machines

MDPI

Article

A Hierarchical and Self-Evolving Digital Twin (HSE-DT) Method for Multi-Faceted Battery Situation Awareness Realisation

Kai Zhao [1,2], Ying Liu [1,*], Yue Zhou [2], Wenlong Ming [2] and Jianzhong Wu [2]

[1] Department of Mechanical Engineering, School of Engineering, Cardiff University, Cardiff CF24 3AA, UK
[2] Centre for Integrated Renewable Energy Generation and Supply, School of Engineering, Cardiff University, Cardiff CF24 3AA, UK
* Correspondence: liuy81@cardiff.ac.uk

Abstract: Accurate battery state estimation is important for the operation of energy storage systems, yet existing methods struggle with the complexity and dynamic nature of battery conditions. Conventional techniques often fail to extract relevant spatial and temporal features from basic battery data effectively, leading to insufficient situational awareness in battery management systems. To address this gap, we propose a Hierarchical and Self-Evolving Digital Twin (HSE-DT) method that enhances battery state estimation by coordinating multiple estimation techniques in a hierarchical framework and enabling adaptive updating through transfer learning. The model integrates a Transformer–Convolutional Neural Network (Transformer-CNN) architecture to process historical and real-time data, capturing dynamic state variations with high precision. Simulations indicate that the values of root mean square error (RMSE) for state of charge (SOC) and state of health (SOH) are lower compared to other algorithms, being less than 0.9% and 0.8%, respectively. Its hierarchical structure allows the integration of different estimation models, and the self-evolving method allows the method to adapt to changes in different operating conditions. The experimental results show that the method can estimate the battery state with high accuracy and stability, thus enhancing multi-faceted situational awareness.

Keywords: Digital Twin; battery energy storage system; battery state estimation; deep learning

Academic Editors: Xiang Li and Ke Feng

Received: 17 December 2024
Revised: 14 February 2025
Accepted: 21 February 2025
Published: 23 February 2025

Citation: Zhao, K.; Liu, Y.; Zhou, Y.; Ming, W.; Wu, J. A Hierarchical and Self-Evolving Digital Twin (HSE-DT) Method for Multi-Faceted Battery Situation Awareness Realisation. *Machines* **2025**, *13*, 175. https://doi.org/10.3390/machines13030175

1. Introduction

The estimation of accurate battery states is important in energy storage technology owing to the inherent complexity and non-linearity of these systems. Multi-faceted modelling has drawn increasing research attention over a diverse range of research domains, including energy storage because it can reflect real-world problems from multiple perspectives [1,2]. For example, a variety of material composition, operating conditions, and environmental factors can influence the performance of a battery [3]. Considering these multiple facets allows for a better understanding of the behaviour of a battery, which in turn improves BESS decision-support in battery management systems. Traditional techniques for monitoring and managing battery systems do not fully capture the multifaceted nature of battery behaviour. These methods employ single source data or models that are not capable of fully representing the dynamic changes in a battery system. Because of this limitation, situational awareness of the battery system is poor, and there are risks to battery management, including over-charging/discharging, and thermal runaway [4]. Therefore, there is a need for an advanced method to estimate multiple battery states, to combine various estimation techniques, to provide decision support based on different battery states, and to achieve continuous and accurate monitoring and management of the battery.

Recent advancements in battery state estimation have introduced sophisticated approaches that leverage deep neural networks and multi-timescale feature extraction to enhance predictive accuracy. Fan et al. proposed a SOC and SOH co-estimation framework that utilises convolutional filters of varying sizes to extract multi-timescale features, improving estimation accuracy across both laboratory and real-world scenarios [5]. Similarly, Zhou et al. developed a novel capacity estimation method based on singular value decomposition (SVD) and information energy theory, which demonstrated strong robustness against environmental variations and driving conditions [6]. These studies underscore the potential of advanced data-driven methodologies in battery management while also highlighting persistent challenges in achieving reliable real-world implementation. Many existing models, despite their success in controlled environments, lack the flexibility to adapt to dynamic operational conditions. Furthermore, they often overlook the interconnected nature of battery states, which is crucial for accurate long-term monitoring and predictive maintenance. By incorporating these insights, our study strengthens the understanding of battery management challenges and emphasises the necessity of an adaptive and intelligent framework for state estimation and decision support.

In the last decade, Digital Twin (DT) has become an important technique across many industries as a dynamic digital replica of physical assets with the ability to collect real-time data and incorporate advanced simulation models. Michael Grieves first conceptualised Digital Twins in 2002, and their use has become common due to their ability to improve operational efficiency, optimise performance, and predict the future behaviour of physical assets [7,8].

The complexity of battery systems makes DT valuable. Renewable energy relies heavily on batteries, whose complicated performance is influenced by many factors [9–11]. However, the multi-facets of these systems are overlooked by the traditional monitoring methods leading to inefficiencies and safety risks [12]. Combining multi-faceted modelling and real-time updating of system performance, DT provides a general solution. This capability allows the remaining useful life of the battery to be extended, provides safety guarantees, and improves the overall energy storage system efficiency.

A robust DT for battery management includes several key components: physical battery and sensors, data acquisition systems, computational models, and user interfaces. Real-time data of various parameters (temperature, voltage, current, etc.) are collected by the physical battery and its associated sensors. Computational models are then used to process these data to simulate battery behaviour (e.g., state of charge (SOC), state of health (SOH), and thermal dynamics). Predictive maintenance comes with a Digital Twin which enables real-time monitoring of equipment and predictive fault detection. Chen et al. [13] have performed a comprehensive review of DT-based PdM that integrates different sources of sensor data and machine learning techniques to improve prediction accuracy. The DT can be interacted with by its user interfaces where stakeholders can pass on DT insights on battery performance and make informed decisions [14,15]. Through interacting with these components, a detailed and dynamic view of the battery system can be continuously monitored and optimised.

Preliminary research on DT in battery management systems shows promising results. The accuracy in SOC and SOH estimates is improved and the risk of over-charging or over-discharging is minimised while system reliability is improved [16]. For instance, case studies have shown that DT can effectively monitor and manage the performance of lithium-ion batteries in electric vehicles and results in longer battery useful life and better overall performance [17]. This research shows the potential that DT has to revolutionise battery management through a more sophisticated and more reliable approach to monitoring and maintenance.

However, there are many challenges and limitations to the use of DT. A major problem is the high cost and complexity involved with developing and maintaining accurate digital models. The process of producing a DT is expensive in terms of data collection and processing. Moreover, technical challenges include the integration of different data sources and the requirement for continuous real-time updates [18]. Another concern is the reliability of the data used; inaccurate or incomplete data can lead to erroneous predictions and suboptimal decision-making [19]. In addition, the systems must be interconnected so that integrity and confidentiality of the data can be enforced, and the cybersecurity risks involved. As a result, there is an urgent need for more cost-effective, reliable, and secure DT solutions that can be easily integrated into existing systems.

To address these challenges, we present a hierarchical and self-evolving Digital Twin (HSE-DT) specifically designed for battery management systems. This method utilises Transformer and Convolutional Neural Network (CNN) models to improve predictive accuracy and flexibility. The data used in this paper was pre-processed to achieve the quality and reliability of the input data. The method comprises data acquisition, storage, processing, and real-time update mechanisms to keep the Digital Twin up to date. Moreover, we have added some extra advanced cybersecurity measures which will help us maintain the data integrity and have a secure link between the physical and the virtual ends [20,21].

Traditional battery monitoring approaches primarily rely on single-source data and static models, limiting their ability to comprehensively capture the dynamic and multi-faceted nature of battery behaviour. Integration of multi-source data plays a very important role in efficient predictive modelling of a complex system. In the work by Qin et al. [22], they proposed a hybrid approach to combine deep learning and clustering techniques with IoT data in order to optimise energy consumption in Additive Manufacturing (AM). Deep learning has shown significant promise in predictive maintenance applications, particularly when integrating diverse data sources. Chen et al. [23] introduced a Merged Long Short-Term Memory (M-LSTM) network to model both sequential and spatial data for predictive maintenance. Inspired by these methodologies, our work applies similar multi-source data analytics principles to improve Digital Twin-driven situation awareness for battery management. The HSE-DT method enhances real-time adaptability by integrating diverse data streams and dynamically updating system models to reflect the evolving state of the battery. Furthermore, it provides predictive insights that enable proactive maintenance and optimised battery control strategies. By leveraging a multi-layered structure, HSE-DT ensures that decision-making is informed by accurate and up-to-date information. This approach not only improves battery longevity but also enhances the overall efficiency and reliability of battery energy storage systems.

The HSE-DT method is developed and implemented in this paper as a method for battery management systems. The framework simulation models and mechanism are detailed and the components and functionalities of the method are described. The results from the case study show that the method is effective for battery monitoring and state estimation. We also discuss broader potential applications of DT to other complex systems and future research directions for improving and validating this new method.

2. Related Work

Accurately estimating battery states based on integrating multiple data sources and accounting for the inherent complexity of these systems is one of the challenges in battery management systems. In this context, this section reviews existing research work on DT technology. Specifically, this section first introduces battery situation awareness, including battery monitoring and state estimation. Then, the latest research on Digital Twins in energy storage systems is presented. Finally, the application of machine learning techniques, especially CNNs and Transformer models, applied within the Digital Twin is discussed.

2.1. Battery Situation Awareness

Digital Twins employ physical models, sensors, and operation and history data that are integrated to give a simulation process in which several physical quantities, temporal scales, and probability scenarios are combined. Such DT offers an authentic representation of energy storage systems in a virtual domain, which can be dynamically evolved, to reflect the full lifecycle [19].

Effective management of battery systems depends on battery situation awareness (BSA). It includes monitoring key parameters and accurate state estimation. This section summarises the existing methodologies and the recent advances in BSA from battery monitoring and state estimation perspectives.

2.1.1. Battery Monitoring

BSA is founded on battery monitoring which provides data to understand and manage battery performance. Most effective monitoring consists of measuring mission-critical parameters, which can be current, voltage, and temperature, continuously. The operational state and health of battery systems are of particular importance for high-demand applications such as electric vehicles and renewable energy storage.

Given the complexity and non-linearity of battery systems, advanced monitoring techniques are important for improving safety, reliability, and overall performance. In traditional BMS, embedded sensors capture real-time parameters, which are then utilised to assess battery health and operational efficiency. The performance, longevity, and safety of batteries strongly depend on accurate monitoring of current, voltage, and temperature. These parameters play a fundamental role in estimating the SOC, predicting battery behaviour under various load conditions, and preventing operational risks.

Traditional methods, such as shunt resistors and Hall effect sensors, provide highly accurate real-time current data, enabling precise SOC estimation and load condition analysis [24]. Nevertheless, with recent developments in sensor technology and data acquisition systems, measurement precision and reliability have been further improved [25]. In the same way, voltage monitoring is critically important in SOC estimation and anomaly detection such as over-charging and deep discharging prevention. Voltage monitoring systems with differential voltage techniques and high precision analogue-to-digital converters (ADCs) can detect very small voltage variations, enabling the battery dynamics to be observed and cell imbalance in battery packs to be identified [26]. The ability to perform this is critical for the implementation of effective balancing strategies, in order to increase battery longevity and performance. Among the key factors was temperature measurement, which directly affects the battery performance and safety. Modern battery management systems include many temperature sensors distributed in the battery pack and use infrared thermography and fibre optic sensing for high-resolution temperature mapping [27]. This overall thermal management strategy enables the battery to work within the best temperature ranges which extends the life of the battery and makes for overall battery safety.

