Enhancing Battery Voltage Prediction with Deep Learning: A Comparative Analysis of LSTM and Traditional Models

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***Abstract*—The growing demand for efficient energy storage solutions has sparked increased interest in precise battery voltage prediction. In this study the Long Short-Term Memory networks, are applied in the time series forecasting, to improve battery voltage prediction compared to conventional models. The developed forecasting system includes three main parts: Pre-processing, modeling, and evaluation. In the pre-processing, the voltage and current time series are normalized, and divided to the test and train subsets. Then the windows of consecutive samples are generated for both train and test subsets. The forecasting LSTM models are learnt from training data set, in the modeling phase. Finally, the Mean Absolute Error (MAE) is used as the evaluation criterion. This model is compared to two other neural network models. The study concludes that LSTM outperforms the other models, highlighted by a significantly lower MAE. With a comprehensive methodology and successful experimental framework, this paper demonstrates the efficacy of LSTM in predicting battery voltage, indicating its superiority over simple neural networks for time series forecasting.**

Keywords—Battery voltage prediction, Deep learning, Long Short-Term Memory neural networks

I. Introduction

Batteries are ubiquitous in modern life, powering a wide range of devices and systems, from smartphones and laptops to electric vehicles and renewable energy storage solutions [1][2]. Accurate prediction of battery performance, particularly forecasting battery voltage, is critical for optimizing battery management and ensuring the reliable operation of these devices and systems [1]. This research paper delves into the realm of battery voltage prediction, employing a deep learning-based approach, specifically Long Short-Term Memory (LSTM) neural networks, to enhance the accuracy of time series forecasting [3][4][5].

The importance of battery voltage prediction cannot be overstated. A battery's voltage is a key indicator of its state of charge, health, and overall performance [2]. Accurate predictions of battery voltage can enable efficient energy utilization, prevent unexpected power interruptions, extend battery lifespan, and enhance the safety of battery-dependent systems [6]. In applications such as electric vehicles, the ability to forecast battery voltage accurately is vital for optimizing energy consumption and ensuring the smooth operation of these systems [6].

Traditional methods of battery voltage prediction have often relied on simplistic statistical models or linear regression approaches, which may not capture the complex temporal dependencies and non-linear patterns inherent in battery behavior [5]. This limitation has motivated the exploration of advanced machine learning techniques, particularly deep learning, for improving battery voltage forecasting.

Deep learning models, such as LSTM neural networks, have demonstrated considerable capabilities in capturing intricate patterns in time series data. LSTMs are well-suited for sequential data and have gained prominence in various fields, including natural language processing, image recognition, and, more recently, time series forecasting [7][5][8]. Their ability to model long-range dependencies and adapt to changing input patterns makes them an attractive choice for battery voltage prediction.

This research paper focuses on the utilization of LSTM neural networks for battery voltage forecasting. The research begins by collecting time series data representing battery voltage and current measurements over a specific time period. The data pre-processing phase, in which data sets are normalized, divided into train and test subsets, and reformatted into data windows, is crucial to prepare the data set for the second step, named modeling.

Once the data is prepared, the training data windows set is used in the modeling step, to train the LSTM neural network model, allowing it to learn the underlying patterns and relationships between historical voltage and current measurements and future values. The testing data is reserved for evaluating the model's performance and assessing its ability to make accurate predictions on unseen data [9].

To quantify the accuracy of the LSTM-based battery voltage forecasting model, the Mean Absolute Error (MAE) metric is employed [10]. MAE measures the average absolute difference between the predicted and actual voltage values, providing a quantitative assessment of prediction quality. Additionally, this research paper conducts a comparative analysis, pitting the LSTM model against two other neural network models commonly used for time series forecasting [5].

The preliminary findings of this study reveal the superiority of LSTM neural networks in battery voltage prediction, as indicated by significantly lower MAE values compared to the alternative models [11][12]. This demonstrates the effectiveness of deep learning, particularly LSTM, in capturing the intricate patterns of battery behavior. The research also identifies an interesting trend: an increase in the number of input steps leads to improved prediction accuracy for all models, highlighting the importance of selecting an appropriate input window size for time series forecasting tasks [13].

