Forecasting EV Charging Demand: A Graph Convolutional Neural Network-Based Approach

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***Abstract*—Electric vehicles (EVs) are expected to revolutionize the global transportation sector by promoting sustainability and eco-friendliness. The continuous proliferation of EVs requires an expansion of the existing charging infrastructure to meet the corresponding increase in electricity demand. Such an expansion requires an accurate forecasting of charging demand in both space and time domains for a well-planned allocation of charging stations (CSs). This paper proposes a Graph Convolutional Neural Networks (GCNN) based approach combined with a Long Short-Term Memory (LSTM) to predict the future charging demands of EVs. The proposed architecture fuses the benefits of both GCNN and LSTM to extract the underlying spatio-temporal features from the collected dataset. The training dataset reflects the coupling between the power and transportation systems, and thereby it helps the proposed deep learning architecture to capture the spatio-temporal patterns of the inter-connected environment. A comparative analysis is conducted with other state-of-the-art EV charging load prediction models to assess the prediction performance of the proposed load forecasting strategy.**

***Index Terms*—Electric vehicles, Charging demand, forecasting, deep learning, and graph neural networks.**

I. Introduction

The rapid increase in the world population is accompanied by a significant increase in fossil energy consumption. This raises major socio-economic concerns, such as increase in greenhouse gas emissions, as well as congestion and services shortage in critical infrastructures [1]. The use of electric vehicles (EVs) and the integration of renewable energy sources represent a promising solution to address the concerns related to the extensive use of fossil fuels [2]. Despite the zero-emission characteristic of EVs, a number of challenges still need to be tackled to facilitate their wide penetration in the EV market. One of these challenges is devising an effective planning strategy for satisfying EVs charging requests.

Efficient planning, expansion, and placement of CSs require accurate forecasting of EVs traffic demand. Such a forecasting model should consider the volatility and the stochastic nature of EVs charging load to establish a reliable and accurate allocation of CSs and also to prevent under-utilization and overloading of the CSs. In addition, accurate forecasting of EVs charging demand allows for a better and optimum utilization of the available planning budget and resources.

A. Literature Review

Multiple load forecasting schemes were proposed in earlier literature. In [2], the authors used a Monte Carlo approach to generate experimental scenarios by analyzing occupant travel behavior. The Monte Carlo simulations were also implemented on a large-scale system to predict the EV charging load in [3]. Other works implemented the Auto-Regressive Moving Average (ARIMA) model to predict the individual buses' charging demand [1] and the aggregated charging demand [4]. The work in [5] employed a Markov-chain-based traffic strategy to design a spatio-temporal EV charging demand prediction model, where real-time CCTV data were analyzed to predict the charging power demand in an urban road network. As an improvement to the Markov-chain-based implementation in [5], the authors in [6] proposed a more realistic hidden Markov model to predict the future charging demands. Although the aforementioned approaches predicted the future EV charging loads, in a realistic system setting, they fail to capture the inherent uncertainties (i.e., CSs capacity or driving habits) associated with EV charging demand patterns.

Considering the uncertainties in predicting EV charging load, computational intelligence-based approaches have gained popularity in prediction due to their strong generalization abilities [7]. In [8], the authors implemented artificial neural networks (ANN), rough ANN (RANN), and recurrent RANN (RRANN) to predict future EV charging loads. Results revealed that the RRANN model produced the most accurate forecast compared to the other models. As the RANNs are susceptible to vanishing and exploding gradient problems, another work overcame this limitation by implementing a long short-term memory (LSTM) based approach [9]. Other implementations in this direction have explored diverse adaptations of LSTM that include LSTM with an attention mechanism [10], Gaussian process regression [11], or with convolutional neural network (CNN) [12]. All of these modifications to the LSTM model contribute to the refinement and optimization of the overall model. Unfortunately, all these aforementioned works fail to capture the long-term dependencies of charging data.

