논문 25-50-04-02 The Journal of Korean Institute of Communications and Information Sciences '25-04 Vol.50 No.04
https://doi.org/10.7840/kics.2025.50.4.549

HyBaTwin: Web-Based Hybrid Digital Twin Platform for Electric Vehicle Battery Capacity Estimation

Judith Nkechinyere Njoku◆, Anthony Uchenna Eneh*,
Cosmas Ifeanyi Nwakanma**, Jae-Min Lee***, Dong-Seong Kim°

ABSTRACT

This study presents early results of a web-based digital twin (DT) for battery management systems (BMS). The proposed DT explores a hybrid of model-based and data-driven approaches, enabling the exploitation of each approach's distinctive merits and constraints. Experiments employing explainable artificial intelligence (XAI) techniques were undertaken to select the most trustworthy and explainable approach to be deployed to a web server. First, a model-based DT was developed using physics based modelling and AI to achieve the hybrid model. Next, four models, including a deep neural network, a long-short-term memory network, a graph neural network (GNN), and a transformer neural network (TNN) model, were independently trained to minimize the residual between the actual battery data and the prediction of the model-based DT. All hybrid DT models were assessed based on mean squared error, latency, and prediction confidence. With the best confidence score of 98.255% and lowest latency of 0.079, the hybrid GNN DT model emerged as the best, demonstrating the viability of the proposed explainable hybrid approach in approximating actual battery behavior and the utility of a web-based DT.

Key Words : digital twin, AI-based, electric vehicles, capacity estimation, battery management system

Ⅰ. Introduction

Battery management systems (BMS) play a significant role in monitoring and regulating the health and performance of batteries in electric vehicles (EVs)[1,2]. One critical functionality of BMS is estimating the battery capacity - a key parameter that directly influences the EV's range, efficiency, and overall reliability. Accurate and robust capacity estimation is indispensable for informed decision-making during the charge and discharge process[1]. With the surge in EVs, there is an equal urgency in refining and enhancing capacity estimation methodologies.

1.1 Background and Motivation

Digital twins (DT) are an emerging subset of the metaverse ecosystem[3,4], providing virtual replicas of physical entities that enable seamless integration between the digital and physical worlds. The concept

※ This work was partly supported by Innovative Human Resource Development for Local Intellectualization program through the Institute of IITP grant funded by the Korea government(MSIT) (IITP-2024-RS-2020-II201612, 33%) and by Priority Research Centers Program through the NRF funded by the MEST(2018R1A6A1A03024003, 33%) and by the MSIT, Korea, under the ITRC support program(IITP-2024-RS-2024-00438430, 34%) supervised by the IITP.
◆ First Author : Kumoh National Institute of Technology, Department of IT Convergence Engineering, judithnjoku24@kumoh.ac.kr, 학생회원
° Corresponding Author : Kumoh National Institute of Technology, Department of IT Convergence Engineering, dskim@kumoh.ac.kr, 종신회원
* Africhange Technologies, Nigeria
** Computer Science and Electrical Engineering, West Virginia University, Morgantown, 26506, WV, USA
*** Kumoh National Institute of Technology, Department of IT Convergence Engineering
논문번호 : 202410-258-A-RN, Received October 28, 2024;Revised November 26, 2024; Accepted November 26, 2024

of DTs[1] has been explored for BMS due to their ability to simulate and predict real-world battery behaviors accurately[5]. Two main DT types can be developed for BMS: Model and data-driven approaches. Model-based DTs leverage the principles of battery physics to model the intricate processes within the battery[6]. For instance, in [7], models were constructed to describe the physical processes that occur in Lithium-ion (Li-ion) batteries, such as diffusion. The equations that govern these models were presented in [8], [9] highlighted the relevance of these models, with the impending limitation. Ultimately, these models face complexities introduced by diverse operating conditions and dynamic environments by EVs. On the other hand, the data-driven DTs are powered by machine learning (ML) algorithms[10,11].

1.2 Related Works

Numerous studies have explored data-driven approaches for developing battery DTs. The DT presented in [12] explored various ML algorithms for the prediction of battery state, including models such as deep neural networks (DNN), long-short-term memory networks (LSTM), and gated recurrent units (GRU). In [1], similar ML algorithms were explored for predicting battery state based on a DT framework. Other ML models such as Transformers have been utilized by studies in [13] and [14] for predicting battery states. Another advanced ML algorithm, graph neural network was introduced by [15] and [16] were introduced for the state of health estimation in lithium-ion batteries. [17] introduced a reference methodology for developing DTs for Li-ion batteries, highlighting the role of ML in optimal battery modelling. These models excel at capturing non-linear relationships and complex patterns but often need more interpretability.

Hybrid DTs are an approach that combines the strengths of both methods. A hybrid DT aims to harness the accuracy of physics-based models and the adaptability of data-driven models, creating a synergistic solution that excels in precision and versatility. This integration addresses the limitations of standalone models and provides a holistic representation of the battery. In [9], the relevance of exploring the strengths of these two types of DTs and utilizing a hybrid DT was postulated. However, there were no experiments to validate this, and there were no demonstrations to show performance. Nevertheless, the pursuit of accuracy is only part of the equation. The need for explainability arises as a critical consideration in deploying AI-based solutions, particularly in safety-critical applications like EVs. Understanding why a model makes a specific prediction is paramount for user trust, regulatory compliance, and overall societal acceptance[18].

