2021-01-1252 Published 21 Sep 2021

A Comparative Study of Recurrent Neural Network Architectures for Battery Voltage Prediction

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Citation: Cho, G., ZHU, D., and Campbell, J., "A Comparative Study of Recurrent Neural Network Architectures for Battery Voltage Prediction," SAE Technical Paper 2021-01-1252, 2021, doi:10.4271/2021-01-1252.

Abstract

Electrification is the well-accepted solution to address carbon emissions and modernize vehicle controls. Batteries play a critical in the journey of electrification and modernization with battery voltage prediction as the foundation for safe and efficient operation. Due to its strong dependency on prior information, battery voltage was estimated with recurrent neural network methods in the recent literatures exploring a variety of deep learning techniques to estimate battery behaviors. In these studies, standard recurrent neural networks, gated recurrent units, and long-short term memory are popular neural network architectures under review. However, in most cases, each neural network architecture is individually assessed and therefore the knowledge about comparative study among three neural network architecture is limited. In addition, many literatures only studied either the dynamic voltage response or the voltage relaxation. This paper presents a comparative study on the battery voltage predication using all three neural network architectures. In this study, all neural network architectures use common pulse data for training and validation. The selected pulse data covers the voltage response in not only dynamic events but also during relaxation. Then the predictions are made in severe battery operation conditions such as high current, low temperature, and long duration. The results indicate the LSTM has the best prediction accuracy across various temperatures and current pulse sizes. All three neural network structures show the robustness at -30°C. But the standard RNN and GRU show the prediction error increases when the pulse size is higher.

Introduction

Electrification of transportation is a primary way to limit carbon emission and to modernize vehicle controls due to less computational intensity in autonomous vehicle applications [1]. Batteries are regarded as an essential device for successful implementation of electrification in both transportation and stationary applications [2, 3] because electrical energy storage is a major bottleneck in electrification. However, recent technical advancements in Lithium ion batteries improve the energy density and safety of the battery [4]. These advancements help accelerate the applications for electrification but there remain key areas that must advance in parallel with lithium ion batteries to ensure safe and efficient operation.

Cost, safety and performance such as power and energy are three major aspects considered in lithium ion battery design. Battery voltage is a response from a battery that is usually controlled to enhance all three aspects in battery design. For instance, a lithium battery has a voltage range (e.g. 2.5 ~ 4.1V) for safe operation. Any departures from this voltage range induces hazardous events such as swelling, venting and thermal runway. In order to maintain safety during the operation, battery power and energy are limited by this voltage range. For instance, the maximum power of the lithium ion battery is designed in a manner to avoid the violation of the safe voltage range. In addition to this function, battery voltage is also utilized to estimate battery characterization parameters such as state of charge (SOC). System-level rule-based control strategies [5] and optimization-based strategies [6] rely on the accurate voltage prediction as well. Therefore, an accurate voltage prediction improves battery safety and battery performance by eliminating errors when estimating performance parameters during battery control. Furthermore, an accurate voltage prediction also reduces the cost of the battery since it can reduce the design margin while maintaining a high level of the battery safety and increasing the overall life of the battery.

Model-based design is the state-of-art for battery voltage prediction [7]. More specifically, equivalent circuit model (ECM) and electrochemical battery models are popular methods to simulate battery voltage response. ECM builds an electrical circuit to replicate the lithium ion battery behavior by using electrical circuit elements such as resistance, inductance, and capacitance. Electrochemical models consist of eight differential equations governing the microscopic phenomena inside the lithium ion battery. In general, ECM is less accurate than the electrochemical battery model, but ECM involves less computation. To improve the accuracy of ECM, often modern control methods such a Kalman filter is combined with ECM for online voltage or battery characterization such as SOC. In the case of the electrochemical battery model, it is applied to perform offline battery simulation.