The accuracy of the charging load prediction strategy depends on the non-linearity and generalization ability of the deep learning model. In this direction, a CNN-based approach with an attention mechanism was proposed in [13]. The CNN-based approach can extract more complex coupling relationships and minimize the computation time. An autoencoder-based model was proposed in [14] to generate the EVs load profiles. With the evaluation of deep learning-based load prediction models, some studies advance the proposal of hybrid strategy where two or more models are combined together to predict the future charging demand. For instance, the authors in [15] combine a stacked autoencoder with an LSTM-based model. Autoencoder was also combined with Restricted Boltzmann Machines (RBM) with the aim of better feature extraction [16]. However, these works failed to capture the inherent temporal dependencies present in dataset.

The later developments in this domain have harnessed various innovations and progressions such as employing Bayesian deep learning [17] to capture uncertainties in forecasting and probabilistic queuing models with CNN to capture the driver behaviors and charging service limitations [18]. With the significant increase in computing power, deep learning algorithms such as gated recurrent units [19] and recurrent neural networks [20] further enhanced the precision of load forecasting accuracy. However, the aforementioned algorithms often struggle to effectively capture the complex relationships and dependencies present in power systems data.

B. Problem Formulation

In practice, the power system and the transportation network are tightly coupled. Failing to integrate such a coupling in the model results in poor prediction performance. Next we summarize the main limitations of literature.

- First, existing deep neural networks (DNNs) strategies are topology-unaware, and thus, they fail to capture the spatial features.
- Second, existing works show a high degree of redundancy for geographically scattered data, and ignore the power-transportation systems dependencies.
- Third, the literature fails in handling heterogeneous data that comes from multiple sources including the power flow and traffic density.

Thus, graph-based detection techniques represent a more suitable solution that is more powerful and computationally more efficient than standard DNNs. Some works that proposed graph neural networks (GNNs)-based approaches are i) [21], which implemented a spatiotemporal GNN to predict the operating status of a CS, and ii) [22], which used a graph reinforcement learning method for a CSs recommendation system. Therefore, this paper uses a graph convolutional neural network (GCNN)-based approach for predicting future EV charging demand. The GCNN captures the spatial characteristics of the power and the transportation systems simultaneously. Moreover, the LSTM cell is combined with GCNN to capture the long-term temporal dependencies in the load data. By fusing LSTM with GCNN, the model can capture both the spatial and temporal patterns in the charging load data.

C. Major Findings

The major contributions of this research are summarized as follows. First, a GCNN-LSTM fusion model is proposed in this paper, where GCNN captures the graph-structured feature information, and LSTM models the temporal correlations of the charging load data. The trained dataset captures the coupling between the power and transportation systems, leading to an accurate charging demand prediction. Then, we compare our proposed approach with the existing benchmark strategies in terms of different accuracy metrics. Our results have revealed that the fusion of GCNN and LSTM models produces an average error of 4.55 % only over the considered time period. This confirms the model's ability to capture complex patterns in both the transportation and power data.

II. Power-Transportation System Modeling

This section presents the system model of the coupled power and transportation systems. The power-transportation system is modeled as a heterogeneous graph, $\mathcal{G} = (N_{\text{P}}, E_{\text{P}})$, where $N_{\text{P}} = \{1, 2, .., B\}$ with B denoting the total number of buses and E_{P} indicates the set of all nodes and edges in the network. The load or generator substations are considered as power nodes, and each of the power nodes has its own active/reactive power and voltage profile. The power flows in the transmission lines are determined by the associated line impedances.

We use the geographical coordinates of power substations and CSs in a given geographical region to integrate existing CSs within the power system. We define a circular boundary of a particular radius for all load substations and assign all CSs that remain inside the radius to the respective load substations. If a single CS is located inside the boundaries of multiple load substations, we determine the Haversine distances between power substations and CSs and allocate those CSs to load substations based on the shortest Haversine distance.

III. EV Charging Demand Prediction Model

In this section, we outline the procedure of dataset generation, and describe the proposed deep-learning architecture. The efficacy of the proposed model relies heavily on the effective extraction of the multi-dimensional features from the coupled power and transportation systems data. In this regard, a GCNN architecture combined with LSTM is proposed to improve the prediction accuracy of EV charging demand by leveraging the spatio-temporal dependencies present in the coupled dataset.

