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Battery Management with Artificial Intelligence and Machine Learning

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ABSTRACT:

Our modern world relies heavily on batteries, especially lithium-ion batteries, to power everything from electric cars and renewable energy storage to portable electronics. However, because of internal chemical interactions, they produce heat when charging and discharging. If not well controlled, this heat can result in decreased performance, a shorter lifespan, and potentially safety hazards. Because machine learning can evaluate massive datasets and forecast battery temperatures and improve thermal management, it has become a transformative tool in battery technology to address this issue. In this study, we examine the properties of machine learning and examine its different learning categories, frameworks, and uses. The several neural networks and machine learning techniques utilized in battery temperature prediction and thermal management are examined in detail, as well as the numerous training procedures that are employed. Additionally, this study examines and synthesizes a number of research studies that look at battery temperature prediction and thermal management using different machine learning techniques. because the training algorithm, data set, and other factors can affect how well the model performs. However, because of their accuracy and model complexity, artificial neural networks are the machine learning algorithm of choice for academics.

1. Introduction:

Lithium-ion batteries have been widely used in many applications over the past few decades, including electric vehicles, portable electronic devices, and aerospace vehicles. This is because of a number of factors, such as system stability and dependability, high energy/power, lowering utility demand, and climate change [2]. However, temperature-related issues, such as cycle life reduction at high temperatures, continue to impede the use of batteries in the emerging energy storage sectors. In the past few decades, many numerical models have been proposed to aid in our understanding of the thermal properties of batteries [2]. Among these, the precise internal temperature distribution and heat generation of the battery can be determined via thermoelectric models. These models are difficult to utilize, though, because there are a lot of equations and physical and thermal properties. Due to their benefits, which include quick self-learning from training data and low computing load, machine learning technologies and hybrid combinations of machine learning and numerical models may be efficient and helpful tools for predicting the electrical and thermal behaviour of non-linear energy storage devices. Several sources addressed the issues with battery technology through machine learning. [1] Rechargeable battery materials and energy storage are two areas where machine learning is being applied. The author looked at the application of machine learning in energy storage systems. The lithium-ion battery's stability and performance will quickly deteriorate [3]. LIBs work best in the 20–40°C temperature range, with a temperature differential of no more than 5°C. The primary thermal modelling techniques for battery temperature prediction are partial differential equation modelling, artificial neural network modelling, finite element modelling, and so on. An artificial neural network (ANN) offers special benefits for handling extremely nonlinear issues. Using comparatively straightforward structures and techniques, it is able to fit the complex nonlinear relationship between input and output parameters, and the fitted relationship possesses outstanding performances.

2. Objectives:

This article aims to give a general overview of machine learning algorithms that are useful for predicting lithium-ion battery temperature. This research also focuses on conducting performance testing under test and sample settings to confirm the validity and accuracy of the neural network thermal model.The objective is to identify the best neural network model for lithium-ion battery temperature prediction.The goal is to use artificial neural networks (ANNs) and machine learning techniques to forecast the rate at which heat is generated by lithium-ion batteries.

3. Literature Review:

Numerous numbers of researches have been carried by the different researchers in the relevant field. The summary of the outcome of the researches have listed below.

3.1 Artificial Intelligence and machine learning.

The creation of computer systems capable of carrying out tasks that normally require human intelligence is referred to as artificial intelligence. These assignments involve problem-solving, reasoning, and learning. These artificial intelligence (AI) systems are made to resemble cognitive processes and adjust to different environments. Through machine learning algorithms, they frequently perform better over time.

Machine learning is the branch of artificial intelligence that focuses on creating statistical models and algorithms that let computer systems get better over time at a given activity without having to be explicitly programmed. To generate predictions and choices, machine learning algorithms draw conclusions from patterns and inference.

3.2 Learning algorithms for battery temperature prediction.

Learning algorithm is an essential part for applying machine learning in temperature prediction [1]. The aid of these algorithms and fair amount of dataset, it becomes possible to establish a nonlinear mapping function to preform prediction.

