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Multi-Scale Analysis of Polymer Based Energy Storage Systems for High Performance Battery Applications

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Abstract

The energy storage systems based on polymers are becoming promising materials for the next generation of high performance batteries because of their excellent mechanical flexibility, improved safety, and favorable electrochemical properties. Even with computational tools in Python, polymer-based energy storage systems remain plagued by poor ionic conductivity, complicated electrochemical reactions and potential thermal runaway. Therefore, a multi-scale model is proposed to improve battery performance, thermal stability, reliability, and large-scale deployment safety. The approach integrates material-level modeling with system-level evaluation and risk assessment. Raw data are preprocessed using min–max normalization for uniform scaling, followed by PCA for feature extraction and dimensionality reduction to retain essential characteristics while removing redundancy. At the microscopic level, ion transport and polymer chain dynamics are modeled using continuum transport based on non-equilibrium thermodynamics with electrochemical–mechanical coupling via free energy formulations. These insights are shared across scales to evaluate the macroscopic battery properties of efficiency, thermal stability and reliability. To better evaluate safety, the deep learning-based Archerfish Hunting Optimizer (AHO) driven Intelligent Deep Neural Network (IntDNN) model is added to the risk assessment module to predict thermal runaway and failure probability in large-scale battery systems. The proposed AHO-IntDNN shows better accuracy (0.99), precision (0.99), recall (0.99), F1 score (0.99) and ROC-AUC 0.97, indicating high reliability in the predictive performance. The model is based on multi-source simulation and operational data for capturing the nonlinear relationships in the prediction of risk. The unified multi-scale model allows for design, optimization and safe deployment of polymer-based energy storage systems, whereas the validated numerical results demonstrate improved performance.

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INTRODUCTION

In energy, storage systems have emerged as an essential part of modern technological developments and are a key component in the successful integration of renewable energy, electric vehicles, and portable electronic devices, by facilitating effective energy conversion, storage, and utilization [1]. Through continuous improvements in energy density, life cycle, and charging efficiency, batteries have come a long way since their inception, progressing from simple cells to highly advanced lithium-ion batteries [2–3]. Despite the above-mentioned improvements, there

are many challenges associated with traditional lithium-ion batteries, including frequent cycling, leakage of the electrolyte, and thermal runaway, among others. Polymer electrolytes offer numerous benefits, particularly in the field of solid-state battery designs, including improved mechanical strength, flexibility, and minimized leakage risks [4–5]. There remain some application challenges, particularly in High-performance applications low ionic conductivities, temperature dependence and instability of the interfaces [6]. In polymer electrolytes, complex mechanisms of polymer sequential movement of chains and ion bouncing affect ionic transference and consequently its conductivity and electrochemical efficiency [7]. Besides, mechanical stress and deformation of polymer structures during battery usage can affect long lasting durability and reliability. The battery activity is related to the interactions at the molecular, microscale and macroscale levels, so multi-scale analysis approach should be used to fully understand and enhance these networks [8–9]. Macroscopic evaluation methods are energy density, power density, thermal stability and cycle life, while microscopic evaluation methods are polymer dynamics and ion transport. Modeling and simulator approaches are key to connecting with various scales through enabling predictive research of material behaviors, reducing experimental costs, and optimizing system design parameters [10, 11]. AI is integrated with battery management systems, which can predict battery failures and thermal runaway based on operational data. Optimization algorithms when used with DL can enhance nonlinear modeling, anomaly detection, and continuous risk assessment in a wide range of operating conditions [12].

The object of this research is to build a multi-scale analytical model for polymer-based energy storage systems, which integrates material modelling, system assessment, and AI-based risk prediction methods for the proposed AHO-IntDNN, to improve the performance, safety, and reliability of batteries.

The structure of the research includes the following

- *Section 1.* Dataset description and related background
- *Section 2.* Preprocessing, feature extraction, and AHO-IntDNN approach
- *Section 3.* Experimental results and performance analysis
- *Section 4.* Conclusion and further research section 5.

Related work

This research [13] was to use gel polymer electrolytes with better ionic conductivity, mechanical stability, and safety to improve solid-state battery performance. Numerous battery technologies incorporated different polymer, inorganic, and ionic liquid-based electrolytes. Dendritic inhibition, thermal protection, ionic conductivity of 10^{-3} S/cm, and electrical stability over 4.5 V were all demonstrated by experimental evaluations in batteries. Using comparative analysis of adsorption, MEMS, vapor-phase etching, oxidization, carbonization, hydrolysis, and ALD processes, the research examines [14] porous silicon synthesis, surface modification, and multifunctional applications. Porous silicon highlighted achieving 95% accuracy with better sensing, energy storage, and MEMS performance using flexible topology and surface design; however, issues with reliability, scaling, and CMOS efficient commercial interfaces remain. The research [15] evaluates innovative anode components and SSBs for sustainable energy storage by analyzing surface coatings, Nano structuring, electrolyte compatibility, and composite optimization methods. While highlighting issues with conductivity, scalable production, and electrode–electrolyte interface knowledge, the results show enhanced energy density (~20%), safety, thermal resistance, and lifespan under 7 MPa stack pressure conditions. The research assessments the super capacitor technologies and advanced electrode materials for high-performance energy storage, involving the evaluation of electrochemical characterization methods, nanostructured materials, hierarchical pores, hybrid devices and unconventional electrolytes [16]. The results highlight improved power density, cycling stability, charge–discharge performance, and energy storage capacity, achieved by tuning electrode–electrolyte interactions and material engineering.