In addition to the model-based battery voltage prediction, there are some recent studies implementing more advanced techniques such as neural networks to predict the battery voltage response. A group of researchers built a real-time recurrent neural network (RNN) to predict battery voltage [8]. Their claimed their approach provides a powerful tool to consider battery dynamics. They concluded that their RNN-based prediction is better than the model-based one by having one order of magnitude lower mean square error. Another group of researchers also developed an RNN to predict battery voltage [9]. Unlike the previous group, they included temperature as one of their six inputs. In addition, they used SOC from the past three-time steps while the researchers in [8] only used the past time step. Instead of directly predicting the battery voltage, they employed recursive least square algorithm with the RNN to predict the battery voltage. However, the error in [9] is at the same magnitude as the error in [8]. Besides the standard RNN, researchers in [10] investigated a pipelined recurrent neural network (PRNN) that essentially stacks three RNNs together.

It is apparent that the standard RNNs are very powerful for predicting battery voltage. However, they suffer from the vanishing gradient problem. One solution is to implement gates to the standard RNNs so they can decide what information gets passed along. There are two special RNNs with the gating mechanism: gated recurrent unit (GRU) and long-short term memory (LSTM). Zhao et al. [11] proposed a GRU to predict the battery voltage with less than 10% error. More recently, Hong et al. [12] developed a LSTM to estimate the battery voltage. Their LSTM takes voltage, SOC, brake pedal stroke value and vehicle speed as inputs. Similarly, Li et al. [13] also proposed a LSTM in combination with an ECM to predict the battery voltage which used cell voltage, pack voltage and pack SOC as inputs. It is obvious that the research focus has moved from standard RNNs to GRUs and LSTMs. However, it is still unclear if any of the three outperforms the rest under the same training conditions. If so, the difference needs to be answered with supporting evidence. Therefore, a comparative study is necessary.

This paper assesses the three different RNNs for the prediction of battery voltage from time series input data such as current, SOC and temperature. Also, this paper presents the comparison among three RNN architectures during cold, high c-rate and long duration profile. Furthermore, this paper investigates the battery voltage response with and without load. This study not only identifies the optimum RNN architecture in battery voltage prediction but also provides an explanation.

The remainder of this paper is organized as follows. The Method section discusses all three RNN architectures and the training process. The test conditions (temperature, average c-rate and profile duration) are also discussed in the Method section. The Result section presents the comparison of results from the three RNN architectures. We further analyze the results in the Discussion section. Finally, we conclude this paper with the optimum RNN architecture for the voltage prediction.

Methods

This section introduces three RNN architectures: generic RNN, LSTM, and GRU. Following the introduction of the architectures, the error measures are reviewed. After that, how the data was collected and prepared is discussed in detail. At last, the training process is presented.

Generic Recurrent Neural Network

RNN is a type of artificial neural network that is similar to the feed forward neural network except for the connection between the input and output. Figure 1 shows a single cell RNN and the unrolled through time representation of the single cell RNN. In the figure, the output of the previous time-step feeds to the input of the current time step [14].

The output of RNN structure is given below:

$$Y(t) = \sigma\left(W_{XH} X_t + W_{HH} H_{t-1} + b_{XH}\right) \tag{1}$$

where $Y(t)$ denotes the output at time t, σ is the activation function, W_{XH} is the weight between the input layer and the hidden layer, X_t represents the input at time t, W_{HH} is the weight for the hidden layer, H_{t-1} is the hidden layer at time $t-1$, and b_{XH} is the bias.

Among various types of RNNs, this paper develops a "sequence to vector" network. A sequence of voltage, battery

FIGURE 1 A single cell RNN.

