Research Article

AI-Driven Digital Twin Model for Reliable Lithium-Ion Battery Discharge Capacity Predictions

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The present study proposes a novel method for predicting the discharge capabilities of lithium-ion (Li-ion) batteries using a digital twin model in practice. By combining cutting-edge machine learning techniques, such as AdaBoost and long short-term memory (LSTM) network, with a semiempirical mathematical structure, the digital twin (DT)—a virtual representation that mimics the behavior of actual batteries in real-time—is constructed. Various metaheuristic optimization methods, such as antlion, grey wolf optimization (GWO), and improved grey wolf optimization (IGWO), are used to adjust hyperparameters in order to optimize the models. As indicators of performance, mean absolute error (MAE) and root-mean-square error (RMSE) are applied to the models after they have undergone extensive training and ten-fold cross-validation. The models are rigorously trained and cross-validated using the NASA battery aging dataset, a widely accepted benchmark dataset for battery research. The IGWO-AdaBoost digital twin model emerges as the standout performer, achieving exceptional accuracy in predicting the discharge capacity. This model demonstrates the lowest mean absolute error (MAE) of 0.01, showcasing its superior precision in estimating discharge capabilities. Additionally, the root mean square error (RMSE) for the IGWO-AdaBoost DT model is also the lowest at 0.01. The findings of this study offer insightful information about the potential utilization of the digital twin model to accurately predict the discharge capacity of batteries.

1. Introduction

In the modern world, greenhouse gas emissions and their effects on global warming continue to be major concerns. To address this challenge, nations worldwide have implemented robust measures aimed at reducing waste emissions and promoting a sustainable future [1–3]. Energy storage devices, frequently utilizing batteries, are essential elements in addressing the need for more sustainable energy sources. Energy storage systems not only mitigate reliance on non-renewable energy sources but also enhance the stability and cost-effectiveness of renewable energy [4]. Batteries find extensive utilization across a wide spectrum of applications throughout the domain of renewable energy, apart from their primary roles in energy storage and transmission. Additionally, they are employed to energize off-grid infrastructure, such as telecommunications and meteorological stations [5, 6]. The degradation of battery performance is a result of the repeated charging and discharging cycles [7]. As per the findings of studies [8], the malfunctioning of an aged battery has the potential to result in considerable loss of human life and financial harm. The evaluation of the health
status of a lithium-ion battery, commonly referred to as the state of health (SOH), is of utmost importance in the reduction of system risks and the minimization of maintenance costs [9, 10]. Vigilantly monitoring the degradation of a battery is essential to maximizing its energy delivery, preventing premature failures, and improving its dependability and lifetime. Within a battery management system (BMS), this oversight involves a meticulous evaluation of the battery’s state of health (SOH), an accurate prediction of its state of charge (SOC), and a precise estimation of its remaining useful life (RUL). A considerable investigation has been carried out to assess SOH in various studies. Capacity directly measures the quantitative assessment of a battery’s current state in relation to its ideal state, known as SOH. Battery modeling is required to establish correlations between various battery operating characteristics, such as temperature, life cycle, and charging and discharging voltage. The electrochemical model proposed by Goebel et al. [11] employs electrochemical impedance spectrometry to assess the internal impedance of the battery. The model establishes a negative linear correlation between the battery’s impedance and capacity to determine its overall capacity. The battery aging model proposed by Daigle and Kulkarni [12], which is based on electrochemical principles, was subjected to a series of randomized discharge patterns for testing purposes.

In the past twenty years, machine learning (ML) has been a popular method for creating accurate prediction models. Numerous engineering fields have benefited from its successful applications, including the prediction of bearing degradation [13], RUL estimation [14], and the prediction of fractures in welded connections [15]. ML is a data analysis technique that automates the creation of analytical models. It focuses on the idea that machines are capable of learning from information, identifying trends, and making judgments or predictions with little assistance from humans. Computational methodologies and AI techniques have significantly advanced the domain of battery systems. Patil et al. [16] conducted a study to determine the RUL of Li-ion batteries from the features extracted by discharge cycles and support vector machine. A model based on a feed-forward neural network to track estimated lithium-ion battery RUL is proposed in [17, 18]. Testing and numerical evaluations are conducted in order to verify the accuracy and validity of the proposed method. The findings indicate that the proposed methodologies exhibit a high degree of accuracy when applied in practical scenarios. Wang et al. [19] suggested a better robust multitime scale singular filtering-Gaussian process regression-long short-term memory modeling method for figuring out the remaining life-cycle capacity. In another study, Deng et al. [20] proposed a battery capacity prognostic method based on charging data and data-driven algorithms. Gaussian process regression and a sequence-to-sequence model were employed to predict future capacity trajectories. Interesting research was conducted to identify the degradation patterns from discharge capacity curves of batteries using a transfer learning approach. Data of 124 cells from public sets were used for verification, and the LSTM model gives the best prediction accuracy with less errors [21]. Jiao et al. [22] conducted a study that examines the use of a regularized extreme learning machine trained using the spectral Fletcher-Reeves algorithm to achieve accurate and resilient state of charge (SOC) estimation, providing accurate predictions about the capacity of batteries. Liu et al. [23] introduced an improved sparrow search-optimized LSTM network to estimate the RUL of the battery. Comparative analysis with other ML algorithms suggests that an optimized LSTM model is more accurate and robust. Recently, DT has gained worldwide attention due to its utility in providing solutions for various applications. This virtual counterpart provides ongoing monitoring, captures complex patterns with ML approaches, and promotes adaptation in the context of predictions. Incorporating ML into the digital twin framework [24] improves the models’ ability to manage complicated patterns and nonlinear interactions. Additionally, the digital twin facilitates predictive maintenance by employing machine learning and historical data to identify potential issues before they become significant. Recently, several authors utilized and applied DT in various domains. Ramos et al. [25] conducted a comprehensive study to establish a smart water grid (SWG) with DT live monitoring of system components and to improve system efficiency. In another study, the role of DT in improving urban water system efficiency and achieving sustainable development goals was explored after utilizing a pressure-reduction strategy by developing a digital twin model [26].

