Prediction of Electric Vehicles Charging Load Using Long Short-Term Memory Model

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ABSTRACT

The number of Electric Vehicles (EV) has increased significantly in the past decades due to its advantages including emission reduction and improved energy efficiency. However, the adoption of EV could lead to overloading the grid and degrading the power quality of the distribution system. It also demands an increase in the number of EV charging stations. To meet the charging needs of 15 million EVs by the year 2030 with limited charging stations, prediction of charging needs and reallocating charging resources are in emerging needs. In this study, long short-term memory (LSTM) and autoregressive and moving average models (ARMA) models were applied to predict charging loads with temporal profiles from 3 charging stations. Prediction accuracy was applied to evaluate the performance of the models. The LSTM models demonstrated a significant performance improvement compared to ARMA models. The results from this study lay a foundation to efficiently manage charge resources.

INTRODUCTION

The adoption of electric vehicles is growing very fast due to their many advantages such as emission reduction and increased energy efficiency (Xiong, Wang, Chu, & Gadh, 2018).

However, this increased adoption has negative impacts and risks on the resiliency of the power grid by overloading it and inflating the demand peaks (Mu, Wu, Jenkins, Jia, & Wang, 2014). These new system load peaks may degrade the power quality of the distribution system and cause voltage drops (Foley, Tyther, Calnan, & Ó Gallachóir, 2013).

In the year 2020, level 3 (DC fast charging), level 2 (240V with 16-40A), and level 1 (120V) EV supply equipment are 49.6%, 12%, and 38.2%, respectively, of all charging points. More charging stations are expected to meet the need of serving 15million EVs by the year 2030 in the United States. Therefore, there is a growing demand for developing effective management strategies for the large-scale integration of EVs. Different algorithms have been developed to address the following questions: 1) improving energy-efficient EV routing with or without recharging (Artmeier, Haselmayr, Leucker, & Sachenbacher, 2010)-(Storandt, 2012), 2) calculating reachable locations from a certain starting point given an initial battery level (Storandt & Funke, 2012), 3) enhancing the use of supercapacitors with machine learning and data mining techniques to maximize the range of EVs (Ermon, Xue, Gomes, & Selman, 2013), and 4) routing EVs to charging station where the least congestion exists, considering drivers' final destination and amount of electricity to charge (Weerdt, Gerding, Stein, Robu, & Jennings, 2013)-(Qin & Zhang, 2011). Besides, many methods have been developed to schedule and control the charging of EVs. This allows peaks and possible overloads of the electricity network to be avoided while minimizing electricity cost (Ma, Callaway, & Hiskens, 2013; Sundström & Binding, 2010; Vandael, Boucké, Holvoet, Craemer, & Deconinck, 2011).

However very limited research effort has been dedicated to predicting energy consumptions of EV charging stations partially due to the complexity of the problem including the location of charging stations, the number of EVs in the vicinity, cost, travel planning, and period for a full charging. Most of all, one challenge is the availability of EV charging data. We have collected hourly energy consumption for 3 EV charging stations on the campus of the University of Texas at San Antonio for 2 years. The data is a typical time series representing the energy consumption for each EV charging station with respect to time. Time series analysis algorithms have been widely studied with statistical approaches such as auto-correlation, random walk, moving average, autoregressive process, and integrated autoregressive and moving average (ARIMA) (Ho & Xie, 1998). However, the order of such models and embedded noises will give inaccurate predictions. Meanwhile, deep learning methods have shown extraordinary performance on prediction systems with nonlinear properties in nature (Hochreiter & Schmidhuber, 1997; Schmidhuber, 2015). Specifically, the LSTM approach as an excellent method for temporal predictions has been applied in this study to analyze the collected EV charging data to predict short-term energy consumptions.

METHODS

Preliminary data process.