Explainable artificial intelligence (XAI) techniques, like Local Interpretable Model-agnostic Explanations (LIME), serve as indispensable tools for shedding light on the decision-making processes of complex models[19]. These techniques allow users to interpret the factors influencing a model's predictions, transforming a seemingly opaque model into a transparent and trustworthy ally. Moreover, most previous studies need to present a working battery DT that processes battery data in real-time and produces results. The main objective of this study is to develop a web-based, explainable hybrid DT that can resolve the above-listed drawbacks.

1.3 Contribution

The key contributions of this paper are as follows:

1. We integrated physics-based modeling and ML algorithms to develop hybrid DT models that create a synergistic effect, enhancing both the accuracy and adaptability of the capacity estimation process.
2. We developed and evaluated the performance of four variants of hybrid DT models.
3. We employed the LIME XAI technique to give users a transparent view of the decision-making process and instill confidence in the estimated battery capacity values.
4. We deploy the model to a web-based system to ensure accessibility and ensure that the benefits of the Hybrid DT Platform extend beyond specialized laboratories, reaching a broader audience.
5. The experimental results highlight a hybrid GNN

DT as the best with the best confidence score and lowest latency.

Ⅱ. Methodology

The methodology employed in this research is a multilayered approach consisting of five modules: Physical module, data module, cognitive module, communication module, and virtual module, as illustrated in Fig. 1. Each module contributes uniquely to the overall system, ensuring accuracy, interpretability, and user engagement. The following subsections detail the processes and tools employed in each module, emphasizing the seamless integration of diverse technologies for a holistic solution.

2.1 Physical Module - Data Collection

The physical module serves as a bedrock for the Hybrid DT, capturing real-world data from the EVs. Sensors measure the relevant data within the battery. In this work, a dataset that replicates real-life data collection was employed. This dataset, from NASA's Ames Prognostics Center, includes Li-ion battery experiments with diverse operational profiles and intentional aging effects. Discharge cycles conclude at end-of-life criteria-30% fade in rated capacity (2 Ah to 1.4 Ah)[8].

2.2 Data Module - Data Pre-processing

A data pre-processing phase occurs after acquiring raw data from the physical module. This involves comprehensive data analysis, outlier detection, exploratory data analysis, handling missing data, and data normalization, as illustrated in Fig. 2. Correlation analysis is also conducted to identify features highly correlated to the battery capacity and can be used in model development.

2.3 Cognitive Module - Model development

The cognitive module is the heart of our methodology, representing the convergence of the two DT approaches to form the Hybrid DT. This module is instrumental in harnessing the strengths of both approaches to achieve accurate and interpretable predictions of battery capacity.

2.3.1 Model-based Digital Twin

The physics that represents the life degradation of a typical Li-ion battery is complex. The end-of-life

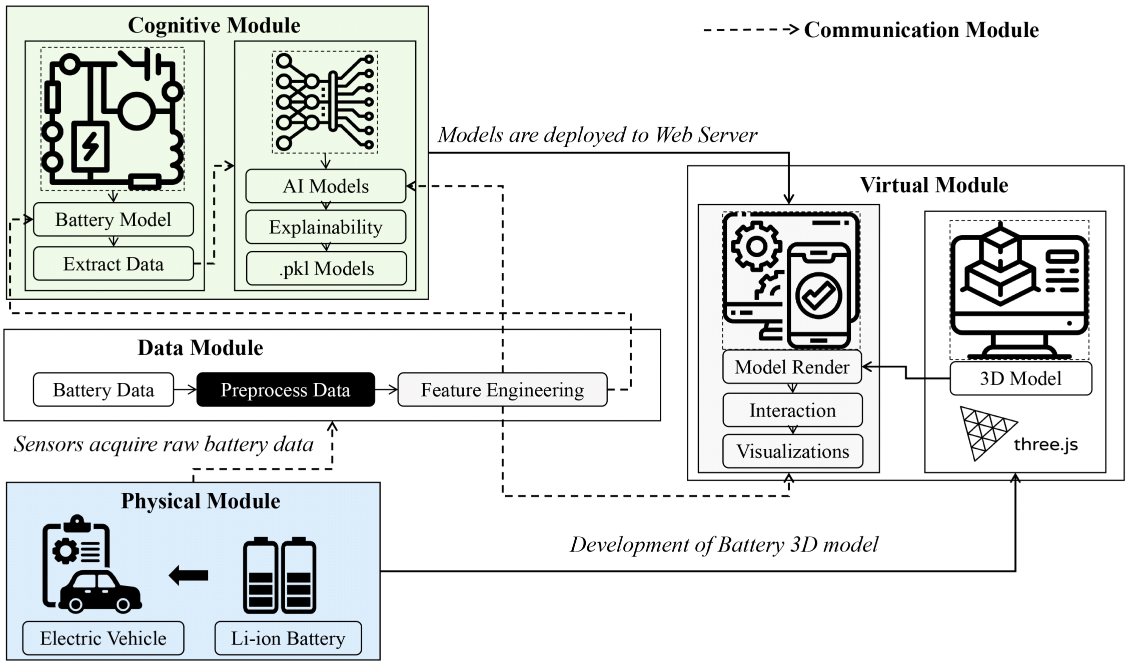


Fig. 1. Architecture of Proposed Web-based Hybrid Digital Twin

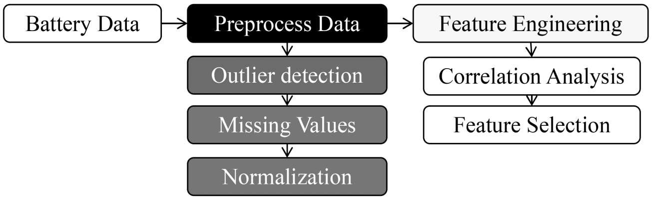


Fig. 2. Process flow of the Data module

of batteries is typically represented as those with 80% availability of their rated maximum capacity. This degradation can be represented using one of the empirical models[20]:

$$L = 1 - (1 - L^{'})e^{f_d}, \tag{1}$$

where: L represents the actual battery lifetime at any given time. L^1 signifies the initial available battery lifetime. f_d characterizes the linearized degradation rate per unit time and cycle[20]. t is the discharge time. δ is the discharge cycle depth, σ is the average cycle state of charge, and T_c is the cell temperature. This formulation enables a dynamic representation of the degradation process over time. The exponential term e^{f_d} accounts for the cumulative impact of degradation, influencing the overall battery health and availability. The linearized degradation rate can thus be represented as:

$$f_d = f_d(t, \delta, \sigma, T_c). \tag{2}$$

Substituting the variable L with battery capacity, C, Eq.1, can be rewritten as:

$$C = C_0 e^{f_d}, \tag{3}$$

where, C is the battery capacity, and C_0 is the initial capacity.

The following approximation can represent f_d.

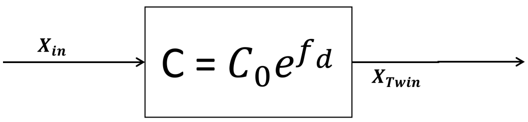


Fig. 3. Model-based Digital Twin

$$f_d = K\frac{i \cdot T_c}{t_i}, \tag{4}$$

where i denotes the charge-discharge cycle, T_c represents the temperature measured in the cell during the cycle, t_i is the discharging time and k is an empirical constant with a fixed value of 0.13[20]. The current and future battery capacity can be determined by passing capacity, temperature, and cycle details through this model. Fig. 3 illustrates the model-based DT.

2.3.2 Data-driven Digital Twin

The data-driven employs ML models to simulate the battery behavior. The models learn from data and identify patterns and relationships that physics-based approaches may overlook. Various ML models can be explored for this purpose. This study employed four ML models: a DNN, LSTM, GNN, and a TNN, as illustrated in Fig. 4.

1. Deep Neural Network (DNN): The model employed in this study comprises three dense layers with 64 units in two layers and 1 units in the last dense layer. All layers were activated using the ReLU activation function.
2. Long Short-Term Memory (LSTM): This model comprises an LSTM layer with 64 units, a dense layer of 64 units, and another dense layer with 1.
3. Graph Neural Networks (GNN): This model comprises a 64 unit embedding layer for graph nodes, a global average pooling layer, and another dense layer with a 1 unit.
4. Transformers Neural network (TNN): The model employed here is composed of a dense layer of 64 units, which provides shared representation for the input sequence, an attention mechanism consisting of attention weights in a dense layer, a flattened layer, *Softmax* activation layer, and

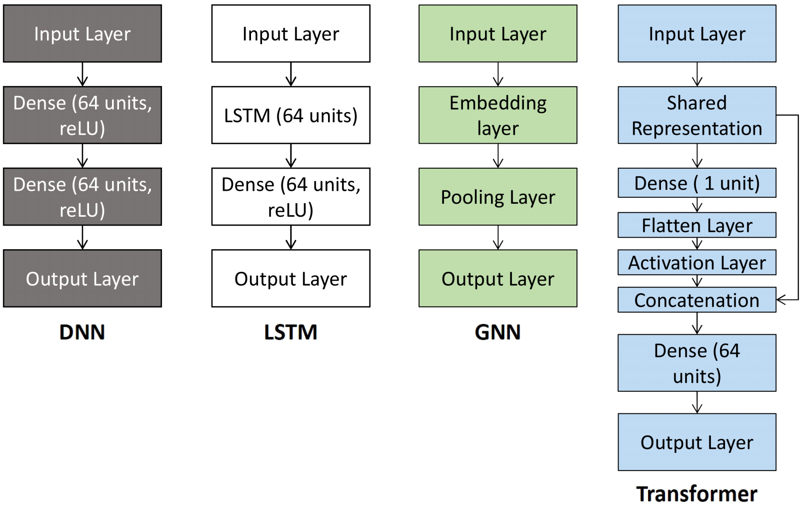


Fig. 4. Data-Driven Digital-Twin Approaches

a concatenation layer. The model terminates with a fully connected dense layer of 64 units and the ReLU activation function.

2.3.3 Hybrid Digital Twin

The model-based and data-driven approaches are combined to form a hybrid digital twin, as illustrated in Fig. 5. To achieve this hybrid, the dataset is transformed by passing the necessary variables through the model-based formulation; then, the ML models are trained to minimize the difference between the model-based twin and the actual battery data. This difference is termed the *residual*. Thus, all models are trained to minimize the mean-squared error function represented as:

$$MSE_{Loss} = \frac{1}{n}\sum_{i=1}^{n}(X_{in,i} - X_{twin,i})^2, \quad (5)$$

where n is the number of data points. $X_{twin,i}$ and $X_{in,i}$ are the predicted value from the model-based twin and the actual value from the real battery data for the *i-th* data point, respectively. As illustrated in Fig. 5, both model-based and data-driven approaches receive the experimental data. The output of the model-based approach serves as part of the hybrid model objective.

Integrating the degradation model within the Hybrid DT allows for a comprehensive understanding of battery health and longevity. The empirical nature of the model ensures adaptability to various scenarios, making it a valuable tool in the realm of battery prognostics and digital twin development. Furthermore, the ML models can adapt to complex and non-linear scenarios of actual battery data.

