Research Article

Dynamic Load Prediction Model of Electric Bus Charging Based on WNN

Chang Zheng,[1] Tao Peng,[2] Zhang Chao,[2] Zhao Shasha,[2] Liu Xiaoyu [ID],[2] and Li Han[2]

[1]*State Grid Hebei Electric Power Co. Ltd, Shijiazhuang City 050000, China*
[2]*State Grid Hebei Marketing Service Center, Shijiazhuang City 050000, China*

Correspondence should be addressed to Liu Xiaoyu; 1764100123@e.gzhu.edu.cn

Electric buses have a significant penetration rate and high charging frequency and amount. Therefore, their charging load has a momentous influence on the power grid's operation and dispatch. There are important theoretical and practical reasons to study electric bus charging load prediction; however, the intermittent and random charging behavior of buses makes it more difficult to predict charging load predictions, particularly, in real time. To accomplish this, in this paper a WNN (wavelet neural network)-based dynamic load prediction model for charging electric buses is suggested. We start by using distance and shape to group the charging load curve which, in fact, is done with spectral clustering. As a second step, we take into account a wide range of charging load-affecting variables such as temperature and time of day, in order to better train the WNN. Moreover, the charge loads for each cluster are predicted based on model parameters; subsequently, the forecast day's total charging load is then calculated by summing the prediction results for each cluster; finally, the proposed method is validated using a real city data set. In our empirical evaluation, it has been found that, under various indicators, the proposed method's ability to precisely forecast the charging load of electric vehicles has significantly improved. In fact, this allows for better guidance of charging user, planning, and expanding the power grid in consideration of electric vehicle charging loads.

1. Introduction

The USA, the European Union, and the Republic of China all plan to achieve carbon neutrality goals by 2050, indicating that the energy system's transformation and reform are imminent. It has become critical to the transformation of the energy system to rapidly advance the development of electric vehicles and the efficiency with which those vehicles use energy [1, 2]. In light of the widespread adoption of electric vehicles, the planning and operation of the energy system will face new challenges. There is a lot of interest in dispatched energy systems and related topics from both domestic and international researchers [3–5].

As smart grids and intelligent transportation networks come together, the development, application, and research of electric vehicles and their charging infrastructure have all been moving forward at breakneck speed in recent years [6]. A large number of public transportation vehicles are being used in the promotion and application of transportation electrification, including buses. Electric buses have a significant penetration rate and high charging frequency and amount, so their charging load has a momentous influence over the power grid's operation, management, and dispatch. Consequently, the study of electric bus charging load prediction is of great theoretical and practical importance. Buses, on the other hand, depart at set times each day and only stay for a short period of time. As a result, it is more difficult to predict the charging load over time due to the intermittent and random charging behavior of buses [7, 8].

There are a wide range of traditional methods for predicting power loads. New load types, such as distributed generation and electric vehicles, have posed significant challenges to traditional methods of load forecasting because of the widespread availability of these new load types. The distribution of EV (electric vehicle) charging load time is different from the law of electric load because of the

characteristics of different charging methods, travel rules, charging efficiency, charging frequency, etc. As a result, the EV charging load is subject to a greater degree of randomness in time. This is due to a wide range of factors, including weather, road conditions, and operating status [9].

Many AI (artificial intelligence) and learning-based methods have recently been used to predict the amount of electricity needed to charge an electric vehicle, such as shallow networks and deep learning algorithms. A common problem with traditional approaches established on shallow networks is their inability to deal with both learning and convergence at the same time. As an example, deep learning (DL) can characterize complex functions with less parameters thanks to its excellent feature learning ability. In order to predict EV charging load at multiple time scales, some researchers proposed a new DL method utilizing an LSTM, i.e., long short-term memory [9, 10]. The kernel principal component analysis (PCA) and a noninferior sorting genetic algorithm have been proposed as a way to optimize the parameters of convolutional neural networks for EVs. Besides these approaches, numerous methods for predicting the short-term demand have been also suggested in the literature. To predict electric vehicle charging loads, some researchers used the LSTM network model, and experiments have shown that LSTM forecasting is accurate and effective. In addition, the charging load of electric buses is intermittent and temporal because of the short interval between electric buses. As an example, the LSTM neural network model can be used to effectively solve the time scale problem of EV charging and improve the accuracy in load prediction [11–13].

Through comparing electric buses with electric taxis or private cars, we find that their operating times and routes are more predictable. However, depending on how frequently and at what times they run, different routes of electric buses are affected [14]. It is because of the characteristics that the driving laws are quite different, which results in a large difference in charging load. Current electric bus loading forecasting methods focus on charging loads for individual electric bus groups. A clustering algorithm can be used to group EV users with similar characteristics into one cluster, which can then be analyzed to better understand individual differences in order to improve overall load forecasting accuracy. Load clustering allows us to gain a better understanding of the electricity consumption patterns of individual customers by comparing trends and periodicities in the load curve and by accurately measuring similarities in the load's shape and contour over time clustering.

