



A Hybrid Unet-MLP Neural Network Enabling Ultra-Fast and High-Accuracy Prediction for Low-Gradient Temperature Field in Lithium-ion Batteries

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Abstract

Accurate prediction of the internal temperature field in batteries is of critical importance for ensuring safe operation, extending battery lifespan, and ultimately accelerating the global transition to electric vehicles (EVs). Unsafe thermal conditions not only degrade battery performance but also hinder EV adoption. However, conventional 3D thermal models involve complex computations that struggle to meet the fast computational speed requirements of Battery Management Systems (BMS), and traditional neural network models are not accurate enough for temperature field prediction, especially for low-gradient fields. To achieve precise and rapid prediction of the internal battery temperature field, this paper proposes a hybrid neural network combining Unet and MLP architecture (HNNUM) as a green energy storage technology assurance tool

to enable safe, durable battery operation. In this framework, the Unet module captures the relative magnitude relationships of temperatures across different locations in the temperature field, while the MLP module learns the temperature field range information. Finally, an inverse MinMax method integrates these two modules to output the predicted internal battery temperature field. The results demonstrate that the proposed HNNUM can achieve accurate prediction of the internal battery temperature field with only 5.16×10^{-4} K RMSE, and takes only 16.59s to complete the prediction of 3000 temperature fields. The source code is available at <https://github.com/kon9chun/hnnum>.

Keywords: temperature field prediction, lithium-ion batteries, hybrid neural network, 3D thermal model.

1 Introduction

The global climate crisis is intensifying, and energy supply is facing significant challenges. Lithium-ion batteries have emerged as a cornerstone technology for decarbonizing transportation and power grids while storing renewable energy [1]. However, the safety bottlenecks they face—particularly the risk of



Submitted: 29 April 2026

Revised: 21 May 2026

Accepted: 13 June 2026

Published: 02 September 2026

Vol. 1, No. 2, 2026.

10.62762/JCN.2026.807406

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Citation

Kong, C., Li, Z., & Zhao, L. (2026). A Hybrid Unet-MLP Neural Network Enabling Ultra-Fast and High-Accuracy Prediction for Low-Gradient Temperature Field in Lithium-ion Batteries. *Journal of Carbon Neutrality*, 1(2), 83–96.



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thermal runaway—remain one of the most formidable barriers to mass EV adoption and, by extension, to achieving global carbon neutrality targets [1]. To overcome this barrier, accurate and fast prediction of internal battery temperature is essential. It serves as the foundation for preventing thermal runaway, ensuring safe battery operation, optimizing charge and discharge efficiency, extending battery life, and guiding thermal management system design [2]. Such capability directly contributes to carbon neutrality by enabling safer, longer-lasting, and more efficient batteries, which in turn accelerates the adoption of electric vehicles and renewable energy storage — two critical pathways for global decarbonization.

To achieve rapid prediction of battery temperature, most of simplified electrochemical thermal coupled models adopt the battery as a point heat source through spatial homogenization, which significantly simplifies the thermal model structure and reduces its computational complexity. Lin et al. [3] proposed a lumped-parameter electro-thermal model for cylindrical batteries, coupling electrochemical dynamics with a single-node thermal equation to efficiently predict cell temperature evolution. Zhu et al. [4] proposed a fractional-order lithium-ion battery model which integrates electrolyte polarization and thermal effects. By employing Padé approximation and polynomial simplification of the diffusion equation to simplify the electrochemical model and combining it with a simplified lumped thermal model that treats the entire battery as a single-point heat source, the computational speed of the electrochemical-thermal coupling model has been significantly enhanced. With optimized computational efficiency, it is suitable for fast battery management systems (BMS) in electric vehicles, balancing precision and processing speed. Li et al. [5] proposed a simplified electrochemical model for lithium-ion batteries based on an equivalent homogeneous thermal approach, which significantly enhances the prediction accuracy of battery performance across a wide temperature range (-20°C to 45°C) by incorporating a concentration-dependent solid-phase diffusion mechanism. While adopting volume-averaged thermal parameters, the model employs a stepwise parameter identification method, integrates a thermal-electrical coupling design through lumped thermal model, and experimentally validates its advantages in voltage and temperature prediction under low-temperature conditions.

However, these simplified electrochemical-thermal coupled models are incapable of describing the internal thermal distribution of the battery, and cannot meet the scenarios that require high-precision temperature field prediction, which has motivated spatiotemporal neural network approaches to directly model the battery thermal process [6].

Although simplified electrochemical-thermal coupled models based on lumped heat sources can quickly predict battery temperature, they neglect the temperature differences inside the battery. Amietszajew et al. [7] found that when the 18650 battery is discharged at a 1C current rate, the temperature difference between the core and the surface of the battery can reach up to 5 degrees. Using the battery surface temperature or lumped temperature for battery thermal management carries a high risk. Therefore, three-dimensional (3D) thermal models are frequently employed to characterize the accurate non-uniform temperature field inside lithium-ion batteries. He et al. [8] developed a three-dimensional electrochemical-thermal coupled model to analyze the discharge behavior of a 14Ah LiFePO_4 battery. The model integrates electrochemical kinetics and thermodynamic mechanisms, revealing that intensified polarization during high-rate discharge leads to a surge in heat generation. Validation experiments show that the model accurately predicts voltage and temperature at 1C-5C rates, providing crucial theoretical support for optimizing thermal management in high-rate batteries and highlighting the central role of electrochemical-thermal coupling effects in safety design. Liu et al. [9] developed a 3D thermal model specifically for high-power lithium-ion batteries and utilized this model to guide the design of a thermal management system based on thermoelectric coolers. The findings reveal that the thermoelectric cooler-based battery thermal management system is effective in cooling the batteries under extreme temperature conditions, ensuring a more uniform temperature distribution within the battery pack.

