



Article

Short-Term Forecasting of Electric Vehicle Load Using Time Series, Machine Learning, and Deep Learning Techniques

Gayathry Vishnu ^{1,*}, Deepa Kaliyaperumal ^{1,*} , Peeta Basa Pati ² , Alagar Karthick ³ , Nagesh Subbanna ⁴ and Aritra Ghosh ^{5,*}

- ¹ Department of Electrical and Electronics Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru 560035, Karnataka, India; bl.en.r4eee21006@bl.students.amrita.edu
- ² Department of Computer Science & Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru 560035, Karnataka, India; bp_peeta@blr.amrita.edu
- ³ Renewable Energy Lab, Department of Electrical and Electronics Engineering, KPR Institute of Engineering and Technology, Coimbatore 641407, Tamilnadu, India; karthick.power@gmail.com
- ⁴ Amrita Center for Wireless Networks and Applications, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Kollam 690525, Kerala, India; snag1978@yahoo.com
- ⁵ Faculty of Environment, Science and Economy (ESE), Renewable Energy, Electric and Electronic Engineering, University of Exeter, Penryn TR10 9FE, UK
- * Correspondence: k_deepa@blr.amrita.edu (D.K.); a.ghosh@exeter.ac.uk (A.G.)

Abstract: Electric vehicles (EVs) are inducing revolutionary developments to the transportation and power sectors. Their innumerable benefits are forcing nations to adopt this sustainable mode of transport. Governments are framing and implementing various green energy policies. Nonetheless, there exist several critical challenges and concerns to be resolved in order to reap the complete benefits of E-mobility. The impacts of unplanned EV charging are a major concern. Accurate EV load forecasting followed by an efficient charge scheduling system could, to a large extent, solve this problem. This work focuses on short-term EV demand forecasting using three learning frameworks, which were applied to real-time adaptive charging network (ACN) data, and performance was analyzed. Auto-regressive (AR) forecasting, support vector regression (SVR), and long short-term memory (LSTM) frameworks demonstrated good performance in EV charging demand forecasting. Among these, LSTM showed the best performance with a mean absolute error (MAE) of 4 kW and a root-mean-squared error (RMSE) of 5.9 kW.

Keywords: electric vehicles; forecasting; ARF; SVR; LSTM



Citation: Vishnu, G.; Kaliyaperumal, D.; Pati, P.B.; Karthick, A.; Subbanna, N.; Ghosh, A. Short-Term Forecasting of Electric Vehicle Load Using Time Series, Machine Learning, and Deep Learning Techniques. *World Electr. Veh. J.* **2023**, *14*, 266. <https://doi.org/10.3390/wevj14090266>

Academic Editor: Grzegorz Sierpiński

Received: 8 August 2023

Revised: 2 September 2023

Accepted: 5 September 2023

Published: 20 September 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Global warming has been a pressing concern across the world over the last few decades. The main contributions toward global warming come from the transportation sector. Khurana et al. [1] found that China emits almost 25.9% of greenhouse gases (GHGs), followed by the USA with 13.87%, and India with 7.45%. The Paris Agreement of 2015 demands that all countries reduce their vehicle emissions with a view to protect the environment [2]. Around the globe, governments are aggressively implementing measures to reduce greenhouse gases and encourage green energy systems [3–6]. De-carbonizing the transportation industry can significantly reduce greenhouse emissions and help in attaining the green energy goal.

EVs are revolutionizing the transportation sector. The benefits offered to society by EVs are tremendous. Along with significant reductions in carbon emissions, the low cost of operation, energy efficiency, and easy integration with renewable sources of energy are the major benefits [7–11]. The introduction of smart grid systems and their widespread acceptance has given new directions to EVs. Some EVs can also provide various ancillary services, collectively called vehicle-to-everything, consisting of vehicle-to-grid, vehicle-to-device,

vehicle-to-home, etc. Such EVs, known as gridable electric vehicles (GEVs) also create many research opportunities and developments in the energy and power sectors [12–14].

The success and implementation of the above developments in the transportation and power sectors require proper planning and management. Like any other technology, even with all the benefits, there are concerns and challenges regarding the implementation and adoption of EVs in society. Charge scheduling problems, charging infrastructure requirements, range anxiety, cost of ownership, sophisticated communication requirements, and consumer ignorance are the critical factors delaying the adoption of EVs [15–18]. Among the above concerns, the charge scheduling of EVs is the prime focus. Studies show that EV sales increased considerably in 2020. By 2030, globally, EVs will account for almost 50% of all cars on the road [19]. A large increase in the number of EVs will adversely affect the utility grid by causing frequency and voltage fluctuations, unexpected peaks, and an overall rise in energy demand. Also, the uncoordinated charging of a large number of EVs simultaneously can even cause power shutdowns.

As a solution to the above, an intelligent coordinated charging strategy for EVs is required. According to the demand, current price rates, and other user needs, the charging of EVs can be shifted or rescheduled. This demands an accurate forecasting of EV load demand. Forecasting the EV load demand also helps utility companies in planning and decision-making. This can also help in preventing faults and adds to system stability [20].

In this work, EV charging demand forecasting was performed using artificial intelligence (AI) techniques. The novelty of the research was in the application and comparison of time series (TS), machine learning (ML), and deep learning (DL) techniques for EV demand forecasting. The work was in alignment with the United Nation's Sustainable Development Goals (SDGs) 7 (Affordable and Clean Energy), 11 (Sustainable Cities and Communities), and 12 (Responsible Consumption and Production). This research could be considered as the primary step toward an efficient charge scheduling strategy and, further, to a reliable and coordinated EV charging system.

The paper is structured in this manner: Section 2 shows the existing research conducted on EV demand forecasting and charge scheduling strategies. Section 3 presents the materials and methods employed in this work. Results and analysis are explained in Section 4. Finally, the conclusion of the work and future scope is given in Section 5.

2. Literature Review

The impacts of EV charging on various aspects in the distribution grid are discussed in [21–27]. The adverse effects of EV penetration can be remedied through proper scheduling, clustering, and forecasting measures [28]. Scheduling helps decrease the burden on the grid by moving EV charging to light-load hours. Clustering is a technique to discover the most common, similar, and repeating events. The clustering strategy, applied to EV charging data, helps identify groups of similar charging objects. By clustering the data for a period (e.g., a week, a month, or a year), patterns for different charging behaviours can be understood. Accurate and efficient EV load forecasting is critical for grid development decisions. It also helps in the prevention of faults and network stability.

Sharma et al. [29] discussed the impact of plug-in electric vehicles (PEVs) in unbalanced residential distribution systems. Their work showed that the uncontrolled charging of EVs can lead to an increase in feeder current and peak demand and result in low voltage at nodes. The authors also proposed a smart distribution power flow (SDPF) model for calculating the schedules for smart charging. Various schemes for uncontrolled and controlled charging are also compared in the work. The literature by Masoum et al. [30] is directed toward the loading and stress on distribution transformers due to PEV penetrations. The authors studied the various loading scenarios of the transformers, and a coordination scheme to evaluate the stress on the distribution transformers in residential networks was designed. By controlling the rate of EV charging, high penetration levels can be accommodated in the existing systems [31]. The charging rate for each EV was decided using the linear programming method, with an objective to maximize the overall

energy given to the EVs. Clement-Nyns et al. [32] agree upon the impacts on the grid due to uncoordinated charging and emphasize the need for coordinated charging. A coordinated strategy to minimize voltage fluctuation and power loss is proposed. Quadratic and dynamic programming techniques are employed, among which the best results are obtained using quadratic programming.

With regard to the above concerns, forecasting the EV/PEV charging load is imperative. Several studies are currently being conducted on forecasting the charging demand of individuals and fleets of EVs. Demand forecasting can be broadly divided into three groups: short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). STLF refers to the forecasting of charging demand for a short period, which can be from a few hours up to one week. This is very crucial for the next-day operation knowledge. MTLF is the load prediction from a week to a year and helps in system planning, system maintenance planning, etc. LTLF refers to the forecasting of EV charging load for several years in advance. Management decisions related to infrastructure investments and additional power generation facilities depend on LTLF. Considering the stochasticity in the EV charging process, LTLF has more challenges; hence, researchers have seen less accuracy for LTLF, compared to STLF [20,28].

