type affects EV charging demand at working areas rather than at living areas.

According to the SLR results, 10% of the studies include weather features, 21% of them include calendar features, and 23% include both in addition to historical charging data.

More specifically, when forecasting EV charging sessions' power consumption, 33.57% of the studies include weather features, 42.33% include calendar features, and 24.08% include both; while to predict the EV charging sessions' duration, 25% of the articles include weather features, 40% include calendar features, and 20% use both. These results show that the multivariate forecasting strategies proposed in the SLR are similar in both applications: EV charging session power consumption and duration. Nevertheless, taking into account the observations in [64], where the fact that temperature is in inverse proportion to EV charging session duration, further inclusion of weather features should be considered in this application. Finally, other types of features have also been proposed to complement EV historical charging session data: electricity price or charging fees [67–77], cost savings [78], gasoline savings [45,78–80], GHG savings [45,64,78,80], and grid savings [64].

Most of the works in the SLR that include calendar features consider day-type features, such as weekdays and weekends, and seasonal features, such as the month of the year, week number, and day of the month. According to [31], including not only national, but also local holidays could significantly improve forecasting performances. Nevertheless, only 23.88% of the articles that include calendar features take into account holidays. For instance, in [33], the short-term forecasting of individual charging sessions' consumption and time of EVs belonging to a company's EV fleet was performed by integrating information about charging sessions' duration, drawn power, and SOC, with information about weather, holidays, and company events. Different ML-based methods were compared for the forecasting task, including XGBoost, ANNs, LSTM, GB, and SVM, yielding the former the best results. In [81], a parallel-structured ST mutual residual graph convolution-combined Bi-LSTM model is proposed to forecast EV charging session consumption, considering historical charging session data and external factors, such as weather conditions, holidays, and weekends, in the day-type tendency features. These features were processed as follows. First, a mutual adjacency matrix (MAM) was built to consider both static and dynamic attributes of EVCSs. Based on the MAM matrix combination with graph convolution and residual blocks, the multi-level spatial dependencies were captured and the relations between nodes and external factors were mapped. Then, temporal features were considered based on a Bi-LSTM combination, which includes day-type tendency features. Finally, a parallel structure is built to preserve ST dependencies in the final prediction.

As introduced in Section 2.2, feature selection is one of the most critical steps in the ML modeling process, significantly influencing its performance. Moreover, even in the case of DNNs, which can handle large amounts of high-dimensional data without the need for explicit feature selection and expert domain knowledge, carefully choosing the data that will train the ML model is crucial to optimizing the process in terms of time and resources. Many of the SLR studies have resorted to a correlation analysis to determine the most relevant features to predict the EV charging session demand consumption or time duration [31,62,71,82,83]. Another widely used technique in the SLR to classify and better interpret features before training the ML models is feature clustering based on K-means [46,84–91]. In general, they use the K-means algorithm to cluster the charging demand curves of EVs into different categories toward better understanding the patterns and randomness in the charging behavior of EVs. For instance, in [91], K-means clustering was used to group EVCSs into different regions in Copenhagen. In [46], the impact of the beginning of the COVID-19 pandemic (12 December 2019 to 1 February 2020) on the EV charging demand of a charging pile in Beijing was evaluated based on historical charging data. K-means was used to cluster data into three groups, categorized in terms of how the epidemic affected them, from "not affected" to "just affected" and "affected". The forecasting was performed on an LSTM model, which outperformed other RNNs and CNNs. In [90], the impact of the charging demand of a large group of EVs connected to a regional power distribution network in Hubei province, China, was forecasted. The data was collected during the winter—when the number of EVs reaches a peak—from 2014 to 2017. The proposed forecasting approach integrated K-means and LSTM. In particular, K-means clustered the data obtained from the power grid into daily patterns with similar characteristics to improve prediction accuracy. The forecasted daily demand was then used to estimate the EV volume in 2025 through the Bass model, which is a nonparametric conditional likelihood model widely used in the literature for new product demand prediction [90]. According to the simulation results of [90], the number of EVs in Hubei province in 2025 will be 955,363.

In addition, different feature selection techniques have been used in the SLR. In [92], fast and historical features were distinguished using a multi-source feature selection algorithm. According to [92], the former are dynamic features, including drawn energy, weather features, mobility data, and EV driving patterns, which are well suited for real- or near real-time learning tasks like EV charging demand forecasting. The latter are static features, such as the car, battery, user, EVCS, and location profiles, which are suitable for batch or relational learning tasks like EV user behavior analysis. In [64], a Boruta feature importance algorithm was used to select the most relevant features to predict the EV charging session demand consumption and evaluate the seasonality effect, resorting to different ML methods, reaching RF the best performance. In [93], the impact of different factors on the EV charging sessions' energy consumption at EVCSs was assessed based on Shapley additive explanations (SHAP). SHAP is a model-agnostic framework based on game theory that allows comprehending ML algorithms through visualization [94]. According to the results of [93], the charging time is the most influential feature, followed by the maximum power, idle time ratio, transaction ID, start hour, day of the week, connection time, connector, season, coded peaks, day/night, and peak. The work presented in [93] sheds light on the long-standing concern of the lack of interpretability of ML models, especially DL ones.

5.2. ML-Based Approach

The nature of the data related to EV charging session demand forecasting defines a time-series forecasting problem. Figure 9 shows the ML-based approach that obtained the best performance in each SLR study. Details about the core ML technique proposed in each article, the benchmark methods used for comparison purposes, and the ML-based approach that obtained the best performance are shown in Table A3 (Appendix A).

According to the results synthesized in Figure 9, EV charging sessions' demand forecasting has been mainly addressed by DNN-based methods. This suggests that their ability to handle complex, large, and multivariate data, being highly adaptable to updating data and scalable, makes them better suited than traditional ANNs and conventional ML techniques, such as support vector (SV)-based ones and DT ensembles, for EV charging session demand prediction. In particular, the best results have been obtained principally with RNN-based approaches, including LSTM, BiLSTM, and GRU. RNNs' architecture is capable of processing data across different time steps, being well suited to time-series forecasting applications. Moreover, RNNs have advantages with respect to traditional statistical methods—mainly used for univariate forecasting—in the cases of multivariate time-series forecasting, where not only the historical EV charging sessions' data is considered, but also the relationship with other time series, such as weather data, is modeled [44,95–97].

Among the RNN-based approaches, LSTM is the most widely used, with 35% of the articles obtaining their best performance on its basis. LSTMs and GRUs address challenges like gradient vanishing issues encountered in traditional RNNs. LSTMs consist of three gates—input, forget, and output—and a separate memory cell that can store and update information over long time periods. The input gate controls the amount of information to be added to the cell state, the forget gate discards information from the cell state, and the output gate determines the part of the cell state that should be output at the time step [97]. This three-gated architecture provides flexibility and more control over memory and information flow, while its complexity makes LSTM suitable for long-term forecasting. On the other hand, GRUs are simpler than LSTMs, combining the cell and the hidden state, consisting of only two gates: the update gate, which controls the amount of past information to keep and the amount of new information to incorporate, and the reset gate, which decides the amount of data to forget. GRUs' simplicity makes them faster to train and easier to implement and tune, being well suited for real-time applications and reducing the risk of overfitting [97]. According to [97], LSTMs are well suited for high-complexity time-series forecasting applications, whereas GRUs are better suited for low-complexity cases. This explains the preference for LSTMs over GRUs for EV charging sessions' demand forecasting. In addition, this is in line with the current trend in the field of electrical load forecasting, where LSTM models are widely used [98].

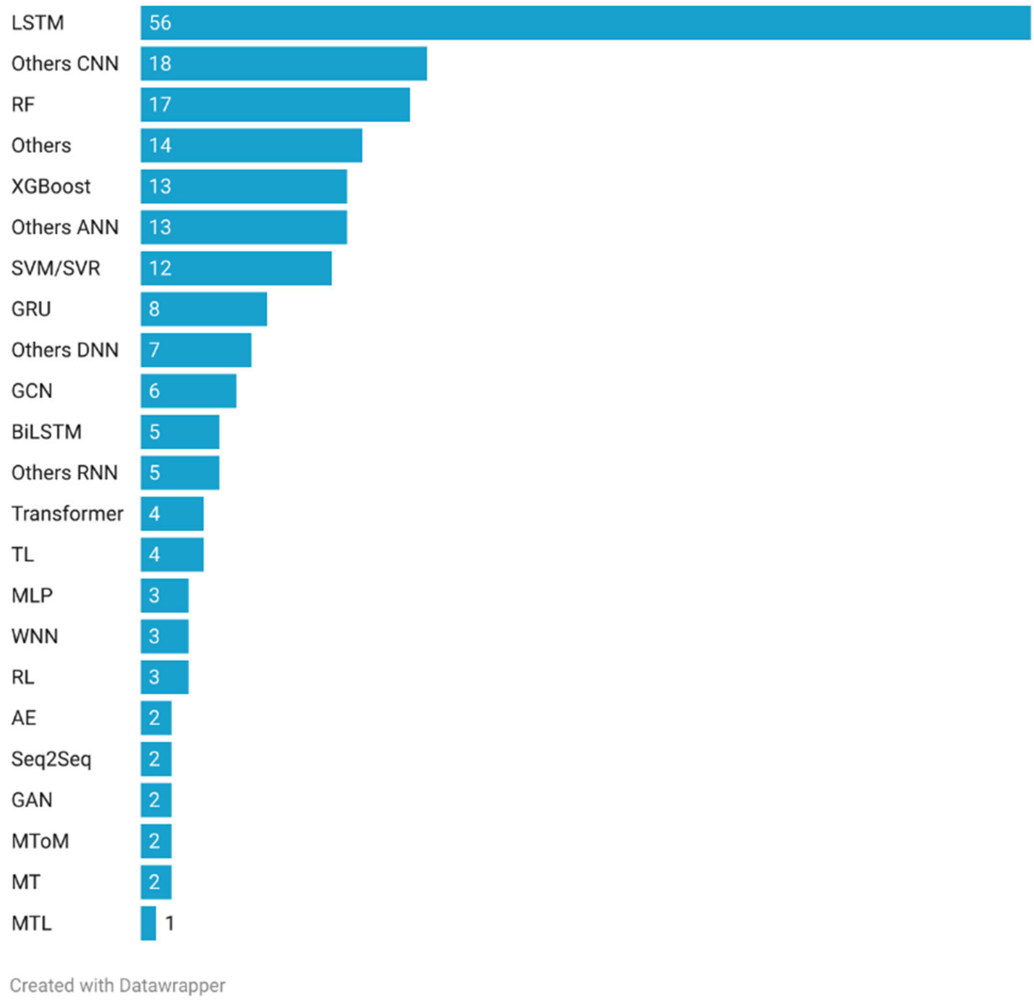


Figure 9. Machine learning techniques obtained the best performance in SLR studies. Note. AE: autoencoder; ANN: artificial neural network; BiLSTM: Bi long-short term memory; CNN: convolutional neural network; DNN: deep neural network; GCN: graph-convolutional network; GRU: gate recurrent unit; LSTM: long-short term memory; GAN: generative adversarial network; MLP: multi-layer perceptron; MT, MTL: multi-task learning; MToM: machine theory of memory; RF: random forest; RL: reinforcement learning; RNN: recurrent neural network; SVM/SVR: support vector machine/regression; TL: transfer learning; WNN: wavelet neural network; XGBoost: extreme gradient boosting.

According to the SLR results, LSTMs are the gold standard to predict EV charging session demand, outperforming not only the traditional ML models most used in the field, such as SVM/SVR [82,99–104], and DT ensembles [82,101,102,105], but also other powerful DL methods, including other RNNs [87,106–113], GRU [44,104,106,110,112,114,115], and CNN [44,87,106,108,112,113]. In addition, LSTMs have been demonstrated to adapt well to a wide variety of EV charging session demand forecasting scenarios. In particular, although they have been mainly used for short-term horizon predictions, they are the best suited to address medium- and long-term ones [111,116,117] (see Section 5.3.4). This is an outstanding advantage due to the complexity of long-term horizon predictions and the lack of research in this direction. Nevertheless, it is important to highlight that, similarly to all DNN-based models, they are computationally expensive and complex to tune. In addition, they require large training datasets to perform well, which may not be the case with every EV charging scenario. Finally, their lack of interpretability can hinder deployment in critical grid operations.

Long-short term memory models are highly sensitive to hyperparameter tuning, including architectural ones (number of hidden layers and units, and activation function), learning rate, number of iterations, regularization type, and batch size [39,43,54]. In this line, several works in the SLR have proposed fine-tuning strategies to improve their performance. In [106], random search (RS) was used to optimize the hyperparameters of an LSTM to forecast the daily EV charging demand. Unlike the widely used grid search (GS), which conducts an exhaustive (and computationally expensive) search that evaluates all the hyperparameter combinations within the grid configuration, RS considers random combinations, minimizing the computational complexity [54]. Using this tuning strategy led the LSTM to outperform RNNs, CNNs, and GRUs, in terms of $R^2 = 0.97$ and Mean Squared Error $(MSE) = 0.0025$. In [63], Bayesian optimization (BO) is proposed to tune LSTM's hyperparameters toward improving its capability of forecasting day-ahead EV charging consumption with a time resolution of 15 min within the context of a private hospital charging site. BO iteratively detects the optimal hyperparameters on a surrogate model of the objective function instead of using the real one, applies them to the real objective function, and updates the surrogate model [54]. In this way, it is more efficient than GS and RS algorithms since training a surrogate model is cheaper than training the real objective function. Three different experiments were conducted in [63]. First, only the historical charging data, EV charging demand, and the average weekly EV demand were used. Then, calendar features—quarter-hour number, day number, working day, and holiday—were included. Third, weather, temperature, and rainfall features were used. The results of [63] showed that the BO-optimized LSTM reduced the MAE by 23.2% and the RMSE by 19.22% when including calendar features, while when using weather features, the MAE was reduced by 28.8% and the RMSE by 16.16%. In [118], a genetic algorithm (GA) was used to determine the optimal set of parameters to efficiently combine Prophet and LSTM models toward predicting the daily charging capacity of an EVCS in a southern Chinese city. GAs are metaheuristic nature-inspired algorithms capable of finding high-quality solutions to optimization and search problems via operators such as selection, crossover, and mutation [54]. In particular, they evolve a population of candidate solutions toward better solutions, based on mutations and alterations. Based on the GA optimization approach proposed in [118], the combination of Prophet's periodic prediction trend—based on its capability of handling large-scale time series considering the changing trend, periodicity, and holiday effect of data—and the high precision prediction of LSTM at a single point improves the EVCS charging capacity forecasting.

Despite the supremacy of LSTMs, there are cases in the SLR where GRU outperforms them. In a case study conducted in Morocco, a single hidden-layered GRU model outperformed it as well as other ANNs and RNNs in predicting EVCS power demand [49]. The results of [49], obtained on a dataset consisting of 2000 observations collected from two public EVCSs in Morocco, showed that although LSTM yielded better results than ANNs and RNNs, especially in the peak hours, it performed poorly during low energy demand periods. On the other hand, GRU achieved the best results in terms of RMSE and MAPE. In [74], the performance of LSTM, RNN, and GRU to predict the short-term EVCS charging demand on an hourly basis was evaluated. The data, owned by an EVCS company in Shenzhen, China, included charging time, charging quantity, and real-time electricity price. The results in [74] showed that GRU outperformed RNNs and LSTMs in terms of the normalized RMSE (NRMSE) = 2.89% and normalized MAE (NMAE) = 0.77%.

Convolutional neural network-based methods, including graph convolutional networks (GCNs) and temporal convolutional neural networks (TCNs), have obtained the best performance in 15% of the SLR studies. CNNs are a regularized type of FFNN capable of automatically learning features via kernel optimization. They consist of a convolutional layer that extracts features from the input, a pooling layer that reduces dimensionality, and a fully connected layer that receives the input from the previous layer and processes the output [119]. Although CNNs are used mainly for two-dimensional processing tasks, such as image processing, they can be adapted to forecast one-dimensional data. On the one hand, GCNs handle graph-structured data by leveraging both the nodes' features and their locality. On the other hand, TCNs capture hierarchical relationships at different time scales. The main advantages of CNNs for the EV charging session demand forecasting application are their capacity for learning spatial/structural patterns, as well as their efficiency on large-scale data.

In recent years, advancements in sensing technologies and the widespread use of Internet of Things (IoT)-based EV charging data management infrastructure have made available diverse EV charging-related data [120]. Traditionally, EV charging sessions' demand forecasting has focused mainly on temporal data. Nevertheless, spatial features, such as the EVCSs' location and availability, influence EV charging demand, and considering them can improve forecasting accuracy. The availability of spatial data in addition to the traditionally used temporal data challenges researchers to develop EV charging sessions' demand forecasting approaches capable of extracting and capturing the underlying ST patterns and their correlations properly. The SLR has shown an increasing trend in ST-based methods to forecast EV charging sessions' demand, with several studies proposing architecture modifications to better capture EV-specific characteristics. In this scenario, and due to their capability for feature extraction, many works have combined CNNs, mainly GCNs, and RNNs, especially LSTMs, leveraging the former's ability to capture spatial information and the latter's efficiency for modeling the temporal correlations of the data [11,78,81,117,121–126]. This combination has already shown promising results in electrical [127] and residential [128] load forecasting. Table 5 summarizes the main CNN-based approaches in the SLR addressing ST modeling, including their proposals, and describes the context in which the forecasting took place. It is important to highlight that all these ST-based adaptations have been published since 2020, suggesting a growing trend toward domain-specific model tuning in the field of EV charging demand forecasting.

Table 5. Main CNN-based approaches in the SLR addressing ST modeling.

Ref.	Year	Proposed Method	Application
[129]	2024	Luong AM-based recurrent CNNs.	Short-term forecasting of EV charging sessions' energy consumption at public EVCSs (aggregated) from different Chinese regions.
[117]	2024	GCN-LSTM	EV charging sessions' energy consumption forecasting at public EVCS (aggregated) with a monthly resolution for the next two years.
[78]	2023	CNN-GRU-JBOA	Short-term forecasting of individual EV charging session time, consumption, GHG savings, cost savings, and gasoline savings at public parking areas.
[124]	2023	CNN-GRU-ISSA	Short-term EV charging sessions' energy consumption forecasting at workplace (aggregated).
[125]	2023	CNN-LSTM-Transformer	Short-term EV charging sessions' energy consumption forecasting at public EVCS (aggregated).
[126]	2022	CNN-AM-GRU	Daily-ahead probability density of EV charging demand forecasting for a group of EVs within the context of residential charging.
[81]	2024	Mutual residual GCN-Bi-LSTM	Short-term EV charging sessions' energy consumption forecasting at workplace (aggregated).
[123]	2023	ConvLSTM and BiConvLSTM	Daily EV charging sessions' energy consumption forecasting at EVCSs (aggregated).
[75]	2021	MLP-based attention-based GCNN	Daily EV charging sessions' energy consumption forecasting at different public EVCSs (aggregated).
[122]	2024	Spectral clustered CNN-LSTM	Daily EV charging sessions' energy consumption forecasting at public EVCSs (aggregated).
[120]	2024	Federated MT-based GCN	Short-term EV charging sessions' energy consumption forecasting at public EVCSs (aggregated).
[130]	2023	Hybrid CNN-BiLSTM-T transfer learning-based model	Short-term EV charging sessions' demand and system voltage forecasting at different public EVCSs (aggregated).
[131]	2022	Dilated Causal CNN	Short-term EV charging sessions' energy consumption forecasting at different public EVCSs (aggregated).
[91]	2023	Temporal GCN	Daily EV charging sessions' energy consumption forecasting at different public EVCSs (aggregated) based on EVCS occupancy data.

Note. AM: attention mechanism; BiLSTM: bidirectional LSTM; CNN: convolutional neural network; EV: electric vehicle; EVCS: electric vehicle charging session; GCNN: graph convolutional network; GRU: gated recurrent unit; LSTM: long-short term memory; MLP: multi-layer perceptron; ST: spatio-temporal.

Together with the rise of CNN-LSTM hybrid methods to capture spatial correlations between EVCSs and temporal trends in usage patterns, transformers [125] (see Table A3), [121] and FL paradigms [120] have also been adopted to improve scalability in distributed datasets. For instance, in [120], a sophisticated model for EV charging sessions' demand forecasting at different Chinese regional levels was built on a federated meta-learning (MT) concept implemented with GCNs. The FL is a collaborative learning that enables decentralized training [120]. MT, also called "learning to learn", trains ML algorithms on metadata for the sake of flexibility. In [120], the generalization ability of the proposed approach was particularly evaluated. The dataset consisted of information from 25,246 public EV charging piles, including EV charging sessions' demand, geographic information, socio-economic indicators, and weather features. The approach proposed in [120] consisted of two modules that perform the main tasks: the ST modeling and the distributed training. The ST module captured the charging patterns of the different cities and regions. First, an ST attention-based mechanism calculated the correlation of EV charging sessions' demand in ST dimensions. Then, spatial and temporal features were extracted via spatial and temporal convolutions, respectively, and a linear decoder performed the prediction. Finally, the distributed pre-trained module used federated MT to enhance the generalizability of the forecasting. The results of [120], evaluated by MAE, RMSE, MAPE, and R^2, showed the superiority of the proposed federated-based MT approach not only in terms of EV charging sessions' demand forecasting accuracy, but also in the speed of convergence, accelerating it 62.16% on average compared to baseline methods. Moreover, the model proved to be highly generalizable, obtaining $R^2 > 0.85$ in most of the regions. These results suggest that the combination of FL, MT, and ST feature modeling can efficiently adapt to different prediction tasks, where the data of each client is isolated and heterogeneous and perform well across several regions. This is a promising result to support related services, such as smart grids. In [121], EV trajectory and charging data were collected for the Chinese city of Wuhan. A graph attention (GAT)-based autoformer approach was proposed to forecast the EV charging demand. On the one hand, the GAT, which integrates GCNs and an attention mechanism (AM), handles spatial information. On the other hand, the autoformer is responsible for the temporal information. Autoformers are transformers where an autocorrelation mechanism is employed rather than the self-AM, and a deep decomposition architecture is incorporated to enhance the performance in long-term time prediction applications. Results in [121] showed that the GAT-based autoformer outperforms other LSMT- and transformer-based approaches in terms of MAPE, MAE, and RMSE.

Despite a remarkable trend of using DNNs being identified in the SLR, DT ensembles, mainly RF and XGBoost, have also been utilized, outperforming other ML techniques in 10.62% and 8.12% of the SLR studies. Ensembles train several individual ML techniques and combine their outputs to improve the accuracy compared to the case of using each of them separately [41]. DT ensembles combine DTs, which are well-known tree-like structured ML models that can be used for regression or classification tasks [132]. Individual DTs are usually prone to overfitting, have high variance, and lack robustness to noise and outliers [132]. DT ensembles overcome these drawbacks. In addition, they are more robust to hyperparameter optimization (number of trees, maximum tree depth, feature sampling, and regularization [54]) than DNNs, which represents an advantage in EV charging forecasting applications where fine-tuning is not possible or a fixed-hyperparameter ML model needs to be flexible enough to perform well in different scenarios. For instance, in [31], different ML techniques—LinR, ANNs, LSTM, CNN, and DT-ensemble methods (GB, AdaBoost, bagging, and RF)—were used to forecast EV charging power demand at different aggregation levels, including a group of EVCSs, a postal code level, a TSO zone level, an EV portfolio, and random site groups of various sizes. DT ensembles outperformed the others, showing AdaBoost, bagging, and GB robustness across all the aggregation levels. In particular, AdaBoost obtained the best results, with an NRMSE of 0.42 and a mean absolute scaled error of 0.36. On the other hand, RF had difficulties in handling finer data granularity, but outperformed AdaBoost (NRMSE = 0.41 and mean absolute scaled error of 0.34) at the highest aggregation level. According to the authors of [31], the poorer performance of DNNs on the evaluated application could be due to the hyperparameters' selection, which was chosen to cover as wide a range as possible. In this line, as DT ensembles are more robust to hyperparameter optimization, they resulted in being better suited to deal with different aggregation levels. In the same line, in [47], the accuracy of MLP, XGBoost, LSTM, CNN-LSTM, Bi-LSTM, GRU, and transformers to predict EV charging session consumption was studied. All the ML models were trained at different training epochs (from 50 to 200), and their forecasting accuracy was assessed at the short-to-medium-term horizon of 7 to 28 days. Results of [47] showed that XGBoost outperformed the other techniques, obtaining an MSE, RMSE, and MAE of 3117.32, 55.83, and 44.57, respectively, when using 150 epochs, demonstrating DT ensembles' robustness to hyperparameter optimization and multi-scale horizon predictions.