Although the 3D multiphysics coupling model can provide accurate internal thermal distribution predictions for batteries, its computation time is extremely long and struggles to meet the fast requirements of BMS. While the training of deep neural networks (DNNs) is highly time-consuming, the computation of their forward pass is remarkably fast. Adopting a deep neural network model as a

surrogate for temperature prediction can significantly reduce the computational cost and time of the 3D multiphysics coupling model. Deng et al. [10] proposed a physics-dominated neural network for spatiotemporal modeling of the battery thermal process, which embeds physical constraints into the network architecture to accurately predict the three-dimensional temperature field of lithium-ion batteries with a small amount of simulation data, significantly reducing computational costs compared to full-order physical models. Pang et al. [11] developed a 3D multiphysics model integrated with machine learning (ML) to enhance lithium-ion battery performance and thermal risk prediction. Validated against Panasonic NCR18650B/BD batteries, the model predicts voltage and temperature accurately. Combining physics-based modeling with ML enables robust surrogate models for battery systems, offering insights into thermal management and safety optimization, as comprehensively reviewed by Liu et al. [12]. This framework advances AI-driven BMS for electric vehicles, emphasizing efficiency and safety under extreme conditions. Jeong et al. [13] further proposed a multiphysics-informed deep operator network (MPI-DeepONet) trained on finite element method-generated virtual data as a surrogate for the physics-based model, achieving internal temperature field prediction speeds at least 10,000 times faster than conventional finite element simulations, demonstrating the strong potential of neural network surrogates to replace computationally intensive thermal models. Shen et al. [14] further developed a deep learning-based digital twin model for the temperature field of large-scale battery systems, achieving rapid thermal state estimation without repeated physical simulations. Beyond temperature field surrogate modeling, machine learning has also proven effective in accelerating other battery model components: Zhu et al. [15] proposed a simplified electrochemical model based on ensemble learning, further demonstrating the broad applicability of data-driven methods in reducing the overall computational burden of battery simulation pipelines. However, when the battery is charged and discharged at a low rate, the internal temperature gradient of the battery is small. Most traditional DNNs fail to capture the characteristics of low-gradient temperature field inside the battery, leading to relatively large temperature field prediction errors.

Therefore, a hybrid neural network that integrates a

U-shaped neural network (U-net) with a multi-layer perceptron (MLP) is proposed to rapidly and accurately predict the internal temperature field of lithium-ion batteries. The data characteristics of low-gradient fields are enhanced by sample-level normalization, so that the Unet module can learn the relative numerical relationships of elements within the temperature field effectively. The MLP module is used to predict the maximum and minimum values of the temperature field, so that the low-gradient temperature field can be accurately restored with the outputs of Unet and MLP modules by denormalization methods. The structure of this paper is as follows: Section 2 introduces the physics-based 3D thermal model structure and the generation of training data. Section 3 presents the network architecture of the proposed HNNUM. A comparative analysis of HNNUM with traditional DNNs and the physics-based 3D thermal model is provided in Section 4. The conclusion is made in Section 5.

2 Physics-based 3D Thermal model

While the main focus of this paper is not physical-based 3D thermal model, it is essential to first establish an accurate physical model of the battery thermal system. This physical model serves two critical purposes:

1. to generate comprehensive thermal behavior data under various operating conditions that would be impractical or costly to obtain through experiments alone.
2. to provide a ground truth reference for training the neural network. The physical model incorporates fundamental thermodynamic principles and material properties to simulate the 3D temperature field inside the battery, which will subsequently be used as training datasets for the neural network model.

2.1 Battery Structure

The battery geometry and dimensions considered in this study are derived from a commercial cylindrical lithium-ion battery, the jelly roll 3D volume of the simulation battery is shown in Figure 1. Since the battery is a rotationally symmetric cylinder, obtaining the temperature field along the radial longitudinal cross-section (the red rectangular in Figure 1) is sufficient to determine the complete internal temperature field of the cylindrical battery. The cathode and anode current collector are small

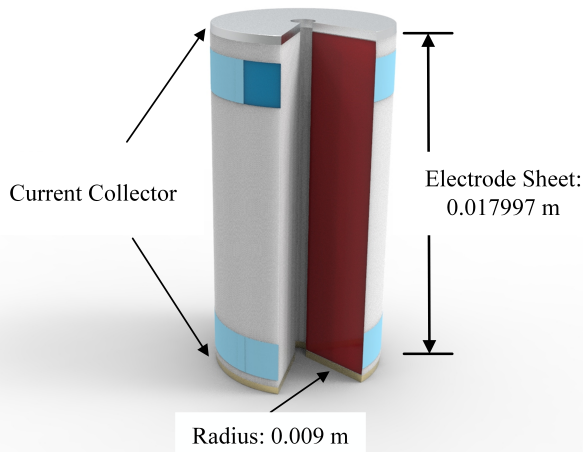


Figure 1. The 3D structure of the battery.

in volume and made of highly conductive metal materials, allowing them to be treated as isothermal bodies. Therefore, the focus of this study is to achieve rapid and accurate prediction of the temperature field along the radial longitudinal cross-section of the battery cell (the red rectangular in Figure 1). The height of the electrode sheet in the simulation battery is 0.017997 m, the radius of the battery is 0.009 m. Therefore, the objective of the proposed model is to predict the temperature field across a $0.017997 \times 0.009 \text{ m}^2$ area.

2.2 Thermal model development

The heat generation and dissipation of the battery directly affect its temperature changes. According to the energy conservation equation, the relationship between battery temperature variation and heat generation/dissipation can be expressed by Eq. 1.

$$\rho C_p \frac{\partial T}{\partial t} = Q_{gen} + \nabla \cdot (k \nabla T) \quad (1)$$

where ρ ($\text{kg} \cdot \text{m}^{-3}$) is the battery density, C_p ($\text{J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$) is the battery specific heat, T (K) is the battery temperature, t (s) is the time, Q_{gen} ($\text{W} \cdot \text{m}^{-3}$) is the heat generation rate, k ($\text{W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$) is the thermal conductivity.

The heat generation power of the battery consists of irreversible heat power Q_{ir} and reversible heat power Q_r , as shown in Eq. 2.

$$Q_{gen} = \underbrace{(V_{cell} - OCV)I}_{Q_{ir}} + \underbrace{\left(\frac{\partial U_p}{\partial T} \Big|_{\theta_p} - \frac{\partial U_n}{\partial T} \Big|_{\theta_n} \right) IT}_{Q_r} \quad (2)$$

where V_{cell} (V) is the battery terminal voltage, OCV (V) is the open-circuit potential, I ($\text{A} \cdot \text{m}^{-3}$) is the current density, $\frac{\partial U_i}{\partial T} \Big|_{\theta_i}$ ($\text{V} \cdot \text{K}^{-1}$) is the entropic heat coefficient of the electrode, whose magnitude depends on the degree of lithium intercalation in the electrode θ_i , $i = n, p$ represents the electrodes. The irreversible heat is generated by Joule heating due to ionic and electronic resistance, while the reversible heat arises from electrochemical reactions at the electrodes.

Battery heat dissipation is primarily caused by thermal convection on the battery surface, which can be described by the thermal convection boundary condition in Eq. 3.

$$-k \frac{\partial T}{\partial n} \Big|_S = h(T_s - T_{amb}) \quad (3)$$

where $\frac{\partial T}{\partial n} \Big|_S$ is the temperature gradient along the outward normal direction, h ($\text{W} \cdot \text{m}^{-2} \cdot \text{K}^{-1}$) is the heat transfer coefficient, T_s (K) is the battery surface temperature, and T_{amb} (K) is the ambient temperature.