The dataset used in this study was acquired from 3 charging stations on the campus of the University of Texas at San Antonio. The raw datasets were collected by the city energy utility provider with observations ranging from 02/06/2012 to 05/14/2019, accounting for a total of 8095 hourly observations. To focus on normal workday charging patterns, all data on holidays, spring, summer, and winter breaks were filtered due to the distinct patterns. To illustrate the latest charging loads, the time-series data from 01/08/2018 to 05/14/2019 was used and plotted in Figure 1. The pre-processed data consisted of 750 hourly observations.

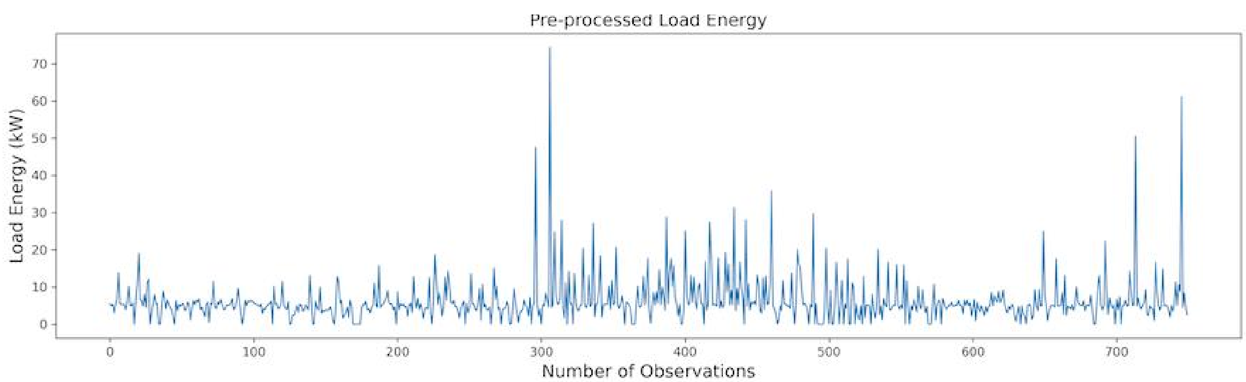

Figure 1. Illustration of hourly energy consumption of 3 charging stations with respect to time. The time point was represented by the number of observations in a given period.

The data is normalized as $x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$ by using the minimum and maximum scaler to accelerate the network convergence and decrease training time. The variable, x_{norm} represents the normalized value, x represents an original value, x_{min} and x_{max} represents the minimum and maximum value in the dataset, correspondingly.

Description of LSTM model.

The long short-term memory model is an extension of Recurrent Neural Networks (RNN) models without the vanishing gradient problem. The LSTM model will determine the importance of input data and is more robust for long-term dependency problems compared with the RNN models. LSTM models include input, hidden, and output layers (Hochreiter & Schmidhuber, 1997). There may exist multiple cells in the hidden layer of the LSTM model and each cell is typically made up of 3 gates, namely the forget gate, input gate, and output gate. These gates will determine the output of a cell based on the input, activation function, and memory of a cell. Weights in the network will be adjusted by optimizing/reducing the loss function and iterations will be repeated until the desired performance is achieved.

Training of LSTM model.

The pre-processed 750 hourly observations served as input data to establish the LSTM models following the rule of 80% data for training and 20% for testing. Different time steps, 1, 5, and 15, were used to determine how long the memory will be used to predict the output of the model. A total of 150 hours of energy consumption are predicted as the output of the models. A flow chart of the LSTM model design is shown in Figure 2.