Predictive modeling, material evaluation, high-throughput screening, and optimizing methods are used for exploring [17] AI and Machine Learning (ML) for polymer-based energy storage. Accelerated polymer discovery, improved conductivity, flexibility, and energy storage capability are all shown by the analysis. The development of sustainable materials, restricted datasets, model accuracy, and synthetic capability continues to be a major research issue. The research [18] evaluates energy storage devices using lifecycle cost analysis, entropy weighting, improved grade-one technique, and fuzzy comprehensive assessment across economic, technical, and ecological dimensions. The results indicate that compressed air and pumped storage systems exhibit superior long-term economic efficiency, while lithium iron phosphate batteries demonstrate outstanding flexibility and rapid response capability, with the lowest score change rate of 15.2%. In this work [19] a proactive method is investigated for battery safety assessment for EVs based on neural network models and anomaly detecting. The techniques applied to detect the abnormal behavior in batteries included the Autoencoder, LSTM, One-Class SVM, and Isolation Forest. The Autoencoder achieved efficient and trustworthy battery defect finding performance with the highest accuracy of 0.92.

In this research [20] the authors intend to detect battery failures at an early stage, taking into account the electrochemical data measured during charging periods during the start-up and delta impedance. The models tested were GBDT, Random Forest (RF) and NB. It has been found that RF and GBDT models are the most accurate model with an accuracy of 98% with high reliability and high prediction capability while the error of education and testing was low.

Methodology

The method starts by gathering polymer-based battery data sets that include electrochemical, thermal, and operational data for batteries. Min–Max normalization is applied to the data in order to eliminate inconsistencies and normalize the heterogeneous features. Then, PCA is used for feature extraction and dimensionality reduction. The processed data are subsequently analyzed by multi-scale modelling to assess ion transport and electrochemical behavior. Finally, the proposed AHO-IntDNN is implemented for thermal runaway prediction, safety assessment and high-performance battery analysis. The polymer battery analysis, optimization and performance evaluation are summarized in a workflow in Figure 1.

Data collection

The Kaggle collection provided the simulated Distributed Battery Management System dataset utilized in current investigation. This data set has 601 rows and 12 columns: voltage, current, temperature, power, SOC, SOH, anomaly scores, latency, diagnostic indicators. It can be used for multi-scale analysis, thermal stability assessment, anomaly detection, safety evaluation, and intelligent performance prediction of energy storage systems based on polymers. For performance evaluation and prediction analysis, 80% of the dataset was used for training, and 20% was used for testing.

Source: *https://www.kaggle.com/datasets/micamadi/synthetic-distributed-battery-management-system?utm_source*

Data Preprocessing Using Min-Max Normalization

To improve the consistency and reliability of polymer-based energy storage datasets, preprocessing is performed to remove redundant values, noise, and inconsistencies from electrochemical measurements. Since battery parameters such as voltage, ionic conductivity, energy density, temperature, and cycle stability have different numerical scales, Min–Max normalization is applied to transform all features into a common range of $[0-1]$is mathematically expressed in Equation (1):

$$u' = \frac{u-min(B)}{max(B)-min(B)}(new\_max_B - new\_min_B) + new\_min_B \quad (1)$$

Where u is the initial inputs metric,$u'$is the normalised characteristic parameter, and min_B and $max(B)$correspond are the minimum and maximum levels of element B, accordingly. The desired normality limit, that is typically chosen as $1\ and\ 0$ for standardised battery attribute expansion, is defined by the words$new_max_B$and new_min_B.

