Analysis of Deep Neural Networks-Based Digital Twin for Lithium-ion Batteries

Judith Nkechinyere Njoku†, Robin Matthew Medina †, Nkoro Ebuka Chinaechetam †, Cosmas Ifeanyi Nwakanma*, Jae-Min Lee †, and Dong-Seong Kim†
*ICT Convergence Research Center, †IT Convergence Engineering, Kumoh National Institute of Technology, Korea

***Abstract*—The adoption of electric vehicles is affected by the use of batteries which need to be constantly monitored and controlled. The creation of battery digital twins can help make battery management more effective. In this paper, three deep neural networks were used to develop digital twins of a battery. The digital twin models were developed using battery data from NASA and were trained to predict battery capacity. The performances of these models were verified using three other batteries. The best performing digital twin model achieved RMSEs of 0.12097, 0.43378 and 0.20219 on all tested batteries.**

***Index Terms*—digital twins, capacity prediction, batteries, DNN, BMS**

I. Introduction

With the rising influx of electric and hybrid-electrical vehicles, there is an equally increasing need to ensure the general and functional safety of vehicles by means of concrete supervision and control. This is especially necessary because of the batteries that power the vehicles [1]. An efficient battery management system (BMS) needs to be put in place to maximize the life of the batteries in use. Nowadays, numerous digital services have been incorporated into transportation services, including motor vehicles and trains [2]. One of the growing research directions is the creation of battery digital twins that can aid in a more robust estimation of the necessary battery parameters and hence determine the current and future states of the battery while in use [3]. To develop digital twins of batteries or any other platform, it is essential that sufficient data is available to ensure the accurate creation of the twin [4]. Fig. 1 illustrates the elements of a typical battery digital twin. The battery data can used to model a cloud-based digital copy of the battery with the aid of machine learning. The system allows for a local computation of the necessary control parameters of the real vehicle, while the results of the cloud computation can be transferred from the digital to the physical battery.

Numerous methods exist for the design of digital models of batteries [4]. However, these models most often do not utilize real-world data and thus do not reflect the true dynamics of the battery. Numerous studies have explored the use of machine learning for the creation of battery digital twins [5], [6]. Capacity prediction is a critical function of BMS. If a battery digital twin can accurately predict the capacity of the real batteries, then it would have proved to be a near replica of the real battery [2]. Deep neural network (DNN) have been successfully employed in some battery state estimation tasks. Motivated by these, this paper presents preliminary results for a battery digital twin. Specifically we developed three DNN based digital twin models for the task of capacity prediction. The trained models are then tested using the battery data of three different batteries. The results prove the robustness of the models in predicting battery capacity.

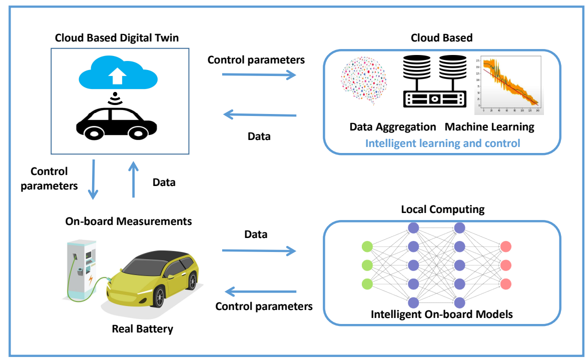

Fig. 1. Battery Digital twin [4]

II. Methodology

A. Battery Data Description

The dataset employed in this work was obtained from NASA's open data portal. The dataset was developed from four Lithium-ion batteries labelled $B0005$, $B0006$, $B0007$ and $B0018$. While at room temperature, these batteries were subjected to three different operational profiles including the charge, discharge and impedance.

B. DNN Models

Three different DNN-based Digital twin models were employed and their performances were verified for the task of capacity prediction. The first DNN model is composed of three dense layers, each of then having 8 units and activated using the ReLu activation function. These layers are all followed by a dropout layer with a rate of 0.25 and an output dense layer with 1 unit. The second DNN model is composed of three dense layers, each of then having units 32, 64 and 128 and activated using the ReLu activation function. These layers are all followed by a dropout layer with a rate of 0.25 and an output dense layer with 1 unit. The third DNN model is composed of three dense layers, each of then having units 64, 32 and 8 and activated using the ReLu activation function.

TABLE I
PERFORMANCE COMPARISON OF THE REAL AND PREDICTED CAPACITIES OF ALL THREE BATTERIES ON THE THREE IMPLEMENTED DNN MODELS

	Battery B0006 Capacity (mAH)				Battery B0007 Capacity (mAH)				Battery B0018 Capacity (mAH)			
	Real Capacity	Model 1	Model 2	Model 3	Real Capacity	Model 1	Model 2	Model 3	Real Capacity	Model 1	Model 2	Model 3
0	2.035338	1.957872	1.881970	1.855931	1.891052	2.108690	1.917528	1.909852	1.855005	1.922951	2.013961	1.918474
1	2.025140	1.960014	1.886467	1.859385	1.880637	2.112758	1.925022	1.913906	1.843196	1.933932	2.035662	1.932541
2	2.013326	1.963483	1.886802	1.860124	1.880663	2.117747	1.925572	1.925842	1.839602	1.959142	2.046760	1.938246
3	2.000528	1.964204	1.885390	1.859379	1.880771	2.122917	1.923244	1.916718	1.832700	1.974399	2.057631	1.936353
4	2.013899	1.981964	1.883425	1.858165	1.879451	2.125515	1.920988	1.916372	1.828529	1.951695	2.053518	1.945128

These layers are all followed by a dropout layer with a rate of 0.25 and an output dense layer with 1 unit.