Cluster analysis of user load has been the subject of numerous studies in the last few years. Algorithms for clustering data include the well-known and most widely used K-means, DBSCAN, FCM, and spectral algorithms. To perform a load curve clustering analysis, some researchers have proposed an improved variant of the K-means algorithm that incorporates agglomerative hierarchical clustering [15]. Additionally, some researchers have employed spectral clustering to categorize the load curves in massive data sets using information direct segmental aggregation approximation. In fact, the spectral clustering has

advantages in data dimensionality reduction, load classification effectiveness, stability, and computational complexity. Most current clustering methods, on the other hand, rely solely on distance to determine how similar two curves are [16–18].

This paper uses a spectral clustering algorithm based on distance and morphological similarity measures to address the aforementioned issues, and it takes into account the unique characteristics of electric buses when clustering the information. In addition, EV charging load has time series characteristics such as trend and periodicity, as is typical for time series data. Spectral clustering and a WNN are used in this paper to develop a charging load prediction method for electric buses. The foremost and most important contributions of the research conducted in paper could be shortened as follows.

(i) A WNN-based dynamic load prediction model for charging electric buses is suggested.

(ii) By using distance and shape to group the charging load curve, a particular spectral clustering approach is presented.

(iii) We take into account a wide range of charging load-affecting variables such as temperature and time of day in order to better train the WNN.

(iv) Finally, charge loads for each cluster are predicted based on model parameters, and the forecast day's total charging load is then calculated by summing the prediction results for each cluster.

The rest of the paper is arranged as follows. In Section 2, state-of-the-art related work is discussed. The methodology of the research is presented in Section 3. This section also discusses the proposed method in detail. In Section 4, we deliberate experimental settings, parameters, and the attained outcomes. Lastly, we conclude this paper in Section 5 and also deliberate several directions for future consideration.

2. Related Work

As a result of the double carbon target and the related strategic layout, it is becoming increasingly challenging for the distribution network to keep up with the rapid growth and disorderly charging of electric vehicles [1, 3–5]. This is because of the double carbon target. When electric vehicles are allowed to connect to the power grid, there is a risk that the local distribution network will become overloaded, there will be a decline in the power's quality, and there will be a decline in the economy of the grid. It is possible to reduce the negative effects of EV charging on the distribution grid while also creating significant economic and social benefits if new technology can be used to charge electric vehicles in an orderly manner. This is made possible by the fact that electric vehicles can be charged on demand [6, 8].

Therefore, an accurate EV charging load prediction is essential for assessing the impact of disorderly charging on the distribution network, formulating distribution network power planning, and implementing an orderly charging

control Xiao strategy. These three processes are all related to implementing an orderly charging control Xiao strategy [9]. It is important to collect basic load data from a variety of locations, including neighborhoods, office buildings, and commercial areas, as well as massive travel data from users and data on the demand for charging electric vehicles. Because people, vehicles, roads, and piles all affect the charging load of electric vehicles, it is also important to collect data on the demand for charging electric vehicles. Because there are so many different data categories and information dimensions [11], it is possible to derive a variety of widely used methods for predicting the amount of load that will be generated when charging an electric vehicle.

Because electric vehicles are mobile loads, each one's charging characteristics are unique. The charging behavior of each vehicle is difficult to analyze and accurately model. Research approaches for electric vehicle (EV) charging load are currently separated into three different groupings: (i) behavior analysis, (ii) simulation, and (iii) data analysis [8, 13, 14]. The vehicle travel patterns can be analyzed using Markov chains and other models, such as traffic travel matrices, to build models that reflect the travel patterns of vehicles in a specific area and time period. The Monte Carlo simulation and hypercube sampling algorithms are used in simulation analysis [15]. Create a probability model for the charging load of electric vehicles. Analysis of historical data is accomplished by applying statistical methods, machine learning, and cloud computing. For example, some academics have used survey data to estimate the probability distribution of EV charging behavior and then developed an EV charging load model, realizing that the enormous and difficult-to-explain EV charging load can be broken down into an EV charging load probability model with multiple types. A multi-objective optimization model of the charging network is built using the Monte Carlo simulation technique, which simulates the EV charging load and incorporates the random characteristics of the EV charging load. A power supply imbalance can occur when models of EV charging load are limited to just time series or space, as discussed above [16, 17]. But these models do not account for the full spatiotemporal characteristics of EV charging load. As a result, the distribution network must take into account the EV charging load and duality of space and time. To better understand the impact on network reliability, some researchers have constructed a spatiotemporal model of the EV charging load in the full trajectory space. It is important to take into account the spatiotemporal characteristics of EV charging loads when developing an integrated energy system plan [18].

