Digital Twin-supported Battery State Estimation Based on TCN-LSTM Neural Networks and Transfer Learning

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***Abstract*—Estimating battery states such as State of Charge (SOC) and State of Health (SOH) is an essential component in developing energy storage technologies, which require accurate estimation of complex and nonlinear systems. A significant challenge is extracting pertinent spatial and temporal features from original battery data, which is crucial for efficient battery management systems. The emergence of digital twin (DT) technology offers a novel opportunity for performance monitoring and management of lithium-ion batteries, enhancing collaborative capacity among different battery state estimation techniques and enabling optimal operation of battery storage units. In this study, we propose a DT-supported battery state estimation method, in collaboration with the temporal convolutional network (TCN) and the long short-term memory (LSTM), to address the challenge of feature extraction. Firstly, we introduce a 4-layer hierarchical DT to overcome computational and data storage limitations in conventional battery management systems. Secondly, we present an online algorithm, TCN-LSTM for battery state estimation. Compared to conventional methods, TCN-LSTM outperforms other cyclic networks in various sequence modelling tasks and exhibits reduced reliance on the initial state conditions of the battery. Our methodology employs transfer learning to dynamically adjust the neural network parameters based on fresh data, ensuring real-time updating and enhancing the DT's accuracy. Focusing on SOC, SOH and Remaining Useful Life (RUL) estimation, our model demonstrates exceptional results. When testing with 90 cycle data, the average root mean square error (RMSE) values for SOC, SOH, and RUL are 1.1%, 0.8%, and 0.9% respectively, significantly outperforming traditional CNN's 2.2%, 2.0% and 3.6% and others. These results unequivocally demonstrate the contribution of the DT model to battery management, highlighting the outstanding robustness of our proposed method, showcasing consistent performance across various conditions and superior adaptability compared to other models.**

***Index Terms*—Battery energy storage system, battery state estimation, deep learning, digital twin, transfer learning.**

I. Introduction

BATTERY Energy Storage System (BESS) has emerged as a fulcrum within the prevailing energy face, specifically amid the global shift towards renewable energy sources such as wind and photovoltaic (PV) generation. However, this shift is not just a technological development if it responds to increasingly urgent issues of universal nature such as climate change, energy security, and sustainable development. As nations grapple with the imperative of reducing carbon emissions, the role of BESS in ensuring energy reliability and grid stability becomes paramount [1]. The shift towards a carbon-neutral power system, a goal of paramount importance, is laden with a spectrum of technical challenges. Improving energy management under uncertainties in power distribution and reserve coordination has become increasingly important, highlighting the necessity for precise and adaptive state estimation of energy storage [2]. BESS presents a practical solution to address specific issues within this spectrum. The project's main challenges are controlling intermittent renewable energy resources, maintaining the real-time supply-demand balance, and preserving the reliability and stability of the power grid. BESS is crucial in overcoming these obstacles, facilitating a smoother transition to carbon-neutral energy systems.

Lithium-ion batteries, among the array of emerging storage technologies, have been at the forefront due to their inherent technological attributes and economic considerations. This versatility has been proven in the field as diverse as the portable issue mobile phones, online-pop-frass grid-scale energy storage, electric vehicles et al. Using these attributes of the batteries i.e. quick charging capacity, long cycle life, high specific energy; high specific power, rechargeable and without a memory effect, both their large and wide set has wider application and wide research on their optimization and safety [3]. Monitoring parameters such as State of Charge (SOC) is not a mere operational requirement but a safety imperative. Furthermore, the derivation of health indicators, such as State of Health (SOH) and Remaining Useful Life (RUL), through capacity or resistance measurements is of paramount importance [4]. However, the landscape of direct online measurements for battery state estimation is complex. Achieving reliable and real-time estimation in this domain is an ongoing challenge and a key research focus area. This complexity is primarily due to the dynamic nature of battery behaviours and the need for high-precision data for accurate estimation [5], [6]. Data-driven approaches using real-time and historical data have been used to optimize operation of energy

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storage system such as data driven predictive voltage control for improved system performance without relying on explicit physical models [7]. Consequently, data-driven methods are used in order to extract meaningful temporal and spatial features from battery data for accurate state estimation. Our research addresses this gap by developing methodologies that increase the accuracy and reliability of battery state estimation in real time, thereby contributing to the field.

In the domain of battery management systems (BMS), the accurate estimation of SOC and SOH is critical for operational efficiency and ensuring the longevity and safety of the battery systems. These metrics are vital indicators of the battery's operational status and degradation trajectory, respectively. Over the years, many methodologies have been proposed for SOC estimation, encompassing traditional techniques and more recent computational approaches [8]–[15]. The indirect nature of SOC measurement presents significant challenges, which require advanced methodologies for accurate estimation. This complexity has driven substantial research into developing reliable and robust SOC estimation methods, encompassing look-up tables, ampere-hour integration, and strategies based on filtering, observation, and data analytics. While the simplicity of look-up table and ampere-hour integral methods is appealing, their accuracy and robustness are compromized by sensor inaccuracies [16], [17].

In contrast, filter-based and observer-based methods offer high precision, self-correction, and noise resistance but require detailed battery testing for model calibration [18], [19]. Wang developed a neural network model AdaBoost-AOA-BPNN with a cascade structure for state-of-charge (SOC) estimation of lithium-ion batteries, which showed better estimation accuracy and stability under different temperature conditions, reflecting the promise of data-driven approaches in battery management [20]. Data-driven methods utilize machine learning algorithms to reduce the necessity for deep knowledge of a battery's electrochemical properties, focusing on the correlation between input and output [21]. However, these approaches contend with potential overfitting or underfitting, tied to the quality of training data and the algorithmic framework, which can hinder their practical application.

The intricacies associated with battery ageing mechanisms assess SOH as a complex endeavour. Direct capacity measurement, while being the most straightforward indicator of battery health, is challenging in real-world scenarios. This has shifted towards indirect measurements, with parameters like internal resistance emerging as potential degradation indicators. The research community has been actively exploring these indirect measurements, focusing on their potential for predicting SOH and RUL [22], [23]. However, the dynamic nature of battery operations, influenced by many factors including environmental conditions, usage patterns, and manufacturing inconsistencies, often poses challenges to these methodologies. These challenges include the difficulty in accurately predicting battery life, variability in performance under different environmental conditions, and the need to constantly adapt to varying usage patterns. Additionally, manufacturing inconsistencies can lead to significant variations in battery behaviour, further complicating the developing of universally applicable estimation methods.

While traditional methodologies have demonstrated effectiveness within this field, they commonly utilise static model's incapable of incorporating the dynamic data and environmental effects which impact battery performance. This deficiency is notably pronounced during instances when batteries experience unpredictable operational shifts. Moreover, most methods rarely provide a holistic framework that concurrently addresses SOC estimation, SOH monitoring, and RUL prediction. This landscape focuses on improving individual aspects without considering their synergy and influence on battery management systems. Such a segmented method might result in inefficiencies in contexts demanding a strategy for optimal battery operation and lifecycle.

