Digital Twin-supported BESS Decision Support of RUL-Based Maintenance

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***Abstract*—The management of battery energy storage systems (BESS) faces significant challenges due to the limitations of traditional maintenance approaches, which often make it hard to capture real-time health states and lead to inefficiencies and unexpected failures. While digital twin (DT) offers a promising solution for real-time monitoring and predictive maintenance. This gap hinders the development of comprehensive decision support systems that can optimise maintenance schedules, ultimately affecting the reliability and cost-effectiveness of BESS operations. Here, we propose a novel integration of DT with an advanced strategy: an RUL-based maintenance approach that combines remaining useful life (RUL) prediction with battery availability to optimise maintenance scheduling and spare parts management. The results illustrate that this approach improves operational decision support. By addressing the specific gap in integrating advanced data-driven strategies within a DT framework, the research enhances system reliability and reduces maintenance costs for BESS. This comprehensive solution advances the broader field by providing a robust framework for real-time decision support in BESS management.**

Keywords—digital twin, decision support, battery energy storage system, deep learning, predictive maintenance

I. INTRODUCTION

Digital twin (DT) technology integrated with battery energy storage systems (BESS) is increasingly recognised as a way to improve operational decision support [1]. However, traditional maintenance strategies, either reactive or following predefined schedules, typically fail to capture the real-time health state of BESS components [2]. The use of these strategies may lead to suboptimal performance, higher costs and unexpected failures. Therefore, there is a need for advanced methods which use real-time data and sophisticated analytical models to enable continuous monitoring and predictive maintenance of BESS for improved system reliability and longevity. Digital Twins are a promising solution that provides a complete digital replica of physical systems, able to collect real-time data, monitor health status, and make operational decisions [3, 4].

Integrating DT technology into BESS is generally regarded as a very effective way to enhance operational decision support. Unlike DT-supported maintenance, reactive response or schedule-based approaches are unable to capture the real-time health status of BESS components [5]. Therefore, such approaches often lead to suboptimal performance, higher costs, and unexpected failures because they are based on fixed maintenance intervals and lack predictive ability [6].

To address these challenges, this paper presents a DT-supported decision support system that employs advanced methodologies for predictive maintenance and fault analysis. A remaining useful life (RUL)--based maintenance approach integrates RUL prediction with equipment availability to optimise maintenance decisions dynamically [7].

The RUL-based maintenance strategy significantly improves traditional approaches by integrating real-time health status data with equipment availability metrics [8]. Unlike conventional methods that solely rely on RUL predictions, this approach incorporates both remaining lifespan and real-time equipment availability to determine optimal maintenance timing [9]. By balancing these two critical factors, the strategy minimises maintenance costs while maximising system availability and reliability. Additionally, integrating RUL with availability allows for more precise scheduling of maintenance activities and spare parts management, thereby reducing the risk of unexpected failures and stockouts [10].

With the development of sensor technology, the use of real-time battery health status information to predict the RUL and then use it for battery health management decisions has become the core content of fault prediction and health management [11-14]. Based on RUL, scholars have developed a joint optimisation of maintenance and spare parts ordering decisions, and the sequential joint optimisation strategy model proposed by Wang [15] firstly determines the optimal time for equipment replacement and then optimises the ordering point. Based on this study, Jiang [16] optimised both the equipment replacement time and the spare parts ordering time and compared them with the results of the sequential joint strategy optimisation, which ultimately showed that the joint decision was more effective. However, none of them considered the costs associated with ordering spare parts [15, 16]. Wang [17] proposed a joint spare parts ordering and replacement strategy for unrepairable systems, under which historical state information is used to predict the remaining life at any monitoring moment, and various scenarios that may occur at the ordering point, the time of preventive replacement, and the time of the next monitoring moment are combined to construct an objective function that minimises the expected cost per unit of time while optimising the ordering point and the replacement time. The objective function is constructed to minimise the expected cost per unit of time by combining various scenarios that may occur at the ordering point, the preventive replacement moment, and the next monitoring moment, while optimising the ordering point and preventive replacement moment. Although the above studies consider the remaining life of the equipment, they are mainly used in maintenance decisions, where the ordering decision for spare parts is based on the degradation level or the moment of equipment replacement. However, the decision maker will judge whether to order or not by comparing the length of the remaining useful life of the equipment with the length of the lead time for spare parts [18].