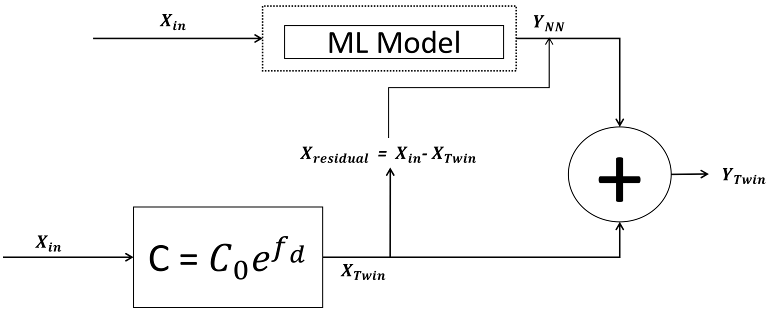


Fig. 5. Hybrid Digital Twin

2.3.4 Explainable Hybrid Digital Twin

We incorporated the LIME XAI approach to shed light on the intricate decision-making process of the DT, thus enhancing its interpretability. LIME creates interpretable models locally around specific instances. For the prediction of capacity (C) at a given cycle (i), the LIME explanation (ϕ) can be approximated as a linear model:

$$\phi_i^L(f) = \arg\min_{\phi \in \Phi} L(f, g_\phi, \pi_i)$$

Here, g_ϕ is a linear model in the local region around cycle i, L is a loss function measuring the difference between the Hybrid DT's predictions and the linear model's predictions. π_i is a proximity measure between cycle i and the instances sampled for LIME. A confidence score can be derived by aggregating coefficients from the explanation for a given instance. A high score indicates high confidence in the model predictions, and a low prediction indicates otherwise. This XAI technique provides valuable insights into how specific cycles contribute to the Hybrid DT's predictions, elucidating the underlying decision mechanisms and facilitating a more transparent interpretation.

2.4 Communication Module

This is the bridge between the physical and subsequent modules of the hybrid DT platform. Its primary role is to ensure the smooth transmission and reception of data. Wireless communication protocols such as MQTT or HTTP may be employed for seamless data transmission. Processed and pre-processed data from the data module are forwarded to the cognitive module for model training and development. Web socket communication was employed in this study.

2.5 Virtual Module

A 3D battery model is created and hosted on this module, along with the hybrid DT model.

This module provides a bridge between the insights gained from the ML models in the cognitive module and the visualization of these insights for analysis and decision-making. Fig. 6 summarizes the logic behind how users can access the web server and create custom DTs.

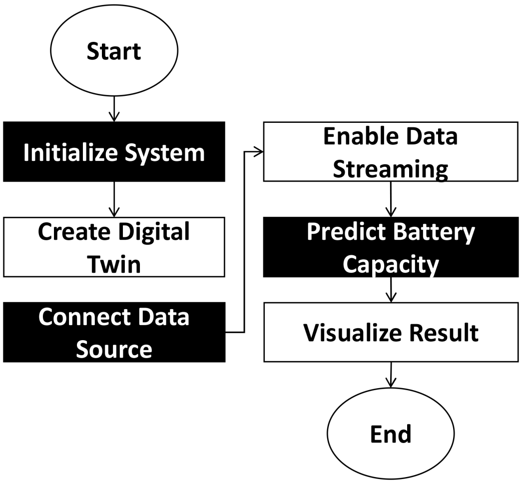


Fig. 6. Process flow of the platform

Web-Based Platform Deployment This aims to make the virtual module accessible to users. An interactive web application was developed using the *Flask* framework for the backend and *React* for the front end.

Development of 3D Battery Models A 3D model was made in the *Blender* software in the *.gltf* format to reproduce the battery in a digital format. By exploring *Three. js* JavaScript library, the 3D model was embedded in the web application.

Integration of Real Data and Simulation Real data is incorporated from the physical module to test the fidelity of the hybrid DT. Diverse scenarios can also be simulated and visualized to examine the impact on battery capacity. Users can input different parameters and observe the corresponding results.

Ⅲ. Performance Evaluation and Results

To analyze the feasibility and explainability of the proposed model, we employed all models independently for all battery types. All models were trained using Google Colaboratory with the NVIDIA Tesla K80 GPU. The best model was saved as a file for deployment to the server.