In recent years, the digital twin landscape has undergone transformative advancements, with the emergence of cloud computing and the Internet of Things (IoT) [24] leading the way. These innovations have presented novel solutions to the challenges traditionally faced by the BMS. Among these solutions is the concept of cloud-based digital twins, which involves crafting digital replicas of physical battery systems. These replicas, virtual mirrors of their physical counterparts, transmit real-time battery data to cloud platforms. The synergy between these digital twins and cloud platforms' robust data processing, analytics, and storage capabilities unlocks many applications, ranging from real-time monitoring, diagnostics, and anomaly detection to predictive maintenance and optimization [25], [26]. However, the journey to seamlessly integrate digital twins into BMS is not without hurdles. Assembling precise digital models of batteries requires a diverse range of full-scale real-world datasets that are rarely available. Additionally, battery degradation, which is highly variable due to many factors, creates additional layers of complexity in the modelling process.

In this study, a Digital Twin (DT) for battery systems is introduced, encompassing its structure, operational mechanisms, modelling, and state estimation with a particular focus on SOC estimation, SOH monitoring, and RUL prediction for lithium-ion batteries via the optimized TCN-LSTM network. Its effectiveness is corroborated through comprehensive validation. The contributions of this paper are the development and validation of a DT framework that integrates TCN-LSTM models enhanced by transfer learning. This integration enables the DT to dynamically adapt its parameters in response to real-time data, thereby improving its predictive accuracy and adaptability over successive cycles. The notable work of this research encompasses: 1) Established DT for computing SOC, SOH, and RUL across diverse operational conditions, obviating the requirement for multiple models or reference tables. 2) Established the TCN-LSTM network which directly captures measurements from the battery, thus facilitating streamlined SOC estimation. 3) Introduced an approach that considers the impact of local regeneration on SOH monitoring, utilizing the LSTM-TCN network for enhanced battery performance prediction. 4) The incorporation of transfer learning, allows the digital twin to be configured for various battery conditions, thereby mitigating modelling costs and dataset prerequisites.

Section II synthesizes the prevailing literature on battery digital twins and provides an in-depth analysis of state estimation. Section III articulates the proposed framework and relevant algorithms associated with battery digital twins. Also, the data-driven methodologies for SOC and SOH estimation and RUL prediction using the TCN-LSTM network are detailed. Section IV is complemented by a case study on lithium-ion battery datasets, highlighting the framework's practicality and prompting discussion on the experimental results. Section V presents conclusions and outlines potential directions for future academic research.

II. Battery Digital Twin and State Estimation

A. Battery Digital Twin

Digital twin technology harnesses sophisticated physical models, intelligent sensor readings, and comprehensive operation and maintenance data history, amalgamating multidisciplinary insights for a simulation process that spans various physical quantities, temporal scales, and probability scenarios. Such twins authentically represent energy storage systems within a virtual domain, capable of real-time updates and dynamic evolution, thereby mirroring the full lifecycle of the pertinent energy system [27].

While research into batteries has deepened and advanced over the years, numerous challenges persist. State estimation for Li-ion batteries serves as a foundational element for both battery and equilibrium management systems are crucial in averting overcharge or over-discharge situations. Nevertheless, crafting accurate models for lithium-ion batteries remains an intricate task, given the pronounced non-linearity and tight interrelation of internal battery dynamics [28]. DT technologies have demonstrated notable efficacy in the aerospace domain, particularly in SOC estimation, RUL predictions, and optimal controls, suggesting their potential applicability to battery state management issues.

The integration of DT with BMS commenced recently, further enhanced by incorporating cloud computing and IoT frameworks [29]. Present-day investigations into battery digital twins primarily address three core challenges inherent to contemporary BMS: the complexities in data integration from diverse BMS providers, the constrained computing power of embedded systems, and the restricted data storage capabilities. To address the data-sharing challenges in battery management, Li [25] integrated DT technology, consolidating all battery-related data into a cloud-based platform to enhance the BMS structure. This integration is critical as the volume of battery data surges, resulting in exponential increases in computational and storage demands for BMS. Machine learning approaches, particularly data scarcity models, are utilized to predict and refine system states to navigate these complexities, offering new insights into battery ageing processes. A notable example is the study [30], which combines a Health Indicator (HI) with the Long Short-Term Memory (LSTM) algorithm for precise estimation of battery discharge capacities.

However, the digital twins' real-time and self-evolving capabilities warrant further improvement. Research [31] introduces a 'Hybrid Twin', a pioneering digital twin model for lithium-ion batteries in the automotive sector, employing techniques such as Proper Orthogonal Decomposition (POD), sparse-proper Generalized Decomposition and Dynamic Mode Decomposition. These methods significantly boost the real-time performance and flexibility of BMS. Similarly, a study establishes a digital battery twin and data pipeline for electric vehicle batteries, leveraging a cloud-based system for health and performance analysis, underscoring digital twins' role in enhancing battery system management in vehicles. Tang [32] proposes a digital twin-supported framework to surmount BMS constraints, using a joint HIF-PF online algorithm for precise SOC estimation and efficient real-time monitoring. This approach exemplifies the transformative impact of digital twin technology in BMS. Paper [33] details a digital twin framework for real-time SOH assessment of lithium-ion batteries under variable conditions, utilizing a unique method that incorporates energy discrepancy-aware cycling synchronization and time-attention modelling, facilitating accurate SOH predictions without complete discharge cycles. Lastly, another study [34] models a large-scale, grid-connected lithium-ion battery system through a digital twin methodology, focusing on the influence of system design and ancillary controls on degradation and efficiency, thereby highlighting digital twins' effectiveness in optimizing battery system performance.

B. Battery State Estimation

The management of batteries is crucial for the optimal operation, safety, reliability, and cost efficiency of prevalent battery-powered energy systems, including electrified transportation and renewable-integrated smart grids [35]. A central technological advancement for advanced battery management lies in precisely and consistently estimating and monitoring vital internal states. Reliable data on SOC and SOH are essential for proficient charging, thermal regulation, and overall health upkeep of batteries. Fundamental battery behaviours are typically delineated by a synergized electrochemical-thermal-aging framework, with each subcomponent of the multi-physics model operating on its distinct timescale. Certain battery states, such as SOC, fluctuate contemporaneously due to rapidly evolving microscopic electrochemical attributes. Conversely, the battery's SOH, associated with gradual parameter variations like internal impedance augmentation and capacity degradation, exhibits minor shifts over brief durations. The overarching safety state of a battery can be ascertained through the assessment of the states previously mentioned. Fig. 1 shows a general procedure of DT-supported battery state estimation that, using data, mechanisms, and semi-empirical models, the dynamic model of the complex coupling system of the battery and environment was accurately identified and evaluated.

