An LSTM-PINN Hybrid Method to Estimate Lithium-Ion Battery Pack Temperature

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ABSTRACT Physics-based models for battery temperature prediction are often not suitable for online applications due to the large number of fitted parameters, low fidelity results from parameter inaccuracy and unaccounted model dynamics, limited high quality experimental data, and slow convergence of predictions from unknown initial conditions. On the other hand, data-driven models require much less computational power but a large dataset to learn the time dependent behavior. This paper proposes a physics-informed neural network (PINN) to take full advantage of both physics-based and data-driven models. Four comparative studies were performed to investigate the effectiveness of including chamber temperature with two different activation functions, the optimal number of neurons and hidden layers, the dependance on reversible heat generation, and the performance of long short-term memory (LSTM)-PINN model. The results show that the LSTM-PINN with chamber temperature as one of the inputs delivers better prediction accuracy. The LSTM-PINN with an exponential activation function for the chamber temperature has a more accurate prediction for the direct current fast charge (DCFC) test profile and similar prediction accuracy for the grade load (GL) 100 test profile. The root mean square errors (RMSEs) of the LSTM-PINN are 0.57°C for DCFC and 0.52°C for GL 100, respectively. In addition, having 55 neurons and 4 hidden layers gives the lowest prediction error. Furthermore, the improvement by having reversible heat generation is negligible. At last, the LSTM-PINN model has less prediction error than the LSTM model, especially when the battery temperature range is enormous.

INDEX TERMS Long short-term memory, physics-informed neural network, lithium-ion battery, battery temperature, temperature prediction.

I. INTRODUCTION
As the electrification revolution continues, the importance of lithium-ion battery technologies is increasing daily. In order to meet the needs of being reliable, efficient, and safe, further research and development of lithium-ion battery technologies are necessary. One of the areas that still need significant improvement is temperature prediction. Battery characteristics and performance are heavily influenced by battery temperature. Since both mass transfer and electrochemical reactions are dominated by temperature, having an accurate prediction of battery temperature is the key to operate batteries safely and reliably. Battery temperature prediction methods can be classified into two categories: physics-based models and data-driven models.

Several studies on physics-based models are available in the literature. A group of researchers combined the electrochemical battery model with the battery heat transfer model to predict the battery temperature [1]. The battery heat transfer model consists of a heat transfer equation mathematically formulating heat generation, accumulation, convection, conduction, and radiation. In their work, the heat generation includes electrolyte ohmic heating, solid phase, entropic effect, and irreversible heat. A lump thermal model was created to simplify the heat transfer equation assuming a uniform distribution of the battery temperature in all directions during...
the transient state. Another group of researchers applied this lump thermal battery model with a simplified heat generation term to predict heat generation [2]. They achieved under 2 °C maximum error at various C-rates with inputs like open-circuit voltage (OCV), voltage, and current.

Data-driven models are also widely used by a number of researchers to predict battery temperature. One group of researchers developed a thermal fault detection leveraging a long short-term memory (LSTM) model in conjunction with a walk-forward technique [3]. They used voltage, current, state-of-charge (SOC), ambient temperature, and past surface temperature to predict the surface temperature at the current time stamp for several battery cell chemistries. After knowing the predicted temperature, the difference between the predicted and measured temperatures was analyzed and a fault detection threshold was used to determine if any fault conditions existed. Another group of researchers developed a model that combines various feed-forward neural networks (FNN) and LSTM [4]. They successfully limited the prediction error to a few degrees Celsius under a wide range of drive cycles and ambient temperature conditions. The key to their success was to use the ambient temperature as an input. Although these researchers achieved a low prediction error, it remains unclear if the accuracy can be translated to battery cells installed in a module configuration inside a battery pack. Besides that, what is more important is to accurately predict the temperature distribution inside a module.

Knowing the temperature distribution and reducing the temperature gradient are critical as the temperature considerably influences both the performance and life of batteries. Low temperatures reduce the available capacity and power of the battery while high temperatures accelerate the aging process [5], [6], [7]. Non-uniform temperature distribution results in an imbalance in power capability, state of charge, and capacity [5], localized deterioration [6] and different aging processes inside an array or pack [7]. In addition, having an acceptable temperature distribution is indispensable during a fast-charging event [8]. The temperature distribution inside a module or a pack has been studied by several researchers [5], [6], [7], [8], [9], [10], [11], [12], [13].