These methodologies collectively establish a robust framework to enhance the operational decision-support capabilities of BESS [19]. By integrating diverse data sources—including real-time sensor data, historical operational records, and expert insights—the DT-supported system dynamically assesses the health state of BESS components and offers actionable maintenance strategies [20]. The RUL-based optimisation addresses the limitations of conventional maintenance strategies while extending the lifespan of BESS components, reducing operational costs, and improving system reliability [21].

The remainder of this paper is organised as follows: Section 2 outlines the methodology for the DT-supported operational decision support approach. Section 3 describes the experimental setup used to validate the proposed approach, while Section 4 presents the results and their implications, followed by a conclusion in Section 5.

II. METHODOLOGY

The RUL of the estimation models used in the maintenance strategies is often based only on RUL prediction, causing a mismatch between the predicted and the actual service life [22]. This may increase maintenance costs and reduce system reliability due to inaccuracies of this kind [23].

However, operational availability is a broader indicator of how the battery can do its stated task. The fraction of time that the battery is available for use (less downtime for maintenance or failures) is available [24]. RUL and availability are integrated to allow maintenance decisions to be made based on the health status of the component and the operational readiness of the system [25]. RUL predictions and availability metrics are combined to form a maintenance index used to assess the urgency and timing of maintenance activities [26].

This section introduces a predictive maintenance strategy that takes into consideration RUL and availability in optimising the maintenance decisions. The method we propose in this work combines both of these two indicators into a unified model to measure maintenance needs, ranking actions that reduce maintenance costs and increase battery life.

A. Data Acquisition and Pre-processing

Effective data gathering and early data processing are critical to the reliable performance of the DT-supported operational decision support system. The dataset is real-time sensor data of key parameters such as voltage, current and temperature [27]. These measurements provide detailed information on the operational conditions and performance of BESS components [28]. Monitoring systems data is used not only to determine the current physical asset health status but also to predict its RUL [29]. The DT analyses the RUL prediction and battery availability to determine the optimal maintenance scheduling and the need for spare parts ordering at certain monitoring points. Taking predictive operations such as this minimises failure and downtime, ensuring that replacement parts are available in time.

Several steps are involved in the data pre-processing. For the first case, data cleaning is performed to remove errors and treat missing values that might jeopardise model performance. In this, we are required to detect and reject outliers, impute missing values with statistical methods and finally normalise sensor readings to a common scale [30]. Then, we apply data transformation techniques on the data, like data feature engineering and dimensionality reduction [31], to make the data more relevant and high-quality. This results in a dataset optimised for real-time health state estimation, RUL prediction and spare parts management as multiple data sources are combined and rigorous preprocessing techniques are applied. The DT-supported system covers the dynamic behaviour of BESS components comprehensively and allows for effective decision support and maintenance strategy optimisation.

B. Integration of Digital Twin to Decision Support System

Decision support systems are integrated with DT to enhance the monitoring, diagnosis and prediction of BESS's health status of its components [32]. Using real-time operational data and historical maintenance data, the DT framework can perform precise fault diagnosis and decision-making. This integration supports this integrated maintenance optimisation and system reliability approach. The overall framework is shown in Figure 1. This work focuses on the decision support end of the overall framework.