In conclusion, this research paper presents a comprehensive methodology and a successful experimental framework for battery voltage prediction using deep learning-based approaches, with a specific focus on LSTM neural networks. The findings suggest that LSTM outperforms other neural network models in this context, emphasizing its potential to enhance the accuracy of time series forecasting for battery management. As batteries continue to play a pivotal role in our daily lives and in emerging technologies, the insights from this study contribute to the development of more reliable and efficient battery-dependent systems.

II. Methodology

In this study, we employ deep learning, a cutting-edge approach, to model time series forecasting of battery voltage based on its current state. Consider a scenario where we have two time series datasets representing the voltage and current of a battery. At a given time step t, we access to the sequential history of the battery's voltage and current from time step 1 to t-1. Using this historical information, deep learning models are employed to predict the voltage for multiple future time steps, taking the current as a crucial input variable. Consequently, the current serves as the model's input, while the predicted voltage becomes the output.

In the realm of deep neural networks for time series forecasting, it is essential to transform the sequential data into a format suitable for model ingestion. To achieve this, we generate consecutive data windows from the historical input and output time series. Subsequently, deep neural networks are trained on the training portion of the data and evaluated on the testing portion. In this section, we outline the steps involved in developing a deep learning-based approach for time series forecasting, tailored specifically for battery voltage prediction while considering the concurrent battery current. The entire process is visually depicted in Fig. 1.

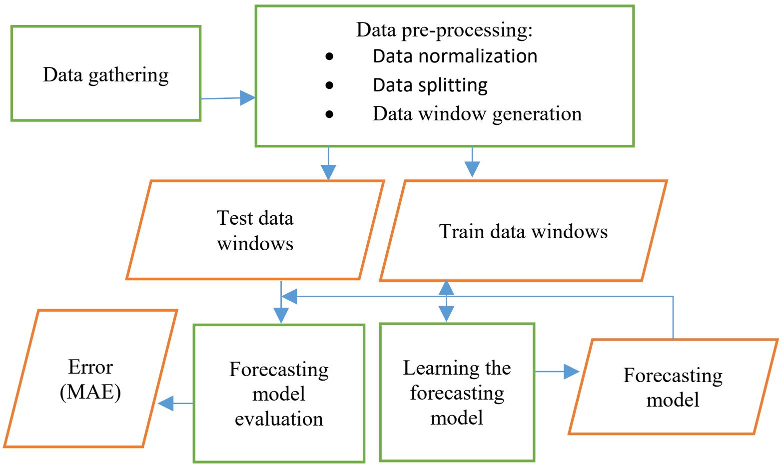

Fig. 1. The process of the developed forecasting system

A. Data pre-processing

In this study, we utilized the DC pulse method to characterize the Equivalent Electric Circuit (EEC) of the battery. The EEC parameters are subject to variations based on the battery's State of Charge (SOC), load current, and temperature. To account for these dependencies, we applied the current pulse pattern shown in Figure 2 for SOC values ranging from 5% to 95% with a 5% increment, and we repeated this for various temperature levels. As shown in the Figure 2, the amplitude of the current pulse spanned from 0.1C to 4C. Consequently, we achieved comprehensive parameterization, enabling the dynamic model to accurately predict battery voltage behavior under both low and high current conditions. The impact of the C-rate (load current) on the battery's voltage response, as observed during the parameterization test, is depicted in the Figure. We set the duration of each current pulse at 18 seconds to encompass the effects of key internal processes within the battery, including ohmic, charge-transfer, and diffusion processes. Furthermore, we allowed a 15-minute pause before each pulse to allow the battery to attain thermodynamic stability.

Our dataset includes two time series of voltage and current, with 256826 rows of the records. Fig. 2 shows the sequential data of two time series. Here, the goal is to develop the deep learning model for voltage time series forecasting, regarding the corresponding current time series.