The two common problems in the existing thermal management system are the limited number of temperature sensors and parameter errors. Ref. 4 proposed a framework to evaluate the worst-case temperature estimation under one of the parameter errors: unknown resistance variability among cells. Their framework also minimizes the effect of the worst case and optimizes the sensor locations. Thermal resistor models were used to capture the thermal dynamics of the module.

Besides observability, understanding the effects of different factors on the temperature distribution is another important aspect. Ref. 5 studied the effect of current magnitude, which is one of the factors on the temperature distribution pattern inside a module. Their study developed a reduced order non-uniform model to trace the temperature gradient inside a module under different load profiles. They found the maximum temperature location for most of the cases is the middle of the module. In addition, as the current magnitude increases, the hottest cell moves to the positive side of the module. Furthermore, the temperature difference between the hottest and coldest cells is in reverse relation with the current magnitude. Similar studies were done in [8] and [9] using both heat transfer equation and energy conservation equation.

Another factor that plays an important role on the temperature distribution is cell voltage deviation. A group of researchers used three voltage balancing strategies to minimize the temperature gradient of a battery array for high depth of discharge applications in [7]. They believe if cells touch one another, heat is usually accumulated in the middle of the module and the distribution is mainly affected by the arrangement of the cells. However, if there are air gaps between cells, power losses determine the temperature distribution of the module.

In addition to the current magnitude and cell voltage deviations, the spacing among cells was investigated in [10] and [11]. Some researchers studied the temperature distribution of an 8-cell array by varying the air gap spacing and height of the air inlet and outlet [10]. The eight cells were discharged under normal driving conditions and an easily applied optimization method was employed to find the optimum. Heat transfer equations were used in this study. Similarly, another group of researchers investigated the temperature distribution for square and rectangular cell arrangements with forced convection [11]. The heat transfer equation and energy conservation equation were used in the models. It was found that the temperature distribution varies between these two arrangements. The square arrangement had a higher temperature difference than the rectangular one.

The design of cooling channels is the last factor reviewed in this paper. Ref. 11 studied how the temperature distribution is affected by cooling channel parameters. With the assumptions that the thermal conductivity of the battery is anisotropic and other properties are homogenous, an energy conservation equation and heat transfer equation were used in their models. Experimental data was used to fit the heat generation rate and state of charge formulas. They found increasing the discharge current will reduce the temperature uniformity and increase the maximum temperature of the pack.

Modeling heat distribution is challenging due to requiring high-order physics-based models. A common approach to address this is order reduction. Thus, a reduced lumped model to estimate the temperature distribution was proposed in [13]. In their work, partial differential equations and ordinary differential equations were reduced to algebraic equations.

In summary, works [5], [6], [7], [8], [9], [10], [11], [12], [13] use physics-based models such as equivalent circuit model, heat transfer equations and/or energy conservation equation to predict temperature distribution inside an array. However, this approach has three shortcomings. The first one is the number of fitted parameters is usually high [13] and the fidelity of a battery model is negatively affected by parameter inaccuracy and unaccounted model dynamics [5]. The second
one is the quality of the experimental data dictates the model performance [13]. The last shortcoming is the convergence of estimation from unknown initial conditions can be slow due to the large time constant associated with the thermal mass of the system [5]. Thus, these physics-based models are often not suitable for online applications. On the other hand, data-driven models require much less computational power. The shortcoming of using data-driven models is to have a large dataset to learn the time dependent behavior.

This paper proposes a novel hybrid model in which a physics-based model is combined with two data-driven models (i.e., FNN and LSTM) to predict battery surface temperatures in separate locations within the pack. This work is an extension of existing research in [14]. Instead of using the LSTM alone, heat transfer equations are incorporated into the cost function of the FNN along with the outputs from LSTM to enable the hybrid model to converge faster and provide more accurate results. The proposed hybrid model has the novelties with the following benefits.

1. The proposed hybrid model shows an improved lithium-ion battery module temperature prediction in the battery pack compared to the LSTM method.
2. The proposed hybrid model does not require performing the parameter identification which is often necessary for physics models.
3. The proposed hybrid model implements the physics-informed neural network (PINN) to improve the temperature prediction accuracy at the location where the temperature information is not available in the training data.