Artificial neural network (ANN) a machine learning method is based on the structure of the human brain [2]. Regression issues and function approximation are two areas in which ANN are well-known. Artificial neural networks are typically composed of nodes, which are linked entities [2]. establishing an output layer, an input layer, and one or more hidden layers. There is a weight threshold that determines how one node is connected to the others. A fixed nonlinear function called f(x) is associated with each node and is used to compute the output. If the calculated output is greater than the threshold, the individual node is activated and passes the data to the next layer node; if not, no data is passed to the next layer node. Every neuron's Y output value can expressed as

Y = F (2 i ΣPiWij + bj) [2]

Where

Y is the output value

F is the activation function

P is the input vector

W is the weight value

B= is the biases value

I and j are input number vector and neuron number respectively

There are three commonly used activation functions in the nodes which are

- logistic function
- hyperbolic tangent function, and
- ReLU function [3].
- Logistic function also known by sigmoid function can be presented as follows

f (x) = 1 1 + e −x (3)

The sigmoid function saturates and becomes less responsive at higher and lower values of x, while it becomes more sensitive near the value of x = 0.

- Hyperbolic tangent function also known by tanh function and it can be presented in equation below f(x) = tanh (x) = e x − e −x e x + e –x[3]. The tanh function is similar to the sigmoid function, but tanh function is centered at 0 rather of that of sigmoid where it is centered at 0.5 which makes learning a little bit easier.
- ReLU function is a rectified linear function typically used in all hidden layers as a default activation function. ReLU function will activate the node if the input is positive. ReLU function. 0. ReLU can be presented in form of the equation below.

ReLU (x) = { 0 if x < 0 ,x otherwise Artificial neural network can make accurate decisions without human intervention. ANN can be categorized into feed-forward, recurrent, modular, and convolutional neural networks [3].

3.3 Architecture of ANN

As seen in Figure 1, an ANN model is a multi-layered network made up of several neurons with one input layer, one or more hidden layers, and one output layer. As a feedforward ANN, the Back propagation (BP) neural network demonstrates a significant nonlinear mapping capability. As a result, we chose the sigmoid as the activation function and trained and tested the BP neural network. Because of its quick convergence, the Levenberg-Marquardt algorithm was chosen as the learning algorithm. A learning rate of 0.01 was used. The number of hidden layers and neurons can be chosen in any way;

there are no set guidelines [9]. By building and training networks with various designs and carrying out independent testing, we used the trial-and-error approach to ascertain the architecture of the ANN model. The first choice for the number of hidden layers was one, and that for the number of neurons was in the range of 1–20. Lastly, we selected the architecture with a smaller test root mean square error (RMSE) and fewer hidden layers and neurons for each case.

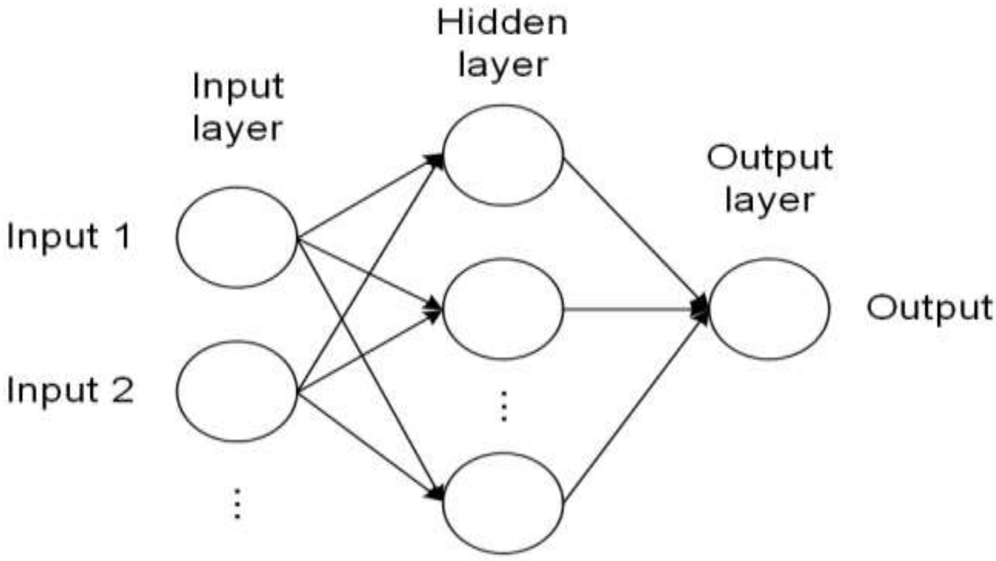

Fig 1 : Architecture of ANN [9]

