Deep Learning Tackles Temporal Predictions on Charging Loads of Electric Vehicles

***Abstract*—** As a prediction of 145 million electric vehicles on the road by 2030, accommodation of charging needs of the electric vehicles will impose extra challenges to power grid strength. It is imperative to predict charging loads for future infrastructure improvement including installations of new charging stations to meet the charging needs and reduce the power grid overload. In this study, deep learning approaches including artificial neural networks, recursive neural networks, and Long-Short Time Memory models are used to predict the charging load with daily and weekly patterns using a public dataset. The performance of the deep learning models was compared against the auto-regressive moving average model with respect to convergence speed, MSE, MAE, and R2. The long-short time memory model outperformed all other models concerning the evaluation metrics.

Keywords— Charging Load, Electric Vehicles, Deep Learning

I. INTRODUCTION

Adopting Electric vehicles (EVs) has been considered as one of the most promising remedies to reduce greenhouse gas emissions in many countries. However, with the increase in the number of EVs connected to the distribution network, the load level of the power system increases which results in negative impacts on the stability and resiliency of the power grid. [1]. These new system load peaks may degrade the power quality of the distribution system causing harmonic distortions and degradation of the voltage profile [2]. Past literature presented the impact of EV charging loads on different parameters of the distribution network [3, 4]. As a prediction of 145 million EVs on the road by the year 2030, accommodation of charging needs of these EVs will impose extra challenges to the power grid strength and may cause the grid to collapse due to the lack of EV's load charging management in the worst scenario. The EV charging loads are also affected by the behavior of the EV users, the impact of utility charging price variations, and the location of the charging stations. Therefore, it is important to have a reliable prediction of the charging loads.

Deep learning (DL) and machine learning models have been vastly used to study complicated systems including predicting residential load for power systems and EV charging behaviors [5-7]. Further, comparative studies have shown that DL models such as artificial neural network (ANN) outperformed statistical models to predict the energy load [8, 9]. Currently, very few efforts have contributed to predicting real-time EV charging loads due to the limited data on temporal EV charging profiles despite there is an emerging need for predicting charging loads to reduce the impact of EV charging on power load at peak time. This is the first comprehensive investigation of DL approaches to predict the temporal profiles of real-time EV's charging loads with multiple public datasets collected from different working places. [10].

II. METHODS

The DL models were established in this study with three steps: data pre-processing, model training, and model validation as shown in fig 1.

Data Pre-Processing: All raw data downloaded as JSON files was processed to collect information including charging station ID, connecting and disconnecting time of a charging session, charging current, energy delivered, date of charging session, and space ID. Observations of the data were selected from 09/05/2018 to 03/25/2020. The data were further separated into weekday and weekend patterns. The charging power/current was normalized with respect to the maximum changes as shown in equation (1) to decrease training time and accelerate convergence:

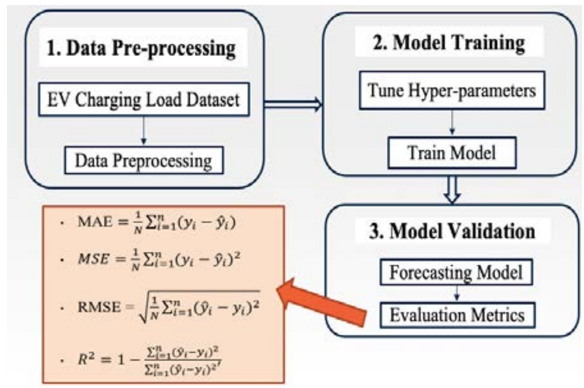

Figure 1. The framework of this study includes 3 components: data pre-processing, model training, and model validation. Evaluation metrics for model evaluation are also illustrated in the orange box.

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

After normalization, the data was partitioned as 80% of data for training, 10% for testing to fine-tune model parameters, and 10% for model validation.

Modeling Training: Artificial Neural Network (ANN), Recursive Neural Network (RNN), and Long-Short Memory Models (LSTM) models were established using Python.

1. ANN model: We first use the Keras package to process part of the training data and choose the best structure of the ANN model, which includes 1 input layer, 2 hidden layers, and 1 output layer. To reduce the computational cost, only 2 hyper-parameters have been automatically tuned during the training process: batch size and the number of units. The training has led to an ANN model with a batch size of 80, the number of units as 120 for all layers. The model prediction

converges within 50 epochs with Adam optimizer and sigmoid activation functions. The established ANN model was run for 50 iterations.

2. RNN model: RNN model has a feedback loop that cycles the information by considering both the current and the previous inputs to produce an output. While an ANN model is the most basic deep learning model, an RNN model is normally adopted for temporal data processes. 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.
3. LSTM model: RNN models may have gradient-vanish problems leading to very slow convergence of a model. To overcome the gradient-vanish problem, LSTM models were established as an extension RNN models. 1-step, 5-step, and 10-step RNN and LSTM models were established in this study to predict the EV charging power. Model parameters of RNN and LSTM were shown in Table 1.

Table 1: Model parameters in RNN and LSTM models for both JP and Caltech datasets

Hyper-parameter	JPL LSTM & RNN	Caltech LSTM & RNN
Activation Function	Sigmoid	Sigmoid
Hidden Units Size	120	160
Loss	MAE	MAE
Batch size	60	80
Dropout Rate	0.2	0.2
Optimizer	ADAM	ADAM

Model Validation: 3 evaluation metrics were used: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Goodness of Fit (R^2). The MSE and MAE have the same evaluation principle: the smaller the better. On the other hand, R^2 values range from 0 to 1 and the closer it is to 1 the better. Besides the AI approaches, auto-regressive moving average (ARMA) models, as a traditional modeling approach, were also established. Results obtained from ARMA models were used as a standard to evaluate the performance of AI models.