The remainder of the paper is organized as follows: Section II explains the physics-model and data-driven models used in this hybrid model and how they are organically incorporated. It also discusses the datasets, cost function, hyper-parameter turning, and training process. Section III presents the ability of this hybrid model to predict battery surface temperatures under the list of test conditions. Section IV discusses the results of the four comparative studies in depth and sheds lights on the effectiveness of each design factor. Finally, the paper is concluded in Section V and future work is discussed.

II. METHODOLOGY

Physics-informed neural network (PINN) is a neural network method conducting biased learning by inserting physics laws into the loss function. This method is expected to overcome the limitations of the conventional neural network method related to the availability and noise in the training data. Also, this method edges over the model-based method by avoiding the model identification and accepting incomplete models for the accurate predictions [15]. Recently, this method has caught researchers’ attention and the research areas applying the physics-informed neural network reported in the literatures are included in but not limited to fluid dynamics [16], [17], [18], [19], [20], solid mechanics [21], optics [22], metallurgy [23], and earth system science [24].

A. ARTIFICIAL NEURAL NETWORK

One of the most common and simple forms of neural networks used in practice is known as artificial neural networks (ANN). These networks are made up of multiple layers where each layer is constructed with numerous neurons. These neurons map the input data to output data by applying a set of weights and offsets to the data to minimize the error between an expected outcome or prediction and a known value. In this case, information only flows in one direction and these types of ANNs are known as FNNs. Other network architectures exist such as bidirectional networks, but these will not be considered for this study because they require more computational power than FNNs. Combining a physics-based model with a bidirectional network does not reduce the compute-intensive of the bidirectional network.

The cell structure utilized in this analysis is illustrated in Figure 1. The ANN cell takes a vector of inputs at time \( t \) denoted as \( x_t \). As information flows through the ANN, the input vector is multiplied by a matrix of weights labeled as \( W_{x_1} \) and an offset vector \( b_1 \) is applied. Lastly, the data is passed through an activation layer which dictates what information is allowed to flow to the output vector \( Y_t \). Equations 1 and 2 illustrate the mathematical operations inside the ANN cell to map data from \( x_t \) to \( Y_t \).

\[
Y_t = \text{ReLU} (x_t, W_{x_1} + b_1)
\]

\[
\text{ReLU} = \max(x_t, 0)
\]

FIGURE 1. Artificial neural network cell.

Taking the cell structure of the ANN, the FNN is created with an input layer, hidden layers, and output layer. The hidden layers are fully connected to all inputs in the vector \( x_t \) and each layer is composed of numerous ANN cells. Figure 2 gives a high-level illustration of a generic FNN.

FIGURE 2. Feed-forward neural network.

Note that from Figure 2, there are multiple hidden layers consisting of an arbitrary number of ANN cells. Since the FNN is fully connected, each input is passed through all
neurons and all hidden layers. Mathematically, this results in a slight variation from (1) above:

\[ Y_t = \sum_i \text{ReLU}(\mathbf{x}_t \mathbf{W}_{xi} + \mathbf{b}_i) \]  

(3)

where \( Y_t \) is a vector containing all outputs at time \( t \), \( \mathbf{W}_{xi} \) is a matrix of weights for the \( i \)th hidden layer, \( \mathbf{x}_t \) is a vector containing the input to the \( i \)th hidden layer at time \( t \), and \( \mathbf{b}_i \) is a vector containing the bias for the \( i \)th hidden layer. As information is fed through the FNN and compared to the expected result, the FNN weights and bias are then updated to reduce the overall error using an optimization function.

**B. BATTERY THERMAL MODEL**

A lumped capacitance battery thermal model represents the physics portion of the physics-informed neural network (PINN) in this study to predict battery temperature. In this thermal model, the energy balance is described in (4).

\[ m C_p \frac{dT}{dt} = \dot{Q} + \frac{T - T_1}{R_1} + \frac{T - T_2}{R_2} + h A (T_1 + T_2 - 2 T_{amb}) \]  