Monitoring the dynamic properties of batteries in real time is challenging due to their complex and nonlinear behavior. Traditional empirical models are insufficient for accurately identifying degradation patterns and faults in Li-ion batteries, as they overlook unknown factors and lack adaptability. By leveraging the algorithms, DT is capable of determining the intricate patterns and dependencies in the battery’s performance data, accounting for previously unconsidered factors. The present work proposes constructing an AI-assisted data-driven DT model that seamlessly integrates various metaheuristic optimization algorithms and deep learning models with a semiempirical battery capacity estimation model that can accurately estimate the discharge capacity of a lithium-ion battery. These integrated models proposed by the authors are further analyzed using the data acquired from different batteries, resulting in the formulation of proposed DT models.

The study summarizes the key objectives and contributions as follows:

(a) The main goal of the research is to build a data-driven, AI-assisted DT model that accurately estimates lithium-ion battery discharge capacity by utilizing a semiempirical model and a combination of deep learning and metaheuristic optimization algorithms.

(b) This study makes a significant contribution by combining advanced machine learning techniques with traditional empirical models. The methodology resolves the issues that current models have with understanding how batteries behave in a complex
and nonlinear way, which allows for continuous and real-time monitoring.

(c) The study fine-tunes the hyperparameters of machine learning models, namely, AdaBoost, LSTM, and a Stacked LSTM model, thereby greatly improving their predictive accuracy. It does this by using sophisticated metaheuristic optimization techniques, including antlion, GWO, and IGWO.

(d) An extensive evaluation approach is carried out to evaluate the efficacy of the models, utilizing performance measures, such as MAE and RMSE, and including ten-fold cross-validation and analysis.

The establishment of ML models aided by DT for estimating Li-ion battery discharge capacity represents a significant advancement in achieving global energy and environmental and sustainability goals. Numerous applications in industries, such as boosting renewable energy storage systems or increasing battery efficiency in electric cars, could benefit from this research. This work advances the global search for sustainable energy solutions by tackling the difficulties associated with predicting and optimizing battery performance. It is in line with the United Nations Sustainable Development goals, especially those that deal with clean and affordable energy, industry innovation, and responsible consumption.

Figure 1 shows a flowchart that illustrates the methodological process of creating an optimal DT model for accurately predicting the discharge capacity of lithium-ion batteries. The remaining sections of the research are organized as follows. Section 2 provides a concise explanation of machine learning and metaheuristic algorithms. Section 3 provides a description of the dataset for Li-ion batteries, enabling the utilization of the suggested approach. In Section 4, the authors describe the semipirical model in a general sense, and in Section 5, they discuss the optimized digital twin model. Section 6 summarizes and examines the results in more depth, while Section 7 highlights the conclusions.

2. Machine Learning and Metaheuristic Optimization

ML is a branch of AI that studies training computers to accomplish intelligent tasks [27]. Researchers accomplish this by searching for connections, patterns, or correlations among the variables in a dataset. The process usually begins with a mathematical algorithm or model. After training on a set of datasets, standard metrics measure the model’s accuracy. The trained model may categorize new data (called “classification”) or predict a number value (called “regression”) [28]. Choosing the best hyperparameter values within a specific search space reduces machine learning prediction errors. Battery state-of-health is nonlinear; therefore, machine learning can improve prediction accuracy and real-time management decision-making. This method speeds up calculations and boosts system efficiency, making it a strong tool for real-time battery health and performance optimization [29]. The ML and optimization algorithms used in this work are briefly explained as follows.

2.1. AdaBoost. The iterative AdaBoost methodology converts multiple low-performing classifiers into an individual, more resilient classifier by incrementally changing the weight of each instance in the data distribution. It builds this algorithm by incrementally changing the weight of each instance in the data distribution. The weight is determined based on the characterization reliability of the associated instance and the general accuracy of predictions from the last iteration. The instances and the changed weights are further trained for the respective iterations. The weight scores of poor classifiers are progressively aggregated through successive steps to produce the final robust classifier. AdaBoost will allow the classifier to concentrate on the examples that need to be accurately classified by ignoring the unneeded instances [30]. Similarly, the algorithm can be adapted to predict continuous variables, such as in regression [31]. Within the AdaBoost algorithm, every incident i as well as its associated labels \( y \in Y \) will receive an initial weight denoted as \( w_1(y) \). The function \( w_1 \) representing initial weight is based on the density \( D(i) \) defined in Algorithm 1. The weights are normalized in Step 1 to obtain a density \( \rho_i \). Subsequently, the weak learner employs the information obtained in Step 1 to determine a hypothesis \( h: X \rightarrow Y \) that aims to minimize a loss function defined as \( \varepsilon_i \), as defined in Step 3. The weights are revised in accordance with the diminution calculated using \( \varepsilon_i = \sum_{i=1}^{N} f_{h_i(x_i),y_i} | \) as described in [32]. An algorithmic representation of the working methodology of AdaBoost is shown in Algorithm 1.

2.2. Long Short-Term Memory (LSTM). LSTMs, a subset of RNN networks, are widely used in modern ML/AI tasks for their ability to effectively process sequential data. It has been demonstrated that LSTMs perform better than typical RNNs in time series prediction tasks by their capacity to handle the problem of short-term memory loss. This is accomplished with the use of cells and gates that regulate the flow of data throughout the network. LSTM gates play a critical role in determining which information to retain and discard, while the cell maintains essential data processing information [33]. A network based on LSTM consists of an input layer, one or more hidden layers, and an output layer. The fundamental characteristic of LSTM networks resides in the presence of memory cells within the hidden layer(s). The memory cells are equipped with three gates, namely, the forget gate \( (ft) \), the input gate \( (it) \), and the output gate \( (ot) \), computed utilizing \( (1) \)-(3), respectively. These gates are responsible for maintaining and regulating the cell states “i.” At every timestep when the network is provided with an input \( X_t \) and the output \( h_{t-1} \), the gates serve their purpose, such as defining which information is removed or added and which information is used as output from the cell state by the forget, input, and output, respectively [34]. The input node memory cell is computed using (4), while the memory cell’s internal state is calculated using (5). The hidden state is calculated using an activation function as indicated in (6). An algorithmic representation of the working methodology of LSTM is shown in Algorithm 2.
Figure 1: Digital twin blueprint for the estimation of discharge capacity of lithium-ion battery.
2.3. Antlion Optimization (ALO). ALO is an optimization method based on antlion hunting behavior, aiming to find the best hyperparameters for an objective function. Antlions randomly place themselves in the search domain and hunt for prey, which are candidate solutions with the highest fitness value in their vicinity. Antlions use a random walk tactic to approach their prey, and the mathematical implementation of ALO is described in [35, 36]. The ants’ movement is influenced by the antlion, and vectors $C$ and $d$ determine their random walks.