1) SOC Estimation

Within the purview of BMSs, the SOC stands as a pivotal parameter and can be represented through diverse mathematical formulations [3]. Fundamentally, SOC delineates the available capacity Q_a as a fraction of the nominal capacity Q_n, with Q_n denoting the peak charge a battery can retain. Given a current I that is positive during charging and negative during discharging, a standard formulation for SOC is:

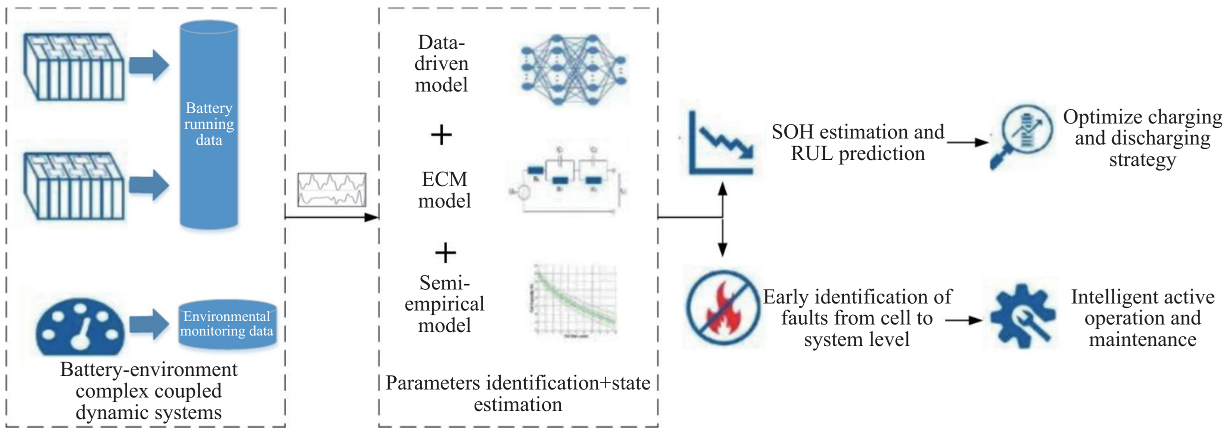

Fig. 1. State estimation for the battery-environment coupled systems.

$$SOC(t) = SOC(t_0) + \int_{t_0}^{t} \frac{I(t) - \eta}{Q_n} \mathrm{d}t \tag{1}$$

Here, $SOC(t)$ and $SOC(t_0)$ represent the SOC values at instances t and the commencement time t_0, respectively. The parameter η signifies the coulombic efficiency, mirroring the quotient of energy discharged fully to the requisite energy for restoring original capacity.

For BMSs, precise SOC data is imperative, signifying the residual accessible energy within a battery during operational phases. Pertaining to the battery, such state intel furnishes foundational insights for charging/discharging modalities, ensuring operation within bounded safety and dependability margins. Under controlled lab environments, post-ascertainment of the initial SOC, the benchmark SOC values are predominantly derived through a rigorously managed coulomb counting technique that aggregates the transmitted charge [8]. Nonetheless, owing to multifaceted electrochemical interplays and pronounced interactive traits, direct measurement of battery SOC in practical settings proves challenging. As such, real-time SOC estimation emerges as an essential competency within BMSs, garnering significant attention.

2) SOH Estimation and RUL Prediction

During their operational lifespan, electrochemical batteries invariably undergo incremental performance attrition due to side reactions [36]. This leads to the ageing phenomenon characterized by the depletion of lithium inventory and loss of active materials [37]. The SOH is a pivotal metric that quantitatively assesses battery ageing, specifically in relation to capacity diminution and internal resistance alterations [38]. Mathematically, SOH is articulated as:

$$SOH = \frac{C_a}{C_r} \times 100\% \text{ or } SOH = \frac{R_a - R_r}{R_r} \times 100\% \tag{2}$$

In this equation, C_a and C_r present and nominal capacity values. R_r and R_a present Nominal and present internal resistances.

For battery management, demarcations for a battery's End-of-Life (EOL) typically include a 20% capacity reduction or a 100% surge in internal resistance. SOH of a battery underscores its safety, reliability, and operational efficacy [39].

The RUL is defined as:

$$RUL(t) = t - t_{\mathrm{EOL}} \tag{3}$$

where t_{EOL} Denotes the cycle count upon the battery's EOL and t represents the ongoing cycle iteration.

RUL is deduced from the variance between the extant capacity and EOL. The overarching challenge is to devise strategies that enable multi-step RUL forecasts utilizing archived datasets [40].

C. Deep Learning and Its Application in Li-ion Battery State Estimation

Deep learning, a specialized branch of machine learning, has gained prominence across various scientific disciplines, primarily due to its exceptional capability to model complex non-linear relationships. Utilizing architectures like neural networks, and deep learning algorithms autonomously extract feature representations from raw data, eliminating the necessity for manual feature engineering. This unique strength has elevated deep learning to a pivotal role in numerous applications, ranging from computer vision to natural language processing.

Within the context of Li-ion battery research, deep learning's integration has marked a significant paradigm shift. The inherent complex dynamics and non-linear behaviours of Li-ion batteries pose challenges that often surpass the capabilities of traditional modelling techniques. However, deep learning, adept at unravelling these complex patterns, provides a novel solution to these intricacies.

LSTM, a specialized form of Recurrent Neural Networks (RNN), is particularly lauded for its proficiency in processing sequential data. A testament presented the Auto-CNN-LSTM model. By merging convolutional neural networks with LSTM, this model offers enhanced predictions for the remaining useful life of lithium-ion batteries, marking a milestone in battery prognostics [41]. Reinforcing this, a study highlighted the superiority of LSTM-based models over traditional neural networks in predicting the RUL of such batteries [42].

Temporal Convolutional Networks (TCN), characterized by their sequence-focused convolutional design, have also made significant strides in Li-ion battery research. For instance, Bi *et al*. undertook a comparative analysis of LSTM and TCN to estimate the SOH of lithium-ion batteries. Their research accentuated the advantages of TCN in recognizing long-term data patterns, indicating a promising avenue for subsequent studies [43]. Further emphasizing the adaptability of TCNs, Liu delved into combining TCN with transfer learning, revealing breakthroughs in SOC estimation for lithium-ion batteries [44].

To conclude, adopting deep learning architectures, especially LSTM and TCN, has undeniably advanced the domain of Li-ion battery research. Their advanced methodologies in analysing sequential data forecast a bright future for developing battery management systems, prognostics, and health monitoring.

III. Digital Twin-supported Battery State Estimation

In this section, we delve into the framework's virtual aspect, which integrates model-driven and data-driven algorithms. These algorithms work in tandem, and their combined operation is central to the framework. As battery capacity decreases, an iterative learning methodology is employed to update the model parameters, ensuring the continuous updating of the digital twin.

A. Framework

The digital twin framework is distinguished by its hierarchical structure, bidirectional interaction capability, and inherent ability to evolve autonomously. Within this structure, specific models are designed for various objectives, including state estimation, RUL prediction, and energy management. It is essential that data, regardless of its multi-dimensional nature, can flow smoothly across these hierarchical divisions.

Our research's primary objective is to leverage the digital twin to uncover the underlying relationship between the SOC and measured variables. Fig. 2 presents a detailed battery digital twin framework, which forms the backbone of our entire system. This system is organized into four key segments:

Physical End: This pertains to the real-world components of the system, such as battery packs, motors, BMS, and sensors. It enables real-time monitoring of parameters like open-circuit voltage, current, and temperature.

Virtual End: This is the digital reflection of the physical components, designed to emulate real-world systems to meet specific objectives. At its core, it employs a mix of model-driven and data-driven algorithms to integrate objectives from different hierarchical levels and timeframes.