Some researchers have developed a real-time dynamic path stochastic simulation based on travel chains and Markov decision processes [13]. This simulation helps researchers circumvent the issue of having to charge electric vehicles at fixed locations at the same time and more accurately reflects the stochastic nature of the spatial movement of electric vehicles in real time. Other researchers categorize the travel space according to the purpose of the activity, and then they use the travel chain and the Markov primary state transfer matrix to obtain the characteristics of the vehicle's spatial movement [19]. This allows them to determine the spatiotemporal distribution characteristics of the charging load. The abovementioned literature is able to determine how various factors affect the charging load by simulating a user's travel demand and analyzing the results. On the other hand, due to the randomness and complexity of the model, it is difficult to predict [20]. A number of researchers have proposed a model for the prediction of charging demand. This model takes into account the road topology and travel speed in the area surrounding the charging station. Additionally, this model supplies parameter values for the queuing theory model by employing a dynamic traffic flow model as an additional type of probabilistic analysis method [7, 14, 21]. Furthermore, methods comparable to these are, albeit, able to take into consideration the spatial distribution features of charging load and, subsequently, can show a significant part in the design, production, and process of charging stations; however, they have some limitations in manipulating the complete charging load of the system and need to be studied further to overcome these limitations.

The station network configuration layout of integrated energy systems is currently being researched in both the USA and other countries, and it can be roughly divided into two categories. One of these categories is known as a hybrid configuration, and the other is known as a distributed configuration [22]. The first thing that needs to be done is to optimize the equipment selection and capacity of the pipe network layout in the station's energy supply area based on the configuration of the station's energy supply area. Second, it is necessary to simultaneously optimize the capacity selection or network layout of each station in addition to the energy supply station and its supply range in the planned area. The first approach takes into consideration only the planning of the supply side because, in today's world, energy supply and demand scenarios are becoming increasingly complex and diverse. These are the kinds of investigations that fall under the rubric of related studies, and their objectives include not only optimizing the lower-layer structure of a number of energy hubs but also planning the upper-layer expansion of the energy network. Others suggest a two-layer method for optimizing the configuration of the distribution network in order to cut down on the daily operating costs as well as the total cost of multiple optical storage. The concept of a smart integrated energy system has been floated by a number of scholars in the academic community. This system creates an optimization model for the location and sizing of multiple integrated energy stations while taking into account traffic flown; however, it does not take pipeline network optimization in the region into consideration. Others investigate how to optimally plan the pipe network according to the characteristics of the region's load, but they do not take into account how to optimally optimize station selection and capacity within the region's multiple combined cooling, heating, and power systems. When planning the energy station network, the literature cited above takes into account load characteristics; however, EV charging load is not one of those characteristics [13–15].

The ability to accurately forecast short-term electric load has a momentous influence on both the dispatching and planning of electric energy. Accurate load forecasts can help grid dispatching units develop cost-effective and reasonable dispatching plans, and they are also a successful manner to increase the entire utilization and management of power generation equipment and the grid's reliable and safe operation. In addition to this, accurate load forecasts can help improve the grid's reliability and safety. In the past few years, load forecasting has seen an increase in the application of both swarm intelligence algorithms and neural network models. Several researchers came up with the idea of a fruit fly optimization algorithm that was improved as well as a generalized regression neural network. An enhanced method for load forecasting has been developed through the utilization of particle swarm algorithms and RBF neural networks. The accuracy of a BP neural network prediction model was improved with the help of a multi-island genetic algorithm. A new wavelet network-optimized firefly algorithm is a suggestion that has been made by a number of researchers. The overall performance of all of the models described above is superior to the performance of just one model taken on its own [7, 17, 20].

3. Proposed Method

The conceptual framework for this paper's dynamic load prediction method for charging electric buses is depicted in Figure 1. The charging load characteristics of an electric bus are inextricably linked to the vehicle's operating hours as well as the routes that it takes. Following some basic data preprocessing and cleaning, the charging loads are grouped together into a cluster of electric buses with similar patterns of electricity consumption. This is made possible by the fact that the charging loads are clustered based on distance and shape. WNN is utilized in the process of both group training and charging load prediction. In conclusion, the total predicted charging load is obtained by adding up the predictions that were produced by the various WNNs.

The way in which electric buses are operated can have a significant impact on the amount of load that is placed on the various charging lines. If electric buses are grouped solely according to route, then the daily load of each individual bus will not be taken into account, and neither the load volume nor the load curve trend will be able to provide a clearer picture of the daily load. As a consequence of this, clustering can be utilized to take into account the unique ways in which different people carry out their tasks. Before the raw data can be used for clustering, it must first go through the steps of preprocessing and cleaning as outlined below.