2.3 Data generation

The network training data is generated through simulations using the Pseudo 2-dimensional (P2D) electrochemical-thermal coupled model on the OpenFOAM open-source software platform. The training dataset includes internal battery temperature field data obtained from charge-discharge cycles at constant current rates of -1C, 0.25C, 0.5C, 1C, 1.3C, and 1.6C under an ambient temperature of 298.15K. The P2D model and its parameters can be referenced from our research group's previous work [16], while key parameters of the 3D thermal model are shown in Table 1.

Table 1. Thermal model parameters.

Parameters	Value
ρ ($\text{kg} \cdot \text{m}^{-3}$)	1868
C_p ($\text{J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$)	975
h ($\text{W} \cdot \text{m}^{-2} \cdot \text{K}^{-1}$)	25

The generated battery temperature field data consists of a total of 32,568 entries, with each entry containing the temperature field at the n -th second, the heat production and dissipation information at the n -th second, and the temperature field at the $(n+1)$ -th second. The temperature field, heat production, and dissipation at the n -th second serve as the input for the network, while the temperature field at the $(n+1)$ -th second acts as the ground truth of the output. Each input-output pair represents a one-step mapping of the thermal dynamics, allowing the data to be used as supervised training samples. From these entries, 3,000 are randomly selected as the validation set, and the remaining 29,568 entries are used as the training set.

3 Network architecture

To achieve rapid and accurate prediction of the internal temperature field of batteries, DNNs have been employed to replace the physics-based 3D thermal model of lithium-ion batteries, thereby accelerating the calculation of internal temperature field. However, it is difficult for traditional DNNs to capture the characteristics of low-gradient temperature fields, leading to excessive prediction errors in the temperature field. To improve the prediction accuracy of low-gradient temperature fields inside batteries during low-rate charging and discharging, this paper proposes a hybrid neural network that combines Unet with MLP.

3.1 Hybrid neural network architecture

To address the limitations of traditional DNNs in predicting low-gradient temperature fields within batteries, this paper proposes a hybrid neural network combining Unet and multi-layer perceptron (MLP), termed HNNUM. By amplifying the gradient features of the low-gradient temperature field with sample-level normalization and jointly learning both spatial distribution patterns and global extremum constraints, the proposed model significantly enhances prediction accuracy in low-rate charging/discharging scenarios. As illustrated in Figure 2, the HNNUM framework comprises three core components:

1. Unet module: Extracts spatial features from previous temperature matrices to predict relative temperature distributions.
2. MLP module: Predict extremum values (maximum and minimum) of the temperature field at the next timestep based on historical

temperature fields and thermodynamic parameters.

3. Inverse minmax module: Integrates Unet's relative distribution with MLP's absolute extrema to reconstruct the complete temperature field.

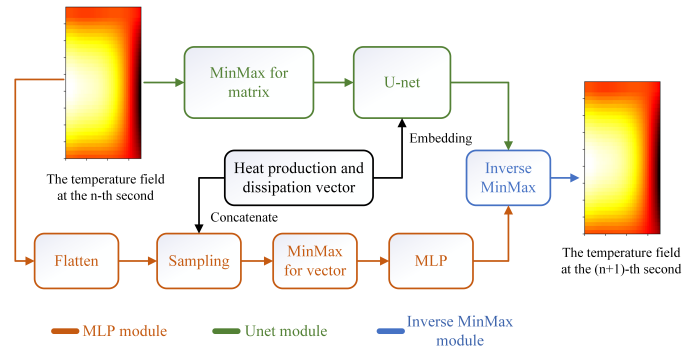


Figure 2. The structural schematic of HNNUM.

The synergy between these components is designed as follows: The encoder-decoder structure of Unet excels at capturing local temperature gradient variations, yet its normalized output lacks absolute temperature scaling. In contrast, the MLP learns the mapping relationship between feature vectors and output results to accurately predict the extremum values of the temperature field. Ultimately, the inverse MinMax transformation fuses these outputs, enabling temperature field predictions that preserve both distribution details and numerical precision.

3.2 Unet for temperature distribution feature extraction

Unet is a deep neural network composed of multiple convolutional layers, proposed by Ronneberger et al. [17] in 2015. Due to its efficiency and flexibility, Unet has been widely applied in tasks such as image segmentation and matrix feature extraction. Given the matrix nature of battery temperature fields, Unet is selected as the spatial feature extractor, and its architecture is designed as shown in Figure 3. The network training data is generated by a three-dimensional electrochemical-thermal coupled model based on the finite volume method. In this model, the internal temperature field of the battery at each second is represented as a temperature matrix with a resolution of 40×40 . The Unet consists of an input, an encoder (downsampling), a decoder (upsampling), and an output, incorporating multiple skip connections to preserve and restore feature information at different resolutions. The network is designed to predict the temperature