(4)

where \( m \) is the mass of the battery module in g, \( C_p \) is the heat capacity of the module in J/°C, \( T \) is battery temperature at the center of the module in °C, \( t \) is time in s, \( \dot{Q} \) is the heat generation of the module in W, \( T_1 \) is the temperature of the module near the center of the pack in °C, \( T_2 \) is the temperature of the module near the edge of the pack in °C, \( R_1 \) is the thermal resistance between \( T \) and \( T_1 \) in °C/W, \( R_2 \) is the thermal resistance between \( T \) and \( T_2 \) in °C/W, \( h \) is the convective heat transfer coefficient in W/(m²·°C), \( A \) is the cross-sectional surface area in m², and \( T_{amb} \) is the ambient temperature inside the climate chamber in °C. Figure 3 illustrates this battery thermal resistance model, where \( R_{cov} \) represents the product of the convective heat transfer coefficient and the cross-sectional surface area.

![Figure 3. A battery thermal model.](image)

The empirical equation summarized by Bernardi et al. [25] is used to determine the heat generation inside the battery module. This equation below considers both reversible and irreversible heat generation.

\[ \dot{Q} = IT \frac{dV_{ocv}}{dT} + (V - V_{ocv}) I \]  

(5)

where \( I \) is the battery current in A, \( V_{ocv} \) is the OCV of the module in V, and \( V \) is the battery voltage in V. The term for the reversible heat generation is described below:

\[ \dot{Q}_r = IT \frac{dV_{ocv}}{dT} \]  

(6)

The above term represents entropic heating and is related to electrochemical reactions with Li ion insertion and extraction between the cathode and anode. The term for the irreversible heat generation is expressed below:

\[ \dot{Q}_{ir} = (V - V_{ocv}) I \]  

(7)

This term describes ohmic loss.

This study explores the prediction of total heat generation in two different ways. One way includes only irreversible heat generation presented in (8). The other way is shown in (9) to include both reversible and irreversible heat generation.

\[ f_{ir} = \frac{dT}{dt} - \lambda_1 (V - V_{ocv}) I - \lambda_2 (T - T_2) - \lambda_3 (T - T_1) + \lambda_4 (T_{amb} - T_2) + \lambda_5 (T_{amb} - T_1) = 0 \]  

(8)

\[ f_{re_{-}ir} = \frac{dT}{dt} - \lambda_1 \dot{Q} - \lambda_2 (T - T_2) - \lambda_3 (T - T_1) + \lambda_4 (T_{amb} - T_2) + \lambda_5 (T_{amb} - T_1) = 0 \]  

(9)

where \( f_{ir} \) and \( f_{re_{-}ir} \) are the parameterized heat transfer models for irreversible heat generation and both reversible and irreversible heat generation, respectively. \( \lambda_1, \lambda_2, \lambda_3, \lambda_4, \) and \( \lambda_5 \) are coefficients for heat generation, thermal conductivity between the center of the module and the inboard cross-section of the module, and thermal conductivity between the center of the module and the inboard cross-section of the module, thermal conductivity between the outboard cross-section of the module and air, thermal conductivity between the inboard cross-section of the module and air, respectively. In PINN, no additional effort is required to find these coefficients. The Adam optimization method obtains the optimum coefficients during the training process.

**C. PHYSICS-INFORMED NEURAL NETWORK**

PINN conducts learning from the data and physics laws. To accommodate this objective, the loss function of PINN contains three terms to bias learning to the physics law. The mathematical expression of the loss function in the physics-informed neural network is defined as follows:

\[ \text{Loss} = \text{Loss}_r + \alpha \text{Loss}_f + \beta \text{Loss}_i \]  

(10)

where \( \text{Loss}_r \) is the loss term associated with the residual between the predicted and the measured temperature, \( \text{Loss}_f \) is the loss term related to the physics law, \( \text{Loss}_i \) is the loss term estimated from the initial condition, and \( \alpha \) and \( \beta \) are the normalized coefficients, respectively. The mathematical expression for each loss term is provided in (11) – (13).

\[ \text{Loss}_r = \frac{1}{N} \sum_{i=1}^{N} |\hat{x}_i - x_i|^2 \]  

(11)

\[ \text{Loss}_f = \frac{1}{N} \sum_{i=1}^{N} |f|^2 \]  

(12)

\[ \text{Loss}_i = |f (t = 0) - x_i|^2 \]  

