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Research Article

Digital twin and metaverse-enhanced battery management for electric vehicles

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ABSTRACT

The Internet of Things (IoT) and cyber–physical systems (CPS) are driving digital transformation and automation. An essential component of CPS is digital twin (DT) technology, which enables real-time synchronization between physical assets and their virtual counterparts. Battery management systems (BMS) in electric vehicles (EVs) face challenges in handling large volumes of sensor data, often leading to reduced accuracy in battery-state estimation. To address these challenges, DTs have been explored to aid real-time diagnosis and monitoring. One critical step toward the success of DTs is to have practical reference architectures. This paper presents proposes a novel six-layer DT architecture tailored for BMS, extending existing CPS/DT-BMS models by integrating high-fidelity electrochemical modeling, robust nonlinear state estimation, and interactive 3D visualization in a Metaverse environment. The architecture is designed with scalability in mind, supporting deployment on lightweight embedded platforms or via cloud-hosted rendering for resource-limited devices. We validate the approach using MATLAB to develop a thermally coupled SPMe-based DT of a lithium-ion NMC battery, synchronized with a virtual battery model in Unreal Engine for immersive visualization. Experimental results demonstrate accurate state-of-charge estimation (RMSE 0.23%) and low-latency real-time monitoring, highlighting the framework's potential for deployment in large-scale EV BMS applications.

1. Introduction

In recent years, rapid advancements in technology have ushered in an era of unprecedented digital transformation and automation [1]. Key technologies like the IoT and CPS are at the forefront, shaping how we interact with the digital world and revolutionizing industries across the board. At the heart of the digital revolution, CPS plays a pivotal role in creating seamless connections between physical objects and the digital realm. CPS amalgamates the physical and virtual worlds, paving the way for innovative applications and enhanced experiences.

A crucial enabler of CPS is the groundbreaking DT technology, garnering immense attention and interest from researchers and industries alike. The concept of DT is a remarkable innovation that holds tremendous promise for bridging the gap between the physical and virtual domains. A DT is a virtual representation of a real-world object, system, or process. It simulates its physical counterpart's real-world behavior, characteristics, and interactions. By mimicking real-world objects virtually, DTs provide valuable insights, optimize performance, and enable predictive maintenance across various sectors.

Beyond its remarkable potential in CPS, DT technology has embraced another revolutionary advancement: The Metaverse. The Metaverse, originally a concept from science fiction, has evolved into a tangible reality [2]. It refers to an interconnected virtual space where users interact with each other and digital entities in real time [3]. This technological advancement holds significant potential for various systems, including BMS. BMSs are crucial in optimizing battery performance and lifespan across diverse applications, such as EVs, mobile robots, and portable devices [4]. Monitoring battery conditions, including state of charge and health, is a fundamental function of BMSs to enable timely proactive actions [5].

Motivation - A significant challenge with traditional BMSs is their limited onboard memory capacity, hindering the real-time processing of extensive data sets [6]. Consequently, they can only access limited data, leading to inaccurate battery state estimates [7]. To address this limitation and advance BMS technology, researchers have explored the concept of DT.

A DT is a virtual counterpart that replicates the behavior of a physical object [8]. This concept becomes essential for BMS

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Table 1
Comparison of this study with related works to highlight contributions.

Ref	Year	State estimation	Reference architecture	BMS	DT	Metaverse	Real-time
[11]	2020	✓	×	✓	✓	×	×
[13]	2020	✓	×	✓	✓	×	×
[9]	2022	✓	✓	✓	✓	×	✓
[14]	2022	✓	✓	✓	✓	×	×
[16]	2022	×	✓	×	✓	✓	×
[17]	2023	×	✓	×	✓	✓	×
[18]	2024	×	✓	✓	✓	×	×
[19]	2024	✓	×	✓	✓	×	×
This study	2025	✓	✓	✓	✓	✓	✓

The ✓ indicates the feature is included.
The × indicates the feature is not included.

improvement, as Li-ion batteries exhibit highly non-linear characteristics, complicating the development of accurate state estimation algorithms. DTs can create virtual replicas of such intricate systems, enabling simulation to avoid exhaustive experimentation on physical objects [5,9]. An ideal digital BMS encompasses a virtual battery mirroring the fundamental battery dynamics, state estimation algorithms, continuous data exchange between batteries, and battery performance visualization [10]. As cutting-edge technologies, like the Metaverse and DT, are explored for system optimization, the BMS industry naturally embraces these innovations.

In recent times, integrating DT technology with BMS has gained significant attention [7]. DTs offer virtual representations of physical objects or systems, facilitating real-time monitoring [3]. Various approaches have been explored, ranging from cloud-based DTs with state estimation in cloud environments [11] to AI-based algorithms for DT creation [12,13], and physics-based or electrochemical models simulating battery behavior [14,15]. Synchronization between digital and physical batteries enables diverse scenario simulations and predictions of battery behavior.

Accurate state of charge (SoC) estimation is critical for effective battery management [20]. Traditionally, SoC estimation methods employ mathematical models and filtering algorithms, including the Kalman filter and its variants [21]. While more advanced models like machine and deep learning approaches exist, filter methods remain popular for their computational efficiency and accuracy [22].