III. RESULT

The results from this study have been evaluated based on the loss function and evaluation metrics described in the previous section. The Predicted EV charging load is compared to the actual ones. The loss functions of ANN, 1-step RNN and 1-step LSTM model for JPL data were shown in fig 2. The 5- step, 10-step RNN and LSTM models for the JPL dataset, and all the models for the Caltech dataset converged within 50 epochs. Interestingly, the ANN model, 1-step RNN, 1-step LSTM model outperformed the 5-, and 10-step models in both JPL and Caltech datasets. In addition, the 5-, and 10-step LSTM models converged much faster than the corresponding RNN models with the same steps.

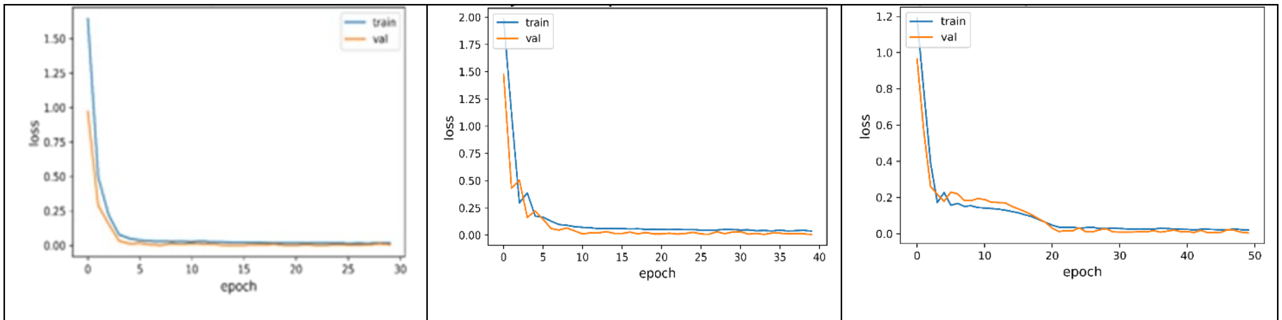

Figure 2. Loss functions of training and validation for ANN (left), 1-step RNN (middle), and 1-step LSTM (right) models using the JPL datasets were shown to illustrate the convergence of the models.

Temporal prediction accuracy of RNN, and LSTM models were shown in Table 2. The 1-step LSTM model also performed better than the 5-step, 10-step LSTM, and RNN models. For the ANN model, MSE=6.25, MAE=39.29, and R^2=0.998. The performance of ANN, 1-step RNN, and 1-step LSTM are all in comparable levels while much better than LSTM and RNN models with multiple steps. The predicted temporal profiles of EV charging power and the real data collected with LSTM models were shown in fig 3. The ANN, 1-step RNN and 1-step LSTM models were further compared to the ARMA model and performed much better than the ARMA model, validating the AI approach is a better choice for the EV charging prediction. The complete results will be shown in the full paper.

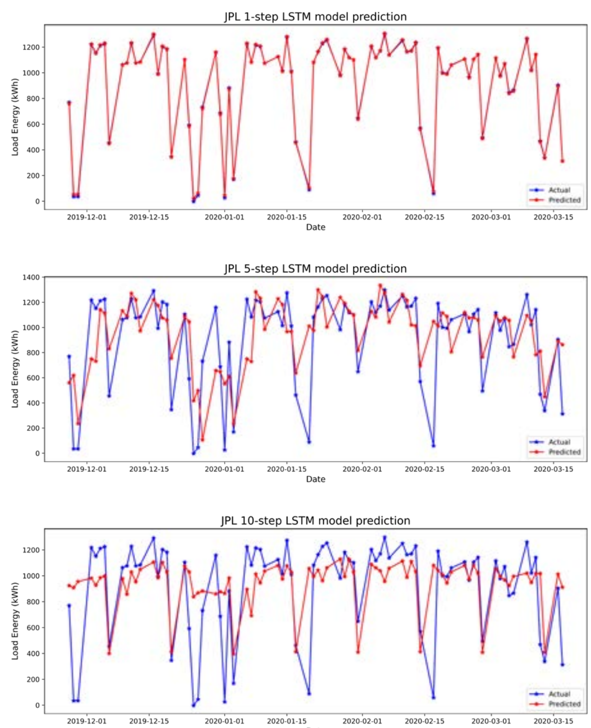

Figure 3. Temporal prediction of EV charging load using JPL data with LSTM models.

IV. CONCLUSIONS AND FUTURE WORKS

Table 2. Performance comparisons of LSTM and RNN models using the evaluation metrics.

Timestep	Metrics	LSTM	RNN
1	MAE	5.8960	8.7630
	RMSE	7.7531	10.4141
	MSE	60.1105	108.4546
	R^2	0.9996	0.9992
5	MAE	198.2920	73.0294
	RMSE	282.3981	110.8772
	MSE	79748.7168	12293.7694
	R^2	0.4323	0.9124
10	MAE	212.5277	133.7053
	RMSE	321.5901	193.1190
	MSE	103420.1930	37294.9799
	R^2	0.2638	0.7345

In this digest only ANN, RNN, and LSTM models were presented. The full paper will include details on the performance evaluation with ARMA models and other deep learning models. The results presented were only from JPL datasets. A general model using both JPL, Caltech and a third party datasets will be included in the full paper. The predicted EV charging profiles will be used as predicted power requests to assist the scheduling of EVSEs to reduce waiting time of charging and smooth duck curve for a more stable power grid.

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