Despite their strengths, it is important to note that DT ensembles are not the ideal choice for forecasting long temporal sequences, as can be the case in EV charging sessions' demand forecasting, and that DT-based ML models have drawbacks in capturing the trend component of the data. In this line, when using them, it is common to apply time-series processing techniques to handle the trend and seasonality components of the data. In [133], DT ensembles—RF and XGBoost—were employed to forecast the short-term EV charging sessions' power consumption aggregated at the fast chargers installed nationwide in Korea. Features included calendar data, power records, the names of the EVCSs, the region where they were located, and the start and end times of charging. To overcome DT-based ML algorithm drawbacks in capturing the trend component of the data, traditional statistical models, such as ARIMA, were used to handle the trend, whereas Fourier terms were proposed to capture seasonality. The model implemented in [133] using statistical time-series techniques combined with DT ensembles showed promising results. In particular, the one using RF outperformed the one that employed XGBoost, with an RMSE of 0.299 and 0.301, an MAE of 0.199 and 0.210, and an MAPE of 4.107 and 4.285, respectively.

Although to a lesser extent, SV-based methods—SVM (classifier) and SVR (regressor)—first introduced in [40], have also been used in EV charging sessions' demand forecasting applications, obtaining the best results in 7.5% of the SLR studies. SVM aims to find the optimal hyperplane that separates different classes in a high-dimensional space in such a way that its distance to the closest data point of each class, called margin, is maximized [40]. SVM is well suited for nonlinear applications due to the so-called "kernel trick" that allows using kernel functions—being linear, polynomial, or radial basis function (RBF), the most popular—to map data into high-dimensional spaces without the need to explicitly compute the transformation. SVR is an extension of SVM to address regression problems [40]. SVR has been demonstrated to be efficient for time series forecasting, especially for high-dimensional and nonlinear cases, and does not suffer from overfitting issues.

Support vector machines and SVR have the great advantage of being suitable for small datasets due to their strong generalization, based on the hyperplane's margin maximization principle; their regularization capabilities, through a hyperparameter that controls complexity and overfitting, preventing the models from fitting noise; and their ability to model complex patterns with limited samples through kernel methods. In this line, they can be of great help when dealing with scarce data. When no sufficient data are available, ML-based models have no data but the inputs to learn, so they "learn" them, leading to overfitting. In these cases, for instance, in new charging stations or small ones, researchers face the so-called "cold start forecasting problem" [101]. SVM and SVR are well suited to address forecasting in these cases. In [134], SVM was employed to forecast the ultra-short-term EV charging demand in a small EV charging station.

Nevertheless, the generalization capability of SVM and SVR strongly depends on their hyperparameters, including the kernel selection, the kernel's parameters, and the regularization parameter, having the disadvantage of being highly sensitive to their optimization [54]. In this line, when using SVM or SVR, it is common to improve their performance through dedicated hyperparameter optimization techniques. In [134], the improved version of a relatively new swarm-based algorithm called Improved Northern Goshawk Optimization (INGO) [135] was used to enhance the SVM performance for ultra-short-term demand forecasting in a small EVCS. The NGO algorithm belongs to the family of nature-inspired metaheuristic optimization methods, which includes swarm-based algorithms and GAs, being able to solve non-convex, non-continuous, and non-smooth optimization problems [54,135]. In particular, the NGO algorithm mimics the goshawk's hunting strategy, consisting of two phases: prey identification and tail, and chase. It simulates a population of "goshawks" (candidate solutions) and searches for the optimal solution to a problem [135]. The improved version, INGO, switches between exploration and exploitation to avoid being stuck in local optima and increases search capabilities through Lévy flight [135]. The proposed approach in [134] consists of three phases. First, Variational Mode Decomposition (VMD), which has been identified as one of the main techniques used to process time series within the context of EV charging session demand forecasting, was applied to the charging demand time series to extract multiple modal components at different frequencies, enhancing the representation of temporal features. Second, climate-based and holiday data were combined to improve the NGO algorithm using Tent mapping and the Lévy flight strategy. In this way, the optimal SVM parameters of each component were determined. Finally, the EV charging demand forecasting is obtained by aggregating the outputs of the individual SVM models. Comparisons held in [134], with and without including the INGO strategy, demonstrate the need for hyperparameter optimization.

The SLR results shown in Figure 9 (and Table A3) show a remarkable trend in using DL methods, mainly LSTM and CNN, which have outperformed other ML techniques in 50% of the reviewed articles. Moreover, as shown in Table 5, they have demonstrated great potential when used together to model the complex ST patterns associated with many of the EV charging demand forecasting applications. Nevertheless, it is important to highlight that they are computationally expensive, complex to tune, difficult to interpret, and require large training datasets to perform well, which may not be the case with every EV charging scenario. As already discussed, in applications where robustness to hyperparameter fine-tuning is required, DT ensembles are a useful alternative to DNNs, and SV-based methods are a better choice when dealing with data scarcity. In addition, the SLR has revealed a growing trend to resort to advanced ML techniques, such as FL [120], MT [120,136], and transfer learning (TL) [92,101,136], which enable decentralized training, providing flexibility and generalization power within the context of both limited data and fine-tuning issues. As already discussed, in [120], a distributed pre-trained module used federated MT to enhance the generalizability of the EV charging demand forecasting, demonstrating the efficiency of FL and MT to adapt to different prediction tasks, where the data are isolated and heterogeneous, and performing well across several locations. In the same line, TL is an ML paradigm that consists of pre-training a preliminary model on a large dataset and then fine-tuning it on the target (usually smaller) dataset [92,101,136]. In [92], a theoretical framework that combines TL and continual learning (CL) was proposed to address the issue of limited data. Whereas TL allows pre-training on a large dataset and fine-tuning on a smaller one, CL enables continuous learning from new data instances. Then, the approach proposed in [92] allows training the EV charging demand predictor based on DL on limited data and updating it without forgetting past knowledge on a different (larger) dataset. This type of technique provides flexibility, adapting to changing data distributions. Authors of [136] proposed a similar approach, using TL and model-agnostic MT (MAML). MAML overcomes TL's potential fine-tuning drawbacks by being trained on different learning tasks that can then solve new learning tasks on a smaller dataset. The approach in [136] leverages the capabilities of TL and MAML for working within limited data contexts to forecast short-term EV charging demand based only on data from 10 and 20 days. The models were first trained on the Boulder, Colorado dataset [137], and then fine-tuned on the ACN [59] and Trondheim, Norway [138] datasets. In both cases, LSTMs were used. Results of [136], in terms of MAE, RMSE, and R^2 score, obtained by training LSTM models on data from 10 and 20 days, showed that TL and MAML yielded the best accuracy for the ACN and

Norwegian datasets, respectively. In addition, both outperformed LSTMs, demonstrating their forecasting potential across multiple locations and time scales. In [101], TL was used to forecast the plug-out hour and the consumed energy of residential EV charging sessions. The TL model, based on GANs, was implemented by freezing the middle layers of the pre-trained DNN, and a shortcut between the input and output layers was made during backpropagation. In particular, first, the plug-hour was forecasted. Then, it was used as a complementary feature to estimate energy consumption. Results of [101] showed that TL can improve the forecasting accuracy up to 31% and 34% for the plug-out hour and consumed energy, respectively, compared to other baseline ML and DL techniques. In addition, the inclusion of the plug-out hour as an auxiliary feature to predict energy consumption further contributed to enhancing the performance of the proposed TL-based approach. Results of [92,101,120,136] demonstrate how FL, TL, and MT offer generalization (even with limited training data), flexibility, and adaptability to multi-location multi-scale EV charging sessions' demand forecasting applications.

Finally, Table 6 summarizes the advantages, disadvantages, and limitations within the context of the EV charging session demand forecasting application of the most widely used ML methods identified in the SLR, namely LSTM, GRU, CNN, RF, XGBoost, and SVR.

Table 6. Comparative Analysis of ML Methods for EV Charging Session Demand Forecasting.

Algorithm	Advantages	Disadvantages	Limitations
LSTM	- Captures long-term dependencies - Models nonlinear, multivariate time-series - Adaptable to different time scales	- High computational cost - Complex tuning - Lack of interpretability	- Requires large training datasets - Risk of overfitting with short-duration sessions
GRU	- Fewer parameters than LSTM - Faster convergence - Suitable for real-time scenarios	- Less expressive for long-term dependencies - Lack of interpretability	- Best for short- to mid-term forecasts - Limited performance in multi-station modeling
CNN	- Learns spatial/structural patterns - Efficient in large-scale data	- Requires costly architecture tuning - Lack of interpretability	- Better suited to ST fusion - Needs combination with RNN for sequences
RF	- Robust to noise - Low overfitting risk	- Biased toward dominant features	- Ineffective in capturing sequential behavior - Drawbacks in handling trend components of the data
XGBoost	- High predictive accuracy - Fast training - Built-in feature importance ranking	- More sensitive to noise than RF	- Not ideal for long temporal sequences - Drawbacks in handling trend components of the data
SVR	- Effective in high-dimensional spaces - Strong generalization with small datasets	- Sensitive to kernel and hyperparameters - High computational cost	- Poor scalability to large datasets - Limited performance on temporal/sequential data

Note. CNN: convolutional neural network; GRU: gated recurrent unit; LSTM: long-short term memory; RF: random forest; RNN: recursive neural network; ST: spatio-temporal; SVR: support vector regressor; XGBoost: extreme gradient boosting.

5.2.1. Hyperparameter Optimization

As introduced in Section 2.2, the hyperparameter tuning is a crucial step in the ML modeling process, significantly influencing its performance. The hyperparameter sensitivity, which refers to the model's performance variations in response to changes in these settings, is different for each of the most widely used and best performing ML techniques identified in the SLR shown in Figure 9 (and Table A3). Moreover, according to [31], the temporal structure of the EV charging sessions' related data increases the hyperparameter tuning complexity within the context of EV charging sessions' demand forecasting applications. In this scenario, a widely used validation strategy is the so-called walk-forward technique, which mimics real-world situations where the ML model is trained (on the validation dataset) on past data and subsequently evaluated on future data points. In [31], the walk-forward technique was implemented to optimize the hyperparameters of different ML models, including AdaBoost, RF, CNN, and LSTM, among others, to forecast the EV charging sessions' energy consumption in the context of different charging scenarios and at different aggregation levels. ML models were first trained using historical data. Then, the first prediction corresponding to the forecasted time horizon was performed, and it was compared to the actual value of the predicted variable at the current time step. After that, the window was moved, and the training set was updated with the current values. The train-evaluate-update process was repeated iteratively. Finally, different combinations of hyperparameters were validated using the GS—one of the most commonly used hyperparameter optimization methods in the literature—through the walk-forward process. The hyperparameter combination suitability was assessed in terms of the average performance across all time steps, selecting the one that achieved the best overall results.

In the SLR, the GS is the most widely used technique for hyperparameter optimization. RS, BO, GAs, and swarm-based optimization algorithms, which are population-based optimization models that create and update a population with each generation, with each individual in every generation being evaluated until the global optimum is reached, were also used. Among the latter, Particle Swarm Optimization (PSO), which is inspired by the social behavior of birds and fish, is the most popular. PSO is capable of finding optimal solutions to various optimization problems by iteratively updating a population of candidate solutions, called particles, based on their own and their neighbors' best-known positions.

5.3. Application

5.3.1. Forecasted Variable

Most studies in the SLR address the EV charging sessions' electrical energy consumption forecasting, as shown in Figure 10. In fact, 78.48% of the articles are devoted to it, without considering the charging sessions' duration. The attention to the charging sessions' time-related parameters began in 2018. Nevertheless, although to accurately model the EV charging sessions' demand and evaluate its actual impact on the power system, it is crucial to consider not only the power drawn from the grid but also for how long it is drawn [50], only 14.55% of the SLR studies forecast both.

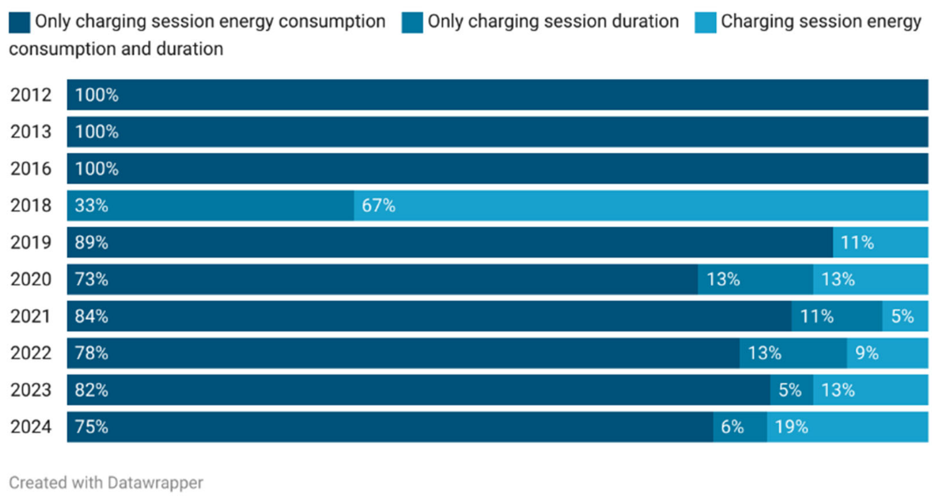


Figure 10. Percentage of forecasted variables per year.

Twelve percent of the studies forecast other variables in addition to the ones related to the EV charging sessions' demand considered in the SLR. It is important to note that since the SLR is focused exclusively on charging sessions' energy consumption and duration, this percentage may not represent all the existing literature about these variables. Among them, the following ones can be highlighted: number of charging sessions for each individual EV [50]; number of EVs charging in an EVCS [139]; number of times an EV will be charged in each time slot [82,102]; whether the next day will be a charging day or not [82,102]; planned day trips for each EV [105]; SOC level [140]; V2G services [141]; travel consumption [142], time [66], and speed [142]; GHG savings, cost savings, and gasoline savings [78]; traffic flow [142] and traffic congestion around EVCSs [143]; and occupancy of EVCSs [91]. These parameters can complement the information given to the EV stakeholders and help their decision-making. On the one hand, travel consumption, time, and speed; planned day trips; cost and gasoline savings; traffic flow; and traffic congestion around EVCSs are useful for EV drivers to reduce range anxiety and costs. On the other hand, the number of charging sessions for individual EVs, the number of EVs charging in EVCSs, and the number of times an EV will be charged in each time slot are especially helpful for EVCS managers to develop planning and scheduling strategies.

There are conflicting results in the literature regarding whether it is more difficult to forecast EV charging session consumption or duration [144]. In line with the results shown in Figure 9 (and Table A3), the most accurate forecasting of the electrical energy consumed during the EV charging sessions has mainly been obtained with LSTM-based approaches (39.37%), followed by CNN-based ones (17.32%), RF (8.66%), SVM/SVR (7.08%), GRU (5.51%), and XGBoost (4.72%). In addition, 12.59% of the studies resort to a combination of different ML techniques to achieve the best forecasting performance. In [145], where different traditional ML techniques were compared to DNNs, ensemble methods, such as RF and bagging regressors, outperformed LSTM and RNNs for forecasting the EV charging sessions' duration. In particular, in [145], RF, XGBoost, KNN, bagging regressors, LSTMs, and RNNs were used to forecast the charging sessions' duration for individual EVs in the context of a workplace parking charging station based on historical charging data, including power consumption, session duration, connection and disconnection times, and climatic data, such as wind, humidity, frost, rainfall, and temperature. The results of [145], in terms of MAE, showed a superiority of the bagging regressor and the RF approaches. In this same line, the SLR articles that are only devoted to EV charging sessions' duration forecasting obtained the best results using DT-ensemble methods, including XGBoost (23.07%), light GB machine (Light GBM) (23.07%), and bagging regressors (7.69%), whereas LSTM and CNN outperformed other ML techniques in 15.38% and 7.69% of cases, respectively. This shows a remarkable superiority of DT ensembles with respect to the gold standard LSTM for forecasting EV charging session duration.

Finally, for studies that forecast both the electrical energy consumption and duration of the EV charging sessions, LSTM and DT ensembles (RF and XGBoost) have a similar performance, obtaining the best accuracy in 25% of the cases each. In addition, hybrid approaches have been demonstrated to be useful in these cases, being employed in 15% of them. Researchers have resorted to different ML-technique combinations, including CNN and bidirectional GRUs (BGRUs) [78], tree bagger, LSTM, and KNNs [144], and a stacking ensemble of RF, XGBoost, SVM, and DNNs [146]. In [78], CNN and BGRU were combined to predict the short-term EV charging demand using a dataset of 150 EVs charged at the conference center parking station of the Georgia Institute of Technology campus in Atlanta, US. First, the input time series was decomposed by the empirical mode decomposition (EMD) technique. Then, CNN was used to extract local features. These features were used to train the BGRU model that was fine-tuned based on a hybrid Jarratt-

Butterfly optimization algorithm (JBOA). The hybrid approach EMD-CNN-JBOA-BGRU proposed in [78] outperformed autoencoder, RNN, LSTM, CNN, and BGRU, achieving 98.18% accuracy. In [144], the combination of a tree bagger, an LSTM, and a KNN was used to predict EV arrival time, EV charging energy demand, and EV plug duration, within a calendar day. The forecasted output was then input to a model predictive control (MPC), showing that the proposed hybrid approach helped to reduce the peak loads and monthly electricity costs over a baseline scenario [144]. In [146], a stacking ensemble of RF, XGBoost, SVM, and DNNs outperformed the individual forecasting power of each ML technique for short-term workplace-based EV charging session consumption and duration forecasting. The results of [146], obtained on the ACN dataset, showed the suitability of the proposed ensemble approach to predict EV charging session consumption and duration based on historical charging data, weather, traffic, and events data, yielding a symmetric MAPE (SMAPE) of 9.9% and 11.6%, respectively.

5.3.2. Charging Scenario

As introduced in Section 1 and described in Section 2.1, drivers can charge their EVs at private or public charging points. The former consists of the ones installed at home or at their workplace. The latter consists of public parking areas, such as the ones in shopping centers, university campuses, and airports, as well as public EVCSs, including regular AC or DC fast ones [7]. The statistical study conducted in [47] analyzes the EV charging demand in different charging station areas in Dundee, Scotland, across the seasons of spring, summer, autumn, and winter. According to its results, EV owners have a remarkable inclination towards home charging, especially during summer, accounting for approximately 28.70% of total EV charging demand. On the contrary, workplace EV charging is preferred during winter (approximately 25.70% of total EV charging demand).

The SLR results show that 90.5% of the studies forecast the EV charging sessions' demand in the context of EVCSs, either private or public. Figure 11 shows the number of articles addressing each of the main charging scenarios: residential, workplace, and public parking areas or public EVCSs from 2012 to 2024. At the beginning of the period, research was focused mainly on residential charging, in line with the fact that early adopters charged their EVs at home. Then, the interest in public EVCSs emerged. Since 2018, it has steadily grown, becoming the most explored charging scenario in recent years, in accordance with the EV popularization and the increasing demand for non-residential charging facilities. Finally, it is worth noting that workplace EV charging has been consistently studied since 2019, when the ACN dataset was made publicly available [59].

On the other hand, 9.5% of the articles study the EV charging sessions' demand forecasting of a group of EVs regardless of where they are charged. For instance, as discussed in Section 5.1.1, in [33], a commercial EV fleet is considered, whereas in [147,148], electrical bus lines are evaluated. According to [147], there is significantly more research addressing the charging needs of private EV fleets than those of electric buses. In [147], RF was used to forecast the bus charging demand for weekdays and weekends in 7 different locations for a selected bus line in Helsinki, Finland. Due to the lack of historical charging data, synthetic one-year period data was generated based on the real-world data of bus timetables, including the arrival time and SOC. The results obtained in [147] showed that RF outperformed SVM in terms of MSE, RMSE, and MAE. In [148], the prediction of the demand for a day of an electrical bus fleet was performed based on a wavelet neural network (WNN). First, spectral clustering was used to group the charging demand curves. Then, the charging demand for each cluster was predicted based on WNN taking into account weather and calendar features. Finally, the sum of each cluster resulted in the total day charging demand.

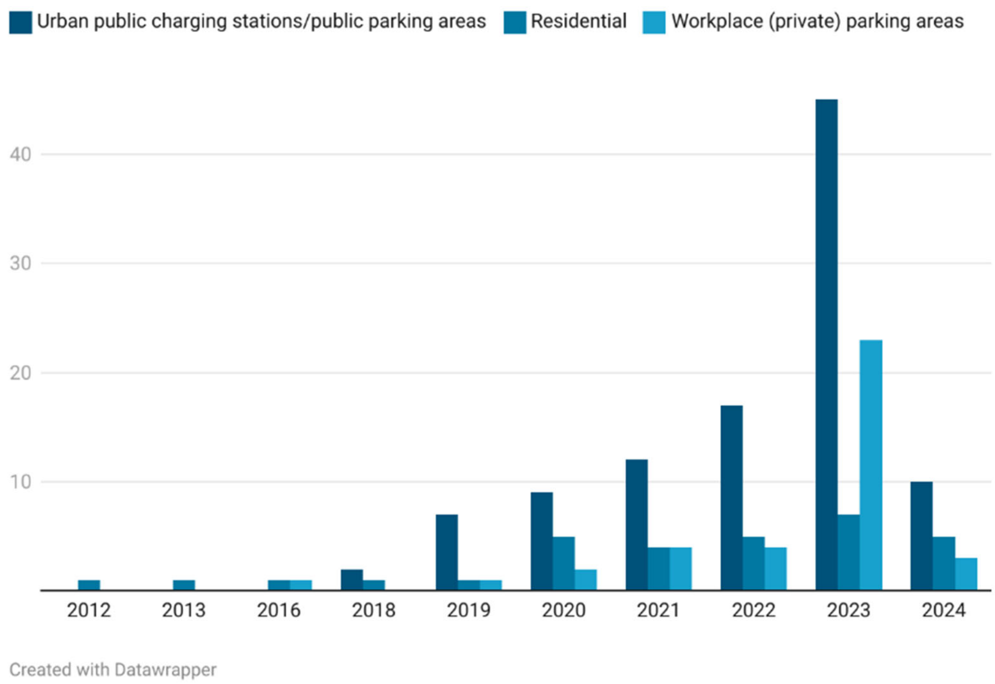


Figure 11. Number of articles that explored the different charging scenarios from 2012 to 2024.

5.3.3. Aggregation Level

In the different charging scenarios, EV charging sessions' demand can be forecasted at an individual or aggregated level. The former considers the charging demand of an individual EV or a specific charging session. The latter takes into account the charging demand of an EV fleet, an EVCS, a group of EVCSs, a city, a broader region, and even a country. Each aggregation level serves different applications and provides EV stakeholders with unique insights for energy management. On the one hand, individual forecasting can inform utility companies about peak demand times and help in developing targeted incentives for EV users, such as customized charging solutions based on their habits. In addition, it allows for charging decision evaluation and dynamic pricing modeling based on user behavioral analysis [31,149]. On the other hand, aggregated forecasting enables large-scale energy management strategies, favoring the effective integration of EVs into the energy system.