Recently, techniques such as Electrochemical Impedance Spectroscopy (EIS) and fibre optic sensing have been developed to monitor batteries. This enables the measurement of impedance on the battery over a wide range of frequencies for detailed insight into the electrochemical processes and the health status of the battery. This technique allows the discovery of internal degradation mechanisms that are not discernible through conventional monitoring methods. High sensitivity and immunity to electromagnetic interference make fibre optic sensors ideal for monitoring in harsh environments [28]. These techniques provide additional layers of diagnostic information to complement traditional monitoring methods and provide additional layers of accuracy and robustness to battery monitoring systems.

Battery management systems thus continuously monitor these parameters as a means of detecting early signs of battery degradation, optimising charging and discharging cycles, and otherwise enabling overall battery system safety and reliability. Advanced monitoring techniques are integrated to improve the quality and robustness of data and to establish a solid basis for further state estimation and predictive maintenance.

2.1.2. Battery State Estimation

Battery state estimation is another key component of BSA that provides key insights into the current state of the battery and estimates the future performance of BSA. Battery states, such as SOC and SOH, must be accurately estimated to allow the battery systems to operate with the desired reliability, efficiency, and safety characteristics.

The complexity and non-linearity of battery systems are inherently complex and non-linear, which makes state estimation a challenging problem. To perform accurate and reliable estimations that are indispensable for efficient battery management, advanced methodologies and models are necessary.

SOC estimation is the available capacity as a percentage of total capacity. Managing and making decisions on the charging and discharging cycles of the battery cannot be measured without SHIN. Various methods for SOC estimation have been developed, each with its advantages and limitations: (a) Coulomb Counting: This involves tracking the charge entering the battery, and the charge being imposed on the battery. This is widely used and straightforward, although subject to cumulative errors over time because of the current measurement inaccuracies and initial SOC estimation errors [24]. (b) Voltage-Based Methods: These methods associate battery voltage with its SOC. While simple and easy to implement, they can be inaccurate due to the non-linear relationship between voltage and SOC, especially under varying load conditions [28]. (c) Model-Based Approaches: Kalman filters and neural networks, by use of mathematical models, intend to give a more accurate estimate of SOC. Popular Kalman philtres, such as the Extended Kalman Philtre (EKF) and Unscented Kalman Philtre (UKF), are used because they can handle non-linear systems and take measurement noise into account. The possibility to learn complex data-specific patterns also provides a significant opportunity for neural networks to improve SOC estimation accuracy. The most recent advancement of SOC estimation has been combined with machine learning algorithms to make it more refined. The underlying concept of these approaches is that they rely on large datasets and advanced computational techniques to increase the accuracy and robustness across many types of operating conditions.

An SOH estimation indicates the overall battery condition and degradation. The procedures range from the evaluation of capacity fade, internal resistance increase, self-discharge rates, etc. For predicting battery lifespan, as well as for scheduling maintenance, accurate SOH estimation is important. Advanced techniques for SOH estimation include (a) EIS: EIS measures the impedance of the battery at different frequencies which gives us a detailed view of electrochemical processes and the health status of the battery. Internal degradation mechanisms that cannot be detected via traditional monitoring tools can be revealed by this technique [29]. (b) Data-driven approaches: These show how different scenarios would have performed in the past and use this information to forecast future health trends. Support vector machines (SVM), random forests as well as deep learning models have been used to improve the accuracy and reliability of SOH estimation. Complex relationships between different health indicators with the overall battery condition may be captured by these models [30].

2.2. Battery Digital Twin

DT technology is a fusion of advanced physical models, intelligent sensor data, and comprehensive operational history to model a variety of physical quantities across different time scales and probabilistic scenarios. This technology provides a virtual representation of an energy storage system that can be updated in real-time according to its dynamic evolution throughout the energy system lifecycle [31].

Battery research has come a long way in recent years but there are still many challenges. State estimation of lithium-ion batteries is vital to BMS and battery balance, and an accurate state estimate can prevent over-charging or over-discharging. However, building precise models of lithium-ion batteries is difficult as their internal dynamics are complex and non-linear [32]. In the aerospace industry, Digital Twin technology was found to be effective in SOC estimation, SOH estimation, and optimal control; promisingly this technology could be used to solve the battery state management challenges [33].

Recently, there has been a development in the integration of DT with BMS using cloud computing and IoT frameworks [34]. Current research on battery Digital Twins primarily focuses on three core challenges facing modern BMS: These constraints are the complexity of integrating data from various BMS providers, the limited computing power of embedded systems, and the constraints of data storage.

To resolve the data sharing issue in battery management, Li [20] integrated DT technology by integrating all battery-related data into a cloud-based platform and enhancing the BMS structure. As the volume of battery data continues to increase, resulting in exponential growth in computational and storage demands for BMS, this integration becomes important. Machine learning approaches, specifically data scarcity models, are utilised to predict and refine system states to manage these complexities and provide new insights into battery ageing processes. For instance, a study [15] combined a Health Indicator (HI) with the LSTM algorithm to accurately estimate battery discharge capacities.

However, Digital Twins have a way to go in terms of their real-time and self-evolving capabilities. The sections that follow discuss the use of Digital Twins for SOC estimation. Research [35] introduced a "Hybrid Twin," an innovative Digital Twin model for lithium-ion batteries in the automotive sector, employing methods like Proper Orthogonal Decomposition (POD), sparse Proper Generalised Decomposition, and Dynamic Mode Decomposition to significantly enhance the real-time performance and flexibility of BMS. A study [36] also created a digital battery twin and data pipeline for electric vehicle batteries, and used a cloud-based system for health and performance analysis, emphasising the role of Digital Twins in improving electric vehicle battery system management. A Digital Twin-supported framework was proposed by Tang [14] to overcome BMS constraints, where a joint HIF-PF online algorithm is used to estimate SOC accurately and to monitor real-time efficiency. This approach shows how Digital Twin technology can transform BMS. A Digital Twin framework for real-time SOH assessment for lithium-ion batteries under variable conditions is presented in another paper [37], featuring a new method combining energy discrepancy-aware cycling synchronisation and time-attention modelling for the accurate prediction of SOH without using complete discharge cycles. Finally, another study [38] modelled a large-scale grid-connected lithium-ion battery system with a Digital Twin to demonstrate the effect of system design and ancillary controls on degradation and efficiency, demonstrating the ability of a Digital Twin to optimise battery system performance.

2.3. Deep Learning in Battery Management

As a specialised subset of machine learning, deep learning has become increasingly popular in scientific fields for its impressive ability to model complex, non-linear relationships. Deep learning algorithms implement neural network architectures that can derive feature representations from raw data without manual feature engineering. However, this capability has driven deep learning as an incredible tool across a lot of applications like computer vision, natural language processing, and more.

Deep learning has become a game changer in the study of lithium-ion battery systems. The dynamics of lithium-ion batteries are often complex and non-linear, and traditional modelling techniques struggle to understand these systems. The challenges of these problems are solved with deep learning due to its ability to find complex patterns.

Unlike model-based approaches [39], which are slower and more complex, data-driven methods [40] operate as black boxes that utilise the routinely monitored and historically collected system operating data, such as temperature, vibration signature, and current measurements, to simulate the complex relationship amongst external battery parameters. In the past decades, sparse Bayesian predictive modelling (SBPM) [41] and machine learning methods such as random forest (RF) [42], support vector machine (SVM) [43], and support vector regression (SVR) [44] have been widely used to trace battery capacity degradation. Recently, there has been growing attention on neural network (NN) approaches, with studies demonstrating that NN-based models outperform RF and SVM in capturing complex battery degradation patterns and achieving higher predictive accuracy. For example, compared to traditional feed-forward neural networks (FNNs), recurrent neural networks (RNNs) are better at processing time-sequential data due to their structure that helps circular connexions, the use of hidden neurons, to simplify the extraction and updating of correlations in sequential data [45]. LSTM is also an example of usage gain in handling sequential data, whereby it deals with the problem in the vanishing gradient [46] by adding more interactions per module, thus is particularly good for retaining information over a long period. As a result, LSTM networks have been broadly adopted for battery state estimation, exploiting their capability to utilise important historical degradation data and manage sequential inputs with high accuracy. LSTM was applied by Han [47] to predict the SOH of lithium-ion batteries, with an additional domain adaptation layer to improve robustness and estimation accuracy across different datasets. Tan [48] used transfer learning with LSTM and fully connected layers to estimate SOH with rapid, precise, and stable predictions. Ma et al. [49] combined a differential-evolution grey wolf optimiser (DEGWO) with LSTM to enhance global search capabilities, producing accurate predictions for different battery types. In optimising LSTM performance, Pearson correlation coefficient (PCC) and neighbourhood component analysis (NCA) were utilised in the feature selection process to reduce the computational load by eliminating irrelevant data and minimising dimensionality. Unlike PCA, which assumes a Gaussian distribution, NCA imposes no such requirement. Li et al. [50] introduced a variant attention-based spatial–temporal LSTM (AST-LSTM) neural network to actively track cell states by simultaneously evaluating old and new data, achieving a lower average root mean square error (RMSE) and conjunct error. This work further demonstrated that integrating PCC with the proposed method could make even weakly correlated parameters effective inputs when training time is not a primary concern.

Transformer models, a class of sequence transduction models, avoid the use of recurrence and instead rely entirely on attention mechanisms to identify global dependencies between input and output using an encoder–decoder architecture [51]. To address the issue of time-consuming training, Transformer models incorporate positional feature embeddings, which provide absolute or relative position information within a sequence, allowing features to be described through positional encodings rather than dependencies. This self-attention mechanism, which is highly parallelizable, enables efficient sequence learning by establishing relationships among features that appear in different locations. However, this focus on global dependencies means that Transformers may overlook local feature details, which are often important for maintaining discriminative power within limited timestamps [52].

3. Proposed Method

As discussed in the preceding sections, the complexities and dynamic nature of battery systems necessitate a robust and adaptive approach to enable effective battery management. Traditional methods are usually insufficient to meet the complex requirements of battery state estimation and management. In this regard, we propose the HSE-DT method, and the framework is illustrated in Figure 1.