Cloud End: This segment is reserved for storing the system's initial and historical data. Additionally, it sets the optimization objectives and defines the time scales for the entire digital twin.

Output: This section provides essential outputs like cell status monitoring, SOC estimation, and reliability recommendations, aiding technicians in making well-informed decisions.

In the proposed experimental framework, the digital twin of the BESS is conceived as a dynamic, multi-dimensional entity. This entity continuously evolves by integrating data from its physical, virtual, and cloud-based components. Central to this system is the Information Flow mechanism, which enables a bidirectional data exchange among these components. Such an exchange is crucial for the autonomous evolution of the digital

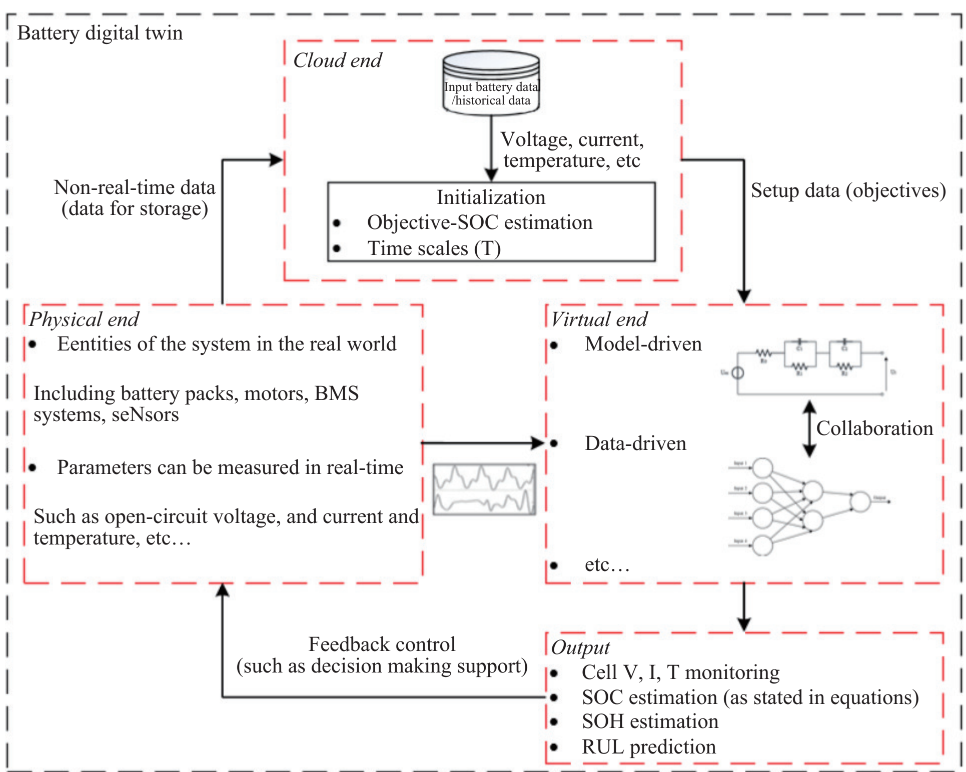

Fig. 2. The proposed battery digital twin framework.

twin, allowing it to adapt and enhance its performance progressively. The virtual segment of the system is of paramount importance. It employs model-driven and data-driven algorithms to predict and simulate the system's future states accurately. This predictive modelling is vital for developing pre-emptive maintenance strategies, optimizing operational efficiency, and extending the lifespan of the BESS. By integrating real-time and historical data from the cloud, the virtual component conducts a thorough analysis of the system's performance and health. This integration significantly improves the efficiency and adaptability of the BESS. Moreover, the output from this system is not limited to data collection; it provides actionable insights. These insights are essential for technicians and engineers, enabling them to make informed decisions and drive innovation in battery storage technologies. In summary, this paper highlights the synergistic effect of the virtual component within the digital twin framework, emphasizing its critical role in enhancing the BESS's overall functionality and resilience.

B. Approaches

1) Battery Modelling

Several model-driven methodologies are available, such as the internal resistance, n-RC, PNGV, and GNL models [45], [46]. In this study, we have chosen the Thevenin model, commonly known as the 2-RC model, for its adeptness at simulating both the steady-state and transient behaviours of the battery [47]. While more complex models might increase computational demands, their selection becomes redundant. This is because the TCN-LSTM [48] can effectively mitigate errors arising from model uncertainties.

Figure 3 illustrates the 2-RC equivalent circuit model. In this representation, Uoc denotes the open-circuit voltage, while R0 indicates the ohmic resistance. The circuits R1 and C1, which represent electrochemical polarization resistance and capacitance, capture the rapid increase in discharge voltage. On the other hand, the R2 and C2 circuits, symbolizing concentration polarisation resistance and capacitance, depict the slow stabilization phase of the discharge voltage. Notably, the elements R1, R2, C1, and C2 reflect the battery's polarisation, with Ut representing the terminal voltage.

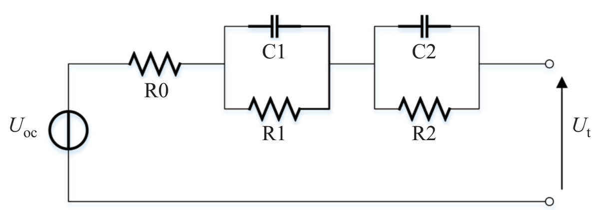

Fig. 3. The 2nd-order ECM structure.

Theoretically, these parameters undergo dynamic changes influenced by factors like SOC state, temperature, and ageing state, leading to potential estimation errors. However, within the digital twin paradigm, such errors are adeptly rectified by the TCN-LSTM neural network.

2) TCN-LSTM for SOC Estimation

Due to its merits of expediency and swift response, the extended Kalman filter (EKF) method for SOC estimation aligns well with the real-time demands of digital twin systems [48]. However, its accuracy is heavily influenced by the initial SOC and the impedance model, highlighting the need for accurate initial SOC values and precise sensors. Addressing this, the LSTM algorithm adjusts the initial SOC before the EKF estimation stages. The LSTM algorithm, while adept at estimating the battery's charge state amidst initial state uncertainties, encounters a significant drawback due to its computational intensity, leading to time inefficiencies. To address this, the TCN emerges as a viable alternative. TCN's primary advantage lies in its flexibility in adjusting the receptive field size and effectively managing the model's memory duration. This combination preserves accuracy in charge state estimation and significantly enhances computational efficiency. One of its key advantages is the ability to address issues such as gradient explosion or vanishing gradients, often seen in RNN.

Additionally, TCN requires less memory during training, especially with long input sequences. This efficiency is credited to its unique dilated causal convolution and the inclusion of the residual model. Combining the strengths of both TCN and LSTM can potentially optimize input parameters and reduce training time.

Figure 4 depicts the process for SOC estimation. A combined TCN-LSTM network captures the non-linear relationship between SOC, current, voltage, and temperature, ensuring accurate initial SOC values for real-time EKF-based SOC estimation. A rolling learning approach [49] is implemented to continuously adjust the TCN-LSTM model parameters to further adapt to varying environments.