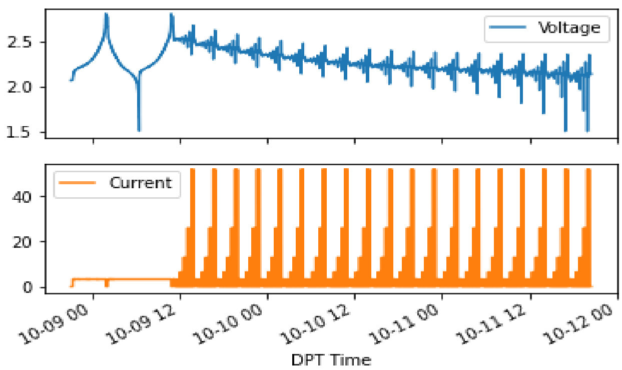

Fig. 2. Current and voltage time series

1) *Data normalization*

To ensure that the numerical input and output features are on a consistent scale, we apply a normalization process. This normalization not only stabilizes the training process but also enables meaningful comparisons between variables. In this context, both voltage and current undergo normalization using a scaling method known as the standard score, which aims to center our features around a mean of 0 and a standard deviation of 1.

The standard score, denoted as z for an observed value x of a variable X, is calculated as follows:

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

In (1), z is the standard score of x, and μ and σ, are the mean and standard deviation of the samples, respectively.

2) Data splitting

In order to train a generalizable model, the available data set is divided into the train and test (and validation) subsets. To estimate its ability to forecast the output of test or unseen data, the learnt model from training subset forecasts the output of the test subset. The comparison among the real and forecasted outputs determines the accuracy of the forecasting model.

A simple rule of thumb is to use something around a 70:30 to 80:20 training: testing split. Here, this approach is used because of our dataset type, including the sequential data that their order should be kept to extract data windows with consecutive data structure. So, the first 70% of the data set is selected as the training part to learn the forecasting deep neural networks, and the remaining part is used to test the developed model.

3) Data window generation

In order to convert the time series dataset to a process able form to make the deep neural networks capable of learning from training set, and evaluating by test set, they are re-formatted as data windows. Each window consists of consecutive samples of data, in which a part of input (and output) features' samples is used to forecast a pre-defined number of output samples.

The data window w_m (m=1, 2,…, n_w; n_w = maximum number of data windows) is determined by:

a) n_i = The constant number of time steps of the input (and output) feature (s);

b) n_f = The constant number of time steps of the output feature, that is forecasted based on the first part of the data window. In this study, n_f >1, because we implement multi-step forecasting.

So, the data window includes two segments: 1. Input segment: The consecutive values of the input (and output) features in the successive n_i time steps. 2. Output segment: The consecutive values of the output feature in the successive n_f time steps.

v_k	v_{k+1}	v_{k+2}	$\cdots$	v_{k+n_i-1}	v_{k+n_i}	v_{k+n_i+1}	$\cdots$	$v_{k+n_i+n_f-1}$
Input segment					**Output segment**			

Fig. 3. A typical data window of voltage, starting at time step k

Fig. 3. shows a typical data window of the voltage, started at time step k, including n_i input time steps, and n_f output time steps. The window is defined to make n_f steps prediction in the future, given n_i time steps of history.

It should be noted that when we have m inputs $X_1, X_2, \dots, X_m$ (Including output feature), and output Y. The data windows, starting at time step k are generated for each $x_j=\{x_{1j}, x_{2j}, \dots, x_{mj}\}$; $(j = k, k+1, \dots, k+n_i-1)$. In this study we have two time series current and voltage, so m is 2.

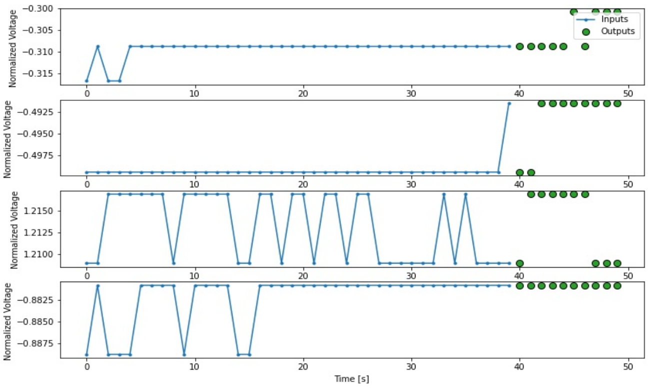

Fig. 4. Four randomly-selected voltage data windows (n_i=40; n_f=10)

Fig. 4 shows four random voltage data windows, selected randomly. In these windows, n_i, and n_f, are 40, and 10, respectively.