(13)

where \( N \) is the number of training data points, \( \hat{x}_i \) is the predicted temperature, \( x \) is the measured temperature, \( f \) is the rearranged physical law equation, \( f (t = 0) \) is the value estimated from the physic law when the time is 0, and \( x_i \) is the initial measured temperature.
In addition to the loss function modification, adaptive normalization in the loss function of PINN is implemented to further improve the prediction accuracy. This study applies the learning rate annealing method developed by Wang et al. [26]. In this method, the instant scaling factors are estimated via the ratios between the maximum backpropagation gradient of the residual loss and the mean backpropagation gradient of other losses associated with the physical law. Equations (14) and (15) describe normalization:

\[
\hat{\alpha} = \frac{\max(|\nabla \text{Loss}_r(T)|)}{\nabla \text{Loss}(T)} \tag{14}
\]

\[
\hat{\beta} = \frac{\max(|\nabla \text{Loss}_r(T)|)}{\nabla \text{Loss}(T)} \tag{15}
\]

where \( \hat{\alpha} \) and \( \hat{\beta} \) are the instant scaling factors, \( \nabla \text{Loss}_r \), \( \nabla \text{Loss}_y \), and \( \nabla \text{Loss}_i \) are the backpropagation gradients related to the loss terms of the residual between the prediction and the measured temperature, the physics law, and the initial condition, respectively. After estimating the instant scaling factors, the normalized coefficients, \( \alpha \) and \( \beta \), are computed form the process formulated in (15) and (16).

\[
\alpha = (1 - \gamma) \alpha_{\text{previous}} + \gamma \hat{\alpha}_{\text{previous}} \tag{16}
\]

\[
\beta = (1 - \gamma) \beta_{\text{previous}} + \gamma \hat{\beta}_{\text{previous}} \tag{17}
\]

where \( \gamma \) is a tunable hyperparameter and 0.9 is used in this study since this value reduces and converges to the loss function as expected.

D. PRE-LAYER ARCHITECTURE

The unique pre-layer of PINN is another feature that allows the PINN to have better prediction accuracy. For instance, the pre-layer and connection layer structures originated from the analytical solution of the physic law improved the prediction outcomes of the PINN in the literature published by Zobeiry and Humfeld [27]. This study implements the pre-layer and connection layer architectures between the input and hidden layers with the sine and exponential activation functions as proposed in [27] and [28]. Two architectures with different input sets are prepared. In the first architecture, the chamber temperature is not included in the inputs as other studies. In the second architecture, the chamber temperature is included in the input to learn the effect of different chamber temperatures in the training data. The graphical overviews of the two PINN architectures used in this paper are provided in Figure 4 and Figure 5.

E. LSTM–PINN HYBRID MODEL

In [14], the temperature prediction made by the LSTM model showed good prediction accuracy when using the measured temperature in one module to predict the temperature of the same position but in a different module. However, the accuracy dropped when using the same input to predict the temperature of a different position in a different module. For instance, the input temperature is measured at the edge of the battery in module 1 and the temperature prediction using LSTM alone is less accurate for the middle than the edge of the battery in module 7. To improve the prediction accuracy, this paper proposes a LSTM-PINN hybrid model. In this model, the LSTM model makes the temperature prediction for the same position in a different module (Temp1 and Temp2 in Figure 6). After that, the predictions of the LSTM model (Temp1 and Temp2 in Figure 6) along with the other inputs feed into the PINN model to generate Temp 3 in Figure 6. The PINN then predicts the temperature in a different position of the interested module. The overview of the LSTM-PINN hybrid model is provided in Figure 6.

F. BATTERY TEST AND DATA PREPARATION

A high-voltage lithium-ion battery pack consisting of 12 electrically connected modules was used to generate the training and test data for the LSTM-PINN hybrid model.
Table 1 details the cell chemistry and specifications used to form the battery pack modules. Modules 1 and 12 have 7 cell groups. Each of the remaining modules have 8 cell groups. Each cell group has 4 cells connected in parallel. In total, there are 94 cell groups in the pack. Additionally, modules 6 and 7 are located above modules 5 and 8, respectively. Every two modules across the center valley of the pack share a cold plate which allows coolant to flow through channels to remove heat from the battery cells. Figure 7 illustrates the battery pack layout.

