Performance Comparison of Data Driven-based Capacity Forecasting for Supercapacitor

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Abstract

Data driven-based capacity forecasting has gained remarkable attention in recent years. The many approach of data driven-based capacity forecasting can be divided into two approaches: statistical model and deep learning model. Both model have their own advantages and disadvantages in forecasting capacity. To opening up the route in further systematic research in this area. This paper provide quantitative result with actual supercapacitor dataset to compare both forecasting accuracy and reliability for statistical and deep learning models.

Keywords—ARIMA, capacity forecasting, lithium battery, LSTM, time series regression.

Ⅰ. *INTRODUCTION*

Supercapacitor (SC) which have higher power density than batteries have been used extensively for energy storage devices especially in renewable energy applications. Accordingly, ensuring that the SCs operate safely and have a long lifespan is crucial for energy management and control of the energy storage device. In particularly, capacity degradation represents battery aging which indicating when a SCs should be replaced. Forecasting capacity degradation which represents SCs aging plays important role in preventing failures, which can occur due to the continuous use of a low-charge SCs. Especially when SCs are used as power supplies for complex electronic systems, the use of a low-charge SCs will lead physical failure in the entire of system [1].

Furthermore, SCs capacity degrade overtime as [2] treated this case as time series forecasting case. In term of forecasting capacity, data-driven method has been developed rapidly in recent years which can be categorized in two models: 1) statistical model e.g., Autoregressive integrated moving average (ARIMA) [3], Kalman filter [4]. 2) Deep learning model e.g., Long short term memory (LSTM) [5]. Capacity forecasting based on data-driven so far employ one of the two aforementioned model and some paper utilized both model as hybrid data-driven method such as in [6]. Both model are data dependent but statistical model relies on rule-based programming which construct the capacity forecasting model with several rule-based programing. In contrast, deep leaning learns from data without any specific rule to construct the capacity forecasting model. Comparing statistical model and deep learning model is important to open up systematic and quantitative performance which can help to choose suitable model for certain case in SC capacity forecasting.

The contributions of this paper are as follows: 1) we provide quantitative result with actual SC dataset to compare both forecasting accuracy and reliability for statistical and deep learning models. 2) We also present the advantages of each model, offering suitable solution for certain of use cases in the future work.

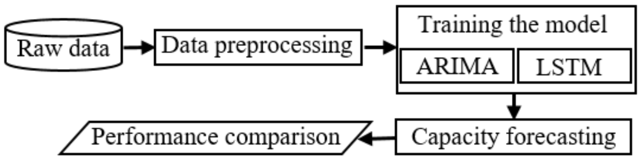

Fig. 1. Flowchart of the performance comparison of data driven-based capacity forecasting for SC.

Ⅱ. *DATA DRIVEN-BASED CAPACITY FORECASTING*

The overall of data-driven based SC capacity forecasting is shown in Fig.1. The system started with collecting the raw data from sensor after several charging-discharging process. Data preprocessing is employed to normalize and remove outlier from the raw data. In the next step, we develop two capacity forecasting model, one model was developed based on statistical model and another model was developed based on deep learning model. Finally, to evaluate the forecasting accuracy, we compute three standard way to measure the forecasting accuracy mean absolute percentage error (MAPE), Mean absolute error (MAE) Root mean square error (RMSE).

A. ARIMA

ARIMA is a forecasting algorithm based on the assumption that previous values carry inherent information and can be used to predict future values. The Autoregressive (*p*), Integrated (*d*), and Moving Average (*q*) values are identified by iterations applied on the following equation:

$$\emptyset(B).(1-B)^{d}.\hat{y}_{ARIMA}(t) = \theta(B)Z_t \quad (1)$$

where the where, the Lag operator B contains the *p, d, and q* terms. $\emptyset(B)$ is the weight corresponding to p term and $\theta(B)$ is the applicable weight for q term. $\hat{y}(t)$ is the resulting prediction and Z_t, the stationary white noise. In this paper, (*p,d,q*) values of (3,1,8) were used to