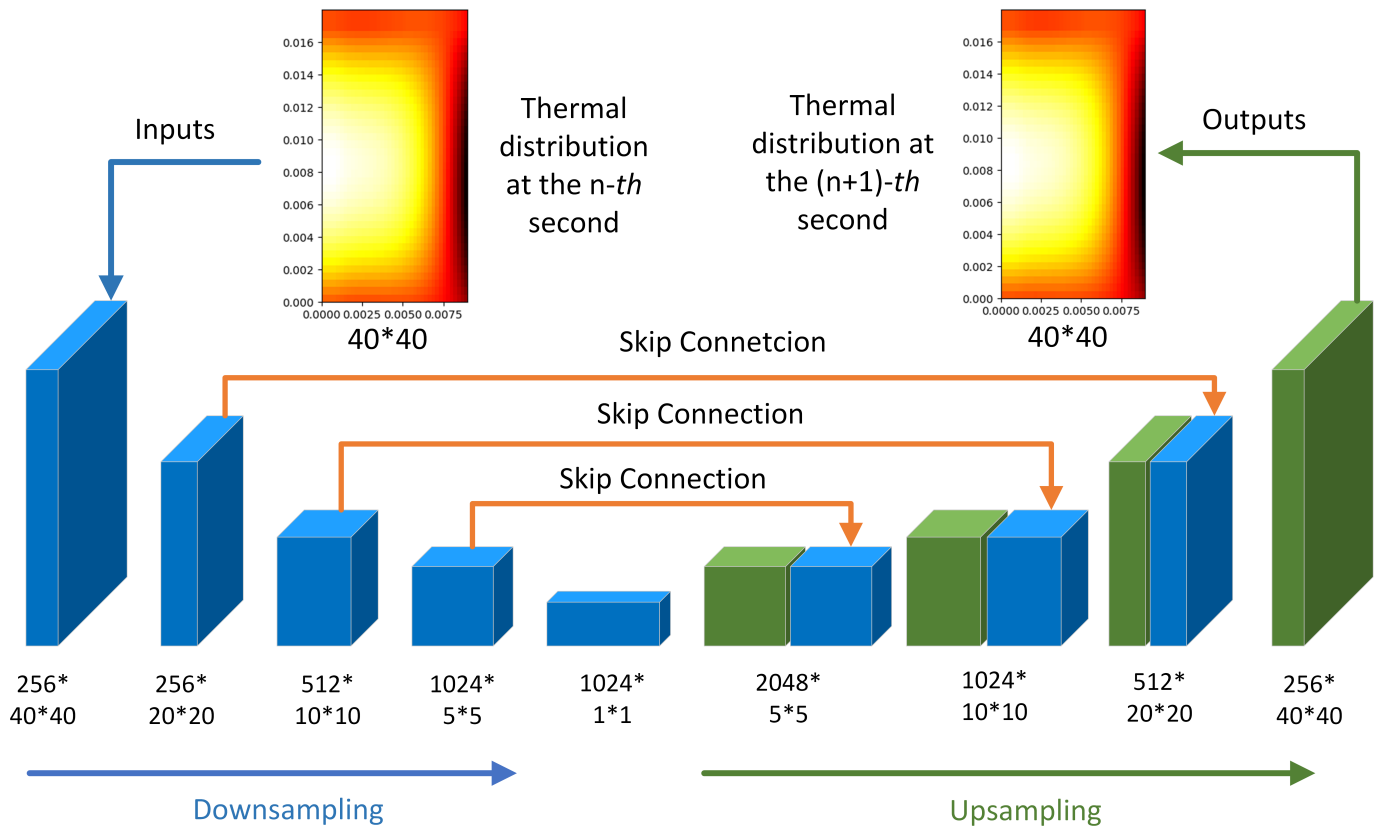


Figure 3. Unet structure for internal temperature distribution prediction.

distribution at the $(n+1)$ -th second from the temperature distribution at the n -th second. The encoder-decoder architecture compresses data dimensions via downsampling ($40 \times 40 \rightarrow 1024 \times 1$) and restores resolution via upsampling, with skip connections preserving multi-scale features.

The heat production and dissipation of the battery directly affect the internal temperature distribution. To integrate this thermodynamic information into the Unet, embedding layers are added during the upsampling process of the Unet to regulate the temperature distribution matrix generated by the model. The embedding layer consists of two fully connected neural network layers, with the input being the heat production and heat dissipation vectors. To enable communication with the upsampling layer, the output of each embedding layer is the same number of channels as the connected upsampling layer. The schematic diagram illustrates the fundamental principle of embedding heat generation and dissipation power into the Unet as shown in Figure 4. The range of heat production in lithium-ion batteries differs from that of heat dissipation. To unify the heat production and heat dissipation data into the same standard range,

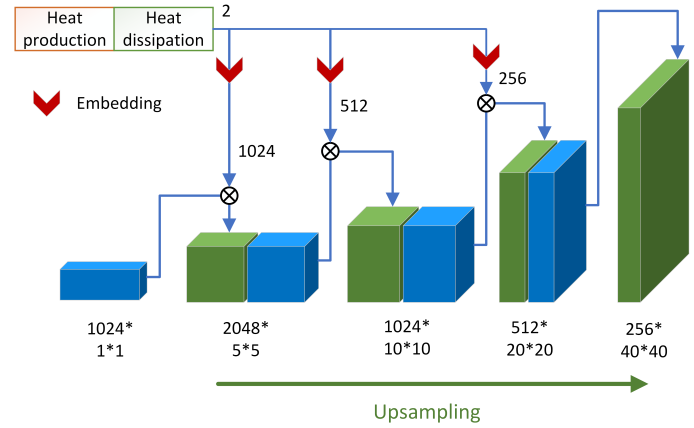


Figure 4. The embedding process of heat generation and dissipation.

MinMax method is employed to normalize the heat production and heat dissipation data. As a standard data preprocessing technique in deep learning, input normalization accelerates the convergence of model training and prevents features with larger numerical ranges from dominating the training process [18]. MinMax normalization method is expressed as shown in Eq. 4.

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (4)$$

where x is the original dataset, x_{max} is the maximum value in the original dataset, x_{min} is the minimum value in the original dataset, and x_{norm} is the normalized dataset.

When the battery is charged and discharged at a lower current rate, the numerical differences between adjacent elements in the internal temperature matrix are relatively small, resulting in less distinct temperature matrix data features, making it difficult for the network to learn the underlying patterns. The difference between the maximum and minimum temperature values in the entire temperature field dataset is relatively large. If MinMax normalization is applied to the entire temperature field dataset, the differences between the element values of the temperature field matrix at a certain moment will be small, and the temperature gradient characteristics will still not be obvious. To amplify the characteristics of the temperature distribution, this study proposes to apply sample-wise MinMax normalization to scale every temperature field individually, linearly mapping each temperature field to the range $[0, 1]$, so as to enhance the low-gradient features that would otherwise be suppressed by dataset-level normalization. However, MinMax for every temperature matrix causes the temperature field dataset lose its extreme value information, Unet can only predict the relative magnitude relationships of the temperature matrix elements, which range in $[0, 1]$.

3.3 MLP for extreme temperature prediction

To help the UNet module accurately reconstruct the temperature field, a multi-layer perceptron (MLP) module is proposed to accurately predict the extreme values of the temperature field. MLP is a classic artificial neural network composed of multiple neuron layers (input layer, hidden layer, output layer), capable of learning complex nonlinear relationships, and has been widely applied in classification and regression tasks [19].

Based on the temperature field of the battery at the n -th second and the heat production and dissipation information, a multi-layer perceptron is used to predict the maximum and minimum temperature of the battery at the $(n+1)$ -th second. Since the temperature matrix cannot be directly input into the MLP, the 40×40 two-dimensional matrix is compressed into a 1600×1 vector. To reduce the input feature dimensions of the MLP, the 1600×1 vector is downsampled at equal intervals to form a 400×1

one-dimensional vector. Finally, the 400×1 vector is combined with the heat production and dissipation to form a 402×1 vector as the input to the MLP. To ensure the 402 features are in the same range, MinMax normalization is also applied in the MLP training dataset. A schematic diagram of the MLP network structure is shown in Figure 5.