The test equipment used in this setup is illustrated in Figure 8. The high-voltage battery pack is placed inside a Thermotron thermal chamber where the ambient temperature is controlled. Additionally, an AV-900 EX cycler, Polyscience coolant chiller, Omega T-type thermocouples (TC), Gantner DAQ, and PC loaded with AVL software for recording data are all instrumented and configured. TCs are installed on the top surface of each battery cell to measure the cell surface temperature. A two-inch-thick insulation box enclosure was added to insulate the battery pack from the ambient chamber temperature. A TC is placed in the air gap between the battery pack and insulation box to measure the surrounding air temperature. This TC is denoted as $T_{amb}$ in Figure 8. Lastly, all TCs were normalized prior to collecting any pack data to reduce measurement error. This normalization was accomplished by soaking the battery pack at -30 °C, 0 °C, 25 °C, and 45 °C in the thermal chamber and comparing steady state data to a high accuracy thermometer with an accuracy of 0.05 °C. Post-normalization the TCs yield an uncertainty of approximately ±0.1 °C.

To generate the test data used for training and testing the LSTM-PINN, various drive cycles listed in Table 2 were conducted on the battery pack using the test equipment outlined previously. These drive cycles are multi-cycle test (MCT), Vmax, US06, federal test procedure (FTP) 20, direct current fast charge (DCFC), and grade load (GL) 100. All data was recorded at 1Hz for use in the LSTM-PINN model. These drive cycles with different charge and discharge patterns were selected to evaluate the ability of the LSTM-PINN model to learn the effects of reversible heat generation. Also, the test profiles contain a rest time and a large current pulse which could disturb the temperature prediction to evaluate the robustness of the LSTM-PINN model during these events. The initial temperature column of Table 2 represents the steady state starting temperature of the battery cell before performing the drive cycle. The chamber temperature is the setpoint of the environmental chamber. The usage column indicates whether the data was used for training or testing the LSTM-PINN. See the appendix section of [14] for current traces of the drive cycles.

Four aspects of the performance were investigated in four comparative studies. Four common inputs of time, pack current, pack voltage, and pack OCV were used to predict the cell temperature in the middle of module 7 as denoted by the blue cross in Figure 7. In addition to the four common inputs, the LSTM predicted temperatures of the end cells in module 7 were used as two additional inputs. They are denoted as $T_1$ and $T_2$ in Figure 7. The differences among
these four comparative studies are as follows. The chamber temperature was used as an additional pre-layer input in the first comparative study to assess the effectiveness of including the chamber temperature. The second comparative study varies the number of neurons in each hidden layer as well as the total number of hidden layers to study their influence. The third comparative study investigates the effects of reversible heating to the loss function. The last comparative study compares the performance of a single LSTM with the LSTM-PINN hybrid model.

G. TRAINING AND PREDICTION EVALUATION
All battery test data allocated for training were normalized based on the mathematical relationship as follows:

\[
\hat{x} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

where \(\hat{x}\) is the normalized data, \(x\) is the raw data, \(x_{\text{min}}\) is the minimum of the raw data, and \(x_{\text{max}}\) is the maximum of the raw data. After this pre-processing step, the normalized data were fed to the LSTM-PINN hybrid model for the training process. In the training step, the hyperparameters of the LSTM-PINN hybrid model were tuned based on the information from the literature and hyperparameter study. Table 3 provides the list of the hyperparameters used in this study. Also, the hyperparameter study for the number of neurons in the hidden layer and the number of the hidden layers based on the design of experiment theory are provided in the result section.

III. RESULTS
In this section, the results of the four comparative studies are presented. The effectiveness of having the chamber temperature as one of the inputs is evaluated first. After determining that having the chamber temperature improves the prediction accuracy, the design of experiments is carried out to find the optimum neuron number and hidden layer number in the PINN architecture. After identifying the optimal numbers of neurons and hidden layers, the effectiveness of having reversible heat generation is investigated. At last, the hybrid LSTM-PINN model is compared with a LSTM model.