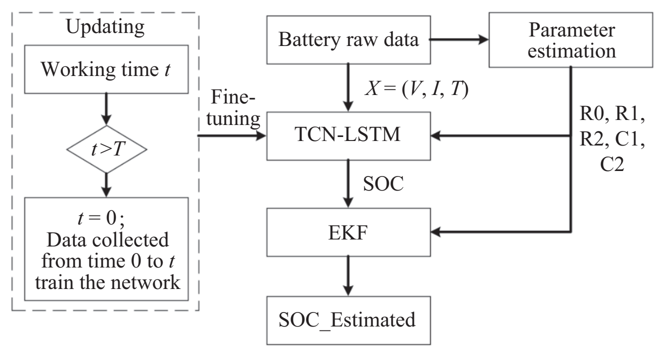

Fig. 4. Flowchart of the SOC estimation in virtual end.

Selecting the right inputs for an estimation algorithm is a complex task. It's worth noting that current, temperature, and voltage, as directly measurable parameters, have been proven to significantly influence battery state estimations [3]. As a result, these parameters serve as inputs for the equivalent circuit model (ECM) and TCN-LSTM in this study. To enhance accuracy, the TCN-LSTM is first initialized and trained using data from the battery's early operational cycles. The EKF then provides the final adjustment for SOC. Compared to traditional EKF estimation, this methodology delivers improved SOC estimation and reduces the uncertainties in initial battery state data.

3) TCN-LSTM for SOH Estimation and RUL Prediction

The TCN model employs 1-D causal convolution to extract historical data, ensuring the preservation of temporal

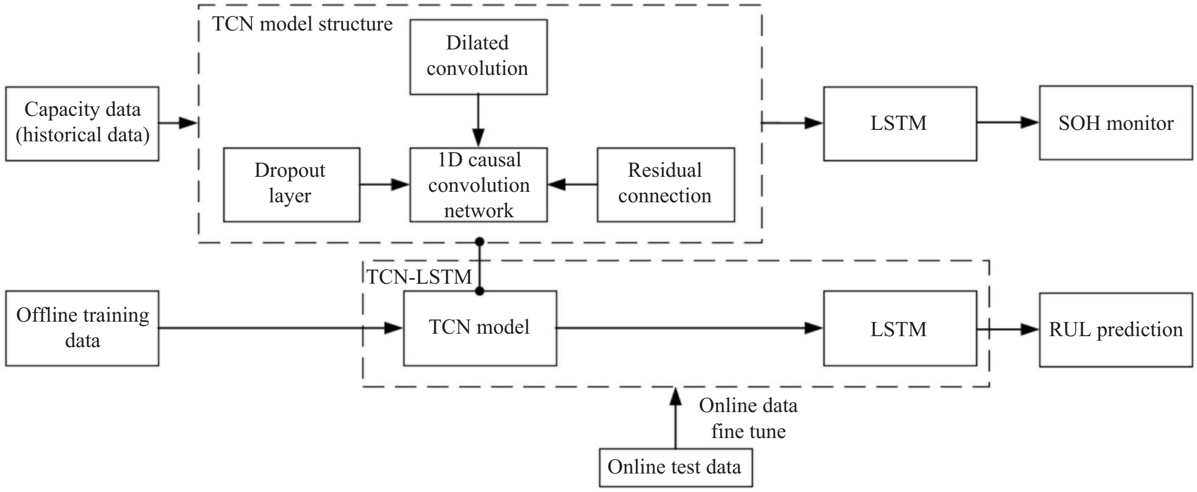

Fig. 5. The framework for SOH estimation of TCN-LSTM.

sequences. This model benefits from the inclusion of residual connections, promoting faster convergence. Additionally, its utilization of dilated convolution is pivotal for temporal feature extraction. In parallel, the LSTM model, characterized by its nonlinear nature, functions as a complex component within a comprehensive deep neural network. This characteristic empowers the LSTM to exhibit robust nonlinear fitting capabilities, optimizing its feature extraction proficiency. As illustrated in Fig. 5, data features are conveyed to the TCN layer for convolutional computations during the feature extraction procedure. After these calculations, parameters are normalized across each layer. The Rectified Linear Unit (ReLU) function is then employed to map these normalized features. Post-computation, the derived sequence features are refined in the TCN layer by combining expansion and causal convolution techniques. This combination ensures a more exhaustive extraction of sequence features, tapping into a wider spectrum of information dependencies. Following this, the TCN layer's output feeds into the LSTM network layer. Here, an additional feature extraction layer takes place, consolidating features from the TCN and LSTM. This combined methodology aids in preventing potential feature degradation. The amalgamated features are then channelled into the fully connected layer. A dropout layer is integrated to ensure the model remains generalized and avoids overfitting. The TCN-LSTM estimation process can be categorized into two phases: offline training and online estimation. In the offline training phase, the network is trained with an extensive set of battery data to identify the nonlinear associations between battery metrics and the corresponding SOH and RUL.

4) *Rolling Transfer Learning*

Due to the need for regular updates to the battery digital twin, particularly given the significant impact of battery ageing on accurate SOC estimation, a rolling transfer learning approach focusing on updating the TCN-LSTM network parameters to address ageing effects is introduced. Transfer learning involves adapting a model trained for one application to another. Given that lithium-ion battery measurement parameters exhibit varied but related spatial features, a primary TCN-LSTM model is trained for SOC estimation. This model then acts as the base for training another SOC estimation model. During the transfer learning process, the network's parameters are adjustable, allowing constant refinement throughout the training period. Fig. 6 illustrates this transfer learning approach, showing the analogous structures of both models, where the target model is initialized with the source model's parameters and subsequently refined with a new dataset. As the battery digital twin runs, it consistently collects data. When the cumulative operational time surpasses a predefined threshold T, the secondary TCN-LSTM network is subject to remote retraining and recalibration. The primary TCN-LSTM network then integrates these updated parameters, ensuring the DT's continuous adaptation and consideration of historical data.

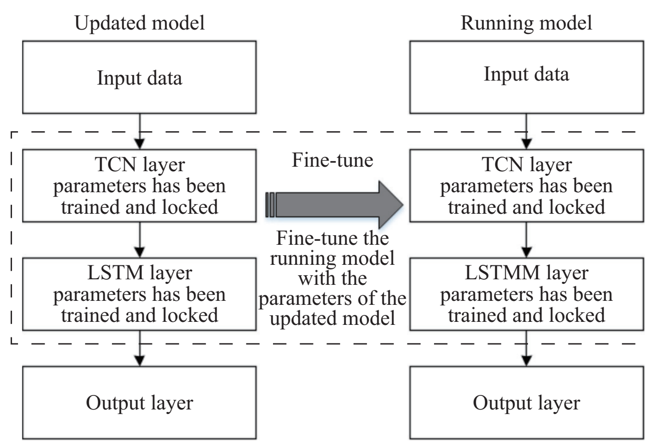

Fig. 6. The rolling transfer learning approach.

5) *Validation of the Predictive Model*

At the physical end, the digital twin and battery state estimation algorithm will be evaluated experimentally using lithium-ion batteries. This approach aims to validate the precision and robustness of the model and algorithm within the digital twin framework.