B. Modeling

As stated before, in this study, deep neural networks are learnt in a deep learning process, to develop the time series forecasting of the battery voltage, regarding the current. As a subset of artificial intelligence, deep learning simulates the human brain function to learn the models, and apply them to infer further results in the future. Inspired by the structure of human brain, that includes millions of interconnected neurons to learn, and infer the knowledge, deep neural network contains connected input, hidden, and output layers to made predictive systems based on available data in a deep learning process. Their function can be both classification and regression analysis. In this study long short-term memory (LSTM), as a deep neural network model, is applied.

LSTM neural networks are special recurrent neural networks (RNNs)[14] to learn tasks that require memories of events that happened thousands or even millions of discrete time steps earlier, to consider the vanishing gradient problem of RNNs facing with the long-term dependency LSTM networks were designed specifically to overcome the long-term dependency.

Unlike the feedforward neural networks, the feedback connections of LSTMs, enable them to analyze the sequential data, such as time series. So, instead of considering each sequence data independently, useful information about previous data in the sequence is kept to help with the processing of new data points.

Truncating the gradient where this does not do harm, LSTM can learn to bridge minimal time lags in excess of 1000 discrete-time steps by enforcing constant error flow through constant error carousels within special units [14].

Suppose $\{x_1, x_2, \dots, x_T\}$ is an input to the LSTM, in which

$x_t \in \mathbb{R}^k$ is k-dimensional vector at the time step t. In order to create temporal relationships, LSTM generates a memory cell s_{t-1}, that interacts with the hidden state of the previous time step h_{t-1}, and the input of time step t x_t, to determine the internal states that should be updated, kept, or deleted. In addition to internal state, internal node i_t, internal gate g_t, forget gate f_t, output gate o_t, are defined, as follows:

$$\begin{cases} f_t = \sigma(w_f x_t + w_f h_{t-1} + b_f) \\ i_t = \sigma(w_i x_t + w_i h_{t-1} + b_i) \\ g_t = \phi(w_g x_t + w_g h_{t-1} + b_g) \\ o_t = \sigma(w_o x_t + w_o h_{t-1} + b_o) \\ s_t = g_t \odot i_t + s_{t-1} \odot f_t \\ h_t = \phi(x_t) \odot s_t \end{cases} \quad (2)$$

In (2), w_{gx} ،w_{gh} ،w_{ix} ،w_{ih} ،w_{fx} ،w_{fh} ،w_{ox} و w_{oh} are the weight matrix, as the inputs of activation function. b_f, b_i, b_g, b_o are bias parameters. $\odot$ is the elementwise product operator, and here σ and ϕ are sigmoid and Hyperbolic tangent activation functions, respectively.

III. Experimental Framework

In this study, the forecasting system is developed by the Tensor flow as an open source machine learning platform by using the Keras API in the Python programming language.

In order to evaluate the applied deep learning model, LSTM, it is compared to two neural networks, using the error value, MAE. The first one includes a simple dense layer without any activation function, named LNN. Dense Layer is simple layer of neurons, in which each neuron receives input from all the neurons of previous layer, thus called as dense or fully connected (FC) layer. The second model includes a simple dense layer like LNN, and a dense layer with activation function, rectified linear unit (ReLU).

Mean Absolute Error (MAE), is used to evaluate the efficiency of the forecasting model, and compare it to LNN and DNN.

$$\text{MAE}= \frac{\sum_{i=1}^{n} |y_i - y_i^*|}{n} \quad (3)$$

where y_i and y_i^* represent the actual and forecasted output of the i^{th} testing sample, respectively. Also, n is the number of testing samples.

Three compared models are implemented in Tensor flow, with maximum epoch equal to 100.

The tuned parameters of the compared systems are displayed in table I.