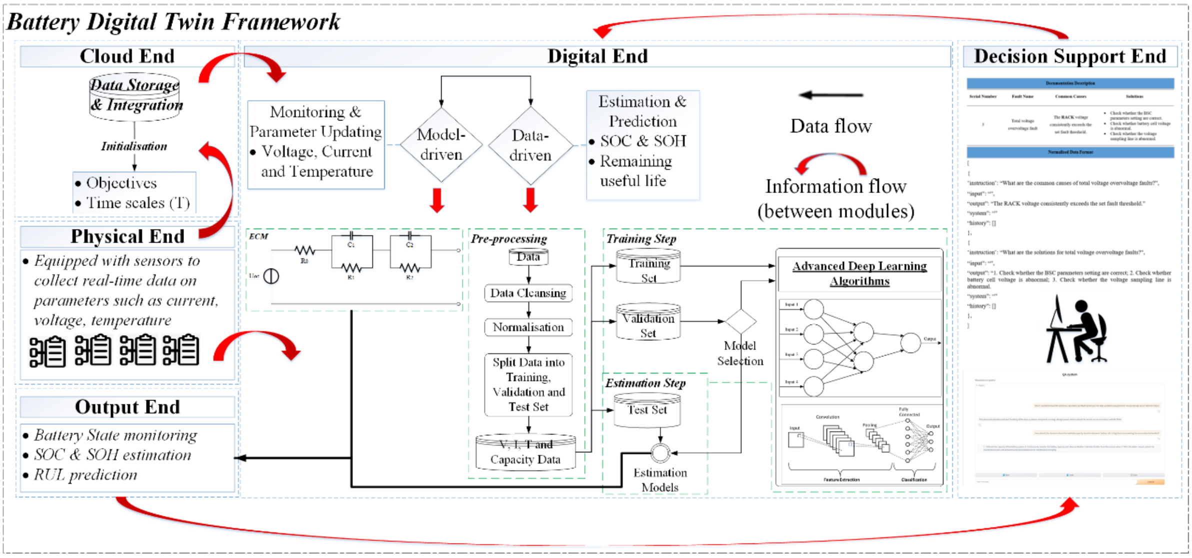


Figure 1. The overall framework of battery digital twin

The battery digital twin framework is structured across five interconnected ends. The physical end constitutes the real entity equipped with sensors that capture operational parameters such as current, voltage, and temperature. The cloud end processes and standardises the data, applying noise reduction and normalisation to ensure data quality and coherence. The digital end hosts hierarchical models that simulate the battery's electrochemical, thermal, and degradation behaviours, employing advanced algorithms to estimate the state of charge (SOC), state of health (SOH), and RUL. The output end delivers diagnostic and prognostic outputs, including updating SOC, SOH, and RUL, thus supporting situational awareness. The decision support end synthesises these outputs into practical recommendations, interacts with the DT, and receives guidance for operational and maintenance decisions.

Insights generated from the DT-supported system are beneficial to the decision–support framework [33]. This integration allows any maintenance decision including best scheduling and part management to be made with a sound and complete knowledge of the current and future health of the system. The DT links predictive maintenance strategy and decision support with dynamic adaptation to changing operational conditions. For the application of advanced maintenance strategies, such as RUL and battery availability-based optimization, it is necessary to be able to determine the state of health of a battery in a way meaningful to the operator.

C. RUL and Availability-based Decision Support

Currently, most maintenance strategies only rely on the RUL prediction, so any inaccuracy in RUL prediction will cause the actual service life to be different from the planned service life [34]. Nevertheless, these errors will raise maintenance costs and lower system reliability.

Operational availability is information about the battery's ability to fulfil its prescribed functions [35]. Availability is the time the battery is available for use, less time down for maintenance, etc. Given the RUL and availability, this work integrates the two quantities to make a maintenance decision based on the component's health and the system's operational readiness.

A maintenance index is calculated to determine when and how urgently maintenance activities need to be performed by combining RUL predictions with availability metrics. Because the batteries have lower index values, maintenance of these batteries is preferred first since they are more likely to fail soon and have a greater impact on system performance [36]. Maintenance has to be done at the right time, not too late and prevent unnecessary replacement or too early and prevent unplanned downtime.

Furthermore, the strategy also includes a proactive spare part ordering policy based on the prediction of RUL. Whenever each part fails, it can be ordered spare parts ahead of time. By taking this forward-thinking approach, not only do out-of-stock situations disrupt less, but the way inventory is managed is reduced, which in turn reduces total operational expenses.

Through the integration of battery RUL predictions and availability, battery performance and maintenance strategy can be optimised. This method improves reliability and BESS efficiency and provides rational, data-driven decision-making.

III. Experimental Setup

This section describes the experimental setup of the proposed DT-supported decision support system for BESS. The experiments concentrate on evaluating the performance of predictive maintenance strategies that use RUL predictions as well as battery availability.

To validate the feasibility of the proposed method, experiments are conducted to demonstrate its capabilities in supporting maintenance decision optimisation, including reducing downtime and maintenance costs. Operational data combined with domain-specific textual information is utilised to substantiate the system's effectiveness. This section presents the data sources and experimental setup.

A. Data Integration and Digital Twin Configuration

Integration of diverse data sources is required to configure the DT effectively to represent the health status and dynamic behaviour of BESS [37]. Through this integration, we combine updated sensor measurements, historical maintenance logs and technical documentation into a single dataset that provides a holistic view of system performance and operational conditions.