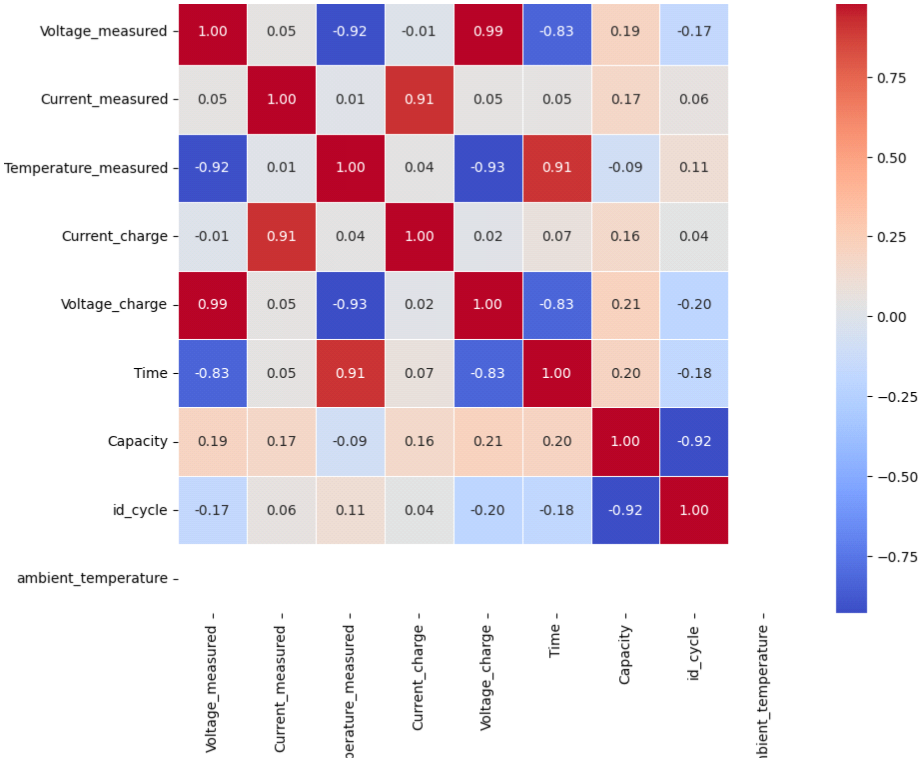


Fig. 7. Correlation Analysis

Results from Data Module Fig. 7 and Table 1 shows the correlation analysis results obtained for Battery B0018. From this result, it is best only to conduct capacity estimation using the capacity data and corresponding cycle, as these features have the best positive and negative correlations.

Results from Cognitive Module After receiving the data from the data module, it was split using a ratio of 80 : 20 for training and validation, respectively. Data from a different battery was then used as a test set. All models were trained to minimize the established loss function, using the *adam* optimizer, for 100 epochs and with a batch size of 20.

Table 1. Features with Highest and Lowest Correlation to Capacity

Feature	Correlation with Capacity
Voltage measured	0.19
Temperature measured	-0.09
Current charge	0.21
Voltage charge	0.21
Time	0.20
id_cycle	-0.92

The model-based and data-driven DTs were evaluated based on MSE, while all hybrid DTs were evaluated on the basis of MSE, latency, and confidence score. Table 2 compares all implemented data-driven DTs with the model-based DT. In analyzing the experimental results, the Model DT demonstrates consistently low MSE values across all batteries, establishing itself as a strong baseline. However, when comparing data-driven approaches, specific observations emerge. The DNN DT variant exhibits higher MSE values, suggesting potential limitations in capturing the underlying patterns of the data. In comparison, the TNN DT incurs the lowest MSE in all batteries.

The data-driven approaches were all independently combined with the model-based DT approach to yield the hybrid variants. The results of this experiment are

Table 2. Comparison of MSE between Model-based DT and Data-driven DT Variants

Battery ID	Model DT	Hybrid DNN	Hybrid LSTM	Hybrid GNN	Hybrid Trans
B0005	0.00880	0.00855	0.00925	0.00805	0.00161
B0006	0.03382	0.04231	0.04324	0.04350	0.00062
B0007	0.00931	0.00323	0.00191	0.00151	0.00095
B0018	0.00947	0.01411	0.0150	0.0151	0.00461

Table 3. Experimental Results Comparing all Variants of the Hybrid DT

Battery ID	Hybrid DNN DT			Hybrid LSTM DT			Hybrid GNN DT			Hybrid TNN DT		
	MSE	Confidence	Latency (s)	MSE	Confidence	Latency (s)	MSE	Confidence	Latency (s)	MSE	Confidence	Latency (s)
B0005	0.00834	0.8991	0.14001	0.00877	0.87562	0.15172	0.00818	0.94526	0.07917	0.00155	0.86589	0.14769
B0006	0.04187	0.80952	0.21979	0.04110	0.89251	0.15288	0.04221	0.95145	0.09328	0.00056	0.82546	0.18940
B0007	0.00126	0.99125	0.22540	0.00154	0.91254	0.15503	0.00147	0.91256	0.13703	0.00081	0.99540	0.39036
B0018	0.01332	0.99357	0.18873	0.01290	0.88521	0.08573	0.01232	0.98255	0.09237	0.00448	0.71015	0.15004

