



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

Gyouho Cho, DI ZHU, and Jeffrey Campbell Ford Motor Co.

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## Abstract

Electrification is the well-accepted solution to address carbon emissions and modernize vehicle controls. Batteries play a critical role 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 prediction 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 runaway. 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

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  $-30^{\circ}\text{C}$  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  $-30^{\circ}\text{C}$  in Table 5. In the case of the voltage prediction at  $25^{\circ}\text{C}$ , 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  $-30^{\circ}\text{C}$  and  $25^{\circ}\text{C}$ . This indicates the robustness of the LSTM in both temperature conditions. In case of the RNN and GRU, the voltage prediction error increases at  $25^{\circ}\text{C}$ .

As described in Figures 7 and 8, the pulse size at  $-30^{\circ}\text{C}$  is less than  $25^{\circ}\text{C}$  in order to compensate the high cell resistance at  $-30^{\circ}\text{C}$  and avoid hitting the voltage limits. This increase of the pulse size may result in the raise of the

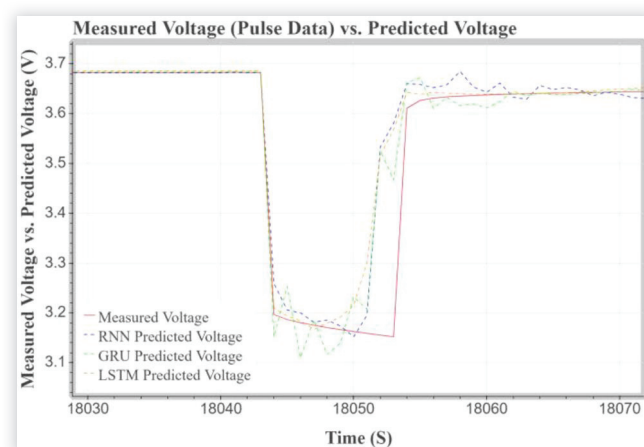
prediction error. With this observation, it is inferred that the neural network approach may have a higher tolerance on the temperature effect. Other voltage prediction methods such as model-based voltage prediction are greatly affected by the temperature. However, it is shown that the pulse size increase 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.

## 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  $-30^{\circ}\text{C}$ . 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  $-30^{\circ}\text{C}$ , 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.

**FIGURE 12** A zoomed in discharge region showing measured voltage vs predicted voltage using the RNN, GRU, and LSTM architectures at  $-30^{\circ}\text{C}$  and 50% SOC.



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## Contact Information

**Gyouho Cho**  
Ford Motor Company  
[gcho1@ford.com](mailto:gcho1@ford.com)

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## 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