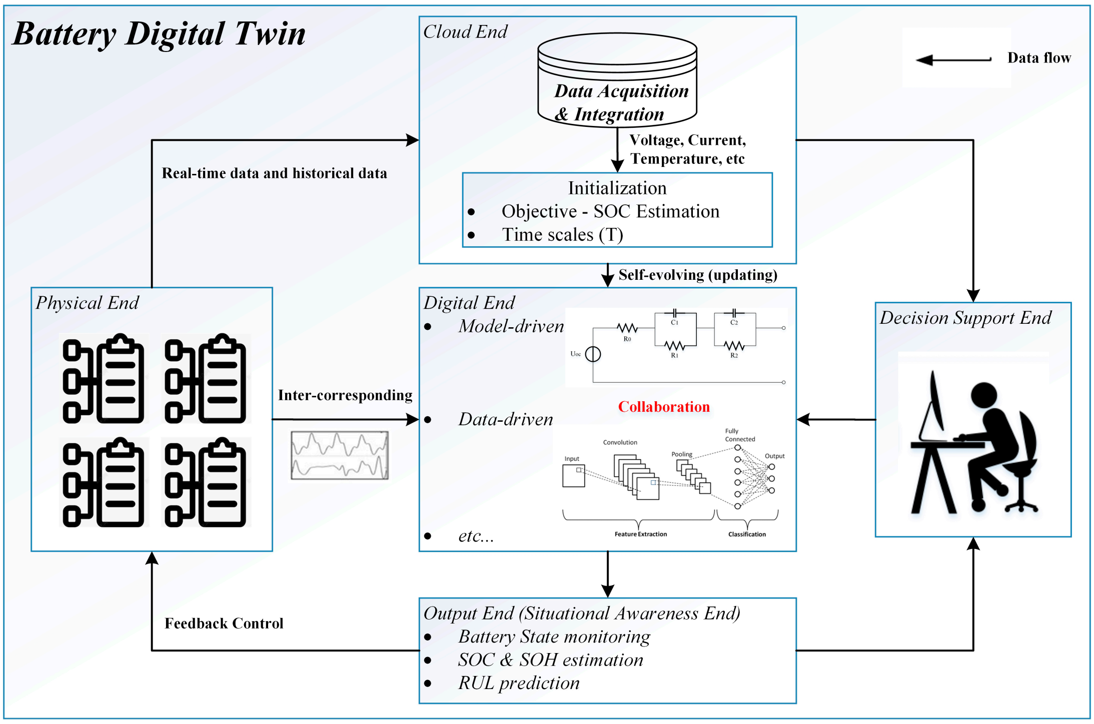


Figure 1. The battery Digital Twin framework.

Firstly, data relevant to the battery's state, such as current, voltage and temperature, is collected from various sensors embedded in the physical battery system. These data are then processed and integrated to develop the Digital Twin, which replicates the physical battery's electrochemical, thermal, and ageing behaviours. Secondly, advanced machine learning algorithms, specifically CNN and Transformer models, are utilised to analyse both historical and real-time data. These models produce accurate predictions and estimations of SOC and SOH. Thirdly, the model self-evolves through continuous learning techniques to update the Digital Twin models with fresh data. This renders the models applicable and accurate as long as required, and able to bear the new set of battery conditions as well as usage patterns. Finally, the insights garnered from the Digital Twin are used for predictive maintenance and battery performance optimisation. The comprehensive method provides enhanced battery situation awareness, improves safety, and extends the life of the battery system.

3.1. Hierarchical and Self-Evolving Digital Twin (HSE-DT) Method

The HSE-DT method is intended to provide a structured Digital Twin architecture to integrate multi-faceted layers. It is composed of multiple layers, each layer performing different aspects of battery management, allowing for a comprehensive battery situation awareness method.

- Physical end: The actual battery system, with sensors to collect real-time data of parameters like current, voltage, temperature, and SOC, form this end. These sensors deliver the requisite data for state estimation.
- Cloud end: This end integrates and preprocesses data collected at the physical layer. This includes noise filtering, data normalising, and having consistency over various data resources.
- Digital end: The Digital Twin models that mimic the physical battery's behaviour are served on this end. The models include electrochemical models, thermal models, and ageing models that are coupled to give a complete representation of the state of the battery. Real-time data are used to keep the models updated and accurate. On the digital end, advanced algorithms (CNN and Transformer models) are used to estimate SOC and SOH. These models use machine learning to analyse historical and real-time data to predict future states and detect anomalies.
- Output end: Critical outputs such as cell status monitoring, SOC estimation, and reliability recommendations are delivered at this end to help technicians make informed decisions.
- Decision Support end: The estimations and predictions are used to provide insights and recommendations at the topmost end. The user interfaces for stakeholders to interact with the Digital Twin, visualise data, and make informed decisions on battery management are part of this layer.

3.2. Battery Model

There are three commonly used approaches for battery modelling, each offering distinct advantages and limitations: the electrochemical model, the equivalent circuit model (ECM), and the data-driven model [53]. This study adopts the ECM approach, as depicted in Figure 2. The ECM is a grey-box model that represents the dynamic behaviour of a battery by integrating resistors, capacitors, and voltage sources. The model's parameters are refined using collected data.

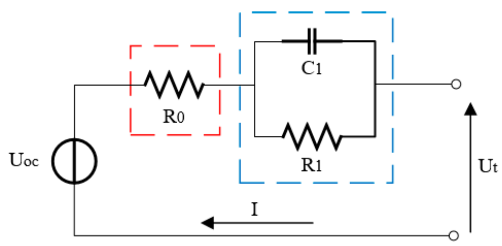


Figure 2. The first-order ECM for a lithium-ion battery.

The electrochemical model offers a detailed representation of internal battery mechanisms, including ion transport and electrode reactions. While highly accurate, this model requires an extensive understanding of battery chemistry and relies on computationally intensive numerical solutions. Consequently, its application in real-time battery management is limited. Instead, it is primarily utilised for in-depth electrochemical analysis and long-term degradation studies, where precision in capturing microscopic processes is paramount.

The data-driven model, in contrast, utilises machine learning techniques to establish correlations between input features and battery behaviour without incorporating explicit physical relationships. This approach is particularly advantageous when substantial historical data are available, as it enables adaptive learning and predictive capabilities. However, data-driven models often demand significant computational resources and may suffer from limited generalizability when applied to unseen conditions, restricting their effectiveness in real-time embedded systems.

By comparison, the ECM provides a well-balanced solution, making it the most suitable choice for this study. It achieves an optimal trade-off between modelling accuracy and computational feasibility, offering a sufficiently precise representation of battery dynamics while enabling real-time implementation. Its straightforward parameterization, low computational complexity, and ease of integration facilitate seamless deployment in Digital Twin environments for battery management applications [54]. By adopting the ECM, this study ensures an efficient and reliable modelling framework that captures essential battery characteristics without imposing the computational burden associated with more complex models.

The ECM is defined by a simple mathematical formulation, in which the dynamics of the charging and discharging processes are governed by the following set of equations:

$$\frac{dSOC^n}{dt} = -\eta\frac{I^n}{E^n} + \omega_1 \tag{1}$$

$$\frac{dU_1^n}{dt} = -\frac{U_1^n}{R_1^n C_1^n} + \frac{I^n}{C_1^n} + \omega_2 \tag{2}$$

$$U_L^N = U_{oc}SOC^n - U_1^n - I^n R_0^n + \beta \tag{3}$$

where the superscript n denotes the nth cell in the battery module, which consists of a total of N cells; η is the Coulombic efficiency of the battery; I is the current and E is the battery capacity in Amp Hour; R_0 is the internal resistance; R_1 and C_1 are the polarisation resistance and capacitance, respectively; U_1 and U_L are terminal voltage of the polarisation capacitance and the battery cell, respectively; ω_1 and ω_2 are process noise, and β is measurement noise; U_{oc} is the open circuit voltage dependent on SOC.

To make the ECM more suitable for computer simulation and model-based predictive control, the continuous-time model is discretised with a sampling time T, as shown in the following equation:

$$SOC_{k+1}^n = SOC_k^n - \eta\frac{I_k^n}{E^n}T + \omega_{1,k} \tag{4}$$

$$U_{1,k+1}^n = U_{1,k}^n e^{-\frac{T}{R_1^n C_1^n}} + R_1^n\left(1 - e^{-\frac{T}{R_1^n C_1^n}}\right)I_k^n + \omega_{2,k} \tag{5}$$

$$U_{L,k}^n = U_{oc}SOC_k^n - U_{1,\,k}^n - I_k^n R_{0,k}^n + \ \beta_k \tag{6}$$

3.3. Transformer-CNN Model

Accurate battery state estimation is vital for the effective management of battery systems, particularly given their inherent complexity and dynamic behaviour. Traditional estimation methods often fall short of capturing the non-linear and temporal dependencies present in battery data. To address these challenges, CNN and Transformer models are used within the HSE-DT method.

CNN and Transformer models are selected for battery state estimation due to their demonstrated ability to deal with large-scale data with complex patterns and dependencies. CNNs are suited for extracting spatial features from time series data and making them an optimal choice for processing sensor data such as battery voltage, current and temperature readings. CNNs can effectively capture local patterns and correlations within the data with a convolutional filter, which is needed for accurate state estimation.

However, long-term dependencies and contextual relationships in sequential data are effectively learned by Transformers through their self-attention mechanism. In particular, this is important for understanding the temporal dynamics of battery states (e.g., SOC and SOH). Transformers have a self-attention mechanism that weighs the importance of different parts of the input sequence and thus provides a complete picture of the data over time.

The strengths of CNN and Transformer models are utilised through the integration. CNNs are designed to extract spatial features and Transformers are designed to extract temporal features of data. The HSE DT method combines this complementary combination to provide increased overall accuracy and robustness of battery state estimation.

While the use of Transformer-CNN models is not novel in itself, they are effective in a wide variety of domains, including natural language processing and computer vision. The models could improve the reliability and accuracy of our battery management system to allow battery systems to perform better and last longer. The design, implementation, and integration of the Transformer-CNN model into the HSE DT method is elaborated in this section and how it improves battery state estimation accuracy and robustness is shown.

Several critical stages in the design and implementation of the CNN and Transformer model within the HSE-DT method are needed to take advantage of their complementary strengths for battery state estimation. The architecture, as well as the data processing pipeline and steps required to deploy the Transformer-CNN model, are presented in this section.

Transformer-CNN model is also designed to accommodate the complex and dynamic nature of battery data, which includes spatial and temporal nature. The architecture comprises two primary modules: The CNN module and the Transformer module. Figure 3 shows the Transformer-CNN model within the HSE-DT method.

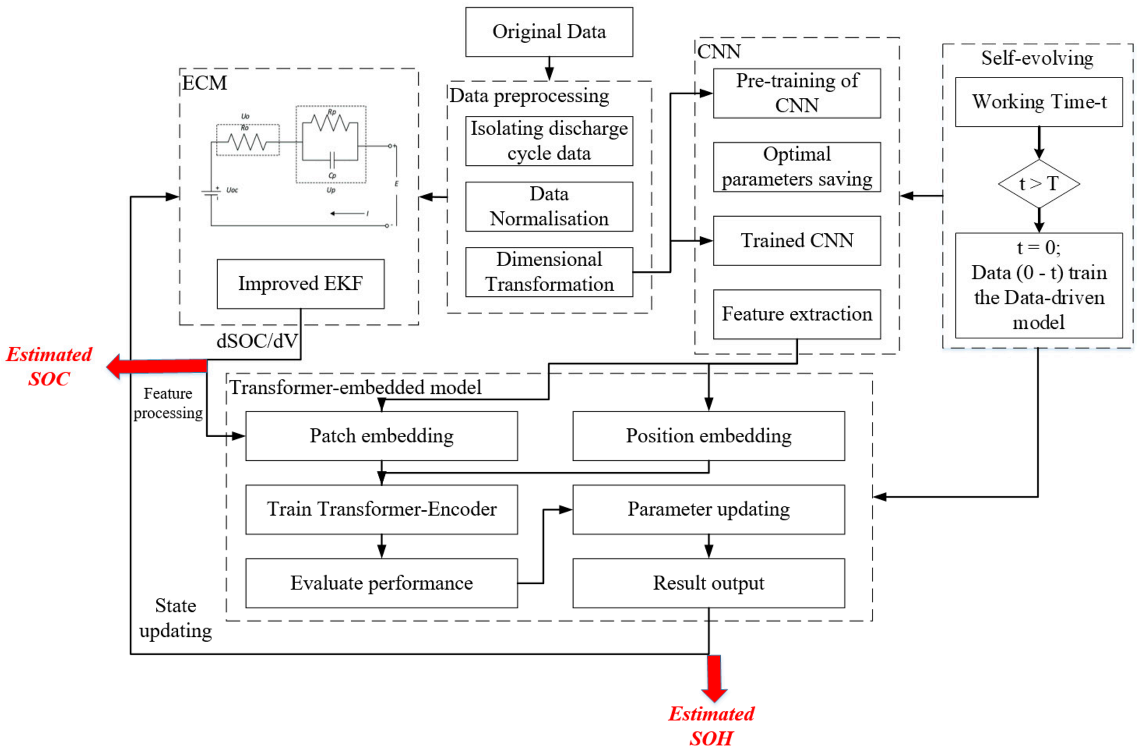


Figure 3. The Transformer-CNN model within the HSE-DT method.