The Mean Absolute Percentage Error (MAPE) has been selected for the cloud end as the primary metric to assess estimation accuracy. It is defined as:

$$MAPE(\%) = \frac{100}{K}\sum_{k=1}^{K}\frac{|l(k)-\dot{l}(k)|}{l(k)} \tag{4}$$

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 Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) are computed as:

$$MAE = \frac{1}{K}\sum_{k=1}^{K}|l(k)-\dot{l}(k)| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(l(k)-\hat{l}(k)\right)^2} \tag{6}$$

The RMSE serves as an indicator of the disparity between predicted and actual values. It is expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(SOC_{ei}-SOC_{ti})^2} \tag{7}$$

In this equation, n signifies the total number of observations, while SOC_{ei} and SOC_{ti} correspond to the ith estimated SOC and true SOC, respectively. SOH and RUL are calculated in the same way.

IV. Validation and Discussion

In this section, experimental validations and discussions are conducted to validate the feasibility of the proposed framework.

A. Data Preprocessing

In this section, we present experimental validations and engage in discussions to validate the effectiveness of the proposed framework. Our case study leverages data from the National Aeronautics and Space Administration's (NASA) dataset on lithium-ion battery charge and discharge experiments to verify the digital twin model [50]. An observation was made regarding the battery tester's logging mechanism: several drive cycles were consolidated into a single extensive file due to its inconsistencies, causing some data repetition. To ensure data integrity, expunging these redundant entries, which could indicate data-logging anomalies is critical. Within the supervised learning framework, Ah quantifies the TCN-LSTM's capacity loss, which serves as the foundation for the reference SOC.

Drawing from the calibrated battery digital twin model detailed earlier, we can incorporate a range of state estimation algorithms, distinguished by their accuracy and resilience, into the virtual endpoint. The process commences with the input of parameters such as voltage (V), current (I), and temperature (T), followed by the extraction of ECM parameters like R0, R1, R2, C1, and C2. Thereafter, the state and measurement equations for the equivalent circuit model are formulated.

In this experiment, the dataset was divided into two sets: one designated as offline data stored in the cloud end for pre-training models, and the other simulated as real-time data collected from the physical end for model validation. Fig. 7 is the schematic diagram of DT running. The three models, SOC estimation, SOH monitoring and RUL prediction, are intricately linked, working collaboratively to provide real-time updates and comprehensive insights throughout the battery's operational phase. This synergy ensures a more holistic understanding and efficient management of the battery system. Specifically, the DT's effective synergy in collating real-time and offline data from the physical end and cloud end and processing it through machine learning algorithms in the virtual end. Then the virtual end of the DT could update the parameters of equivalent circuit models, thus improving SOC estimates which are helpful for subsequent SOH and RUL predictive modelling. The TCN-LSTM network is periodically retrained and refined as part of this cyclical mechanism, assimilating real-time data at predefined intervals T. At the cloud end, the DT plays the role of data analytics and storage, ensuring that substantial volumes of battery operational data are processed efficiently. The DT's ability to recalibrate parameters dynamically in real time enables adaptation to fluctuating

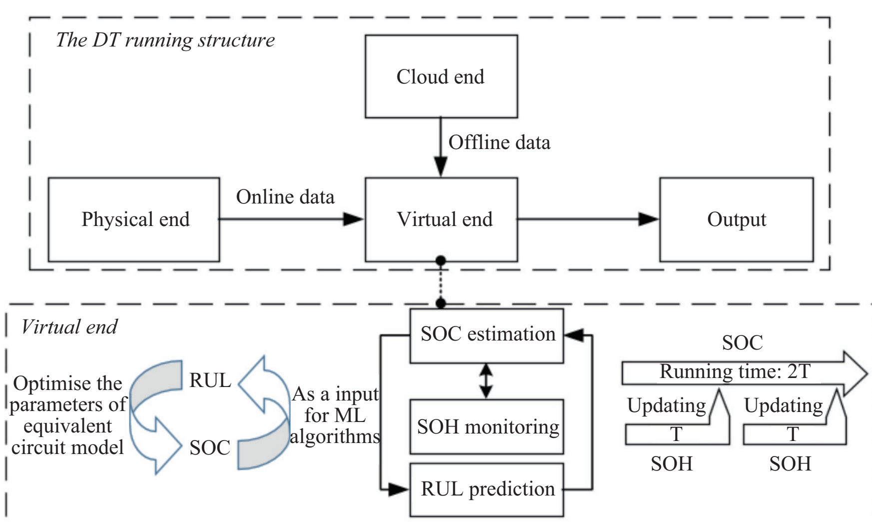

Fig. 7. Schematic diagram of DT running.

operational conditions and battery decay. The DT keeps a reliable link between the virtual and physical ends, ensuring the battery's performance and health are accurately shown in real-time. This ability to reflect the battery's state underlines the DT's role in supporting decisions, allowing early actions to improve battery life and address issues before they occur.

B. SOC Estimation in the Digital Twin

Utilizing the Jupyter Notebook platform, equipped with a deep learning environment, this investigation was centred on developing and assessing the TCN-LSTM network. This network comprises an input layer with a single time series and three specific features: voltage, current, and temperature. After repeated tests and verifications, the relatively optimal parameter is selected based on the operating time and test results. This method ensures a more precise and effective approach to parameter optimization. While the output layer is tailored for SOC estimation, the hidden layer integrates 150 nodes. For refining the model, we adopted the MAE loss function and the Adam optimizer, with an operational batch size of 32. The primary role of both the loss function and the optimizer is to hone the model, driving the loss closer to 0. As presented in Fig. 8, post 20 epochs, the model's loss during training and testing phases converges, not surpassing 0.04. The training set exhibits a particularly low loss of under 0.005, indicative of the model's robust performance. However, a slight elevation in the validation loss compared to the training loss points to a potential overfitting issue.

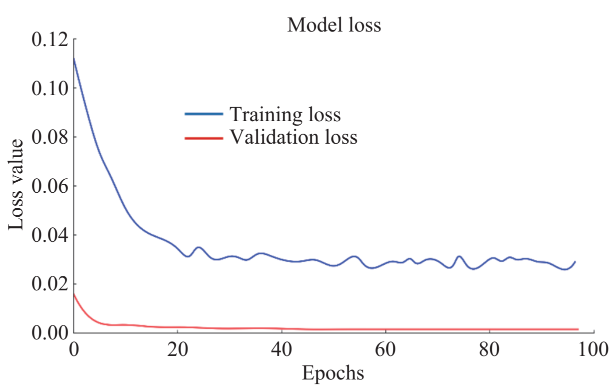

Fig. 8. The model loss of TCN-LSTM at training and test.

Figure 9 provides a comparative analysis of the SOC, as determined by the EKF after the TCN-LSTM correction, against a reference SOC. The graphical representation includes three distinct lines symbolizing the reference value, estimated value during training, and estimated value during testing. While the model aligns well with the training data, there are discernible deviations in the SOC estimation when processing new data. The RMSE is recorded at 1.1% for training and 2.7% for testing. It is generally understood that a model with a lower RMSE indicates better SOC estimation precision.

