Li-ion Battery Voltage Response Forecasting based on LSTM with Kalman filter Correction

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***Abstract*— Nowadays, many researchers focus on the development of Lithium-ion battery (LIB). To ensure the safe application of the battery, an accurate estimation of voltage response is needed. This paper proposed voltage response forecasting method based on Long-short term memory (LSTM) with Kalman filter correction. The experiment results showed that the Kalman filter is able to reduce the RMSE of LSTM forecasting result by 0.2 until 0.25 RMSE.**

Keywords—Battery, Forecasting, Machine Learning, Artificial Intelligence, Electric Vehicle

I. Introduction

Nowadays, LIB is widely used to power portable electronics and electric vehicles. Compared to other batteries, it is known for fast charging capability, low self-discharge rate, high power density and low memory effect [1][2]. Voltage is important quantity to determine the battery model. In electrical circuit's power of the battery, voltage is the pressure that pushes the current through the conducting loop. In EV applications, the driving speed of the EV is depended on the variation in the voltage response of the battery [3]. To ensure the safe application of the battery, an accurate voltage forecasting is needed to estimate when is the voltage response will drop below the cutoff voltage. If the battery model is similar to the actual, it means the battery model is accurate.

This paper proposed voltage response forecasting method using long short-term memory (LSTM) with the correction of Kalman filter. Real data from electric motorcycle has been collected. The root-mean squared (RMSE) error obtained to measure the voltage response. This paper is organized as follows. Section II presents the proposed forecasting methods approach and the dataset driving cycle used. Section III presents the results of experiment. Finally, Section IV summarizes the paper and conclusions.

II. Voltage Response Forecasting

The dataset collected from the real EV consist of drive-cycle, which is a series of data that represented the speed of a vehicle over the time. It consist of potential explanatory variables that includes power consumption, battery output current, motor torque, battery output voltage and motor speed. The drive-cycle consist of eight cycle. First cycle reflect the battery in fully charge state while the last cycle reflect the battery before it fully discharged. To analyze the effect of speed to the voltage response, motor speed and battery voltage response used as the explanatory variable.

Fig.1 shows the flowchart of proposed algorithm. The historical data consist of power consumption, battery output current, motor torque, motor speed and battery output voltage. The parameter used in LSTM discussed in Section B and the

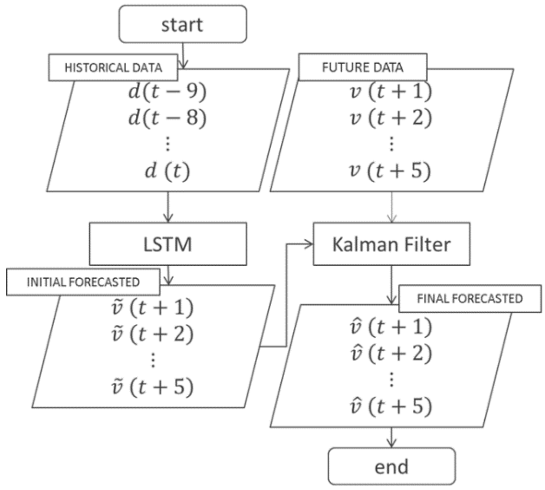

Fig 1. Proposed Algorithm

formula used to correct the initial forecasted is explain in Section C.

A. CVS-40 Cycle Dataset

TABLE I. Explanatory Variable Summary.

Variable	Mean	Standard Deviation
Power	0.30	0.33
Speed	0.35	0.35
Voltage	0.53	0.25
Current	0.29	0.33
Torque	0.52	0.31

Constant volume sampling (CVS)-40 drive cycle is the standard driving cycle used in republic of Korea. One CVS-40 cycle consist six repetition of low, medium and high speed with zero speed in between. Low, medium and high speed moving at respectively 14.95–18.28, 31.39–35.35 and 36.36–46.61 *km/h*. After one cycle, the vehicle is put in rest for 10 minutes before it starts to run the next cycle until it discharged. The series of the data in this study obtained by taking the measurements every 0.1 sec. Table I shows the summary of all of data after normalization with range of zero until one. As can be seen, current and power has similar standard deviation and similar mean. Both of the values also has similar mean and standard deviation with speed, it indicated that it has similar trend. However, torque has different mean and standard deviation, even the plot has same pattern. Based on these data, it concluded that power, speed and current has similar trend.