The CNN module processes time series data coming from battery sensors such as voltage, current, and temperature. The CNN module takes in the input data and extracts spatial features by passing the data sequentially through a series of convolutional filters. Then, each convolutional layer comes down with an activation function, like ReLU, and a set of pooling layers to reduce the dimensionality, retaining the important information. The output of the convolutional layers gives a set of feature maps that encode local patterns and correlations in the battery data and explicitly have a spatial nature.

CNN is structured in three layers: the input layer, hidden layers, and output layer. The input layer receives the original data and forwards it to the hidden layers for feature extraction. The hidden layers include fully connected layers, max-pooling layers, and convolutional layers, which facilitate hierarchical representation learning. The output layer then generates the final predictions based on the learned features.

The CNN architecture is effective in capturing local features hierarchically through convolutional operations. It extracts spatial patterns from battery data, such as voltage, current, and temperature, by progressively refining localised representations. The CNN branch begins with an input layer that preprocesses and structures the incoming raw data. Convolutional layers extract local variables while preserving time-independent characteristics over long distances. Max-pooling layers enhance computational efficiency by reducing dimensionality while retaining essential spatial information. Finally, fully connected layers consolidate the hierarchical representations before passing the processed data to the Transformer module for further analysis.

This is further processed by the Transformer module on top. The first thing is to add positional encoding to keep track of the relative positions of data points so that we can understand the sequence of events over time. The Transformer module then applies self-attention to different parts of the input sequence to give different weights to parts of the sequence and learn about long-term dependencies and contextual relationships. Feedforward layers generate the final feature embeddings and summarised battery data temporal dynamics.

The Transformer module combines pointwise layers with stacked self-attention layers and fully connected layers to support both encoding and decoding operations through its structured design. The self-attention mechanism eliminates both recurrence and convolutional dependencies through its components' scaled-dot-product attention and multi-head attention to achieve global feature aggregation. The Transformer module incorporates positional encoding, which maintains input data sequence order through value assignments between 0 and 1 to uphold temporal coherence.

Through its encoding process, the Transformer produces embedded representations that detect hidden relationships between sequential input segments to extract an extensive range of features. The decoder works with generated decoder outputs and these embeddings to create the sequence of final outputs. Through self-attention mechanisms, the Transformer can reweight importance according to changing battery states while focusing on vital fluctuations and long-term patterns. The adaptive weighting system improves predictive accuracy through its ability to model short-term changes and sustained patterns in battery activity, which produces better state estimation results.

The Transformer-CNN model is effective only if the data processing pipeline is designed carefully so that the input data are optimised for model performance. Real-time measurements of critical parameters are recorded by continuous data collection from battery sensors, which is the basis for subsequent processing steps. Normalisation in data preprocessing is critical for the consistency of different measurement scales and improves model performance. Then, time-series data are segmented into smaller sequences of fixed time windows so that the CNN and Transformer modules can efficiently process the data.

Following the feature extraction, segmented and normalised data are first processed by the CNN module, where convolutional layers extract intricate spatial features from the battery data. Then, these are fed into the Transformer module, which comprises positional encoding, then performs self-attention and feed-forward layers to capture the temporal dependency and contextual relationships to yield an accurate estimation of the state.

The HSE-DT method seamlessly integrates the Transformer-CNN model for real-time battery state estimation and management. In turn, the model is trained in a supervised learning way, using labelled data with SOC and SOH known values. In the training process, the parameters of a model are optimised for a minimum loss function (e.g., Mean Squared Error that tells how far the predicted and actual values are from each other). The trained Transformer-CNN model receives real-time sensor data to estimate the state continuously. The SOC and SOH estimation is used by the HSE-DT method to monitor and manage the battery system. Transfer learning is used to update the model parameters with new data that was not present at training so that the model remains accurate and timely over time without necessitating full retraining.

The Transformer-CNN module extracts local features progressively through its CNN branch which then passes enriched details to Transformer modules for global perception enhancement. All data structures undergo standardisation as a preprocessing step since CNN and Transformer exhibit possible discrepancies in data formats and feature patterns. Cross-entropy losses serve as training mechanisms which unite CNN-derived local features with Transformer-based global information during model learning. The predictive model produces its results through flattened layers which transform multidimensional outputs into a single-dimensional space for effortless model propagation. Dropout layers use random neuron selection to reduce model overfitting. Network density enables every neuron to gather information from all preceding neurons leading to a complete interconnected decision path. The Transformer-CNN model delivers reliable battery state estimation by maximising local features and strengthening global dependencies to achieve better prediction outcomes.

The HSE-DT method with the Transformer-CNN model provides a robust and efficient method for battery state estimation. This model combines the spatial feature extraction capability of CNNs with the temporal analysis strengths of Transformers to significantly improve the accuracy and reliability of battery management systems. Further optimisations and real-world applications will be investigated in future work to validate the model's performance in various operational scenarios.

3.4. Synergistic Interaction Within the Digital Twin

The synergistic interaction between the HSE and the DT method is critical to improving battery state estimation and management. The mechanisms by which different components of the HSE-DT method interact and collaborate to present a complete and accurate representation of the battery system state are discussed in this section.

3.4.1. Multi-Faceted Integration

The battery management functions are organised into several multi-faceted components of the HSE-DT method. The seamless integration makes it so that the system can effectively take advantage of the strengths of each component to give a holistic view of the battery system. The first part of this is to acquire real-time data from sensors embedded within the battery system. These data cover important voltage, current, temperature, and other relevant metrics. The data undergoes preprocessing to remove noise and achieve consistency so that the data are suitable for further analysis. The second component, modelling and simulation, uses the pre-processed data as the input for Digital Twin models of electrochemical, thermal, and ageing processes. These models model the physical and chemical activities within the battery and hence provide insight into the battery's internal states such as SOC and SOH. The estimation and prediction component then makes use of advanced algorithms (including the Transformer-CNN model) to analyse the data and predict the future states of the battery. Using a combination of historical and real-time inputs, these predictions are based on dynamic state estimation. Finally, the estimation process provides insights and predictions that the decision support component uses to inform decision-making. Maintenance recommendations, charging strategies, and operational adjustments are all provided for this component. Furthermore, available to stakeholders are also user interfaces, in the form of detailed reports and visualisations, to support informed decision-making.

3.4.2. Feedback Mechanisms

That Digital Twin can continuously adapt and evolve using new data and new conditions—or not—and it requires effective feedback mechanisms for it to be enabled. The HSE-DT method combines several feedback loops to improve its accuracy and reliability. This method relies heavily on real-time feedback to monitor the battery system continuously. This ongoing observation also allows for immediate changes to the Digital Twin models, so they stay accurate and current with the state of the battery. Also, real-time feedback allows our system to quickly discern anomalies and take corrective action before any failures occur.

In addition to real-time adjustment, the HSE-DT method also includes periodic updates of the models to provide further refinement. The Transformer-CNN has its internal parameters retrained on fresh data, causing an improvement in its predictive accuracy. Transfer learning techniques are used to update the model parameters in an efficient and adaptable manner without a full retraining process.

3.4.3. Collaborative Analysis

The HSE-DT method greatly improves the effectiveness of battery state estimation through the collaborative interaction between different models and algorithms. This collaboration is enabled through several important mechanisms that combine to increase accuracy and reliability.

This method relies on a critical mechanism of data fusion by which data from various sensors and models are fused to form a complete picture of the battery's state. This procedure capitalises on the strong point of every information source in a great estimation. The refined predictions of the Transformer-CNN model are then further improved using the fused data.

However, another important mechanism is cross-validation by which we can make sure all predictions and the insights drawn from different models are accurate and consistent. In this, we compare the outputs of various models and algorithms to determine inconsistencies and reconcile conflicts. Cross validation strengthens the robustness of the Digital Twin and provides reliable and trustworthy information derived from said Digital Twin.

The HSE-DT method contains adaptive learning: The models are infused with new data and new knowledge. That process requires a continuous learning structure to keep the Digital Twin relevant and accurate over time. Moreover, the Digital Twin can adapt to changes in the operating conditions of the battery system, e.g., temperature, load, or usage pattern, through adaptive learning.

To provide accurate and complete battery state estimations, the synergistic interaction within the HSE-DT method is required. The HSE-DT method integrates multiple facets, includes effective feedback mechanisms, and enables collaborative analysis to improve the management and performance of battery systems overall.

3.5. The Self-Evolution Mechanism

A key part of the HSE-DT method is the self-evolution mechanism. Models in Digital Twin are dynamically adapted to remain relevant and effective to the changing conditions and user patterns of the battery as it updates. The self-evolution mechanism consists of three key elements: transfer learning, continuous learning, and adaptive algorithms. Taken together, these elements enable the Digital Twin models to remain robust and truthful as these react to new data and changing operational conditions.

To minimise the need for full retraining, new data are used to update Digital Twin models using transfer learning. With this we only apply this technique to pre-trained models and adapt them to new tasks or datasets, saving us from the computational prerequisites and making it more efficient. In the HSE–DT method, transfer learning enables the Digital Twin to learn new battery data such as temperature, voltage, and current changes without having to start from scratch. Variations in battery chemistry, ageing effects and different operational environments are particularly useful for this.

This leads to fresh data updating and refining the DT. It is supervised and unsupervised learning. To improve the accuracy of the models for the mentioned tasks of SOC and SOH estimation, models are trained under supervised learning in the labelled data. However, one technique, unsupervised learning, discovers patterns and anomalies in the data using features inside the dataset without any labels previously added, making it better suited for the model to adjust to unexpected changes in battery behaviour. The HSE-DT method can be continually learned and thus becomes more accurate and more reliable with time.

They are adaptive algorithms, which means that they will change their behaviour upon detecting anomalies or shifts in the operational environment of the battery. The feedback mechanisms of this algorithm adaptively refine model parameters to achieve near-optimal performance despite changes in the environment. As an example, if the adaptive algorithm detects a sudden change in temperature, it can update its thermal model. The adaptability is important for real-time monitoring and management such as electric vehicles and renewable energy storage systems where the operating conditions vary greatly.