According to the SLR results, 19% of the articles forecast EV charging sessions' demand at an individual level, whereas 81% of them aggregate the forecasting. Different aggregation levels have been addressed in the literature, as shown in Figure 12. From the country level to EV fleets, they can be hierarchically arranged as follows:

1. Country: National-level aggregation.
2. Power network: Broad electric power network, including generation, transmission, and distribution.
3. TSO zone: Area operated by a single TSO.
4. Distribution grid: Local distribution network, including transformers, medium-, and low-voltage lines.
5. City: Urban-level aggregation.
6. Microgrid: Localized grid with self-generation capacity. For instance, local communities.
7. EVCS/group of EVCSs.
8. Workplace: Charging infrastructure in professional environments. For instance, company charging facilities and university campus chargers.
9. Residential: Homes or apartment buildings' charging setups.
10. EV fleet: Centrally managed EV groups, such as logistics fleets or electric taxis.

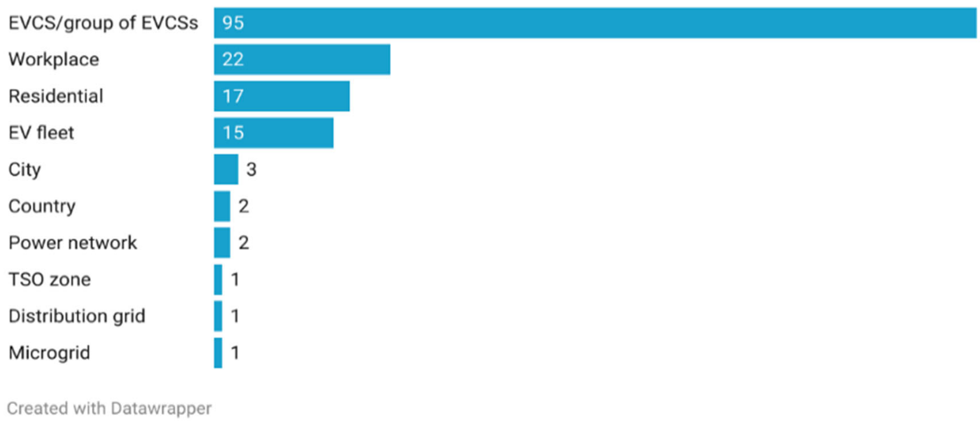


Figure 12. Number of articles that forecasted EV charging sessions' demand at different aggregated levels. Note. EV: electric vehicle; EVCS: electric vehicle charging station; TSO: transmission system operator.

The interaction between these levels is bidirectional. On the one hand, macro-level decisions influence micro-level behaviors. For instance, policies and strategies defined at the country, power network, TSO, or distribution grid levels influence infrastructure deployment and charging availability at lower levels. On the other hand, micro-level demand, which depends on charging behaviors at residential or fleet levels, shapes higher-level energy planning and policy frameworks.

As shown in Figure 12, in line with the most studied charging scenario, the EV charging sessions' demand has been aggregated mainly at the EVCS level, either individually or in groups. Among them, fast charging scenarios pose a major challenge. Their shorter charging process and the relatively high power make the EV charging sessions' demand forecasting volatile and inconsistent compared to that corresponding to slow chargers that have regular patterns and stable trends [150]. In [150], historical data of the EV charging power from 244 fast-charging EVCSs from Jeju Island, Korea, were collected over 150 days to forecast the short-term EV charging sessions' power consumption at a transmission level. In particular, the temporal data used in [150] consisted of the unit with active power and the fast-charging power. To address the latter, a window sliding min–max normalization was proposed in [150], where the well-known sliding window technique—which is widely used to adapt sequential input data in ML applications [83]—scaled the data into short intervals to adapt the standard min–max normalization. Different DL techniques, including LSTM, Bi-LSTM, GRU, and RNNs, were implemented in [150], with LSTM obtaining the best results in terms of RMSE, normalized MAE (NMAE), and NRMSE.

Residential EV charging sessions' demand can be aggregated at the individual charging point level or by considering several residents. Regarding the research conducted in the context of workplace charging scenarios, most of it aggregates the forecasted variable. Aggregating the forecasted variables at EVCS, workplace parking, or residential levels allows for understanding their specific usage patterns and operational needs. In this way, stakeholders are provided with the information to track utilization rates toward managing availability and reducing waiting times; schedule maintenance based on usage patterns, minimizing downtime; implement pricing strategies based on demand, encouraging EV users to charge during off-peak times; and enhance customer experience by providing real-time information on station availability and estimated charging times [31,149]. In addition, in the case of aggregating a group of EVCSs, their operational efficiency can be improved by optimizing their utilization based on the predicted demand, grid load balancing can be performed to prevent overloading during peak charging times, and the strategic placement and number of EVCSs can be planned based on projected usage patterns [31,149].

Finally, aggregating the forecasted EV charging sessions' demand at microgrid [151], distribution grid [152], TSO [31], transmission grid [150], and power network [90,104] levels is crucial for grid management. It can help to improve the operational reliability and capacity of the electrical grid, especially regarding localized factors (peak demand times and grid congestion) and existing infrastructure management, to plan immediate upgrades or reinforcements [31,149]. City [31,34,106,121], regional [90], and national [34,133] levels of aggregation widen the scope of the previous levels of aggregation. In this line, they can guarantee a stable electricity supply by anticipating large-scale demand fluctuations; they can guide strategic investments in charging infrastructure across multiple areas, addressing disparities in accessibility and availability; they allow for policy making; and they provide energy procurement, minimizing costs and risks associated with demand variability [31,149].

In general, there is a lack of work addressing forecasting at different levels of aggregation. Aggregating the data at different levels allows for providing different stakeholders with an optimal model, regardless of the EVs' status or their owners' behavior, while guaranteeing their privacy [34]. In [149], the EV charging demand forecasting accuracy of RF and ANNs for two case studies with different levels of aggregation was evaluated. The first case consisted of a small building with 2 EV charging piles and 3 users, whereas the second consisted of a larger building with 75 charging piles, 8 charging rails, and 70 users. Different features, including holiday and weekend information, weather data, and lag features, were incorporated together with the historical charging features to train the ML models. RF outperformed the ANN when the data was aggregated at both building sizes, obtaining NRMSEs of 0.07 and 0.05 for the smaller and bigger ones, respectively. On the other hand, when EV charging demand forecasting was performed at an individual level, the performance of both ML techniques was similar, but worse than in the case of the aggregated level. In the same line, as discussed in Section 5.2, in [31], EV charging power demand was forecasted using different ML techniques at a group of EVCSs, a postal code level, a TSO zone level, an EV portfolio, and random site groups of various sizes. The results of [31] not only demonstrated the ability of DT ensembles to perform well across all the aggregation levels, but also showed that the prediction accuracy improved as the considered EV fleet grew. In [34], individual EV charging sessions' data from all EVCSs in Korea—including charging time, charging consumption, and EVCS datapoints—obtained over a two-year period, were aggregated at three different levels: EVCS, city, and country. Exogenous data, such as weather features and date type, were included in the dataset. Different forecasting techniques, such as the trigonometric, Box–Cox, autoregressive-moving-average (ARMA), trend, seasonality (TBATS), ARIMA, ANNs, and LSTM, were compared to forecast one-day, one-week, three-week, and one-month ahead EV charging sessions' power consumption at the three aggregation levels. Results of [34] in terms of MAPE showed that ARIMA was the best predictor for city and nationwide cases, whereas LSTM outperformed the other techniques at the EVCS level. In addition, while exogenous data proved to be useful at the larger levels of aggregation, these data did not improve the forecasting at the EVCS level when the length of the historical training charging data was larger than 6 months. In this line, exogenous data did not unconditionally contribute to EV charging sessions' power consumption in the challenging case of individual EVCS forecasting, where only a few charging events occur per day. Finally, the results of [31,34,149] suggest that aggregated forecasting is usually more accurate than individual forecasting. On the one hand, aggregating the data favors its collection and analysis. On the other hand, the highly uncertain EV user behavior leads to significantly fluctuating individual EV charging patterns with complex temporal and spatial distributions, making them more difficult to model.

Table 7 summarizes the percentage of articles aggregating the forecasting at the three main charging scenarios of Figure 11 that achieved the best performance with the ML techniques that are more widely used in the SLR studies according to Figure 9 (and Table A3). Note for the reader that the tendency stands, with LSTM being the most widely used DL method regardless of the data being aggregated at residential, workplace, or public chargers. On the other hand, studies that forecast individual EVs or charging sessions mainly resort to DT ensembles (37%), followed by LSTM (29.62%), GRU (8.33%), and CNN (7.4%). In addition, in 7.4% of the cases, the best performance was obtained with hybrid approaches. It is worth noting that in the individual forecasting case, DT ensembles achieve the best performance more times than LSTM. This is in line with the fact that 81.81% of the studies that forecast the EV charging session demand at an individual level are focused on session duration prediction, which, as highlighted in Section 5.3.1, tends to be better forecasted by DT ensembles than LSTM.

Table 7. Main ML techniques used in each aggregated charging scenario.

Charging Scenario	LSTM [%]	GRU [%]	DT Ensemble [%]	CNN [%]	SVM/SVR [%]	Hybrid ML [%]
Residential	**31.81**	4.54	13.63	18.18	9.09	13.63
Workplace (private)	**40**	4	28	12	0	12
Urban public EVCS	**38.63**	4.54	12.5	15.9	3.4	14.77

Note. CNN: convolutional neural network; DT: decision tree; EVCS: electric vehicle charging session; GRU: gated recurrent unit; LSTM: long-short term memory; ML: machine learning; SVM/SVR: support vector machine/regressor. The bold indicates that LSTM got the highest % of articles aggregating the forecasting at the three main charging scenar-ios of Figure 11.

5.3.4. Time Horizon

Forecasting time horizons can be classified into four main levels: ultra-short term, short term, medium term, and long term [152]. Table 8 describes each of them and the application for which they are useful [152]. Figure 13 shows that most of the studies in the SLR are focused on the short-term forecasting of the EV charging sessions' demand. The plethora of research existing on short-term predictions in comparison to the other time horizons can be explained in terms of data availability. It is timely and resourcefully easier to collect historical EV charging sessions' data within an hourly or daily framework than for a longer time horizon. The same stands for online forecasting, which is rarely found in the literature [51]. For instance, in [116], LSTM was used for month-ahead demand forecasting of a distribution grid with EV residential charging for the sake of maintenance decision-making. The experimental distribution grid consisted of 232 residential transformers of 25 kVA, and the data was created by combining the household and EV load profiles from the Midwestern city of the US provided in [153], with the EV diffusion model proposed in [154]. In [139], the EV charging demand aggregated at a regional grid is analyzed for a 10-year-ahead period (2021–2030). To this end, the number of EV owners from 2021 to 2030 was estimated based on a Sparrow search algorithm-improved backpropagation neural network. In particular, it was trained using the following features: gross domestic product (GDP) per capita, the average government subsidies, the average sustainable mileage of EVs, the number of public charging piles, and the percentage of EV ownership in the region from 2011 to 2020. In addition, the number of data samples was increased by data enhancement. On the other hand, the charging behavior of electric buses, taxis, and private cars was analyzed based on survey data. Then, the initial charging time and the initial SOC of the EVs were simulated using the MC method, and the obtained charging time and surveyed charging power of each EV were superposed to obtain the total charging demand curve of the region.

Table 8. **EV charging session demand forecasting time horizons.**

Time Horizon	Description	Application
Ultra-short term	From a few minutes to an hour	Real-time grid management, immediate response to load fluctuations, EVCS operation optimization, and stability in power system.
Short-term	From one hour to one week	Charging schedule optimization and short-term energy trading.
Medium term	From a week to a year	Maintenance planning, scheduling EVCS availability, and medium-term energy procurement.
Long-term	Longer than a year	Strategic planning, investment decisions, and long-term grid capacity expansion.

Note. EV: electric vehicle.

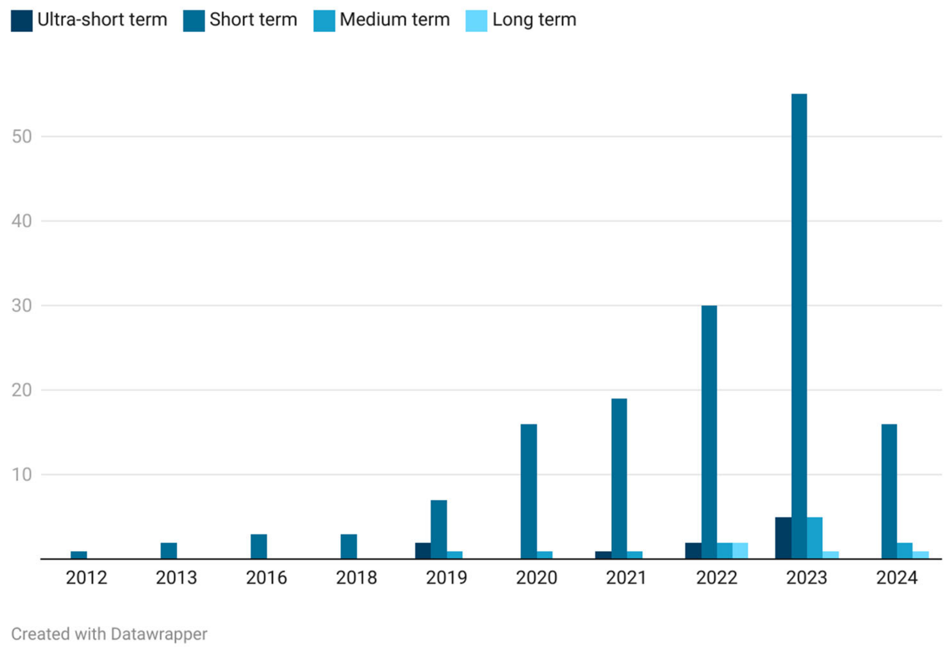


Figure 13. Number of studies forecasting EV charging sessions' demand at different time horizons per year.

In general, short-term forecasting tends to achieve higher accuracy than other time-horizon predictions. Only since 2019 have other time horizons been considered, with ultra-short-term and medium-term horizons more studied than the long-term ones. Table 9 summarizes the percentage of SLR articles addressing the different time-horizon forecasts that achieved the best performance with the most widely used ML techniques in the SLR studies according to Figure 9 (and Table A3). For short-term forecasting, which accounts for most of the works in the SLR, the tendency to use LSTM is observed for the total of studies in the SLR. For long-term predictions, LSTM has obtained the best results in 75% of the cases, which was expected due to its adaptability for long-term applications. Nevertheless, for medium- and ultra-short-term horizons, other ML techniques arise as the best performing ones.

Table 9. **Main ML techniques used for forecasting each time horizon.**

Time Horizon	LSTM [%]	GRU [%]	DT Ensemble [%]	CNN [%]	SVM/SVR [%]	Hybrid ML [%]
Ultra-short term	40	20	0	0	10	0
Short term	35.52	3.28	19.73	13.15	4.60	11.18
Medium term	8.33	0	41.66	0	0	0
Long term	75	0	0	25	0	25

Note. CNN: convolutional neural network; DT: decision tree; GRU: gated recurrent unit; LSTM: long-short term memory; ML: machine learning; SVM/SVR: support vector machine/regressor.

On the one hand, DT ensembles achieved better accuracy in 41.66% of the articles that forecast medium-term EV charging sessions' demand, whereas only 8.33% of the most accurate methods correspond to LSTMs. On the other hand, as already introduced, GRUs are better suited for real-time forecasting since they are faster to train than LSTMs. In this line, a greater percentage of articles have obtained the best results with GRUs for ultra-short-term predictions in comparison to the other time horizons. In [72], a GRU model forecasted the real-time EV charging power consumption in a V2H system based on the time-of-day electricity pricing, the load curve of the house, and the power generation of the rooftop solar photovoltaic (PV) in the state of Maharashtra, India, achieving benchmark results. In [84], a GRU-based approach was used to forecast the 15-min-ahead EV charging demand of a group of EVCSs (more than 2600) in Northern China based on historical charging, weather, and calendar data. The average relative percentage error of 10.59% obtained by a GA-optimized GRU outperformed the manually tuned GRU and the SVM approach used for benchmarking. Finally, it is important to note that GRU, which first appeared in 2014 [155], is a relatively new technique compared to LSTM. This can explain the preference for LSTM among the SLR studies, even for ultra-short-term applications.

Most of the research in the SLR analyzes the EV charging sessions' demand forecasting at a single time horizon, with a lack of studies proposing approaches that can perform forecasting at different time horizons. Nevertheless, in [34,36,45,47,156,157] short- and medium-term horizons were addressed, whereas in [111], short- and long-term predictions were performed. Among them, [45] conducted a comprehensive comparison of different techniques—LSTM, BiLSTM, RNN, CNN, GRU, and transformers—to forecast EV charging demand at three time horizons: next day, next week, and next month. On the one hand, LSTM, BiLSTM, and GRU performed better for longer horizons, such as weekly- and monthly-based ones, than for daily term forecasting, with BiLSTM being the most accurate one. This is in line with the well-suited nature of LSTM-based approaches for long-term forecasting applications. On the other hand, transformers achieved the best forecasting performance across the three time horizons.

Transformers use self-AMs to selectively focus on certain input data and ignore others [158]. Similar to LSTM, they are well suited for long-term forecasting. Moreover, since they do not require recurrent units, they are faster to train, advancing LSTMs. In the same line of [45], in [156], a transformer-based approach was used to forecast EV charging demand considering 7-day, 30-day, and 90-day horizons. In this case, transformers were compared to traditional statistical methods, such as ARIMA and seasonal ARIMA (SARIMA), outperforming them for the three time horizons. Being both well suited for long-term forecasting and in light of [45,156] results, transformers have demonstrated higher flexibility and adaptability than LSTM to perform well across different time-horizon predictions, standing out as a promising ML technique for such applications. Nevertheless, it is important to highlight that they were first introduced in 2017 in [158]. This may explain their incipient use in the literature of EV charging demand forecasting, in spite of their potential as the four studies in the SLR ([45,121,125,156]) suggest.

In [157], the forecasting of the EV charging sessions' energy consumption of five IoT-enabled EVCSs in Utah, US, for the next 15, 20, and 24 days was performed. According to [120], DL systems can be challenged when accessing huge amounts of frequently exchanged data from the IoT, leading to data silos and model training issues. As discussed in Section 5.2, authors of [120] resorted to a federated-MT approach to address the forecasting in such cases. In [157], the multi-task learning (MTL) concept was employed to address them. MTL, which is a new paradigm of ML, learns from multiple datasets (tasks), identifying similarities (in the form of a shared covariance function) and transferring the meaningful information between them [157]. In [157], MTL was implemented via a Gaussian process (GP) that learns from the EV charging sessions' start time, end time, and consumed energy for each EVCS and transfers the knowledge between them. The results of [157] showed that the MTL approach outperforms the single GP one and SVMs by 7% and 15.3% in terms of RMSE, respectively. As expected, longer time horizons had larger forecasting errors, but the proposed MTL-based approach performed well on three of them.

6. Discussion

6.1. Main Research Findings Identified Based on the Systematized Literature Review

The conducted SLR has shown an increasing interest in ML-based EV charging demand forecasting since 2019, accelerating significantly in 2022. This phenomenon is multifactorial. On the one hand, although EV adoption has grown progressively since the early 2010s—when massive production began—it has consolidated in recent years, specifically after the Paris Agreement celebration. In this scenario, research regarding EV efficient integration into the power grid has intensified. On the other hand, recent technological advances have also favored the implementation of ML-, DL-, and even generative artificial intelligence (Gen AI)-based approaches in EV charging demand-forecasting applications. First, new sensing technologies and the widespread use of IoT-based EV charging infrastructure have made available (not always publicly available) huge amounts of diverse EV charging-related data—including ST data—enabling ML models, more specifically DL ones, to improve their performance. Second, new Gen-AI algorithms, such as transformers introduced in 2017, have brought new opportunities to the field, overcoming some of the DL issues, providing better context analysis, and enabling faster processing [45,121,125,156]. Third, new ML paradigms, including TL [92,101,136], MTL [157], FL [120], and MT [120], enable decentralized and collaborative training, improving forecasters' generalization, flexibility, and scalability.

According to the SLR results, researchers have mainly relied on LSTM to forecast EV charging sessions' energy consumption, which is the primary focus of the reviewed studies, making it a well stablished technology in the field. The obtained results have shown LSTM's suitability for the forecasting application in different charging scenarios, including residential, workplace parking areas, and public EVCSs—the latter being of increasing interest in line with the recent rising demand for public charging services—and across all time horizons. Nevertheless, GRUs can be better suited for real-time applications due to their faster training; transformers can potentially outperform LSTMs for long-term forecasting due to their AM-based approach; and DT ensembles have demonstrated similar performance for medium-term forecasting (having the advantage of being simpler and more robust to hyperparameter optimization). Moreover, in the less investigated case of EV charging session duration forecasting, DT ensembles, such as RF and XGBoost, have obtained better results.

Figure 14 summarizes the EV charging sessions' demand forecasting evolution in terms of the used ML technique, the considered features, and the studied charging scenario, according to the SLR results. At the early stages of EV adoption, standard ML techniques, such as SVM/SVR and DT ensembles, have been used to forecast EV charging sessions' demand based on historical charging data. In particular, these data were acquired mainly from residential chargers, which were widely used by early adopters. Currently, there is a remarkable trend of leveraging the LSTM potential for time-series forecasting. In addition, taking advantage of the ability of DL methods to process huge amounts of high-dimensional data without the need for expert feature selection, weather and calendar features have been gradually included in the EV charging sessions' demand forecasting approaches, enhancing their accuracy. According to the increasing demand for public charging facilities, much of the recent research has focused on forecasting EV charging sessions' demand at EVCSs, mainly at an aggregated level.

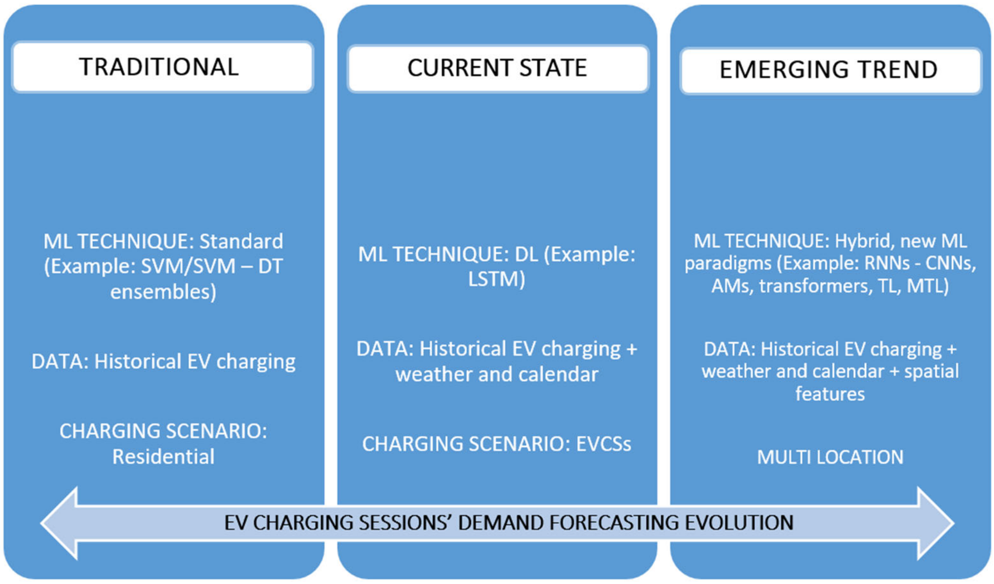


Figure 14. Evolution of the EV charging sessions' demand forecasting. Note. AM: attention mechanism; CNN: convolutional neural network; DL: deep learning; DT: decision tree; EV: electric vehicle; EVCS: electric vehicle charging station; LSTM: long-short term memory; ML: machine learning; MTL: multi-task learning; RNN: recurrent neural network; SVM/SVR: support vector machine/regressor; TL: transfer learning.