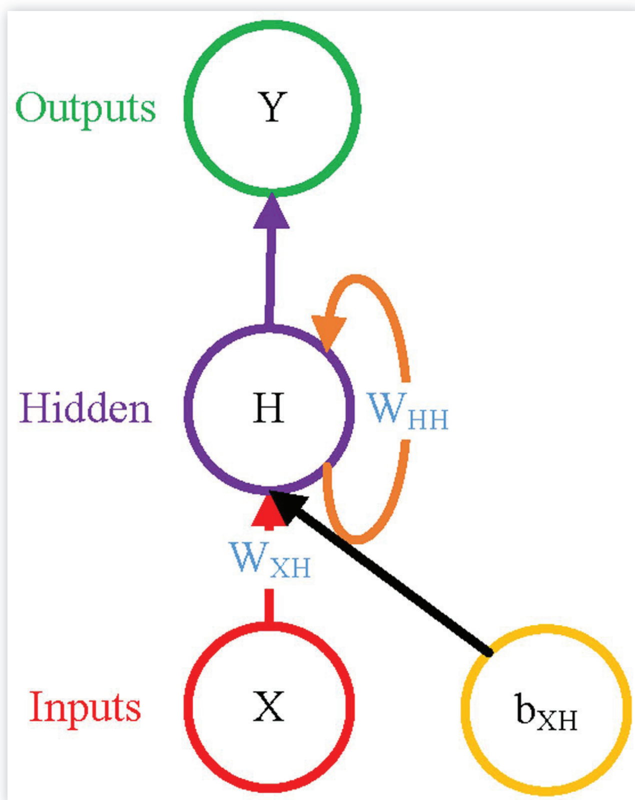
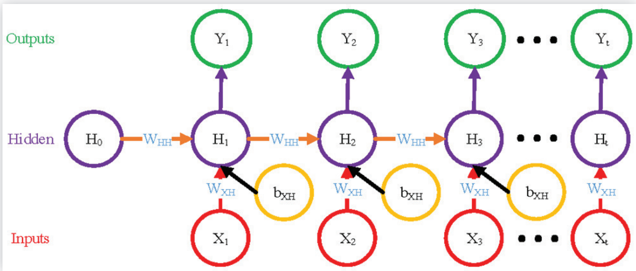


FIGURE 2 An unrolled RNN through time representation.



temperature, current and state of charge feeds to the RNN to predict a future voltage. Figure 2 shows the "sequence to vector" network.

Long Short-Term Memory

Although RNN improves learning the ordered nature of the input data for sequence input data, it suffers from the vanishing gradient and overflow problem when updating the weights in the network [15]. In 1997, Sepp Hochreiter and Jurgen Schmidhuber proposed LSTM which eventually improved its design and solved the two challenges that RNN creates during training. In a single LSTM cell, there are four layers. The main layer functions like the RNN with addition of a connection to the long-term state memory. The forget gate controller layer erases the unnecessary part of the long-term state memory. The input gate controller layer adds part of the output to the long-term state memory. The output gate controller layer decides which part of the long-term state memory is added to the output [14]. Figure 4 shows the LSTM cell and Eqs. 2-7 provide the equations in the LSTM cell.

$$f(t) = \sigma\left(W_f X_t + W_f H_{t-1} + b_f\right) \tag{2}$$

$$i(t) = \sigma\left(W_i X_t + W_i H_{t-1} + b_i\right) \tag{3}$$

$$g(t) = tanh\left(W_g X_t + W_g H_{t-1} + b_g\right) \tag{4}$$

$$o(t) = \sigma\left(W_o X_t + W_o H_{t-1} + b_o\right) \tag{5}$$

$$c(t) = f(t) \cdot c(t-1) + i(t) \cdot g(t) \tag{6}$$

$$h(t) = o(t) \cdot \tanh\left(c(t)\right) \tag{7}$$

FIGURE 3 The "sequence to vector" RNN.