\begin{align*}
\text{it} &= \sigma(W_{ixt} + U_{iht} - 1 + \beta_i), \\
\text{ot} &= \sigma(W_{oxt} + U_{oht} - 1 + \beta_o), \\
\text{ft} &= \sigma(W_{fxt} + U_{fht} - 1 + \beta_f), \\
\text{at} &= \tanh(W_{cxt} + U_{cht} - 1 + \beta_c), \\
\text{ct} &= \text{ft} \odot \text{at} - 1 + \text{it} \odot \text{at}, \\
\text{ht} &= \text{ot} \odot \tanh(\text{ct}).
\end{align*}

The term “Vanilla LSTM” refers to a type of neural network architecture that has a separate hidden layer made up of LSTM units and then a normal forward-thinking output layer. Stacked LSTM is a modified version that integrates several concealed LSTM layers, which consist of an extensive number of memory cells.

\textbf{Algorithm 1: AdaBoost regression.}

\begin{itemize}
\item[(1)] Initialize the LSTM cell state and hidden state with zeros.
\item[(2)] For each input in the sequence, do the following:
  \begin{itemize}
  \item[(i)] Compute the forget gate, input gate, and output gate values using the current input and previous hidden state.
  \item[(ii)] Compute the candidate value to be added to the cell state using the current input and previous hidden state.
  \item[(iii)] Update the cell state by forgetting the old state and adding the new candidate value multiplied by the input gate.
  \item[(iv)] Update the hidden state by applying the output gate to the updated cell state.
  \item[(v)] Store the updated cell state and hidden state.
  \end{itemize}
\item[(3)] Return the sequence of hidden states.
\end{itemize}

\textbf{Algorithm 2: LSTM.}

\begin{align*}
\text{C}_i^t &= \text{Antlion}_i^j + C_i, \\
\text{d}_i^t &= \text{Antlion}_i^j + d_i.
\end{align*}

A roulette wheel operator relying on fitness values emulates the antlion’s capacity to construct traps. It is presumed that the antlion with the highest fitness rating has captured the ants. The diameter that defines the random movements of the ants reduces adaptively to simulate confined ants slipping toward an antlion. Equations (7)–(10) describe the methods.

\begin{align*}
\text{C}_i^t &= \frac{C_i}{T}, \\
\text{d}_i^t &= \frac{d_i}{T}.
\end{align*}

Here, $t$ represents the most recent iteration, throughout which $C_i^t$ is the smallest and $d_i^t$ is the largest variable at the beginning of the iteration, and $I$ represents the ratio of the current repetitions to the highest number of repetitions multiplied by $w_{ij}^0$ to the 10th power, when $w$ is an unchanged value used to modify the level of exploitation accuracy.

Equation (11) represents updating procedure during which an ant revises the location to the most recent of the preyed upon ant (least solution) in order to get close to the most optimum solution.
Antlion\(_i^t\) = Ant\(_i^t\) if \(f(\text{Antlion}\_i^t)\) is better than \(f(\text{Antlion}\_i^{t-1})\),

\[(11)\]

where Antlion\(_i^t\) represents location of \(i^{th}\) antlion, and Ant\(_i^t\) represents the location of \(i^{th}\) ant at \(t^{th}\) iteration. The best antlion is maintained as the elite with every ant randomly walking around the elite and other antlions by roulette wheel using the following equation:

\[\text{Antlion}^t_i = r_1^t + r_2^t,\]

\[(12)\]

where \(r_1^t\) and \(r_2^t\) are random walks in vicinity of the selected antlion and elite antlion. An algorithmic representation of the working methodology of ALO is shown in Algorithm 3.

### 2.4. Grey Wolf Optimization (GWO)

GWO is a population-based algorithm based on metaheuristics presented by Mirjalili et al. [37]. The algorithm starts with an initial set of potential solutions, each representing a unique combination of hyperparameters. Pack hierarchy and the predatory behavior of grey wolves are utilized to iteratively update the population. The search is conducted by alpha, beta, and delta wolves, representing the optimal, second-, and third-best solutions in the current population [38, 39].

The mathematical structure of GWO is as follows.

The algorithm initiates by dissociating the positions of grey wolves as they engage in the pursuit of prey. During the pursuit, the AM component regulates the degree of deviation exhibited by a search agent from its target, thereby controlling the level of randomness. Likewise, CM employs stochastic weights to explore the search space for potential prey. Similarly, CM initiates arbitrary weight values in order to search for prey (fit values) in the domain. CM also depicts the effect of a predator’s approaching prey, \(r_1\), and \(r_2\) vectors both have values between 0 and 1. Furthermore, vector \(\rightarrow a\) undergoes a linear decrease from a value of 2 to 0.

\[\text{AM} = 2a \cdot r_1 - a,\]

\[\text{CM} = 2r_2.\]

\[(13)\]

The top three wolves in the hierarchy labelled as alpha, beta, and delta evaluate as well as influence the positions of remaining pack of wolves. \(D\) represents the encircling movement of the grey wolf which can be expressed as equation (14). The following equations theoretically express the anticipated boundary:

\[D\text{M} = |C\text{M} \cdot X(P(t) - X(t))|,\]

\[(14)\]

\[X(t + 1) = X(P(t) - AM \cdot DM).\]

\[(15)\]

Here, \(t\) indicates the latest iteration cycle, \(X(P(t))\) is the location of the prey, and \(X(t)\) represents the location vector of the grey wolf.