A. CHAMBER TEMPERATURE INPUT TO PINN
In the literature adapting the PINN for the thermal application [27], the chamber temperature of the application is assumed to be constant. Therefore, their PINN architecture does not have the chamber temperature as one of the inputs to the PINN. However, the chamber temperature often varies as heat exchanges between the chamber air and the pack. Therefore, this paper treats the chamber temperature as a variable. By using it as one of the inputs to the LSTM-PINN model, the effect of chamber temperature is analyzed. The analysis in this section compares three different predictions from the three different LSTM-PINN structures. One is the LSTM-PINN without the chamber temperature input layer. The other two are the LSTM-PINN with the chamber temperature input layer but different activation functions: sine and exponential. Figures 9 and 10 provide the prediction outcomes with the mean square errors in Tables 4 and 5.

TABLE 4. Prediction errors for the DCFC test profile.

| Case                             | RMSE Error (°C) |
|----------------------------------|-----------------|
| No \(T_{\text{amb}}\) pre-layer  | 1.03            |
| \(T_{\text{amb}}\) pre-layer with sine activation function | 0.96            |
| \(T_{\text{amb}}\) pre-layer with exp activation function | 0.57            |

After the training process, the LSTM-PINN hybrid model predicts the battery temperature at the middle of module 7 for the DCFC test profile and GL100 test profile. The prediction accuracy was evaluated by assessing the root mean square error (RMSE) between the prediction and true values. The mathematical formula for RMSE is provided in (19).

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}}
\]

where \(N\) is the total number in the test data, \(i\) is the variable, \(x_i\) is the true value in the test data and \(\hat{x}_i\) is the prediction value.
profiles, the initial temperature prediction has the most significant error, and it takes time to converge to the true value. The predictions done by the LSTM-PINN with the chamber temperature input layer show no significant prediction error at the beginning of the prediction. These benefits of the LSTM-PINN with the chamber temperature input layer outweigh the computation complexity increase and additional effort in the hyperparameter optimization. Among the two LSTM-PINNs including chamber temperature in the input layer, the one with the exponential activation function shows a more accurate prediction in the DCFC test profile and similar prediction accuracy for the GL 100 test profile. In the case of the GL 100 profile, the prediction accuracy improvement is more significant than that of the DCFC test profile due to the presence of a large current pulse in the GL 100 profile. This paper picks the exponential activation function for the chamber temperature input layer.

**B. NEURON # AND HIDDEN LAYER #**

For the LSTM-PINN, which includes the chamber temperature input layer with the exponential activation function, the neuron number and hidden layer number are optimized with the test conditions defined by the full factorial design of the experiment (DOE). In the DOE study, the number of the hidden layer has four levels, and the number of neuron numbers per the hidden layer has five levels. Pre-screen prediction runs predetermine the levels and ranges of the neuron number and the hidden layer number in the DOE study. Table 6 and Table 7 show the outcome of the test results. The prediction accuracy varies with the number of hidden layers and neurons in the DCFC test profile. 50, 55, 60, and 55 neurons are the best performer for 3, 4, 5, and 6 hidden layers, respectively. 4, 3, 4, 5, and 3 are the best performer for 45, 50, 55, 60, and 64 neurons, respectively. However, the prediction accuracy table for the GL100 test profile shows no large error difference due to the neuron number and hidden layer number changes. Thus, the subsequent two comparative studies used 55 neurons per hidden layer and 4 hidden layers.

**C. EFFECT OF IRRIVERIBLE HEATING**

One of PINN’s benefits is its acceptance of the incomplete physical law [15]. Two battery thermal models were incorporated into the proposed LSTM-PINN to analyze the effect of the incompleteness in the physical law with the LSTM-PINN. One battery thermal model only contains irreversible heat generation. The other battery thermal model includes both irreversible and reversible heat generations to describe the physics better. The two battery thermal models are provided in (8) and (9). The results of the temperature prediction with the test profiles are provided in Figure 11 and Figure 12.

**FIGURE 10.** With and without chamber temperature inputs study for GL100 test profile.

**FIGURE 11.** PINN with only irreversible heat vs. PINN with both irreversible and reversible heat generation for the DCFC test profile.
irreversible heat generation is less than the LSTM-PINN with the battery thermal model with the irreversible and reversible heat generations. The difference in RMSE between the two prediction errors is 0.27 °C. The opposite outcome is observed for the GL100 test profile: the PINN with the battery thermal model with the irreversible and reversible heat generations has a lower prediction error of 0.08 °C.