Furthermore, a critical step towards the success of DTs is the establishment of practical reference architectures. These references provide a structured approach for developers, guiding them in building efficient and scalable systems within the Metaverse. By offering clear guidelines and best practices, reference architectures promote collaboration, standardization, and innovation within the Metaverse community. They empower developers to focus on building novel functionalities and applications, driving the evolution of a decentralized, user-centric systems that thrives on openness, innovation, and inclusivity. Unlike prior CPS-oriented DT-BMS architectures [7,9,19] which focus on cloud-hosted or model-specific implementations, our six-layer design uniquely integrates high-fidelity electrochemical modeling, real-time nonlinear state estimation, and immersive 3D visualization into a unified, scalable architecture. In contrast to [18], which presents a DT-based BMS without immersive interaction, our framework enables bidirectional engagement in the Metaverse, supporting real-time anomaly detection and scenario simulation.

Contribution - This article presents the following contributions:

(1) A novel six-layer DT architecture for BMS that extends existing CPS/DT-BMS frameworks with an integrated immersive visualization and interaction layer.
(2) Development of a DT using a thermally coupled single Particle Model with electrolytes (SPMe) model in MATLAB, accurately replicating real battery behavior.
(3) Integration of a Unscented Kalman Filter (UKF)-based state estimation approach for improved nonlinear prediction accuracy.
(4) Implementation of an interactive 3D visualization of battery states in the Metaverse using Unreal Engine.
(5) Scalability considerations enabling deployment in both embedded and cloud-hosted environments.
(6) Experimental validation of the system on a toy-scale vehicle, showing low-latency (under 200 ms) real-time interaction and high SoC estimation accuracy (root mean square error (RMSE) of 0.23%).

While traditional BMS and DT-based BMS studies exist in the literature, none have integrated real-time 3D Metaverse visualization with state estimation as demonstrated in this work. As such, direct numerical baselines are not readily available for comparison. To address this, Table 1 highlights the feature-level comparison of our proposed framework with related works, emphasizing its novelty and unique contributions. In addition, our reported SoC estimation accuracy (RMSE 0.23%) and low-latency Metaverse interactions provide evidence of superior performance relative to traditional Kalman filter-based BMS implementations, which typically exhibit higher RMSE values (0.5–1.2%) [21].

The rest of this paper is organized as follows: The preliminaries are introduced in the next section. Section 3 introduces the framework for the implemented Metaverse and DT-assisted system. In Section 4, the experiment procedure and the results obtained were presented. Finally, the paper is concluded in Section 5.

2. Preliminaries

2.1. Battery models

Various electrochemistry or physics-inspired models have been explored for representing the behavior of lithium-ion batteries, including (i) The Doyle-Fuller Newman model (DFN), (ii) The Single Particle Model (SPM), and (iii) The SPMe. This subsection discusses each of these models and their respective advantages and disadvantages.

2.1.1. The Doyle-Fuller Newman model (DFN)

The DFN model is a widely adopted lithium-ion battery simulation approach that accurately characterizes the intricate interplay between the battery's current and voltage dynamics, capturing solid-state and electrolyte diffusion phenomena [23]. The movement of lithium ions within the electrolyte adheres to Fick's law of diffusion, augmented by the intercalation current density term denoted as J, which facilitates the efficient transfer of Li-ions between the solution and the solid electrode. This intricate relationship is mathematically expressed as

$$\varepsilon_2 \frac{dc_2}{dx} = \nabla \cdot \left(\mathrm{d}2^{eff} \nabla c2\right) + \frac{1-t}{F} J, \quad (1)$$

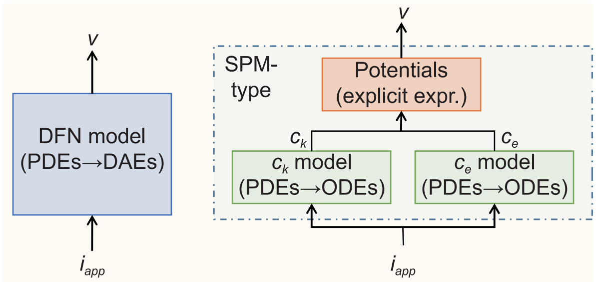

Fig. 1. A block diagram of the three electrochemical models.

where: ε_2 represents the electrolyte volume, $\frac{dc_2}{dx}$ signifies the spatial concentration gradient of lithium ions, ∇ represents the gradient operator, d_2^{eff} stands for the effective diffusion coefficient of lithium ions in the electrolyte, t denotes time, F is Faraday's constant, J symbolizes the total intercalation current density, and c_2 signifies the concentration of Li-ions in the electrolyte. The primary intercalation reaction between the current density J_1 is governed by the Butler–Volmer equation, given as

$$J_1 = a_i i_{0,j} \left[\exp\left(\frac{\alpha_{a,j} F}{\overline{RT}} \eta_j\right) - \exp\left(-\frac{\alpha_{c,j} F}{\overline{RT}} \eta_j\right) \right], \tag{2}$$

where: J_1 denotes the intercalation current density, a_i represents the surface area per unit volume of the electrode, $i_{0,j}$ stands for the exchange current density of the electrode, $\alpha_{a,j}$ and $\alpha_{c,j}$ are the anodic and cathodic transfer coefficients, respectively, $\overline{RT}$ signifies the product of the universal gas constant and temperature, η_j represents the overpotentials of the negative or positive electrode. Furthermore, the solid potential is governed by Ohm's law, where:

$$\nabla \cdot \left(\sigma_j^{eff} \nabla \phi_{i,j} - J\right) = 0, \tag{3}$$

with: σ_j^{eff} representing the effective electrical conductivity of the solid electrode, and $\phi_{i,j}$ denoting the electric potential in the solid electrode. The DFN model is composed of several coupled partial differential equations (PDEs) which can be computationally expensive to solve. Thus, they are converted differential–algebraic equations (DAEs) as illustrated in Fig. 1 [24].