3.4 Common used ML algorithms in temperature prediction and thermal management application.

ML algorithm	Application
Linear regression	BTP
Gaussian model	BTM
Support vector machine	BTP, BTM
k-nearest neighbor	BTP
Random forest	BTP
Decision tree	BTP,BTM
Artificial neural networks	BTP,BTM
Long short term memory	BTP
Gated recurrent unit	BTP
Nonlinear autoregressive network with exogenous input	BTP,BTM
Temporal and conventional neural network	BTP,BTM
Adaptive neurofuzzy inference system	BTP

3.5 Optimization training algorithms in battery temperature prediction and thermal management

To be able to handle the problems of clustering, regression, and classification, machine learning algorithms need to be trained. A collection of input data is fed through a machine learning algorithm during the training phase of the process. By analyzing the data and comparing it with the output of a sample, the machine learning technique modifies the model based on the correlation results. In order to lower error and identify the optimal solution, the model output is updated during each iteration of this iterative procedure. ANNs and linear regression are two popular machine learning techniques that require an optimization strategy. These algorithms find the ideal weight and bias settings while minimizing the cost function. The quality of the training dataset and the algorithm used have a direct effect of the model performance and the output. Selection of the optimizer algorithm depends on the size of the dataset and on the designer sense. This section will mention most popular optimization algorithms used in battery temperature prediction and thermal management.

3.5.1 Gradient descent

Gradient descent is an optimizing algorithm used to train machine learning model. Gradient descent simply finds the local minimum of a function. Gradient descent tends to reduce the cost function by finding the optimal weight and bias it can be expressed as follows:

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J\left(\theta_i, \theta_j\right)$$

where θj is the weight, α is the learning rate of the gradient descent, J (θi, θj) is the cost function, i & j are number index[10].

3.5.2. Stochastic gradient descent

Stochastic gradient descent is very similar to gradient decent. The only difference is that Stochastic gradient descent chooses a random data from the dataset to compute the gradient at each step saving time and computational effort. Stochastic gradient decent gives a good result but not optimal as of that given by gradient descent [11].

3.5.3 levenberq–Marquardt

Levenberg–Marquardt algorithm is a widely trusted region algorithm also called by damped least-squares. This algorithm is used to solve nonlinear least square mathematical problems. Levenberg–Marquardt algorithm is a combination between Gauss–Newton iterations and gradient descent that can be express in the equation below. The substrate t presents the time step.

$$X_{t+1} = X_t - \left(J^T J + zD\right)^{-1} * J^T c$$

where Xt is weight vector, J is Jacobian matrix, D is unit mtrix, z is test scalar, c is network error. As shown from the equation above, gradient descent is a good practice to reach the optimal solution [5].

3.5.4 Root mean square propagation

RMS prop which is known as root mean square propagation. It is unpublished optimization algorithm proposed by Geoff Hinton in his lecture notes. The algorithm merge between gradient sign and step size adapting for each weight to find optimal solution. In other words, the algorithm accelerates the learning in the right direction by adapting step size for each parameter over time. The algorithm is expressed in the equation below.

$$E\left[\nabla^2\right]_t = \gamma E\left[\nabla^2\right]_{t-1} + 0.1\nabla^2{}_t$$
$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E\left[\nabla^2\right]_t + \varepsilon}} \nabla_t$$

where γ is momentum term(recommended of value 0.9), η is learning rate, ∇t is derivative of the loss function with respect to weight time step k, ε is smoothing factor, E [∇ 2] t average moving of squared gradient, θ is set of hyper parameters or weights[12].