Load forecasting techniques for EVs are of multiple types: mathematical modeling techniques, statistical methods, and AI methods [33].

Mathematical Modeling Techniques:

In [34], the authors propose a model using fluid dynamic traffic model and M/M/s queuing theory. Here, the first 'M' indicates the Poisson distribution of vehicle arrival at the charging station. The second 'M' indicates the time taken to charge each EV. Thirdly, 's' indicates the number of charging pumps in a station. The traffic model is used to predict the entry of EVs to a charging station. The queuing theory predicts the charge requirement. This model very well captures the EV charging dynamics. In [35], a Monte Carlo model is employed for EV load forecasting in China. The charging period is determined based on the probability distribution. Charging time is calculated depending on the state of charge (SoC), charging methods, and the needs of various types of vehicles. The initial charging point is decided using the Monte Carlo method. Shao et al. [36] propose another probability modeling-based forecasting technique. This consists of an origin–destination analysis, followed by the Monte Carlo method for estimating the EV charging characteristics for a day. A Baskett-Chandy-Muntz-Palacios (BCMP) queuing model is proposed in [37] to evaluate the demands from multiple stations. The model is validated using real vehicle traffic statistics. All the mathematical models have uncertainties in some or the other factors, which makes the results unreliable.

Statistical Methods:

Several statistical methods, including regression, exponential smoothing method, etc., are discussed in the literature. An autoregressive integrated moving average (ARIMA) model is proposed in [38]. EV demand and electrical load demand are simultaneously forecasted. The model inputs distances and daily driving patterns and determines the charging load profiles. Louie [39] proposes a time series seasonal ARIMA model for forecasting aggregated demand at EV stations, using two years of data from over 2400 charging stations.

AI Methods:

AI-based methods are extensively used in forecasting applications. The suitability of AI techniques in various forecasting applications is explained in [40–42]. The superior performance of an artificial neural network (ANN) for forecasting applications, compared to conventional methods, is discussed in [43]. Arias and Bae [44] present a model of the hourly traffic and weather information in South Korea. The proposal includes cluster analysis, relational analysis, and classification. Cluster analysis identifies patterns in the traffic; relational analysis assesses the various influencing components; and finally, the decision tree model is used for classification. The validation of the model conducted on real-world scenarios is also presented in their work. Another short-term load forecasting model is discussed in [45]. This work uses a time series reconstruction technique followed

by support vector regression (SVR) using EV data from Jiang Su, China. The method shows good prediction results compared to the conventional SVR method.

Majidpour [46] proposes two forecasting methods: modified pattern sequence forecasting (MPSF) and time weighted dot product nearest neighbor (TWDP NN). Data collected from the UCLA campus, parking lots, and PV panels were used. On account of the speed of prediction, TWDP NN performed better, by decreasing the processing time by one-third. Majidpour et al. [47] employ three algorithms, k-Nearest Neighbor (kNN), ARIMA, and pattern sequence forecasting (PSF), for modeling and forecasting EV charging demand using the UCLA campus data. Using error metric, symmetric mean absolute percentage error (SMAPE), kNN with $k = 1$, performs better than the other two methods. PSF is found to have the worst performance. Therefore, MPSF is designed to combine NN and PSF, for which a better performance is obtained. Three supervised ML-based forecasting models are compared in [48]. Random forest, XGBoost, and support vector machine are the models used. Public charging data from Nebraska, USA, collected over seven years are used. Results show that XGBoost is superior to other techniques in EV load demand prediction.

Kumar et al. [49] use ANN to forecast the charging demand of a building. The model uses initial and final SoC and earlier charging behaviours for demand prediction. Further EV scheduling is also demonstrated using the charging profiles and the predicted demand.

EV load forecasting using LSTM has attracted many research possibilities. Various LSTM models, univariate and multivariate, have shown superior performance compared to ML models. Among LSTM models, multivariate LSTM models, considering features like wind speed, temperature, and humidity, show better performance than univariate ones [50,51]. Elahe et al. [52] study in detail the various possible factors impacting the charging load, like weather, calendar, and seasons, and use five DL models for forecasting. LSTM, Bi-LSTM, CNN-LSTM, ConvLSTM, and GRU are the models studied and performance evaluated.

A unique DL approach using a transformer, which is an attention-based model using an encoding-decoding structure, is mentioned in [53]. Model performance is compared against the methods, ARIMA, SARIMA, recurrent neural network (RNN), and LSTM. Test results demonstrate excellent prediction capabilities for the transformer model, with low training error and faster convergence. A 2D dilated causal convolution neural network is discussed in [33]. The model performance is contrasted with a ConvLSTM model, and the improved accuracy is evident in the test results.

Various hybrid forecasting techniques are also discussed in the literature. Li et al. [54] propose a model employing a convolutional neural network (CNN) and lion algorithm. A variety of features are employed for forecasting the demand, including the type of day, weather, season, and temperature. Load that occurred at the same time for the last five days is also considered. The model has improved stability and accuracy for STL. Also, test results highlight the model performance in terms of prediction precision.

Wavelet neural network (WNN), a combination of wavelet theory and NN, is used in many fields, including forecasting [55–57]. Several exogenous factors influencing the power consumption of electric buses (EBs) are analyzed using gray relational analysis (GRA), and a forecasting model using WNN is developed [57]. The model is validated on real electricity consumption data of EBs in Baoding. Lei et al. [58] propose another wavelet-based technique for the short-period forecasting of EB charging stations' demand.

A multiple decomposition model for EV fleet charging is discussed in [59]. The technique uses swarm decomposition (SWD) and complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) method. The forecasting models used are multi-layer perceptron (MLP), LSTM, and bidirectional LSTM (Bi-LSTM). The method demonstrated good performance with a coefficient of determination (R^2) value of 0.9766.

With respect to the existing literature studies, this paper develops an hourly demand forecaster for EVs, using three prominent techniques, namely AR, SVR, and LSTM. The models are trained on real-world data, and tested and compared using error metrics

MAE, RMSE, and MAPE. The paper underlines the superiority of LSTM in forecasting applications compared to time series analysis and ML methods.

3. Materials and Methods

3.1. Data Collection

We have taken the public dataset from ACN repository for the proposed work. This consists of data from two EV charging points in California: Caltech and JPL. PowerFlex, a smart EV charging startup, manages the data. There are 54 charging points on the Caltech University site, open to the public, whereas the JPL site is a national research lab with 52 electric vehicle supply equipment (EVSE), open to employees only. The details of ACN data are discussed in [60]. There are more than 30,000 charging sessions in this dataset, which is updated daily. A total of 15 features are available in the dataset, including charging details, charging station details, and user details. Caltech data from 24 April 2018 to 31 January 2019 are used in this work. Out of the 15 features in the dataset, three features, 'connectionTime', 'doneChargingTime', and 'kWhDelivered', are used here. From these three features, more features are derived based on analysis, as explained in the following sections.

3.2. Data Preparation

3.2.1. Data Transformation and Aggregation

The raw data obtained from ACN consist of individual charging sessions spread across charging points and time. The work intends to study the hourly power demand in the network, not specific to any charging points. For this purpose, the data have to be transformed into a set of charging profiles, in which, instead of energy in kWh, power in kW will be mentioned. Conversion of charging energy demand to power can be performed in multiple ways. However, we have adopted the average power calculation mentioned in [52], as given by (1):

$$P_{avg} = \frac{\text{EnergyDelivered}}{\text{ChargingDuration}} \quad (1)$$

This converts the dataset to a collection of charging profiles, each with the average power for a specific hour of the day mentioned. Further, these profiles are stacked up to generate time series charging data with hourly frequency.