2.1.2. The Single Particle Model (SPM)

SPM is another widely used model in lithium-ion battery simulations. It provides a simplified representation of the complex electrochemical processes occurring within a single active material particle in the battery [23].

In the SPM, the battery electrode particle is treated as a single entity with uniform properties. The model characterizes the spatial variations of lithium concentration within the particle, along with its corresponding electric potential [25]. The governing equations are usually ordinary differential equations (ODEs) that describe the time-dependent evolution of the state variables. Specifically, the SPM considers: Li-ion diffusion, electrochemical Reactions, and solid-electrolyte interface formation [26].

2.1.3. The Single Particle Model with electrolytes (SPMe)

The SPMe is an extension of the SPM that incorporates the presence of the electrolyte within the battery [27]. The SPMe provides a more comprehensive representation of the lithium-ion battery's behavior, considering the interactions between the electrode particles and the surrounding electrolyte [25].

2.2. State-of-Charge (SoC) estimation

The SoC of a battery is typically defined as the available electric charge of a battery, expressed as a percentage of its rated electric charge;

$$SoC(t) = \frac{Q(t)}{Q_0}, \tag{4}$$

It is essentially a thermodynamic quantity that helps in assessing the potential energy of the battery. This section discusses three main algorithms for determining a battery's SoC.

2.2.1. Kalman Filter (KF)

The Kalman Filter (KF) is a powerful algorithm employed for estimating the internal states of dynamic systems [21]. It offers a recursive approach to predict the SoC and relies on a state space model, which is represented by the state estimation model:

$$x(k+1) = Ax(k) + Bu(k), \tag{5}$$

where: $x(k)$ is the state vector at time step k, representing the internal states of the system. A is the state transition matrix, describing how the state evolves from one time step to the next. B is the input matrix, denoting the effect of the control input $u(k)$ on the state.

2.2.2. Extended Kalman Filter (EKF)

The Extended Kalman Filter (EKF) algorithm is an extension of the Kalman Filter designed to handle non-linear systems [21]. It achieves this by linearizing the mean and covariance of the state estimate. The EKF algorithm is characterized by the following state transition model:

$$x_t = f(x_{k-1}, u_k) + w_k, \tag{6}$$

where: x_t represents the updated state estimate at time step k. f is the non-linear state transition function, which maps the previous state x_{k-1} and control input u_k to the updated state estimate x_t. w_k denotes the process noise, representing uncertainties or disturbances in the system during the state transition.

2.2.3. Unscented Kalman Filter (UKF)

The UKF algorithm employs a sampling technique known as the unscented transformation to select sample points termed "sigma points" around the mean [28]. It provides an alternative approach for state transition in non-linear systems. These sigma points are generated and passed through a function to calculate the resulting sigma points, which are used to approximate the mean and covariance of the state estimate.

The calculation of sigma points involves the following steps:

(1) Weight Calculation:

$$\sum_k w_k = 1, \tag{7}$$

where w_k are the weights assigned to each sigma point. The sum of all weights is set to 1 to ensure proper normalization.

(2) Mean Calculation:

$$\text{mean} = x = \sum_k w_k x_k, \tag{8}$$

where: x represents the mean of the state estimate. x_k denotes the sigma points.

(3) Covariance Calculation:

$$\text{covariance} = P = \sum_k w_k (x_k - x)(x_k - x)^{\mathrm{T}}, \tag{9}$$

where: P represents the covariance matrix of the state estimate. $(x_k - x)$ is the difference between the sigma point and the mean. $(x_k - x)^T$ is the transpose of the difference vector.

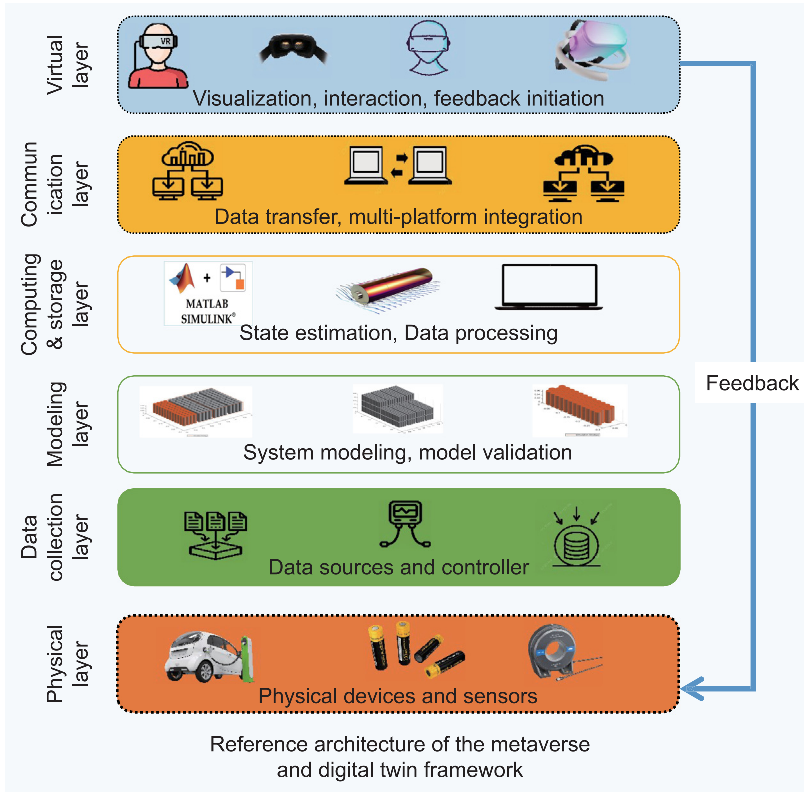

Fig. 2. The proposed DT framework and reference architecture.