The analogous of hunting expressed theoretically in mathematical terms is indicated in equations (16)–(19), where the alpha wolf guides for hunting after encircling, followed by the delta and beta wolves.

\[\vec{X}(t + 1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3},\]

\[(16)\]

where \(\vec{X}_1, \vec{X}_2, \text{ and } \vec{X}_3\) can be calculated as follows:

\[\vec{X}_1 = X_u(t) - AM_1 \cdot DM_u,\]

\[(17)\]

\[\vec{X}_2 = X_u(t) - AM_2 \cdot DM_u,\]

\[(18)\]

\[\vec{X}_3 = X_u(t) - AM_3 \cdot DM_u.\]

\[(19)\]

Grey wolves hunt their target by attacking it when it stops moving. The alpha, beta, and delta wolves’ locations revise the search agents’ locations during the hunting phase. This process is summarized in Algorithm 4.

### 2.5. Improved Grey Wolf Optimization (IGWO)

IGWO is an improved version of GWO that aims to enhance tuning performance. Nadimi-Shahraki [40] proposed IGWO in 2020. The improvement in IGWO is its dynamic search mechanism, which adapts to the optimization process by adjusting the exploration factor. The algorithm dynamically adjusts this factor based on its performance, controlling the degree of exploration and exploitation in the search process. The algorithm proceeds as follows.

To initialize the algorithm, \(N\) number of wolves are arbitrarily distributed in the search space with range \([l_i, u_j]\), represented as follows:

\[X_{ij} = l_j + \text{rand}_j \times (u_j - l_j), i \in [1, N], j \in [1, D],\]

\[(20)\]

where \(X_{ij}(t)\) represents the \(i^{th}\) wolf in the \(j^{th}\) iteration, and the population is expressed by an array with \(N\) rows and \(D\) columns.

IGWO includes an independent movement strategy inspired by wolves’ occasional independent hunting behavior, referred to as a dimension of learning-based hunting. This allows the wolf to learn from its adjacent wolves, thereby enhancing its qualifications for the prospective role of \(X_i(t)\). The DLH selection method involves the utilization of equation (23) to calculate the value of each dimension that ranges in the most recent location of the wolf \(X_i(t)\). This calculation is based on the knowledge acquired from neighbouring wolves and a randomly chosen wolf from the group of wolves. DLH strategy creates new candidate wolf \(X_{i,DLH}(t + 1)\) for the new position of \(X_i(t)\) apart from \(X_{i,GWO}(t + 1)\), which is obtained from the canonical GWO.

\[R_i(t) = \|X_i(t) - X_{i,GWO}(t + 1)\|,\]

\[(21)\]

The neighbor’s \(N_i(t)\) is created utilizing equation (22), where \(D_i\) is the Euclidean distance between \(X_i(t)\) and \(X_j(t)\).
2.5.1. Selecting and Updating Phase. The process of determining the more exceptional candidate involves a comparison of the fitness values derived from the GWO and DLH strategies, as depicted in the following equation:

\[
X_{t+1}(t) = \begin{cases} 
X_{t,GWO}(t+1), & \text{if } f(X_{t,GWO})(t) < f(X_{t,DLH})(t) \\
X_{t,DLH}(t+1), & \text{otherwise.}
\end{cases}
\]

The processes mentioned involved in the functioning of IGWO can be compiled as Algorithm 5.

3. Experimentation and Proposed Framework

The authors showcased the proposed methodology by utilizing the publicly released battery aging dataset from NASA [41]. At the Prognostic Center of Excellence (PCoE) of NASA Ames, researchers conducted the study using a customized testing apparatus on commercially available lithium-ion batteries [42]. The batteries utilized by NASA were of the LiNi0.8Co0.15Al0.05O2 type and had a capacity of 2 Ah. Furthermore, constant current-constant voltage (CC-CV) charging and constant current (CC) discharging profiles were employed to assess the batteries’ aging characteristics, as depicted in Figure 2. The charging rate was set at 0.75 C, and the discharging rate was set at 1 C. The investigation aimed to produce accelerated degradation on these batteries by operating the various batteries through consecutive charge and discharge cycles. At the conclusion of each discharge cycle, measurements were conducted of battery capacity as well as temperature, current, and voltage at both the load and the battery. Table 1 indicates the steps
involved in the lithium-ion battery aging experiment. The batteries were operated in an environmental chamber to maintain and control the ambient characteristics of the investigation. The batteries were charged at 1.5 A as they reached 4.2 V, followed by discharge at 2 A current until the voltages of the batteries fell to their respective cut-off voltages. The cut-off voltages were set under the original equipment manufacturers (OEMs) recommended voltage threshold of 2.7 V to induce profound aging effects and thereby accelerate the fade in battery capacity. Table 2

**Algorithm 5: IGWO.**

![Figure 2: Voltage/current observed during CC-CV charge and CC discharge of Li-ion batteries as specified in Table 1.](image)
4. Empirical Model for Capacity Estimation

A semiempirical model has been utilized to estimate the battery capacity for batteries B0005, B0006, B0007, and B0018. Xu et al. [43] introduced a semiempirical technique to calculate the SOC of a battery by combining fundamental theories of battery degradation. The model accounts for the nonlinear nature of the battery’s fade capacity by considering various factors that affect the deterioration of a Li-ion battery, especially solid electrolyte interphase (SEI) film formation [44]. The empirical model utilizes the initial rated capacity (C), temperature (T), time taken for a discharge cycle (t), and cycle index (i) to calculate the expected discharge capacity for a given lithium-ion battery. The model suggests lifespan of a Li-ion battery can be accurately predicted using a semiempirical formula, as outlined in the following equation:

\[ L = 1 - \alpha_{sei}e^{-\beta_{sei}t} - (1 - \alpha_{sei})e^{-\beta_{sei}t}. \]  
\[ (25) \]

Equation (25) calculates the battery life \( L \) of a fresh battery. For a used battery, the existing battery life must be calculated. In such conditions, equation (25) can be modified as follows:

\[ L = 1 - \left(1 - L\right)e^{dfd}, \]  
\[ (26) \]

\[ fd = k \frac{i \cdot T}{t}, \]  
\[ (27) \]

where \( fd \) is the nonlinear degradation function of the battery expressed as an expression of time, measured temperature, and repetitive cycles of operation that can be calculated as follows:

\[ C = Co e^{fd}. \]  
\[ (28) \]

Table 1: Description of the experimental cycle.