The observed discrepancy in RMSE values between our study's training and testing data can be attributed to overfitting, which might affect the model's handling of previously unseen data. The RMSE values mentioned in the table were calculated based on a dataset using the pervasive network structures. This dataset was also the basis for the reference methods introduced in the analysis. When benchmarked against other algorithms in Table I, the proposed method showcases the least RMSE across the four algorithms evaluated. This underscores the algorithm's enhanced accuracy, particularly once overfitting issues are rectified. The introduction of the reference methods for the same dataset further supports the reliability and robustness of our findings.

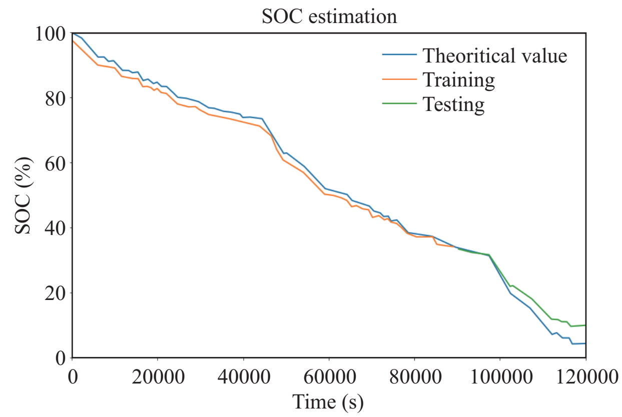

Fig. 9. The SOC estimation by TCN-LSTM.

TABLE I
THE COMPARISON OF SOC ESTIMATION FOR DIFFERENT METHODS

Methods	RMSE
EKF	3.9%
SVM	3.2%
CNN	2.2%
LSTM-EKF	1.7%
TCN-LSTM	1.1%

C. SOH Monitoring in the Digital Twin

Using the capacity series data outlined in the manuscript, this study subjected the model's parameters and structure to an intensive experimental analysis. The study focuses on the SOH of battery B0005, starting from its nth (30th, 60th and 90th) cycle. The first n cycles are thus treated as the training set, and the following cycles are the prediction set. The model systematically incorporates predicted values by adopting the method, which is similar to the sliding window technique. This process aids in predicting the SOH value, leveraging the aggregated SOH data until the complete test set is covered. The choice of parameters mainly draws from the control variable method, a standard practice in neural networks to ascertain optimal parameters. Such a method requires the modification of only one parameter during each tuning phase. The model's core parameters include 1000 iterations, a mini-batch size of 128, a 3×1 kernel dimension, 256 convolution kernels, dilation factors of [1, 2, 4, 8, 16, 32, 64], and it utilizes the Adam optimizer.

Accurate SOH monitoring, marked by a minimal error in predicting subsequent SOH values, is crucial for dependable RUL prediction. Such precise estimations further facilitate. Such precise estimations further facilitate proactive battery maintenance. Therefore, monitoring commenced from the 30th cycle to closely emulate real-world scenarios. In addition, the SOH was assessed at various starting points to validate the predictive precision and resilience of the model. Table II compares the TCN-LSTM model's prediction capabilities for three specific battery cycles (30th, 60th, and 90th) against established methods. For a fair comparison, models like LSTM, TCN, and CNN were all designed with two hidden layers. The model maintained a consistent parameter setup throughout the prediction stage, having been fine-tuned through multiple experiments.

Data from Table II affirms the model's consistent performance, regardless of the prediction start point. For complex neural networks, ample training data typically bolsters prediction accuracy. Fig. 10 visually represents battery cells B0005 under different models and starting points. These visuals emphasize the TCN-LSTM model's proficiency in tracking the degradation trend of the capacity series, surpassing current models and adeptly highlighting local regeneration instances.

D. RUL Prediction in the Digital Twin

This section evaluates the TCN-LSTM model's performance in RUL prediction using offline data and compares it with other models. Accurate RUL prediction is essential for timely battery replacement and maintaining system stability and safety. In the context of this analysis, batteries B0006 and B0018 were used for offline training, while battery B0005 was designated as the test data. To gauge the accuracy of the TCN-LSTM model, we defined several starting points and compared the results with those from different models. During the prediction process, the model, already trained with offline data, was further refined using a selected portion of available online data to bolster its predictive precision. The presented results encapsulate the best outcomes from multiple experimental iterations. Data from Table III indicates that the LSTM model outperforms the CNN model regarding RUL prediction. While the TCN model enhanced iteration of CNN might not excel in early prediction stages, its integration with LSTM consistently delivers optimal RUL outcomes. Notably, predictions' accuracy increases as they draw closer to the battery's failure point. In real-world scenarios, the accuracy of predictions made closer to the end of the battery's life is paramount. The TCN-LSTM model's prediction accuracy for the 90th cycle reaches an impressive 0.9%, highlighting the model's effectiveness. Fig. 11 corroborates this, showing the TCN-LSTM model's alignment with the degradation trend of the volume sequence during the 90th cycle. Finally, Table III contrasts the prediction accuracies, underlining the proficiency

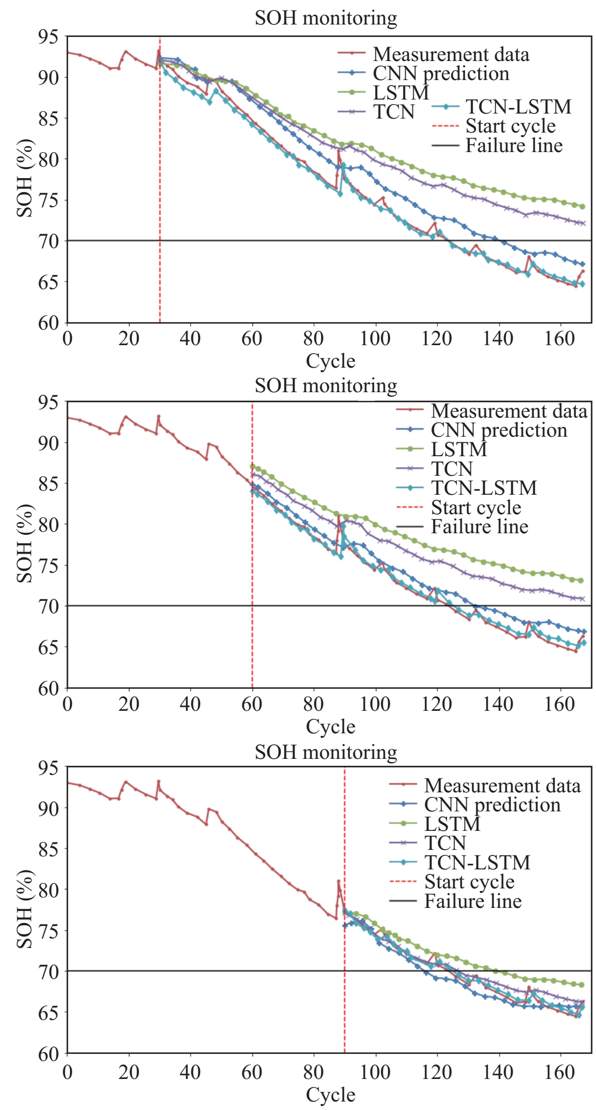

Fig. 10. The SOH monitoring of B0005 with 30th, 60th and 90th start cycles.