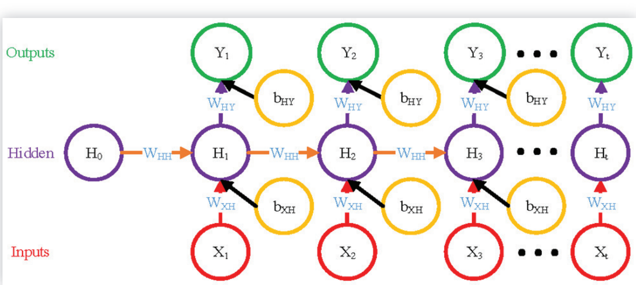
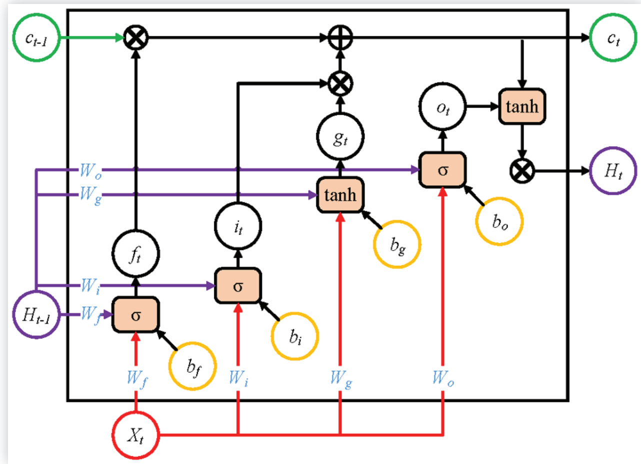


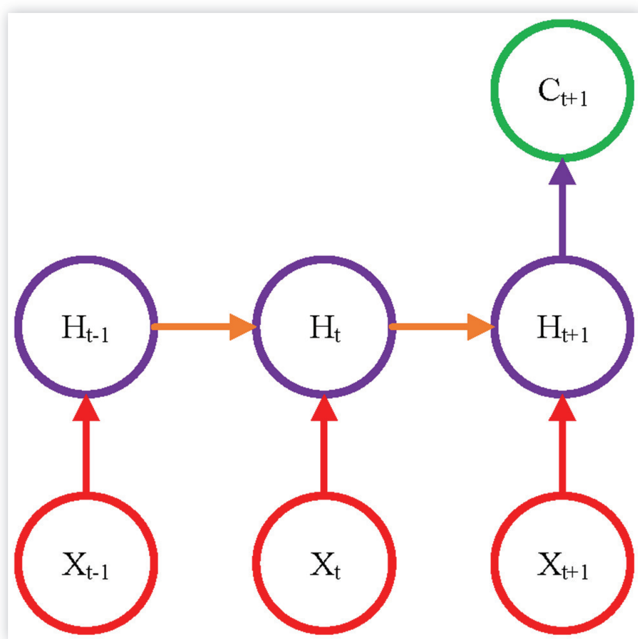
FIGURE 4 A LSTM cell.



where $f(t)$ is the forget gate, σ denotes the sigmoid function, W_f denotes the weight in the forget gate, X_t is the input at time t, H_{t-1} is the output at time step $t - 1$, b_f is the bias in the forget gate, $i(t)$ denotes the input gate, W_i denote the weight in the input gate, b_i is the bias in the input gate, $g(t)$ denotes the input note, W_g represents the weight in the input note, b_g represents the bias in the input note, $o(t)$ denotes the output gate, W_o represents the weight in the output gate, b_o is the bias in the output gate, $c(t)$ denotes the cell state at time t, and $h(t)$ denotes the output.

Like the RNN, this paper develops a "many to one" LSTM network. Time series data of voltage, battery temperature, current and state of charge feed to the LSTM network to predict a future voltage. Figure 5 shows the "many to one" LSTM network.

FIGURE 5 The "many-to-one" LSTM network.



worse than the other two models, although the overall error is small compared to the bumps on the rising and falling edges.

Most notably from Figure 9, the LSTM model has the smoothest response of all the architectures when predicting the cell voltage. Although the LSTM model does suffer from a delay in converging to the measured voltage on the relaxation portion of the IV pulse, the LSTM model does converge quicker than that of the other two models.