The battery operating state can be continuously monitored by updated sensor data such as voltage, current, and temperature. To this data, historical maintenance records are also added, capturing degradation trends and failure patterns across individual components.

After merging the datasets, they receive preprocessing actions like normalisation and feature engineering to guarantee a fit with the DT's analysis tools. Sensor information undergoes normalisation to correct discrepancies and align measurement metrics; at the same time, critical attributes are pulled out to accentuate the influencing factors on system health. By tokenising and vectorising textual data we create numerical forms that can be analysed. The DT receives superior input from these preprocessing actions that allow for exact fault detection and the estimation of RUL.

The final configuration of the DT involves defining relationships between physical components and their digital replica and setting parameters for real-time monitoring and state estimation. Leveraging this configuration, the DT continuously assesses the health status of the battery system, detects anomalies, and generates actionable insights to support predictive maintenance and decision-making.

B. Predictive Maintenance Strategy Optimisation Based on RUL Prediction and Availability

The battery's health state is continuously monitored to predict its RUL and to inform spare parts ordering decisions. An average repair or preventive maintenance time, denoted as q, is introduced as the threshold for decision-making, representing the permissible difference between the RUL and the lead time L. The strategy dynamically adjusts based on updated RUL predictions and whether spare parts have already arrived. The value of q is determined through the joint optimisation model and acts as a critical decision variable, balancing the timing of orders against the degradation rate of the battery and supply lead times.

1) Battery Availability

In practical use, the steady-state availability can be divided into inherent availability A_i, achieved availability A_a, and operational availability A_0. At the battery usage stage, operational availability is the most effective indicator of actual battery utilisation and maintenance support conditions [7]. It represents the proportion of time the battery or system is capable of performing its intended function, indicating the relationship between reliability and maintainability.

The size of operational availability is primarily influenced by three factors: Mean Time Between Maintenance (MTBM), Mean Corrective Maintenance Time (MCMT), and Mean Logistic Delay Time (MLDT). The magnitude of MLDT is determined by the system's support capability. Spare parts supply capability is critical for supportability, as it significantly impacts the frequency of maintenance cycles and overall system operational availability.

In spare parts management, operational availability is calculated as shown in Equation (1):

$$A_0 = \frac{MTBM}{MTBM+MCMT+MPMT+MSD} \quad (1)$$

Spare parts availability:

$$A_a = \frac{MTBM}{MTBM+MCMT+MPMT} \quad (2)$$

Supply availability:

$$A_s = \frac{MTBM}{MTBM+MSD} \quad (3)$$

Therefore, the operational availability can be derived as:

$$A_0 = \frac{1}{1/A_a + 1/A_s} \quad (4)$$

This model calculates availability by dividing it into two parts: achievable availability and spare parts supply availability. Compared with the updated Markov renewal theory for calculating system availability, this method simplifies the calculation by making certain assumptions. However, when there is a constraint on spare parts supply, the model has limitations. Thus, many studies on inventory issues have been conducted to expand the model's applicability [7].

The method proposed in this text optimises the spare parts supply strategy by integrating operational availability with spare parts availability. The optimisation equation is given as:

$$A = \frac{T}{T+q} \quad (5)$$

Where T refers to the mean maintenance time interval and q average repair or preventive maintenance time, including corrective or preventive maintenance intervals.

The RUL of the battery is RUL_k and the spare parts lead time is L, where q satisfies: $RUL_k = L + q$, thereby combining availability with the spare parts supply process to achieve joint strategy optimisation.

2) Joint Maintenance Strategy Optimisation Modelling

Each time, the cost C_i is used to monitor the system status. If $l_p \leq RUL(t_k) \leq L_c$, the cost C_R will initiate preventive maintenance; otherwise, if $X(t_k) \geq L_c$, the cost C_R will initiate corrective maintenance, which will result in losses C_F. The system availability and spare parts supply are comprehensively analysed to establish a joint strategy considering six potential updating events which are shown in Table I.

Typically, the cost of placing an emergency order, C_{eo}, is higher than the cost of placing a normal order, C_0. If the ordered spare part does not arrive, it incurs a shortage cost; if the spare part arrives and is not immediately replaced, it goes into storage and incurs a holding cost; where the shortage cost per unit of time is C_s; and the holding cost per unit of time is C_h.