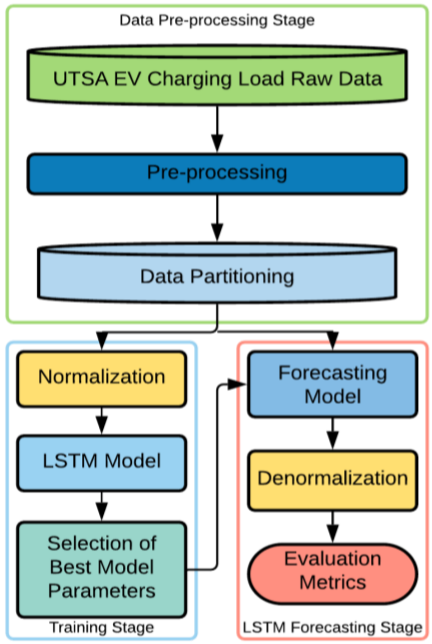

Figure 2. LSTM model framework

Model evaluation

Evaluation metrics such as Mean Average Error (MAE) $= \frac{1}{N}\sum_{i=1}^{n} \quad (y_i - \hat{y}_i)$, Root Mean Square Error (RMSE) = $\sqrt{\frac{1}{N}\sum_{i=1}^{n} \quad (\hat{y}_i - y_i)^2}$, and Goodness of Fit (R-squared) $R^2 = 1 - \frac{\sum_{i=1}^{n} \quad (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} \quad (\hat{y}_i - y_i)^2}$, were applied to compare LSTM models and a traditional ARIMA model, where n represents the total number of data points, y_i represents the actual values and $\hat{y}$ represents the predicted values. The MAE and RMSE have the same evaluation principle: the smaller they are, the better the model. On the other hand, the R-squared metric ranges from 0 to 1. The closer it is to 1, the better the model.

RESULTS

The parameters for each timestep (1, 5, 15) LSTM model are tuned by the grid search method. All LSTM models showed convergence of the loss function. Each LSTM model has 70 runs with different initial conditions. Setups of LSTM models and averaged performances of the 70 runs for 1-step, 5-step, and 15-step LSTM models are presented for comparison as shown in Table 1.

MAE, RMSE, and R^2 of 1-step, 5-step, and 15-step LSTM models were shown in Table 2. It can be seen that the EV charging pattern demonstrated dependence on a relatively short period since 1-step and 5-step LSTM models have R^2 close to 1. The 1-step LSTM model has smaller MAE and RMSE compared against 5-step and 15-step LSTM models. Specifically, the 15 timestep LSTM model demonstrated a significant drop in the performance, suggesting prediction on energy consumption can be generated with a short memory. Besides, 15-step LSTM models converge in more epochs while 1-step LSTM converges very fast.

The worst performance comes from the ARIMA model with R^2=0.18, suggesting a significant performance improvement of LSTM models as shown in (Figure 3 and Figure 4).

Table 1. Model setup and averaged R^2 performance of LSTM models

Timestep	Optimizer	Input Neurons	Epochs	Batch Size	STD	Mean(R^2)
1	Adam	1000	20	20	0.0011	0.9991
5	Adam	800	29	30	0.0089	0.9844
15	Adam	1000	100	10	0.1630	0.7164

Table 2. Evaluation results on LSTM models with single and multiple steps

Timestep	Metrics	LSTM
1	MAE	0.0231
	RMSE	0.0409
	R^2	0.9999
5	MAE	0.1583
	RMSE	0.6037
	R^2	0.9922
15	MAE	0.6715
	RMSE	1.3644
	R^2	0.9602

Statistical Model – ARIMA.

In the ARIMA model, the autoregressive term (p term), differencing (d term), and MA (moving average or q term) have been adjusted to find the best results. The best model (best R^2) achieved has the parameters setup as p=0, d=1, and q=1. Temporal prediction of the ARIMA model against actual data was shown in Figure 3.

The loss functions for all LSTM models converge within 40 epochs. The predicted energy consumptions were plotted against the real data as shown in Figure 4. Predictions of LSTM models follow the actual data very well.

Potential Applications of LSTM model.

With the developed LSTM model in this study, two types of applications can be expected. Users can apply this model structure to train their EV charging data following the same format used in this LSTM model. The input to the LSTM model is a vector representing temporal energy consumption of a charging station with given sampling frequency. It's worth mentioning, the dimension of the vector and sampling frequency is upon user's convenience to collect data. In addition, the LSTM and ARIMA models can be components of more advanced deep learning models such as reinforcement learning models, where parameters from the LSTM or ARIMA models will be further processed and combined with parameters from other models for better performance. The data and codes for this LSTM model are available upon request.