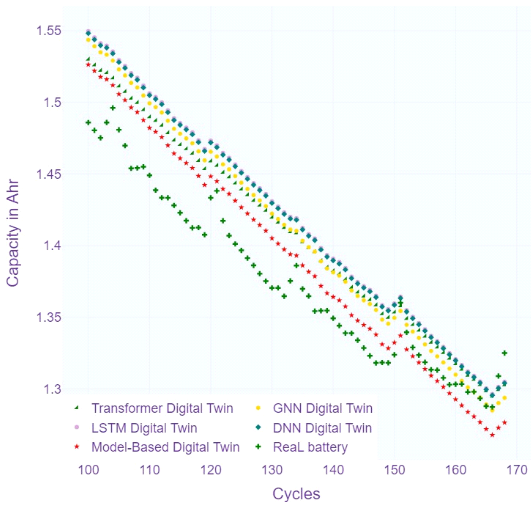


Fig. 8. Comparison of Model and Hybrid Digital Twins for Battery B0005

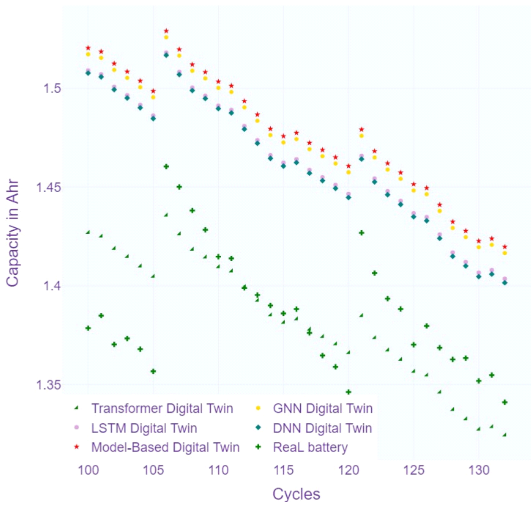


Fig. 9. Comparison of Model and Hybrid Digital Twins for Battery B0018

represented in Table 3. The hybrid LSTM DT variant competes closely with the Model DT in terms of MSE. However, it introduces a slightly higher latency for specific batteries, which warrants careful consideration of the trade-offs between predictive accuracy and computational efficiency. The hybrid GNN DT variant, while showcasing MSE comparable to the Model DT, presents higher latency, which is particularly noteworthy for real-time applications. The hybrid TNN DT variant displays competitive MSE values but is marked by significantly higher latency for select batteries. Regarding explainable AI (XAI) confidence, the hybrid GNN DT for B0007 stands out with high confidence in predictions.

Figs. 8 compares the model and all hybrid DTs. All models in Figs. 8 and 9 were both trained and validated on battery B0005 and tested on B0018 respectively. The results show a competitively close performance across all models.

For results on XAI, we have presented a plot for the explainable model: GNN. Fig. 10 shows an instance prediction by the hybrid GNN DT to highlight the XAI results. The results show a very high confidence score of about 0.8. This is also evidenced by

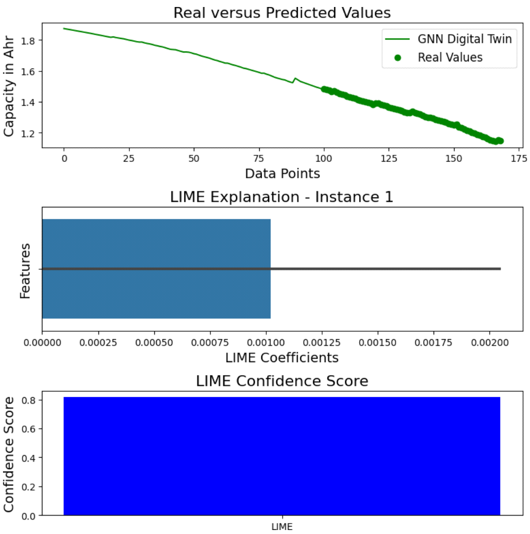


Fig. 10. Explainability result for selected instance on GNN Hybrid DT

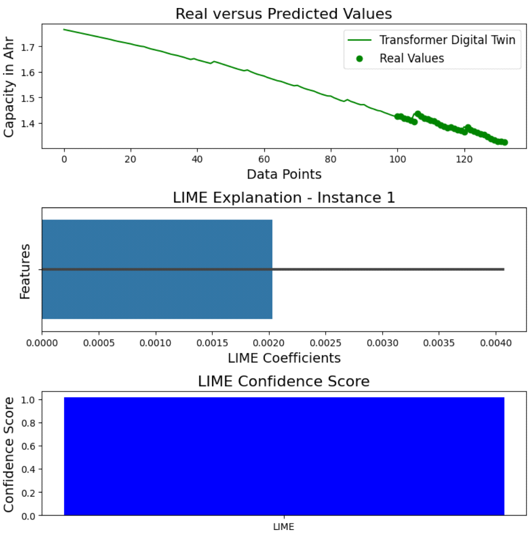
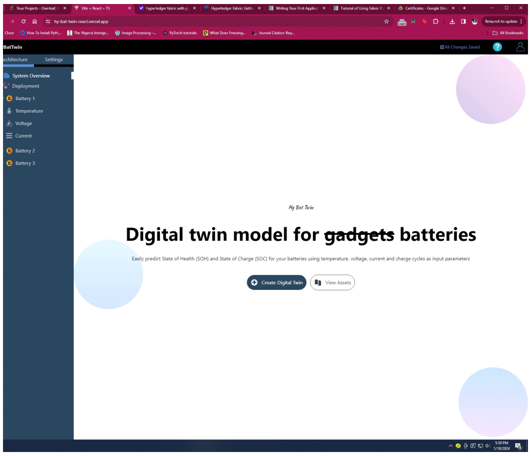


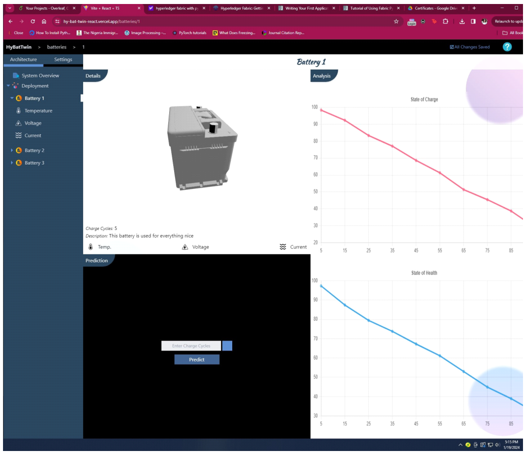
Fig. 11. Explainability result for selected instance on Transformer Hybrid DT

the *Real versus Predicted Values* plot, showing a very accurate prediction for capacity values between cycle 100 and 170. Fig. 11 illustrates a similar result for the Transformer variant. Ultimately, the best approach depends on the specific priorities of the application—balancing predictive accuracy, latency constraints, and the need for explainability.

Results from Virtual Module The GNN Hybrid DT was deployed to the web server for instance-based



a) Menu for creation and customization of digital twin



b) Prediction and analysis using digital twin model

Fig. 12. Web-Based DT Platform for Battery Capacity Estimation

testing. In Fig. 12, a snapshot illustrates the user interface of the web-based platform, providing insight into the interactive experience with a monitored battery.