4. Case Study

4.1. Data Description and Preprocessing

In this section, experimental validation of the HSE-DT method is presented using data from NASA lithium-ion battery charge and discharge experiments. We use this dataset as a robust testbed to demonstrate the effectiveness of our Digital Twin model. The NASA dataset comprises many charge and discharge cycles of lithium-ion batteries under different conditions with critical parameters like voltage, current, temperature, and capacity. Accurate models for battery state estimation require these parameters. The dataset is highly comprehensive and of high quality, making it suitable for our study, offering a rich set of time series data which characterises the dynamic behaviour of batteries. In the data collection phase, we observed inconsistencies with the battery tester logging mechanism. Data were repeated as several drive cycles were consolidated into a single extensive file. However, this consolidation introduced redundancy and possible anomalies, which had to be resolved to allow the integrity of data used in training and validating the models.

Redundant entries indicative of data-logging anomalies were removed to allow data integrity. Data cleaning process consisted of identifying and removing duplicated entries and implementing algorithms to filter out spurious data points that did not follow expected battery behaviour. To improve the performance of machine learning models used in the HSE-DT method, normalisation was applied to scale the data to a standard range. To make them consistent across different measurement scales, we scaled parameters like voltage, current, and temperature to a range of 0 to 1, and transformed the data to have a mean of 0 and a standard deviation of 1.

The CNN and Transformer models were trained over small, manageable sequences of continuous time series data to allow efficient processing. To capture complete cycles of battery charge and discharge, the data were segmented into segments of equal length, and to capture transitional behaviours and improve model robustness, the overlap between segments was introduced. The pre-processed data were further extracted to extract key features to feed in the Transformer-CNN model. To do this, the time-dependent characteristics like the slope of voltage and current versus time and measures like mean, variance, and skewness were calculated for each segment to give a complete picture of the battery state.

Several advantages of the NASA dataset for our study are provided. It covers a broad range of operating conditions and thus allows robust models to be built which can generalise across different situations. The data are meticulously recorded, well documented, and thus reliable and suitable for research purposes. In addition, the NASA dataset is widely used in the battery research community, and, as such, enables meaningful comparisons with other studies and methods. Using this dataset, our results are comparable to existing research, which confirms the efficiency of our HSE-DT method.

In the next section, the above data preprocessing steps are necessary to prepare the NASA dataset for the use of the HSE-DT method. Data redundancy is addressed, data are normalised, time–series sequences are segmented, and relevant features are extracted to allow that the input data are of high quality and usable for accurate battery state estimation. The objective is to demonstrate the effectiveness in enhancing battery situational awareness, which includes not only an accurate estimation of battery states such as SOC and SOH but also a comprehensive understanding of battery conditions and behaviours under various scenarios. We performed a series of experiments using the Transformer-CNN model to assess the performance of the HSE-DT method. The purpose of these experiments was to validate the accuracy, robustness, and overall situational awareness capabilities provided by the method.

4.2. Performance Evaluation

The evaluation process began with training the Transformer-CNN model using the pre-processed NASA dataset. Supervised learning techniques were used, with labelled data and known SOC and SOH values for optimising model parameters. As a loss function, a Mean Squared Error (MSE) was used to measure the discrepancy between the predicted and actual values and the optimisation was performed. During this training phase, the model can learn from the historical data to achieve accurate estimations.

Following the training phase, the model's performance was evaluated on a separate test dataset that was not used before. This test dataset included various battery cycles under different operating conditions to assess the model's generalisation capabilities. The key metrics used for performance evaluation included Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE), which quantified the accuracy of the SOC and SOH estimation. The MAPE has been selected as the primary metric to assess estimation accuracy. It is defined as:

$$MAPE(\%) = \frac{100}{K}\sum\nolimits_{k=1}^{K} \frac{\left|l(k) - \hat{l}(k)\right|}{l(k)} \tag{7}$$

Here, $l(k)$ denotes the actual capacity, $\hat{l}(k)$ represents the estimated value, and K is the total number of cycles. Furthermore, other metrics such as the MAE, RMSE and R^2 are computed as:

$$MAE = \frac{1}{K}\sum_{k=1}^{K}\left|l(k) - \hat{l}(k)\right| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(l(k) - \hat{l}(k)\right)^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{K}\left(l(k) - \hat{l}(k)\right)^2}{\sum_{k=1}^{K}\left(\overline{l(k)} - \hat{l}(k)\right)^2} \tag{10}$$

These metrics were selected for their ability to provide clear and direct assessments of the model's accuracy in estimating key battery states. RMSE is useful for identifying significant deviations in predictions, as it penalises larger errors more severely. Even small misestimations can have a considerable impact on system performance, such as in battery management systems. In contrast, MAE offers a more generalised measure of estimation error by calculating the average absolute differences between estimated and actual values. This metric provides insight into the overall accuracy of the model, offering a comprehensive assessment of its performance. Together, RMSE and MAE provide a balanced evaluation of both the magnitude and distribution of errors, strengthening the overall assessment of the model's reliability.

4.3. Collective Situation Awareness

4.3.1. SOC Estimation

The HSE-DT method proposed in this study was validated using public datasets. Due to the absence of specific conditions required for battery model parameter identification, the SOC was provisionally estimated using the Extended Kalman Filter (EKF) as a reliable alternative. The estimation results of the proposed model, along with comparisons to three well-established superior algorithms, are detailed in Figure 4 and Table 1. Overall, all four methods demonstrated strong estimation performance across the NASA battery datasets.

Table 1. The comparison of SOC estimation for different methods using the B0005 dataset.

Methods	RMSE	MAE
HSE-DT	0.009	0.007
LSTM	0.032	0.025
CNN-LSTM	0.011	0.085
Transformer	0.017	0.013

Figure 4 provides a comparative analysis of SOC determined by the EKF, measured against a reference SOC. The graph illustrates SOC, current, voltage, and temperature over time during each cycle (each coloured line represents each cycle) for batteries B0005, B0006, B0007, and B0018. Although the model aligns well with the training data, noticeable deviations are observed in SOC estimation when processing new data. These deviations are reflected in the RMSE values, which are 0.9% for training and 2.5% for testing. Generally, a lower RMSE signifies better SOC estimation accuracy, but the discrepancy between training and testing RMSE suggests potential overfitting, which may affect the model's performance on previously unseen data. These RMSE values were computed using a dataset that used pervasive network structures, the same dataset used for the reference methods introduced in the analysis. When compared to other algorithms in Table 1, the proposed method demonstrated the lowest RMSE among the four algorithms evaluated, underscoring its superior accuracy. This accuracy is anticipated to improve further as overfitting issues are addressed. The consistent use of reference methods with the same dataset further supports the reliability and robustness of these findings.

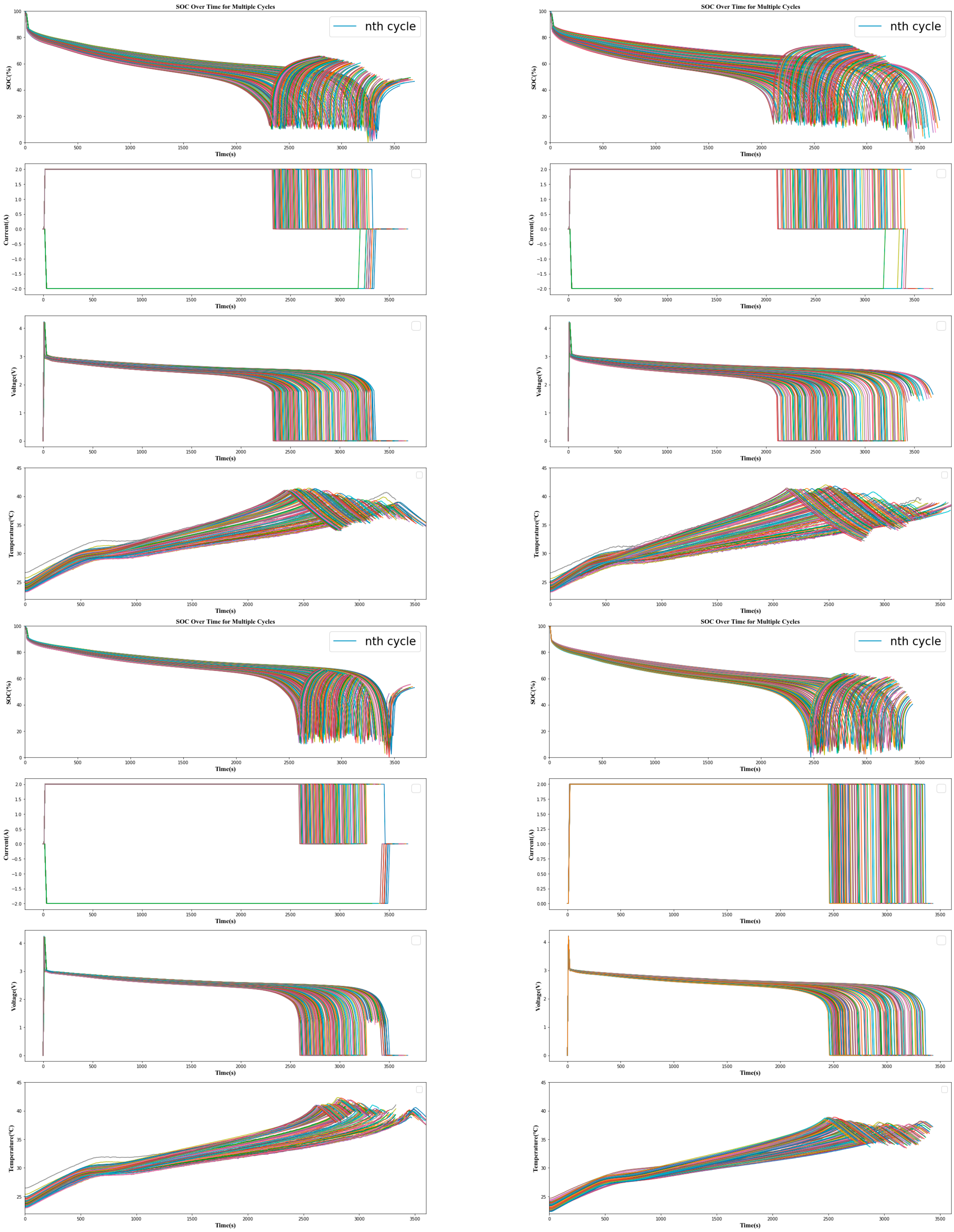


Figure 4. SOC, current, voltage, and temperature over time during each cycle.

4.3.2. SOH Estimation

Pearson correlation coefficient (PCC) analysis measures the linear relationship between two variables. It is defined as the ratio of the covariance of the two variables to the product of their standard deviations [55]. The PCC is calculated as follows:

$$PCC = \frac{\sum_{i=1}^{n} (z_i - \overline{z})(q_i - \overline{q})}{\sqrt{\sum_{i=1}^{n} (z_i - \overline{z})^2} \sqrt{\sum_{i=1}^{n} (q_i - \overline{q})^2}} \quad (11)$$

where z_i is the values of the x-variable in a sample, z is the mean of the values of the x-variable, q_i is the values of the y-variable in a sample, and $\overline{q}$ is the mean of the values of the y-variable [56].