Finally, promising emerging trends to have been identified based on the SLR:

- **ST-based forecasting**: The advances in sensing technologies and IoT devices to collect EV charging-related ST data have allowed researchers to consider spatial in addition to temporal features to improve the performance of EV charging sessions' demand forecasting models. Several studies have been published in recent years addressing ST modeling. In particular, they resort mainly to CNNs, especially GCNs, to model spatial features, and rely on RNNs, mainly LSTM and GRU, to model temporal features.
- **New ML-, DL-, and Gen AI-based technologies**: AMs have revolutionized the DL landscape, enabling more versatile forecasting approaches. LSTMs, which are currently the *de facto* technology, are not able to avoid the so-called catastrophic forgetting that leads to the sudden loss of previously acquired knowledge when retraining them with new samples [159]. In this line, the recent development of AMs that allows focusing attention selectively offers new perspectives [160]. For instance, in [159], the quantiles of EV charging sessions' demand aggregated at the EVCS level for 15 min ahead were predicted based on a self-attention-aided machine theory of mind (MToM) approach implemented with LSTM. MToM predicts agent behaviors based on the agent's character and its mental state at the moment [159]. In [159], this concept was used to balance historical EV charging habits and current charging demand variation trends via an LSTM, using the self-attention module to mitigate its long-range forgetting issue. Results of [159], obtained on the ACN dataset, outperformed different baseline methods.

Among the new technologies, transformers, based on AMs, have been demonstrated to be well suited to solve the scalability and generalizability problem of EV charging sessions' demand forecasting [45,121,125,156]. Moreover, they have demonstrated the ability to outperform the gold standard LSTM for multiple time horizons, multiple aggregation levels, and long-term prediction applications [45]. According to the authors of [45], a key advantage of transformers is their capability of attending to relevant observations across the entire time sequence—disregarding irrelevant data when necessary—thereby enabling the detection of long-range temporal patterns and being more robust to data sequences with longer time intervals and longer delays.

- **Decentralized and collaborative training**: The adoption of new ML paradigms, such as TL [92,101,136], MTL [157], FL [120], and MT [120], opens new opportunities, providing adaptability, flexibility, generalizability, and scalability, making it possible to develop ML-based forecasters that can perform accurately in a wide variety of multi-scale and multi-location applications, even with limited amounts of data.

For the sake of summarizing, Figure 15 shows the main ML paradigms and technologies that have been incorporated into the EV charging sessions' demand forecasting applications in recent years, where transformers [45,121,125,156] and TL [92,101,136] stand out from the rest. In this context, sophisticated forecasting approaches have been developed to build ST-aware, scalable, and generalizable models, as shown in Figure 16, which depicts how the ML-based approaches proposed in the SLR studies have become more complex in recent years, increasing the trend of employing hybrid ML-based methods.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	TOTAL
FL	0	0	0	0	0	0	0	1	0	0	0	0	1	2
TL	0	0	0	0	0	0	0	0	0	0	1	1	2	4
CL	0	0	0	0	0	0	0	0	0	0	1	0	0	1
MTL	0	0	0	0	0	0	0	0	1	0	0	0	0	1
MT	0	0	0	0	0	0	0	0	0	0	0	0	2	2
MToM	0	0	0	0	0	0	0	0	0	1	1	0	0	2
Transformer	0	0	0	0	0	0	0	0	0	0	0	4	1	4
TOTAL	0	0	0	0	0	0	0	1	1	1	3	4	6	16

Created with Datawrapper

Figure 15. Number of studies that include new ML paradigms and techniques per year. Note. CL: continuous learning; FL: federated learning; ML: machine learning; MT: meta learning; MTL: multitask learning; MToM: machine theory of mind; TL: transfer learning.

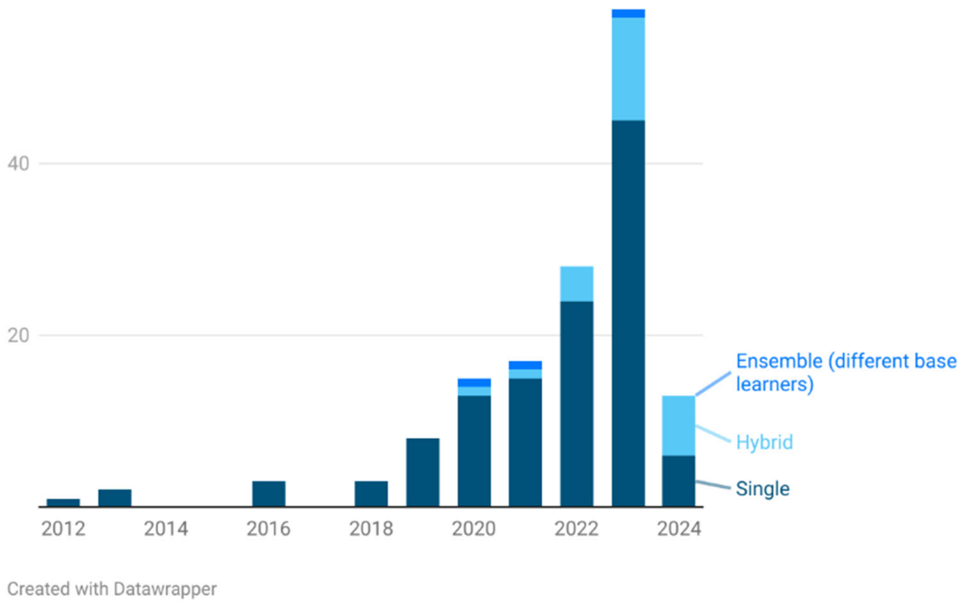


Figure 16. Proportion of studies proposing single, hybrid, or ensemble ML-based approaches per year. Note. ML: machine learning.

6.2. Main Research Gaps Identified Based on the Systematized Literature Review

According to the SLR results, LSTM-based techniques are currently the *de facto* standard technology for EV charging session demand forecasting in a wide variety of scenarios. Nevertheless, they are computationally expensive and require large amounts of training data and a complex hyperparameter optimization process to perform accurately. Moreover, superior technologies, such as transformers [45,121,125,156], and the incorporation of new ML paradigms, including TL [92,101,136], MTL [157], FL [120], and MT [120], have been demonstrated to improve generalizability, flexibility, and scalability, performing better across different aggregation levels, time horizons, and locations, as well as solving scarce data issues. In this line, several research gaps still need to be addressed.

Data-related research gaps:

At the time of conducting this SLR, four years have passed since the last comprehensive review on ML-based approaches applied to EV charging demand forecasting [35]. In this previous work, the authors called for more open datasets. Despite the fact that six open datasets have been reported in [62], the lack of publicly available real-world multi-source multi-located datasets to develop robust and scalable EV charging sessions' demand forecasting models is still a major research gap. Then, the main aspects of data that need to be further addressed are as follows:

- **Data openness:** Open datasets are needed for benchmarking, comparison, and replicability purposes, enabling the forecasting models' performance evaluation. Nevertheless, only 40% of the studies in the SLR resort to them. Different strategies have been proposed in the SLR to face the lack of publicly available datasets. On the one hand, some studies resorted to simulated data [106,147], with MC techniques commonly used for this task. For instance, in [106], a synthetic EV charging demand dataset was created using MC simulations based on EV travel motifs, including daily travel distances and times calculated by resorting to features like the number of EVs, the energy consumption per kilometer, and the locations of the places where people travel. On the other hand, in order to consider different scenarios to develop their ML-based EV charging demand forecasting models, many researchers collected their own data [31,90,121]. Nevertheless, in these cases, datasets cannot be opened due to privacy concerns, making it difficult to conduct benchmark experiments.
- **Multi-located datasets:** Most of the publicly available datasets are concentrated in the US, with ACN being the most popular one. Countries like China and the UK also produce EV charging-related data, but there is a lack of data from other regions, especially from developing countries, where data acquisition technologies have been installed recently. Moreover, as previously highlighted by [35], there is a need for open datasets that cover wider geographies. In this line, the authors of [35] have encouraged researchers to collect and publish data from major cities for benchmarking purposes.

The main issue of the local nature of the currently available datasets is that they only represent the behavior of EV users from a limited geographical area, which may differ from other regions, making the models' scalability more difficult [120]. In the SLR we have identified some studies that forecast EV charging sessions' demand at different levels: microgrid [151]; distribution grid [152]; TSO [31]; transmission grid [150]; power network [90,104]; city [31,34,106,121]; region [90]; and nation [34,133]. However, only a few of them use publicly available data, mainly from government electricity facilities [151] or environmental services [34,133]. For instance, authors in [34,133] used open data from the Korean Ministry of Environment [161] and the Korea Environment Corporation (http://keco.or.kr/, accessed on 10 December 2024), respectively, whereas in [66], data is obtained from the U.S. Department of Transportation (https://www.bts.gov/, accessed on 10 December 2024). In [34], the data of EV charging sessions' power consumption from all Korean EVCSs during 2018 and 2019 were used to forecast one-day, one-week, three-week, and one-month ahead EV charging sessions' power consumption at EVCS, city, and country levels. In [133], the short-term EV charging sessions' power consumption at the fast chargers installed nationwide in Korea was forecasted.

ML-based models' generalizability and scalability-related research gaps:

The increasing adoption of EV-based mobility around the world calls for EV charging session demand forecasting models capable of adapting to different charging scenarios to be implemented within the context of diverse EV charging management applications. In particular, there is a growing need for developing flexible and scalable ML-based forecasting models capable of efficiently adapting to different data sources, including IoT-based ones, different locations, different aggregation levels, and different time horizons. On the one hand, transformers have been demonstrated to outperform the gold standard LSTM when addressing different aggregated levels and time horizons, as well as long-term predictions [45,121,125,156]. On the other hand, ST-robust approaches, such as the RNN-CNN hybrid ones, combined with ML paradigms that allow distributed and collaborative training, such as TL [92,101,136], MTL [157], FL [120], and MT [120] ones, have been demonstrated to enable knowledge learning by propagation among different geographical areas, achieving high generalizability. The results of [120], where federated-MT was combined with GCNs to forecast short-term EV charging sessions' energy consumption at the public EVCSs of six different regions, confirm this. In the same line, TL is a promising alternative [92,101,136], enabling the pre-training of a preliminary model on a large dataset. The pre-training dataset can be more generic, leading to a base EV charging session demand forecasting model that could then be adapted to different EV charging conditions and locations by fine-tuning it on the target (usually smaller) dataset. In this way, the TL-based concept could fulfill the need for a standard pre-trained EV charging session demand predictor.

Nevertheless, the SLR results show that the use of new technologies, such as transformers [45,121,125,156], and new ML paradigms, including TL [92,101,136], MTL [157], FL [120], and MT [120], in the context of EV charging sessions' demand forecasting is still in its early stages. In this line, the promising results these methods have obtained in terms of forecasting scalability and generalizability across different locations, aggregation levels, and time horizons encourage researchers to develop further research in this direction.

Application-related research gaps:

- **"Cold start" scenarios:** Not only the lack of publicly available data, but also their scarcity or inadequacy has long been discussed in the literature [51]. In several cases, data collection may be difficult because of technical, economic, or regulatory issues [136]. As already discussed, ML algorithms, especially DL ones, which are currently the most widely used, need a great amount of data to be efficiently trained. In this line, further research is needed to potentiate the implementation of ML new paradigms, including TL [92,101,136], MTL [157], FL [120], and MT [120], that can efficiently handle limited data applications.
- **Lack of real-time and long-term EV charging session demand forecasting applications:** Most of the studies in the SLR forecast the EV charging sessions' demand at a short-term horizon, due to a lack of research addressing online forecasting and long-term applications. On the one hand, this is related tightly to the technical and economic challenges of acquiring data for these time horizons. On the other hand, there is a lack of ML-based approaches to address them. In this line, further research is needed to better adapt GRU models, which are the best suited for real-time applications, and transformers, which have been demonstrated to outper-

form LSTM for long-term horizon predictions, to adapt them to the EV charging demand-forecasting scenario.

In the same line, there is also a lack of ML-based models capable of supporting EV charging sessions' demand forecasting at different time horizons. In this line, the good results obtained by transformers across various time resolutions in [45,156] provide a solid line for further research.

- **Individual EV charging demand is less studied (and usually less accurately forecasted) than aggregated ones:** EV charging demand forecasting at an individual level has been demonstrated to be harder than at an aggregated level, leading usually to greater prediction errors. On the one hand, the highly uncertain EV user behavior leads to significantly fluctuating individual EV charging patterns with complex temporal and spatial distributions, making them more difficult to model. On the other hand, in individual forecasting, only a few charging sessions occur per day, making it difficult to predict the demand based only on them. Moreover, according to results in [34], in these cases, exogenous data, such as weather or calendar, cannot improve the prediction. In this line, developing new individual forecasters based on new ML paradigms that can manage limited data efficiently could be an interesting research line.
- **Lack of EV charging demand forecasting within the context of fast chargers:** Fast chargers' shorter charging process and their relatively high power make the EV charging sessions' demand forecasting volatile and inconsistent compared to the one corresponding to slow chargers that have regular patterns and stable trends [150]. In this line, they have demonstrated to pose a major challenge, being addressed rarely in the SLR.
- **Lack of ML-based models' interpretability**: The lack of interpretability of DL models, such as LSTMs and CNNs, and Gen-AI approaches, such as transformers, can hinder deployment in critical real-world scenarios.

Security-related research gaps:

As new sensing technologies and IoT-based EV charging infrastructure are made available, data security challenges may arise. In this context, stakeholders will need to prevent data leakage during information exchanges through IoT protocols [120]. For instance, authors of [120] proposed the use of FL to train models in a data-isolated scenario to address security issues. Nevertheless, this is still an unexplored research area that should be addressed in the upcoming years.

6.3. Most Relevant Future Research Directions

Based on the current trends and research gaps identified as a result of the conducted SLR, the following future research directions can be highlighted to take a step further in the development of accurate, flexible, and scalable ML-based EV charging session demand forecasting:

- **Use of GenAI**: Transformers have been demonstrated to provide better and faster multivariate management, being capable of efficiently handling complex and varied applications and performing well across different aggregation levels and time horizons [45,125,156]. More specifically, they have outperformed the gold standard LSTM in such tasks. Moreover, they have also shown better results for long-term predictions. Nevertheless, only a few studies of the SLR (less than 2.5%) have resorted to transformers to forecast EV charging session demand. Considering the promising results transformers have shown for the application, further research is needed to take advantage of these kinds of superior Gen-AI methods and adapt them to the context of EV charging session demand forecasting.

- **Use of new ML paradigms**: Further studying the possibilities of new ML paradigms, including TL [92,101,136], MTL [157], FL [120], and MT [120], in the context of EV charging sessions' demand forecasting is paramount. Based on their capability of handling distributed and collaborative training, they have demonstrated the ability to provide accurate solutions to long-standing issues, including limited data, multi-scale, multi-resolution, and multi-location applications, enhancing forecasters' generalizability and scalability.
- **Development of pre-trained EV charging session demand predictors**: A promising research line is the development of standard pre-trained EV charging session demand forecasting models that could then be adapted to local needs by a fine-tuning process. As previously discussed, this can be built based on new ML paradigms, such as TL.
- **Interpretability improvement**: Taking into account that deep learning, especially LSTM, dominates the landscape, and that the future relies on Gen AI, such as transformers, as well as on new ML paradigms, working on interpretability enhancement will be crucial to safeguard ML-based EV charging demand-forecasting deployment in critical grid operations.
- **Security research**: The need to address security needs within the context of EV charging session demand forecasting will grow in the following years. In this context, the development of training strategies capable of avoiding data leakage, such as the one based on FL proposed in [120], constitutes a solid future research line.

6.4. SLR Limitations

The conducted SLR has the following limitations:

- Global South studies are underrepresented in the three databases considered for the literature search.
- Although there exist different error measures for ML models' assessment, the lack of standardized performance metrics across the analyzed studies in the SLR makes it difficult to conduct fair comparisons between their proposed ML-based approaches.

7. Conclusions

Since the EV's massive production began in the early 2010s, people have progressively adopted them. In recent years, especially after the Paris Agreement celebration, EV sales have increased, posing several challenges to the power grid. In particular, the EV charging needs, together with the uncertain EV drivers' behavior, make their integration on a massive scale difficult, increasing the risk of overloading, network congestion, voltage and frequency imbalance, harmonic injection, power losses, and grid instability. Smart charging strategies can mitigate these adverse effects by using ICT to optimize EV charging schedules in terms of power systems' constraints, electricity prices, and users' preferences, benefiting the different EV stakeholders by minimizing distribution networks' losses, providing additional flexibility and support for grid stability, maximizing aggregators' profit, and reducing users' driving range anxiety. To this end, accurately forecasting EV charging demand is paramount. Nevertheless, as the EV market expands, traditional forecasting methods, such as model-driven and statistical ones, become increasingly inadequate due to their reliance on simplified assumptions and limited flexibility, making emerging ML techniques a superior approach.

The SLR conducted in this paper has explored the current state of the art of ML-based EV charging demand-forecasting methods, highlighting their crucial role in improving forecasting performances. The proposed SLR contributes uniquely to the field by reviewing a large body of literature consisting of 162 documents and offering a comprehensive, multidimensional classification framework that considers application heterogeneity. In this way, it expands upon the results of previous works in the field by systematically analyzing the role of charging contexts, deep-learning methodologies, ST challenges, and novel learning paradigms—such as TL, ML, and FL—in shaping EV charging demand-forecasting applications.

As a result, this SLR confirms that a plethora of research has been conducted addressing short-term EV charging sessions' energy consumption forecasting in the context of residential and public EVCSs based on historical charging data—incorporating weather and calendar information—using RNNs, specifically LSTM ones. More importantly, it uncovers critical gaps, such as the lack of adaptable forecasting models across locations and user behaviors, and points to novel intersections that deserve further exploitation. In this line, the use of transformers and the combination of novel learning paradigms, such as TL, ML, and FL, have shown promising results. These insights provide a valuable roadmap for advancing methodological innovation and addressing real-world deployment challenges in terms of adaptability, scalability, and generalizability toward the sustainable integration of EVs into the power system.

Author Contributions: M.A.: Conceptualization, Methodology, Investigation, Writing—original draft, Visualization, Project administration, Funding acquisition. M.R.: Conceptualization, Writing—Review and Editing, Investigation, Supervision. E.A.: Conceptualization, Visualization, Validation. M.M.: Methodology, Project administration. M.D.: Conceptualization, Supervision. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: Author Mohammed Radi was employed by the company UK Power Networks. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Table A1. Selected studies included in the SLR.

Ref.	Title	Authors	Publication Year	Publication
[31]	Probabilistic forecast of electric vehicle charging demand: analysis of different aggregation levels and energy procurement	A. Ostermann and T. Haug	2024	Energy Informatics
[162]	Electric Vehicle Load Forecasting using Data Mining Methods	E. Xydas, C. Marmaras, L. Cipcigan, A. Sani Hassan, and N. Jenkins	2013	IET Conference Publications
[67]	Research on Load Forecasting of Charging Station Based on XGBoost and LSTM Models	M. Xue, L. Wu, Q. P. Zhang, J. X. Lu, X. Mao, and Y. Pan	2021	Journal of Physics: Conference Series
[99]	Short-Term Forecasting of Electric Vehicle Load Using Time Series, Machine Learning, and Deep Learning Techniques	G. Vishnu, D. Kaliyaperumal, P. B. Pati, A. Karthick, N. Subbanna, and A. Ghosh	2023	World Electr. Veh. J.
[63]	Day-Ahead Forecast of Electric Vehicle Charging Demand with Deep Neural Networks	G. Van Kriekinge, C. De Cauwer, N. Sapountzoglou, T. Coosemans, and M. Messagie	2021	World Electr. Veh. J.
[118]	Load Forecasting of Battery Electric Vehicle Charging Station based on GA-Prophet-LSTM	Y. Wei, Y. Jiang, J. Song, Z. Sheng, X. Song, and Z. Meng	2023	Journal of Physics: Conference Series
[50]	User Behavior Clustering-Based Method for EV Charging Forecast	A. Nespoli, E. Ogliari, and S. Leva	2023	IEEE Access
[163]	Unsupervised Machine Learning-based EV Load Profile Generation	H. Lee, K. Park, and B. Lee	2021	CIRED-The 26th International Conference and Exhibition on Electricity Distribution
[164]	Ultra-Short-Term Prediction Method of Electric Vehicle Charging Load Based on the Fluctuation Characteristic Learning	T. Li, L. Wang, Y. Zhou, S. Sun, S. Chen, and X. Ma	2023	5th International Conference on Power and Energy Technology (ICPET)
[100]	A Novel Ultra Short-Term Load Forecasting Method for Regional Electric Vehicle Charging Load Using Charging Pile Usage Degree	J. Tang, G. Ge, J. Liu, and H. Yang	2023	Energy Eng. J. Assoc. Energy Eng.
[106]	Travel Motif-Based Learning Scheme for Electric Vehicle Charging Demand Forecasting	M. Rashid, T. Elfouly, and N. Chen	2023	IEEE Vehicle Power and Propulsion Conference (VPPC)
[101]	Transfer Learning-Based Framework Enhanced by Deep Generative Model for Cold-Start Forecasting of Residential EV Charging Behavior	A. Forootani, M. Rastegar, and H. Zareipour	2024	IEEE Trans. Intell. Veh.