TABLE II
PERFORMANCE OF SOH MONITORING

Training cycle	RMSE				MAE			
	CNN	LSTM	TCN	TCN-LSTM	CNN	LSTM	TCN	TCN-LSTM
30C	4.8%	12.3%	10.1%	1.4%	4.6%	11.1%	9.2%	0.9%
60C	3.1%	12.0%	8.7%	1.3%	2.8%	11.4%	8.3%	0.8%
90C	2.0%	4.4%	1.9%	0.8%	1.5%	4.0%	1.5%	0.6%

TABLE III
COMPARISON OF EVALUATION RUL PREDICTION AMONG DIFFERENT METHODS

Training cycle	RMSE				MAE			
	CNN	LSTM	TCN	TCN-LSTM	CNN	LSTM	TCN	TCN-LSTM
30C	3.7%	2.9%	3.0%	2.0%	3.3%	2.3%	2.3%	1.7%
60C	4.4%	2.7%	1.8%	1.5%	4.2%	2.4%	2.5%	1.2%
90C	3.6%	2.4%	1.5%	0.9%	3.4%	2.1%	1.3%	1.6%

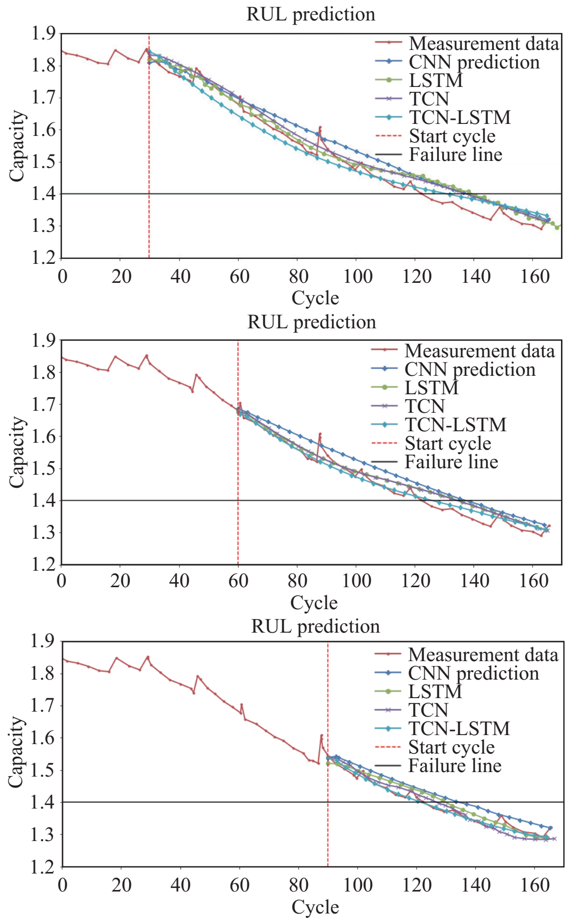

Fig. 11. The RUL prediction of B0005 with 30th, 60th and 90th start cycle.

of our model in reliably predicting the RUL of lithium batteries.

E. Validation of Transfer Learning Model

In this section, we conduct a detailed comparative analysis using two distinct TCN-LSTM models, with the primary distinction being the application of transfer learning, to validate the real-time updating ability. We use the NASA dataset to train both models by the first 30th cycles, with subsequent data reserved for the validation. The analysis revealed RMSE for SOH predictions at 1.4% for the model incorporating transfer learning and 1.42% for its counterpart, indicating a slight difference. However, as Fig. 12 demonstrates, initial assessments of both TCN-LSTM algorithms during the early battery cycle tests showed significant consistency. As the study progressed beyond 105 cycles, an apparent disparity emerged: the model without transfer learning displayed notable jitter in its SOH estimations, contrasting to the model that employed transfer learning. This performance gap underscores the models' varying adaptation to the complex, evolving nature of battery data through successive cycles and highlights transfer learning's crucial role in enhancing battery state estimation stability. The transfer learning-augmented model's ability to dynamically adjust its parameters and neural networks in reaction to real-time data showcases its exceptional adaptability and resilience, which is important for accurate state estimation.

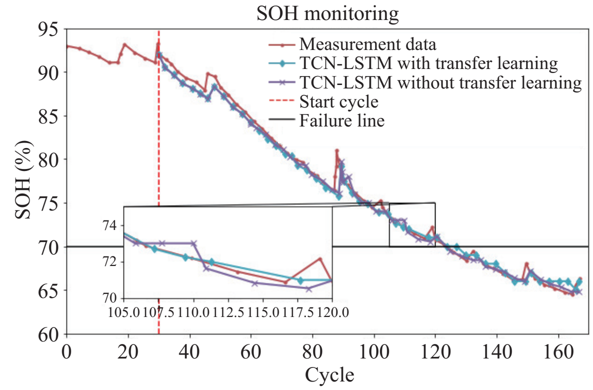

Fig. 12. The SOH prediction of B0005 with the 30th start cycle.

V. Conclusion and Future Work

In conclusion, this study has presented a novel methodology for battery state estimation and RUL prediction. Utilizing an equivalent circuit as its foundational basis, a DT model has been developed, integrating factors such as voltage, current, and ambient temperature. Recognizing the complexities of battery state estimation, we introduced the TCN-LSTM approach. This innovative method reduces dependence on initial values, especially in scenarios with limited training data. To support this, we incorporated the battery digital twin framework and used transfer learning techniques to ensure continuous model refinement during operational phases through rolling learning.

This research offers a comprehensive analysis of the digital twin framework, focusing on its complex structure and key stages in the learning process. The empirical results confirm the efficiency of combining online SOC estimation, SOH monitoring, and RUL prediction. Importantly, the model demonstrates exceptional adaptability and superiority in battery digital twins, achieving average RMSE values of 1.1%, and maximum errors of 0.8% and 0.9% in these respective areas.

Underlining the practical implementation aspect of the method, forming a multi-layered digital twin structure enables the integration of SOC estimation, SOH monitoring, and RUL prediction. Consequently, battery operations are minimized, thereby improving the life cycle of the battery and elevating system efficacy. Integrating TCN-LSTM techniques with the digital twin paradigm is a novel and innovative combination that contributes to breakthroughs in battery management and storage system optimization in various applications.

In the near-term horizon, our focus will be directed towards addressing key research challenges that hold the potential to further refine the digital twin framework for battery storage. This includes the development of a comprehensive digital twin that synergizes both dynamic and static models (aims at historical data and real-time data) for enriched situational awareness. This integrated approach might require overcoming the challenge of merging heterogeneous data sources and formats through advanced data integration techniques, employing deep learning algorithms for comprehensive analysis. Additionally, optimizing the digital twin to achieve reduced latency will be pivotal, ensuring its capability for real-time synchronous updates and adaptive feedback control. This may necessitate adopting high-performance computing (HPC) and edge computing solutions to process complex simulations and perform localized data analysis. Assessing battery state estimation methods under various operational conditions is also a potential direction. It is important to evaluate the models' adaptability and resilience beyond the uniform charging and discharging environments initially outlined. Exploring these research dimensions will undoubtedly augment the capabilities and impact of battery digital twin technologies.

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