A. Dataset Generation

Future planning and operation of the EV charging infrastructure require accurate prediction of the EV charging demand. Therefore, generating a dataset over a wide temporal horizon is crucial. Consequently, we generate the temporal features of the constructed graph in the form of time-series data that simulate the power flow within the system. To execute the power flow analysis, we employ Newton's method to determine the active and reactive power flows on MATLAB's MATPOWER platform [23]. The first step involves normalizing the load data obtained from the Electric Reliability Council of Texas (ERCOT) [24] into a scalar vector, F. The active and reactive power values from the previous timestamp are then multiplied by a scaling factor obtained from a normal distribution with a mean of $1 + 0.025 * F$ and a standard deviation of 0.01. This process introduces dynamic variations in the time-series data, contributing to the dynamic range of charging load values.

Specifically, the transportation data contains information on hourly traffic density at each CS, based on which, the hourly demand is estimated. The active and reactive power required by the CSs at a power substation is calculated by aggregating the total power demand of the CSs connected to that specific substation. Such a comprehensive dataset, containing the traffic flow information and the EV charging demand data, enables accurate training of the proposed GCNN-LSTM model.

B. Graph Data Representation and Spectral Graph Filtering

As the coupled power and transportation systems can be represented as a graph, they can be effectively analyzed using GCNN. The GCNN can predict the future charging demand by fusing the temporal features from the power and transportation systems (e.g., power injections, traffic flow rate, etc.) and the topological features (i.e., the spatial distribution of the power substations and CSs and their connectivity).

In the context of EV charging demand forecasting, the power system can be represented as an undirected graph, $\mathcal{G} = (\mathcal{N}, \mathcal{E}, \mathbf{W})$, where each node corresponds to a power substation; $\mathcal{N}$ denotes the set of B nodes; the edge set $\mathcal{E}$ identifies the power lines; and $\mathbf{W} \in \mathbb{R}^{N \times N}$ is the adjacency matrix. The adjacency matrix entry $\mathbf{W}_{i,j}$ between nodes i and j can be determined using the k-nearest neighbor (k-NN) algorithm. Thus, each node is connected to its k nearest neighbors using the Gaussian kernel as a distance function:

$$A_{i,j} = \begin{cases} e^{\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right)}, ||x_i - x_j||^2 \leqslant \omega \\ 0, \quad \text{otherwise}, \end{cases} \tag{1}$$

where x_i and x_j denote the feature vectors of nodes i and j, respectively; σ stands for the width of the Gaussian kernel; and ω represents the distance threshold.

The graph data needs to be represented in the spectral domain to apply the spectral graph filtering technique and GCNN-based feature extraction approach. In this regard, the process begins with obtaining the graph Laplacian matrix which contains the feature information of the graph structure. The unnormalized Laplacian matrix $\mathbf{\Delta}_{\text{u}}$ of graph $\mathcal{G}$ is defined as $\mathbf{\Delta}_{\text{u}} = \mathbf{L} - \mathbf{W}$, where $\mathbf{L} \in \mathbb{R}^{B \times B}$ denotes the diagonal matrix with entries $\mathbf{L}_{i,i} = \sum_j \mathbf{W}_{ij}$. The normalized graph Laplacian matrix is defined as follows:

$$\mathbf{\Delta} = \mathbf{L}^{-1/2} \mathbf{\Delta}_u \mathbf{L}^{-1/2} = \mathbf{I} - \mathbf{L}^{-1/2} \mathbf{W} \mathbf{L}^{-1/2}, \tag{2}$$

where $\mathbf{I}$ indicates the identity matrix. Next, the time-series data is represented in the frequency domain by performing a graph Fourier transform (GFT). This representation decomposes the data into a set of orthogonal basis functions that constitute the eigenvectors of the Laplacian matrix. The GFT takes the signal $f \in \mathbb{R}^n$ as an input, where n indicates the number of features. If ψ collects the orthonormal eigenvectors and $\mathbf{\Lambda}$ identifies the associated set of ordered non-negative eigenvalues $\mu_n \geq ... \geq \mu_2 \geq \mu_1 = 0$, then the singular value decomposition (SVD) of $\mathbf{\Delta}$ is given by $\mathbf{\Delta} = \psi \Lambda \psi^\top$. The inverse GFT of signal f is expressed as $f = \boldsymbol{\psi} \hat{f}$. Let g be the filter response signal, then the spectral convolution is performed over f as [25]:

$$g * f = \boldsymbol{\psi} \left(\left(\boldsymbol{\psi}^\top g \right) \odot \left(\boldsymbol{\psi}^\top f \right) \right) = \boldsymbol{\psi} \operatorname{diag} \left(\hat{g}_1, \ldots, \hat{g}_n \right) \boldsymbol{\psi}^\top f, \tag{3}$$

where $\odot$ denotes the Hadamard product. Thereafter, the signal f is filtered by the spectral filter and is expressed as $\boldsymbol{\psi} \boldsymbol{H} \boldsymbol{\psi} f$. However, this type of filter only extracts features from a certain spatial region which makes the process less effective. Therefore, to tackle this problem, the Kth-order Chebyshev polynomials $C_k(\tilde{\mathbf{\Lambda}})$ was adopted in this study [26]. The Chebyshev polynomials can be recursively generated as follows: $C_0 = 1$, $C_1 = x$, and $C_k(x) = 2xC_{k-1}(x) - C_{k-2}(x)$ and the filtering process is formulated as:

$$\boldsymbol{\psi} \boldsymbol{H}(\mathbf{\Lambda}) \boldsymbol{\psi}^\top \mathrm{f} = \boldsymbol{H}(\mathbf{\Lambda}) \mathrm{f} = \sum_{k=0}^{K} \alpha_k C_k(\tilde{\Delta}) \mathrm{f}, \tag{4}$$

where $\tilde{\mathbf{\Delta}} = 2\mathbf{\Delta}/\mu_n - \mathbf{E}$. Concretely, $\mathbf{p}_k = 2\tilde{\mathbf{\Delta}} \mathbf{p}_{k-1} - \mathbf{p}_{k-2}$ is calculated recursively starting with $p_0 = f$ and $p_1 = \tilde{\mathbf{\Delta}} f$. Considering the sparsity of $\mathbf{\Delta}$, the computational complexity of the filtering operation $\boldsymbol{H}(\mathbf{\Lambda})\mathrm{f}$ is $\mathcal{O}(K|\mathcal{E}|)$. The aforementioned formulation of the spectral convolution on the graph is thereafter used to implement GCNN, which is discussed next.

C. GCNN Architecture

The proposed GCNN architecture for EVs charging load prediction is depicted in Fig. 1. The input X is passed through the graph convolution layers L, then to the fully connected layer, L_f, where a softmax activation function is applied to the input X. Particularly, the jth feature map is obtained as:

$$\mathbf{y}_j = \sum_{i=1}^{H_{in}} \boldsymbol{H}(\mathbf{\Delta}) \mathbf{d}_i, \tag{5}$$

where $\mathbf{d}_i \in \mathbb{R}^n$ signifies the ith feature map; H_{in} and H_{out} denote the number of input and output filters, respectively; and $H_{in} H_{out} K$ denotes the trainable parameters in the current filter. After being transformed into a one-dimensional array, the output of the final layer is passed to the fully-connected layers. Then the lowest K_n value is measured from each row of $\mathbf{D}$ so as to get $\tilde{\mathbf{D}} \in \mathbb{R}^{n \times K_n}$, and thereafter $\sigma_D = \sum_i \tilde{\mathbf{D}}_{iK_n}/n$. Then, $\tilde{\mathbf{W}} \in \mathbb{R}^{n \times K_n}$ is formed as $\tilde{\mathbf{W}} = e^{-\tilde{\mathbf{D}}_{ij}^2/\sigma_D^2}$.

D. LSTM Cells Fusion

The prediction model takes the historical sequence of the GCNN features as input. In particular, the time-series prediction model performs a nonlinear mapping to analyze the history-driven time-series sequence features $X = (X_1, X_2, ..., X_T)$ and their target values $y = (y_1, y_2, ..., y_{T-1})$ to obtain the predicted value $\tilde{y_T}$, where $\tilde{y_T} = f(X, y)$. The objective is to learn the nonlinear mapping function $f(\cdot)$.