3.5.5 Bayesian regularization

Bayesian regularization is a popular method used to train artificial neural networks. It is a mathematical process that converts a nonlinear regression problem into statistical problem in manner of ridge regression. although Bayesian regularization artificial neural network are considered strong and robust, they are difficult to over-train and over fit [13].

3.5.6 Extreme learning machine

Extreme learning machine (ELM) is a training algorithm for a single layer feed-forward neural network (SLFNS). This technique was firstly proposed by [14]. ELM tends to randomly select weights and biases, between the input and hidden layers, and in the hidden layers respectively. the nonlinearity of the system is given by a nonlinear activation function found in the hidden layer. The advantage of ELM is that the weights found between the output and the hidden layer, is the only learned parameters. This advantage makes ELM converges faster and give better performance compared to traditional networks trained by backpropagation. Although ELM can deal and solve big data machine problems, its computational complexity is high [15].

3.6 Temperature prediction:

Battery life and temperature have been major research topics since batteries were first used in electric cars and other applications. There are various methods for forecasting temperature. One kind of modeling is electrochemical modeling, which is based on physics and necessitates a reasonable amount of data as well as knowledge of chemical and physical laws. While the semi-empirical model, which is based on performance, is less sophisticated and less precise than the electrochemical model, it is still thought to be the most accurate. Data-driven models, on the other hand, are a new technique for temperature prediction. A data-driven model is regarded as a "black box" since its underlying workings are only visible through its inputs and outputs [4]. Recently, data-driven models have been extensively used by researchers and scientists due to their applicability and accuracy, requiring less time and computational effort. Various machine learning algorithms and models are widely employed in battery temperature prediction.The most difficult step in data preparation, is selecting the regression machine learning model. Manh kien Tran et al. investigated the performance of four different types of regression models to predict the temperature and voltage of a prismatic 25 Ah Lithium ion battery cell. Temperature and voltage were experimentally measured during a constant current cycle of 1C at ambient temperatures 5 ◦C, 22 ◦C, 35 ◦C. Using scikit-learn library on python the authors developed four regression models linear regression, k-nearest neighbors, decision tree, and random forest and validated them experimentally. The four models were trained, validated by 70% of the total data, and tested with the remaining 30%. The input -parameters for the four models are ambient temperature, battery capacity, current, past battery current and voltage. Using a statistical measure method R-squared, the authors reported and compared the performance of the four proposed methods. Results showed that the best fit algorithm for the studied case is the decision tree regressor where it scored the best value of 0.99 R-squared [4]. Because battery temperature is dependent on numerous factors, ANN are frequently seen to be a superior method than more conventional machine learning algorithms like decision trees. ANNs are said to be more adaptable than other types of machine learning since they can manage intricate and sizable datasets and are better at identifying intricate non-linear correlations between input and output data.The authors came to the conclusion that the charging current, charging duration, and ambient temperature have the greatest effects on surface temperature. The study uses a feed-forward artificial neural network (FFNN) with back-propagation to forecast the battery's surface temperature. There are three layers in the authors' artificial neural network. The input layer consisting of three nodes (charging current, ambient temperature, and charging time), the hidden layer made up of 5 neurons, and the output layer made of one neuron which is the surface temperature. Hyperbolic tangent function and Logistic function are used as an activation function in the last two layers respectively. The dataset for training, validating, and testing the model is collected experimentally. A cylindrical 8 Ah Ni-MH battery is charged at different rates of 1C, 3C, and 5C under different ambient temperatures of 10 ◦C, 20 ◦C, 30 ◦C, and 40 ◦C. The model was trained using Levenberg–Marquardt algorithm (LM) operating in MATLAB software to predict the surface temperature at elevated ambient temperatures of 50 ◦C, 60 ◦C and 70 ◦C.