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[165]	Trade-Off Selection of Data-Driven Methods for EV Demand Forecasting in a Real Office Environment	S. Zhang, K. Thoelen, T. Peirelinck, and G. Deconinck	2023	IEEE Belgrade PowerTech
[33]	Towards a short-term forecasting framework to efficiently charge company EV fleets	S. Gohlke and Z. Nochta	2023	7th E-Mobility Power System Integration Symposium (EMOB 2023)
[166]	The Load Forecasting of Charging Stations Based on Support Vector Regression	L. Yi, X. Ting, W. Song, G. Yun, H. Hui, and Q. Ziwen	2023	ICPET
[45]	Performance Comparison of Deep Learning Approaches in Predicting EV Charging Demand	S. Koohfar, W. Woldemariam, and A. Kumar	2023	Sustain.
[139]	Electric Vehicle Participation in Regional Grid Demand Response: Potential Analysis Model and Architecture Planning	Q. Wang, X. Yang, X. Yu, J. Yun, and J. Zhang	2023	Sustain.
[156]	Prediction of Electric Vehicles Charging Demand: A Transformer-Based Deep Learning Approach	S. Koohfar, W. Woldemariam, and A. Kumar	2023	Sustain.
[79]	Deep Learning LSTM Recurrent Neural Network Model for EV Charging Prediction of Electric Vehicle Charging Demand	J. Shanmuganathan, A. A. Victoire, G. Balraj, and A. Victoire	2022	Sustain.
[133]	Hybrid Predictive Modeling for Charging Demand Prediction of Electric Vehicles	Y.-E. Jeon, S.-B. Kang, and J.-I. Seo	2022	Sustain.
[150]	Aggregated electric vehicle fast-charging power demand analysis and forecast based on an LSTM neural network	M. Chang, S. Bae, G. Cha, and J. Yoo	2021	Sustain.
[64]	Seasonality effect analysis and recognition of charging behaviors of electric vehicles: A data science approach	J. A. Dominguez-Jimenez, J. E. Campillo, O. D. Montoya, E. Delahoz, and J. C. Hernández	2020	Sustain.
[81]	Spatial-Temporal Graph Convolutional-Based Recurrent Network for Electric Vehicle Charging Stations Demand Forecasting in the Energy Market	H. J. Kim and M. K. Kim	2024	IEEE Trans. Smart Grid
[131]	Spatial-temporal Dynamic Forecasting of EVs Charging Load Based on DCC-2D	S. Peng, H. Zhang, Y. Yang, B. Li, S. Su, S. Huang, G. Zheng	2022	Chinese J. Electr. Eng.
[167]	Short-term load prediction of electric vehicle charging station based on Long-Short-Term Memory Neural Network	Z. Sun, Z. Yu, L. Ma, J. Tang, B. Qian, X. Lin, F. Zhang	2023	4th International Conference on Computer Engineering and Intelligent Control (ICCEIC)

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[17]	Short-term load forecasting at electric vehicle charging sites using a multivariate multi-step long short-term memory: A case study from Finland	T. Unterluggauer, K. Rauma, P. Järventausta, and C. Rehtanz	2021	IET Electr. Syst. Transp.
[82]	Short-term Individual Electric Vehicle Charging Behavior Prediction Using LSTM Networks	A. S. Khwaja, B. Venkatesh, and A. Anpalagan	2020	IEEE 25th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)
[168]	Short-Term Forecasting of EV Charging Load Using Prophet-BiLSTM	C. Li, Y. Liao, L. Zou, R. Diao, R. Sun, and H. Xie	2022	IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific)
[114]	Short-Term EV Charging Load Prediction Based on Adaptive VMD and LSTM Methods	Q. Guan, Q. Liu, D. Zhou, Y. Xu, and X. Tan	2023	IECON 49th Annual Conference of the IEEE Industrial Electronics Society
[84]	Short-term EV Charging Load Forecasting Based on GA-GRU Model	L. Guo, P. Shi, Y. Zhang, Z. Cao, Z. Liu, and B. Feng	2021	3rd Asia Energy and Electrical Engineering Symposium (AEEES)
[136]	Short-term Electric Vehicle Charging Load Forecasting Using Transfer and Meta-learning	K. Nath, S. N. Gowda, C. Zhang, R. S. Gowda, and R. Gadh	2024	IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)
[85]	Short-Term Forecasting Method of Charging Load Based on Multilevel Discrete Wavelet Transform and LSTM Model	B. Qin, J. Cai, C. Du, Y. Lv, and C. Guo	2022	4th International Academic Exchange Conference on Science and Technology Innovation (IAECST)
[141]	Short-Term Electric Vehicle Demand Forecasts and Vehicle-to-Grid (V2G) Idle-Time Estimation Using Machine Learning	P. Rajagopalan, J. Thornby, and P. Ranganathan	2023	IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC)
[159]	Self-Attention-Based Machine Theory of Mind for Electric Vehicle Charging Demand Forecast	T. Hu, H. Ma, H. Liu, H. Sun, and K. Liu	2022	IEEE Trans. Ind. Informatics
[44]	Comparative Analysis of Deep Learning Models for Electric Vehicle Charging Load Forecasting	M. P Sasidharan, S. Kinattingal, and S. P. Simon	2023	J. Inst. Eng. Ser. B
[86]	Integrated human-machine intelligence for EV charging prediction in 5G smart grid	D. Sun, Q. Ou, X. Yao, S. Gao, Z. Wang, W. Ma, and W. D. Li	2020	Eurasip J. Wirel. Commun. Netw.
[80]	A Data-Driven Temporal Charge Profiling of Electric Vehicles	D. Usman, K. Abdul, and D. Asim	2023	Arab. J. Sci. Eng.
[68]	A deep learning-based approach for predicting the demand for electric vehicle charging	M. D. Eddine and Y. Shen	2022	J. Supercomput.
[129]	LA-RCNN: Luong attention-recurrent-convolutional neural network for EV charging load prediction	D. E. Mekkaoui, M. A. Midoun, and Y. Shen	2024	Appl. Intell.

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[169]	Robust Identification of EV Charging Profiles	S. Wang, L. Du, J. Ye, and D. Zhao	2018	IEEE Transportation Electrification Conference and Expo (ITEC)
[170]	Reinforcement Learning-Based Load Forecasting of Electric Vehicle Charging Stations Using Q-Learning Technique	M. Dabbaghjamanesh, A. Moeini, and A. Kavousi-Fard	2021	IEEE Trans. Ind. Informatics
[107]	Probabilistic Forecasting of Electric Vehicle Charging Load using Composite Quantile Regression LSTM	Y. Chen, B. Pang, X. Xiang, T. Lu, T. Xia, and G. Geng	2023	IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia)
[171]	Probabilistic Electric Vehicle Charging Demand Forecast Based on Deep Learning and Machine Theory of Mind	T. Hu, K. Liu, and H. Ma	2021	IEEE Transportation Electrification Conference f Expo (ITEC)
[172]	Probabilistic Charging Power Forecast of EVCS: Reinforcement Learning-Assisted Deep Learning Approach	Y. Li, S. He, Y. Li, L. Ge, S. Lou, and Z. Zeng	2023	IEEE Trans. Intell. Veh.
[173]	Predictive Performance of EV Charging Behavior in COVID-19	M. Gupta, J. Mittal, and A. Tomar	2023	IEEE 3rd International Conference on Sustainable Energy and Future Electric Transportation (SEFET)
[174]	Prediction of the temporal and spatial distribution of electric vehicle charging load considering the characteristics of mountainous cities	F. Chen, W. Xiang, Z. Guan, H. Tan, J. Yu, and H. Long	2022	4th International Academic Exchange Conference on Science and Technology Innovation (IAECST)
[145]	Prediction of Session Duration of Electric Vehicle Using Machine Learning and Neural Networks	H. Rathore, H. K. Meena, P. Jain, and A. Choudhary	2023	International Conference on Computer, Electronics & Electrical Engineering & their Applications (IC2E3)
[175]	Prediction of Probability Density of Electric Vehicle Load Based on Deep Learning QRDCC Model	S. Peng, G. Zheng, and J. Zou	2019	IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2)
[176]	Prediction of EV Energy Consumption Using Random Forest And XGBoost	H. Rathore, H. K. Meena, and P. Jain	2023	International Conference on Power Electronics and Energy (ICPEE)
[177]	Prediction of EV Charging Load Using Two-Stage Time Series Decomposition and DeepBiLSTM Model	C. Li, Y. Liao, R. Sun, R. Diao, K. Sun, J. Liu, L. Zhu, Y. Jiang	2023	IEEE Access
[146]	Prediction of EV Charging Behavior Using Machine Learning	S. Shahriar, A. Osman, S. Dhou, and M. Nijim	2021	IEEE Access
[178]	Predicting real-life electric vehicle fast charging session duration using neural networks	A. Deschênes, J. Gaudreault, and C.-G. Quimper	2022	IEEE Intelligent Vehicles Symposium (IV)
[121]	Predicting Electric Vehicle Charging Load Using Graph Attention Networks and Autoformer	Z. Tang, Q. Hu, Y. Cui, W. Rao, and Y. Li	2024	IEEE 4th International Conference on Power, Electronics and Computer Applications (ICPECA)

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[179]	Plug-in Electric Vehicle Behavior Modeling in Energy Market: A Novel Deep Learning-Based Approach With Clustering Technique	H. Jahangir, S. S. Gougheri, B. Vatandoust, M. A. Golkar, A. Ahmadian, and A. Hajizadeh	2020	IEEE Trans. Smart Grid
[102]	Performance Analysis of LSTMs for Daily Individual EV Charging Behavior Prediction	A. S. Khwaja, B. Venkatesh, and A. Anpalagan	2021	IEEE Access
[180]	Overload risk evaluation of DNs with high proportions of EVs based on adaptive net-based fuzzy inference system	W. Ma, F. Wang, J. Zhang, and Q. Jin	2020	IEEE 4th Conference on Energy Internet and Energy System Integration: Connecting the Grids Towards a Low-Carbon High-Efficiency Energy System
[181]	Optimized Scheduling for Urban-Scale Mobile Charging Vehicle	H. Zhang, B. Jin, J. Li, J. Gao, J. Zhao, M. Hou, G.M Yu, H. Liu	2019	2nd World Symposium on Communication Engineering (WSCE)
[152]	Online forecasting of electrical load for distributed management of plug-in electric vehicles	K. Basu, A. Ovalle, B. Guo, A. Hably, S. Bacha, and K. Hajar	2016	3rd International Conference on Renewable Energies for Developing Countries (REDEC)
[69]	Online Energy Management of Electric Vehicle Parking Lots	A. Alahyari, D. Pozo, and M. A. Sadri	2020	International Conference on Smart Energy Systems and Technologies (SEST)
[61]	Non-intrusive Extraction and Forecasting of Residential Electric Vehicle Charging Load	R. Zhou, Y. Xiang, Y. Wang, Y. Huang, and S. Xia	2020	IEEE Sustainable Power and Energy Conference (iSPEC)
[32]	Neural Network-based Load Forecasting Model for Efficient Charging of Electric Vehicles	H. Khan, M. J. Khan, and A. Qayyum	2022	7th Asia Conference on Power and Electrical Engineering (ACPEE)
[157]	Multi-Task Gaussian Process Learning for Energy Forecasting in IoT-Enabled Electric Vehicle Charging Infrastructure	M. Gilanifar, M. Parvania, and M. E. Hariri	2020	IEEE 6th World Forum on Internet of Things (WF-IoT)
[182]	Modeling daily electrical demand in the presence of PHEVs in smart grids with supervised learning	M. Pellegrini and F. Rassaei	2016	IEEE 2nd International Forum on Research and Technologies for Society and Industry Leveraging a better tomorrow (RTSI)
[183]	Reinforcement Learning-Enabled Electric Vehicle Load Forecasting for Grid Energy Management	M. Zulfiqar, N. F. Alshammari, and M. B. Rasheed	2023	Mathematics
[184]	Prediction of electric vehicle charging duration time using an ensemble machine learning algorithm and Shapley additive explanations	I. Ullah, K. Liu, T. Yamamoto, M. Zahid Khattak, and A. Jamal	2022	Int. J. Energy Res.
[185]	Machine Learning-based Electric Vehicle User Behavior Prediction	A. Lilhore, K. K. Prasad, and V. Agarwal	2023	IEEE IAS Global Conference on Renewable Energy and Hydrogen Technologies (GlobConHT)

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[35]	Machine Learning Approaches for EV Charging Behavior: A Review	S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim	2020	IEEE Access
[116]	LSTM-Based Load Prediction for Distribution Power Grid with Home EV Charging	S. S. Shuvo and M. M. Islam	2022	IEEE Kansas Power and Energy Conference (KPEC)
[70]	Load Forecasting of Electric Vehicle Charging Stations: Attention-Based Spatiotemporal Multi-Graph Convolutional Networks	J. Shi, W. Zhang, Y. Bao, D. Gao, and Z. Wang	2023	IEEE Trans. Smart Grid
[186]	Load Forecasting of Electric Vehicle Charging Station Based on Edge Computing	A. Luo, J. Yuan, F. Liang, Q. Yang, and D. Mu	2020	IEEE 3rd International Conference on Computer and Communication Engineering Technology (CCET)
[87]	An electric vehicle charging load forecasting method considering the impact of the emergency	W. Wu and Z. Chi	2022	Acad. J. Eng. Technol. Sci
[134]	Improved SVM Method for Forecasting Recent Charging Load in Small Electric Vehicle Charging Stations	M. Yao, C. Wang, Y. Chen, and Z. Zhou	2023	4th International Conference on Smart Grid and Energy Engineering (SGEE)
[187]	Improved Prediction of Electric Vehicle User Behavior with Machine Learning-based Analysis	K. K. Prasad, A. Mali, and V. Agarwal	2023	IEEE 3rd International Conference on Smart Technologies for Power, Energy and Control (STPEC)
[188]	Improved Forecasting of Electric Vehicle Charging Load using Neural Architecture Search	S. Kar, S. Das, and P. Chattopadhyay	2023	7th International Conference on Computer Applications in Electrical Engineering-Recent Advances (CERA)
[144]	Hybrid Machine Learning Forecasting for Online MPC of Workplace Electric Vehicle Charging	G. McClone, A. Ghosh, A. Khurram, B. Washom, and J. Kleissl	2024	IEEE Trans. Smart Grid
[71]	Hierarchical High-Resolution Load Forecasting for Electric Vehicle Charging: A Deep Learning Approach	Z. Yang, T. Hu, J. Zhu, W. Shang, Y. Guo, and A. Foley	2023	IEEE J. Emerg. Sel. Top. Ind. Electron.
[92]	Heterogeneous Multi-Source Deep Adaptive Knowledge-Aware Learning for E-Mobility	M. W. Ali	2022	IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C)
[72]	GRU-based EV Charging Algorithm for Vehicle-to-Home Applications	P. P. Patankar, Z. H. Rather, A. Liebman, and S. Doolla	2023	IEEE PES Innovative Smart Grid Technologies—Asia
[189]	Grey wolf optimizer-based machine learning algorithm to predict electric vehicle charging duration time	I. Ullah, K. Liu, T. Yamamoto, M. Shafiullah, and A. Jamal	2023	Transp. Lett.

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[190]	Forecasting of EVs' Charging Behavior Using Deep Neural Networks.	H. Rathore, H. K. Meena, and P. Jain	2023	International Conference on Communication, Circuits, and Systems (IC3S)
[117]	Forecasting EV Charging Demand: A Graph Convolutional Neural Network-Based Approach	S. R. Fahim, R. Atat, C. Kececi, A. Takiddin, M. Ismail, K. R. Davis, E. Serpedin	2024	4th International Conference on Smart Grid and Renewable Energy (SGRE), 2024, pp. 1–6, doi: 10.1109/SGRE59715.2024.10428726.
[191]	Forecasting Electric Vehicle charging demand using Support Vector Machines	E. S. Xydas, C. E. Marmaras, L. M. Cipcigan, A. S. Hassan, and N. Jenkins	2013	48th International Universities' Power Engineering Conference (UPEC)
[120]	FMGCN: Federated Meta Learning-Augmented Graph Convolutional Network for EV Charging Demand Forecasting	L. You, Q. Chen, H. Qu, R. Zhu, J. Yan, P. Santi, C. Ratti	2024	IEEE Internet Things J.
[108]	Fleet Load Charge Forecasting in Electric Vehicles Using a Hybrid Deep Learning Model: LSTM-AQOA	M. G. Kumar, N. Kolla, V. Kotagi, and M. Mathapati	2023	International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE)
[192]	Dynamic time prediction for electric vehicle charging based on charging pattern recognition	C. Li, Y. Fu, X. Cui, and Q. Ge	2023	Front. Inf. Technol. Electron. Eng.
[122]	Research on an electric vehicle charging load prediction method based on spectral clustering and a deep learning network	F. Xin, X. Yang, W. Beibei, X. Ruilin, M. Fei, and Z. Jianyong	2024	Front. Energy Res.
[193]	Electric vehicle charging load prediction based on variational mode decomposition and Prophet-LSTM	N. Cheng, P. Zheng, X. Ruan, and Z. Zhu	2023	Front. Energy Res.
[47]	EVisionary: A Prediction Platform for Electric Vehicle Charging Capacity based on the Impact Analysis of Climate Factors	D. C. Li, P.-C. Ku, W. Tai, Y.-C. Lan, and J. L. Kingsang	2024	IEEE 7th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)
[48]	EV Fleet Charging Load Forecasting Based on Multiple Decomposition With CEEMDAN and Swarm Decomposition	E. Dokur, N. Erdogan, and S. Kucuksari	2022	IEEE Access
[194]	Ensemble Learning for Charging Load Forecasting of Electric Vehicle Charging Stations	X. Huang, D. Wu, and B. Boulet	2020	IEEE Electric Power and Energy Conference (EPEC)
[46]	Energy Demand Prediction with Federated Learning for Electric Vehicle Networks	Y. M. Saputra, D. T. Hoang, D. N. Nguyen, E. Dutkiewicz, M. D. Mueck, and S. Srikanteswara	2019	IEEE Global Communications Conference (GLOBECOM)

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[123]	Energy Demand Load Forecasting for Electric Vehicle Charging Stations Network Based on ConvLSTM and BiConvLSTM Architectures	F. Mohammad, D.-K. Kang, M. A. Ahmed, and Y.-C. Kim	2023	IEEE Access
[195]	Energy Consumption Prediction of Electric Vehicles Through Transformation of Time Series Data	X. Hu and B. Sikdar	2023	IEEE 3rd International Conference on Sustainable Energy and Future Electric Transportation (SEFET)
[196]	Insights into Household Electric Vehicle Charging Behavior: Analysis and Predictive Modeling	A. Almaghrebi, K. James, F. Al Juheshi, and M. Alahmad	2024	Energies
[197]	Multi-Feature Data Fusion-Based Load Forecasting of Electric Vehicle Charging Stations Using a Deep Learning Model	P. Aduama, Z. Zhang, and A. S. Al-Sumaiti	2023	Energies
[147]	Prediction of Charging Demand of Electric City Buses of Helsinki, Finland by Random Forest	S. Deb and X.-Z. Gao	2022	Energies
[198]	Short-Term Load Forecasting Model of Electric Vehicle Charging Load Based on MCCNN-TCN	J. Zhang, C. Liu, and L. Ge	2022	Energies
[30]	Machine Learning for Solving Charging Infrastructure Planning: A Comprehensive Review	S. Deb	2021	5th International Conference on Smart Grid and Smart Cities (ICSGSC)
[34]	Forecasting the charging demand of electric vehicles using time-series models	Y. Kim and S. Kim	2021	Energies
[151]	An advanced machine learning-based energy management of renewable microgrids considering hybrid electric vehicles' charging demand	T. Lan, K. Jermsittiparsert, S. T. Alrashood, M. Rezaei, L. Al-Ghussain, and M. A. Mohamed	2021	Energies
[73]	Data-driven charging demand prediction at public charging stations using supervised machine learning regression methods	A. Almaghrebi, F. Aljuheshi, M. Rafaie, K. James, and M. Alahmad	2020	Energies
[199]	Electric vehicles plug-in duration forecasting using machine learning for battery optimization	Y. Chen, K. S. S. Alamin, D. J. Pagliari, S. Vinco, E. Macii, and M. Poncino	2020	Energies
[200]	End-to-End Smart EV Charging Framework: Demand Forecasting and Profit Maximization With Causal Information Enhancement	P. Udomparichatr, P. Vateekul, and K. Rojviboonchai	2023	International Electrical Engineering Congress (iEECON)
[201]	Electric vehicle load forecasting in a distribution transformer based on Feature Engineering	X. Yang, C. Chen, W. Zhao, and Y. Li	2021	IEEE 4th International Electrical and Energy Conference (CIEEC)
[36]	Electric vehicle load forecasting: A comparison between time series and machine learning approaches	L. Buzna, P. De Falco, S. Khormali, D. Proto, and M. Straka	2019	1st International Conference on Energy Transition in the Mediterranean Area (SyNERGY MED)

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[109]	Electric vehicle charging load clustering and load forecasting based on a long short-term memory neural network	H. Wang, X. Huang, S. Gao, Z. Yang, T. Gao, Q. Zhao, and H. Ding	2022	IEEE 5th International Electrical and Energy Conference (CIEEC)
[88]	Electric Vehicle Driver Clustering using Statistical Model and Machine Learning	Y. Xiong, B. Wang, C.-C. Chu, and R. Gadh	2018	IEEE Power & Energy Society General Meeting (PESGM)
[202]	Electric vehicle charging profile prediction for efficient energy management in buildings	K. N. Kumar, P. H. Cheah, B. Sivaneasan, P. L. So, and D. Z. W. Wang	2012	10th International Power & Energy Conference (IPEC)
[203]	Electric Vehicle Charging Load Time-Series Prediction Based on Broad Learning System	W. Sike, Y. Liansong, P. Bo, Z. Xiaohu, C. Peng, and S. Yang	2023	IEEE 6th International Conference on Industrial Cyber-Physical Systems (ICPS)
[204]	Electric Vehicle Charging Load Prediction Method Based on Nonlinear AutoRegressive Neural Networks	Y. Zhao, J. Dong, X. Fan, X. Lin, J. Tang, B. Qian, F. Zhang	2023	4th International Conference on Computer Engineering and Intelligent Control (ICCEIC)
[142]	Electric Vehicle Charging Load Prediction Based On Real-Time Road Traffic	C. Meng, L. Xu, J. Cheng, and Z. Shao	2023	China Automation Congress (CAC)
[110]	Electric vehicle charging load forecasting: A comparative study of deep learning approaches	J. Zhu, Z. Yang, M. Mourshed, Y. Guo, Y. Zhou, Y. Chang, Y. Wei, and S. Feng	2019	Energies
[89]	Electric Vehicle Charging Behavior Prediction using Machine Learning Models	P. Rajagopalan and P. Ranganathan	2022	IEEE Electrical Power and Energy Conference (EPEC)
[205]	Electric vehicle charging demand forecasting using a deep learning model	Z. Yi, X. C. Liu, R. Wei, X. Chen, and J. Dai	2022	J. Intell. Transp. Syst. Technol. Planning, Oper.
[206]	Application and machine learning methods for dynamic load point controls of electric vehicles (xEVs)	D. Cao, J. Lerch, D. Stetter, M. Neuburger, and R. Wörner	2020	E3S Web of Conferences
[207]	Design of Charging Station Load Forecasting Model Based on Image Classification	D. Yan, C. Zhao, B. Zhu, K. Zhang, and J. Zhan	2023	China Automation Congress (CAC)
[111]	Deep Learning Tackles Temporal Predictions on Charging Loads of Electric Vehicles	E. Cadete, R. Alva, A. Zhang, C. Ding, M. Xie, S. Ahmed, Y. Jin	2022	IEEE Energy Conversion Congress and Exposition (ECCE)
[78]	Deep Learning-Based Optimization Model for Energy Consumption of New Electric Vehicles	G. Kotapati, P. K. D. Selvamani, K. K. Lella, K. S. Shaik, V. R. Katevarapu, and N. J. Bommagani	2023	Rev. d'Intelligence Artif.
[208]	A combination prediction method of electric vehicle charging load based on the Monte Carlo method and a neural network	W. Yang, Y. Li, H. Wang, J. Feng, and J. Yang	2022	Journal of Physics: Conference Series