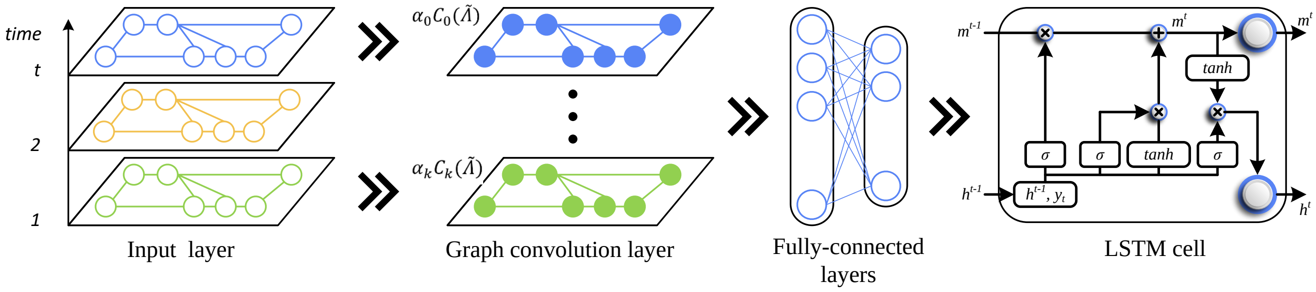

Fig. 1. Architecture of the GCNN-LSTM prediction model.

In this context, we use LSTM cells to capture the long-term dependencies in data. The main component of LSTM is the memory cell that is capable of memorizing information over an extended period of time. Specifically, LSTM assumes a gated architecture consisting of an input gate, a forget gate, and an output gate. The input gate takes the current input and the prior hidden state as inputs and passes them through a sigmoid activation function to produce a vector of values ranging between 0 and 1. As for the output gate, it determines which components of the cell state should be given as output to the next layer based on the current input and hidden states. On the other hand, the forget gate plays a key role in determining which data from the previous time period should be discarded using a sigmoid activation function. Once the output from the GCNN layer is fed into the LSTM, the nonlinear mapping function can be learned by the gated structure of LSTM as:

$$i^t = \sigma\left(W_i \cdot [h_{t-1}, y_t] + b_i\right) \tag{6}$$

$$f^t = \sigma\left(W_f \cdot [h_{t-1}, y_t] + b_f\right) \tag{7}$$

$$o^t = \sigma\left(W_o \cdot [h_{t-1}, y_t] + b_o\right), \tag{8}$$

where $\sigma(\cdot)$ denotes the activation function; m_{t-1} and h_{t-1} indicate the state and output of the LSTM cell at $t-1$, respectively; and b_i, b_f, b_o stand for the biases for the input gate, the forget gate, and the output gate, respectively. The cell's current memory states, $\tilde{m}^t$ can be calculated as $\tilde{m}^t = \sigma\left(W_c \cdot [h_{t-1}, y_t] + b_c\right)$. Moreover, the cell state m^t and cell output h^t are: $f^t \odot m_{t-1} + i^t \odot \tilde{m}^t$, and $h^t = o^t \odot \tanh\left(m^t\right)$.

E. Loss Function

The loss function of the GCNN-LSTM model is defined as:

$$L_{\text{GCNN-LSTM}} = \text{CE}\,(p, l) + \alpha \|\Omega\|_2, \tag{9}$$

where p is the predicted value of the model; l denotes the label; Ω represents all of the model's parameters; α is the regularization coefficient; and $\text{CE}\,(p, l)$ is the cross-entropy function that determines the difference between the actual and predicted label. The last term, $\alpha\|\Omega\|_2$, reduces the overfitting of the model's learning parameters. Next, we define the update rule of the graph convolution parameters in each iteration as:

$$\beta^* = \beta^* + \gamma \frac{\partial L_{\text{GCNN-LSTM}}}{\partial \beta^*}, \tag{10}$$

where γ denotes the learning rate and $\beta^* \in \mathbb{R}^{K \times T}$ is the Chebyshev polynomial coefficient of GCNN.