Table I. Parameters of the Three Compared Models

Model	Parameter	Value	Model	Parameter	Value
LNN	Dense layer neurons	20	**LSTM**	Hidden layer units	64
DNN	First Dense layer neurons	64		Dense layer neurons	20
	Second Dense layer neurons	20		dropout	0%
	Activation function	ReLU		Activation function	Hyperbolic tangent
				Recurrent activation function	Sigmoid
				Learning rate	0.001

Fig. 5 shows the MAE of 100 epochs for LSTM. It is clear that it has a downward trend during consecutive epochs. It seems that after 40 epochs, the MAE does not experience considerable fluctuations. So, it could be concluded that converges to stable MAE in 100 epochs.

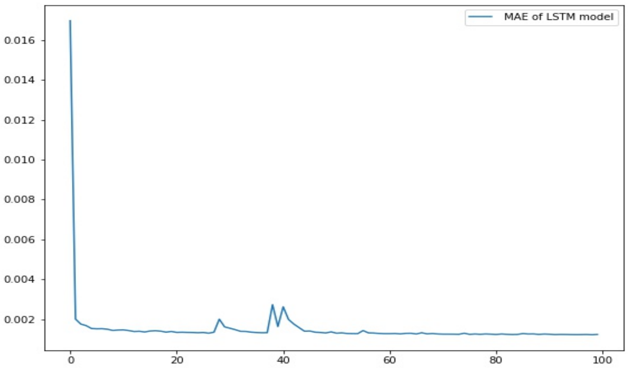

Fig. 5. The MAE of LSTM during 100 epoch

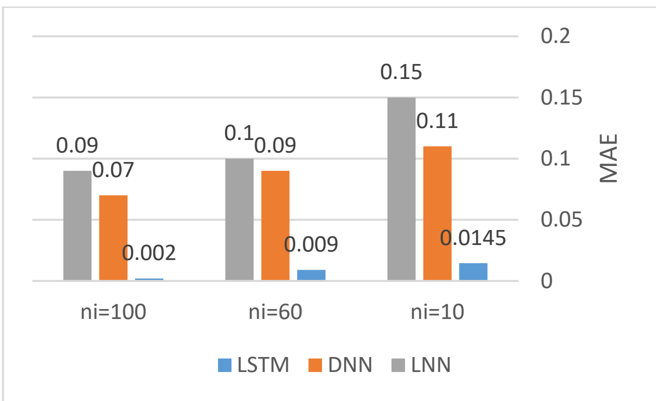

Fig. 6. The MAE of three compared forecasting models (n_f=10)

The MAE of the LSTM in comparison with other two neural networks, DNN and LNN, is presented in Fig. 6. As stated before, the time steps of input and output segments, are n_i and n_f, respectively. Although we implemented the experiments for different numbers of these parameters, in this figure n_f is equal to 10. But, the MAE of three n_i s is presented. The results show that with constant output time steps, increasing the input steps improves the MAE for all three models.

On the other hand, the MAE of test data for LSTM is less than other two models, considerably. The results display that the MAE of two simple neural networks (LNN and DNN), is about 20 times more than LSTM in average. The results confirm the superiority of the deep learning approach (LSTM) to time series forecasting rather that other simple neural networks.

IV. Conclusion

The research paper demonstrates the efficacy of a deep learning-based approach in predicting battery voltage, thereby offering substantial contributions to the existing body of knowledge on battery voltage forecasting. The study unequivocally proves that Long Short-Term Memory (LSTM) models deliver superior results simple dense layer Neural Network (DNN) and a dense layer with activation function, rectified linear unit (ReLU), named LNN. The LSTM model's Mean Absolute Error (MAE) is notably lower, with LNN and DNN models exhibiting an average MAE that was around 20 times greater. Further improvements in forecast accuracy were achieved by increasing the number of input time steps. Consequently, the adoption of LSTM models can significantly enhance the precision of battery voltage predictions, which can lead to notable advancements in this field. The research also highlights a potential area of future study which lies in exploring other ways of improving the deep learning-based techniques for even more accurate forecasting.

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