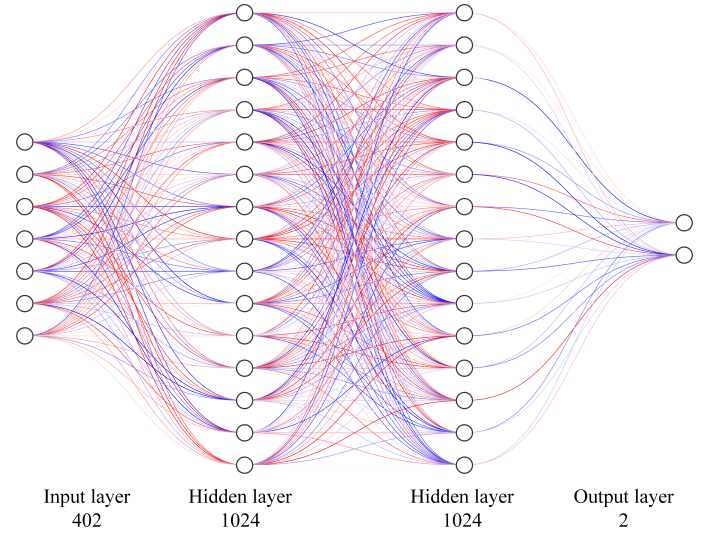


Figure 5. Schematic diagram of the MLP network structure.

The MLP network input layer consists of 402 neurons, the first hidden layer contains 1024 neurons, the second hidden layer also has 1024 neurons, and the output layer comprises 2 neurons for predicting the maximum and minimum temperature values of the temperature field at the $(n+1)$ -th second.

3.4 Model integration and inverse MinMax transformation

To accurately reconstruct the temperature field $\tilde{T}_{n+1}$, the inverse MinMax transformation maps Unet's normalized relative temperature distribution $\tilde{T}_{n+1}^{norm}$ to the temperature field using the output temperature range from MLP module. The inverse MinMax transformation is shown as Eq. 5.

$$\tilde{T}_{n+1} = \tilde{T}_{n+1}^{norm} \cdot (\hat{T}_{n+1}^{max} - \hat{T}_{n+1}^{min}) + \hat{T}_{n+1}^{min} \quad (5)$$

where $\hat{T}_{n+1}^{max}$ and $\hat{T}_{n+1}^{min}$ are the maximum and minimum values of the $(n+1)$ -th temperature field by the MLP.

4 Results and discussion

4.1 Model precision comparison

To demonstrate the advantages of the proposed HNNUM model, the Unet and MLP models used for

predicting the internal temperature field of the battery are added for comparison. The Unet model used for comparison has the same structure as the Unet model in HNNUM. To enhance the features of the temperature field data, the training data for the Unet model is normalized with MinMax across the entire temperature field dataset.

The input for the MLP model used to predict the internal temperature field of the battery consists of a downsampled 400×1 one-dimensional vector at the n -th second and the battery's heat generation and dissipation power at the n -th second. The output is a 1600×1 temperature vector at the $(n+1)$ -th second, which is derived by flattening the 40×40 temperature field matrix at the $(n+1)$ -th second. The 1600×1 temperature vector corresponds element-wise to the 40×40 temperature field matrix. Therefore, the input layer of the MLP model for predicting the battery's internal temperature field contains 402 neurons, the first hidden layer contains 1024 neurons, the second hidden layer also contains 1024 neurons, and the output layer contains 1600 neurons. To ensure that the input and output features of the MLP model vary within the same range and to accelerate the convergence of the model, the 402 input features and 1600 output features of the MLP model are normalized with MinMax.

For the regression task of continuous temperature field prediction, the mean squared error is selected as the loss function for network training, as shown in Eq. 6.

$$Loss = \frac{1}{2n} \sum_{i=1}^n (\hat{y}_i - y_i)^2 \quad (6)$$

where y_i is the true value of the i -th sample. $\hat{y}_i$ is the predicted value of the i -th sample. n is the number of samples.

The adaptive moment (Adam) estimation algorithm is a widely used neural network optimization algorithm that accelerates convergence with historical gradient directions, and adaptively adjusts the learning rate according to the gradient magnitude [20]. Adam optimizer is selected to train Unet, MLP and HNNUM, the initial learning rate is set to 0.001, the number of iterations is set to 500.

The root mean square error (RMSE) and mean absolute percentage error (MAPE) were employed to evaluate the prediction error magnitude and the relative percentage of the prediction error to the true value. Since each temperature field matrix contains

1600 elements, the RMSE and MAPE for the entire validation set were defined as

$$RMSE = \sqrt{\frac{1}{n} \frac{1}{1600} \sum_{i=1}^n \sum_{j=1}^{1600} (y_{i,j} - \hat{y}_{i,j})^2} \quad (7)$$

$$MAPE = \frac{100\%}{n \times 1600} \sum_{i=1}^n \sum_{j=1}^{1600} \left| \frac{y_{i,j} - \hat{y}_{i,j}}{y_{i,j}} \right| \quad (8)$$

where j is the elements of the temperature matrix, when $n = 1$, RMSE_i and MAPE_i represent the root mean square error and absolute percentage error of the i -th sample, respectively. The RMSE and MAPE values of the Unet, MLP, and HNNUM models across the entire validation set are shown in Figure 6.

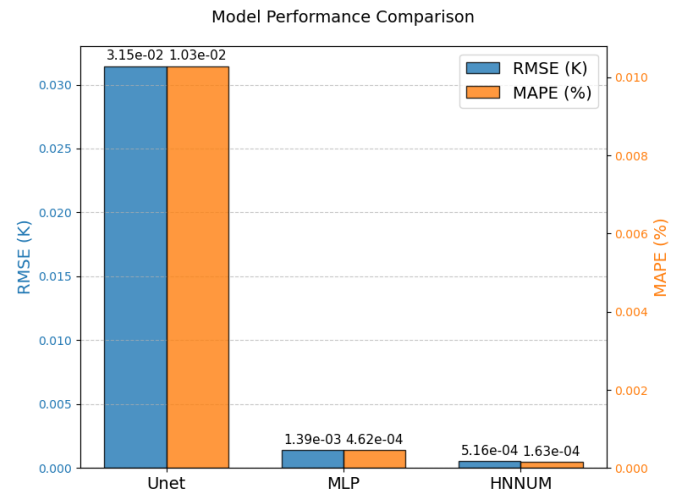


Figure 6. Error comparison between Unet, MLP and HNNUM.