IV. Experimental Results

In this section, the results of the EV charging demand prediction are evaluated. First, the efficacy of the prediction model is assessed in terms of different performance metrics. Second, the performance of the proposed model is compared with the state-of-the-art deep learning models.

A. Model Evaluation

In this paper, we present and evaluate three different prediction schemes based on the type of data used: 1) prediction using power system data only, 2) transportation data only, and 3) combined power and transportation data.

- *Power system data:* The original load data obtained from ERCOT [24], contains a year-long load data. Monte Carlo simulations are employed to extend the existing power data to a five-year period.
- *Transportation system data:* The transportation data is obtained from [27], which contains the traffic flow information of 720 CSs located at Texas from the year 2016 to 2020. In the transportation data, a significant growth in the traffic volume is observed. Analyzing this growth is important for making accurate charging load predictions.
- *Combined power-transportation system data:* To achieve a comprehensive view on the power and transportation network, the growth in the traffic volume over the years is scaled to the power data. Such scaling provides a meaningful integration of both systems, providing a holistic view of the coupled system.

Given a dataset over five years, the proposed GCNN-LSTM model is trained on the first three-year data and tested on the last two-year data using the three approaches mentioned above. The model performance is evaluated in terms of normalized root mean square error (NRMSE), and normalized mean absolute error (NMAE). The performance metrics are formulated as:

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_a(i) - x_b(i)\right)^2}}{\max\left(x_b\right) - \min\left(x_b\right)} \times 100 \tag{11}$$

$$\text{NMAE} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left|x_a(i) - x_b(i)\right|}{\max\left(x_b\right) - \min\left(x_b\right)} \times 100\%, \tag{12}$$

where n stands for the number of samples; $x_b(i)$ indicates the i^{th} predicted data; and $x_a(i)$ denotes the i^{th} ground truth data. The maximum and minimum values of ground truth data are represented by $\max(x_b)$ and $\min(x_b)$, respectively. The prediction model is implemented using 150 iterations. Our investigations reveal that the model achieved on average a 4.29% NMAE and a 5.82% NRMSE, which fall in the range of expectation and indicate a good prediction performance.

The prediction results for the three different schemes over the two-year period are depicted in Fig. 3. The figure shows that the model performs better for the combined power and transportation data. This is explained by the fact that by integrating the information from both the power and transportation systems, the model can capture the dependencies between power utilization and traffic patterns. Thus, the coupled system has the potential to provide more accurate and reliable decisions than the other two schemes. In case of using the power data only, the model relies on the historical power consumption only and overlooks the influence of the transportation-related features such as the traffic flow density. On the other hand, using the transportation data only, the model fails to capture the direct relationships between the power system and the EV charging system, which leads to a less accurate prediction. Overall, fusing the data from both the power and transportation systems enables capturing more complex relationships, which in turn helps to achieve robust prediction performance.

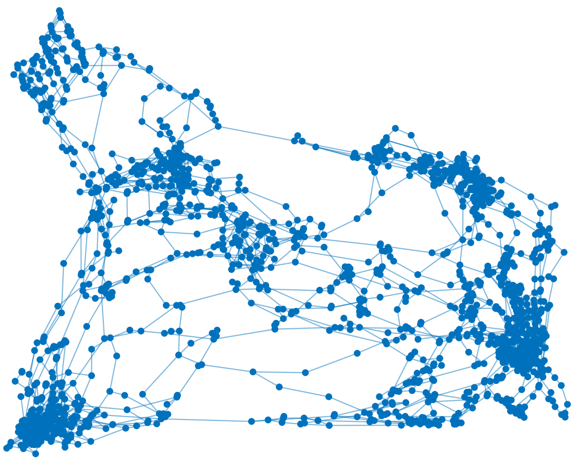

Fig. 2. The graph structure of the synthetic 2000-bus power system of the State of Texas.

V. Performance Comparison

A. Benchmark Detectors

This section compares the EV charging load prediction performance of the proposed GCNN-LSTM model with benchmark models. In Table I, the prediction performances of different benchmark strategies are presented for three different time periods in terms of NMAE and NRMSE. The prediction model assessed in the table includes CNN, FNN, SVM, and ARIMA models. The adopted benchmark models represent diverse attributes, encompassing structure (shallow/deep/graph) and training methodology (unsupervised/supervised).