2.3. Modeling environments

This subsection introduces the various modeling environments and tools that were used in this paper.

2.3.1. PyBaMM

Python Battery Mathematical Modeling (PyBaMM) is a Python package designed to facilitate rapid and versatile simulations of battery models. It accomplishes this by solving physics-based electrochemical models formulated as DAEs and ODEs [29]. PyBaMM's architecture relies on two fundamental components: Expression trees and a pipeline process.

PyBaMM uses expression trees to represent mathematical equations in symbolic form. By combining expression trees and the pipeline process, PyBaMM streamlines the simulation process, making it fast and adaptable.

2.3.2. MATLAB

MATLAB is a widely-used programming environment and numerical computing platform that offers powerful tools for various scientific and engineering applications. Within MATLAB, two notable subprograms, Simulink and Simscape, cater to specific aspects of system modeling and simulation [30,31]. Simulink is a block diagram environment integrated into MATLAB, primarily focused on modeling and simulating dynamic systems using a graphical interface. Simscape is another powerful simulation tool integrated into MATLAB, specifically designed for modeling multi-domain physical systems. The Simscape environment enables encapsulating the electrochemical and thermal battery equations into modular components, which can be deployed both in high-performance computing environments and in embedded platforms, aligning with our goal of scalable DT deployment.

2.3.3. UnrealEngine

Unreal Engine is a cutting-edge game development platform developed by Epic Games. It offers a comprehensive set of tools and functionalities for creating high-quality and immersive video games, virtual reality experiences, and augmented reality applications. Unreal Engine is renowned for its stunning graphics, realistic physics simulation, and robust real-time rendering capabilities. By leveraging on its BluePrints visual scripting, interactions can be enabled within virtual environments and connections with external systems can be established [32].

These modeling and estimation components form the foundation of our proposed six-layer DT architecture. By combining a computationally efficient TSPMe model, a robust UKF-based estimator, and a flexible visualization environment, the system supports accurate real-time battery monitoring while maintaining scalability from prototype platforms to full commercial EV implementations.

3. Dt framework and methodology

This section introduces the proposed DT framework and the methodology adopted in this study.

3.1. Dt framework

The proposed DT framework comprises six distinct layers, as shown in Fig. 2. This subsection provides an overview of each layer's role in the process, from capturing data from physical devices to visualizing their states and conditions. This architecture is designed for deployment in both high-performance and lightweight/cloud-hosted environments.

3.1.1. Layer 1- physical layer

The foundational layer of the architecture is the physical twin. It includes the various physical devices, such as vehicles, batteries, sensors, and actuators onboard the vehicle. The physical twin serves as the real-world representation of the physical entities within the system.

3.1.2. Layer 2- data collection layer

This layer acts as the sensor that enables gathering essential data and information from the physical entities. This layer can be combined with the first layer and plays a pivotal role in collecting and capturing essential data and information directly from these physical devices.

3.1.3. Layer 3-modeling layer

At the heart of the DT framework lies the modeling layer, a crucial stage that covers all system modeling activities. Here, meticulous efforts are dedicated to developing and refining models that serve as digital shadows of the batteries.

These digital shadows are essentially intricate representations of the actual batteries, captured in virtual form. Through rigorous development and validation processes, these models accurately replicate the behavior, characteristics, and functionalities of their real-world counterparts.

Once the models reach a level of robustness and accuracy, they become deployable assets for the subsequent layer. The information and insights derived from these digital shadows form the basis for advanced simulations, predictive analysis, and informed decision-making in the DT ecosystem.

3.1.4. Layer 4- computing and storage layer

Layer 4 serves as a vital hub within the DT framework. At this stage, the digital model of the battery is securely stored, and essential battery state estimations are carried out. The digital model, created and refined in the previous layers, finds its home in this computing and storage layer. By housing the digital model, the system ensures seamless accessibility and efficient processing of data whenever required. This digital representation serves as the core reference point for all subsequent simulations, analyses, and optimizations.

A key function of this layer is battery state estimation. Leveraging the power of the digital model, real battery current data is intelligently parsed through the DT. This enables the system to perform precise and accurate computations, resulting in highly reliable state estimations.

3.1.5. Layer 5- communication layer

The Communication Layer, residing at the heart of the DT framework, serves as the vital conduit for seamless data exchange and interaction. At this stage, the DT system establishes a network of communication channels, connecting the digital model with real-world devices and external systems.

The primary objective of Layer 5 is to enable the smooth flow of information between the physical and digital realms. It facilitates bidirectional communication, ensuring that the DT receives real-time data from the physical twin while also providing the means to disseminate insights and control instructions back to the physical devices. This layer is also responsible for establishing a connection to the virtual and visualization layers.

3.1.6. Layer 6- virtual layer

The culminating layer of the DT framework is an immersive and visionary stage - the visualization Layer. Here, the state of the battery and its intricate details come to life within the metaverse environment. In this environment, users can access a 3D experience and interaction with the battery. They can effortlessly engage with specific batteries that have been seamlessly connected with their corresponding physical twins.