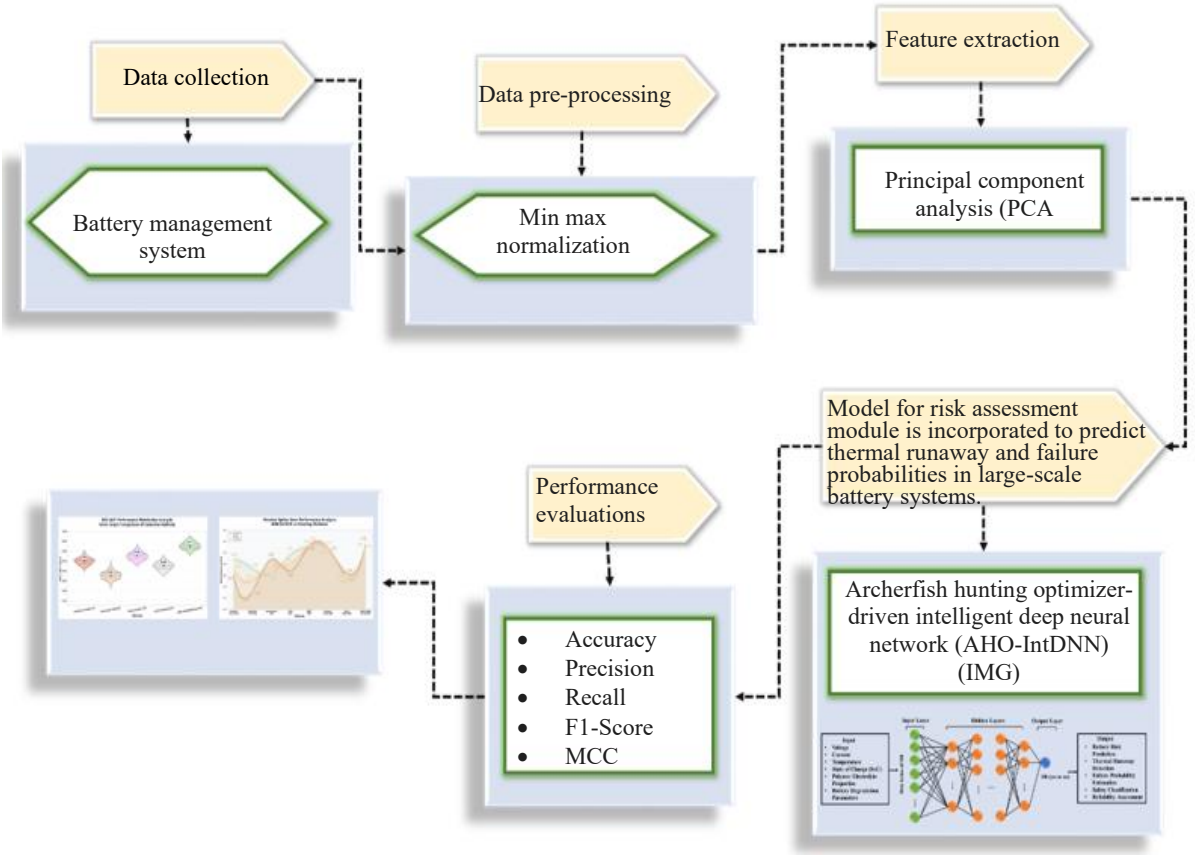


Figure 1. Multi-scale polymer-based battery risk assessment system.

Feature Extraction Employing Principal Component Analysis (PCA)

High-dimensional battery data is utilized to generate representative features, and PCA is employed to preserve crucial information.Through converting a large set of associated variables into fewer of independent primary elements that preserve the majority was initial information and variation included that battery database, it lowers complexity.Lowering the computing burden, mitigating redundancy, enhancing the interpretability of features, and improving learning efficiencies for electrochemical performance analysis, thermal stability assessment and intelligent battery prediction modeling. To reduce repetition and increase battery analysis performance, PCA was used in this experiment to extract significant molecular, structure, electrical, and thermal properties for storing energies made of polymeric. PCA finds linear combinations of the original variables, which maximize the variance in the dataset, as defined by Equation (2):

$$Y = X_a \Longleftrightarrow S_a = \lambda_a \tag{2}$$

Where X is the standardized feature matrix, a is the loading vector containing principal component coefficients, and Y is the transformed principal component score. Where$\lambda$the associated eigenvalue that represents the difference, and S is the average vector.The contribution ratio of each principal component is calculated as Equation (3):

$$\pi_j = \frac{\lambda_j}{\sum_{j=1}^{p} \lambda_j} = \frac{\lambda_j}{tr(s)} \tag{3}$$

In this case, π_j is the variance contribution ratio of the jthprincipal factor, λ_j is its equivalent eigenvalue, p is the total number of features, $\sum_{j=1}^{p} \lambda_j$ is total average and $tr(s)$ is the trace of the correlation matrix S, which equals the dataset's total variance.

Battery Safety Assessment Using Archerfish Hunting Optimizer-driven Intelligent Deep Neural Network (AHO-IntDNN) model

The proposed AHO-IntDNN integrates the optimization capability of the AHO with the predictive IntDNN to enhance battery safety and performance analysis. The AHO efficiently tunes network parameters, improves feature selection, and minimizes prediction errors, thereby enhancing convergence and computational efficiency. Simultaneously, the IntDNN learns complex nonlinear relationships among electrochemical, thermal, and operational battery parameters for accurate prediction of thermal runaway, degradation behavior, and failure probability. This hybrid model enables reliable, real-time risk assessment in polymer-based energy storage systems. Algorithm 1 presents the proposed AHO-IntDNN pseudocode for battery analysis.

Algorithm1: AHO-IntDNN
INPUT:
X -> Battery dataset (voltage, current, temperature, SoC, SoH)
y -> Target outputs (thermal runaway, failure risk, performance metrics)
OUTPUT:
y_pred -> Predicted battery performance/risk
model -> Optimized AHO-IntDNN
Loss function:
Loss = -Σ[y log(z) + (1-y) log(1-z)]
STEP 4: AHO OPTIMIZATION
Initialize population:
O(j,0) = random positions
for each iteration s:
Exploration:
O_in = O(j,s) + random + sin(2θ)
Position update:
O(j,s+1) = -(O(j,s) - O_in)*exp(-dist^2) + O(j,s)
Lévy flight:
O(j,s+1) = O(j,s) + σ * Lévy(β)
Evaluate fitness = Loss(y, y_pred)
Update best solution
y_pred = optimized IntDNN using best AHO parameters
returny_pred, model

Intelligent Deep Neural Network (IntDNN)

Learns Complex Battery Behaviors for Real-Time Thermal Runaway Prediction

The IntDNN learns complex nonlinear relationships among electrochemical, thermal, and operational battery parameters. It enables accurate prediction of battery behavior, thermal runaway conditions, and failure probabilities while improving system reliability, safety monitoring, and decision-making in high-performance energy storage applications. The model processes multi-scale descriptors, including molecular, structural, electrochemical, thermal, and mechanical properties, and learns complex nonlinear relationships to accurately estimate energy density, cycle life, stability, and overall battery performance. For a network with three hidden layers, the forward propagation process is expressed as Equation (4–7):

$$g_j^{(l)} = \varphi^{(l)}\left(\sum_i x_{ji}^{(l)} w_i + a_j^{(l)}\right) \quad (4)$$

$$g_j^{(2)} = \varphi^{(2)}\left(\sum_i x_{ji}^{(2)} g_i^{(l)} + a_j^{(2)}\right) \quad (5)$$

$$g_j^{(3)} = \varphi^{(3)}\left(\sum_i x_{ji}^{(3)} g_i^{(2)} + a_j^{(3)}\right) \quad (6)$$

$$z_j = \varphi^{(4)}\left(\sum_i x_{ji}^{(4)} g_i^{(3)} + a_j^{(4)}\right) \quad (7)$$