Firstly, standardize the bus electric load data using

$$y_i(t) = \frac{x_i(t) - x_{i,\min}}{x_{i,\max} - x_{i,\min}}, \tag{1}$$

where $x_i(t)$ is the load value of load curve i in time t, and $x_{i,\min}$ and $x_{i,\max}$ are the minimum and maximum load values of the load curve i, respectively. Then, we have the load matrix $\mathbf{Y}$ which is given by
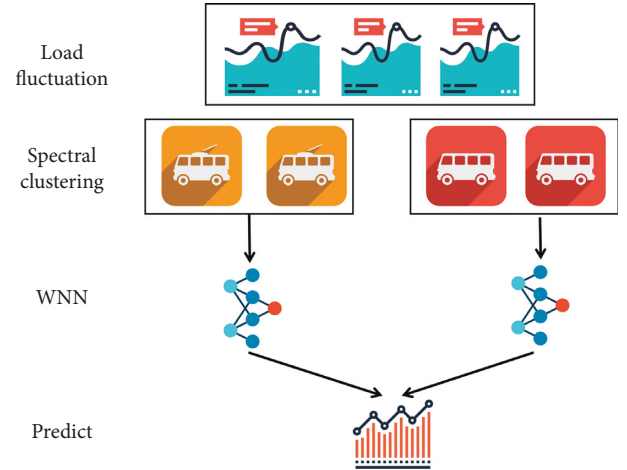

FIGURE 1: Framework of dynamic load forecasting method for electric bus charging.

$$\mathbf{Y} = \begin{bmatrix} y_{11} & \cdots & y_{1T} \\ \vdots & \ddots & \vdots \\ y_{n1} & \cdots & y_{nT} \end{bmatrix}, \tag{2}$$

where n is the amount of load curves, and we assume that its value is predefined in this work. The spatial characteristics of the charging load are, to a large extent, predetermined, as the working hours and driving routes of buses, as well as the locations of charging stations, are clearly defined. Due to the relatively short amount of time that passes between electric bus departures, it is not possible to maintain continuous long-term charging, as shown in Figure 2. As a direct consequence of this, the charging load curve for electric buses exhibits characteristics of being intermittent.

The spectral graph theory is the theoretical foundation for another type of clustering algorithm called the spectral clustering algorithm. By first constructing an undirected weighted graph based on similarity, the problem of clustering is converted into that of graph partitioning. The weight of the connection that corresponds to each piece of data that has been preprocessed and cleaned is used by the algorithm to determine which data point will serve as the vertex of the graph. If you are going to divide the graph using graph theory, the best way to do it is to maximize the similarity between subgraphs and minimize the similarity between subgraphs. In other words, you want to maximize the amount of overlap. The spectral clustering algorithm is utilized to determine distance and shape similarity, in addition to load curve similarity, in order to classify the data. This allows for the classification of load curves.

The distance between different load curves d_{ij} is given and can be estimated in

$$d_{ij} = \left(\sum \left(y_i(t) - y_j(t) \right) \right). \tag{3}$$

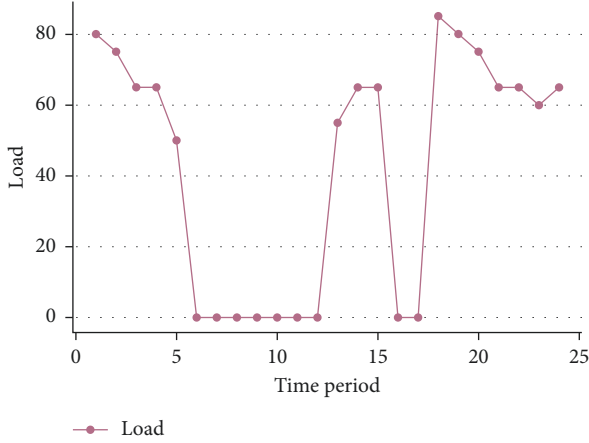Similar to the load matrix, at this time we can obtain the similarity matrix $\mathbf{D}$ using

FIGURE 2: The load during the different time periods in a day.

$$\mathbf{D} = \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & d_{nn} \end{bmatrix}, \qquad (4)$$

$$d_{11}, d_{22}, \ldots, d_{nn} = 0. \qquad (5)$$

After obtaining the distance matrix, we also need additional indicators to describe the difference between different load curves. In this paper, the gray correlation coefficient is used to describe the similarity of different load curves. The gray correlation coefficient is illustrated mathematically as given in

$$L_{ij} = \frac{\min_{ij} |y_i(t) - y_j(t)| + \alpha \max_{ij} |y_i(t) - y_j(t)|}{|y_i(t) - y_j(t)| + \alpha \max_{ij} |y_i(t) - y_j(t)|}, \qquad (6)$$

where α is the resolution factor. The calculation method of the degree of correlation is as follows:

$$C_{ij} = \frac{\sum L_{ij}}{T}. \qquad (7)$$

Then, we can get the similarity matrix $\mathbf{C}$ using

$$\mathbf{C} = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{bmatrix}. \qquad (8)$$

Then, we can run spectral clustering to get classification results.