Unlike prior CPS or DT-BMS frameworks which typically integrate sensing, computation, and visualization in loosely coupled or cloud-only pipelines, our six-layer architecture explicitly separates the modeling, computing/storage, and immersive visualization layers. This separation enables modular upgrades, distributed deployment (edge/cloud), and direct integration with real-time 3D environments. Furthermore, compared to [18,19], which also implements a DT-BMS, our framework uniquely incorporates a bidirectional communication layer optimized for low-latency physical–digital synchronization and supports immersive, interactive visualization for both diagnostics and decision-making.

3.2. Methodology

To validate the architecture, we implemented it on a scaled-down robotic EV platform and synchronized a MATLAB-based TSPMe battery DT with an Unreal Engine–based visualization environment. The following subsections describe the process from data selection to real-time visualization. The system model shown in Fig. 3 illustrates the entire framework of the proposed system, in line with the predefined DT architecture. Fig. 4 is a simplified diagram that describes the steps followed to develop the DT.

3.2.1. Data selection

The first step in the methodology is the selection of appropriate datasets. By leveraging on previous research conducted by [23], which already validated parameters for lithium battery modeling, the dataset was selected. The data is based on a commercial LG M50 cell with temperature settings of 0 °C, 10 °C and 25 °C [33]. The data includes battery current, temperature, and voltage.

3.2.2. Model selection

To create a digital battery that can mimic the physical battery's behavior with minimal error, it is very important to consider the model to be used [33]. The aim of this step was to simulate different battery models and select the one that most accurately represents the battery data, based on R^2 and root-mean-squared error (RMSE) metrics. The PyBaMM programming environment was used. Battery current data was passed through the models to predict other parameters like voltage and temperature. Six different battery models were simulated, including SPM, TSPM, SPMe, thermally coupled SPMe (TSPMe), DFN, and thermally coupled DFN (TDFN). The battery model that best replicates the behavior of the real battery was then used to develop the battery DT. The results of this experiment are presented in Section 4.

3.2.3. Dt model development

The battery DT model was developed in MATLAB using the Simscape battery library. This library enables complex equations to be organized into components for easy packaging and execution. All equations used were obtained from [23]. By following the SPMe model, the relevant equations were used to set up the Simscape battery model. To verify that this model accurately portrays the characteristics of the battery, current data of the real battery is channeled to flow through the Simscape DT battery.

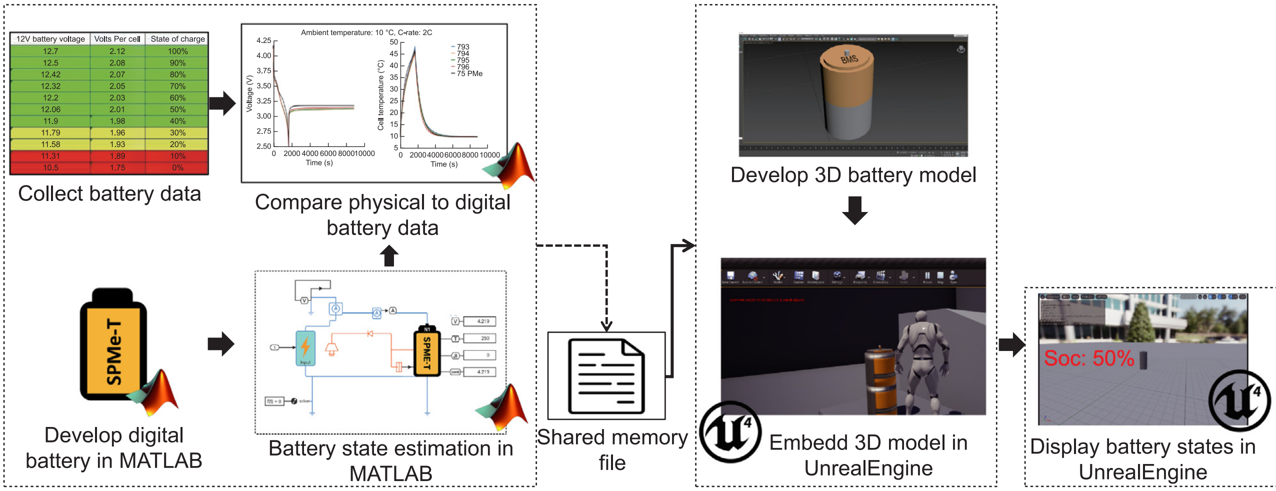

Fig. 3. System model of the proposed DT and Metaverse assisted BMS.

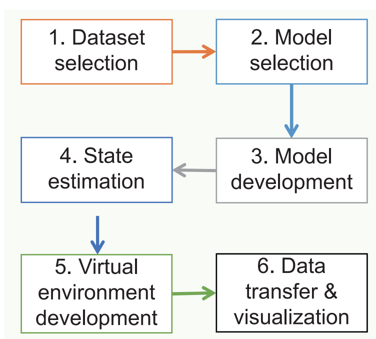

Fig. 4. The DT development process Flow.

3.2.4. State estimation

The state estimation process was conducted using variants of EKF and UKF.

(1) Extended Kalman Filter for State Estimation
(2) UKF for State Estimation
(3) Bucy Variants of EKF and UKF: The Bucy variant is a continuous-discrete Kalman filter as opposed to the regular filter which is for non-linear system dynamics. It is modeled using differential equations.

3.2.5. Metaverse environment development

In this step, the Metaverse environment for visualizing the batteries and their respective statuses is developed using the Unreal Engine platform. Creating the virtual environment for battery state visualization involved the utilization of Unreal Engine's BluePrints tool. The process began with the construction of a 3D representation of the battery components, embedding this 3D model in Unreal Engine and enabling an interactive environment.