Ⅳ. Conclusions and Future Works

This study presented early results for a Web-based battery digital twin. The main objective was to address the complexities faced by battery models for developing digital twins. Since battery digital twins can be created from either model-based approaches or data-driven approaches, each with its distinctive merit and constraint, we adopt a hybrid approach. Our hybrid digital twin approach fuses model-based and data-driven methods for precise battery capacity estimation. Enhanced with XAI, our model demonstrated appreciable accuracy and reliability.

Future studies will focus on improving prediction accuracy and latency and exploring more complex physics-based models and data-driven approaches. Future efforts will also focus on ensuring security in the DT space.

References

[1] S. Jafari and Y.-C. Byun, "Prediction of the battery state using the digital twin framework based on the battery management system," *IEEE Access*, vol. 10, pp. 124685-124696, 2022. (https://doi.org/10.1109/ACCESS.2022.3225093)

[2] Y. Qin, A. Arunan, and C. Yuen, "Digital twin for real-time li-ion battery state of health estimation with partially discharged cycling data," *IEEE Trans. Industrial Inf.*, vol. 19, no. 5, pp. 7247-7257, 2023. (https://doi.org/10.1109/TII.2022.3230698)

[3] G. C. Amaizu, J. N. Njoku, J.-M. Lee, and D.-S. Kim, "Security in metaverse: A closer look," in *Proc. KICS Winter Conf.,* pp. 199-200, Pyeongchang, South Korea, 2022.

[4] R. M. Medina, J. N. Njoku, and D.-S. Kim, "Audio-based hate speech detection for the metaverse using cnn," in *KICS Fall 2022*, Gyeongju, South Korea, 2022.

[5] N. Padmawansa, K. Gunawardane, S. Madanian, and A. M. Than Oo, "Battery energy storage capacity estimation for micro-grids using digital twin concept," *Energies*, vol. 16, no. 12, 2023, ISSN: 1996-1073. (https://doi.org/10.3390/en16124540) [Online] Available: https://www.mdpi.com/1996-1073/16/12/4540

[6] J. N. Njoku, C. I. Nwakanma, J.-M. Lee, and D.-S. Kim, "Model comparison and selection for battery digital twin development using pybamm," in *The 33rd JCCI*, 2023.

[7] Y. Merla, B. Wu, V. Yufit, R. F. Martinez-Botas, and G. J. Offer, "An easy-to-parameterise physics-informed battery model and its application towards lithium-ion battery cell design, diagnosis, and degradation," *J. Power Sources*, vol. 384, pp. 66-79, 2018, ISSN: 0378-7753. (https://doi.org/10.1016/j.jpowsour.2018.02.065) [Online] Available: https://www.sciencedirect.com/science/article/pii/S0378775318301861

[8] M. Doyle, T. F. Fuller, and J. Newman, "Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell," *J. The Electr. Soc.*, vol. 140, no. 6, p. 1526, 1993. (https://doi.org/10.1149/1.2221597)

[9] M. Dubarry, D. Howey, and B. Wu, "Enabling battery digital twins at the industrial scale," *Joule*, vol. 7, no. 6, pp. 1134-1144, 2023, ISSN: 2542-4351. (https://doi.org/10.1016/j.joule.2023.05.005 [Online] Available: http://www.sciencedirect.com/science/article/pii/S2542435123001952

[10] J. N. Njoku, R. M. Medina, N. E. Chinaechetam, C. I. Nwakanma, J.-M. Lee, and D.-S. Kim, "Analysis of deep neural networks-based digital twin for lithium-ion batteries," in *KICS Fall Conf.*, pp. 665-666, 2022.

[11] J. N. Njoku, C. I. Nwakanma, and D.-S. Kim, "Explainable data-driven digital twins for predicting battery states in electric vehicles," *IEEE Access*, vol. 12, pp. 83 480-83 501, 2024. (https://doi.org/10.1109/ACCESS.2024.3413075)

[12] N. Kharlamova and S. Hashemi, "Evaluating machine-learning-based methods for modeling a digital twin of battery systems providing frequency regulation," *IEEE Syst. J.*, vol. 17, no. 2, pp. 2698-2708, 2023. (https://doi.org/10.1109/JSYST.2023.3238287)

[13] S. El Fallah, J. Kharbach, J. Vanagas, et al., "Advanced state of charge estimation using

deep neural network, gated recurrent unit, and long short-term memory models for lithium-ion batteries under aging and temperature conditions," *Applied Sci.*, vol. 14, no. 15, 2024, ISSN: 2076-3417. (https://doi.org/10.3390/app14156648) [Online] Available: https://www.mdpi.com/2076-3417/14/15/6648

[14] H. Shen, X. Zhou, Z. Wang, and J. Wang, "State of charge estimation for lithium-ion batteries in electric vehicles by transformer neural network and l1 robust observer," in *2022 American Control Conf.* (*ACC*), pp. 370-375, 2022. (https://doi.org/10.23919/ACC53348.2022.9867247)

[15] X.-Y. Yao, G. Chen, M. Pecht, and B. Chen, "A novel graph-based framework for state of health prediction of lithium-ion battery," *J. Energy Storage*, vol. 58, p. 106437, 2023, ISSN: 2352-152X. (https://doi.org/10.1016/j.est.2022.106437) [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2352152X22024264