The genetic algorithm (GA) is an evolutionary technique that determines the optimal parameter assignment for complex calculations by using the genetic and evolutionary properties of natural organisms. This method is named after the computer program that uses this approach, which is called a genetic computer. The GA is a form of random algorithm, in its most basic form. It starts with a population in a set of representative problems that already have solutions and then performs constant evolution in accordance with the evolution mode of the language and the fitness function of the proportion. It is possible to determine, through the processes of

GA evolution and mutation crossover, which parameters from a global pool of parameters produce the best results. The fitness function for this paper is as follows in

$$\text{Fit} = \frac{1}{1 + E}, \qquad (9)$$

where E is the loss function of the WNN model. This should be noted that when used with a wavelet neural network, the GA improves the speed and accuracy of finding the optimal starting point for the network. This should be noted that the WNN model contains (a) an input layer, (b) a hidden layer, and (c) an output layer. The basic organization of the WNN model is shown in Figure 3.

The wavelet neuron can be articulated mathematically as given in

$$w(x) = \cos(1.75x)\exp(-0.5x^2). \qquad (10)$$

The output of the hidden layer h_i is expressed in

$$h_i = h_i \left(\frac{\sum w_{ij} x_i - b_i}{a_i} \right). \qquad (11)$$

The output of the output layer is mathematically expressed in

$$z(m) = \sum w_{im} h(i). \qquad (12)$$

Lastly, the predicted value is characterized by E and is estimated using

$$E = \sum (\hat{y}(m) - y(m)). \qquad (13)$$

In conclusion, the methodology of this paper is systematized into the succeeding three contiguous sections:

(1) The first concern is the management of data. The data that were acquired are subsequently evaluated and subjected to correlation analysis. Following the removal of factors that did not exhibit a significant correlation with the data on energy consumption, multiple linear regression is carried out on the factors that continue to have an effect, and the data are then split into a training set and a test set.

(2) The second strategy is called GA optimization, and it involves adding the training set and test set to the GA for training, encoding the initial value, setting the fitness function, and then carrying out operations such as selection and crossover mutation, after selecting appropriate network weights and scaling translation scale values. After this, the original value should be replaced in WNN.

(3) At long last, the conclusion of the WNN prediction model is presented. After determining the optimal weights and scaling translation scale values, the next step is to determine whether or not the training process should be stopped based on the maximum number of network model training iterations and the convergence error of the training network. This is done after obtaining the optimal weights. After running the simulation, the results are obtained.
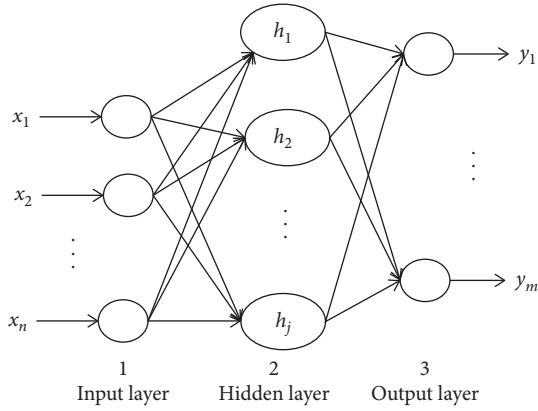
FIGURE 3: The framework of the WNN model.

4. Experiments and Results

In the data set that was released in February 2022, and which was used for this investigation, there are a total of 85 electric bus numbers, as well as, other important information of EVs, for instance, transaction volume, charging start time, charging end time, and electric bus numbers. In February 2022, the Meteorological Data Network will be capable of providing complete day-to-day weather data while also taking into account the effects of climate change. The assumption is made that the weather will continue to be the same for the full twenty-four hours; consequently, the charging loads are counted every sixty minutes.

The data from 85 different electric buses' daily charging loads are selected and then clustered using spectral analysis in this paper. The data cover a period of 31 days. SC and DBI are the indicators that are being used for the evaluation, and Figure 4 illustrates the change curve. Figure 4 demonstrates that when K is equal to 8, both the SC index and the DBI index have reached their ideal values. These values are shown to be optimal in the figure. In light of this, the ultimate number of clusters decided upon was eight.

As a result of the cluster analysis performed in the second section, a total of eight distinct clusters of charging load curve classification are obtained, with each cluster containing a unique set of line vehicles and charging load curves originating from a distinct range of dates. The actual value of the charging load that is taking place in each cluster at the given date and time is accumulated as the input of each WNN for the purpose of load training and prediction. A ratio of 8 : 2 is maintained between the training set and the test set for every data type.