Unreal Engine's BluePrint system enabled the implementation of user interactions, such as dissecting the battery, zooming in on components, and triggering animations to showcase different states.

3.2.6. Data transfer and visualization

The battery's predictive data generated in MATLAB was integrated into the Unreal Engine environment through a shared memory file. By using the BluePrints function, the contents of the shared memory file can be visualized in the Metaverse environment. The visualization components translated the received data into visual cues that accurately represented the battery's predicted states. To visually understand the battery state, certain conditions were set in place; The battery also alters its color based on the specific battery state.

4. Results & discussions

4.1. Results

4.1.1. Model selection

Three distinct electrochemical models were simulated and compared in this study. Each model was evaluated in two variations, considering temperature effects (thermal coupling) and without. The simulation process involved using PyBaMM, where the real battery's current was passed through the models to predict battery voltage and cell temperature. This was conducted under conditions similar to real-world battery data. Model parameters were sourced from the work of Brosa Planella et al. [23], with specific parameters highlighted in Table 2. Table 3 presents the results derived from all six model implementations. Notably, the thermally coupled DFN model demonstrated the highest accuracy in terms of temperature (R^2) and the lowest temperature RMSE, albeit with a longer processing time. Following this, the thermally coupled model exhibited a commendable balance between processing time and voltage prediction accuracy. As a result, the TSPMe model was selected as the optimal choice for the battery's dynamic thermal model. While the thermally coupled DFN achieved slightly higher temperature accuracy, its 23 ms computation time per step is unsuitable for our real-time architecture. TSPMe provides a favorable trade-off between accuracy and execution speed, making it more compatible with the computing/storage layer in our six-layer design

4.1.2. Experimental setup for EV dt

To validate the proposed DT and Metaverse-enhanced battery management architecture within an EV context, a physical testbed was developed, as shown in Fig. 5. The setup consists of three core components:

(1) EV Platform: A small-scale wheeled robot simulates an EV equipped with a Raspberry Pi, a motor driver, a Li-ion battery, and sensors for current, voltage, and temperature. This embedded setup enables real-time data acquisition during operation.

Table 2
Electrochemical and thermal parameters used in the simulation.

Symbol	Meaning	Units	Value
h	Heat exchange coefficient	Wm^{-1}	20
k	Thermal conductivity	Wm^{-1}	1.05
θ	Volumetric heat capacity	m^{-3}	2.85×10^6
T_{AMB}	Ambient temperature	K	298
L_{batt}	Battery length scale	m	1×10^{-2}
a_{cool}	Cooling surface density	m^{-1}	219.42
F	Faraday constant	C	96 485
i_{app}	Applied current density	Am^{-2}	$48.69C$
R	Gas constant	mol^{-1}	8.314
t^+	Transfer number	–	0.2594

The – indicates the parameter is dimensionless (no units).

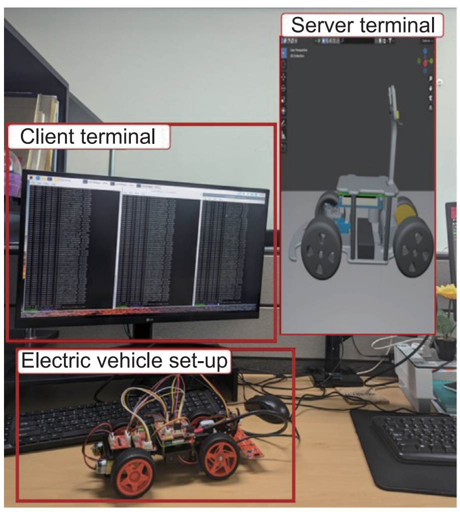

Fig. 5. Experimental setup of the EV platform.

(2) Client Terminal: Running on a local computer, the client terminal is responsible for capturing sensor data and transmitting it using MQTT/HTTP protocols to a cloud-hosted server. It also executes battery state estimation algorithms (e.g., UKF), simulating the real-time processing layer of the DT.
(3) Server Terminal: Hosted on a high-performance machine, the server runs a Metaverse-based DT environment built using Unreal Engine. The vehicle's 3D model is synchronized with live data, allowing users to visually inspect battery states, simulate anomalies, and interact with system metrics in an immersive virtual space.

4.1.3. Model development

By utilizing the established mathematical formulations governing the TSPMe, as predefined in Section 2, we leveraged the Simscape library to engineer a comprehensive battery model. Building upon the foundation set by [34], a simplified battery cycling apparatus and an Electrical source were integrated into the framework. Drawing inspiration from their battery development demonstration, we proceeded to meticulously formulate the TSPMe battery model.

These equations, alongside supplementary formulations, were meticulously sourced from the study by Taheri et al. [35], ensuring a robust theoretical foundation. Furthermore, critical parameters essential for the battery model's fidelity were meticulously derived from [36].

4.1.4. State estimation

In this study, four different Kalman filtering approaches were compared, for estimating the SoC of the developed battery DT, including, (i) EKF, (ii) Extended Kalman-Bucy Filter (EKBF), (iii) UKF, and (iv) Unscented Kalman-Bucy Filter (UKBF). The entire evaluation framework was realized within the Simulink environment. All models achieved an overall RMSE of 23.45, 23.34, 0.23 and 5.45 respectively, highlighting UKF as the best algorithm for estimation (Table 4).