In Figure 6, the battery's internal temperature field prediction error of Unet model is significantly higher than that of MLP and HNNUM, with RMSE and MAPE on the validation dataset reaching 3.15×10^{-2} K and $1.03 \times 10^{-2}\%$, respectively. HNNUM achieves the most accurate predictions, with RMSE and MAPE of 5.16×10^{-4} K and $1.63 \times 10^{-4}\%$, respectively. Although MLP also delivers relatively good prediction results, its errors remain more than twice as large as those of HNNUM.

To demonstrate the distribution and dispersion of RMSE values for temperature field predictions by Unet, MLP, and HNNUM, the box plots of RMSE for temperature field predictions by Unet, MLP, and HNNUM on the validation set are shown in Figure 7.

The box plot shows, from top to bottom, the maximum value, upper quartile, median, lower quartile, and

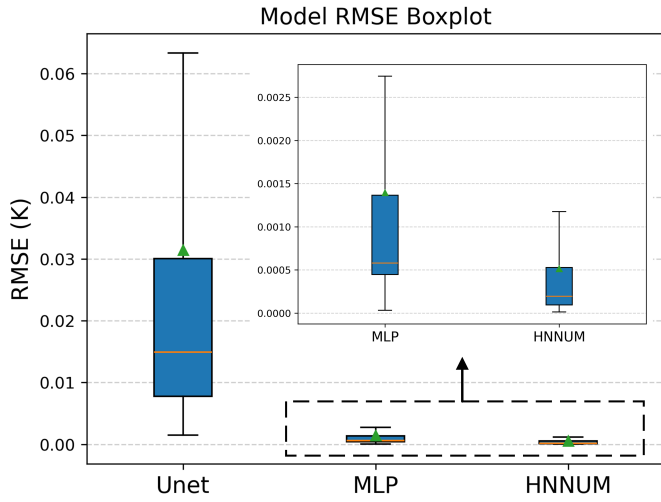


Figure 7. Box plots of temperature field prediction errors.

minimum value in the discrete dataset, respectively. The height of the box indicates the dispersion of the middle 50% of the data. The box errors comparison among Unet, MLP and HNNUM is shown in Table 2.

To verify the accuracy of the proposed HNNUM in long-term sequential temperature field generation (generating the next field with the previous generated field), HNNUM generates the internal temperature field continuously for 3000 seconds at 1C rate constant current discharge, and compares with the ground truth. The RMSE error of the 3000s sequential temperature field generation is shown in Figure 8.

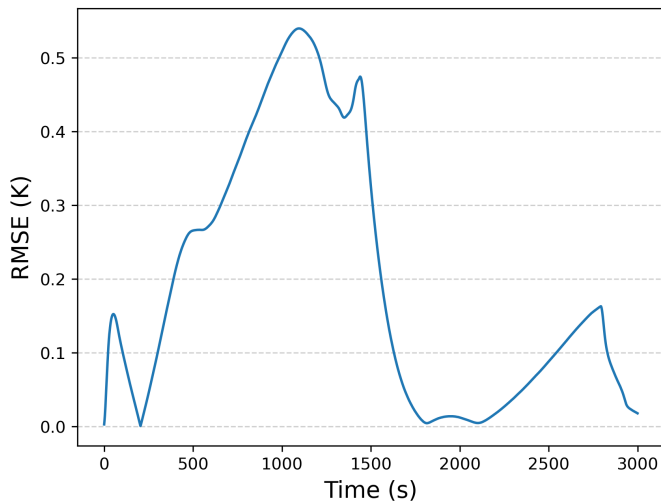


Figure 8. Long-term sequential temperature field generation error of HNNUM.

Although the single-step prediction error of HNNUM is small, multi-step iteration over long-term sequence leads to an increase in the temperature field prediction

error. Fortunately, the HNNUM prediction errors include both positive and negative deviations, which keeps the long-term temperature field prediction errors within a range. In Figure 8, during the 3000s sequential temperature field generation, HNNUM exhibits the maximum prediction error at the 1096s approximately 0.5398 K, and the average error is about 0.1947 K. The results show that HNNUM exhibits an oscillatory pattern rather than a monotonic trend in prediction error for long-term continuous temperature field generation tasks, with a maximum cumulative increase RMSE not exceeding 0.5398 K.

Because it is impossible to display all validation dataset temperature fields in the paper, a sample of data is randomly selected from the validation dataset to compare the differences between these models. The battery temperature field prediction results of Unet, MLP, and HNNUM are compared with the ground truth, as shown in Figure 9.

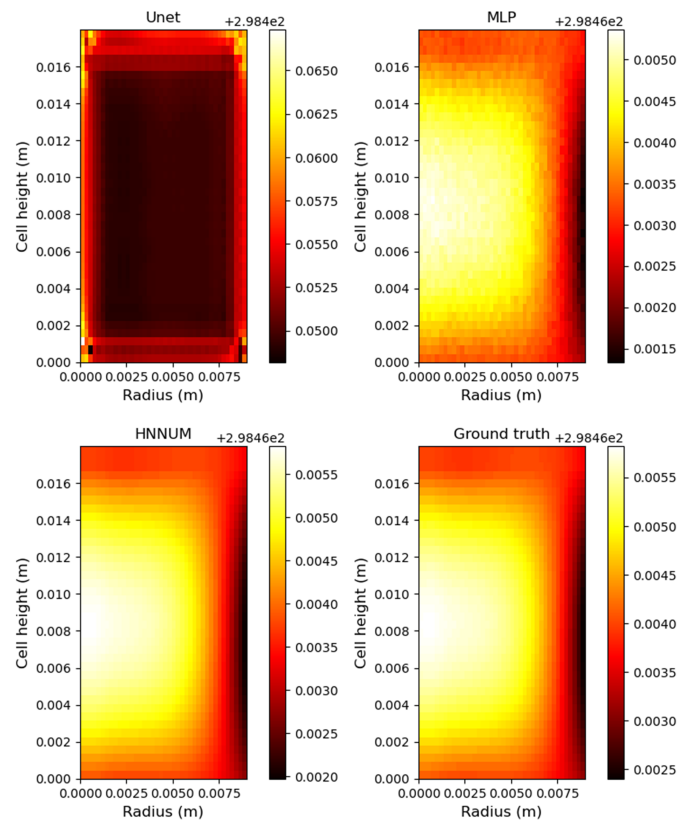


Figure 9. Comparison of temperature field prediction among Unet, MLP, and HNNUM.

From Figure 9, it can be observed that due to the small internal temperature difference of the battery, the Unet model (MinMax for the entire dataset) failed to learn the temperature distribution information inside the battery, resulting in the prediction of the entire cross-section temperature as an approximation of the

Table 2. Comparison of box plot statistics.