As can be seen in Figures 5–7, predictions are made for the first three classes in order to determine how well our method performs in terms of its ability to make predictions. Although it is obvious that the EV charging loads of various classes vary considerably from one another, the daily load distribution rules between classes are relatively consistent, and the level of accuracy with which they can be predicted is high.

Figure 8 illustrates how the loss value shifts during class 3 training as the amount of time spent in the training phase increases. The example used here is class 3. The data
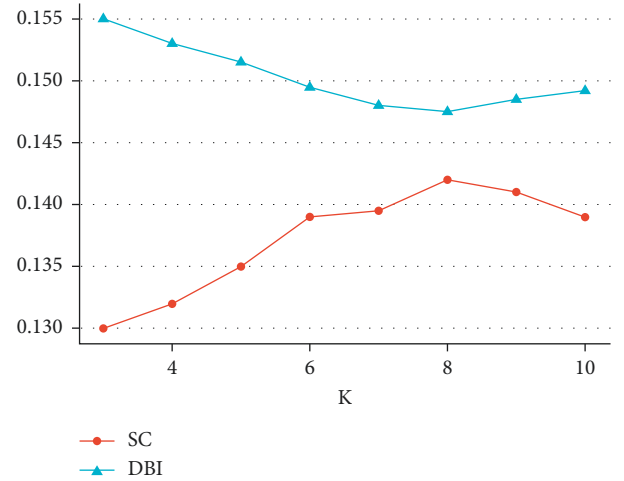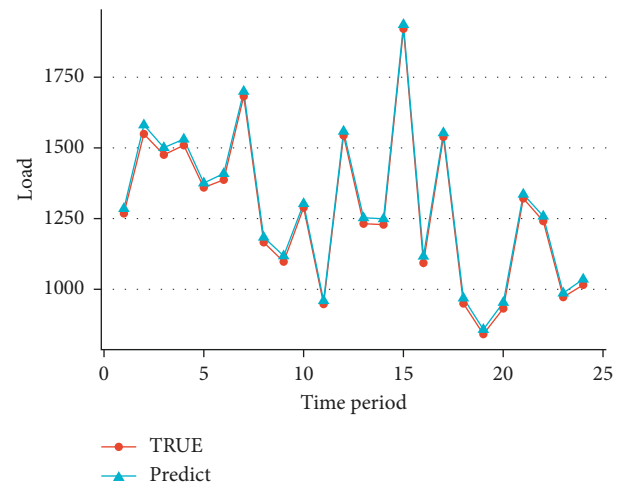

FIGURE 4: The SC and DBI values and their change with respect to K.
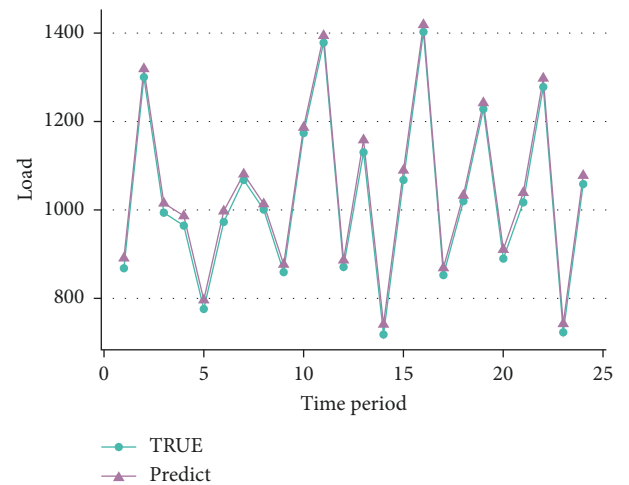

FIGURE 5: Predict performance of class 1.

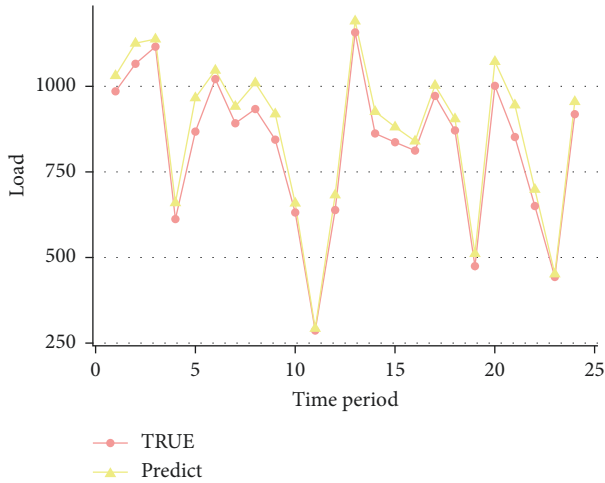FIGURE 6: Predict performance of class 2.