B. Hyperparameter Optimization

For hyparameter optimization, we use a grid-search hyperparameter selection strategy, where each hyperparameter

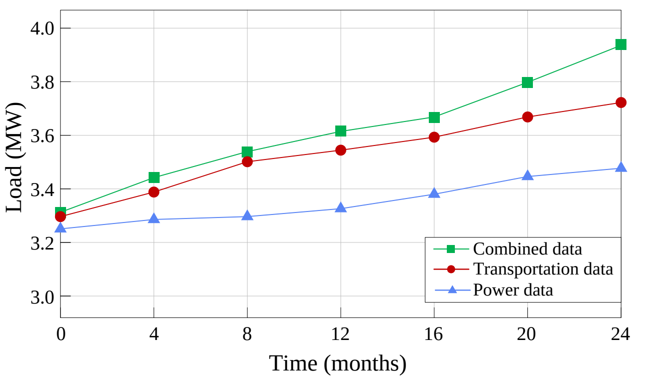

Fig. 3. Predictions of EV charging load over a 2-year period.

is chosen within a specific stage [24]. For instance, in the case of ARIMA, the parameters for differencing and moving averages are fixed at 1 and 0, respectively. On the other hand, SVM utilizes the scale and sigmoid kernels for the kernel and gamma parameters. CNN's design incorporates four layers with 32 units, a neighborhood order of 5, Rmsprop optimizer, and a ReLU activation function. Notably, for the proposed model there were 4 layers in each stage with 32 units, 3 neighborhood orders, Adam optimizer, and ReLU activation.

C. Comparison Results

The Table I illustrates that the GCNN-LSTM model exhibits the best forecasting performance over all the considered time periods. Moreover, Table I shows that for all the models, the errors increase with an increase in the time horizon. The ARIMA model shows the lowest accuracy as it lacks adaptability with the change in data patterns or trends. The support vector machine (SVM) and the feed-forward neural network (FNN) models perform better than the ARIMA model; however, their performances are not in line with the expectations as they still show more than 20% error. The CNN model outperforms the ARIMA, SVM, and FNN models but still underachieves the proposed model. That is because CNN-based model primarily focuses on extracting local features and may not be as effective in capturing temporal dependencies in the data. The proposed model reduces the errors by 15-20% over the compared models. The aforementioned comparison highlights the superiority of the proposed model in capturing the complex patterns and dependencies in the coupled data, resulting in more precise and accurate prediction performance.

VI. Conclusions

In this paper, we have presented a combined GCNN-LSTM-based model for forecasting future EV charging demand. The performance of the proposed model was tested using three different datasets: one using power system data only, one using transportation system data only, and one combining data from both systems. Our investigations have revealed that the proposed model exhibits less than 6% error for all considered time periods. Moreover, we have compared the proposed model with benchmarks, and we showed that the proposed model provides 8% performance improvement over the CNN and 15% improvement over the ARIMA, SVM, and FNN models. Forecasting EV charging demand accurately enables better budget allocation, charging infrastructure development, and power grid management. This, in turn, improves the user satisfaction rate as well as optimizes the allocation of available resources. Thus, our approach can be effectively used as a powerful tool for the strategic planning of EVs charging infrastructure. As directions for the future, we will focus on refining the model to explore the impact of other aspects, such as socio-economic factors, on the charging demand.

TABLE I. Performance comparison between GCNN-LSTM and other models.

Forecasting model	Time stage	NMAE [%]	NRMSE [%]
ARIMA	4	29.12	33.41
	12	31.86	34.79
	24	34.56	36.01
SVM	4	19.53	20.33
	12	20.19	21.43
	24	21.08	22.97
FNN	4	18.65	20.65
	12	19.21	20.99
	24	19.93	21.56
CNN	4	12.33	11.00
	12	12.94	11.61
	24	13.84	13.74
GCNN-LSTM	**4**	**4.41**	**6.27**
	12	**4.50**	**6.31**
	24	**4.69**	**6.97**

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