3.2.2. Data Analysis

The transformed data are analyzed to observe the patterns and trends in EV charging. Figure 1 plots the average power demand during different hours of the day. It is highly evident from the plot that the charging demand at Caltech is higher during evening hours, especially 4:00 p.m. to 7:00 p.m., with the highest values recorded at around 5:00 p.m. Also, the lowest demand is visible from 10:00 a.m. to 12:00 p.m. The significant variance in the demand during different hours of the day is notable.

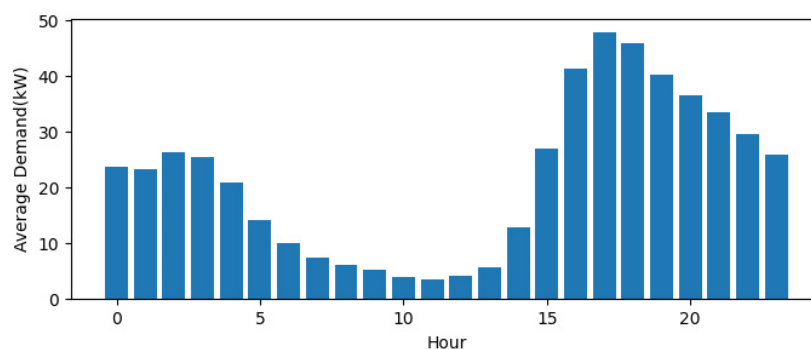


Figure 1. Average power demand for each hour of the day.

Similarly, Figure 2 illustrates the mean charging demand for days of the week. The decrease in demand during weekends compared to working days is evident in the plot.

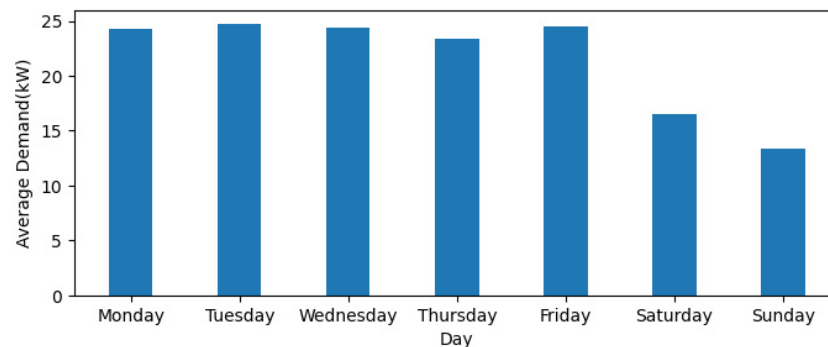


Figure 2. Average power demand for each day of the week shows the difference in a pattern during weekdays and weekends.

The variation in power demand across various weeks of the year is seen in Figure 3. The dataset from April 2018 to December 2018 is plotted. The highest demand is observed during weeks near 40 and the lowest demand is visible during the 52nd week. This low demand during the 52nd week is very much related to the vacation time, owing to Christmas and New Year.

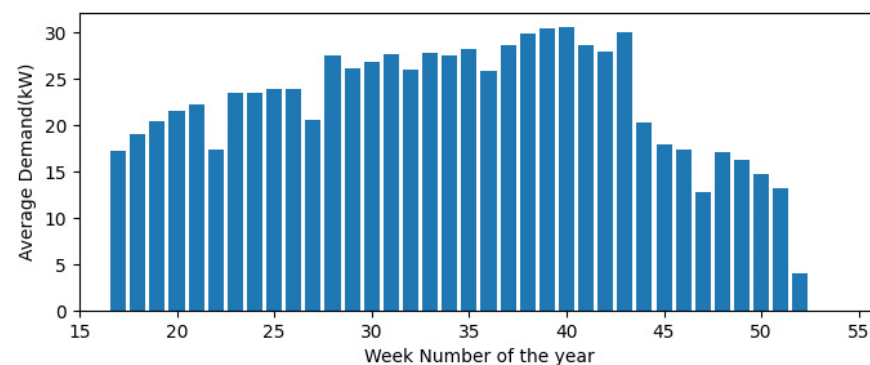


Figure 3. Average power demand across weeks of the month.

3.2.3. Outliers Removal

Outliers can be removed by multiple techniques. In this work, we have used outlier removal by interquartile range method [61]. The significance of this method lies in the ‘five number summary’ or ‘five-point-summary’ concept. The five number summary is a statistical measure of the data distribution, consisting of five values: minimum, maximum, median, first-quartile (Q1), and third-quartile (Q3) values. From these, the difference between the third and first quartiles of the data distribution is known as the interquartile range (IQR). In this method, boundary values are calculated as given in (2) and (3):

$$L_l = Q1 - 1.5 \times IQR \quad (2)$$

$$L_u = Q3 + 1.5 \times IQR \quad (3)$$

where L_l and L_u are lower and upper limits, respectively. The data points above L_u and below L_l are treated as outliers, and will be capped with L_u and L_l , respectively.

3.2.4. Normalization

Among the various data normalization techniques, min-max normalization is proven to have better performance, especially on similar datasets, as pointed out in [51]. Hence,

this technique is also adopted here, with a feature range of [0, 1]. The normalized value is calculated as given by (4):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (4)$$

where x is the data point prior to normalization; x_{norm} is the data after normalization; x_{max} and x_{min} are the maximum and minimum values of the feature, respectively.

3.3. Feature Addition, Correlation Analysis, and Feature Selection

Additional features like day of the week (e.g., Sunday, Monday), week number, and working status (working day or holiday) are derived from the raw dataset. Also, the average power demand for the hour is calculated. In addition, the average demand that occurred in the previous 24 hours is also calculated for each profile. The dataset features are given in Table 1.

Table 1. Dataset features.

Feature	Description
ConnectionHour	Hour of the day at which the vehicle is connected to the charging port
DayofWeek	Day number e.g., 0—Sunday, 1—Monday
Week	Week number of the year
WorkingStatus	Binary value, indicating working day or holiday: 1 for working day, 0 for holiday
HourlyAverageDemand	Average power demand for the given connection hour
Previous24HrAverageDemand	Average demand for the previous 24 h
AggregatedPower	EV charging demand (kW)

Various techniques are employed to uncover the relationship and dependency among the attributes in the dataset, including dependent and independent features.

3.3.1. Autocorrelation Plot

Autocorrelation function (ACF) is used to evaluate randomness in the data. Values in a time series data can have positive or negative correlations over time. ACF calculates the correlation of a feature with its time-lagged version. The value of ACF varies from -1 to 1 . It identifies the significant lags and helps to understand the trends and patterns in the data. The plot of ACF for the target variable, ‘AggregatedPower’ is shown in Figure 4. The time-repeatability of the charging demand is evident in the plot.

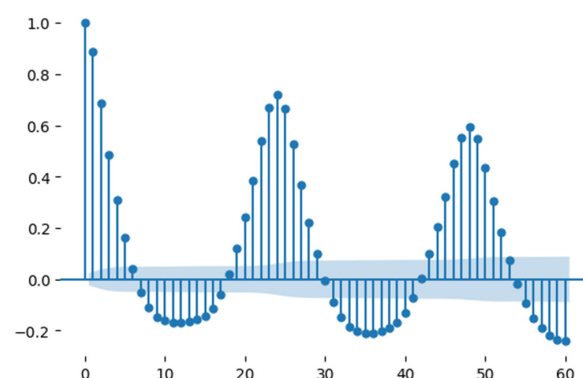


Figure 4. Autocorrelation plot.

3.3.2. Correlation Matrix

Preliminary modeling and testing were conducted using all the features mentioned above. However, the performance was unsatisfactory. Further, a correlation analysis of the data is conducted to study the interdependency among features as well as the dependency of the target variable on features. The correlation matrix is shown in Figure 5.