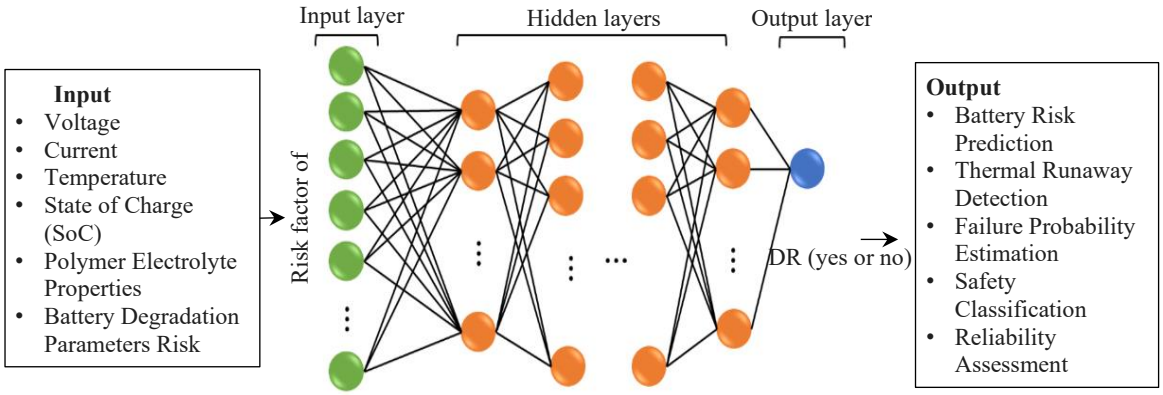


Figure 2. Architecture of the IntDNN for multi-scale analysis of polymer-based energy storage systems.

Ionic conductivity, a crystallization, and temperature are examples of input properties that are represented by z_j. The weight $x_{ji}^{(1)}, x_{ji}^{(2)} \ldots . x_{ji}^{(4)}$ where l=1, 2, 3, or 4, connects neurone j in the preceding layer to neurone i in layer l. The bias term of neurone$i$in the layer is $a_j^{(1)}, a_j^{(2)} \ldots . a_j^{(4)}$. Where$\sum_i$ denotes summation. The activating variable is represented by $\varphi^{(1)}, \varphi^{(2)} \ldots . \varphi^{(4)}$. While z_j reflects anticipated battery characteristics, comprising energy density, cycle life, and capacity retained$g_j^{(1)}$, $g_j^{(2)}$,and $g_j^{(3)}$are hidden-layer outputs. The IntDNN uses several activation tasks, such as the rectified linear unit (ReLU), sigmoid, and exponential tangents, as shown in Equation (8–10):

$$\varphi(u) = \frac{1}{1+e^{-u}} \quad (8)$$

$$\varphi(u) = \frac{e^{2u}-1}{e^{2u}+1} \quad (9)$$

$$\varphi(u) = \max\{u, 0\} \quad (10)$$

The weighted inputs to a neurons is represented by u in Equations (8-9), the activating exit is represented by $\varphi(u)$, and Euler's constant is represented by e. The sigmoid function maps values between 0 and 1, tanh maps values between -1 *and* 1.When u is positive in Equation (10), max$\{u, 0\}$yields$v$; otherwise, it returns 0. For regression-based prediction, the loss function is defined as Equation (11):

$$Loss = -\sum_j \left(z_j' \log(z_j) + (1 - z_j') \log(1 - z_j)\right) \quad (11)$$

Wherez_j is expected likelihood, z_j' was the actual label, and j is the output index. The natural logarithm, orlog, quantifies the discrepancy between actual and expected values. The error across all outputs are summed by $\sum_j (z_j' \log(z_j))$. To increase prediction accuracy, the model decreases this $loss$. Figure 2 illustrates the proposed IntDNN architecture accurately predicts high-performance energy storage characteristics by processing multi-scale polymer and battery features across numerous hidden layers.

Archerfish Hunting Optimizer (AHO)

Optimizes Neural Network Parameters for Accurate and Stable Battery Risk Prediction

The proposed employs the AHO within a multi-scale analysis model for polymer-based energy

storage systems in high-performance battery applications. AHO helps to optimize the parameters of the neural networks; select features, converge faster, and reduce computational complexity. Such optimization makes performance analysis and risk prediction more accurate and efficient. It allows evaluating the electrochemical performance, thermal stability, and safety properties. To accurately predict thermal instability, operational risks, and energy storage system failures, it effectively finds the best options for battery safety analysis. To improve prediction accuracy, thermal validity, electrochemical strength, and general battery performance analysis, that suggested method makes using AHO to identify the ideal system characteristics. Equation (12) represents the starting positions of thejth archerfish, $O(i,0)$:

$$O(i,0) = \left[\left(o_1^K + \sigma_1\left(o_1^V - o_1^K\right)\right), \ldots, \left(o_c^K + \sigma_c(o_c^V - o_c^K)\right)\right] \tag{12}$$

In this case, σ is a random number $between\ 0\ and\ 1$ for various solution generations, $o_c^K and o_c^V$ stand for upper and lower limits, and $O(i,0)$ indicates the starting location. Equation (13) describes the archerfish's motion at iteration $(r+1)$:

$$O(i,r+1) = -\left(O(i,r) - O_{in}(i,r)\right)f^{-(O_{in}(i,r)-O(i,r)|\ |_2)^2} + O(i,r) \tag{13}$$