CONCLUSION

In this study, three modeling methods, multi-step LSTM, one-step LSTM, and ARIMA were applied to predict charging loads with temporal profiles for 3 charging stations in two years on the campus of the University of Texas at San Antonio. Prediction accuracy, loss function, MAE, RSME, and R^2 were applied to evaluate the performance of the models. The LSTM models demonstrated a significant improvement in prediction compared to the traditional ARIMA models. The results from this study lay a foundation to efficiently manage charge resources.

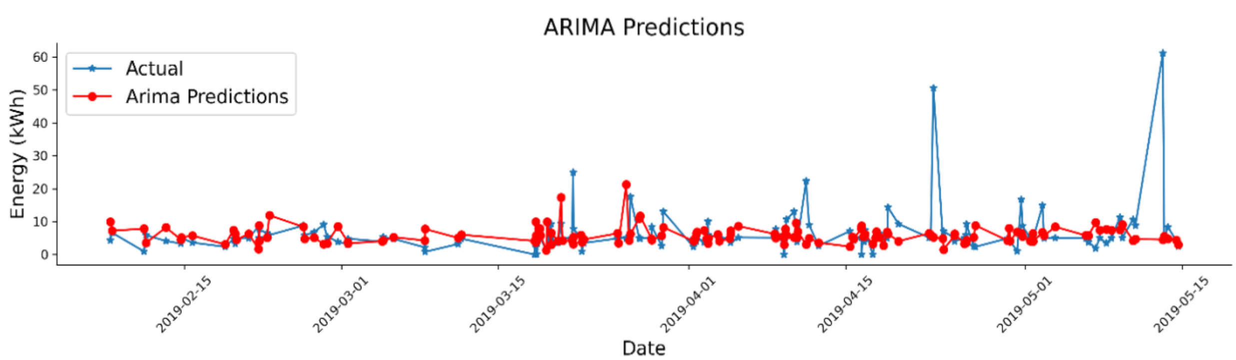

Figure 3. ARIMA model predictions

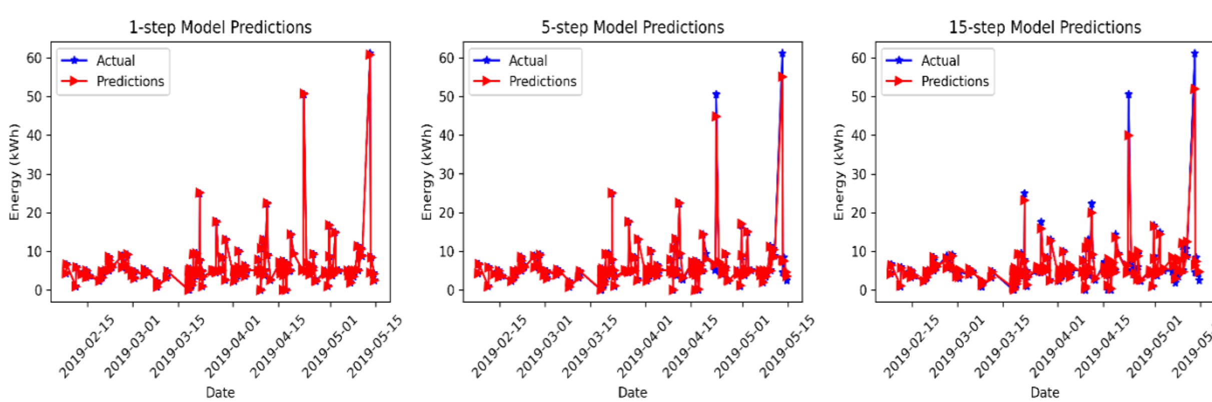

Figure 4. Predictions for energy consumption from 1-step, 5-step, and 15-step LSTM models

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