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[209]	Coherent Hierarchical Probabilistic Forecasting of Electric Vehicle Charging Demand	K. Zheng, H. Xu, Z. Long, Y. Wang, and Q. Chen	2023	IEEE Trans. Ind. Appl.
[66]	Charging Load Prediction of Electric Private Vehicles Considering Travel Day Type and Traffic Conditions	Y. Wu, Y. Wan, and Y. Cao	2022	41st Chinese Control Conference (CCC)
[210]	Charging load forecasting of electric vehicles based on the sparrow search algorithm-improved random forest regression model	D. Wang, Y. Ge, J. Cao, Q. Lin, and R. Chen	2023	J. Eng.
[103]	Charging Load Forecasting of Electric Vehicle Based on Monte Carlo and Deep Learning	Q. Gao, T. Zhu, W. Zhou, G. Wang, T. Zhang, Z. Zhang, M. Waseem, S/Liu, C. Han, and Z. Lin	2019	IEEE Sustainable Power and Energy Conference (iSPEC)
[124]	Charging load prediction method for electric vehicles based on an ISSA-CNN-GRU model	F. Yao, J. Tang, S. Chen, and X. Dong	2023	Dianli Xitong Baohu yu Kongzhi/Power Syst. Prot. Control
[211]	Asynchronously updated predictions of electric vehicles' connection duration to a charging station	M. Straka, M. Jančura, N. Refa, and L'. Buzna	2022	7th International Conference on Smart and Sustainable Technologies (SpliTech)
[212]	Research on electric vehicle charging load prediction and charging mode optimization	Z. ZHANG, H. SHI, R. ZHU, H. ZHAO, and Y. ZHU	2021	Arch. Electr. Eng.
[115]	Hybrid Model Based on an SD Selection, CEEMDAN, and Deep Learning for Short-Term Load Forecasting of an Electric Vehicle Fleet	A. Mohsenimanesh, E. Entchev, and F. Bosnjak	2022	Appl. Sci.
[74]	Short-term load forecasting for electric vehicle charging stations based on deep learning approaches	J. Zhu, Z. Yang, Y. Guo, J. Zhang, and H. Yang	2019	Appl. Sci.
[213]	Analyzing the Travel and Charging Behavior of Electric Vehicles—A Data-driven Approach	S. Baghali, S. Hasan, and Z. Guo	2021	IEEE Kansas Power and Energy Conference (KPEC)
[93]	Analyzing the factors influencing energy consumption at electric vehicle charging stations with Shapley additive explanations	P. K. Mohanty and D. S. Roy	2023	International Conference on Microwave, Optical, and Communication Engineering (ICMOCE)
[214]	Analysis of Electric Vehicle Charging Demand Forecasting Model based on Monte Carlo Simulation and EMD-BO-LSTM	M. Akil, E. Dokur, and R. Bayindir	2022	10th International Conference on Smart Grid (icSmartGrid)
[215]	An EV Charging Station Load Prediction Method Considering Distribution Network Upgrade	X. Li and Q. Han	2024	IEEE Trans. Power Syst.
[216]	A Scheme for Charging Load Prediction of EV Based on Fuzzy Theory	S. Wang, L. Yu, P. Cao, H. Hu, B. Pang, W. Luo, X. Ge	2024	Frontiers in Artificial Intelligence and Applications

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[143]	A radial basis function-based approach for electric vehicle charging load forecasting	G. Wang, X. Ji, B. Zhou, H. Li, and H. Wang	2018	The 11th IET International Conference on Advances in Power System Control, Operation and Management (APSCOM 2018)
[75]	A Prediction Method of Charging Station Expected Demand Based on Graph Structure	C. Wang, C. Zhou, X. Song, and X. Zhang	2021	International Conference on Electronic Information Engineering and Computer Science (EIECS)
[217]	A novel LSTM-based deep learning approach for multi-time scale electric vehicle charging load prediction	J. Zhu, Z. Yang, Y. Chang, Y. Guo, K. Zhu, and J. Zhang	2019	IEEE Innovative Smart Grid Technologies—Asia (ISGT Asia),
[90]	A Novel Large-Scale Electric Vehicle Charging Load Forecasting Method and Its Application on Regional Power Distribution Networks	M. Liu, Z. Zhao, M. Xiang, J. Tang, and C. Jin	2022	4th Asia Energy and Electrical Engineering Symposium (AEEES)
[125]	A Method of Short-Term Load Forecasting At Electric Vehicle Charging Stations Through Combining Multiple Deep Learning Models	X. Xiong and L. Zhou	2023	2nd Asia Power and Electrical Technology Conference (APET)
[218]	A Load Forecasting Method of Electric Vehicles Charging Station Group Based on GAN-RF Model	W. Gang, L. Wu, and G. Xuan	2021	IEEE 5th Conference on Energy Internet and Energy System Integration (EI2)
[219]	A Hybrid Multi-model Ensemble Feature Selection and SVR Prediction Approach for Accurate Electric Vehicle Demand Prediction: A US Case Study	F. Marzbani, A. Osman, and M. S. Hassan	2023	IEEE International Conference on Environment and Electrical Engineering and 2023 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)
[220]	A Deep Generative Model for Non-Intrusive Identification of EV Charging Profiles	S. Wang, L. Du, J. Ye, and D. Zhao	2020	IEEE Trans. Smart Grid
[148]	Dynamic Load Prediction Model of Electric Bus Charging Based on WNN	C. Zheng, T. Peng, Z. Chao, Z. Shasha, L. Xiaoyu, and L. Han	2022	Mob. Inf. Syst.
[112]	Improving the Efficiency of Deep Learning Models Using a Supervised Approach for Load Forecasting of Electric Vehicles	T. Rasheed, A. R. Bhatti, M. Farhan, A. Rasool, and T. H. M. El-Fouly	2023	IEEE Access
[113]	A Method of Prediction of Charging Time Based on an LSTM Neural Network	W.-D. Fang, C.-D. Xu, J.-S. Pan, H.-L. Chen, and S. Wang	2021	J. Netw. Intell.
[49]	A deep learning approach for the prediction of electric vehicle charging stations' power demand in regulated electricity markets: the case of Morocco	M. Boulakhbar, M. Farag, K. Benabdelaziz, T. Kousksou, and M. Zazi	2022	Clean. Energy Syst.

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[140]	Secure and efficient prediction of electric vehicle charging demand using α2-LSTM and AES-128 cryptography	M. Bharat, R. Dash, K. J. Reddy, A. S. R. Murty, D. C., and S. M. Muyeen	2024	Energy AI
[221]	A novel forecasting approach to schedule aggregated electric vehicle charging	N. Brinkel, L. Visser, W. van Sark, and T. AlSkaif	2023	Energy AI
[65]	Seasonal electric vehicle forecasting model based on machine learning and deep learning techniques	H.-A. I. El-Azab, R. A. Swief, N. H. El-Amary, and H. K. Temraz	2023	Energy AI
[222]	A data-driven framework for medium-term electric vehicle charging demand forecasting	A. Orzechowski, L. Lugosch, H. Shu, R. Yang, W. Li, and B. H. Meyer	2023	Energy AI
[130]	Assessment of a hybrid transfer learning method for forecasting EV profile and system voltage using limited EV charging data	P. Banda, M. A. Bhuiyan, K. N. Hasan, and K. Zhang	2023	Sustain. Energy, Grid Networks
[104]	Short-term electric vehicle charging load forecasting based on deep learning in low-quality data environments	X. Shen, H. Zhao, Y. Xiang, P. Lan, and J. Liu	2022	Electr. Power Syst. Res.
[223]	A hybrid electric vehicle load classification and forecasting approach based on the GBDT algorithm and temporal convolutional network	T. Zhang, Y. Huang, H. Liao, and Y. Liang	2023	Appl. Energy
[105]	Electricity peak shaving for commercial buildings using machine learning and vehicle-to-building (V2B) system	M. Ghafoori, M. Abdallah, and S. Kim	2023	Appl. Energy
[126]	Probability density function forecasting of residential electric vehicles' charging profile	A. Jamali Jahromi, M. Mohammadi, S. Afrasiabi, M. Afrasiabi, and J. Aghaei	2022	Appl. Energy
[76]	An Edge Computing-oriented Net Power Forecasting for PV-assisted Charging Station: Model Complexity and Forecasting Accuracy Trade-off	J. Shi, N. Liu, Y. Huang, and L. Ma	2022	Appl. Energy
[224]	An ensemble machine learning-based algorithm for electric vehicle user behavior prediction	Y.-W. Chung, B. Khaki, T. Li, C. Chu, and R. Gadh	2019	Appl. Energy
[225]	Forecasting the EV charging load based on customer profile or station measurement?	M. Majidpour, C. Qiu, P. Chu, H. R. Pota, and R. Gadh	2016	Appl. Energy
[226]	Data-driven spatial-temporal prediction of electric vehicle load profile considering charging behavior	X. Ge, L. Shi, Y. Fu, S. M. Muyeen, Z. Zhang, and H. He	2020	Electr. Power Syst. Res.

Table A1. *Cont.*

Ref.	Title	Authors	Publication Year	Publication
[77]	Load forecasting of an electric vehicle charging station based on grey theory and neural network	J. Feng, J. Yang, Y. Li, H. Wang, H. Ji, W. Yang, and K. Wang	2021	Energy Reports
[227]	Research on EV charging load forecasting and orderly charging scheduling based on model fusion	W. Yin and J. Ji	2024	Energy
[51]	Self-supervised online learning algorithm for electric vehicle charging station demand and event prediction	M. A. Zamee, D. Han, H. Cha, and D. Won	2023	J. Energy Storage
[91]	Mind the gap: Modeling the difference between censored and uncensored electric vehicle charging demand	F. B. Hüttel, F. Rodrigues, and F. C. Pereira	2023	Transp. Res. Part C Emerg. Technol.

Note: BiLSTM: bidirectional long-short term memory; BO: Bayesian optimization; CEEMDAN: complete ensemble empirical mode decomposition with adaptive noise; CNN: convolutional neural network; DN: deep network; EMD: empirical mode decomposition; EV: electric vehicle; EVCS: electric vehicle charging station; FMGCN: federated meta learning-augmented graph convolutional network; GA: genetic algorithm; GAN: generative adversarial networks; GBDT: gradient boosted decision tree; GRU: gated recurrent unit; IoT: Internet of Things; ISSA: improved Sparrow search algorithm; LA-RCNN: Luong attention-recurrent-convolutional neural network; LSTM: long short-term memory; MCCNN: multi-channel convolutional neural network; MPC: model predictive control; PHEV: PV: photovoltaic; QRDCC: quantile regression dilated causal convolution; RF: random forest; SD: similar day; SVM: support vector machine; SVR: support vector regressor; TCN: temporal convolutional network; V2B: vehicle to building; VMD: variational mode decomposition; V2G: vehicle-to-grid; WNN: wavelet neural network; XGBoost: extreme gradient boosting.

Table A2. Thematic synthesis of the studies included in the SLR.

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[31]	LinR, bagging, GB, Ada, RF, CNN, ANN, LSTM	Aggregated on different charging points and geographical areas: site, postal code, TSO zone, portfolio, and random site aggregation	EV charging demand	different charging levels: commercial, public EVCSs, and private setups	Unavailable due to privacy restrictions	Germany	short-term: next 24 h horizon with a resolution of 15 min	timestamp, plugin time, plug out time, duration, site ID, number of chargers, number of charging points, site fuse limits, postal code, TSO zone, charge power max, energy consumed. Public holiday information in Germany was integrated into the dataset.

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[162]	SVM, ANN, tree-based ML	aggregated for large fleets of EVs	EV charging consumption	residential, commercial parking areas, and DC fast chargers	proprietary	USA	day-ahead, whole week on a half-hourly basis	Previous Day consumption: charging consumption of previous day for each half hour; number of the week (1–53); number of the day (1–7) starting with Monday; Type of Day: Weekday or Weekend; Half Hour: 1–48 half hour parts of each day; Number of the new EV plug-in connections for every half hour; number of EV that are connected and charging for every half hour.
[67]	LSTM	aggregated	EV charging demand (bus)	urban EVCSs (no level specified)	collected for the study	Jiangsu Province, China	one hour	historical data (charging times, charging power, and state of charge), time-of-use electricity price, and the number of charged cars
[99]	Comparison: LSTM, SVM	aggregated	EV charging demand	workplace EV charging: one public, one employees only	publicly available (https://openenergyhub.ornl.gov/explore/dataset/acn-data/information/ (accessed on 25 November 2024))	California, USA	short term	Connection hour, the complete charging time, and the kWh delivered. Additional features: day of the week (e.g., Sunday, Monday), week number, and working status (working day or holiday) derived from the raw dataset.
[63]	LSTM	aggregated	EV charging demand	hospital semi-public charging site	proprietary (because of privacy concerns)	Not informed	day-ahead; 15 min time resolution	the EV users' radio frequency identification, the arrival and departure times, and the energy consumed (in kWh)
[118]	LSTM	aggregated	EV charging demand	urban EVCSs (no level specified)	collected for the study	China	daily	historical demand data
[50]	LSTM	individual and cumulative energy forecast	energy demand (time of arrival, connection duration, power) and the number of charging sessions for EVs	workplace EV charging: employees only	publicly available at https://openenergyhub.ornl.gov/explore/dataset/acn-data/information/ (accessed on 25 November 2024)	California, USA	week ahead	time arrival, connection duration, power

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[163]	LSTM	aggregated	maximum charging demand session	EVCSs (low and fast)	collected for the study	Jeju, South Korea	daily	1. Charging station data: Headquarters ID, Office ID, Charging station ID, Charger name, Charger ID, Address, Type of charging, Charger capacity, Charging amount, Charging time, Date, Charging start date and time, and Charging end date and time 2. Days of the week 3. Slow/fast charging patterns
[164]	BiLSTM, LSTM	aggregated	EV charging demand	Carpark and public areas in London, UK (different charging patterns)	proprietary	London, UK	ultra-short term (1–4 h)	historical charging demand and weather features
[100]	LSTM	aggregated	EV charging demand	urban and highways circumjacent EVCSs	collected for the study		ultra-short term	historical charging demand (EV charging transaction data includes the start time of the charging process, power consumption of the charging process, the charging cost, the charging pile location, and the end time of the charging process) and estimated charging pile degree
[106]	LSTM	aggregated	EV charging demand	Total number of EVs in a city	simulated	Not applicable	daily	travel motif (daily travel distances and times) used to create a synthetic EV charging demand dataset.
[101]	DNN	aggregated	plug-out hour, required energy to charge	residential	publicly available	UK	daily	month of the year, day of the month, day of the week, arrival hour, plug-out hour, and required energy
[165]	RF, XGBoost, KNN, GPR	aggregated	EV charging demand	office environment	collected for the study	Belgium	30-day	historical energy consumption, time information, car type, and weather information
[33]	ARIMA, XGBoost, ANN, LSTM, GBDT, SVM	individual	EV charging consumption, arrival, and departure of individual EVs	company's parking area	collected for the study	Not informed	short term (15 min within the next 2 h)	information about charging sessions: duration of charging, SoC of the EVs, and the power drawn during the charging sessions. External features: holidays, company events, and weather conditions
[166]	SVR	aggregated	EV charging consumption	urban public EVCSs	collected for the study	Nanjing, China	daily	daily actual power data along with influencing factors such as temperature and weather type, considering users' charging habits, seasonal variations, and working day determination

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[45]	RNN, LSTM, Bi-LSTM, GRU, CNN, Transformer	aggregated	EV charging demand	urban public EVCSs (level 2)	publicly available	Boulder, Colorado, USA	daily, weekly, and monthly	station ID, location, connection port, start and end times, connection durations, charging durations, kWh consumed, greenhouse gas reductions, gasoline savings, and unique driver identification
[139]	BPNN	aggregated	Future number of EVs in a region from 2021 to 2030 and their charging demand based on different types of EVs like private cars, buses, and taxis	urban public EVCSs, parking areas, and residential	publicly available	China	2021 to 2030	GDP per capita, average government subsidies, average sustainable mileage of electric vehicles, the number of public charging piles, and the percentage of electric vehicle ownership in the region's car ownership from 2011 to 2020
[156]	RNN, LSTM, Transformer	aggregated	EV charging demand	urban public charging stations (level 2)	publicly available	Boulder, Colorado, USA	7 days, 30 days, and 90 days	historical real-world data (EV charging session: type of the plug, address, arrival and departure time, date, and energy consumption in kW for each charging record), weather, and weekend data
[79]	LSTM	aggregated	EV charging demand	campus parking area	proprietary	Atlanta, USA		Charging Time (hh:mm:ss), Energy (kWh), GHG savings (kg), Gasoline savings (gallons), and the cost incurred (USD)
[133]	RF, XGBoost	aggregated	EV charging demand	FC installed nationwide	publicly available	Korea	hourly, daily, weekly	calendar, power records, name of the charging station, the region where it is located, the start and end times of charging, and the charging demand
[150]	LSTM	aggregated	EV charging demand	EVCSs (FC)	proprietary	Jeju Island, Korea	short term	historical charging data: the unit with active power, and the other factor is fast-charging power
[64]	RF, QPM, GLMNET, SVM, LDA, XGBoost, BLR, DTs, NB	aggregated	EV charging demand	urban public EVCSs	publicly available	Boulder, Colorado, USA	short term	1. charging time (in minutes), the amount of energy dispensed (in kWh) during each charging session, number of Charging Sessions, unique Drivers, and Number of Ports. 2. Average temperature data was included, Day of the Week. 3. Additional features identified through exploratory analysis, such as GHG savings, grid savings

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[81]	Bi-LSTM, GCN	aggregated	EV charging demand	urban public EVCSs	publicly available	Palo Alto, California, USA	hourly, daily	historical charging sessions data and external factors such as weather conditions, holidays, and weekends are considered in the day-type tendency features
[131]	CNN	aggregated	EV charging consumption	EVCSs (power consumption from 0 to 800 kW, with an average power range of 200 to 400 kW), offering a diverse range of consumption scenarios.	collected for the study	China	short term (one hour)	historical charging consumption data, weather data, and day type
[167]	LSTM	aggregated	EV charging demand	urban public EVCS	collected for the study	Not informer	short term (3 h)	connection type, connection duration, charging power, charging post number, and total energy consumption
[17]	LSTM	aggregated	EV charging consumption	shopping centers, residential areas, public car parks, and workplaces	collected for the study	Finland	1 h or 1 day	charging consumption data, day type
[82]	LSTM	individual	EV total charging duration, the number of times the EV will be charged in each of these time slots, and determine whether the next day will be a charging day or not	residential	publicly available	Austin, USA	short term (day ahead)	historical power consumption
[168]	BiLSTM	aggregated	EV charging demand	urban public EVCS	proprietary	southern China	short term (hourly and daily)	time-series weather features and historical EV demand data
[114]	LSTM	aggregated	EV charging consumption	airport EVCS	collected for the study	Shenzhen, China	short term	total power consumption of the charging station (sampling interval set at 15-min intervals)
[84]	GRU	aggregated	EV charging consumption	urban public EVCS	collected for the study	North China	short term (15 min)	historical charging consumption data, weather conditions, and date types

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[136]	TL, MAML	aggregated for the groups of charging stations	EV charging demand	public urban charging station and public workplace parking areas (smaller)	publicly available	Boulder, Colorado, USA; California, USA; Trondheim, Norway	short term (hourly)	10 features such as hour, quarter-of-day, day, day-of-week, week-of-year, month, quarter-of-year, season, and load (kW)
[85]	LSTM	aggregated	EV charging demand	urban public EVCS	collected for the study	Zhejiang, China	short term	historical demand data
[141]	NNs, RF, SVM	aggregated	EV charging demand and probability of available capacity for V2G services (idle time of EVs after they are fully charged, and how much of this capacity can be sold back to the grid	workplace EV charging: one public, one employees only	publicly available	California, USA	short term	connect time, which indicates the connection time of the charger, and kWh delivered, which indicates the daily power consumed by users at the charging station. The data is aggregated into historical weekdays and weekend data separately
[159]	MToM	aggregated	EV charging demand	workplace EV charging: one public, one employees only	publicly available	California, USA	short term (15 min)	historical charging habits and current charging demand trends
[44]	LSTM, GRU, hybrid models combining CNN, LSTM, GRU	aggregated	EV charging demand	workplace EV charging: one public, one employees only	publicly available	California, USA	24, 48, and 72 h	connection time, disconnection time, and energy delivered in kilowatt-hours (kWh), additional variables, such as the time of the day and month of the year
[86]	LSTM	individual	EV charging behavior: charging time, charging amount (power)	urban public EVCS	publicly available			user ID, charging connection time, charging completion time, disconnection time, and charging amount
[80]	XGBoost	aggregated	EV charging demand	urban public EVCS	publicly available	Boulder, Colorado, USA; Palo Alto, USA; Perth and Kinross, UK	one month	GHG savings, gasoline savings, port type, charging start date, time, and energy consumed during the charging sessions
[68]	LSTM	aggregated	EV charging demand	urban public EVCS	proprietary and public	China	hourly	timestamp, pile voltage, pile current, SOC, car battery temperature, pile temperature, gun temperature, current charge, vehicle demand voltage, current vehicle demand, electricity meter report, electricity bill, and service fee

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[129]	RCNN	aggregated	EV charging demand	urban public EVCS	proprietary	Beijing, Guangzhou, and Shanghai	daily	EV power consumption, real-time connected EVs, and weather conditions (such as temperature)
[169]	CNN	individual	starting time and charging periods in EV charging profiles	residential	publicly available	Austin, USA		start time of EV charging, initial battery SOC, total charging time, number of EVs at different times of the day, and advanced metering infrastructure data such as smart meters
[170]	Q-learning based on ANN and RNN	aggregated	EV charging demand	EV fleet	simulated data	Not applicable	hour ahead	charging strategy, charging duration, charged PHEVs, start time, battery capacity, and SOC of battery
[107]	LSTM	aggregated	EV charging consumption	residential	collected for the study	Hangzhou, China	day ahead	historical EV charging consumption data and temperature, weather conditions, and day type (weekday or weekend)
[171]	MToM	aggregated	EV charging demand	workplace EV charging: one public, one employees only	publicly available	California, USA	short term	users' living habits from historical charging behaviors, users' current stochastic behavior
[172]	LSTM	aggregated	EV charging power	workplace EV charging: one public, one employees only	publicly available	California, USA	72 h	EV historical charging session data
[173]	DT, XGBoost, DNN	individual	EV charging duration, number of charging sessions per month	workplace EV charging: one public, one employees only	publicly available	California, USA	number of charging sessions per month	time of arrival, session duration, user ID, connection time, departure time, cyclic and ordinal temporal details, such as hour, day, and month, and holidays
[174]	WNN	individual	EV traffic flow. Derived variables: Road Section Impedance, Electric Vehicle Power Consumption	23 roads	publicly available	California, USA	day ahead	historical traffic data
[145]	RF, XGBoost, KNN, Bagging regressor, LSTM, RNN	individual	EV charging session duration	workplace EV charging: one public, one employees only	publicly available	California, USA		disconnection time, connection time, time duration, power consumption, climatic data such as wind, humidity, frost, rainfall, and temperature
[175]	QRDCC	aggregated	EV demand probability density function	urban public EVCS	collected for the study	Not informed	100 h	historical demand data

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[176]	RF, XGboost	aggregated	EV charging consumption	workplace EV charging: one public, one employees only	publicly available	California, USA		detailed charging sessions
[177]	DeepBi-LSTM	aggregated for the charging stations in the studied region	EV charging consumption	urban public EVCSs in the region (data aggregated as the sum of the EVCSs)	Collected for the study	Shenzhen, China	1-ahead, 2 h ahead, 4 h ahead, and 24 h ahead	active power demand
[146]	RF, SVM, XGBoost, DNN	individual	EV charging session duration and consumption	workplace EV charging: one public, one employees only	publicly available	California, USA		historical charging data in conjunction with weather, traffic, and events data
[178]	RF, LinR, NN, SVR	individual	EV charging session duration	FC EVCSs	collected for the study	Canada		Historical one-year charging sessions data, external temperature, and number of charges made the same day
[121]	SA-based temporal model, GAT-Autoformer	aggregated	EV charging demand	EVs from a city	sensitive user information collected ad hoc	Wuhan, China		13 features: user charging and user trajectory
[179]	LSTM	individual (arrival time, departure time), aggregated (charging demand)	EV arrival time, departure time, EV charging demand (aggregator)	residential	publicly available	Not informed	day ahead	historical data: arrival time, departure time, traveled distance
[102]	LSTM	individual	EV charging behavior: duration of charging within a specified range, the time slots when charging will occur, the number of times charging will happen in each time slot, and whether the next day will be a charging day or not.	individual EV behavior residential	Collected for the experiments	Not informed	day ahead	historical charging data
[180]	ANFIS	aggregated	EV charging demand	urban public EVCSs	simulated data of charging stations within an urban area	Not applicable	day ahead	historical charging data