Based on the expected cost and length of each update event, the update payoff theory is used to establish the objective function of minimising the expected cost per unit of time, and the optimal decision variables are obtained: the ordering threshold q^* and the preventive maintenance threshold L_p^*. The specific formulas are as follows:

$$\min E\left(C\left(L_p,q\right)\right)=\frac{\sum_{s=1}^{6}E\left(C_s\left(L_p,q\right)\right)}{\sum_{s=1}^{6}E\left(L_s\left(L_p,q\right)\right)}$$
$$s.t.\quad l_k-L\le q;\ L_p<L_c \tag{6}$$

where $E(C_i(L_p,q))$ and $E(L_i(L_p,q))$ correspond to the expected cost and expected length.

The steps of the experiment are as follows:

TABLE I. ALL POSSIBLE RENEWAL SCENARIOS OF THE JOINT POLICY MODELLING

Events	Status	Spare parts status	Decision
E1		Not Ordered	Urgent order and immediate maintenance
E2	$l_p\le RUL(t_k)\le l_c$ Preventive Maintenance	Ordered but not arrived	Wait for spare parts to arrive for maintenance
E3		Arrived	Immediate maintenance
E4		Not Ordered	Urgent order and immediate maintenance
E5	$RUL(t_k)\ge l_c$ Fault maintenance	Ordered but not arrived	Wait for spare parts to arrive for maintenance
E6		Arrived	Immediate maintenance

Step 1: Set initial cost parameters C_i, C_o, C_{eo}, C_R, C_F, C_s, C_h and maximum number of calculations $N_{max}, L_p=0, A=\frac{T}{T+q}, q=\frac{T}{A}-T$;

Step 2: Setting preventive maintenance thresholds $L_p=L_p+1, q=0$;

Step 3: Average repair/preventive maintenance time $q=q+1$;

Step 4: Set total expected cost $TC=0$; total expected duration $TL=0$ and number of runs $i=0$;

Step 5: With L_p and A fixed, $i=i+1$;

Step 6: Updated the $RUL(t)$ of the system every T period, at time t, if $l_k-L\le q$, then if $t_0\ge 0$, whether it has been ordered or not, if not then order spare parts, otherwise go to step 7;

Step 7: If the RUL at time t, if $RUL(t)\le L_p$, then return to step 5. If $L_p\le RUL(t)\le L_c$, then perform preventive maintenance; and make the following decisions: when $t_0=0$, spare parts have not been ordered, E1 occurs; when $t_0\le t\le t_0+L$, spare parts have been ordered but not arrived, E2 occurs; when $t_0+L\le t$, spare parts have arrived, E3 occurs. If $RUL(t)\ge L_c$, then perform fault maintenance, similarly, according to the various states of spare parts, E4, 5, and 6 may occur.

Step 8: If the number of operations under the current q, L_p has reached the maximum number $i=N_{max}$, if satisfied, calculate and record $C(A,l_p)$, otherwise return to step 5.

Step 9: If $C(A,L_p)>C(A-1,L_p)$, find the minimum objective function value and availability under fixed L_p, record it as $C(A^*,L_p)$, and return to step 2; otherwise, return to step 3.

Step 10: If $C(A^*,L_p)>C(A^*,L_p-1)$, it means find the minimum objective function value, $minC(A^*,{L_p}^*)$, the optimal preventive replacement threshold ${L_p}^*$ and availability A^*; otherwise, return to step 2.

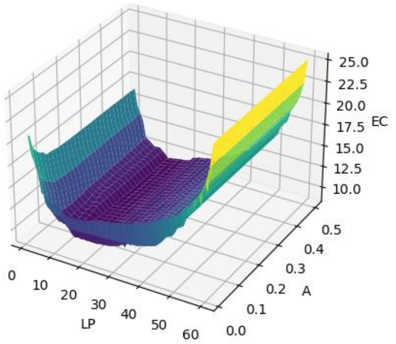
IV. RESULTS

The experiment leverages data from the National Aeronautics and Space Administration's (NASA) dataset on lithium-ion battery charge and discharge experiments to predict RUL. Historical maintenance records were conducted from two primary technical resources: the 'GB/T 40090-2021 national standard' and the 'PowerTitan Operation and Maintenance Guide'. These documents contain detailed information regarding the standard operating procedures, fault diagnostics, and maintenance strategies for energy storage systems. The dataset includes information on fault categories, troubleshooting methods, component-level repair instructions, and decision-making strategies for optimal maintenance planning. The RUL is updated every T charge and discharge cycle, the fault threshold $L_c=0$, and the cost parameters are shown in Table II.