<table>
<thead>
<tr>
<th>Step</th>
<th>Action</th>
<th>Conducted at (A)</th>
<th>Exit condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Battery charging</td>
<td>1.5</td>
<td>4.2 V is reached</td>
</tr>
<tr>
<td>2</td>
<td>Battery discharging</td>
<td>2</td>
<td>Cut-off voltages are reached as specified in Table 2</td>
</tr>
</tbody>
</table>

Table 2: Selected batteries and their operational parameters.

<table>
<thead>
<tr>
<th>ID</th>
<th>Operational temperature (°F)</th>
<th>Cycles recorded</th>
<th>Discharge cut-off (V)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B0005</td>
<td>75.2</td>
<td>168</td>
<td>2.7</td>
</tr>
<tr>
<td>B0006</td>
<td>75.2</td>
<td>168</td>
<td>2.5</td>
</tr>
<tr>
<td>B0007</td>
<td>75.2</td>
<td>168</td>
<td>2.2</td>
</tr>
<tr>
<td>B0018</td>
<td>75.2</td>
<td>132</td>
<td>2.5</td>
</tr>
</tbody>
</table>
future scenarios where the direct determination of the battery’s discharge capacity is not feasible, the semiempirical model will serve as a crucial tool, facilitating accurate determination in these contexts. The semiempirical model will serve as a crucial tool in future scenarios where direct determination of the battery’s discharge capacity is not feasible, facilitating accurate determination in these contexts. It is believed that this approach offers a comprehensive and effective method for predicting the discharge capabilities of lithium-ion batteries in real-time.

5. Optimized Digital Twin Model

A digital twin refers to a virtual version of a physical process or system that leverages data from sensors and other sources to simulate its behavior and performance. To obtain a precise estimate of the lithium-ion battery’s ability to hold a charge, the model must be as close as possible to the real thing. In machine learning modeling, the utilization of digital twins has the potential to enhance the precision and effectiveness of predictive models. It is possible to train and test machine learning models in a simulated environment by using real-time sensor data in conjunction with other sources to create a virtual model of a physical system or process. Similarly, the application of a digital twin can be leveraged within the domain of anticipatory maintenance to track the behavior and performance of equipment, such as turbines or engines, and predict when it needs to be fixed before it breaks down.

In the current work, authors integrate the semiempirical model with the experimental Li-ion battery dataset to create a DT model. The difference, delta (Δ), is computed as Δ = C - C_{act}, where C is the calculated battery capacity procured from the semiempirical model and C_{act} is the actual capacity. The ML models are given the value of C as the input feature and the target is to predict the corresponding value of Δ. In ML models, hyperparameter tuning is extremely important and needed to significantly reduce prediction errors. The necessity of metaheuristic optimization techniques for hyperparameter tuning arises because the hyperparameter space is often huge, and the exhaustive search for the ideal hyperparameters may be computationally costly and time-consuming. Metaheuristic optimization methods can compress the search space greatly and identify effective solutions quicker, making them a powerful tool for hyperparameter tuning. Tables 4–6 highlight the default hyperparameters and the optimized parameters obtained after applying antlion, GWO, and IGWO to three ML models. The RMSE values of the machine learning model are selected as an objective function for the optimization algorithms, intending to minimize them. Each optimization algorithm is made to iterate 100 times for the hyperparameter search space, and the hyperparameter combination that yields the least RMSE value is subsequently selected. The hyperparameters obtained from antlion, GWO, and IGWO are incorporated individually in all ML models, and the optimal combination of ML and the optimization algorithm is selected to construct the DT to estimate the discharge capacity.

6. Results and Discussion

This section conducts a thorough investigation of the efficacy of a novel approach that uses digital twin technology to predict Li-ion battery discharge capacity. The dataset is first split into training and testing portions, with 70% of the data assigned for DT model training and the remaining 30% put aside for accuracy testing. A 10-fold cross-validation (10-CV) technique is used, which is a common practice in ML and statistical analysis for assessing model performance, to assure unbiased predictions. This method divides the dataset into ten equal subsets or “folds.” Every iteration rotates over all folds, using one for validation and the remaining nine for training. Before undergoing validation testing, the model goes through nine training cycles. Each fold acts as the validation set once, and this cycle is repeated ten times. As explained in Section 5, for every battery cycle, the difference (Δ) between the actual capacity measured from the dataset and the estimated discharge capacity, derived using empirical equation (28), is computed. By allowing the machine learning models to forecast the variance of the calculated discharge capacity from the actual data, this deviation aids in the integration of the DT model. Figures 3(a)–3(c) indicate a sample of the prediction results with grey wolf optimized for all three ML models: AdaBoost, Vanilla LSTM, and Stacked LSTM. The estimation results seem to have varied considerably after looking at the figure, but careful observations reveal that the numerical prediction errors are in the permissible range. Figures 4(a)–4(c) show the mean absolute error (MAE) obtained in training and 10-CV in three ML models with and without hyperparameter tuning with metaheuristic optimization algorithms. MAE quantifies the average absolute disparity between the observed and predicted values. Figure 4(a) shows that the IGWO-AdaBoost DT model has the least MAE, followed by the GWO-AdaBoost DT, the ALO-AdaBoost DT, and the default-AdaBoost DT model after training and a ten-fold on Li-ion batteries. Here, the default condition refers to the DT model without hyperparameter optimization. The IGWO-Vanilla LSTM DT and IGWO-Stacked LSTM DT models from all Li-ion batteries achieved the lowest MAE when conducting training and 10-CV, as demonstrated in Figures 4(b) and 4(c). A lower MAE value indicates that the
Table 4: AdaBoost parameters identified by the metaheuristic algorithms.