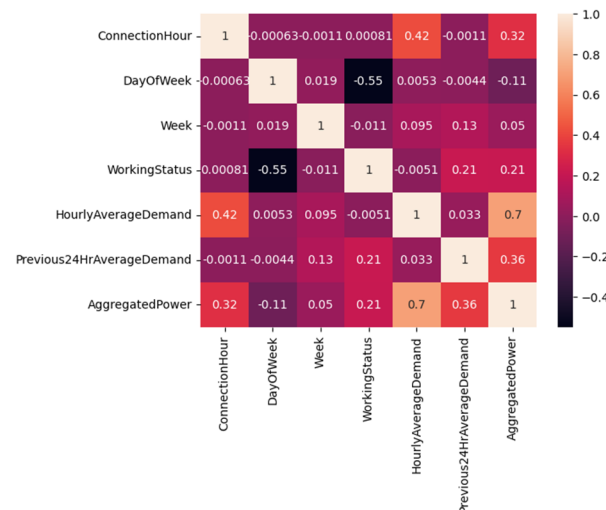


Figure 5. Correlation matrix showing correlation among the features and between dependent and independent features.

The matrix shows that the attribute 'HourlyAverageDemand' has the greatest impact on the outcome, 'AggregatedPower'. Also, the features 'Previous24HrAverageDemand', 'WorkingStatus', and 'ConnectionHour' have more impact on the 'AggregatedPower' than 'DayOfWeek', 'Week', etc. Hence, these four features are selected to be included in the model.

3.3.3. Data Partitioning

The complete dataset is divided into training, validation, and test data. Data till 31 October 2018 are used for training the models. Data for November 2018 and December 2018 are used for validation. Data for January 2019 are allocated for testing the performance. The distribution of data is plotted, as shown in Figure 6.

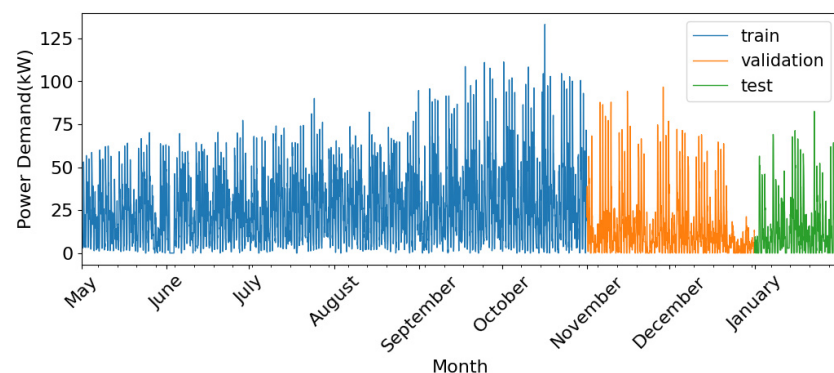


Figure 6. Dataset divided for training, validation, and testing.

3.4. Algorithms and Implementation

The forecasting techniques employed in this work are explained in this section.

3.4.1. Auto-Regressive (AR) and Auto-Regressive Exogenous (ARX) Forecasting

AR forecasting is a TS method in which previous values are provided as inputs to a regression equation to predict the present or future values. In an AR model, the response variable is predicted using a linear combination of the previous values of the same variable. In other words, 'AutoRegression' is a regression of the response variable against itself. An AR model of order 'n' is given in (5):

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_n y_{t-n} + \varepsilon_t \quad (5)$$

where y is the target, a_i is the i th AR parameter, and ε_t is the noise [62]. ARX is similar to AR, but it also considers exogenous inputs. Here, the present output is a function of previous outputs and previous system inputs. An ARX model can be represented as given by (6):

$$y_t = c_1 y_{t-1} + c_2 y_{t-2} + \dots + c_n y_{t-n} + d_1 u_{t-1} + d_2 u_{t-2} + \dots + d_n u_{t-n} + \varepsilon_t \quad (6)$$

where u is the input to the model; c_i is the i th AR parameter; and d_i is the i th exogenous parameter [63].

3.4.2. SVR

SVM is an ML algorithm for classification and regression and is well suited for high-dimensional data from diverse sources [64,65]. SVM tries to obtain the optimal hyperplane by maximizing the margin.

Consider N input-output pairs, $(x_i, y(x_i))$, $i = 1, \dots, N$. If $x_i \in$ category 1, then $y(x_i) = 1$. If $x_i \in$ category 2, then $y(x_i) = -1$.

For a linearly separable dataset, the decision function is $F = W^\top \phi(x) + B$, where W denotes the weight and B , the bias. For a non-linear dataset, the decision boundary is obtained using the optimization in (7):

$$\text{Minimize} : Q(w, \zeta) - \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \zeta_i$$

subject to:

$$y(x_i) (W^\top \phi(x) + B) \geq 1 - \zeta_i \quad (7)$$

where C is the regularization parameter and ζ_i is the slack variable. Kernel trick is used to handle the non-linear dataset. Kernels are mathematical functions which provide mapping to a higher dimensional space and are denoted by (8):

$$K(x, x') = \phi(x)^\top \phi(x') \quad (8)$$

Commonly used kernels are linear, radial basis function (RBF), polynomial, etc.; the choice of selection depends on the dataset.

3.4.3. LSTM

ANN is an interconnected network of artificial neurons, made to work in a way inspired by the human brain system. Among various ANN models, RNN is mostly suited for forecasting applications. However, RNN experiences the drawback of vanishing gradient, so it cannot learn from long-term dependencies [66]. LSTM is similar to RNN, but it has memory cells and special gating mechanisms, which makes it better suited for long-range applications. Figure 7 shows the internal architecture of LSTM [51], where f , i , and o are forget, input, and output gates, respectively, and m is the internal memory unit.

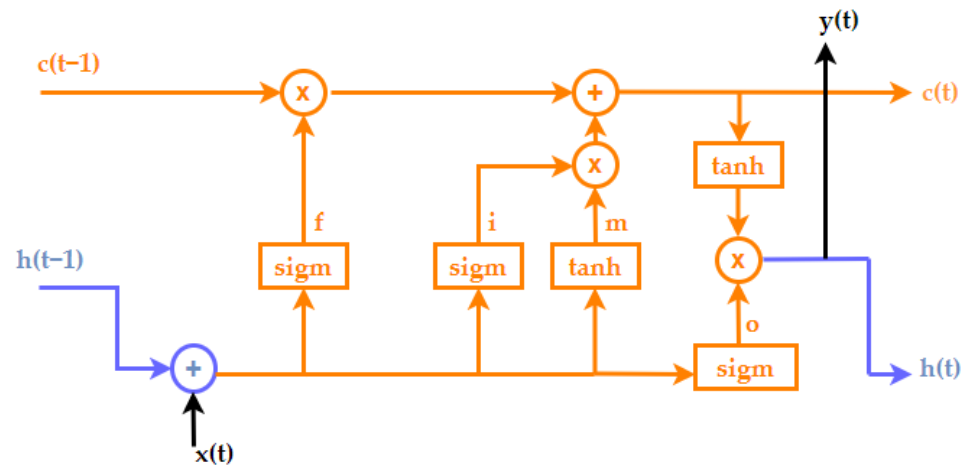


Figure 7. LSTM architecture, including memory cell and gating mechanisms.

At time t , the operations of the gates and output of the unit are as given in (9)–(14):

$$f_t = \text{sigm}(W_f(x_t + h_{t-1}) + b) \quad (9)$$

$$i_t = \text{sigm}(W_i(x_t + h_{t-1}) + b) \quad (10)$$

$$o_t = \text{sigm}(W_o(x_t + h_{t-1}) + b) \quad (11)$$

$$m_t = \tanh(W_m(x_t + h_{t-1}) + b) \quad (12)$$

$$c_t = f_t \times c_{t-1} + i_t \times m_t \quad (13)$$

$$h_t = o_t \times \tanh(c_t) \quad (14)$$

where W_f , W_i , W_o , and W_m are the weights associated with the gates and the memory units and b is the bias.

3.4.4. Implementation

The models are developed and tested in Google Co-Lab environment, in Python language. The algorithms and related functions are implemented using Tensor flow and Keras libraries.