III. EVALUATION

A. Experimental Setup

The battery digital twin models were developed using Tensorflow. 7 battery parameters were employed as inputs to the model development, including voltage, current and temperature measured, voltage and current load, ambient temperature and time. The *Adam* optimizer was used to optimize all models. Battery $B0005$ was used in the development of the models, while Batteries $B0006$, $B0007$ and $B0018$ were used for testing. All models were trained with a batch size of 25 for 50 epochs and to minimize the mean absolute error, $MAE = max\,|cap_i - \hat{cap}_i|$, where cap_i represents the real capacity and $\hat{cap}_i$ is the predicted capacity.

During the testing stage, the differences between the predicted capacity and real capacity were evaluated based on the root mean squared error, $RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(cap_i - \hat{cap}_i)^2}$, where cap_i also represents the real capacity and $\hat{cap}_i$ is the predicted capacity.

B. Results

Results Fig. 2 shows a comparison between the predicted and real capacities of model 1 for all three batteries. Table I shows that Model 1 was the best at modelling the capacity of the real batteries. Although, according to Table II, Model 2 incurs the least computation time, it has the highest RMSE.

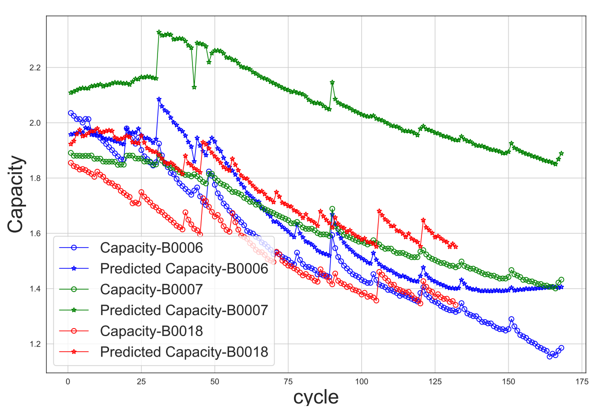

Fig. 2. Figure showing the performance of the three batteries for Digital Twin model 1

TABLE II
RMSE AND COMPUTATION TIME RESULTS OF ALL BATTERIES

Batteries	Battery B0006			Battery B0007			Battery B0018		
Models	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
RMSE	0.12097	0.12913	0.10216	0.43378	0.49749	0.33962	0.20219	0.25798	0.20484
Time (s)	2.27	2.22	2.25	2.02	1.88	1.92	1.5	1.41	1.45

IV. CONCLUSIONS AND FUTURE WORKS

This paper analyzed the performance of three different DNN based Digital twin models for the task of capacity prediction. Battery data from four different batteries were used for the development and analysis of the model. Results show that a shallow DNN is most suited for this task. Future research will focus on the exploration of more robust models and the optimal parameters to employ in developing digital twins.

ACKNOWLEDGMENTS

This research was supported by MSIT, Korea, under the Grand Information Technology Research Center support program(IITP-2022-2020-0-01612) supervised by the IITP and Priority Research Centers Program through the NRF funded by the MEST (2018R1A6A1A03024003).

REFERENCES

[1] L. Merkle, A. S. Segura, J. Torben Grummel, and M. Lienkamp, "Architecture of a digital twin for enabling digital services for battery systems," in *2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS)*, 2019, pp. 155–160.

[2] H. Chun, J. Kim, M. Kim, J. Lee, T. Lee, and S. Han, "Capacity estimation of lithium-ion batteries for various aging states through knowledge transfer," *IEEE Transactions on Transportation Electrification*, vol. 8, no. 2, pp. 1758–1768, 2022.

[3] X. Tang, Y. Sun, Y. Zhao, W. Pei, N. Li, and L. Kong, "Digital twin based bess state estimation and operating opimization," in *2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2)*, 2021, pp. 3402–3405.

[4] M. Olteanu and D. Petreus, "Battery digital twins," in *2022 45th International Spring Seminar on Electronics Technology (ISSE)*, 2022, pp. 1–5.

[5] K. Zhao, Y. Liu, W. Ming, Y. Zhou, and J. Wu, "Digital twin-driven estimation of state of charge for li-ion battery," in *2022 IEEE 7th International Energy Conference (ENERGYCON)*, 2022, pp. 1–6.

[6] K. S. S. Alamin, Y. Chen, E. Macii, M. Poncino, and S. Vinco, "A machine learning-based digital twin for electric vehicle battery modeling," in *2022 IEEE International Conference on Omni-layer Intelligent Systems (COINS)*, 2022, pp. 1–6.