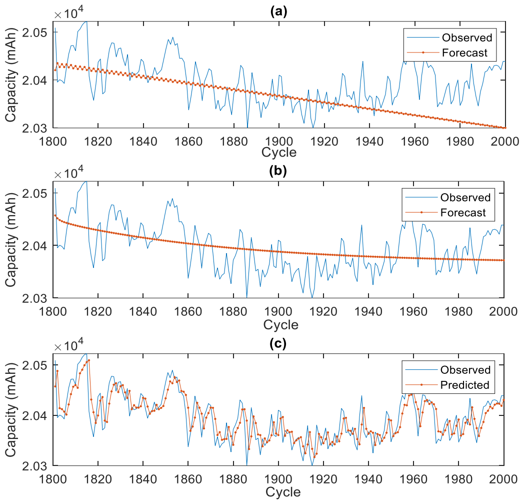

Fig. 2. Capacity forecasting result using 90% of dataset as training dataset: (a) ARIMA, (b) LSTM – update without actual capacity, and (c) LSTM – update with actual capacity.

forecast the future capacity of SC based on its prior performances.

B. *LSTM*

LSTM is designed to learn long-term dependencies. It remembers information for long periods of time. Also, it can discard redundant information and select key information to be stored in the internal state via the forget and input gates respectively. In the training process, the LSTM layer had 50 hidden units, while the training options had maximum epochs of 250 and Adam optimizer was utilized. In term of testing trained LSTM model, we employed LSTM with two scenarios: 1) LSTM – update without actual capacity. That is LSTM use the previous output as input and 2) LSTM – update with actual capacity which update the model with actual capacity instead of the previous predicted capacity.

Ⅲ. *PERFORMANCE ANALYSIS*

A. *Comparison of Capacity Forecasting Results with Different Models*

The entire SC dataset consists of 2000 cycles. Fig. 2. is a zoom-in of the results of the capacity forecasting where 90% of dataset were used as training dataset. As shown in Fig. 2.(a), the ARIMA model forecast capacity tend to straight line as the ARIMA is a linear regression based forecasting approach. Unlike the ARIMA model result, the LSTM model result is more dynamic. The LSTM model without actual capacity update as shown in Fig. 2.(b), does not capture actual capacity measurement from sensors, therefore it updates and forecasts each cycle using the capacity forecast output of preceding cycle. On the other hand, the LSTM model with actual capacity, Fig. 2.(c), updates each forecast with actual capacity measurement from sensors hence it is more dynamic and better in capturing actual capacity.

B. *Comparison of Capacity Forecasting Results with Different Number of Datasets*

Table 1 shows forecasting result using several number of training dataset. For ARIMA, at 50% training data; the RMSE, MAPE and MAE were 257.5, 0.0125% and 257.5

TABLE I
PERFORMANCE OF DATA DRIVEN-BASED CAPACITY FORECASTING

Model	No training data (%)	RMSE	MAPE (%)	MAE
ARIMA	50	257.5	0.0125	257.5
	70	74.03	0.0036	74.03
	90	**45.56**	**0.002**	**45.56**
LSTM Update without actual capacity	50	125.3	0.0061	125.3
	70	117.7	0.0058	117.7
	90	**35.5**	**0.0017**	**35.50**
LSTM Update with actual capacity	50	26.13	0.0013	26.13
	70	24.55	0.0012	24.55
	90	**23.76**	**0.0012**	**23.76**

respectively. Increasing the number of training data from 50% to 70% to 90%, saw the RMSE improve from 257.5 to 74.03 to 45.56. This shows that with multiple datasets, ARIMA performance for capacity forecasting can be improved. Also a similar result trend was observed with LSTM with and without actual capacity update. Although the LSTM model performed better than ARIM, for the LSTM with actual capacity update, increasing the number of training dataset did not have significant corresponding increase on the RMSE, MAPE and MAE values. This is because of the interactive update of the method with actual capacity at every forecast cycle.

Ⅳ. *CONCLUSION*

This paper presented the performance comparison with two different model of data driven – based: ARIMA as the statistical model and LSTM as the deep leaning model. The experimental result shows that LSTM has better accuracy than ARIMA. Furthermore, we also provide the performance comparison with several number of training data. The experimental result shows that adding more training data is able to improve the accuracy but in LSTM – update with actual data model, there are no much accuracy improvement. Since this model prioritize the update actual capacity to forecast the next capacity.

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