Temperature and Pulse Size Effects

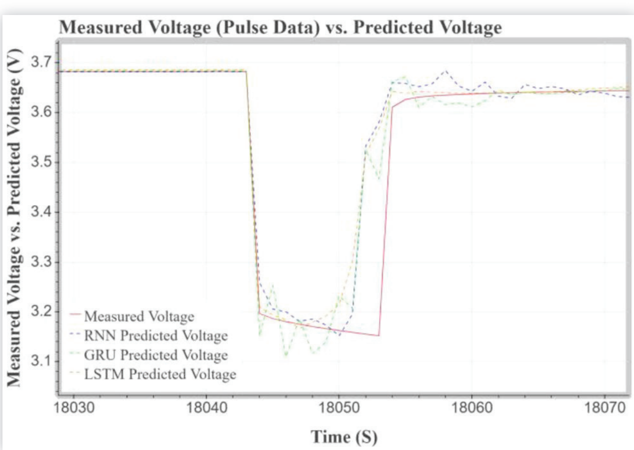
As a final comparison, the MSE for each network model is listed in Table 5 for the same data as shown in Figure 7. Note the MSE is for the entire test data set and not limited to the single charge and discharge events shown in the referenced figures. The MSE shows the GRU network had the least error when predicting voltage at -30°C while the LSTM had the largest overall error. Although the LSTM had more error, it is important to note the response from the LSTM was overall smoother. This could be critical in control applications where the GRU prediction could drive a large overcompensation in the system. As a further study, it could be beneficial to attempt to combine these layers in the same network to achieve better accuracy and control but that is outside the scope of this analysis.

Additionally, all three neural networks have the same order of magnitude of the MSE at -30°C in Table 5. In the case of the voltage prediction at 25°C, the LSTM has the smaller prediction error compared to the other two neural networks. This is because the prediction error increases in the RNN and GRU. The LSTM maintains the same order of magnitude at both -30°C and 25°C. This indicates the robustness of the LSTM in both temperature conditions. In case of the RNN and GRU, the voltage prediction error increases at 25°C.

As described in Figures 7 and 8, the pulse size at -30°C is less than 25°C in order to compensate the high cell resistance at -30°C and avoid hitting the voltage limits. This increase of the pulse size may result in the raise of the prediction error. With this observation, it is inferred that the neural network approach may have a higher tolerance on the temperature effect. Other voltage prediction methods such as model-based voltage prediction are greatly affected by the temperature. However, it is shown that the pulse size increase is a major factor for the increase of the prediction error.

These observations can be explained by the nature of the neural network approaches. In the case of the voltage predictions at the low temperature, low temperature information in the training data improves the prediction error at low temperature. For the larger pulse size leads to an increase of the input gradient to the neural networks. For the standard RNN and GRU, this sudden increase in the inputs deteriorates the prediction accuracy because they don't handle the exploding gradient in the inputs. For the LSTM, it is robust against this kind of sudden changes in the current as it is immune to the exploding gradient in the input data.

FIGURE 12 A zoomed in discharge region showing measured voltage vs predicted voltage using the RNN, GRU, and LSTM architectures at -30°C and 50% SOC.



Summary/Conclusions

Unlike previous work, which either solely studied one of the three RNN architectures or merely investigated dynamic voltage responses under a given drive cycle, this study compared the performance of battery voltage prediction among the standard RNN, LSTM, and GRU. In addition, this study investigated voltage responses in the worst scenario: cold temperature, high c-rate, and long duration. Both the dynamic voltage response and voltage relaxation were explored. The results indicate the GRU network had the least overall error when predicting voltage at -30°C. Particularly, it had a smaller error on the rising and falling edge of the pulse. It failed to steadily track the discharge voltage and ended up with large corrections during the relaxation. The standard RNN suffered from a large excitation during the rising and falling edge of the pulse. It was also found that the standard RNN took more time to converge during the relaxation after the discharge event. Although the LSTM had the largest overall error at -30°C, it is important to note the response from the LSTM was overall smoother. Also, the LSTM was robust for both low temperature and high current pulse input.

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Acknowledgments

We would like to thank the guidance and support from Kevin Vander Laan, Kristen Tamm, Stefan Pototschnik, and Brett Hinds at Ford Motor Company.

Definitions/Abbreviations

ECM - equivalent circuit model

GRU - gated recurrent unit

LSTM - long short-term memory

PRNN - pipelined recurrent neural network

RNN - recurrent neural network

SOC - state of charge

ISSN 0148-7191