[16] K. Q. Zhou, Y. Qin, and C. Yuen, "Graph neural network-based lithium-ion battery state of health estimation using partial discharging curve," *J. Energy Storage*, vol. 100, p. 113502, 2024, ISSN: 2352-152X. (https://doi.org/10.1016/j.est.2024.113502) [Online] Available: https://www.sciencedirect.com/science/article/pii/S2352152X24030883

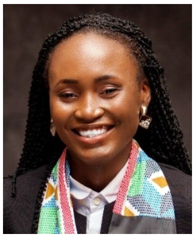
[17] C. Semeraro, H. Aljaghoub, M. A. Abdelkareem, A. H. Alami, M. Dassisti, and A. Olabi, "Guidelines for designing a digital twin for li-ion battery: A reference methodology," *Energy*, vol. 284, p. 128 699, 2023, ISSN: 0360-5442. (https://doi.org/10.1016/j.energy.2023.128699 [Online] Available: http://www.sciencedirect.com/science/article/pii/S0360544223020935

[18] C. I. Nwakanma, L. A. C. Ahakonye, J. N. Njoku, et al., "Explainable artificial intelligence (xai) for intrusion detection and mitigation in intelligent connected vehicles: A review," *Applied Sci.*, vol. 13, no. 3, 2023, ISSN: 2076-3417. (https://doi.org/10.3390/app13031252) [Online] Available: https://www.mdpi.com/2076-3417/13/3/1252

[19] S. Suhail, M. Iqbal, R. Hussain, and R. Jurdak, "Enigma: An explainable digital twin security solution for cyber-physical systems," *Comput. in Industry*, vol. 151, p. 103961, 2023, ISSN: 0166-3615. (https://doi.org/10.1016/j.compind.2023.103961) [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0166361523001112

[20] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, "Modeling of lithium-ion battery degradation for cell life assessment," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1131-1140, 2018. (https://doi.org/10.1109/TSG.2016.2578950)

Judith Nkechinyere Njoku



Dec. 2014 : B.Eng. Petroleum Engineering, Federal University of Technology, Owerri, Nigeria

Aug. 2021 : M.Sc. Aeronautics, Mechanical and Electronics Engineering, Kumoh National Institute of Technology, Gumi, South Korea

Apr. 2017-Aug. 2019 : Analyst, Sterling Bank PLC, Nigeria

Sept. 2019-Aug. 2021 : Researcher, Future Communications Systems Laboratory, Kumoh National Institute of Technology, South Korea

Jan. 2022-Current : Researcher, ICT Convergence Research Center, Kumoh National Institute of Technology, South Korea

<Research Interests> Digital Twin, Data-driven Intelligent Transportation Systems (DDITS), Signal Processing, Sensor Fusion, Metaverse for Industry.

[ORCID:0000-0002-2294-9204]

Anthony Uchenna Eneh

Dec. 2014 : B.Eng. Electrical & Electronic Engineering, Federal University of Technology, Owerri, Nigeria

Aug 2022-Present : Frontend Engineer, Africhange Technologies, Nigeria

June 2021-July 2022 : Frontend Engineer, Evolutics Technologies, Nigeria

Oct. 2019-May 2021 : Software Engineer, Telixia Limited, Nigeria

<Research Interests> Artificial Intelligence, Machine Learning.

[ORCID:0009-0000-6339-3225]

Cosmas Ifeanyi Nwakanma

May 2005 : B.Eng. Electrical/ Electronics Engineering, Federal University of Technology, Owerri, Nigeria

Oct. 2012 : M.Sc. Information Technology, Federal University of Technology, Owerri, Nigeria

Feb. 2016 : MBA Project Management Technology, Federal University of Technology, Owerri, Nigeria

Feb. 2022 : Ph.D. IT-Convergence Engineering, Kumoh National Institute of Technology, Korea

Apr. 2009-Feb 2022 : Lecturer, Department of Information Technology, Federal University of Technology, Owerri, Nigeria

Mar. 2022-Current : Postdoctoral Research Fellow, Kumoh National Institute of Technology, Korea

<Research Interests> Explainable AI, Metaverse, Intrusion detection, Smart IoT Applications, Communication Engineering.

[ORCID:0000-0003-3614-2687]

Jae-Min Lee

2005 : Ph.D. Electrical and Computer Engineering, Seoul National University, Seoul, Korea

2005-2014 : Senior Engineer, Samsung Electronics Engineering, Suwon, Korea

2015-2016 : Principal Engineer, Samsung Electronics Engineering, Suwon, Korea

2017-Current : Associate Professor, School of Electronic Engineering, Kumoh National Institute of Technology, Gyeongbuk, Korea

<Research Interests> Blockchain, TRIZ, Smart IoT convergence Application, industrial wireless control network, UAV, Metaverse.

[ORCID:0000-0001-6885-5185]

Dong-Seong Kim

2003 : Ph.D. Electrical and Computer Engineering, Seoul National University, Korea.

2003-2004 : Postdoctoral researcher, Cornell University, NY, USA

2007-2009 : Visiting Professor, The University of California, Davis, CA, USA

2004-Current : Professor, Kumoh National Institute of Technology (KIT), Gyeongbuk, Korea

2014-Current : Director, ICT Convergence Research Center, KIT, Gyeongbuk, Korea

2017-2022 : Dean, Industry-Academic Coopera- tion Foundation and Office of Research (ICT), KIT, Gyeongbuk, Korea

2022-Current : CEO, NSLab co. Ltd., Korea

<Research Interests> Blockchain, Metaverse, Industrial IoT, real-time systems, industrial wireless control network, 5G+, and 6G.

[ORCID:0000-0002-2977-5964]