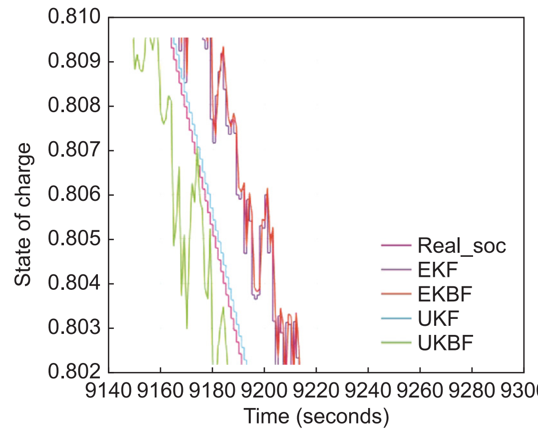

Fig. 6. Comparison of all filters for SoC estimation.

Visualized in Fig. 6, the performance assessment showed that the UKF approach as the one most closely aligned with actual battery SoC prediction. UKF's low RMSE and moderate computational cost make it suitable for both high-performance systems and low-power embedded hardware. This aligns with our goal of enabling deployment in commercial EVs where onboard computing resources are constrained. Consequently, the UKF algorithm was seamlessly integrated into the Simulink-based framework, which encapsulated the battery model, electrical source, and the shared memory interface. This integration ensured the precise incorporation of the UKF algorithm's estimations into the broader simulation framework, enhancing the model's overall predictive accuracy.

4.1.5. Metaverse visualization

The Metaverse visualization serves as a key interface for interacting with the BMS DT. Fig. 7 illustrates an example interaction with the digital battery within the Unreal Engine environment.

Table 5 provides an overview of the computational cost of different scenarios in the Metaverse. The GPU, CPU, and RAM utilization increase progressively as the complexity of the simulation grows. This progressive increase in computational demand highlights the need for efficient resource management when deploying Metaverse-based BMS visualization, especially for real-time monitoring.

While GPU usage for full-scale Unreal Engine rendering can be significant, the architecture supports lightweight 2D/3D front-ends or cloud-rendered streams to reduce onboard computational load. This allows scalability to lower-power EV controllers without sacrificing real-time monitoring capabilities.

Table 6 evaluates how well the Metaverse interface responds to user interactions. These results show that while most interactions are highly responsive, perceived delay could be optimized further by improving rendering pipelines or preloading battery model textures.

By combining the execution times for the main computational components, TSPMe ($\approx$ 5 ms), UKF state estimation ($\approx$ 7 ms), and Unreal Engine visualization update ($\approx$ 30 ms), the total wall clock time per update cycle is approximately 82 ms. This corresponds to an effective update rate of over 12 Hz, which is well within the 200 ms latency threshold typically required for real-time

Table 3
Performance comparison of electrochemical models.

Model	Voltage RMSE (mV)	Temp. RMSE (°C)	Voltage R^2	Temp. R^2	Time (ms)
SPM	91.69	13.37	0.5604	−0.4471	3.24
TSPM	103.69	5.75	0.4379	0.7324	2.29
SPMe	85.57	13.38	0.6175	−0.4471	5.46
TSPMe	**70.56**	1.15	**0.7397**	0.9894	4.99
DFN	99.15	13.38	0.4868	−0.4471	5.12
Thermally Coupled DFN	77.86	**1.03**	0.6831	**0.9914**	23.00

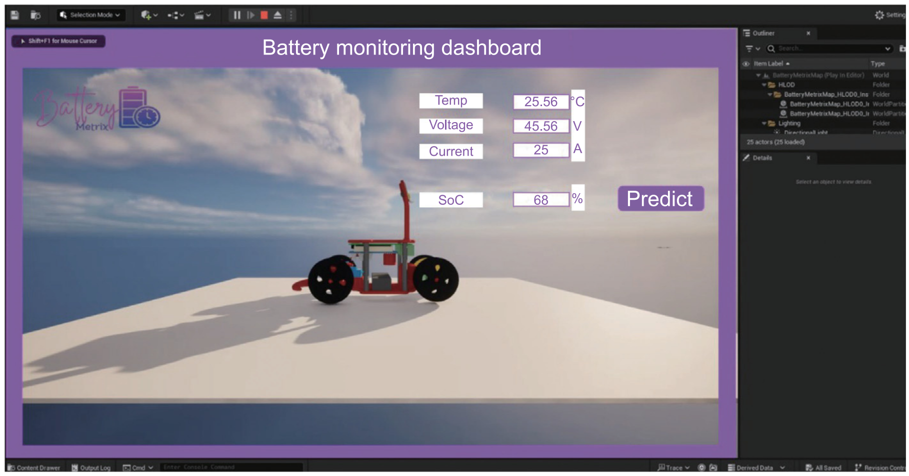

Fig. 7. Visualization of battery state in the Metaverse environment.

Table 4
State estimation accuracy across filters.

Algorithm	SoC RMSE (%)	Execution time (ms)	Complexity
EKF	23.45	5	Medium
EKBF	23.34	10	High
UKF	**0.23**	7	Medium
UKBF	5.45	12	High

BMS diagnostics in EVs. These results confirm that the proposed architecture can meet real-time operational requirements while maintaining high accuracy and immersive visualization.

4.2. Discussions

By creating a DT for a lithium-ion battery using MATLAB and synchronizing it with a corresponding virtual battery model housed in Unreal Engine, an immersive and interactive battery DT was developed. The immersive visualization capabilities of Unreal Engine help in facilitating real-time monitoring and a more comprehensive BMS. In an era where data-driven insights are key, this integration offers a cutting-edge solution. The dynamic and immersive setting ensures that stakeholders can not only observe but also interact with the battery under a spectrum of scenarios, enriching their understanding.