- (a) AR and ARX: The AR model is univariate, considering the target-predicted variable as the only feature. Here, the only feature considered is 'AggregatedPower'. Forecaster-Autoreg class in sklearn package is used to implement the regression model. Among the various regressors, Ridge regressor is found to present the best performance on the dataset. A lag parameter of 48 is decided, meaning that output at each step depends on the previous 48 steps. ARX is multivariate, where it considers multiple attributes for prediction. The model considers 'ConnectionHour', 'WorkingStatus', 'HourlyAverageDemand', and 'Previous24HrAverageDemand' features as exogenous variables along with the target variable 'AggregatedPower'. The model uses a Ridge regressor and a lag of 48.
- (b) SVR: In the SVR model with RBF kernel, the attributes 'ConnectionHour', 'WorkingStatus', 'HourlyAverageDemand', and 'Previous24HrAverageDemand' are considered as the independent features and 'AggregatedPower' as the target. The best values for hyperparameters are obtained using grid search. Regularization parameter (C) is obtained as ten and gamma as one.

- (c) LSTM: Multivariate LSTM model is considered where the features are ‘Connection-Hour’, ‘WorkingStatus’, ‘HourlyAverageDemand’, ‘Previous24HrAverageDemand’, and ‘AggregatedPower’. A step size of 48 is chosen after trial and error, which means, the output power at any step is influenced by the values of these features for the previous 48 steps. Multiple LSTM configurations were tried, and performance was evaluated. Finally, the model having one LSTM layer of 50 neurons and tanh activation, followed by a fully connected layer with 50 neurons and ReLu activation and a single neuron at the output layer, is chosen as the best model. The configurations chosen for the models are given in Table 2.

Table 2. Model configurations.

Model	Parameter	Value
ARF	Regressor	Ridge
	Lags	48
	Kernel	RBF
SVR	C	10
	Gamma	1
	Epochs	30
	Batch Size	192
LSTM	Optimizer	Adam
	Learning Rate	0.001
	Output Activation Function	Linear

3.4.5. Performance Metrics

The metrics used for the performance evaluation of the models are maximum error (ME), MAE, RMSE, and MAPE. For a dataset with n records, if y_i and \hat{y}_i are the i th actual and predicted values, respectively, then the various metrics are given as follows:

- (a) ME:

ME is the maximum of the absolute errors, given by

$$ME = \text{Max}|y_i - \hat{y}_i| \quad (15)$$

- (b) MAE:

MAE is the mean value of the absolute errors or the mean magnitude of the prediction errors. In this, all the individual errors are equally weighted.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (16)$$

- (c) RMSE:

RMSE provides more weightage to larger errors and is used when larger errors are not desirable in the system:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (17)$$

This can be equal to or greater than MAE. The difference between RMSE and MAE is an indication of the variance in the prediction errors.

- (d) MAPE:

MAPE is a normalized metric and hence suitable for comparison across works:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} * 100 \quad (18)$$

However, this produces extreme values, when the actual values are very small.

4. Results and Discussions

Data for the month of January 2019 are used for testing the models. The effectiveness of all three models is evaluated using the error metrics and analyzed. Figure 8 plots the predicted demand against actual demand for the three models. The spread of the data points from the black line indicates the deviation of the predicted values from the actuals.

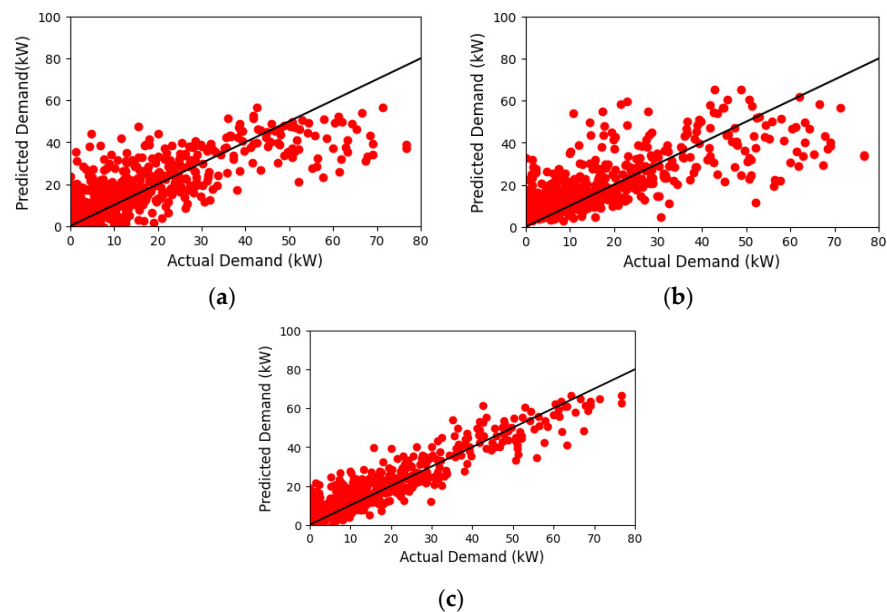


Figure 8. Actual and predicted demand for (a) ARX, (b) SVR, and (c) LSTM models.

4.1. Prediction on a Normal Weekend

Figure 9 shows the demand prediction for 6 January 2019, a Sunday. The plot in black represents the actual demand values, whereas the blue, green, and red shows ARX, SVR, and LSTM model predictions, respectively. The low demands during the morning and afternoon till 3:00 p.m. were forecasted by the models successfully. Further, for the late evening hours, the AR model showed a significant variation; however, LSTM depicted a satisfactory performance, as seen in the figure.

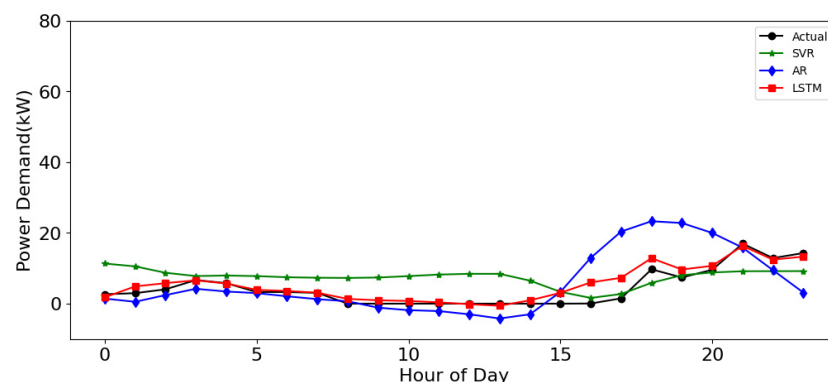


Figure 9. Demand prediction for 6 January, a Sunday.

4.2. Prediction on a Normal Weekday

Figure 10 shows the forecast for 16 January 2019, a typical weekday. All the models track the charging pattern; however, the LSTM model presents a better prediction than others. The lowest demands during the morning hours are correctly predicted by the LSTM

model. The maximum errors incurred for the models on the day are 26 kW, 36 kW, and 17 kW for ARX, SVR, and LSTM, respectively.

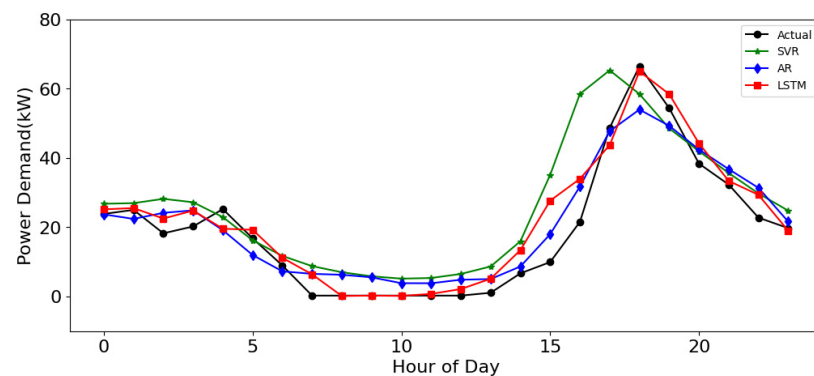


Figure 10. Demand prediction for 16 January, a normal working day, showing the models following the actual demand closely.