Model	Minimum	Lower quartile	Median	Upper quartile	Maximum
Unet	1.505×10^{-3}	7.765×10^{-3}	1.495×10^{-2}	3.004×10^{-2}	6.331×10^{-2}
MLP	3.276×10^{-5}	4.475×10^{-4}	5.802×10^{-4}	1.367×10^{-3}	2.744×10^{-3}
HNNUM	1.225×10^{-5}	9.417×10^{-5}	1.949×10^{-4}	5.273×10^{-4}	1.176×10^{-3}

average temperature of the battery. Normalizing each input feature allowed the MLP to learn the characteristics of each element in the temperature matrix, but the MLP model still failed to capture the positional relationships between the matrix elements. This led to some predicted matrix elements not satisfying the temperature gradient relationships governed by Fourier's law of heat conduction. The HNNUM model, however, combines the strengths of both Unet and MLP. It uses the Unet module to predict the battery temperature distribution and the MLP module to accurately predict the extreme values of the battery temperature field, ultimately reconstructing the battery temperature field precisely through the inverse MinMax method.

The gradient errors are employed to evaluate the accuracy of temperature distribution predictions across various models, the gradient RMSE (gRMSE) is used to assess the error of gradient vectors. The gRMSE measures the root-mean-square of the ℓ_2 -norm of the difference between the predicted and true gradient vectors, pixel by pixel:

$$\text{gRMSE} = \sqrt{\frac{1}{n} \sum_{i,j} \left[\left(\frac{\partial \hat{T}}{\partial x} - \frac{\partial T}{\partial x} \right)^2 + \left(\frac{\partial \hat{T}}{\partial y} - \frac{\partial T}{\partial y} \right)^2 \right]} \quad (9)$$

where $\hat{T}$ is the predicted field, and T is the ground-truth field.

The gradient magnitude error (GME) is used to assess the accuracy of temperature change rate, the gradient magnitude at each pixel is defined as:

$$|\nabla T| = \sqrt{\left(\frac{\partial T}{\partial x} \right)^2 + \left(\frac{\partial T}{\partial y} \right)^2} \quad (10)$$

The GME is then computed as the mean absolute error (MAE) between the predicted and true gradient magnitudes:

$$\text{GME} = \frac{1}{n} \sum_{i,j} \left| |\nabla \hat{T}| - |\nabla T| \right| \quad (11)$$

The direction error (DE) measures the angle between the predicted and true gradient vectors.

$$\text{DE} = \arccos \left(\frac{\nabla \hat{T} \cdot \nabla T}{|\nabla \hat{T}| |\nabla T|} \right) \quad (12)$$

The mean gradient errors of three models on 3000 validation samples are compared in Table 3. The gRMSE measures the point-wise root mean square deviation between the predicted and true temperature field gradient vectors, comprehensively reflecting errors in both gradient magnitude and direction. DE is calculated only for valid pixels with gradient magnitudes greater than 0.01 K/m, averages the angle between the predicted and true gradient directions to assess prediction accuracy for heat diffusion orientation. GME represents the mean absolute error of gradient magnitude, indicating the prediction bias in temperature change rate. All three metrics consistently show that HNNUM performs the best, with a gRMSE of only 0.095 K/m and a direction error of only 4.6°, indicating the model accurately captures the spatial variation of the temperature field. MLP follows closely, with each metric approximately 1.5–3 times that of HNNUM. In contrast, Unet lags significantly behind; its gRMSE and GME are both two orders of magnitude higher, and its direction error approaches 90°, indicating that the predicted temperature gradients are largely uncorrelated with the true field. This is related to Unet's use of global normalization, which results in the loss of per-sample temperature range information.

Table 3. Comparison of gradient-based metrics across models.

Model	gRMSE (K/m)	DE (°)	GME (K/m)
HNNUM	0.095	4.6	0.064
MLP	0.135	16.7	0.078
Unet	8.745	86.3	4.181

Figure 10 shows the variation trend of gradient RMSE (vertical axis) of three models over 3,000

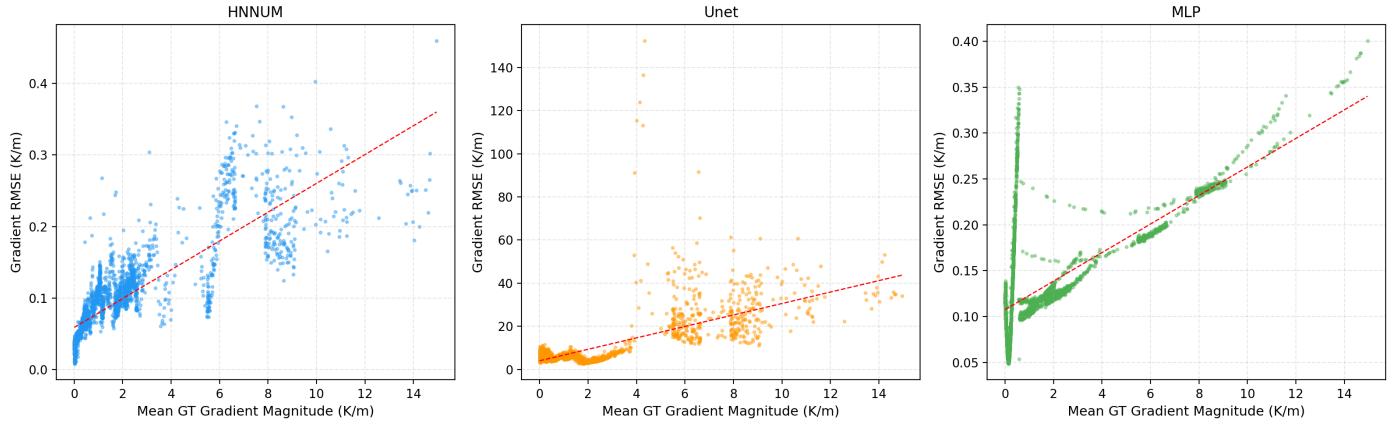


Figure 10. Variation of Gradient RMSE with Ground Truth Gradient Magnitude.

validation samples as the average ground truth gradient magnitude (horizontal axis) changes. The scatter points of HNNUM (blue) and MLP (green) are concentrated in a narrow vertical range of 0–0.5 K/m, and their trend lines are nearly horizontal, indicating that regardless of the temperature gradient of the samples, the gradient errors of both models remain stable. They both demonstrate reliable predictive capabilities for scenarios with sharp or gradual temperature increases, with HNNUM slightly outperforming MLP in terms of absolute error and dispersion. In contrast, the trend line of Unet (orange) is significantly steeper, and its vertical-axis magnitude reaches 0–150+ K/m, far exceeding the other two models: the error is already significantly large in low-gradient regions (< 1 K/m), and it increases sharply further in high-gradient regions (> 5 K/m), indicating that Unet’s gradient prediction capability is severely insufficient for scenarios with rapid temperature changes.