The $i-th$archerfish's current location at iteration r is indicated by $O(i,r)$, and its updated position is indicated by $O(i,r+1)$. The position of the target insect is indicated by $O_{in}(i,r)$, while the separation between the archerfish and the target is measured by$f^{-(O_{in}(i,s)-O(i,r)|\ |_2)^2}$.The insect position is estimated using in Equation (14):

$$O_{in}(i,r) = O(i,r) + \left(0, \ldots, \frac{u^2}{2^6} \times sin2\emptyset, \ldots, 0\right) + \epsilon \tag{14}$$

$O_{in}(i,t)$denotes the insect position at iteration s, $O(i,r)$represents the current archerfish position, u^2 indicates the velocity of the water droplet, ϕ denotes the shooting angle, $sin2\phi$determines the projectile movement direction, andϵ represents a random vector within the interval.In the exploitation phase, the archerfish jumps toward the prey after striking it successfully. The movement equation during exploitation is expressed as Equation (15):

$$O(i,r+1) = -\left(O(i,r) - O_{in}(i,r)\right)f^{-(||O_{in}(i,r)-O(i,r)||)^2} + K(i,r) \tag{15}$$

The variable $K(i,r)$ denotes the jumping movement of the archerfish toward the prey. The remaining parameters $O_{in}(i,r)$, and the Euclidean norm maintain similar meanings as in Equation (13). Additionally, the position of the insect can be modeled as Equation (16):

$$O_{in}(i,r) = O(i,r) + \left(0, \ldots, \frac{u^2}{26} \times sin2\emptyset, \ldots, \frac{u^2}{2h} \times sin^2\emptyset, \ldots, 0\right) + \epsilon \tag{16}$$

$O_{in}(i,r)$denotes the insect position, u^2 indicates the shooting velocity, h denotes gravitational acceleration, ϕ represents the perception angle, $sin^2\emptyset$, and $sin2\phi$ determine the projectile trajectory, and ϵ denotes the random vector added for search diversity.If the archerfish position $O(i,r)$remains unchanged during optimization iterations, a new search position is generated using Equation (17-18):

$$O(i,r+1) = O(i,r) + \sigma\left[\frac{o_1}{u_1^{(1/\beta)}}, \ldots, \frac{o_c}{u_c^{(1/\beta)}}\right] \tag{17}$$

I$O(i,r)$ represents the current archerfish position, $O(i,r+1)$denotes the updated search position,σ indicates the step size parameter, o_1, o_c are random variables, u_1 , u_c represent adaptive scaling variables, β denotes the power-law index controlling Lévy flight behavior, and $s$represents the problem dimension.

$$\begin{cases} o_j \sim e_m(0,\gamma^2), \gamma = \left(\dfrac{\Gamma(\beta+1)\times\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{\beta+1}{2}\right)\times 2^{\left(\frac{\beta-1}{2}\right)}\times\beta} \right), i\epsilon\{1,\ldots,c\} \\ u_j \sim e_m(0,\gamma^2), \acute{\gamma} = 1 \ , i\epsilon\{1,\ldots,c\} \end{cases} \quad (18)$$

In Equation (18), o_j and $u_j$represent random variables generated using the normal distribution function $e_m$denotes the mean value, γ, γ^2 represents the standard deviation, Γ denotes the Gamma function, The trigonometric termsin$\left(\frac{\pi\beta}{2}\right)$,$\beta$ indicates the Lévy flight power-law index, while $i\,\epsilon\{1,\ldots,c\}$ indicates the dimensional index that searching planetary, where i represents the overall amount are optimization variables and c indicates the target spatial depth. The proposed AHO model substantially enhances optimization accuracy, convergence stability, and computational efficiency for multi-scale analysis of polymer-based energy storage systems. Table 1 shows configuration parameters utilized for training and optimizing the proposed AHO-IntDNN model.

RESULT

The existing methods like Isolation Forest, One-Class SVM, Autoencoder, LSTM Network [19] and GBDT, Random Forest and Naive Bayes [20] suffer from the inability to capture the true thermal risk behavior and the complex multi-scale electrochemical interactions in real-time. The proposed AHO-IntDNN model was developed to enhance prediction accuracy, safety assessment and battery reliability. The combinations of experimental hardware and software used a implementation of the recommended method was presented in Table 2.

The correlation analysis of battery management parameters utilized that proposed AHO-IntDNN method was presented a Figure 3. Strong positive relationships are observed between module current, power, SOH, and SOC while negative correlations highlight thermal dependencies. These correlations assist the proposed model in accurate thermal runaway prediction and battery performance analysis.

The relationship between temperature and power with anomaly score distribution, highlighting abnormal operational conditions in polymer-based battery systems shows in Figure 4(a). Figure 4(b) displays that three-dimensional view a voltage, current and power characteristics. These visualizations help in the proposed AHO-IntDNN model to detect the nonlinear behavior of the battery, operational dependency, and thermal risk pattern for accurate battery performance prediction.

Table 1. Hyperparameter configuration of proposed AHO-IntDNN model.

Parameter	Value
Optimizer	Archerfish Hunting Optimizer (AHO)
Learning rate	0.001
Batch size	64
Epochs	150
Hidden layers	4
Neurons per layer	128, 64, 32, 16
Activation function	ReLU
Output activation	Softmax
Dropout rate	0.3
Loss function	Categorical Cross-Entropy
Validation split	20%
Regularization	L2 (0.0001)
Optimized parameters	Weights, Biases
Population size	30
Maximum iterations	100

Table 2. Hardware and software specifications of experimental environment.