4.3. Prediction on a Weekday Holiday

A case of significant error in peak prediction was observed on 21 January 2019, Monday, as shown in Figure 11. The error in predictions across the day is clearly visible in the plots, with a significant error evident at the evening peak. Evidently, this error is due to a different charging pattern that occurred on the day. It is further observed that 21 January 2019 was a holiday in the region. This unexpected weekday holiday scenario, with peak demand even less than half the hourly average demand, accounts for the large error in peak prediction. The numeric of the measures is tabulated in Table 3.

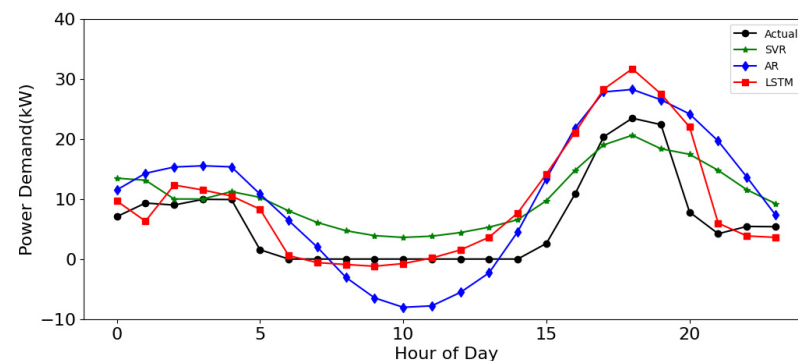


Figure 11. Prediction for 21 January, a Monday holiday, shows more errors in the prediction.

Table 3. Performance metrics for the configurations.

Performance Metric	AR	ARX	SVR	LSTM
ME (kW)	63.2	42	43	24
MAE (kW)	8.5	7.4	7.7	4.2
RMSE (kW)	12.6	10.1	10.5	5.9
MAPE *	0.73	0.86	0.71	0.4

* Sessions with extremely small or zero actual values are ignored.

The LSTM model shows a significant performance improvement compared to the other models. LSTM reduces the MAE by almost 50% compared to the AR model, and approximately 43% compared to ARX and SVR models. From the RMSE perspective, the LSTM model has reduced the RMSE by 53% compared to AR and almost 42% compared to ARX and SVR. The MAPE values are on a slightly higher side. This is because the actual

demand takes very small values for several sessions, mainly on weekends. Out of the total 744 sessions in the test dataset, 277 sessions have an actual demand of less than 5 kW. Such small values give rise to the high MAPE results. Among the models considered, LSTM has a relatively better MAPE score. All the performance metrics highlight the superior performance of LSTM compared to the other models.

There has been no attempt to compare the abovementioned performance metrics with similar works, because of the nature of the data and the associated relatively high MAPE values. Even though sessions with extremely small actual values are neglected, there are sessions with small actual demands, which give rise to high values of MAPE.

The major contribution of this work is the demonstration of LSTM ability in demand forecasting by utilizing fewer carefully chosen features. A comparison of some of the works, in terms of the number of features considered for prediction, is shown in Table 4.

Table 4. Feature comparison.

Literature	Number of Features	System Complexity
[20]	9	Moderate
[48]	12	Moderate
[51]	8	Moderate
[52]	50, consisting of seven types of features	High
Current work	4	Less

Compared to the existing literature, the present work is able to achieve good performance using a fewer number of features. This leads to reduction in computational and system complexity.

5. Conclusions and Future Scope of Work

With the rapid increase in EVs in the market and their associated benefits, the challenges and concerns associated with EVs demand fast, smart, and intelligent solutions. The impacts of the non-coordinated, unplanned charging of EVs on the utility are extensive. To efficiently resolve this issue, EV load forecasting and proper management are necessary. The forecasting of EV demand is imperative in this context. This work focuses on short-term EV demand forecasting using three techniques: AR, SVR, and LSTM. Real-world EV charging data from ACN repository are used. The applicability of forecasting techniques on the data and the various influencing features are analyzed and finalized using ACF plot and correlation matrix. Learning models are designed using the mentioned techniques, and performance is compared. Test results on the test dataset show that the models can track and predict the EV load demand successfully. Also, compared to other models, LSTM model greatly reduces the MAE and RMSE. This also underlines the superiority of the DL techniques in forecasting. From the EV perspective, this work can be a primary step toward designing an efficient, coordinated EV load scheduling and management system.

The work can be expanded by the use of advanced DL models for forecasting. The present work uses ACN data from April 2018 to January 2019. Charging data till the present can be considered for analysis and training in future work. This may include more variations in the data, e.g., COVID-19 pandemic effects on EV charging patterns. Additional features like temperature and weather will also be considered for forecasting in future work.

Author Contributions: Conceptualization, G.V. and D.K.; methodology, G.V., D.K., P.B.P. and N.S.; software, G.V.; validation, G.V.; formal analysis, G.V., D.K., P.B.P. and N.S.; data curation, G.V.; writing—original draft preparation, G.V.; writing—review and editing, G.V., D.K., P.B.P. and N.S.; visualization, G.V.; supervision, D.K., A.K., P.B.P. and N.S.; project administration, D.K., A.K., A.G.; funding acquisition, A.K. and A.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Publicly available datasets were analyzed in this study. The data can be found here: <https://ev.caltech.edu/dataset> (accessed on: 1 October 2022).

Acknowledgments: Authors express their gratitude to Amrita Vishwa Vidyapeetham for the help and support received for this work.