B. Long-short term memory (LSTM forecasting)

TABLE II. LSTM PARAMETER

Parameter	Values
Explanatory variables	$[v, i, p, t, s]$
Target	$v(t + \Delta T)$
Output	$\tilde{v}$
Epoch	500
Activation Function	Adam optimizer
Batch Size	50
Hidden layer	2
Neuron	200,50
Losses	RMSE

LSTM is a machine learning technique that has memory associated with the model so it can solve sequential data [4]. It has the capability to catch the linearity and non-linearity of the data. In order to forecast the voltage response, we considered a multivariate time series based on the historical values of the battery voltage response and motor speed. First, cycle 1 data used as training,. The LSTM model sets Adam as an optimizer with fifty number of batch. The model run with one-hundred iterations. The RMSE obtained by measuring the forecasted one -cycle ahead data with the actual one-cycle ahead data for the comparison.

C. Kalman filter correction

Due to its ability to achieve optimal estimation [5], Kalman filter is used to correct the forecasted LSTM. Kalman filter consist of two equations, prediction

$$\hat{X}_{kf}(t) = F(t)x(t) + G(t)(c(t) + w(t)) \quad (1)$$

where $\hat{\boldsymbol{x}}_{\boldsymbol{kf}}$ is forecasted Kalman filter without correction, $x(t)$ is measurement, $\boldsymbol{c}(t)$, $w(t)$ is control variable unit and noise respectively. $F(t)$ and $G(t)$ are general form of matrices**.** The other equation is correction:

$$\hat{X}(t+1) = \hat{X}_{kf}(t)K(t) + K(t)(y(t) - \hat{X}_{kf}(t) \quad (2)$$

where $\hat{x}$ is the final forecasted, $K$is kalman gain and y is the measurement with noise. In our methodology, the prediction of Kalman filter ignored and the result of LSTM is use instead, and the correction of Kalman filter used to correct the forecasting result of LSTM. The Kalman filter correction is the final result of our proposed method.

III. RESULT

Table III shows the comparison result using LSTM individually compared with LSTM with Kalman filter correction. The less RMSE achieved while cycle 1-3 used as training to forecast the cycle 4.with 0.40 RMSE. It shown that using more training data does not affect the forecasting accuracy since the RMSE achieved using cycle 1 until cycle 5 is the highest RMSE compared to using less cycle as training. Forecasting using LSTM with Kalman filter correction achieved less RMSE than using LSTM individually. As an example, LSTM with Kalman filter correction achieved 0.95 RMSE in the first training. It has 0.03 less error than LSTM result which is 0.98.

TABLE III. VOLTAGE RESPONSE FORECASTING RESULT IN RMSE.

Training	Test	LSTM	LSTM+KF
Cycle 1	Cycle 2	0.98	0.95
Cycle 1-2	Cycle 3	0.58	0.54
Cycle 1-3	Cycle 4	0.42	0.40
Cycle 1-4	Cycle 5	0.67	0.64
Cycle 1-5	Cycle 6	1.11	0.86

IV. CONCLUSIONS

In this paper, we proposed forecasting approach using LSTM with Kalman filter correction. First, LSTM used to forecast first cycle to forecast one-cycle ahead. Next training, we consistently used one cycle ahead as an addition. RMSE obtained using LSTM with Kalman filter correction achieved better overall RMSE than using LSTM only. It means Kalman filter is able to reduce the error of LSTM forecasting.

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