Component	Specification
Processor	Intel Core i7 13th Gen
GPU	NVIDIA RTX 4060
RAM	32 GB
Storage	1 TB SSD
System Type	64-bit Workstation
Software	Specification
Operating System	Windows 11
Programming Language	Python 3.11
Deep Learning model	TensorFlow 2.15

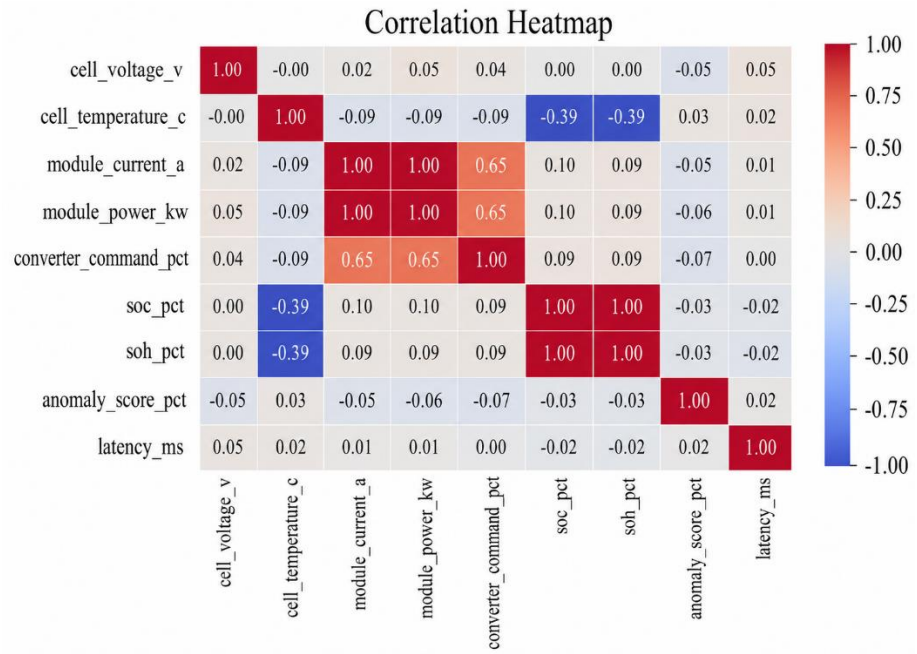
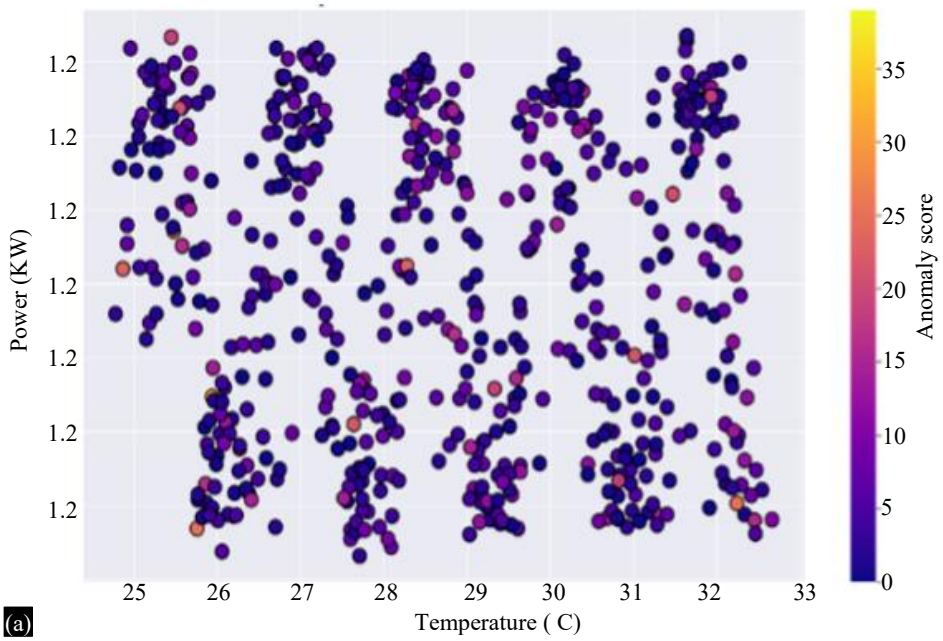
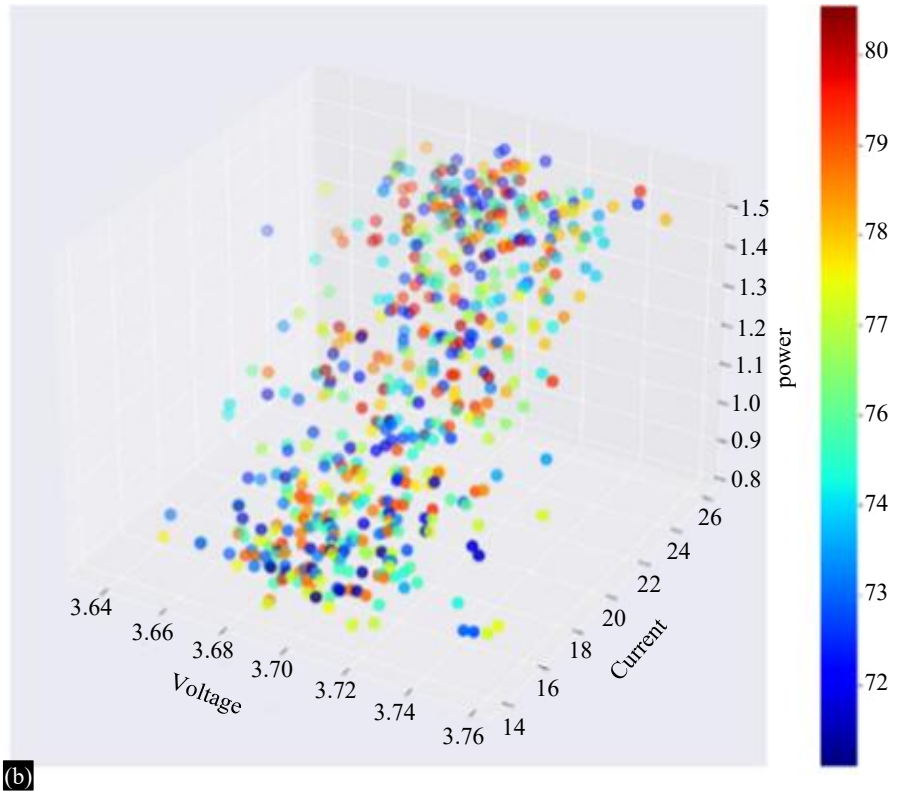