The effectiveness of the proposed framework stems from the complementary roles of its constituent components. The thermally coupled SPMe model offers a computationally efficient yet accurate representation of battery electrochemical dynamics, while accounting for temperature effects on reaction kinetics and ion transport. This enables more realistic predictions under varying operating conditions, improving the accuracy of downstream state estimation and prediction reliability during dynamic load cycles. The UKF algorithm further enhances accuracy by handling nonlinear system dynamics without explicit linearization, capturing higher-order statistics through sigma-point propagation. This capability led to a SoC RMSE of 0.23%, markedly outperforming the EKF and other tested filters. The Metaverse-based visualization extends these technical advantages by providing an intuitive and immersive environment for real-time interaction with battery states. Such visualization facilitates rapid situational awareness, anomaly detection, and spatially coherent inspection of multiple state variables, bridging the gap between raw data and actionable insights. The synergy between high-fidelity thermal modeling, robust nonlinear state estimation, and immersive visualization forms the foundation for the enhanced effectiveness observed in our system.

While the current implementation leverages a small-scale robotic EV platform for validation, the proposed architecture was designed with scalability in mind. A critical factor for real-world EV deployment is minimizing latency in state estimation and Metaverse rendering. In our prototype, the average latency for real-time data exchange between the physical system and Unreal Engine visualization is under 200 ms, which aligns with the acceptable response time for onboard BMS diagnostics. However, full-scale EV scenarios may require additional optimizations such as distributed edge computing or cloud offloading to handle larger datasets and multiple concurrent DTs. Regarding power consumption, the primary computational load originates from the Unreal Engine rendering pipeline and the UKF-based state estimation. In a real-world EV context, rendering can be delegated to remote servers (e.g., cloud-hosted visualization) to reduce GPU/CPU load on embedded hardware. Edge AI accelerators (e.g., NVIDIA Jetson or similar platforms) can also be employed to balance inference workloads, ensuring that the DT-BMS runs efficiently without impacting the EV's powertrain operations. The modular separation of computation, communication, and visualization layers enables independent scaling of each component. In a fleet setting, edge-based state estimation can be combined with centralized cloud rendering, allowing hundreds of EV DT instances to be monitored without overloading onboard GPUs. This architecture is therefore adaptable for both individual EV monitoring and large-scale fleet operations.

Table 5
Computational time & resource utilization in metaverse simulation.

Scenario	Model used	GPU load (%)	CPU load (%)	RAM usage (MB)	FPS
Basic visualization	TSPMe	50	30	1024	60
Full battery model	DFN	85	50	2048	45
Real-time monitoring	DFN (Thermal)	90	60	3072	30

Table 6
Metaverse interaction metrics.

Interaction type	Response time (ms)	Accuracy (%)	Perceived delay (ms)
Click to view battery data	150	99.8	200
Zoom on battery component	180	98.9	220
Change battery color (SoC-based)	100	99.5	120

Furthermore, the communication layer can be enhanced using lightweight protocols such as MQTT or DDS to ensure high-frequency data synchronization without bandwidth overhead. By combining these optimizations with adaptive sampling strategies, the architecture can scale effectively to real commercial EVs while maintaining real-time performance and low energy overhead. While direct numerical baselines with other DT-based BMS implementations are not readily available due to the novelty of integrating a 3D Metaverse interface, the feature-level comparison in Table 1 highlights the distinctiveness of our approach. The reported SoC estimation accuracy and low-latency interaction capabilities demonstrate the potential of this framework to deliver both technical precision and user-oriented operational value in future large-scale EV deployments.

Overall, unlike prior DT-BMS studies that mainly focus on offline or cloud-only monitoring, our results demonstrate a fully integrated architecture combining real-time UKF-based state estimation with an immersive Metaverse interface, running at $<$ 200 ms latency. This validates the practical applicability of our six-layer design for both high-fidelity and lightweight deployment scenarios.

5. Conclusion

The IoT and CPS are accelerating the shift toward intelligent, connected mobility. In this work, we addressed key challenges in BMS, particularly the difficulty of handling large, diverse datasets for accurate state estimation. We presented a novel six-layer DT architecture for BMS that uniquely integrates real-time UKF-based state estimation with an immersive Unreal Engine-powered visualization layer. Using a lithium-ion NMC battery case study, we demonstrated that the proposed DT achieved high-accuracy state-of-charge estimation (RMSE = 0.23%) while maintaining sub-200 ms end-to-end latency, meeting real-time operational requirements. The modular design supports deployment in both high-performance and lightweight/cloud-hosted environments, making it scalable from single-vehicle monitoring to fleet-wide applications.

This architecture goes beyond traditional DT-BMS implementations by providing an extensible reference model that can accommodate edge/cloud computation, adaptive communication protocols, and multi-vehicle interoperability. Future work will focus on integrating security-aware communication layers, optimizing rendering for low-power embedded GPUs, and validating the system in commercial EV testbeds. This combination of accuracy, scalability, and immersive visualization positions the proposed framework as a strong foundation for next-generation BMS solutions in real-world deployments.

CRediT authorship contribution statement

Judith Nkechinyere Njoku: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ebuka Chinaechetam Nkoro:** Software, Conceptualization. **Robin Matthew Medina:** Methodology, Investigation, Conceptualization. **Paul Michael Custodio:** Software, Methodology. **Cosmas Ifeanyi Nwakanma:** Supervision, Methodology, Investigation. **Jae-Min Lee:** Supervision, Project administration, Funding acquisition. **Dong-Seong Kim:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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