<table>
<thead>
<tr>
<th>Model/parameters</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
</tr>
</thead>
<tbody>
<tr>
<td>AdaBoost default</td>
<td>050</td>
<td>1.00</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>Best</td>
<td>None</td>
<td>None</td>
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<tr>
<td>AdaBoost antlion</td>
<td>211</td>
<td>0.01</td>
<td>5</td>
<td>8</td>
<td>3</td>
<td>Best</td>
<td>sqrt</td>
<td>8.04</td>
</tr>
<tr>
<td>AdaBoost GWO</td>
<td>200</td>
<td>0.01</td>
<td>6</td>
<td>4</td>
<td>1</td>
<td>Best</td>
<td>auto</td>
<td>8.58</td>
</tr>
<tr>
<td>AdaBoost IGWO</td>
<td>201</td>
<td>0.01</td>
<td>8</td>
<td>7</td>
<td>5</td>
<td>Best</td>
<td>sqrt</td>
<td>7.75</td>
</tr>
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</table>

Table 5: Vanilla LSTM parameters identified by the metaheuristic algorithms.

<table>
<thead>
<tr>
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<th>P2</th>
<th>P3</th>
<th>P4_1</th>
<th>P4_2</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vanilla LSTM default</td>
<td>050</td>
<td>Tanh</td>
<td>Tanh</td>
<td>0.00</td>
<td>0.00</td>
<td>Tanh</td>
<td>MSE</td>
<td>100</td>
<td>0.3</td>
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<tr>
<td>Vanilla LSTM antlion</td>
<td>138</td>
<td>Relu</td>
<td>Sigmoid</td>
<td>0.05</td>
<td>0.04</td>
<td>Relu</td>
<td>MSE</td>
<td>106</td>
<td>1.0</td>
</tr>
<tr>
<td>Vanilla LSTM GWO</td>
<td>022</td>
<td>Tanh</td>
<td>Tanh</td>
<td>0.00</td>
<td>0.02</td>
<td>Linear</td>
<td>MSE</td>
<td>150</td>
<td>1.0</td>
</tr>
<tr>
<td>Vanilla LSTM IGWO</td>
<td>070</td>
<td>Relu</td>
<td>Relu</td>
<td>0.00</td>
<td>0.08</td>
<td>Relu</td>
<td>MSE</td>
<td>108</td>
<td>1.0</td>
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</tbody>
</table>

Table 6: Stacked LSTM parameters identified by the metaheuristic algorithms.

<table>
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<tr>
<th>Model/parameters</th>
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<th>S</th>
<th>P2</th>
<th>P3</th>
<th>P4_1</th>
<th>P4_2</th>
<th>S4_1</th>
<th>S4_2</th>
<th>P5</th>
<th>P6</th>
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</thead>
<tbody>
<tr>
<td>Stacked-LSTM default</td>
<td>050</td>
<td>050</td>
<td>Tanh</td>
<td>Tanh</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>Tanh</td>
<td>MSE</td>
<td>100</td>
<td>0.3</td>
</tr>
<tr>
<td>Stacked-LSTM antlion</td>
<td>147</td>
<td>043</td>
<td>Tanh</td>
<td>Tanh</td>
<td>0.0</td>
<td>0.0</td>
<td>0.19</td>
<td>0.02</td>
<td>Relu</td>
<td>MSE</td>
<td>099</td>
<td>3.0</td>
</tr>
<tr>
<td>Stacked-LSTM GWO</td>
<td>30</td>
<td>082</td>
<td>Relu</td>
<td>Relu</td>
<td>0.0</td>
<td>0.0</td>
<td>0.02</td>
<td>0.00</td>
<td>Relu</td>
<td>MSE</td>
<td>142</td>
<td>1.0</td>
</tr>
<tr>
<td>Stacked-LSTM IGWO</td>
<td>100</td>
<td>150</td>
<td>Relu</td>
<td>Relu</td>
<td>0.0</td>
<td>0.0</td>
<td>0.01</td>
<td>0.25</td>
<td>Relu</td>
<td>MAE</td>
<td>150</td>
<td>1.0</td>
</tr>
</tbody>
</table>

model has better predictive accuracy and is better at predicting the target variable. Conversely, a higher MAE value indicates that ML models are less capable of predicting target variables. Therefore, the proposed IGWO-AdaBoost DT model exhibits the least MAE as compared to the IGWO-Vanilla LSTM DT model and the IGWO-Stacked LSTM DT model, respectively. The proposed work indicates that ML models are less capable of predicting target variables. Conversely, a higher MAE value implies that the ML model has better predictive accuracy and is better at predicting the future and was more stable. Models with the default DT configuration had the highest values of MAE and RMSE, indicating a major contribution of hyperparameter altering to improved model performance. Models optimized using IGWO consistently displayed lower error metrics than the Vanilla LSTM and Stacked LSTM models, reinforcing the significance of metaheuristic optimization techniques in fine-tuning ML models. The results of the sensitivity analysis show that the AdaBoost model performs better than other models, especially when boosted with IGWO. AdaBoost’s capacity to integrate several weak learners and adapt to prediction errors is probably the cause of this. Furthermore, it appears that the IGWO optimization method is useful for exploring the hyperparameter space and discovering configurations that reduce prediction errors. The effectiveness of various ML models applied to the NASA AMES battery dataset is compared in Table 7, with an emphasis on how well models predict the discharge capacity of Li-ion batteries. There are six different studies, with recent publications varying from 2021 to 2023, and each study incorporated a different methodology. The table presents an overview of how predictive modeling techniques have advanced over time, with the most current models, particularly the proposed work, displaying exceptionally precise predictions. The proposed work achieved equal RMSE and MAE values of 0.01, the lowest among the studies, highlighting its significant efficacy.