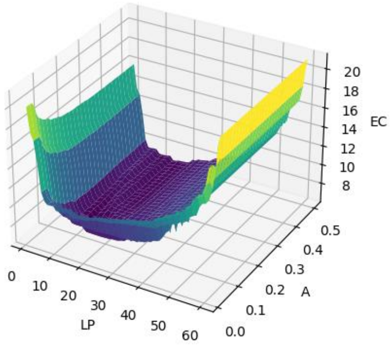
TABLE II. COST PARAMETERS

C_i	C_o	C_{eo}	C_R	C_F	C_s	C_h
500	100	4000	12000	50000	25	5

Based on the above parameters, Python is used to program the discrete event simulation algorithm, and the minimum objective function value is $EC(A^*, L_p{}^*) = 5.35$, where the optimal availability $A^* = 0.11$ and the preventive maintenance threshold $L_p{}^* = 16$. Figure 2 (a)-(c) shows the trend of the expected cost (EC) per unit time with the ordering threshold and the availability (A) under different period T. When L_p is fixed, the expected cost per unit time shows a trend of first decreasing and then increasing with the increase of availability. Because if A is too small, ordering spare parts will easily lead to no spare parts available when the system fails, increasing downtime losses and costs; but a larger A will increase the holding cost of spare parts. Similarly, when A is fixed, the expected cost per unit time first decreases and then increases with the increase of L_p. This is because an excessively large L_p increases the possibility of preventive replacement and reduces the expected length, resulting in a higher expected cost per unit time; a small L_p is prone to failures, and failure to prevent them increases the expected cost per unit time.



(a)



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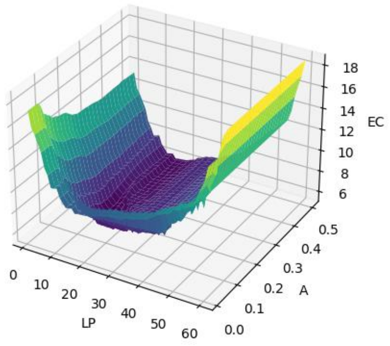
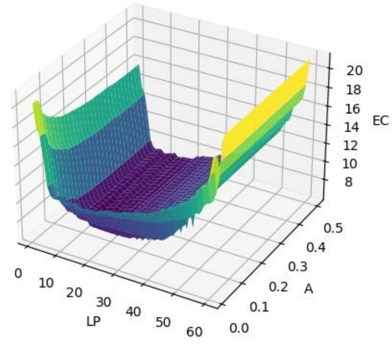


(c)

Figure 2. The expected cost per unit time in terms of the preventive maintenance threshold $\boldsymbol{L_p}$ and the availability $\boldsymbol{A}$ with different period T (T=100, 200, 300)



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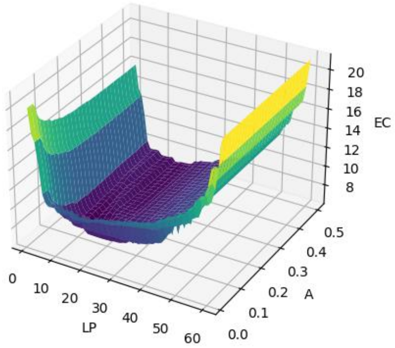

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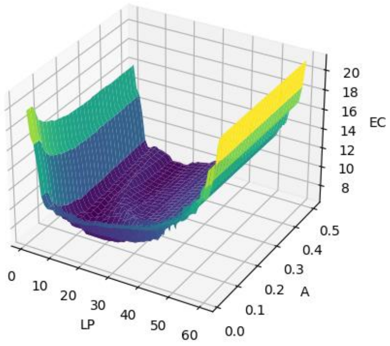