Figure 3. Correlation heatmap of battery management system parameters.





(b)

Figure 4. Multi-scale battery performance visualization: (a)Temperature versus power with anomaly scores; (b) Three-dimensional voltage, current, and power distribution.

Table 3. Performance evaluation of conventional and proposed battery failure prediction methods.

Method	Accuracy	Precision	Recall	F1-score	ROC-AUC
Isolation Forest [19]	-	0.85	0.92	0.88	0.94
One-Class SVM [19]	-	0.78	0.88	0.83	0. 91
Autoencoder [19]	-	0.92	0.86	0.89	0.95
LSTM Network [19]	-	0.87	0.94	0.90	0.93
GBDT [20]	0.98 (98)	0.98 (98)	0.98	0.98	-
Random Forest [20]	0.97 (97)	0.97 (97)	0.97	0.97	-
Naive Bayes [20]	0.88 (88)	0.86 (86)	0.84	0.85	-
AHO-IntDNN [Proposed]	0.99	0.99	0.99	0.99	0.97

Performance Evaluation

The evaluation of machine learning model uses the matrix for evaluating its performance such as accuracy, precision, recall, F1 score, and ROC-AUC. The Accuracy shows overall prediction correctness while Precision represents correctly classified positive samples. The Recall focuses on detecting all positive samples, while F1 score calculates both Precision and Recall together. ROC-AUC gives us the capability of classification of the ML model.

The comparative performance analysis of current models and the proposed AHO-IntDNN model for battery failure and thermal runaway prediction was showed Table 3 and Figure 5 (a-b). The method demonstrated extremely dependable classification capacity with 0.99 accuracy, 0.99 precision, 0.99 recall, and 0.99 F1-score.

Furthermore, the suggested approach obtained a ROC-AUC value of 0.97, demonstrating superior durability and differential performance for automated battery safety evaluation in polymer-based high-performance energy storage systems.