PCC is a statistical metric used to determine the linear relationship between two variables, and it is in the range from −1.0 to 1.0. An absolute value of 1.0 means a perfect linear relationship, that is all data points lie exactly on a straight line in either a positive or negative direction. A value of zero for the PCC indicates no linear dependency of the variables and positive or negative values indicate direct or inverse linear dependences, respectively. In the framework of battery SOH modelling, PCC analysis is employed to choose input features from each discharging cycle: capacity (Ah), output current (A), terminal voltage (V), sampling time (s), and temperature (°C). These features are quantitatively evaluated based on their linear dependencies, which are categorised into five levels of strength: Correlations were extremely strong (0.9–1), strong (0.7–0.89), moderate (0.4–0.69), weak (0.1–0.39), or negligible (0–0.1) [57]. By categorising these correlations, we can find out which features are most relevant for accurate SOH prediction.

It is necessary to evaluate these features to understand the relationships between battery characteristics and how they affect SOH estimation. Battery capacity, the primary target of prediction, has a moderate correlation with temperature (0.15), weak correlations with current (0.13) and voltage (−0.14), and a negligible correlation with sampling time, according to PCC analysis. According to this analysis, terminal voltage, output current, temperature, and capacity are chosen as the input features for the prediction model. Correlation diagrams further visualise these relationships as measures of correlation strength and direction between battery characteristics to facilitate the identification of major factors that will impact performance of battery life and performance. Figure 5 shows the SOH degradation curves of the dataset. Figure 6 shows a strong negative correlation (−0.92) between cycles and capacity, meaning that as the number of cycles increases, the capacity decreases, and better battery health is associated with higher capacity. On the other hand, a strong negative correlation is observed between cycles and SOH, meaning that battery health decreases as the cycles increase. Knowing these correlations is necessary to correctly estimate battery life and performance, and it identifies important features—number of cycles, capacity, and SOH—for battery lifetime. Through detailed diagrams of these correlations, these interrelationships of the battery characteristics are visualised and enable effective feature selection and model development of SOH estimation.

As discussed in Section 3.1, data from four batteries labelled B0005, B0006, B0007, and B0018, sourced from NASA, were utilised to validate the prediction performance of the HSE-DT method. In our experiment, the complete dataset starting from the 30th, 60th, and 90th cycles were used for offline training, while the remaining data were employed for online testing. To further evaluate the robustness and effectiveness of the Transformer-CNN model, three additional methods—LSTM, Transformer, and CNN-LSTM—were also employed to estimate battery SOH using the same offline training strategy.

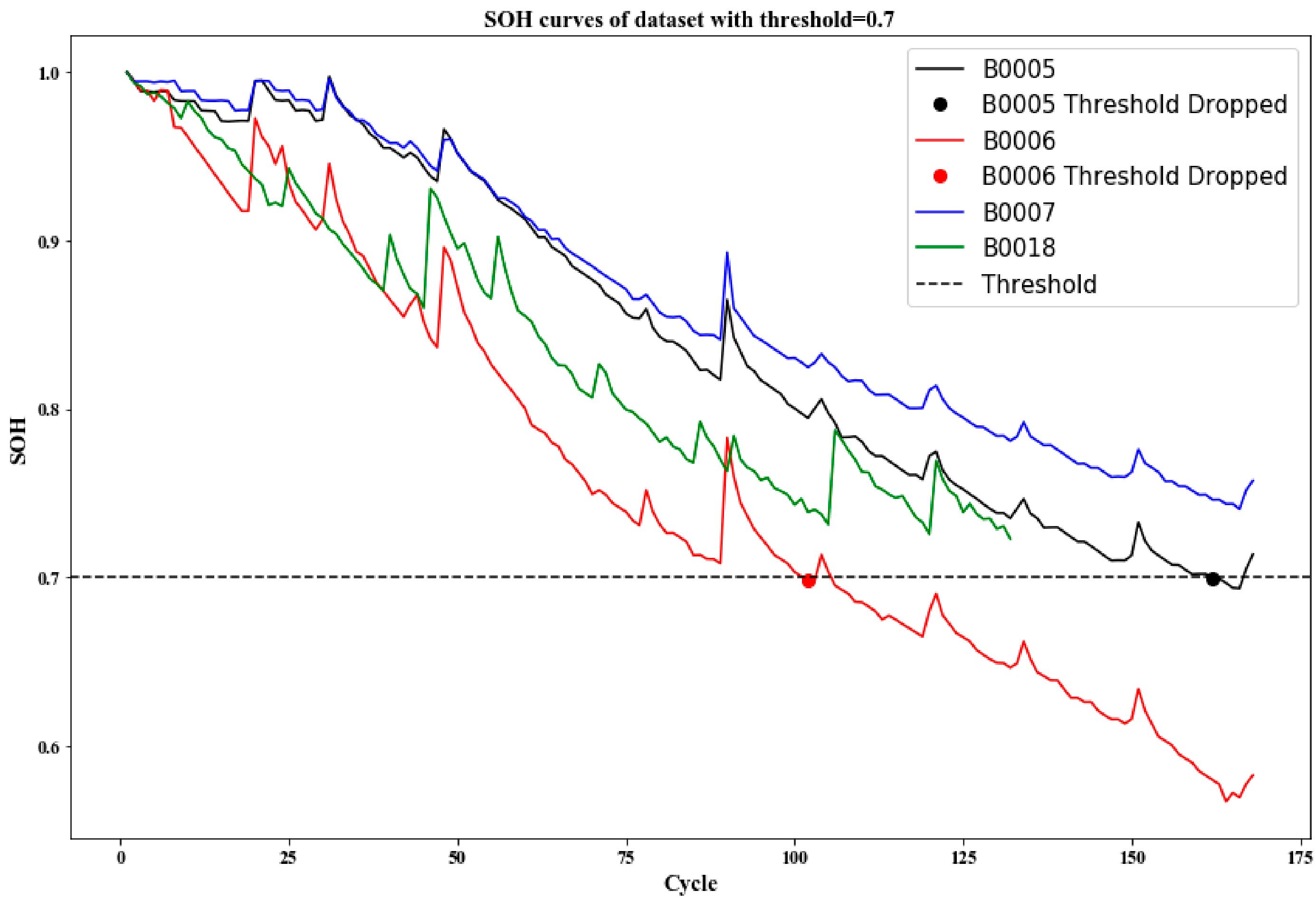


Figure 5. The theoretical SOH of the NASA dataset.

Figure 7 presents the SOH estimation from the proposed model along with the relative errors for each cycle of B0005. As depicted in Figure 7a–c, the predicted SOH values align closely with the reference SOH values, clearly demonstrating the effectiveness of the HSE-DT method.

A summary of the results of the first 90 cycles for pre-training across all four datasets is given in Table 2. As can be seen, the MAEs, MAPEs, and RMSEs of the proposed model are less than 0.5% while the R^2 value exceeds 99%, which means the Transformer-CNN model outperforms the others in SOH estimation. Additionally, these results show a substantial reduction in SOH estimation error for lithium-ion batteries using the HSE-DT method. This cut-off value was chosen because it captures more features of battery ageing than the first 30 or 60 cycles, thus stabilising the training process and making the results consistent and representative.

Results suggested that applying the HSE-DT method resulted in high accuracy for estimating battery states. The model was effective in capturing complex relationships and dependencies within the battery data, with MAE, MAPE, RMSE and R^2 values of SOC and SOH estimation significantly lower than traditional methods. The model was proved to be able to give reliable and precise estimations, which are crucial for comprehensive situational awareness.

Additionally, the self-evolving mechanism of the HSE-DT method enhances its situational awareness capability by leveraging the transfer learning technique, which periodically updates the model with new data, such that predictions are accurate and up to date. This continuous learning process results in the method being able to adjust to changing battery behaviours over time and to improve estimation accuracy and lead time of the battery condition and operational status information.

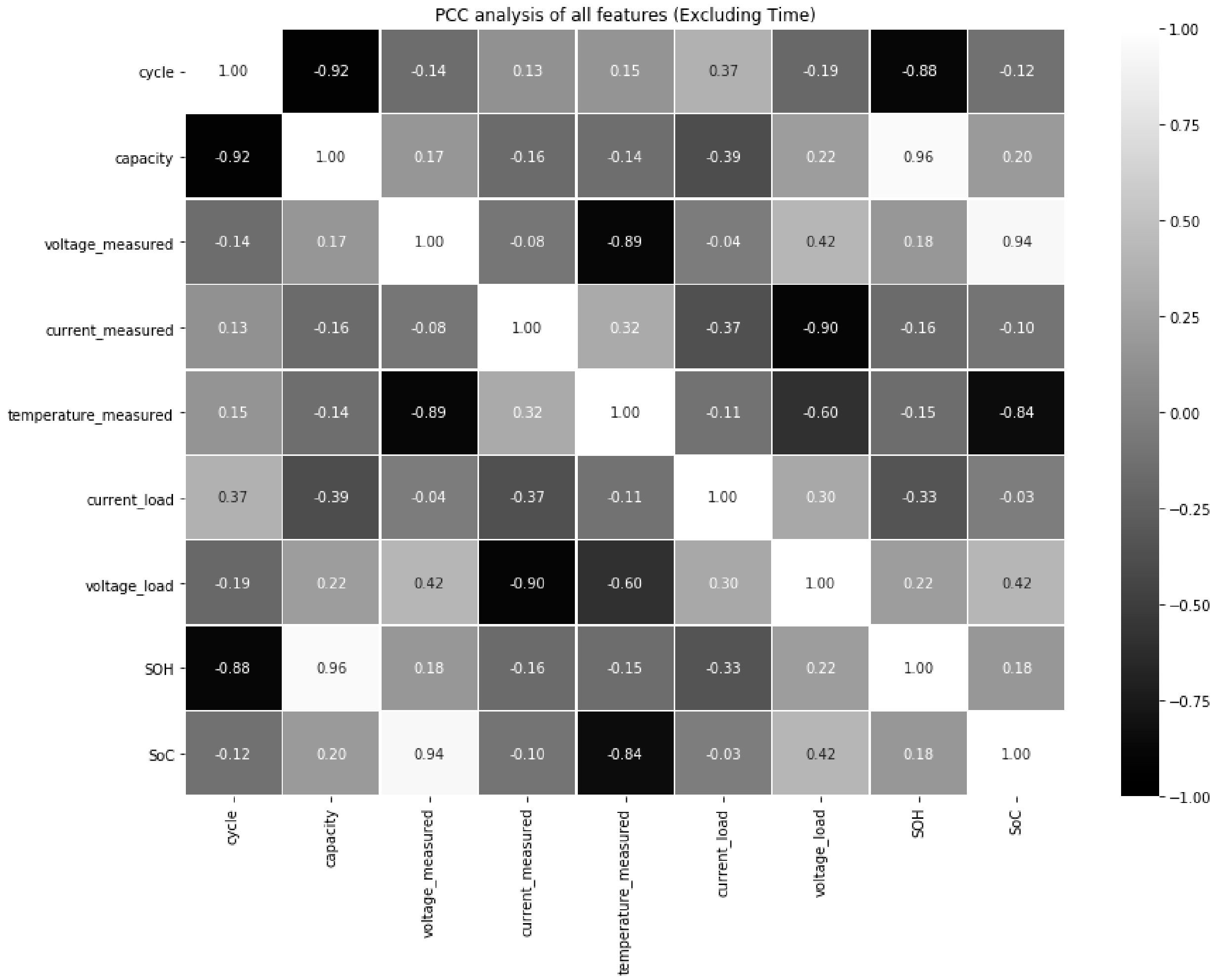
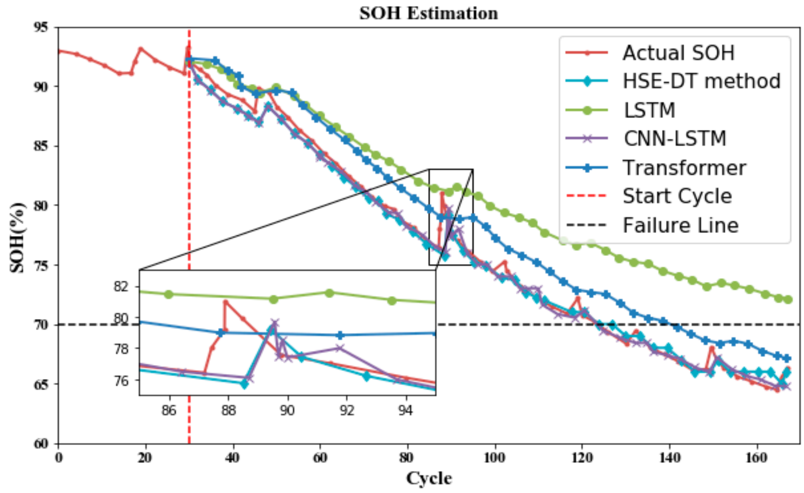