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

References

1. Khurana, A.; Kumar, V.V.R.; Sidhpuria, M. A Study on the Adoption of Electric Vehicles in India: The Mediating Role of Attitude. *Vis. J. Bus. Perspect.* **2019**, *24*, 23–34. [CrossRef]
2. Dimitrov, R.S. The Paris Agreement on Climate Change: Behind Closed Doors. *Glob. Environ. Politics* **2016**, *16*, 1–11. [CrossRef]
3. Available online: [https://olawebcdn.com/ola-institute/OMI_White_Paper_Vehicle_to_Grid_\(V2G\)_in_India.pdf](https://olawebcdn.com/ola-institute/OMI_White_Paper_Vehicle_to_Grid_(V2G)_in_India.pdf) (accessed on 13 February 2023).
4. Bjerkan, K.Y.; Nørbech, T.E.; Nordtømme, M.E. Incentives for Promoting Battery Electric Vehicle (BEV) Adoption in Norway. *Transp. Res. Part D Transp. Environ.* **2016**, *43*, 169–180. [CrossRef]
5. Song, S.; Lin, H.; Sherman, P.; Yang, X.; Chen, S.; Lu, X.; Lu, T.; Chen, X.; McElroy, M.B. Deep Decarbonization of the Indian Economy: 2050 Prospects for Wind, Solar, and Green Hydrogen. *iScience* **2022**, *25*, 104399. [CrossRef]
6. Bistline, J.E.T.; Young, D.T. The Role of Natural Gas in Reaching Net-Zero Emissions in the Electric Sector. *Nat. Commun.* **2022**, *13*, 4743. [CrossRef] [PubMed]
7. Sortomme, E.; El-Sharkawi, M.A. Optimal Charging Strategies for Unidirectional Vehicle-To-Grid. *IEEE Trans. Smart Grid* **2011**, *2*, 131–138. [CrossRef]
8. Chan, C.C. The State of the Art of Electric, Hybrid, and Fuel Cell Vehicles. *Proc. IEEE* **2007**, *95*, 704–718. [CrossRef]
9. Ehsani, M.; Gao, Y.; Gay, S.E.; Emadi, A. *Modern Electric, Hybrid Electric and Fuel Cell Vehicles*; CRC Press: Boca Raton, FL, USA, 2004.
10. Eldho, K.P.; Deepa, K. A comprehensive overview on the current trends and technological challenges in energy storages and charging mechanism in electric vehicle. *J. Green Eng.* **2020**, *10*, 9.
11. Poornesh, K.; Nivya, K.P.; Sireesha, K. A Comparative Study on Electric Vehicle and Internal Combustion Engine Vehicles. In Proceedings of the 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 10–12 September 2020. [CrossRef]
12. Vempalli, S.K.; Deepa, K. A Novel V2V Charging Method Addressing the Last Mile Connectivity. In Proceedings of the 2018 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), Chennai, India, 18–21 December 2018. [CrossRef]
13. Wang, Z.; Wang, S. Grid Power Peak Shaving and Valley Filling Using Vehicle-To-Grid Systems. *IEEE Trans. Power Deliv.* **2013**, *28*, 1822–1829. [CrossRef]
14. Yilmaz, M.; Krein, P.T. Review of the Impact of Vehicle-To-Grid Technologies on Distribution Systems and Utility Interfaces. *IEEE Trans. Power Electron.* **2013**, *28*, 5673–5689. [CrossRef]
15. Biresselioglu, M.E.; Demirbag Kaplan, M.; Yilmaz, B.K. Electric Mobility in Europe: A Comprehensive Review of Motivators and Barriers in Decision Making Processes. *Transp. Res. Part A Policy Pract.* **2018**, *109*, 1–13. [CrossRef]
16. Berkeley, N.; Jarvis, D.; Jones, A. Analysing the Take up of Battery Electric Vehicles: An Investigation of Barriers amongst Drivers in the UK. *Transp. Res. Part D Transp. Environ.* **2018**, *63*, 466–481. [CrossRef]
17. Powell, S.; Cezar, G.V.; Min, L.; Azevedo, I.M.L.; Rajagopal, R. Charging Infrastructure Access and Operation to Reduce the Grid Impacts of Deep Electric Vehicle Adoption. *Nat. Energy* **2022**, *7*, 1–14. [CrossRef]
18. Almaghrebi, A. The Impact of PEV User Charging Behavior in Building Public Charging Infrastructure. Master's Thesis, University of Nebraska-Lincoln, Lincoln, NE, USA, May 2020.
19. Global Electric Vehicle Market 2020 and Forecasts Canalys Newsroom. Available online: <https://canalys.com/newsroom/canalys-global-electric-vehicle-sales-2020> (accessed on 13 February 2023).
20. Xydas, E.S.; Marmaras, C.E.; Cipcigan, L.M.; Hassan, A.S.; Jenkins, N. Forecasting Electric Vehicle Charging Demand Using Support Vector Machines. In Proceedings of the 2013 48th International Universities' Power Engineering Conference (UPEC), Dublin, Ireland, 2–5 September 2013. [CrossRef]
21. Yusuf, J.; Hasan, J.; Sadrul, U. Impacts of Plug-in Electric Vehicles on a Distribution Level Microgrid. In Proceedings of the 2019 North American Power Symposium (NAPS), Wichita, KS, USA, 13–15 October 2019. [CrossRef]
22. Yang, Z.; Li, K.; Niu, Q.; Xue, Y. A Comprehensive Study of Economic Unit Commitment of Power Systems Integrating Various Renewable Generations and Plug-in Electric Vehicles. *Energy Convers. Manag.* **2017**, *132*, 460–481. [CrossRef]
23. Hadley, S.W.; Tsvetkova, A.A. Potential Impacts of Plug-in Hybrid Electric Vehicles on Regional Power Generation. *Electr. J.* **2009**, *22*, 56–68. [CrossRef]
24. Brouwer, A.S.; Kuramochi, T.; van den Broek, M.; Faaij, A. Fulfilling the Electricity Demand of Electric Vehicles in the Long Term Future: An Evaluation of Centralized and Decentralized Power Supply Systems. *Appl. Energy* **2013**, *107*, 33–51. [CrossRef]

25. Rahman, S.; Shrestha, G.B. An Investigation into the Impact of Electric Vehicle Load on the Electric Utility Distribution System. *IEEE Trans. Power Deliv.* **1993**, *8*, 591–597. [\[CrossRef\]](#)
26. Gomez, J.C.; Morcos, M.M. Impact of EV Battery Chargers on the Power Quality of Distribution Systems. *IEEE Trans. Power Deliv.* **2003**, *18*, 975–981. [\[CrossRef\]](#)
27. Qian, K.; Zhou, C.; Allan, M.; Yuan, Y. Modeling of Load Demand due to EV Battery Charging in Distribution Systems. *IEEE Trans. Power Syst.* **2011**, *26*, 802–810. [\[CrossRef\]](#)
28. Al-Ogaili, A.S.; Tengku Hashim, T.J.; Rahmat, N.A.; Ramasamy, A.K.; Marsadek, M.B.; Faisal, M.; Hannan, M.A. Review on Scheduling, Clustering, and Forecasting Strategies for Controlling Electric Vehicle Charging: Challenges and Recommendations. *IEEE Access* **2019**, *7*, 128353–128371. [\[CrossRef\]](#)
29. Sharma, I.; Canizares, C.; Bhattacharya, K. Smart Charging of PEVs Penetrating into Residential Distribution Systems. *IEEE Trans. Smart Grid* **2014**, *5*, 1196–1209. [\[CrossRef\]](#)
30. Mohammad; Moses, P.S.; Hajforoosh, S. Distribution Transformer Stress in Smart Grid with Coordinated Charging of Plug-in Electric Vehicles. In Proceedings of the 2012 IEEE PES Innovative Smart Grid Technologies (ISGT), Washington, DC, USA, 16–20 January 2012. [\[CrossRef\]](#)
31. Richardson, P.; Flynn, D.; Keane, A. Optimal Charging of Electric Vehicles in Low-Voltage Distribution Systems. *IEEE Trans. Power Syst.* **2012**, *27*, 268–279. [\[CrossRef\]](#)
32. Clement-Nyons, K.; Haesen, E.; Driesen, J. The Impact of Charging Plug-in Hybrid Electric Vehicles on a Residential Distribution Grid. *IEEE Trans. Power Syst.* **2010**, *25*, 371–380. [\[CrossRef\]](#)
33. Peng, S.; Zhang, H.; Yang, Y.; Li, B.; Su, S.; Huang, S.; Zheng, G. Spatial-Temporal Dynamic Forecasting of EVs Charging Load Based on DCC-2D. *Chin. J. Electr. Eng.* **2022**, *8*, 53–62. [\[CrossRef\]](#)
34. Bae, S.; Kwasinski, A. Spatial and Temporal Model of Electric Vehicle Charging Demand. *IEEE Trans. Smart Grid* **2012**, *3*, 394–403. [\[CrossRef\]](#)
35. Luo, Z.; Song, Y.; Hu, Z.; Xu, Z.; Yang, X.; Zhan, K. Forecasting Charging Load of Plug-in Electric Vehicles in China. In Proceedings of the 2011 IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 24–28 July 2011. [\[CrossRef\]](#)
36. Shao, Y.; Mu, Y.; Yu, X.; Dong, X.; Jia, H.; Wu, J.; Zeng, Y. A Spatial-Temporal Charging Load Forecast and Impact Analysis Method for Distribution Network Using EVs-Traffic-Distribution Model. *Proc. CSEE Smart Grid* **2017**, *37*, 5207–5219. [\[CrossRef\]](#)
37. Liang, H.; Sharma, I.; Zhuang, W.; Bhattacharya, K. Plug-in Electric Vehicle Charging Demand Estimation Based on Queueing Network Analysis. In Proceedings of the 2014 IEEE PES General Meeting | Conference & Exposition, National Harbor, MD, USA, 27–31 July 2014. [\[CrossRef\]](#)
38. Amini, M.H.; Kargarian, A.; Karabasoglu, O. ARIMA-Based Decoupled Time Series Forecasting of Electric Vehicle Charging Demand for Stochastic Power System Operation. *Electr. Power Syst. Res.* **2016**, *140*, 378–390. [\[CrossRef\]](#)
39. Karthick, A.; Mohanavel, V.; Chinnaiyan, V.K.; Karpagam, J.; Baranilingesan, I.; Rajkumar, S. State of Charge Prediction of Battery Management System for Electric Vehicles. In *Active Electrical Distribution Network*; Academic Press: New York, NY, USA, 2022; pp. 163–180.
40. Ghosh, A. Possibilities and challenges for the inclusion of the electric vehicle (EV) to reduce the carbon footprint in the transport sector: A review. *Energies* **2020**, *13*, 2602. [\[CrossRef\]](#)
41. Prabha, P.P.; Vanitha, V.; Resmi, R. Wind Speed Forecasting Using Long Short Term Memory Networks. In Proceedings of the 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICT), Kannur, India, 5–6 July 2019. [\[CrossRef\]](#)
42. Kumar, D.T.S. Video Based Traffic Forecasting Using Convolution Neural Network Model and Transfer Learning Techniques. *J. Innov. Image Process.* **2020**, *2*, 128–134. [\[CrossRef\]](#)
43. Chandran, L.R.; Jayagopal, N.; Lal, L.S.; Narayanan, C.; Deepak, S.; Hari Krishnan, V. Residential Load Time Series Forecasting Using ANN and Classical Methods. In Proceedings of the 2021 6th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 8–10 July 2021. [\[CrossRef\]](#)
44. Arias, M.B.; Bae, S. Electric Vehicle Charging Demand Forecasting Model Based on Big Data Technologies. *Appl. Energy* **2016**, *183*, 327–339. [\[CrossRef\]](#)
45. Chen, W.; Chen, X.; Liao, Y.; Wang, G.; Yao, J.; Chen, K. Short-Term Load Forecasting Based on Time Series Reconstruction and Support Vector Regression. In Proceedings of the 2013 IEEE International Conference of IEEE Region 10 (TENCON 2013), Xi'an, China, 22–25 October 2013. [\[CrossRef\]](#)
46. Majidpour, M. Time Series Prediction for Electric Vehicle Charging Load and Solar Power Generation in the Context of Smart Grid. Ph.D. Thesis, University of California, Los Angeles, CA, USA, 2016.
47. Majidpour, M.; Qiu, C.; Chu, P.; Gadhi, R.; Pota, H.R. Modified Pattern Sequence-Based Forecasting for Electric Vehicle Charging Stations. OSTI OAI (U.S. Department of Energy Office of Scientific and Technical Information) 2014. In Proceedings of the 2014 IEEE International Conference on Smart Grid Communications (SmartGridComm), Venice, Italy, 3–6 November 2014. [\[CrossRef\]](#)
48. Almaghrebi, A.; Aljuheshi, F.; Rafaie, M.; James, K.; Alahmad, M. Data-Driven Charging Demand Prediction at Public Charging Stations Using Supervised Machine Learning Regression Methods. *Energies* **2020**, *13*, 4231. [\[CrossRef\]](#)
49. Kandasamy, N.K.; Cheah, P.H.; Sivaneasan, B.; So, P.L.; Wang, D.Z. Electric Vehicle Charging Profile Prediction for Efficient Energy Management in Buildings. In Proceedings of the 2012 10th International Power & Energy Conference (IPEC), Ho Chi Minh City, Vietnam, 12–14 December 2012. [\[CrossRef\]](#)