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[181]	Temporal Characteristics DNN	aggregated	EV charging demand	urban public EVCSs	proprietary	Beijing, China	day ahead	ID of charging stations, charging start times, names of charging stations, latitude and longitude coordinates, and the district of each charging station
[152]	SVM	aggregated for the EVs connected to the system	electrical consumption at the medium voltage to low voltage (MV-LV) transformer level	EVs connected to a particular distribution grid	collected for the study	Savoie, France	day ahead (1 h resolution)	historical consumption data and weather data, including temperature and humidity
[69]	MLP	aggregated	amount of energy that should be bought by the parking lot operator	workplace EV charging: one public, one employees only	publicly available	USA	next day (5 min resolution)	small set of historical consumption data (arrival time, departure time, initial energy, maximum required energy, number of EVs, remaining energy, and time of the day), and data from utility prices
[61]	LSTM	aggregated for the entire household	EV charging consumption	residential	free for academic uses (available at: https://www.pecanstreet.org/ (accessed on 25 November 2024))	USA	short term	historical consumption data
[32]	LinR, BTR, and ANN	aggregated for a group of EVs	EV charging consumption	electric consumption for small geographic area	publicly available	USA	day ahead (1 h resolution)	historical consumption data
[157]	MTL	aggregated	EV charging consumption	urban public EVCSs	Collected for the experiments	Utah, USA	24 days, 20 days, and 15 days ahead	start and end times of charging, and the total energy consumed for a charging session at the five charging stations
[182]	SVM	aggregated	EV charging demand	residential	available for academic uses	Texas, USA	daily	historical consumption data
[183]	Q-learning	aggregated	EV charging demand	workplace EV charging: one public, one employees only	publicly available	California, USA	day ahead	time of connection, accomplished charging time, time of disconnection, kWh supply, session ID, station ID
[184]	RF, XGBoost, Categorical Boosting, LightGBM	individual	EV charging duration	urban EV fleet (private and commercial) normal and FC operations	Collected for the experiments (sensitive information such as vehicle ID, vehicle type, location, and charging events)	Japan		SOC at the start and end, lighting conditions, season, day of the week, time of day, and the use of the air conditioning compressor and heater

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[185]	Stacking/voting ensemble: RF, SVM, XGBoost	individual	EV user behavior (energy consumption and session duration)	workplace EV charging: one public, one employees only	publicly available	California, USA		historical consumption data, session duration, weather features, and holidays
[35]	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW
[116]	LSTM	aggregated	EV charging demand	residential	simulated data from experimental data from other projects	USA	long term	consumption data, temperature, number of EVs, and holidays
[70]	Multi-Graph CNN	aggregated	EV charging consumption	public fast EVCSs	licensed access	China		historical charging power, weather features, electricity price, and calendar features
[186]	SAE-NN	aggregated	EV charging consumption	urban public EVCSs (fast and low)	Collected for the experiments	Not informed	day ahead	historical consumption, temperature, weather type, and day type
[87]	LSTM	aggregated	EV charging demand	urban public EVCS	Collected for the experiments	Beijing, China	short term	historical demand data
[134]	SVM	aggregated	EV charging consumption	small EVCS	collected for the study	Not informed	ultra-short term	consumption data, basic meteorological data, and holiday data
[187]	RF, SVR, XGBoost	individual	session duration, charging duration, and energy consumption	workplace EV charging: one public, one employees only	publicly available	California, USA	hourly	consumption data, traffic, charging currents, number of connections-disconnection events, and weather data
[188]	Bi-LSTM	aggregated	EV charging demand	workplace EV charging: one public, one employees only	publicly available	California, USA	short term	historical demand data
[144]	TreeBagger, LSTM, KNN	individual	arrival time (AT), energy demand (ED), and plug duration (PD) for individual electric vehicles (EVs)	workplace charging	collected for the study	San Diego, USA	day ahead	historical charging data
[71]	LSTM	aggregator and individual	EV charging demand	urban public EVCS	collected for the study	Shenzhen, China	ultra short term (minute ahead)	charging data, temperature data from a nearby climate station, local electricity prices, and holiday information
[92]	TL, CL	THEORETICAL ANALYSIS	EV charging energy demand	THEORETICAL ANALYSIS	THEORETICAL ANALYSIS	THEORETICAL ANALYSIS	THEORETICAL ANALYSIS	historical data features, weather features

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[72]	GRU	individual	EV charging and discharging power	residential	publicly available (https://neemdashboard.in/index.php (accessed on 25 November 2024))	India	real time	SOC of the EV battery, the electricity prices at different times of the day, the consumption curve of the home, and the power generated from rooftop solar panels
[189]	ELM, FFNN, SVR	individual	EV charging duration time	Residential, commercial, and public EVCSs (private vehicles are household vehicles, and commercial vehicles are fleet vehicles, including government)	collected for the study (sensitive information, vehicle ID, GPS location)	Japan		GPS coordinates, vehicle ID, odometer, vehicle state, start SOC and end SOC, start charging time and end charging time, day of the week, time of the day
[190]	LSTM, RF, XGBoost	aggregated	EV energy charging demand	workplace EV charging: one public, one employees only	publicly available	USA and The Netherlands	short term	charging data, weather, traffic, and event data
[117]	GCNN-LSTM	aggregated	EV charging demand	urban public EVCS	collected for the study	Texas, USA	long term (2-year period, monthly resolution)	historical power data and transportation data (containing hourly traffic density at each charging station)
[191]	SVM	aggregated	EV charging demand	urban EV fleet of different types of vehicles (mainly passenger and goods-carrying ones)	collected for the study	UK	daily	historical charging data, days of the week
[120]	FMGCN	aggregated	EV charging demand	urban public EVCSs	collected for the study	China	short term	EV charging demand, number of nodes, edges, stations, piles, GDP, and population, geographic information, socio-economic indicators, and weather conditions
[108]	LSTM	aggregated at fleet level	EV charging demand	urban public EVCSs and commercial charging points	publicly available	Leeds, UK; Beijing, China	short term	start and finish times of charging, total charging energy, and plug-in duration
[192]	LSTM	individual	dynamic EV charging time	urban public EVCS	proprietary	Shenzhen, China		SOC, charging voltage, charging current, and electric quantity
[122]	LSTM	aggregated	EV charging demand	urban public EVCS	collected for the study	Pukou District, Nanjing, Jiangsu Province, China	daily	Historical charging data, days of the week

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[193]	LSTM	aggregated	EV charging demand	urban public EVCS	collected for the study (can be accessed upon request to the authors)	Fujian Province, China	short term	historical charging data and holiday data
[47]	Comparison: MLP, XGBoost, LSTM, CNN-LSTM, Bi-LSTM, GRU, Transformer	aggregated	EV charging demand	public EVCSs, parking areas, and residential use	collected for the study	Dundee, Scotland, UK	short-term and medium-term (7 days to 28 days)	consumption, weather, and calendar
[48]	Comparison: MLP, LSTM, Bi-LSTM	aggregated at EV fleet level	EV charging demand	urban public EVCS	publicly available (Available at https://www.data.gov.uk/dataset/2279b730-bf4e-40c4-b2de-c82d43ae16d2/ev-fleet-chargepoint-use (accessed on 25 November 2024))	Leeds, UK	short term	historical charging data
[194]	Ensemble: ANN, LSTM, RNN	aggregated	EV charging demand	urban public EVCSs	collected for the study	Boulder, Colorado, USA	hourly	transaction start time, charging time, energy consumption
[46]	Comparison: centralized EDL, FEDL, and clustering-based EDL	aggregated (entire network of EV charging stations)	EV charging demand	urban public EVCSs	collected for the study	Dundee, Scotland, UK		CS ID, EV ID, charging date, charging time, and consumed energy within a particular period
[123]	ConvLSTM, BiConvLSTM	aggregated	EV charging demand	workplace (public) and public urban EVCSs	publicly available	Perth and Dundee (Scotland) and Palo Alto, California and Boulder, Colorado (USA)	daily	historical charging data
[195]	CNN	aggregated and individual	EV energy consumption	Set of EVs (different types)	simulated data with emobpy (Python open-source tool)	Not applicable		Number of passengers, Vehicle speed, Driving Cycle, Road gradient, Road type, Temperature, Wind speed, Weekday, Driver category

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[196]	XGBoost, RF, ANN	individual	connection duration, charging duration, charging demand, time to the next charge	residential level 2	proprietary	Omaha, NE, USA		EV users' IDs, start and end times for connection and charging, the amount of energy consumed, time of the day, day, month, season
[197]	LSTM	aggregated	EV charging consumption	urban public EVCSs	publicly available (Available online: https://archive.ics.uci.edu/dataset/321/electricityloaddiagrams20112014 (accessed on 25 November 2024))	USA	day ahead	historical power data and weather (wind speed, temperature, and humidity)
[147]	RF	aggregated at EV fleet level	EV charging demand (bus)	EV fleet (line bus)	synthetic data	Finland		charging consumption data and weekday data
[198]	MCCNN-TCN	aggregated	EV charging demand	residential, commercial, work, and leisure areas, with a total of 298 charging poles, each having a maximum charging power of 60 kW	collected for the study	Northern city in China	short term	active power of the charging poles, the transaction power, the charging start time and the charging end time, and weather data (temperature, humidity, precipitation, visibility, wind speed, and weather type)
[30]	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW	REVIEW
[34]	Comparison: TBATS, ARIMA, ANN, LSTM	aggregated	EV charging demand	urban public EVCS (single station, city, and country)	publicly available (Available online: http://eng.me.go.kr (accessed on 25 November 2024))	Korea	one day, one week, three weeks, and one month ahead	charging past data (charging time, charging consumption, and charging station datapoints), special day indicators, and weather
[151]	SVR	aggregated	EV charging demand	Charging demand for a microgrid	publicly available (Available online: https://www.eia.gov/electricity/annual/ (accessed on 25 November 2024))	California, USA	daily	charging demand and time of day

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[73]	XGBoost	session-by-session analysis	EV charging demand	Education (universities and schools), which included a total of 14 ports; Workplace (EVCSs owned by companies), with 4 ports; Shopping Center (malls and other retail centers), with 4 ports; Public Parking (downtown and other public parking lots), with 75 ports	collected for the study	cities in Nebraska, USA		Charging Demand, Time of Day, Time Seq, User Sessions Count, User Energy, Number of days since the last charge, Season, Weekday, Location, Port Number, Fee
[199]	LightGBM	aggregated (charge point)	EV plug-in duration	residential	publicly available	UK		dates and times of the start and end of the plug-in, as well as the acquired energy in KW, the plug-in duration, the charge point identifier, and the charge event identifier.
[200]	XGBoost, RF, TabNet	individual (Statistical features grouped by user ID and period)	EV charging power demand and session duration	University public, workplace (employees only), and office building parking area	publicly available	California, USA	short term	historical charging data, user-specific features, weekdays, and holidays
[201]	LSTM	aggregated	EV charging demand	residential	publicly available	southern Germany	continuous day ahead	historical charging data, date data, and weather data
[36]	RF and GBDT	aggregate load imposed by EV charging on the grid at the level of a Utrecht COROP region	EV demand forecasting	urban public EVCSs	proprietary	The Netherlands	7-day, 14-day, and 28-day	identifier of a connector, GPS coordinates of a connector, start time, stop time, connected time, idle time, charge time, number of the used RFID card, consumed energy, and unique identifier of the charging event, each meter-reading taken every 15 min when an EV is charging by recording the identifier of the charging connector, UTC time stamp, and value of the meter
[109]	LSTM	individual	EV demand forecasting and driver clustering	EV fleet	collected for the study	Jiangsu Province, China	short term	historical demand data, weather data, and calendar data

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[88]	MLP	individual and aggregated	EV charging start and end time, EV charging energy consumption	public parking lots	publicly available	California, USA	day ahead	plug-in time, charging start time, charging stop time, charger plug-out, as well as charging current and power consumption
[202]	BPNN	aggregated (building)	EV charging demand	residential building	collected for the study	Singapore	daily	EV ID, Battery capacity (kWh), Arrival time (hours), Departure time (hours), initial SOC (%), Desired final SOC (%)
[203]	BLS	aggregated	EV charging demand	regional urban public EVCS	collected for the study	UK		charging time, charging power, holidays, weather, temperature
[204]	NA-RNN	aggregated	EV charging demand	urban public EVCS	collected for the study	Northern city in China	next 3 h	connection types, connection durations, charging powers, charging pile numbers, and total energy consumption; time-based features such as the time of day
[142]	Residual NN	individual	real-time traffic flow	Residential, working, and commercial areas	proprietary	China	day ahead	traffic flow: date, weather, and traffic data
[110]	ANN, RNN, LSTM, GRU, SAE, BiLSTM	aggregated for the entire station	EV charging demand	public urban EVCS	collected for the study	Shenzhen, China	one minute, five minutes, and fifteen minutes	charging start time, charging end time, and total charging amount
[89]	RF and XGBoost	aggregated	EV charging duration, charging station utilization	University public EVCS	publicly available	California, USA	short term (next 10 days)	connection time, disconnection time, and energy delivered in kilowatt-hours (kWh)
[205]	Seq2Seq	aggregated	EV charging demand	urban public EVCSs	publicly available	Utah and Los Angeles, USA	month ahead and several months ahead	charging demand data (opening hours, parking availability, and other attributes)
[206]	DT, RF, LightGBM, KNNR	aggregated	EV charging demand	car park	collected for the study	Germany	short term	charging data, weather, holidays
[207]	Combination: RF-BIRCH, EMD, CNN-LSTM, Bi-LSTM	aggregated	EV charging demand	University public, workplace (employees only) parking area	publicly available	California, USA	day ahead	historical charging data, day of the week, holidays, and seasonal variations
[111]	ANN, RNN, LSTM	aggregated	EV charging demand	University public, workplace (employees only) parking area	publicly available	California, USA	short and long term	charging station ID, connecting and disconnecting time of a charging session, charging current, energy delivered, date of charging session, and space ID

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[78]	BGRU	individual	EV charging time, charging consumption, GHG savings, cost savings, gasoline savings	conference center parking station	collected for the study	Atlanta, USA	short term	charging time, energy consumption (in kWh), GHG savings (in kg), gasoline savings (in gallons), and cost savings (in USD)
[208]	Seq2Seq	aggregated for an EV fleet	EV charging consumption and parking time	residential use, parking areas, and potentially public EVCSs	publicly available	USA	daily	initial travel time, starting travel place, and parking time
[209]	PICNN	aggregated	EV charging demand	University public, workplace (employees only), and office building parking area	publicly available	California, USA	day ahead	charging data, weather features, and calendar features
[66]	MLR	aggregated for different types of charging points	EV travel time and charging consumption	residential use, parking areas, and potentially public EVCSs	publicly available	USA	daily	travel mileage, type of starting place, type of destination, purpose of travel, number of vehicles owned by the traveler's family, and age of the traveler
[210]	RF	aggregated at each level of charging scenario (residential, workplace, commercial)	EV charging consumption	residential, commercial, and working parking areas	Not informed	Not informed	daily	Date attribute: working days and rest days; Weather attribute: sunny and rainy; Area attribute: work area, commercial area, residential area; Time index: take 15 min as the sampling point; Electric quantity index: accumulated charging consumption within a day
[103]	LSTM	aggregated for each type of EV	EV (buses, taxis, and private) charging demand	different types of charging points	Not applicable	Not applicable	short term	initial charging state and the charging time of electric vehicles
[124]	GRU	aggregated	EV charging demand	University public, workplace (employees only) parking area	publicly available	California, USA	short term	historical charging demand, date type, temperature, and holiday info
[211]	LightGBM	individual	EV connection duration	urban public and semi-public EVCSs (slow charging)	proprietary	The Netherlands	short term	historical charging data, date type
[212]	WNN	aggregated	EV charging demand	urban public EVCS	collected for the study	Not informed	daily	historical consumption data, time of the day, SOC, charging capacity

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[115]	GRU, LSTM, BI-LSTM	aggregated for the EV fleet	EV charging demand	three charging levels	proprietary	nine provinces in Canada	short term	charging start and end times, energy consumption, energy loss, SOC, weather, and date type
[74]	RNN, GRU, LSTM	aggregated	EV charging demand	urban public EVCS	proprietary	Shenzhen, China	short term	charging time, charging quantity, and real-time electricity price
[213]	ANN, DNN, RNN, and LSTM	aggregated for an EV fleet	EV charging demand, parameters of the next trip of the drivers, including trip start time, end time, and distance	residential use, parking areas, and potentially public EVCSs	publicly available	USA	daily	trip parameters, day type features
[93]	RF	aggregated	EV charging time and maximum consumption	urban public EVCS	collected for the study	city in the Netherlands	daily	charging time, day of the week, connection time, transaction time, and seasonal variations
[214]	LSTM	aggregated	EV charging time and demand		publicly available	Germany	short term	historical EV charge demand dataset (based on MonteCarlo simulations) and EV driver mobility statistics: EV location, parking duration, arrival time, and travel distance.
[215]	LSTM	aggregated	EV charging consumption	urban public EVCS and residential	simulated for the study	Not informed	hourly	node characteristics (active and reactive power, voltage), edge characteristics (resistance and reactance)
[216]	fuzzy CNN, fuzzy BPNN	aggregated	EV charging consumption	charging pile	collected for the study	Dongguan, Guangdong Province, China	hourly, daily	day, hour, temperature, humidity, and power consumption
[143]	RBFNN	aggregated	traffic flow	urban public EVCS	publicly available (http://tris.highwaysengland.co.uk/download/6e8f2a60-e4bc-4805-a5d2-d7f5c4a992db (accessed on 25 November 2024))	England	short term	historical traffic data
[75]	GCNN	aggregated for EVCS	EV charging demand	different types of urban public EVCSs	collected for the study	Shanghai	daily	current charging station usage (recorded every 5 min) and charging station capacity (The number of charging piles), charging fees, parking fees

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[217]	LSTM	aggregated	EV charging demand	urban public EVCS	collected for the study	Shenzhen, China	ultra-short term (15 and 30 min)	historical demand data
[90]	LSTM	aggregated for the network under study	EV charging consumption	large group of EVs	collected for the study	Hubei province in China	daily	power data from the network
[125]	Combination of CNN, LSTM, Transformer	aggregated	EV charging demand	urban public EVCSs	publicly available	Boulder, Colorado, USA	short term	start time, charging time, and total energy consumption of each charging event
[218]	RF	aggregated	EV charging demand	urban public EVCSs	collected for the study	Xiang Yang, China	daily	historical charging data and social behavior
[219]	SVR	aggregated	EV charging demand	urban public EVCSs	collected for the study	Palo Alto, California, USA	day ahead	historical charging data and date type
[220]	CNN	aggregated for all the households	EV charging status and aggregated consumption	residential	publicly available	USA	daily	smart meter data
[148]	WNN	aggregated	EV charging demand	EV (buses) fleet	collected for the study	Not informed	real-time	transaction volume, charging start time, charging end time, electric bus numbers, and weather data
[112]	GRU, LSTM, RNN, FC, CNN	aggregated	EV charging consumption	urban public and private EVCSs	publicly available	Boulder, Colorado, USA	daily, weekly	consumption data, datetime data, and holidays data
[113]	LSTM	individual	EV charging time	EV fleet	collected for the study	Not informed		the total voltage, current, average temperature, average cell voltage, initial charging SOC, required charging energy, and battery capacity of the electric vehicle
[49]	Comparison: ANN, GRU, LSTM, RNN	aggregated	EV charging demand	urban public EVCSs	collected for the study	Rabbat, Morocco	daily	station's ID and location, the connecting port, the start and end time, the charging duration, the kWh consumed, and the driver's ID
[140]	LSTM	aggregated	charging time (average and maximum), SOC level, traffic congestion around charging stations	urban public EVCS	collected for the study	Not informed	1-month	historical charging time, SOC, and traffic data

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[221]	MLR, RF, ANN, KNN	aggregated for different sizes of EV fleet	EV minimum energy required, maximum energy that the EV can store, maximum power that can be drawn or supplied during the charging sessions	urban public (on-street) EVCS	collected for the study	Utrecht, The Netherlands	day ahead	Temporal data, Historical parameter values, and Weather forecasts
[65]	ANN, LSTM, GRU, ANFIS	aggregated	EV average hourly charging demand (KW)	EV fleet	available upon request	Spain	hourly average day ahead	historical charging data, seasonal data
[222]	ANN, RF, LR, SVM, KNN	aggregated for the charging station network	EV charging demand	public urban EVCS	available upon request	county in Scotland, UK	daily up to one week in advance	starting time, charging duration in seconds, and total energy consumption in watt hours, time of day, time of year, or weekend vs. weekday, and weather features
[130]	CNN-BiLSTM	aggregated for each type of charging scenario	EV charging demand and system voltage	residential, slow commercial (shopping center), and fast commercial EVCSs (roadside EVCS)	publicly available (Available: https://data.dundeecity.gov.uk/dataset/ev-charging-data (accessed on 25 November 2024))	Dundee, Scotland, UK	short term	historical EV charging demand and calendar inputs, namely, the hours of the day, the days of the week, the weeks of the year, the months of the year, the quarters of the year, weekend or not weekend, the days of the month, and the days of the year
[104]	LSTM	aggregated	EV charging demand	EVCS in a 35 kV power supply area	collected for the study	Not informed	short term (daily)	historical charging data
[223]	TCN	aggregated for EV fleets	EV charging and discharging load classification and forecasting	urban public EVCS	available upon request	Not informed	12 h	For classification: Initial SOC, Habitual charging critical SOC, Departure SOC, Acceptable discharging critical SOC, Minimum SOC for discharge, User expected SOC when EV leaves, Service duration of EV, Parking duration of EV. For forecasting, the output of the classification

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[105]	HistGB, LSTM, DNN, RF	aggregated for the building	EV electricity consumption profile, planned day trips for each EV	multi-tenant commercial building parking lot	confidential (due to privacy concerns)	Not informed	day ahead	building historical electricity submeter data from Building Management System (BMS); weather data, such as temperature, wind speed, and solar radiation measurements; EV battery specification, such as capacity, minimum SOC, SOC before trips, and maximum power of EV charging and discharging; data of planned day trips, and anticipated electricity consumption for each EV
[126]	CNN, GRU	aggregated for the EV fleet	probability density of EV charging demand	residential	collected for the study	Midwest region of USA	day ahead	historical charging data
[76]	ELM	aggregated	net power of PV-assisted charging stations, which is the difference between the power generated by the PV system and the power consumed by EV charging activities	PV-assisted EVCS	collected for the study	Beijing, China	next hour	historical EV consumption data, historical PV data, weather information, calendar rules, and the period of different electricity price
[224]	EPA: RF, SVM, DKDE	individual	EV energy consumption and stay duration	workplace parking area and residential	publicly available (EA technology website)	Los Angeles, California, USA, and the UK	daily	charging historical data
[225]	TWDP-NN, MPSF, SVR, RF	aggregated	EV charging demand	workplace parking area	publicly available	Los Angeles, California, USA	daily	outlet records: voltage, current, and power factor of the charging outlet user records: start and end time of charging, charging consumption
[226]	RF	SOC and charging location at individual levels; charging consumption aggregated for EV clusters and charging station	EV (different types of EVs, such as BEV, OBEV, PBEV, and PHEV) charging consumption, SOC, and charging location	public urban EVCS (slow charging)	publicly available	Shangai	daily	historical charging data and weather features

Table A2. *Cont.*

Ref.	Core ML Method	Aggregated Level	Forecasted Variable	Charging Scenario	Availability of the Dataset	Data Origin	Time Horizon Predicted	Features Used for the Prediction
[77]	LSTM	aggregated	EV charging consumption	EVCS (not specified) from a province	collected for the study	China	daily	historical charging data, temperature, and electricity price
[227]	LightGBM	aggregated	EV charging demand	workplace parking lot	publicly available	California, USA	short term	historical charging data, calendar data, and weather features
[51]	General regression NN	aggregated	EV charging consumption and event (start and stop charging)	urban public EVCS	publicly available	Boulder, Colorado, USA	real-time	historical charging data, date type, weather
[91]	Temporal GCN	aggregated	Occupancy of charging stations	urban public EVCS	collected for the study	Copenhagen, Denmark	daily	trip parameters, day type features