4.2 Computational time

To reflect the computational time consumption of each model in practical applications, all models were run on the same server platform, with specific details of the server platform shown in Table 4.

Table 4. Operating platform.

Category	Information
Operating System	Ubuntu 22.04.3 LTS
CPU × 2	Intel(R) Xeon(R) Silver 4314
GPU	NVIDIA A30 24GB

To demonstrate the advantage of neural network models in computational speed for battery

temperature fields prediction, the computational time of a 3D thermal model is added for comparison. The 3D thermal model only accounts for the temperature field calculation time, while the P2D model’s computational time has been excluded. The time consumed by all models to compute 3000 temperature fields is shown in Table 5.

Table 5. Computational time comparison.

Model	Computational time
MLP	1.98s
Unet	15.31s
HNNUM	16.59s
3D thermal	145.34s

The MLP model has significantly fewer parameters compared to Unet and HNNUM, resulting in the fastest computation speed, it completes the prediction of 3,000 temperature fields in just 1.98 seconds. Due to the deeper network architecture and numerous parameters of Unet model, Unet model operates slightly slower than MLP model. The computational speed of HNNUM is primarily governed by its Unet module, while the MLP module and the inverse MinMax process contribute to making it marginally slower than Unet model. The 3D thermal model solves the internal temperature field of the battery with the finite element method based on the heat conduction partial differential equation. This approach involves time-consuming steps such as generating complex geometric meshes and performing multi-step iterative solutions, leading to the slowest computation speed among all the models. The proposed HNNUM in this study achieves accurate predictions of the battery’s internal temperature field with relatively low computational

complexity, providing a foundational framework for future fast Battery Management Systems (BMS) to rapidly forecast internal temperature fields.

4.3 Limitations and future work

To address the challenge of small internal temperature gradients in batteries, which makes it difficult for traditional neural networks to accurately and rapidly predict the internal temperature field, a hybrid neural network with Unet and MLP is proposed. The proposed HNNUM framework is potentially generalizable beyond temperature field prediction. The approach of using Unet to extract matrix data distribution features and MLP to predict matrix data extremes provides a novel method for the fast and accurate prediction of physical fields with minimal numerical differences. Due to computational platform limitations, the dataset used in this study also has the following shortcomings.

1. The resolution of the predicted temperature field is relatively low, being only a 40×40 two-dimensional matrix.
2. The dataset exhibits a limited temperature variation range and only contains temperature field data at an ambient temperature of 298.15K.
3. The dataset only includes internal battery temperature field data under various constant-current conditions, without accounting for other dynamic scenarios.

Although the dataset used in this paper has the above limitations, these shortcomings pertain to the dataset itself rather than the HNNUM model, and they do not undermine the accuracy or innovation of HNNUM for the following reasons.

1. By increasing the number of up-sampling and down-sampling layers in HNNUM and modifying the size of its input and output matrices, the resolution of temperature field outputs from HNNUM can be enhanced.
2. By expanding the temperature field dataset across multiple ambient temperatures, HNNUM can learn the variations in the internal temperature field of the battery under different environmental conditions, thereby improving its generalization capability across varying ambient temperatures.
3. The HNNUM training process does not directly utilize current data. Its prediction of the

temperature field at the $(n+1)$ -th second depends on the temperature field, the heat production and the dissipation data at the n -th second. As long as the heat generation and dissipation ranges of the battery under dynamic operating conditions fall within those of constant-current conditions, the temperature field under dynamic conditions can be regarded as an internal interpolation of the data space under constant-current conditions. Therefore, the HNNUM trained solely on constant-current conditions can also achieve satisfactory performance under dynamic operating conditions.

Additionally, if users do not require high precision in battery temperature field prediction and prioritize lower computational costs, the MLP model used for comparison in the study is also a good alternative. Furthermore, by enabling accurate and rapid battery thermal prediction, HNNUM directly supports the optimization of battery thermal management systems in electric vehicles and grid-scale energy storage, contributing to the broader goal of carbon neutrality through safer and more efficient deployment of clean energy technologies.

5 Conclusions

To achieve rapid and accurate prediction of the internal temperature field in lithium-ion batteries, and address the indistinct temperature distribution characteristics inside the battery caused by small internal temperature gradients, a hybrid neural network combining Unet and MLP (HNNUM) is proposed. In HNNUM, the Unet module is employed to capture the main features of the battery's internal temperature distribution and predict the relative numerical relationships among elements in the temperature matrix. The MLP module in HNNUM learns the extreme temperature characteristics within the battery to achieve precise prediction of the maximum and minimum temperature in the temperature field. Finally, the Unet and MLP modules are integrated using an inverse MinMax method for accurate reconstruction of the battery temperature field. The results demonstrate that HNNUM significantly outperforms both Unet and MLP models in temperature field prediction accuracy, achieving an RMSE value of only 5.16×10^{-4} K on a validation dataset of 3000 samples. Moreover, HNNUM completed the calculation of 3000 temperature fields in just 16.59 seconds, which is approximately 8.8 times faster than

traditional physics-based 3D models.

The proposed HNNUM contributes to carbon neutrality in three aspects. First, it dramatically accelerates battery thermal design, shortening research and development cycles and reducing resource consumption. Second, more accurate temperature prediction enables better thermal management, leading to safer batteries with longer lifespan and higher energy efficiency, thereby lowering the carbon footprint of battery production and disposal. Third, by facilitating the development of high-performance batteries, HNNUM supports the widespread adoption of electric vehicles and renewable energy storage, which are critical for decarbonizing transportation and power sectors toward the global goal of carbon neutrality.

Data Availability Statement

The source code supporting the findings of this study is publicly available at <https://github.com/kon9chun/hnnu> m.

Funding

This work was supported by the National Natural Science Foundation of China under Grant 52277220, and by the Independent Research Project of the State Key Laboratory of Intelligent Green Vehicle and Mobility under Grant ZZ-ZD-20250103.

Conflicts of Interest

Lance Zhao is affiliated with the Electroder Co., Ltd., Suzhou 215132, China. The authors declare that this affiliation had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

AI Use Statement

The authors declare that DeepSeek-R1 was used for language editing and translation of the manuscript. The authors have carefully reviewed, revised, and verified the AI-assisted output and take full responsibility for the content of the manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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