50. Aduama, P.; Zhang, Z.; Al-Sumaiti, A.S. Multi-Feature Data Fusion-Based Load Forecasting of Electric Vehicle Charging Stations Using a Deep Learning Model. *Energies* **2023**, *16*, 1309. [\[CrossRef\]](#)
51. Van Krieking, G.; De Cauwer, C.; Sapountzoglou, N.; Coosemans, T.; Messagie, M. Day-Ahead Forecast of Electric Vehicle Charging Demand with Deep Neural Networks. *World Electr. Veh. J.* **2021**, *12*, 178. [\[CrossRef\]](#)
52. Elahe, F.; Kabir, A.; Mahmud, S.; Azim, R. Factors Impacting Short-Term Load Forecasting of Charging Station to Electric Vehicle. *Electronics* **2022**, *12*, 55. [\[CrossRef\]](#)
53. Koohfar, S.; Woldemariam, W.; Kumar, A. Prediction of Electric Vehicles Charging Demand: A Transformer-Based Deep Learning Approach. *Sustainability* **2023**, *15*, 2105. [\[CrossRef\]](#)
54. Li, Y.; Huang, Y.; Zhang, M. Short-Term Load Forecasting for Electric Vehicle Charging Station Based on Niche Immunity Lion Algorithm and Convolutional Neural Network. *Energies* **2018**, *11*, 1253. [\[CrossRef\]](#)
55. Wang, J.; Wang, J.; Li, Y.; Zhu, S.; Zhao, J. Techniques of Applying Wavelet De-Noising into a Combined Model for Short-Term Load Forecasting. *International J. Electr. Power Energy Syst.* **2014**, *62*, 816–824. [\[CrossRef\]](#)
56. Wang, J.-Z.; Wang, J.-J.; Zhang, Z.-G.; Guo, S.-P. Forecasting Stock Indices with Back Propagation Neural Network. *Expert Syst. Appl.* **2011**, *38*, 14346–14355. [\[CrossRef\]](#)
57. Gao, Y.; Guo, S.; Ren, J.; Zhao, Z.; Ehsan, A.; Zheng, Y. An Electric Bus Power Consumption Model and Optimization of Charging Scheduling Concerning Multi-External Factors. *Energies* **2018**, *11*, 2060. [\[CrossRef\]](#)
58. Zhang, L.; Huang, C.; Yu, H. *Study of Charging Station Short-Term Load Forecast Based on Wavelet Neural Networks for Electric Buses*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 555–564. [\[CrossRef\]](#)
59. Dokur, E.; Erdogan, N.; Kucuksari, S. EV Fleet Charging Load Forecasting Based on Multiple Decomposition with CEEMDAN and Swarm Decomposition. *IEEE Access* **2022**, *10*, 62330–62340. [\[CrossRef\]](#)
60. Lee, Z.J.; Li, T.; Low, S.H. ACN-Data: Analysis and Applications of an Open EV Charging Dataset. In Proceedings of the E-Energy'19: Tenth ACM International Conference on Future Energy Systems, Phoenix, AZ, USA, 25–28 June 2019; California Institute of Technology: Pasadena, CA, USA, 2019.
61. Mahajan, M.; Kumar, S.; Pant, B.; Tiwari, U. Incremental Outlier Detection in Air Quality Data Using Statistical Methods. In Proceedings of the 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI), Sakheer, Bahrain, 26–27 October 2020. [\[CrossRef\]](#)
62. Otexts.com. Available online: <https://otexts.com/fpp2/AR.html> (accessed on 13 February 2023).
63. Horner, M.; Pakzad, S.N.; Gulgec, N.S. Parameter Estimation of Autoregressive-Exogenous and Autoregressive Models Subject to Missing Data Using Expectation Maximization. *Front. Built Environ.* **2019**, *5*, 109. [\[CrossRef\]](#)
64. Boser, B.E.; Guyon, I.M.; Vapnik, V.N. A Training Algorithm for Optimal Margin Classifiers. In Proceedings of the Fifth Annual Workshop on Computational Learning Theory–COLT'92, Pittsburgh, PA, USA, 27–29 July 1992. [\[CrossRef\]](#)
65. Hsu, C.W.; Chang, C.C.; Lin, C.J. *A Practical Guide to Support Vector Classification*; Technical Report; Department of Computer Science, National Taiwan University: Taipei, Taiwan, 2016.
66. Hochreiter, S. The Vanishing Gradient Problem during Learning Recurrent Neural Nets and Problem Solutions. *Int. J. Uncertain. Fuzziness Knowl. Based Syst.* **1998**, *6*, 107–116. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.