Note. Ada: Ada boosting; AE: auto encoder; AePPO: adaptive exploration proximal policy optimization; AM: attention mechanism; ANFIS: adaptive network-based fuzzy inference system; ANN: artificial neural network; AOA: arithmetic optimization algorithm; AR: autoregressor; ARIMA: autoregressive integrated moving-average; ARMA: autoregressive moving-average; AQOA: Aquila optimization algorithm; BGRU: bidirectional GRU; Bi-LSTM: bidirectional LSTM; BIRCH: balanced iterative reducing and clustering using hierarchies; BLR: boosted logistic regression; BLS: broad learning system; BO: Bayesian optimization; BPNN: backpropagation NN; CQ: composite quantile; CNN: convolutional neural network; CL: continuous long-life learning; CEEMDAN: complete ensemble empirical mode decomposition with adaptive noise; CNN: convolutional neural network; DA: dragonfly algorithm; DBN: deep belief network; DCCNN: dilated causal CNN; DGM: deep generative model; DLQR: dynamic linear quantile regression; DNN: deep NN; deepAE: deep auto encoder; deepAR: deep autoregressive; deepVAR: deep vector autoregressive; DF: Decision Forest; DKDE: diffusion-based kernel density estimator; DT: decision tree; DTR: DT regressor; EA-LSTM: Enhanced Attention-based LSTM; EDL: energy demand learning; EEMD: ensemble empirical mode decomposition; EGAT: edge aggregation GAT; ELM: extreme learning machine; EMA: exponential moving average; EMD: empirical mode decomposition; EMGM: multivariable residual correction grey model; EPA: ensemble predicting algorithm; ES: exponential smoothing; EV: electric vehicle; EVCS: electric vehicle charging station; FC: fully connected; FEDL: federated energy demand learning; FMGCN: federated-meta-learning graph convolutional network; FFNN: feed-forward NN; FMGCN: federated-meta-learning GCN; GA: genetic algorithm; GAN: generative adversarial networks; GARCH: generalized autoregressive conditional heteroscedasticity; GAT: graph attention network; GB: gradient boosting; GBD: bi-variate Gaussian distribution; GBDR: gradient boost decision-tree regressor; GBDT: gradient boosted DT; GCN: graph convolutional network; GGNN: gated graph sequence NN; GLMNET: Lasso and elastic-net regularized generalized linear model; GPR: Gaussian process regression; GRU: gated recurrent unit; GWO: grey wolf optimizer; HA: historical average; HistGB: histogram-based GB; HT: hyperparameter tuned; INGO: northern Goshawk algorithm; ISL: improved supervised learning; ISSA: improved SSA; ISPSO: improved simplified PSO; IRF: improved RF; JBOA: Jarratt-Butterfly optimization algorithm; KNN: k-nearest neighbors; KNNR: k-nearest neighbor regressor; LA: Loung attention; LDA: linear discriminant analysis; LightGBM: light gradient boosting machine; LinR: Linear regression; LogR: logistic regression; LSTM: long short-term memory; MAML: model-agnostic meta-learning; MC: Monte Carlo; MCCNN: multi-channel CNN; MDA: modified DA; MGAM: multi-graph AM; ML: machine learning; MLP: multi-layer perceptron; MLR: multiple linear regressor; MPSF: modified pattern sequence forecasting; MToM: machine theory of mind; MTL: multi-task learning; NA: nonlinear autoregressive; NAS: neural architecture search; NB: Naive Bayes; NN: neural network; NNAR: Neural Network AutoRegressive; PICNN: partial input convex neural network; PLSR: partial least squares regression; PM: persistence model; PSO: particle swarm optimizer; PV: photovoltaic; QFN: quantile forecast network; QR: quantile regressor; QRDCC: quantile regression dilated causal convolution; QRNN: quasi-RNN; QMC: quasi Monte Carlo; QPM: quasi-Poisson model; RCNN: recurrent CNN; RBFNN: radial basis function NN; RF: random forest; RNN: recurrent neural network; SA: self attention; SAE: stacked auto encoder; SAE-NN: stacked auto encoder neural network; SARIMA: seasonal autoregressive integrated moving average; SARIMAX: SARIMA with exogenous regressors; SARSA: state action reward state action; SC: spectral clustering; SD: similar day; SGDR: stochastic gradient descent regressor; SMOTE: synthetic minority over-sampling technique; SO: snake optimization; SOC: state of charge; SSA: Sparrow search algorithm; STF: strong tracking filter; STGCN: spatio-temporal GCN; SVM: support vector machine; SVR: support vector regression; SWD: swarm decomposition; TBATS: trigonometric seasonality, Box-Cox transformation, ARIMA errors, trend, and seasonal components; T-CKDE: time-adaptive conditional kernel density estimation; TCN: temporal convolutional network; TE-D: temporal encoder-decoder; TL: transfer learning; TLBO: teaching-learning-based optimization; TWDP-NN: time weighted dot product based nearest neighbor; VMD: variational mode decomposition; WNN: wavelet neural network; XGBoost: extreme gradient boosting.

Table A3. Core ML technique, benchmark comparison, and best performance for all the studies included in the SLR.

Ref.	Core ML Method	Benchmark Comparison	Best Performance
[31]	LinR, bagging, GB, Ada, RF, CNN, ANN, LSTM	Naïve weekdays mean	Ada, RF
[162]	SVM, ANN, tree-based ML	SVM, ANN, tree-based ML	SVM
[67]	LSTM	XGBoost-LSTM	XGBoost-LSTM
[99]	Comparison: LSTM, SVM	AR model	LSTM
[63]	LSTM	-	LSTM
[118]	LSTM	ARIMA, Prophet, LSTM	GA-Prophet-LSTM
[50]	LSTM	PM	LSTM
[163]	LSTM	TBATS, SARIMA, ES	LSTM
[164]	BiLSTM, LSTM	-	BiLSTM-LSTM
[100]	LSTM	BPNN, SVR	LSTM
[106]	LSTM	LSTM, RNN, CNN, GRU	LSTM-HT
[101]	DNN	SVR, DTR, KNNR	GAN-DNN
[165]	RF, XGBoost, KNN, GPR	BGD	RF
[33]	ARIMA, XGBoost, ANN, LSTM, GBDT, SVM	ARIMA, XGBoost, ANN, LSTM, GBDT, SVM	XGBoost
[166]	SVR	-	SVR
[45]	RNN, LSTM, Bi-LSTM, GRU, CNN, Transformer	RNN, LSTM, Bi-LSTM, GRU, CNN, Transformer	Transformer
[139]	BPNN	BPNN	SSA-BPNN
[156]	RNN, LSTM, Transformer	ARIMA, SARIMA, RNN, LSTM	Transformer
[79]	LSTM	-	EMD-AOA-DLSTM
[133]	RF, XGBoost	RF, XGBoost	XGBoost
[150]	LSTM	-	LSTM
[64]	RF, QPM, GLMNET, SVM, LDA, XGBoost, BLR, DTs, NB	RF, QPM, GLMNET, SVM, LDA, XGBoost, BLR, DTs, NB	GLMNET, RF
[81]	Bi-LSTM, GCN	-	mRGC-CBi-LSTM
[131]	CNN	ConvLSTM	DCCNN
[167]	LSTM	-	LSTM

Table A3. *Cont.*

Ref.	Core ML Method	Benchmark Comparison	Best Performance
[17]	LSTM	-	LSTM
[82]	LSTM	DF, RF, LogR, ANN, SVM, KNN, NB	LSTM
[168]	BiLSTM	BiLSTM	Prophet-BiLSTM
[114]	LSTM	GRU	SO-VMD-LSTM
[84]	GRU	SVM	GA-GRU
[136]	TL, MAML	MAML, LSTM	TL-MAML
[85]	LSTM	-	LSTM
[141]	NNs, RF, SVM	SARIMA	RF
[159]	MToM	-	SAMToM
[44]	LSTM, GRU, hybrid models combining CNN, LSTM, GRU	LSTM, GRU, hybrid models combining CNN, LSTM, GRU	LSTM
[86]	LSTM	-	LSTM
[80]	XGBoost	-	XGBoost
[68]	LSTM	HA	TE-D LSTM
[129]	RCNN	-	LA-RCNN
[169]	CNN	-	CNN
[170]	Q-learning based on ANN and RNN	-	Q-learning based on ANN and RNN
[107]	LSTM	CQ-RNN	CQ-RLSTM
[171]	MToM	PM, generalized autoregressive conditional heteroscedasticity, DeepAR, T-CKDE, DLQR	MToM QFN
[172]	LSTM	-	LSTM-AePPO
[173]	DT, XGBoost, DNN	DT, XGBoost, DNN	XGBoost
[174]	WNN	-	WNN
[145]	RF, XGBoost, KNN, Bagging regressor, LSTM, RNN	Considers charging behavior patterns to maximize equal share among EVs	Bagging regressor
[175]	QRDCC	QRNN	QRDCC
[176]	RF, XGboost	SVM, ANN, DNN	RF

Table A3. *Cont.*

Ref.	Core ML Method	Benchmark Comparison	Best Performance
[177]	DeepBi-LSTM	-	CEEMDAN-BiLSTM
[146]	RF, SVM, XGBoost, DNN	RF, SVM, XGBoost, DNN	Staking ensemble method
[178]	RF, LinR, ANN, SVR	RF, LinR, ANN, SVR	SMOTE-ANN
[121]	SA-based temporal model, GAT-Autoformer	LSTM, Informer, Autoformer, LSNet, LSTM-Attention	GAT-Autoformer
[179]	LSTM	Copula, QMC, MC	LSTM
[102]	LSTM	DF, RF, LogR, ANN, SVM, KNN, NB	LSTM
[180]	ANFIS	-	ANFIS
[181]	Temporal Characteristics DNN	StackLSTM, CNN-LSTM, SimpleLSTM	TLBO-Temporal Characteristics DNN
[152]	SVM	LinR, KNN, and DT	SVM
[69]	MLP	-	MLP
[61]	LSTM	-	LSTM
[32]	LinR, BTR, and ANN	LinR, BTR, and ANN	ANN
[157]	MTL	SVM and GPR	MTL
[182]	SVM	-	SVM
[183]	Q-learning	RNN, ANN	
[184]	RF, XGBoost, Categorical Boosting, LightGBM	RF, XGBoost, Categorical Boosting, LightGBM	XGBoost
[185]	Stacking/voting ensemble: RF, SVM, XGBoost	RF, XGBoost, SVM, DNN	Staking ensemble
[35]	REVIEW	REVIEW	REVIEW
[116]	LSTM	-	LSTM
[70]	Multi-Graph CNN	CNN-LSTM	STGCN
[186]	SAE-NN	DBN, ELM	SAE-NN
[87]	LSTM	RNN, CNN	LSTM
[134]	SVM	SVM, INGO-SVM, EEMD-INGO-SVM	VMD-INGO-SVM
[187]	RF, SVR, XGBoost	RF, SVR, XGBoost	RF
[188]	Bi-LSTM	LSTM	SARSA-based NAS aided Bi-LSTM
[144]	TreeBagger, LSTM, KNN	TreeBagger, LSTM, KNN	Hybrid combination of TreeBagger, LSTM, KNN

Table A3. *Cont.*

Ref.	Core ML Method	Benchmark Comparison	Best Performance
[71]	LSTM	ANN, RNN, and LSTM	EA-LSTM
[92]	TL, CL	TL, CL	TL-CL
[72]	GRU	-	GRU
[189]	ELM, FFNN, SVR	GWO-ML, GA-ML, PSO-ML	GWO-ML
[190]	LSTM, RF, XGBoost	MLP, RNN	RF, XGBoost
[117]	GCNN-LSTM	ARIMA, SVM, FFNN, CNN	GCNN-LSTM
[191]	SVM	MC	SVM
[120]	FMGCN	HA, ARIMA, SVR, GRU, GCN, applying Chebyshev Polynomial as the convolution kernel, STGCN, GCNSA	FMGCN
[108]	LSTM	CNN, RNN	LSTM-AQOA
[192]	LSTM	LSTM, PSO-LSTM, ISPSO-LSTM	ISPO-LSTM-STF
[122]	LSTM	RNN	SC-CNN-LSTM
[193]	LSTM	ARIMA, LSTM, Prophet	Prophet-LSTM
[47]	Comparison: MLP, XGBoost, LSTM, CNN-LSTM, Bi-LSTM, GRU, Transformer	MLP, XGBoost, LSTM, CNN-LSTM, Bi-LSTM, GRU, Transformer	XGBoost
[48]	Comparison: MLP, LSTM, Bi-LSTM	MLP, LSTM, Bi-LSTM	CEEMDAN-SWD-Bi-LSTM
[194]	Ensemble: ANN, LSTM, RNN	LR, ANN, RNN, LSTM	Ensemble: ANN, LSTM, RNN
[46]	Comparison: centralized EDL, FEDL, and clustering-based EDL	KNN, MLP, SGDR, DT, SVR, RF	FEDL-Clustering
[123]	ConvLSTM, BiConvLSTM	LSTM, CNN	ConvLSTM, BiConvLSTM
[195]	CNN	-	CNN
[196]	XGBoost, RF, ANN	LinR	RF
[197]	LSTM	-	LSTM
[147]	RF	SVM	RF
[198]	MCCNN-TCN	ANN, LSTM, CNN-LSTM, TCN	MCCNN-TCN
[30]	REVIEW	REVIEW	REVIEW
[34]	Comparison: TBATS, ARIMA, ANN, LSTM	TBATS, ARIMA, ANN, LSTM	TBATS

Table A3. *Cont.*

Ref.	Core ML Method	Benchmark Comparison	Best Performance
[151]	SVR	ARMA, ANN, SVR, DA-SVR	MDA-SVR
[73]	XGBoost	LinR, RF, SVR	XGBoost
[199]	LightGBM	HA, EMA, fix duration, fix time	LightGBM
[200]	XGBoost, RF, TabNet	average of the target variables of each user ID	XGBoost
[201]	LSTM	-	LSTM
[36]	RF and GBDT	SARIMAX, PM	GBDT
[109]	LSTM	RNN	LSTM
[88]	MLP	-	MLP
[202]	BPNN	-	BPNN
[203]	BLS	BPNN, LSTM	BLS
[204]	NA-RNN	BPNN	NA-RNN
[142]	Residual NN	-	Residual NN
[110]	ANN, RNN, LSTM, GRU, SAE, BiLSTM	ANN, RNN, LSTM, GRU, SAE, BiLSTM	LSTM
[89]	RF and XGBoost	RF and XGBoost	XGBoost
[205]	Seq2Seq	HA, ARIMA, Prophet, Xboot, LSTM	Seq2Seq
[206]	DT, RF, LightGBM, KNNR	DT, RF, LightGBM, KNNR	RF
[207]	Combination: RF-BIRCH, EMD, CNN-LSTM, Bi-LSTM	ANN, RNN, LSTM, stacked LSTM, Bi-LSTM, CNN-LSTM	Combination: RF-BIRCH, EMD, CNN-LSTM, Bi-LSTM
[111]	ANN, RNN, LSTM	ARIMA	LSTM
[78]	BGRU	MLP, AE, RNN, LSTM, CNN, BGRU	CNN-BGRU-JBOA
[208]	Seq2Seq	-	Seq2Seq
[209]	PICNN	MLP, deepAR, deepVAR	PICNN
[66]	MLR	-	MLR
[210]	RF	RF, IRF	SSA-RF
[103]	LSTM	BPNN, SVM	LSTM
[124]	GRU	RF, GRU, CNN	ISSA-CNN-GRU
[211]	LightGBM	Naive models	LightGBM

Table A3. *Cont.*

Ref.	Core ML Method	Benchmark Comparison	Best Performance
[212]	WNN	BPNN	WNN
[115]	GRU, LSTM, BI-LSTM	GRU, LSTM, BI-LSTM	SD-CEEMDAN-BiLSTM
[74]	RNN, GRU, LSTM	RNN, GRU, LSTM	GRU
[213]	ANN, DNN, RNN, and LSTM	KNN, DT, RF	ANN-based models
[93]	RF	-	RF
[214]	LSTM	-	EMD-BO-LSTM
[215]	LSTM	GCN-LSTM, GGNN-LSTM, GAT-LSTM	EGAT-LSTM
[216]	fuzzy CNN, fuzzy BPNN	BPNN, CNN	fuzzy CNN
[143]	RBFNN	BPNN, SAE	RBFNN
[75]	GCNN	GBR, SVR, RF	MGAM: GCNN-AM
[217]	LSTM	ANN	LSTM
[90]	LSTM	traditional ANN models	LSTM
[125]	Combination of CNN, LSTM, Transformer	CNN, LSTM, Transformer	CNN-LSTM-Transformer
[218]	RF	SVR, BPNN	GAN-RF
[219]	SVR	SVR, multi-model ensemble of SVR	multi-model ensemble of SVR
[220]	CNN	HMM	DGMs based on CNN
[148]	WNN	-	SC-WNN
[112]	GRU, LSTM, RNN, FC, CNN	GRU, LSTM, RNN, FC, CNN	ISL-LSTM, ISL-GRU
[113]	LSTM	CNN, RNN	LSTM
[49]	Comparison: ANN, GRU, LSTM, RNN	ANN, GRU, LSTM, RNN	GRU
[140]	LSTM	NNAR Model, ELM, LSTM	alfa2-LSTM
[221]	MLR, RF, ANN, KNN	MLR, RF, ANN, KNN	similar performances (MLR slightly better)
[65]	ANN, LSTM, GRU, ANFIS	ANN, LSTM, GRU, ANFIS	ANFIS
[222]	ANN, RF, LR, SVM, KNN	ARIMA	ANN
[130]	CNN-BiLSTM	CNN-T, CNN-BiLSTM	hybrid CNN-BiLSTM-TL
[104]	LSTM	LSTM, BI-LSTM, ARIMA, SARIMAX, SVM, GRU	Mogrifier LSTM
[223]	TCN	CNN-BILSTM, LSTM, PSO-BP, ARIMA, WNN	GBDT-TCN

Table A3. *Cont.*

Ref.	Core ML Method	Benchmark Comparison	Best Performance
[105]	HistGB, LSTM, DNN, RF	HistGB, LSTM, DNN, RF	LSTM
[126]	CNN, GRU	ANN, SVM, kNN, LSTM, GRU, AQo	CNN-AM-GRU
[76]	ELM	DBN, SVR, GBDT, ELM, deepAE-ELM	PSO-deepAE-ELM
[224]	EPA: RF, SVM, DKDE	MLR, SVR, DT, RF, and KNN	Depends on the data entropy/sparsity
[225]	TWDP-NN, MPSF, SVR, RF	TWDP-NN, MPSF, SVR, RF	MPSF
[226]	RF	SVR, RF, BPN	IRF
[77]	LSTM	-	EMGM-LSTM
[227]	LightGBM	BP, CNN, LSTM	PLSR-LightGBM
[51]	General regression NN	ANN, DNN, BiLSTM, GRU, RNN	General regression NN
[91]	Temporal GCN	Gaussian, QR	Temporal GCN

Note. Ada: Ada boosting; AE: auto encoder; AePPO: adaptive exploration proximal policy optimization; AM: attention mechanism; ANFIS: adaptive network-based fuzzy inference system; ANN: artificial neural network; AOA: arithmetic optimization algorithm; AR: autoregressor; ARIMA: autoregressive integrated moving-average; ARMA: autoregressive moving-average; AQOA: Aquila optimization algorithm; BGRU: bidirectional GRU; Bi-LSTM: bidirectional LSTM; BIRCH: balanced iterative reducing and clustering using hierarchies; BLR: boosted logistic regression; BLS: broad learning system; BO: Bayesian optimization; BPNN: backpropagation NN; CQ: composite quantile; CNN: convolutional neural network; CL: continuous long-life learning; CEEMDAN: complete ensemble empirical mode decomposition with adaptive noise; CNN: convolutional neural network; DA: dragonfly algorithm; DBN: deep belief network; DCCNN: dilated causal CNN; DGM: deep generative model; DLQR: dynamic linear quantile regression; DNN: deep NN; deepAE: deep auto encoder; deepAR: deep autoregressive; deepVAR: deep vector autoregressive; DF: Decision Forest; DKDE: diffusion-based kernel density estimator; DT: decision tree; DTR: DT regressor; EA-LSTM: Enhanced Attention-based LSTM; EDL: energy demand learning; EEMD: ensemble empirical mode decomposition; EMA: exponential moving average; ES: exponential smoothing; EGAT: edge aggregation GAT; ELM: extreme learning machine; EMD: empirical mode decomposition; EMGM: multivariable residual correction grey model; EPA: ensemble predicting algorithm; ES: exponential smoothing; FC: fully connected; FEDL: federated energy demand learning; FMGCN: federated-meta-learning graph convolutional network; FFNN: feed-forward NN; FMGCN: federated-meta-learning GCN; GA: genetic algorithm; GAN: generative adversarial networks; GAT: graph attention network; GB: gradient boosting; GBD: bi-variate Gaussian distribution; GBDT: gradient boosted DT; GBRT:gradient boosted regression trees; GCN: graph convolutional network; GGNN: gated graph sequence NN; GLMNET: Lasso and elastic-net regularized generalized linear model; GPR: Gaussian process regression; GRU: gated recurrent unit; GWO: grey wolf optimizer; HA: historical average; HistGB: histogram-based GB; HT: hyperparameter tuned; INGO: northern Goshawk algorithm; ISL: improved supervised learning; ISSA: improved SSA; ISPSO: improved simplified PSO; IRF: improved RF; JBOA: Jarratt-Butterfly optimization algorithm; KNN: k-nearest neighbors; KNNR: k-nearest neighbor regressor; LA: Loung attention; LDA: linear discriminant analysis; LightGBM: light gradient boosting machine; LinR: Linear regression; LogR: logistic regression; LSTM: long short-term memory; MAML: model-agnostic meta-learning; MC: Monte Carlo; MCCNN: multi-channel CNN; MDA: modified DA; MGAM: multi-graph AM; ML: machine learning; MLP: multi-layer perceptron; MLR: multiple linear regressor; MPSF: modified pattern sequence forecasting; MToM: machine theory of mind; MTL: multi-task learning; NA: nonlinear autoregressive; NAS: neural architecture search; NB: Naive Bayes; NN: neural network; NNAR: Neural Network Autoregressive; PICNN: partial input convex neural network; PLSR: partial least squares regression; PM: persistence model; PSO: particle swarm optimizer; QFN: quantile forecast network; QR: quantile regressor; QRDCC: quantile regression dilated causal convolution; QRNN: quasi-RNN; QMC: quasi Monte Carlo; QPM: quasi-Poisson model; RCNN: recurrent CNN; RBFNN: radial basis function NN; RF: random forest; RNN: recurrent neural network; SA: self attention; SAE: stacked auto encoder; SAE-NN: stacked auto encoder neural network; SARIMA: seasonal autoregressive integrated moving average; SARIMAX: SARIMA with exogenous regressors; SARSA: state action reward state action; SC: spectral clustering; SD: similar day; SGDR: stochastic gradient descent regressor; SMOTE: synthetic minority over-sampling technique; SO: snake optimization; SSA: Sparrow search algorithm; STF: strong tracking filter; STGCN: spatio-temporal GCN; SVM: support vector machine; SVR: support vector regression; SWD: swarm decomposition; TBATS: trigonometric seasonality, Box-Cox transformation, ARIMA errors, trend, and seasonal components; T-CKDE: time-adaptive conditional kernel density estimation; TCN: temporal convolutional network; TE-D: temporal encoder-decoder; TL: transfer learning; TLBO: teaching-learning-based optimization; TWDP-NN: time weighted dot product based nearest neighbor; VMD: variational mode decomposition; WNN: wavelet neural network; XGBoost: extreme gradient boosting.

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