The trained ANN showed a very small mean square error value of 4.98 e−6 after 5000 training epochs. Moreover, the trained model showed a good linear regression fit between the model output and the target output. the obtained regression line has a slope of 1 and y-interception of 4.04e−5. The prediction results of the NN showed that the surface temperature of the battery may exceed 90 ◦C while charging at rate of 5C at ambient temperature of 60 ◦C and 70 ◦C[6]. [7] used a FFNN backpropagation trained by LM algorithm to predict the battery surface temperature. results showed the R2 is almost 1 and the network can correctly predict the surface temperature.Both authors used FFNN trained by LM algorithm to predict the battery temperature, however, the authors choose two different evaluation techniques to assist their performance. In both studies the networks showed a high performance of mean square error value of 4.98 e−6 and R2 value almost 1.

It is not possible to place an occupied temperature sensor in each battery cell to monitor its temperature, and the sensors can only measure surface temperatures. Numerous sensorless mathematical models have been developed, however solving complex differential equations with them demands a significant processing effort[8]. found that utilizing electrochemical impedance spectroscopy (EIS) data with artificial neural networks (ANNs) is the most effective technique to estimate the temperature of a lithium ion battery. Using the MATLAB toolbox, the authors modeled an FFNN with three layers and a tangent activation function. To get the results, an experimental study is conducted on 36 distinct Samsung INR18650-15L1 1500 mAh Lithium ion battery cells at various SOC and temperatures. A three layers' neural network with one hidden layer is proposed by the authors for estimating temperature, state of charge, and state of health. The input layer was feed with the impedance data and the number of neurons was varied based on the output. The model was trained using two different optimization algorithms Bayesian regularization backpropagation optimization and Levenberg–Marquardt backpropagation optimization. Results of the model showed many advantages compared to other temperature estimation methods. One of the advantages of the proposed method is that the model only needs one single EIS spectrum to predict the temperature of the battery cell[8].Since battery temperature prediction involves analyzing the temperature readings of a battery over time, which is a sequential data problem. FFNN is not considered a good practice for this application, since it cannot handle sequential data. Instead Researchers head toward using recurrent neural network (RNN) instead, were they are especially made to handle sequential data.

4. Application of machine learning in batteries temperature prediction:

As the amount of renewable energy resources increases, energy storage devices are becoming an increasingly important component. Their significance is found in raising the system's power quality, stability, and dependability; raising the market value by utilizing a variety of generating sources; raising the reliability and value of renewable energy sources; and lowering investment costs [16]. By storing the extra energy generated, batteries are a sort of energy storage technology that can support the production of solar and wind energy and be used in electric cars. Battery degradation is still a major worry despite the quick advancements in battery technology [17]. When a battery's ability to store energy decreases, it becomes less appealing. There are different factors that effects ageing such as charging and discharging activities, however, battery cell temperature is known to be the major factor for reducing the life time, increasing degradation of the battery, and escalating safety concerns [18]. One of the studies stated that the lifetime of a li-ion battery is reduced by two months with 1 ◦C increase of cell temperature in an operating temperature range of 30 ◦C to 40 ◦C [19]. The distribution of cell temperature also has a significant impact on battery lifespan. The cell temperature differential must be kept to less than 5 ◦C in order to extend the battery's lifespan [20]. Numerous investigations shown that when a cell is exposed to a high non-uniform temperature distribution, its overall capacity and longevity are decreased [21].To preserve battery life and lower cooling costs, it is crucial to precisely forecast the temperature of the battery cell and implement an optimum thermal management system. When compared to empirical, physics-based, and complicated mathematical calculations, machine learning is a more advantageous technique. One benefit of machine learning is that it requires less computing power to comprehend new information more quickly.

5. Conclusion:

- This report concludes that machine learning algorithms have emerged as a valuable tool in battery technology for predicting battery temperatures.
- Researchers have used various machine learning methods and neural networks for battery temperature prediction with artificial neural networks being preferred due to their accuracy and model complexity.
- Researchers in the domain of energy storage are benefiting from machine learning interface and new promising direction for batteries technology
- The performance of machine learning models for battery temperature prediction may vary depending on the dataset, training algorithm, and other parameters.
- Machine learning is a valuable tool in battery technology for predicting battery temperatures.
- Various machine learning methods and neural networks have been analyzed and discussed for battery temperature prediction.

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