Figures 5(a)–5(c) illustrate the efficacy of decision tree models in terms of RMSE values. RMSE represents the square root of the average squared difference between the actual values and predicted values. The highest RMSE was observed from the default-AdaBoost DT model as compared to other models (Figure 5(a)), while training as well as 10-fold CV were conducted on Li-ion batteries. Similarly, the lowest RMSE values are observed with the IGWO-AdaBoost DT model in all the cases. Figures 5(b) and 5(c) show the RMSE values when Vanilla LSTM and Stacked LSTM DT models are considered. Here, again, maximum RMSE values are observed with default models as compared to the optimized DT models. While considering Vanilla and Stacked LSTM DT models in combination with optimized models, the IGWO-Vanilla LSTM DT model and IGWO-Stacked LSTM DT exhibit the lowest RMSE consistently with all batteries, as observed. Therefore, the IGWO-AdaBoost DT model exhibits the least RMSE as compared to the IGWO-Stacked LSTM DT model, followed by the IGWO-Vanilla LSTM DT model. Figures 6(a)–6(c) indicate the robustness of ML algorithms to predict capacity under various conditions. It is observed that AdaBoost’s prediction capability is much better as compared to the other two ML algorithms. Using the NASA AMES dataset, ML models were analyzed for their sensitivity in predicting Li-ion battery discharge capacity. The objective is to evaluate the relative impact of model configurations and optimization strategies on each model’s predictive ability, as demonstrated by two important metrics: RMSE and MAE. The IGWO-AdaBoost DT model had the lowest MAE and RMSE values (0.01) for the battery datasets (B0005, B0006, B0007, and B0018). This showed that it was better at predicting the future and was more stable. Models with the default DT configuration had the highest values of MAE and RMSE, indicating a major contribution of hyperparameter altering to improved model performance. Models optimized using IGWO consistently displayed lower error metrics than the Vanilla LSTM and Stacked LSTM models, reinforcing the significance of metaheuristic optimization techniques in fine-tuning ML models. The results of the sensitivity analysis show that the AdaBoost model performs better than other models, especially when boosted with IGWO. AdaBoost’s capacity to integrate several weak learners and adapt to prediction errors is probably the cause of this. Furthermore, it appears that the IGWO optimization method is useful for exploring the hyperparameter space and discovering configurations that reduce prediction errors. The effectiveness of various ML models applied to the NASA AMES battery dataset is compared in Table 7, with an emphasis on how well models predict the discharge capacity of Li-ion batteries. There are six different studies, with recent publications varying from 2021 to 2023, and each study incorporated a different methodology. The table presents an overview of how predictive modeling techniques have advanced over time, with the most current models, particularly the proposed work, displaying exceptionally precise predictions. The proposed work achieved equal RMSE and MAE values of 0.01, the lowest among the studies, highlighting its significant efficacy.
The practical impact of research results for the battery industry includes creating methodologies for the development of more robust and efficient battery systems, which will lower costs and improve the economic feasibility of energy storage solutions. The increased discharge capacity prediction accuracy of Li-ion batteries can help manufacturers optimize battery design and performance, which could result in a decrease in greenhouse gas emissions and a shift to cleaner energy sources. This is especially important when considering environmental sustainability and climate change. However, it is important to acknowledge certain constraints in the proposed methodology. Several issues in
our investigation, including dataset limits, model complexity, assumptions regarding battery behavior, and optimization methodologies, could lead to possible inaccuracies. Models’ ability to be broadly applied may be impacted by our overreliance on the NASA Battery Aging Dataset because of possible biases or restrictions in the dataset. ML models, including AdaBoost and LSTM, demonstrate high accuracy; their complexity could introduce errors, especially in new and unseen battery scenarios. There may be inherent uncertainty in the assumptions made regarding the behavior of lithium-ion batteries, especially in digital twin representation. These inaccuracies might be decreased by improving the digital twin model in light of the increasing understanding of
battery chemistry and physics. The dependability of assumptions on the efficacy of metaheuristic optimization techniques, such as antlion, GWO, and IGWO, could be improved by investigating alternative methodologies. Additionally, the predictive models’ exceptional accuracy is based on the dataset used, and their applicability to other datasets or diverse battery scenarios requires further investigation.
Figure 6: Digital twin predicted discharge capacity fitted against observed and empirically calculated capacity for AdaBoost DT, Vanilla LSTM, and Stacked LSTM model, respectively, in ten-fold CV.
The deployment of DT-assisted, optimized ML models for Li-ion battery prediction promises to vastly expand the scope of possibilities in the coming years, potentially transforming the landscape of the energy storage industry. These cutting-edge techniques combine the accuracy of DT with the flexibility of ML to improve battery performance prediction, optimize battery design, and expedite maintenance and operations procedures. In order to solve the present problems with battery technology and provide more reliable, effective, and long-lasting energy storage solutions, this integration is essential. Researchers expect considerable improvements in performance, cost reduction, and overall efficiency as enterprises increasingly adopt Li-ion battery technology. The insights gained from this research are particularly salient for sectors, such as automotive, where the shift to electric vehicles necessitates reliable and efficient battery systems. In the context of renewable energy, better battery technology can also greatly increase the stability and storage of solar and wind energies, which help to lessen the intermittent problems that come with these renewable energy sources. Moreover, this study’s findings about the improved predictability and efficiency of Li-ion batteries play a significant role in encouraging the wider adoption of a variety of sustainable technologies. This advances the goal of a more sustainable, low-carbon future by lowering carbon emissions and supporting global environmental objectives.

The authors also emphasize the significance of investigating the actual implementation of the generated models in real-world situations. Larger-scale field testing and validation with multiple battery types and operating conditions may offer insightful information about how well the models function in various scenarios. Exploring this particular research direction would not only exclusively strengthen the validity of the digital twin-assisted models that are being proposed but also provide pragmatic recommendations for their implementation in a wide range of battery technology applications.