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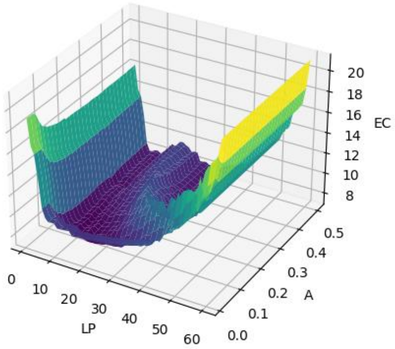

(d)

Figure 3. The expected cost per unit time with different leading time L (=100, 300, 500 and 1000)

Figure 3 (a)-(d) shows the impact of order lead time on the optimal decision, and Table III shows that the expected cost per unit time $EC(A^*, L_p{}^*)$ gradually increases with the increase of L. The reason is the system degradation process does not change. As L increases, it is necessary to start ordering when the remaining life is longer, that is, A^* gradually increases; and once the system needs preventive replacement or fault replacement if the spare parts have been ordered but have not arrived, the out-of-stock loss caused by the long wait for spare parts will increase, which increases the expected cost per unit time, so $L_p$decreases, making the preventive maintenance time closer to the arrival point.

TABLE III. THE INFLUENCE OF THE ORDER LEAD TIME L ON THE OPTIMAL DECISIONS

L	A^*	L_p^*	$EC(A^*, L_p{}^*)$
100	0.14	15	6.03
300	0.16	10	6.28
500	0.19	10	6.49
1000	0.17	9	7.14

A joint maintenance and spare parts ordering strategy based on RUL is proposed for single-component systems. The maintenance strategy adopts a control limit strategy to determine the system degradation at each monitoring point to determine whether to perform preventive replacement or fault maintenance; at the same time, the predicted RUL is used to compare the difference between the remaining service life and the lead time of the monitoring point with the size of the availability to determine whether to order spare parts, thereby integrating the spare parts ordering strategy with the real-time health status of the system. A model for minimising the expected cost per unit time is constructed, and a discrete event simulation algorithm is designed to optimise the preventive replacement threshold and the availability threshold. The optimal solution is given through case analysis, and the influence of the monitoring cycle and the ordering lead time on the optimal decision is analysed.

V. CONCLUSION

The experiment aimed to optimise predictive maintenance strategies, including integrated RUL prediction and battery availability. The results show that considering both RUL and availability improves maintenance decision-making results in a more efficient allocation of resources and reduces unnecessary actions. With RUL, predicted by battery DT, as a primary indicator, the model determined the optimal time for preventive maintenance, avoiding both early replacement and excessive downtime. Furthermore, considering battery availability the strategy also incorporated external factors such as component supply and system availability, which are important in realistic cases. The maintenance method adopts a control limit method to evaluate system degradation at each monitoring point, thereby determining whether to perform preventive or corrective replacements. Concurrently, the predicted RUL is assessed by comparing the difference between the remaining service life and the lead time at each monitoring point against a predefined ordering threshold, which governs the initiation of spare parts procurement. This dual approach facilitates the integration of spare parts ordering strategies with the system's real-time health status. The RUL-based predictive maintenance model demonstrates particular efficacy in optimising both the timing and frequency of maintenance activities, utilising quantitative metrics to enhance operational efficiency and resource utilisation.

Overall, this paper presents a review of how advanced data-driven methods can be integrated into DT to improve maintenance decision support for BESS. Results from experiments show that a spare parts ordering strategy combining RUL prediction and availability can help improve maintenance planning, fault detection, and operational decisions. This paper points out the complementary strengths of these models and proposes that combining them into a DT framework will give a more complete and adaptive BESS management enhance system reliability and reduce maintenance costs.

MATCH & CONTRIBUTION

This contribution aligns closely with the theme of the ICE IEEE 2025 conference on "AI-driven Industrial Transformation: Digital Leadership in Technology, Engineering, Innovation & Entrepreneurship." The paper introduces a digital twin (DT)-supported framework for Battery Energy Storage System (BESS) management, combining predictive maintenance strategies based on Remaining Useful Life (RUL) with real-time operational insights. By integrating RUL estimation with availability-driven decision-making, the study advances the role of intelligent maintenance in energy systems. The research underscores the transformative potential of digital technologies in enhancing operational resilience and reducing lifecycle costs in industrial energy applications. Through its focus on real-world data validation and actionable decision support, this work contributes meaningfully to the conference's emphasis on data-driven engineering and the application of AI in industrial innovation.

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