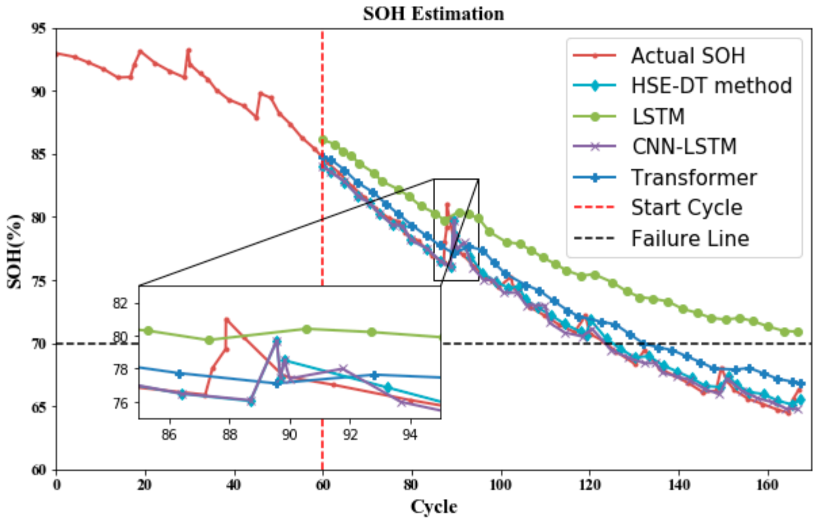
Figure 6. PCC analysis of all features.

In addition to state estimation, the HSE-DT method provides a broader understanding of the battery's health and operational context, which is important for optimising performance, enabling safety, and extending the battery's lifespan. Further, by integrating the Transformer-CNN model with the self-evolving mechanism, the method can monitor and control battery systems more effectively and with greater accuracy.

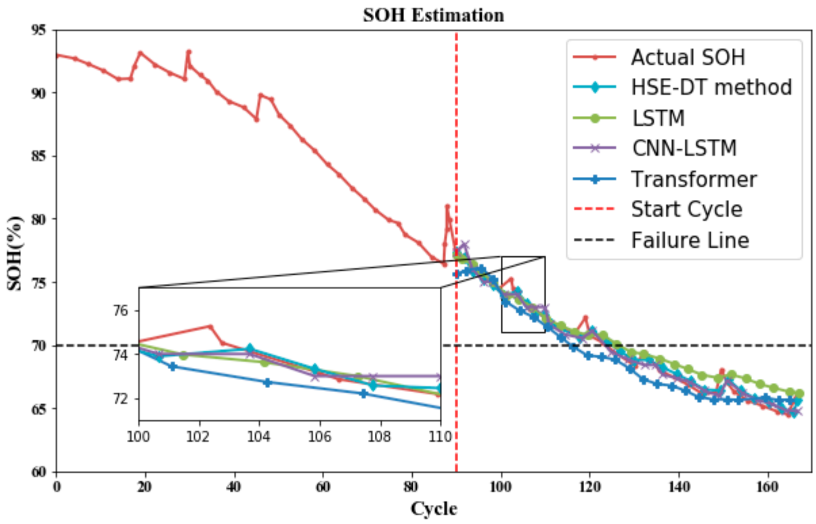
Finally, the performance evaluation using the NASA dataset shows that the HSE-DT method can improve the situational awareness of battery systems. Finally, the performance evaluation using the NASA dataset shows that the HSE-DT method can improve the situational awareness of battery systems under typical operating conditions. However, real-world applications often present more challenging environments, such as extreme temperatures which can influence the accuracy and reliability of state estimations. The dataset used in this study was limited in scope resulting in an evaluation of the model's performance across a wider range of temperature variations that was not feasible. Nevertheless, the results show that the HSE-DT method can accurately and reliably monitor and manage under typical conditions, thus providing accurate condition estimates.



(**a**)



(**b**)



(**c**)

Figure 7. The SOH estimation regarding B0005 by training at (**a**), 30th cycle (**b**), 60th cycle (**c**), 90th cycle.

Table 2. The comparison of SOH estimation for different methods.

Dataset	Models	MAE	MAPE	RMSE	R^2
B0005(90th)	Transformer-CNN	0.0024	0.0031	0.0029	0.9901
	LSTM	0.0043	0.0624	0.0071	0.8981
	CNN-LSTM	0.0029	0.0160	0.0041	0.9721
	Transformer	0.0035	0.0740	0.0045	0.9610
B0006(90th)	Transformer-CNN	0.0024	0.0038	0.0028	0.9938
	LSTM	0.0105	0.0575	0.0135	0.8425
	CNN-LSTM	0.0030	0.0168	0.0045	0.9848
	Transformer	0.0035	0.0752	0.0051	0.9816
B0007(90th)	Transformer-CNN	0.0018	0.0050	0.0022	0.9908
	LSTM	0.0037	0.0520	0.0056	0.9215
	CNN-LSTM	0.0017	0.0335	0.0025	0.9869
	Transformer	0.0021	0.0711	0.0029	0.9809
B0018(90th)	Transformer-CNN	0.0024	0.0038	0.0029	0.9981
	LSTM	0.0569	0.0768	0.0666	0.8491
	CNN-LSTM	0.0204	0.0394	0.0283	0.9330
	Transformer	0.0425	0.0712	0.0498	0.7885

5. Conclusions and Future Work

In conclusion, this study introduced the HSE-DT method, designed to enhance battery situational awareness. The method uses a structured Digital Twin model that integrates critical parameters, such as voltage, current and temperature, along with advanced estimation techniques. To overcome the complexities of battery situational awareness, the HSE-DT method uses the Transformer-CNN model to learn the spatial and temporal dynamics of the battery to obtain a global understanding of the battery conditions and behaviours.

The HSE-DT method employs a self-evolving mechanism using transfer learning and continual learning techniques. This approach allows the model to remain adaptive over time, capable of refining its parameters with new data through rolling learning. Our research provides a detailed analysis of the HSE-DT method, describing its complex structure and key stages in the learning process. Experimental results indicate the efficiency of the method in combining online situational awareness, including real-time monitoring and estimation of battery states. The Transformer-CNN model showed high accuracy with low values of RMSE and MAE, thus validating the use of the HSE DT method to increase battery situational awareness.

The multi-layered structure of the HSE-DT method underscores its integration of several aspects of battery monitoring and management. The implications of this approach include battery health and performance, which can be used to provide advanced battery management strategies. Consequently, battery operations can be optimised, and the overall system efficacy and battery lifecycle can be improved. A promising combination of advanced deep learning and the Digital Twin is presented for improving battery management and situational awareness in different applications.

Looking ahead, our research will focus on addressing key challenges to further refine the HSE-DT method for battery situational awareness. This involves developing a fully integrated Digital Twin that combines dynamic and static models and tries to integrate historical and real-time data to enrich situational awareness. Also, future studies will examine the model's performance under extreme temperatures, varying battery health states, and different usage patterns. Additionally, optimising the Digital Twin to minimise latency will be key to its capability for real-time synchronous updates and adaptive feedback control. Exploring these research dimensions will augment the capabilities and impact of battery Digital Twin technologies.