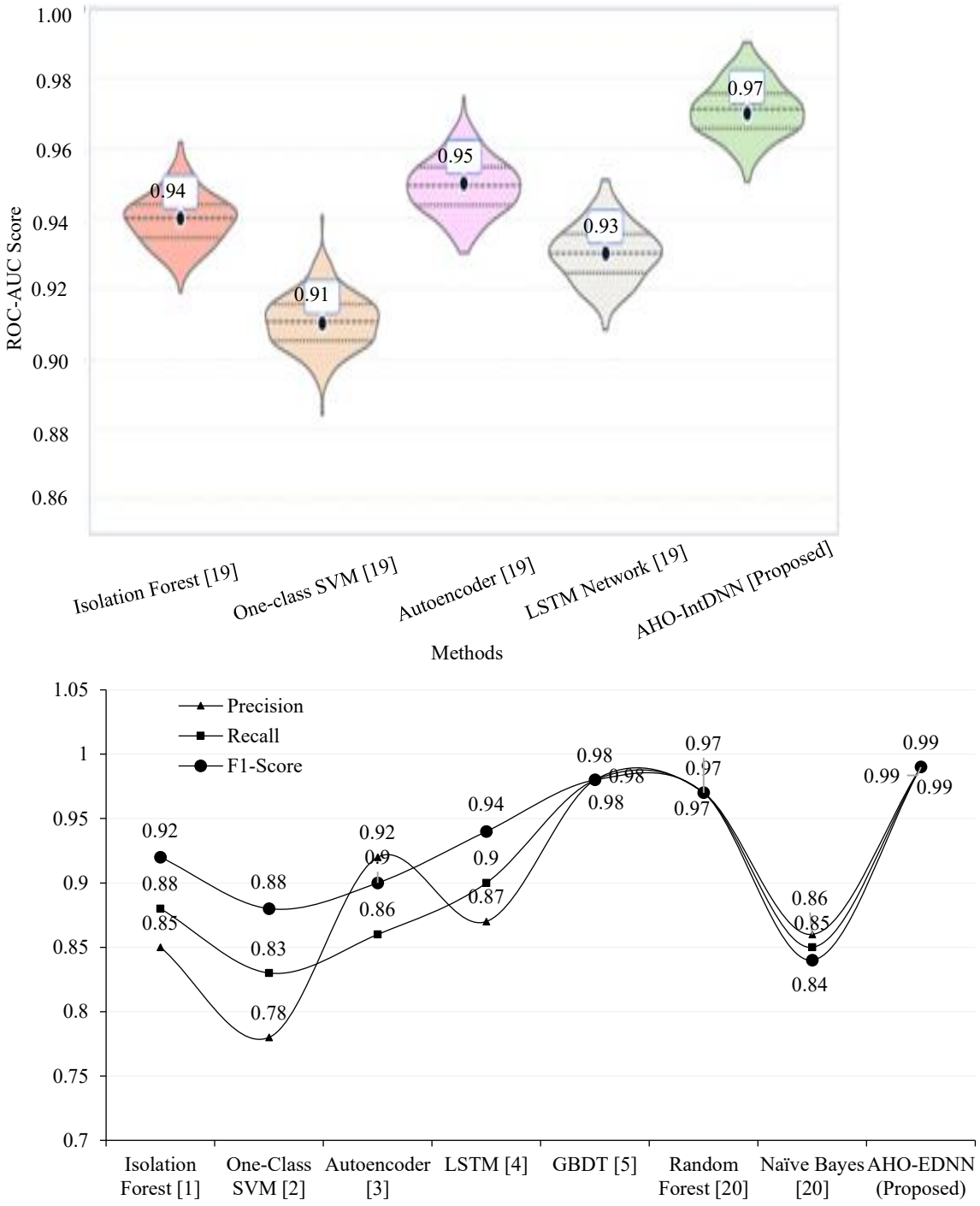


Figure Figure 5. Proposed AHO-based model achieves superior classification and discrimination performance. (a) Stacked Spline Area Performance, and (b) ROC-AUC score distribution across benchmark and proposed models.

The comparative results of the existing algorithms and the proposed algorithm AHO-IntDNN are shown in Table 4 for predicting risks in batteries within the battery management system. All models were re-trained using the same battery management system dataset and the same experimental setup. In this case, Isolation Forest and One-Class SVM have poor results due to low accuracy (0.81–0.84) and low precision-recall trade-off, and so do Naïve Bayes. However, GBDT and RF have improved results that an accuracy score of 0.98. The AHO-IntDNN has better findings those expressions in all metrics: Recall, F1-Score, Accuracy, Precision (0.99), ROC-AUC (0.97).

Table 4. Retrained results of battery fault detection and anomaly prediction method.

Method	Accuracy	Precision	Recall	F1-score	ROC-AUC
Isolation Forest	0.84	0.85	0.92	0.88	0.94
One-Class SVM	0.81	0.78	0.88	0.83	0.91
Autoencoder	0.90	0.92	0.86	0.89	0.95
LSTM Network	0.89	0.87	0.94	0.90	0.93
GBDT	0.98	0.98	0.98	0.98	0.96
Random Forest	0.97	0.97	0.97	0.97	0.95
Naive Bayes	0.88	0.86	0.84	0.85	0.87
AHO-IntDNN [Proposed]	0.99	0.99	0.99	0.99	0.97

DISCUSSION

Multi-scale analysis of polymer-based energy storage systems offers a better understanding of structural, electrochemical, and transport properties, which leads to better charge efficiency, stability, and durability for high-performance battery applications in various operating conditions. Long-duration energy storage and huge-scale grid integration uses are hindered by supercapacitors' lower energy density in comparison to Lithium-Ion batteries, higher self-discharge rates, and cost issues with advanced substances [16]. Although they rely on anomaly detection and feature learning, LSTM, Autoencoder, Isolation Forest, and One-Class SVM Network exhibit weak generality across different battery voltages and operating scenarios.

The challenges with quickly adapting to these techniques and limitations with the requirement of labeled data limit their deployment in dynamic battery safety protocols [19]. GBDT, Random Forest and Naive Bayes are sensitive to noise and sensor errors when combined with delta impedance feature driven prediction techniques. The same is true for the continuous and large-scale battery monitoring and thermal runaway prediction technologies, which are not as scalable and cannot capture the complex non-linear degradation patterns [20].

With this proposed AHO-IntDNN method comes in, which is expected to realize a higher energy density utilization, lower self-discharge, and higher scalability to realize efficient long-duration energy storage. However, the proposed AHO-IntDNN model consistently outperforms the existing techniques in learning multi-scale electrochemical features, reliability, and battery safety and failure prediction in a broad spectrum of working conditions.

CONCLUSION

The multi-scale analysis of polymer-based energy storage systems provides opportunities to improve the electrochemical performance, stability and efficiency of high-performance battery applications with greater durability, scalability and suitability for next generation energy storage applications. The proposed multi-scale model of polymer-based energy storage systems can be used to incorporate the material level model and system level risk assessment, improving the prediction and risk assessment of energy storage systems. The high precision of 0.99, F1 score of 0.99, recall of 0.99, ROC-AUC of 0.97 and accuracy of 0.99show the model AHO-IntDNN has excellent thermal runaway prediction capabilities.

The results show that the polymer electrolytes are more reliable, stable and efficient. This method gives a solid platform for the optimization of high-performance energy storage devices and safe deployment in next-generation application technologies at a large scale. The drawbacks are the heavy computation demands, the dependence of the quality of the multi-source data and the lack of validation of the solution in the real world for large-scale deployment. The potential future research directions involve real-time deployment of edge, further interpretability of AHO-IntDNN to real-world applications, advanced materials and extending of hybrid energy storage systems, to improve their efficiency, security, and scalability.

List of Abbreviations

Abbreviation	Expanded form
ML	Machine Learning (ML)
EVs	electric vehicles (EVs)
One-Class SVM	One-Class Support Vector Machine (One-Class SVM),
LSTM	Long Short-Term Memory (LSTM)
NB	Naive Bayes (NB)
RF	Random Forest (RF),
GBDT	Gradient Boosting Decision Tree (GBDT)
SOC	State of Charge (SOC)
SOH	State of Health (SOH)
AI	Artificial intelligence (AI)
ALD	Atomic Layered Deposit (ALD)
MEMS	Micro-Electro-Mechanical Systems (MEMS)
CMOS	Complementary Metal–Oxide–Semiconductor (CMOS)
SSBs	Solid-State Batteries (SSBs)

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