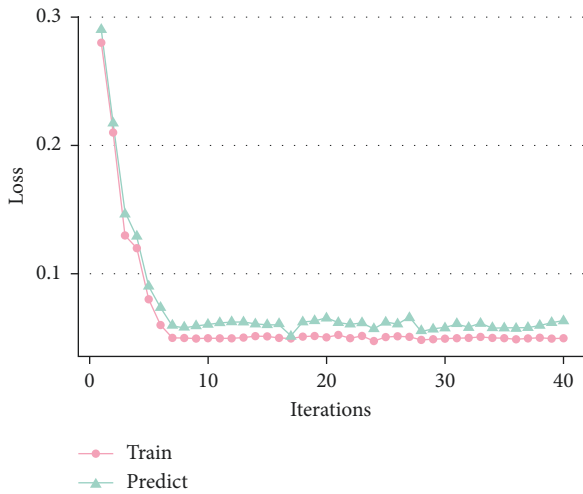Figure 7: The prediction performance of class 3.

Figure 8: The change curve of the loss during training phase.

presented in the figure demonstrate that the training of the model can converge steadily and has a significant predictive effect.

The process of recharging electric vehicles has a significant impact on the distribution network in two different ways:

(1) The first effect is the immediate one that is caused by centralized charging. An electric vehicle is a piece of electrical equipment that has a high power output and a nonlinear load. A temporary voltage drop that is greater than the norm may occur if a large number of electric vehicles are charged at the same time by the same charging station. If only one phase of the grid's power is used for AC charging, an imbalance in all three phases of the grid's power will result. From this point of view, optimizing the charging load curve in such a way that the user's charging time is spread out and the charging load is constant over time can help alleviate the power quality issue that is caused by the charging of electric vehicles on the power grid.

(2) The second step is to expand the capacity of the distribution network so that it can carry a greater load. The total load that is placed on the distribution network is equal to the addition of the charging load to the load that is considered to be conventional. Charging electric vehicles in a disorganized manner raises the total amount of electricity consumed and widens the power gap between the peak and the valley. In the worst-case scenario, transmission congestion will occur because of the superposition of the charging load curve and the conventional load curve if the two curves have complementary shapes. As the total load curve flattens out, there will be an increase in the percentage of time that distribution network equipment is put to use.

5. Conclusions and Future Work

The electric buses have a significant penetration rate, as well as, a high charging frequency and amount; therefore, the charging load that they produce has a momentous impact over the operation, management, and dispatch of the power grid. Despite the fact that the intermittent and random charging behavior of buses makes it more difficult to predict charging load predictions in real time, there are important theoretical and practical reasons to study electric bus charging load prediction. A WNN-based dynamic load prediction model for charging electric buses is being proposed as a means of achieving this goal. We evaluated the proposed model by utilizing distance and shape in order to group the charging load curve. Spectral clustering is the method that is used to accomplish this. In the second step, we trained the WNN, in a better way, by taking into account a wide range of variables that affect the charging load. These variables include temperature and the time of day, for example. The charge loads for each cluster are predicted based on the model parameters, the forecast day's total charging load was then calculated by adding the prediction results for each cluster, and finally, the proposed method was validated utilizing actual data from the city.

The ability of the proposed method to precisely and exactly forecast the charging load of electric vehicles has been found to have improved under a variety of indicators. This allows for better guidance for charging users as well as for planning and expanding the power grid in consideration of electric vehicle charging loads. In the future, we will focus on how to apply deep clustering and deep neural network-related technologies to electric bus power loads. Moreover, we will also investigate that how deep learning methods along with the attention mechanisms can be used to improve the forecasting accuracy. We can also use the proposed method to predict the traffic flow which is also a related research field, and we intend to use the prediction method for similar purposes. The data gathered from the EVs can be huge, and this would also be essential to reduce its size through integrating a data aggregation approach. We plan to integrate a data reduction mechanism and use the edge model to improve the performance of the system. When

complete day-to-day weather data are available, then we will also take this into account to study the effects of climate change.

Data Availability

The data used to support the findings of this study can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] X. Zhang, "Short-term load forecasting for electric bus charging stations based on fuzzy clustering and least squares support vector machine optimized by wolf pack algorithm," *Energies*, vol. 11, no. 6, p. 1449, 2018.

[2] A. Heydari, M. Majidi Nezhad, E. Pirshayan, D. Astiaso Garcia, F. Keynia, and L. De Santoli, "Short-term electricity price and load forecasting in isolated power grids based on composite neural network and gravitational search optimization algorithm," *Applied Energy*, vol. 277, Article ID 115503, 2020.