Author Contributions: Conceptualization, K.Z. and Y.L.; Methodology, K.Z., Y.L., Y.Z., W.M. and J.W.; Formal analysis, K.Z.; Investigation, K.Z.; Writing—original draft, K.Z.; Writing—review & editing, Y.L., Y.Z., W.M. and J.W.; Supervision, Y.L., W.M. and J.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article. The open source dataset can be found at: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#battery (accessed on 16 December 2024).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Che, Y.; Deng, Z.; Lin, X.; Hu, L.; Hu, X. Predictive battery health management with transfer learning and online model correction. *IEEE Trans. Veh. Technol.* **2021**, *70*, 1269–1277. [CrossRef]
2. Hu, X.; Xu, L.; Lin, X.; Pecht, M. Battery lifetime prognostics. *Joule* **2020**, *4*, 310–346. [CrossRef]
3. Ren, Z.; Wan, J.; Deng, P. Machine-learning-driven digital twin for lifecycle management of complex equipment. *IEEE Trans. Emerg. Top. Comput.* **2022**, *10*, 9–22. [CrossRef]
4. Qin, Y.; Adams, S.; Yuen, C. Transfer learning-based state of charge estimation for lithium-ion battery at varying ambient temperatures. *IEEE Trans. Ind. Inform.* **2021**, *17*, 7304–7315. [CrossRef]
5. Fan, J.; Zhang, X.; Zou, Y.; He, J. Multi-timescale Feature Extraction from Multi-sensor Data using Deep Neural Network for Battery State-of-charge and State-of-health Co-estimation. *IEEE Trans. Transp. Electrif.* **2023**, *10*, 5689–5702. [CrossRef]
6. Zhou, N.; Zhao, X.; Han, B.; Li, P.; Wang, Z.; Fan, J. A novel quick and robust capacity estimation method for Li-ion battery cell combining information energy and singular value decomposition. *J. Energy Storage* **2022**, *50*, 104263. [CrossRef]
7. Drath, R.; Horch, A. Industrie 4.0: Hit or hype?[industry forum]. *IEEE Ind. Electron. Mag.* **2014**, *8*, 56–58. [CrossRef]
8. Dubarry, M.; Howey, D.; Wu, B. Enabling battery digital twins at the industrial scale. *Joule* **2023**, *7*, 1134–1144. [CrossRef]
9. Grieves, M.W. Product lifecycle management: The new paradigm for enterprises. *Int. J. Prod. Dev.* **2005**, *2*, 71–84. [CrossRef]
10. Tuegel, E.J.; Ingraffea, A.R.; Eason, T.G.; Spottswood, S.M. Reengineering aircraft structural life prediction using a digital twin. *Int. J. Aerosp. Eng.* **2011**, *2011*, 154798. [CrossRef]
11. Semeraro, C.; Aljaghoub, H.; Abdelkareem, M.A.; Alami, A.H.; Dassisti, M.; Olabi, A. Guidelines for designing a digital twin for Li-ion battery: A reference methodology. *Energy* **2023**, *284*, 128699. [CrossRef]
12. Naguib, M.; Kollmeyer, P.; Emadi, A. Lithium-ion battery pack robust state of charge estimation, cell inconsistency, and balancing. *IEEE Access* **2021**, *9*, 50570–50582. [CrossRef]
13. Chen, C.; Fu, H.; Zheng, Y.; Tao, F.; Liu, Y. The advance of digital twin for predictive maintenance: The role and function of machine learning. *J. Manuf. Syst.* **2023**, *71*, 581–594. [CrossRef]
14. Tang, H.; Wu, Y.; Cai, Y.; Wang, F.; Lin, Z.; Pei, Y. Design of power lithium battery management system based on digital twin. *J. Energy Storage* **2022**, *47*, 103679. [CrossRef]
15. Qu, X.; Song, Y.; Liu, D.; Cui, X.; Peng, Y. Lithium-ion battery performance degradation evaluation in dynamic operating conditions based on a digital twin model. *Microelectron. Reliab.* **2020**, *114*, 113857. [CrossRef]
16. Panwar, N.G.; Singh, S.; Garg, A.; Gupta, A.K.; Gao, L. Recent advancements in battery management system for Li-ion batteries of electric vehicles: Future role of digital twin, cyber-physical systems, battery swapping technology, and nondestructive testing. *Energy Technol.* **2021**, *9*, 2000984. [CrossRef]
17. Zhu, J.; Cui, X.; Ni, W. Model predictive control based control strategy for battery energy storage system integrated power plant meeting deep load peak shaving demand. *J. Energy Storage* **2022**, *46*, 103811. [CrossRef]
18. Naseri, F.; Gil, S.; Barbu, C.; Çetkin, E.; Yarimca, G.; Jensen, A.; Larsen, P.G.; Gomes, C. Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms. *Renew. Sustain. Energy Rev.* **2023**, *179*, 113280. [CrossRef]
19. Wang, Y.; Xu, R.; Zhou, C.; Kang, X.; Chen, Z. Digital twin and cloud-side-end collaboration for intelligent battery management system. *J. Manuf. Syst.* **2022**, *62*, 124–134. [CrossRef]
20. Li, W.; Rentemeister, M.; Badeda, J.; Jöst, D.; Schulte, D.; Sauer, D.U. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. *J. Energy Storage* **2020**, *30*, 101557. [CrossRef]
21. Wang, C.; Xu, M.; Zhang, Q.; Feng, J.; Jiang, R.; Wei, Y.; Liu, Y. Parameters identification of Thevenin model for lithium-ion batteries using self-adaptive Particle Swarm Optimization Differential Evolution algorithm to estimate state of charge. *J. Energy Storage* **2021**, *44*, 103244. [CrossRef]

22. Qin, J.; Liu, Y.; Grosvenor, R. Multi-source data analytics for AM energy consumption prediction. *Adv. Eng. Inform.* **2018**, *38*, 840–850. [CrossRef]
23. Chen, C.; Liu, Y.; Sun, X.; Di Cairano-Gilfedder, C.; Titmus, S. An integrated deep learning-based approach for automobile maintenance prediction with GIS data. *Reliab. Eng. Syst. Saf.* **2021**, *216*, 107919. [CrossRef]
24. Plett, G.L. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation. *J. Power Sources* **2004**, *134*, 277–292. [CrossRef]
25. Khaneghah, M.Z.; Alzayed, M.; Chaoui, H. Fault detection and diagnosis of the electric motor drive and battery system of electric vehicles. *Machines* **2023**, *11*, 713. [CrossRef]
26. Ci, S.; He, H.; Kang, C.; Yang, Y. Building digital battery system via energy digitization for sustainable 5G power feeding. *IEEE Wirel. Commun.* **2020**, *27*, 148–154. [CrossRef]
27. Lin, J.; Liu, X.; Li, S.; Zhang, C.; Yang, S. A review on recent progress, challenges and perspective of battery thermal management system. *Int. J. Heat Mass Transf.* **2021**, *167*, 120834. [CrossRef]
28. He, Y.; Liu, X.; Zhang, C.; Chen, Z. A new model for State-of-Charge (SOC) estimation for high-power Li-ion batteries. *Appl. Energy* **2013**, *101*, 808–814. [CrossRef]
29. Hu, Y.; Lin, L.; Zhang, Y.; Wang, Z.L. Replacing a battery by a nanogenerator with 20 V output. *Adv. Mater.* **2012**, *24*, 110–114. [CrossRef] [PubMed]
30. Fan, J.; Fan, J.; Liu, F.; Qu, J.; Li, R. A novel machine learning method based approach for Li-ion battery prognostic and health management. *IEEE Access* **2019**, *7*, 160043–160061. [CrossRef]
31. Zhou, M.; Yan, J.; Feng, D. Digital twin framework and its application to power grid online analysis. *CSEE J. Power Energy Syst.* **2019**, *5*, 391–398.
32. Rae, C.; Bradley, F. Energy autonomy in sustainable communities—A review of key issues. *Renew. Sustain. Energy Rev.* **2012**, *16*, 6497–6506. [CrossRef]
33. Wu, B.; Widanage, W.D.; Yang, S.; Liu, X. Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. *Energy AI* **2020**, *1*, 100016. [CrossRef]
34. Botta, A.; De Donato, W.; Persico, V.; Pescapé, A. Integration of cloud computing and internet of things: A survey. *Future Gener. Comput. Syst.* **2016**, *56*, 684–700. [CrossRef]
35. Sancarlos, A.; Cameron, M.; Abel, A.; Cueto, E.; Duval, J.-L.; Chinesta, F. From ROM of electrochemistry to AI-based battery digital and hybrid twin. *Arch. Comput. Methods Eng.* **2021**, *28*, 979–1015. [CrossRef]
36. Merkle, L.; Pöthig, M.; Schmid, F. Estimate e-Golf Battery State Using Diagnostic Data and a Digital Twin. *Batteries* **2021**, *7*, 15. [CrossRef]
37. Qin, Y.; Arunan, A.; Yuen, C. Digital twin for real-time Li-ion battery state of health estimation with partially discharged cycling data. *IEEE Trans. Ind. Inform.* **2023**, *19*, 7247–7257. [CrossRef]
38. Reniers, J.M.; Howey, D.A. Digital twin of a MWh-scale grid battery system for efficiency and degradation analysis. *Appl. Energy* **2023**, *336*, 120774. [CrossRef]
39. Qu, J.; Liu, F.; Ma, Y.; Fan, J. A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery. *IEEE Access* **2019**, *7*, 87178–87191. [CrossRef]
40. Feng, X.; Weng, C.; He, X.; Han, X.; Lu, L.; Ren, D.; Ouyang, M. Online state-of-health estimation for Li-ion battery using partial charging segment based on support vector machine. *IEEE Trans. Veh. Technol.* **2019**, *68*, 8583–8592. [CrossRef]
41. Dong, G.; Han, W.; Wang, Y. Dynamic Bayesian network-based lithium-ion battery health prognosis for electric vehicles. *IEEE Trans. Ind. Electron.* **2020**, *68*, 10949–10958. [CrossRef]
42. Li, Y.; Zou, C.; Berecibar, M.; Nanini-Maury, E.; Chan, J.C.-W.; Van den Bossche, P.; Van Mierlo, J.; Omar, N. Random forest regression for online capacity estimation of lithium-ion batteries. *Appl. Energy* **2018**, *232*, 197–210. [CrossRef]
43. Meng, J.; Cai, L.; Luo, G.; Stroe, D.-I.; Teodorescu, R. Lithium-ion battery state of health estimation with short-term current pulse test and support vector machine. *Microelectron. Reliab.* **2018**, *88*, 1216–1220. [CrossRef]
44. Lin, M.; Yan, C.; Meng, J.; Wang, W.; Wu, J. Lithium-ion batteries health prognosis via differential thermal capacity with simulated annealing and support vector regression. *Energy* **2022**, *250*, 123829. [CrossRef]
45. Urolagin, S.; Sharma, N.; Datta, T.K. A combined architecture of multivariate LSTM with Mahalanobis and Z-Score transformations for oil price forecasting. *Energy* **2021**, *231*, 120963. [CrossRef]
46. Cheng, G.; Wang, X.; He, Y. Remaining useful life and state of health prediction for lithium batteries based on empirical mode decomposition and a long and short memory neural network. *Energy* **2021**, *232*, 121022. [CrossRef]
47. Han, T.; Wang, Z.; Meng, H. End-to-end capacity estimation of Lithium-ion batteries with an enhanced long short-term memory network considering domain adaptation. *J. Power Sources* **2022**, *520*, 230823. [CrossRef]
48. Tan, Y.; Zhao, G. Transfer learning with long short-term memory network for state-of-health prediction of lithium-ion batteries. *IEEE Trans. Ind. Electron.* **2019**, *67*, 8723–8731. [CrossRef]

49. Ma, Y.; Shan, C.; Gao, J.; Chen, H. A novel method for state of health estimation of lithium-ion batteries based on improved LSTM and health indicators extraction. *Energy* **2022**, *251*, 123973. [CrossRef]
50. Li, P.; Zhang, Z.; Xiong, Q.; Ding, B.; Hou, J.; Luo, D.; Rong, Y.; Li, S. State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network. *J. Power Sources* **2020**, *459*, 228069. [CrossRef]
51. Zhou, H.; Zhang, Y.; Yang, L.; Liu, Q.; Yan, K.; Du, Y. Short-term photovoltaic power forecasting based on long short term memory neural network and attention mechanism. *IEEE Access* **2019**, *7*, 78063–78074. [CrossRef]
52. Hu, J.; Zheng, W. Multistage attention network for multivariate time series prediction. *Neurocomputing* **2020**, *383*, 122–137. [CrossRef]
53. Wang, W.; Wang, J.; Tian, J.; Lu, J.; Xiong, R. Application of digital twin in smart battery management systems. *Chin. J. Mech. Eng.* **2021**, *34*, 57. [CrossRef]
54. Du, X.; Meng, J.; Zhang, Y.; Huang, X.; Wang, S.; Liu, P.; Liu, T. An information appraisal procedure: Endows reliable online parameter identification to lithium-ion battery model. *IEEE Trans. Ind. Electron.* **2021**, *69*, 5889–5899. [CrossRef]
55. Kong, J.-z.; Yang, F.; Zhang, X.; Pan, E.; Peng, Z.; Wang, D. Voltage-temperature health feature extraction to improve prognostics and health management of lithium-ion batteries. *Energy* **2021**, *223*, 120114. [CrossRef]
56. Jebli, I.; Belouadha, F.-Z.; Kabbaj, M.I.; Tilioua, A. Prediction of solar energy guided by pearson correlation using machine learning. *Energy* **2021**, *224*, 120109. [CrossRef]
57. Benesty, J.; Chen, J.; Huang, Y. On the Importance of the Pearson Correlation Coefficient in Noise Reduction. *IEEE Trans. Audio Speech Lang. Process.* **2008**, *16*, 757–765. [CrossRef]