7. Conclusion

DT technology builds data-driven ML models that estimate lithium-ion battery discharge capacity in this research. The models have been developed through the integration of ML techniques, specifically AdaBoost and LSTM, with empirical battery capacity estimation models. The DT models are created by applying 10-CV approaches in conjunction with normal training. The authors have employed the application of metaheuristic optimization techniques to optimize the DT models’ hyperparameters. The authors outline the principal discoveries as follows:

(1) The IGWO-AdaBoost DT model demonstrates outstanding predictive accuracy in estimating the discharge capacity of Li-ion batteries. It outperforms both the IGWO-Vanilla LSTM DT model and the IGWO-Stacked LSTM DT model, as evidenced by key performance metrics such as MAE and RMSE.

(2) In terms of MAE, the IGWO-AdaBoost DT model achieves impressive precision, recording a minimal MAE of just 0.01. This is significantly more accurate compared to the default-Stacked LSTM DT model, which shows a higher maximum MAE of 0.20.

(3) For RMSE, a crucial metric for model accuracy, the IGWO-AdaBoost DT model again excels, registering a minimal RMSE of only 0.01. This is in stark contrast to the default-Vanilla LSTM DT model, which exhibits a notably higher maximum RMSE of 0.19.

(4) When it comes to predicting the discharge capacity, the AdaBoost DT model consistently demonstrates remarkably low prediction errors, far surpassing the performance of both the Vanilla LSTM DT and Stacked LSTM DT models.

(5) The use of the IGWO technique for hyperparameter tuning in the DT models has been shown to slightly enhance performance. This improvement is evident when compared against models using GWO, ALO, and default hyperparameter settings.

The deployment of DT-assisted, optimized ML models for Li-ion battery prediction promises to vastly expand the scope of possibilities in the coming years, potentially transforming the landscape of the energy storage industry. These cutting-edge techniques combine the accuracy of DT with the flexibility of ML to improve battery performance prediction, optimize battery design, and expedite maintenance and operations procedures. In order to solve the present problems with battery technology and provide more reliable, effective, and long-lasting energy storage solutions, this integration is essential. Researchers expect considerable improvements in performance, cost reduction, and overall efficiency as enterprises increasingly adopt Li-ion battery technology. The insights gained from this research are particularly salient for sectors, such as automotive, where the shift to electric vehicles necessitates reliable and efficient battery systems. In the context of renewable energy, better battery technology can also greatly increase the stability and storage of solar and wind energies, which help to lessen the intermittent problems that come with these renewable energy sources. Moreover, this study’s findings about the improved predictability and efficiency of Li-ion batteries play a significant role in encouraging the wider adoption of a variety of sustainable technologies. This advances the goal of a more sustainable, low-carbon future by lowering carbon emissions and supporting global environmental objectives.

The authors also emphasize the significance of investigating the actual implementation of the generated models in real-world situations. Larger-scale field testing and validation with multiple battery types and operating conditions may offer insightful information about how well the models function in various scenarios. Exploring this particular research direction would not only exclusively strengthen the validity of the digital twin-assisted models that are being proposed but also provide pragmatic recommendations for their implementation in a wide range of battery technology applications.

Table 7: Comparative analysis of recent research study performed on NASA AMES battery dataset.

<table>
<thead>
<tr>
<th>Sr No.</th>
<th>Authors</th>
<th>Machine learning models</th>
<th>RMSE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Zhao et al. [45]</td>
<td>Time convolutional memory neural network (TCMNN)</td>
<td>0.087</td>
<td>0.001</td>
</tr>
<tr>
<td>2</td>
<td>Tarar et al. [46]</td>
<td>Convolutional bidirectional LSTM with attention mechanism (CNN-BiLSTM-AM)</td>
<td>0.004</td>
<td>0.003</td>
</tr>
<tr>
<td>3</td>
<td>Qin et al. [47]</td>
<td>Gradient boosting decision tree (OS_GBDT)</td>
<td>0.011</td>
<td>0.010</td>
</tr>
<tr>
<td>4</td>
<td>Tian et al. [48]</td>
<td>Deep neural networks with memory features (DNNwMF)</td>
<td>4.16</td>
<td>NA</td>
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<td>5</td>
<td>Zhu et al. [49]</td>
<td>Long short-term memory network (LSTM)</td>
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<td>0.281</td>
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<tr>
<td>6</td>
<td>Proposed work</td>
<td>Improved grey wolf optimization- AdaBoost (IGWO-AdaBoost)</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Abbreviations

AdaBoost: Adaptive boosting
AI: Artificial intelligence
ALO: Antlion optimization
LSTM: Long short-term memory
ANN: Artificial neural network
CCCV: Constant current constant voltage
DAQ: Data acquisition system
DL: Deep learning
DT: Digital twin
ECM: Equivalent circuit model
EIS: Electrochemical impedance spectroscopy
EM: Electrochemical model
GBM: Gradient boosting machine
GPR: Gaussian process regression
GWO: Grey wolf optimization
IGWO: Improved grey wolf optimization
LFP: Lithium iron phosphate
Li-ion: Lithium ion
MAE: Mean absolute error
ML: Machine learning
NASA: National Aeronautics and Space Administration
OEM: Original equipment manufacturer
PCoE: Prognostic Center of Excellence
RMSE: Root mean squared error
RUL: Remaining useful life
SEI: Solid electrolyte interphase
SOC: State of charge
SOH: State of health.

Data Availability

The data used in this study are publicly available at the following link: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognosticdata-repository/.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors’ Contributions

Pranav Nair, Vinay Vakharia, Milind Shah, and Yogesh Kumar conceptualized the study, developed the methodology, and provided the software. Marcin Wożniak, Jana Shafi, and Muhammad Fazal Ijaz curated the data and wrote the original draft. Pranav Nair, Vinay Vakharia, Milind Shah, Yogesh Kumar, Yogesh Kumar, Marcin Wożniak, Jana Shafi, and Muhammad Fazal Ijaz visualized, investigated, and supervised the study. Yogesh Kumar, Marcin Wożniak, Jana Shafi, and Muhammad Fazal Ijaz provided the software and validated the study. Pranav Nair, Vinay Vakharia, and Milind Shah reviewed and edited the manuscript.

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References