D. LSTM AND PINN COMBINED NN

In this comparative study, the prediction errors of the LSTM-PINN hybrid model were compared with the prediction errors of the LSTM model in [14]. Unlike our LSTM-PINN hybrid model, the LSTM model only utilizes the training data to learn the features. The comparisons for DCFC and GL100 are provided in Figures 13 and 14, respectively. The LSTM-PINN hybrid model has a slightly lower prediction error than the LSTM model for the DCFC test profile in Figure 13. For the GL100 test profile, the performance of both models is similar.

LSTM model which solely relied on data to train the prediction method, there is a higher prediction error where the geometric location of the prediction is different from the location of the input temperature in the LSTM model. The proposed LSTM-PINN model overcomes the drawback of the LSTM model by implementing the physical law along with the loss function modification, the adaptive coefficient in the loss function and PINN architecture into the neural network structure.

Table 8 summarizes the RMSE for comparative studies of the effectiveness of having the chamber temperature, reversible heat generation and physical law. The first comparative study investigated the effectiveness of having the chamber temperature as one of the inputs. Unlike the other researchers who treat the chamber temperature as a constant in [25], we use it as one of the inputs. The LSTM-PINN without the chamber temperature input layer has a RMSE of 1.03°C and 3.43 °C for DCFC and GL100, respectively.
The performance of the hybrid model with either of the two activation functions is at least directionally better than the performance of the hybrid model without either of the activation functions. Comparing with the sine activation function, the exp activation function not only gives competitive outcomes as 0.57 °C and 0.52 °C RMSE for DCFC and GL100, respectively, but also delivers more reliable performance.

The effect of the physical law completeness is assessed with the two LSTM-PINN models. One is with the battery thermal model with only irreversible heat generation. The other one is with both irreversible and reversible heat generations to enhance the learning. The hybrid model with only the irreversible heat generation delivered two close RMSEs as 0.57 °C and 0.52 °C for DCFC and GL100 respectively. The hybrid model with both reversible and irreversible heat generations had RMSEs of 0.84 °C and 0.44 °C for DCFC and GL100, respectively. It is observed that more completed physics law does not enhance the prediction accuracy but lose consistency. In a test case, the LSTM-PINN model with the less complete thermal model has more accurate prediction. This shows the advantage of the LSTM-PINN model for the incomplete physics equation.

When comparing the LSTM-PINN hybrid model with the LSTM model, the hybrid model has a more consistent performance than the LSTM model. Although the RMSE of the LSTM model for GL100 is 0.48 °C which is slightly better than 0.52 °C delivered by the hybrid model, the RMSE of the LSTM model for DCFC is 0.44 °C higher than 0.57 °C from the hybrid model. Looking at how much the temperature varies in DCFC than GL100, it is clear that the hybrid model advances the LSTM model when the temperature range is large.

V. CONCLUSION AND FUTURE WORK

This work aimed to propose and demonstrate a novel hybrid model. Unlike previous work, which relied on either a physics-based or a data-driven model, this work took full advantage of both physics-based and data-driven models by utilizing the physical laws to accelerate biased learning. Four comparative studies were conducted. The first comparative study demonstrated the effectiveness of having the chamber temperature as one of the inputs. In addition, using the exponential activation function gave a more consistent performance than using the sine activation function. The second comparative study identified the optimum as 55 neurons and 4 hidden layers. The third comparative study demonstrated no apparent difference in prediction accuracy with and without reversible heat generation. The last comparative study showed that having a LSTM model predict the temperatures of two end cells in the interested module and feed them into the PINN improves the prediction accuracy for the middle cell in the same module. In summary, this paper proposed a LSTM-PINN hybrid model to predict the pack battery temperature and this model has the following noble features and characteristics:

1. The proposed LSTM-PINN has a unique PINN architecture from other PINNs developed by other literature. It has input layers for the battery application and the chamber temperature variation.
2. The proposed LSTM-PINN is robust against incompleteness of the physical law such as missing terms and less descriptive formulation.
3. The proposed LSTM-PINN has more accurate predictions than the LSTM model when the input temperature geometrical orientation is different from the prediction temperature. This effect is more significant when the predicted temperature variation increases.

Future studies will compare the performance of the LSTM-PINN model to other network architectures such as recurrent neural networks (RNN) and exiting battery temperature predictive models. Furthermore, the future study will evaluate noise and computational complexity robustness under different initial temperatures.

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