[3] Y. Wang, Q. Chen, T. Hong, and C. Kang, "Review of smart meter data analytics: applications, methodologies, and challenges," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 3125–3148, 2019.

[4] B. Gu, T. Zhang, H. Meng, and J. Zhang, "Short-term forecasting and uncertainty analysis of wind power based on long short-term memory, cloud model and non-parametric kernel density estimation," *Renewable Energy*, vol. 164, pp. 687–708, 2021.

[5] R. Wang, J. Wang, and Y. Xu, "A novel combined model based on hybrid optimization algorithm for electrical load forecasting," *Applied Soft Computing*, vol. 82, Article ID 105548, 2019.

[6] M. Zhou, T. Hu, K. Bian et al., "Short-term electric load forecasting based on v mode decomposition and grey wolf optimization," *Energies*, vol. 14, no. 16, p. 4890, 2021.

[7] M. Akhtaruzzaman, M. K. Hasan, S. R. Kabir, S. N. H. S. Abdullah, M. J. Sadeq, and E. Hossain, "HSIC bottleneck based distributed deep learning model for load forecasting in smart grid with a comprehensive survey," *IEEE Access*, vol. 8, pp. 222977–223008, 2020.

[8] M. A. da Silva, T. Abreu, C. R. Santos-Junior, and C. R. Minussi, "Load forecasting for smart grid based on continuous-learning neural network," *Electric Power Systems Research*, vol. 201, Article ID 107545, 2021.

[9] S. K. Aggarwal, L. M. Saini, and A. Kumar, "Electricity price forecasting in deregulated markets: a review and evaluation," *International Journal of Electrical Power & Energy Systems*, vol. 31, no. 1, pp. 13–22, 2009.

[10] A. Deihimi, O. Orang, and H. Showkati, "Short-term electric load and temperature forecasting using wavelet echo state networks with neural reconstruction," *Energy*, vol. 57, pp. 382–401, 2013.

[11] A. Moradzadeh, A. Mansour-Saatloo, M. Nazari-Heris, B. Mohammadi-Ivatloo, and S. Asadi, "Introduction and literature review of the application of machine learning/deep learning to load forecasting in power system," *Application of Machine Learning and Deep Learning Methods to Power System Problems*, Springer, Cham, pp. 119–135, 2021.

[12] L. Hernandez, C. Baladron, J. M. Aguiar et al., "A survey on electric power demand forecasting: future trends in smart grids, m and smart buildings," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 3, pp. 1460–1495, 2014.

[13] H. Hou, C. Liu, Q. Wang et al., "Review of load forecasting based on artificial intelligence methodologies, models, and challenges," *Electric Power Systems Research*, vol. 210, Article ID 108067, 2022.

[14] D. I. Nastac, G. Anescu, and A. P. Ulmeanu, "Large data analysis for advanced grids," *Power Engineering: Advances and Challenges Part B: Electrical Power*, CRC Press, Boca Raton, Florida, 2018.

[15] A. B. Nassif, B. Soudan, M. Azzeh, I. Attilli, and O. AlMulla, "Artificial intelligence and statistical techniques in short-term load forecasting: a review," 2021, https://arxiv.org/abs/2201.00437.

[16] F. Martínez-Álvarez, A. Troncoso, G. Asencio-Cortés, and J. Riquelme, "A survey on data mining techniques applied to electricity-related time series forecasting," *Energies*, vol. 8, no. 11, pp. 13162–13193, 2015.

[17] S. Deng, F. Chen, X. Dong, G. Gao, and X. Wu, "Short-term load forecasting by using improved GEP and abnormal load recognition," *ACM Transactions on Internet Technology*, vol. 21, no. 4, pp. 1–28, 2021.

[18] Y. Zhang and S. Wang, "An innovative forecasting model to predict wind energy," *Environmental Science and Pollution Research*, vol. 42, pp. 1–17, 2022.

[19] J. Liu and Y. Yin, "Power load forecasting considering climate factors based on IPSO-elman method in China," *Energies*, vol. 15, no. 3, p. 1236, 2022.

[20] H. Luo, H. Zhang, and J. Wang, "Ensemble power load forecasting based on competitive-inhibition selection strategy and deep learning," *Sustainable Energy Technologies and Assessments*, vol. 51, Article ID 101940, 2022.

[21] H. H. H. Aly, "A hybrid optimized model of adaptive n-fuzzy inference system, recurrent kfn-wavelet for wind power forecasting driven by DFIG," *Energy*, vol. 239, Article ID 122367, 2022.

[22] M. Zulfiqar, M. Kamran, M. B. Rasheed, T. Alquathami, and A. H. Milyani, "Hyperparameter optimization of support vector machine using adaptive differential evolution and multivariate empirical mode decomposition for load forecasting in smart grid," *SSRN Electronic Journal*, vol. 23, 2022.