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Review article

Batteries temperature prediction and thermal management using machine learning: An overview

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ABSTRACT

Batteries, particularly lithium-ion batteries, play an important role in powering our modern world, from portable devices to electric vehicles and renewable energy storage. However, during charging and discharging, they generate heat due to chemical reactions within them. This heat can lead to reduced performance, shortened lifespan, and even safety risks if not properly managed. To address this problem, Machine learning has been emerged as a changing tool in battery technology due to its ability to analyze large datasets that can be used in predicting battery temperatures and enhancing their thermal management. In this work, we address machine learning features along with a look at its various learning categories, frameworks, and applications. In a comprehensive study, various machine learning methods and neural networks used in battery temperature prediction and thermal management are analyzed and discussed along with its various training algorithms. Moreover, the paper reviews and summarizes various research publications examining battery temperature prediction and battery thermal management using the various machine learning algorithms. As a result, there is no superior machine learning algorithm for battery temperature prediction and thermal management, as the performance of the model may vary depending on the data set, training algorithm, and other parameters. However, among these machine learning algorithms researchers are preferring to use artificial neural networks due to its accuracy and model complexity. In particular, artificial neural network integrated with proper cooling technology can reduce the battery temperature by more than 25%.

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Nomenclature

AI	Artificial Intelligence
ML	Machine learning
DL	Deep learning
ANN	Artificial neural network
FFNN	Feed-forward neural network
NN	Neural network
CNN	Convolutional neural network
LSTM	Long-short term memory
ANFIS	Adaptive neuro-fuzzy inference system
MLA	Machine learning algorithm
NARX	Nonlinear autoregressive network with exogenous input
NAR	Nonlinear autoregressive
SVR	Support vector regression
LM	Levenberg–Marquardt algorithm
RNN	Recurrent neural network
GRU	gated recurrent unit
SOC	State of charge
SOH	State of health
AT	Ambient temperature
ST	Surface temperature
C	Battery capacity
I	Current
SSE	Sum squared error
MSE	mean square error
V	Voltage
P	Power
R	Internal resistance
t	Charging time
EIS	Electrochemical impedance spectroscopy
T	Temperature
TCN	Temporal convolution network
Q	Heat generation rate
LR	Linear Regression
KNN	K-nearest neighbors
RF	Random forest
DT	Decision tree
TCN	Temporal convolution network
RMSprop	Root mean square propagation
SLFNS	single layer feed-forward neural network
ELM	Extreme learning machine
GA	Genetic algorithm
CPCM	Composite phase change material
PCM	Phase change material
AV	Air velocity
WV	Water velocity
CFD	Computational fluid dynamics
BTMS	Battery thermal management system
BTM	Battery thermal management
BTP	Battery temperature prediction
BBM	Base bars material
CS	Compressor speed
AFV	Air flow velocity
CFR	Coolant flow rate
VS	Vehicle speed
BC	Battery configuration
AP	Air pressure
AFD	Air flow direction
FFD	Fluid flow direction
CD	Channel dimension
FM	Fluid medium
AFR	Air flow rate
DOD	Depth of discharge
DR	Discharge rate
CT	Coolant temperature
HF	Heat flux
AR	Aspect ratio

Pr	Prandtl number
Re	Reynolds number
k	Thermal conductivity
RMSE	Root mean square error
ABE	Average absolute error

Subscripts

N	Index parameter
i	Index parameter
j	Index parameter
ϵ	Insensitive loss
ij	Input number vector and neuron number respectively
t	Index of time step
f	Forget gate
c	Memory cell
z	Update gate
o	Output gate
r	Reset gate
h	Output vector
y	Output
u	Input
ε	Smoothing factor

Superscript

T	Transpose

0. Introduction

The increasing availability of data and the fast advancement in the numerical algorithms have led to significant growth of ML in many different applications, including those in cyber security, health (Sarker et al., 2020), machinery (Zhao and You, 2022), advanced energy materials (Liu et al., 2021), and electronics (Jiang et al., 2022a). ML is acting as an important tool in system design and optimization, due to its ability to effectively identify the optimal solution among multiple factors in a very short period of time (Andersson et al., 2022). Completing this task through experimentation and numerical simulation can be a challenging process. Were, experiments can only provide solution for a small set of predefined settings. conducting experiments to explore every possible scenario can be impractical or even impossible. Therefore, the solutions gained from experiments may be limited to these predefined settings. Furthermore, producing a single solution for a particular case scenario through numerical simulations, such as computational fluid dynamics (CFD) simulations, demands significant amounts of time and computer resources (Li et al., 2023). Therefore, using ML in this applications can be considered to some level a solution for this problem. Were it can find the optimal solution and give the system the capacity to automatically learn from experience and improve without being formally designed using this dataset (El Misilmani et al., 2020).

One of the crucial need for machine learning are batteries technology especially in lithium batteries. Lithium batteries have been widely used in the fields of personal electronic devices, stationary energy storage systems, and electric vehicles, due to numerous factors, including climate change, system stability and dependability, high energy/power, reducing utility demand, etc. however, applications of the batteries in the developing energy storage sectors are still being held back by temperature-related problems, such as cycle life reduction at high temperatures and poor performance at low temperatures. Numerous numerical models have been put forth in the last few decades to help us understand the thermal characteristics of batteries. Among these, thermoelectric models can determine the battery's heat generation and precise internal temperature distribution. However, because there are so many equations and physical and thermal characteristics, these models are challenging to use. Machine learning technologies and hybrid combination between machine learning and numerical models may be effective and useful tools for forecasting the electrical and thermal behavior of non-linear energy storage devices due to their advantages such as speedy self-learning from training data and minimal computing burden, among others (Ilager et al., 2021). Number of references used machine learning to address the problems of batteries technologies. Ng et al. examined how machine learning was used to estimate the status of charge and health of batteries (Ng et al., 2020). The research by Zhang et al. examined the application of deep learning technologies on prognostics and health management, including fault detection, diagnosis, and prognosis in application domains such as batteries (Zhang et al., 2019). The research in Chen et al. (2020) and Gu et al. (2019) examined how machine learning is being used in the fields of energy storage and renewable energy materials for rechargeable batteries, with a focus on how it can help with the research, development, and discovery of novel materials. In another study, The author examined how machine learning is used in energy storage systems (Gao and Lu, 2021). Hossain Lipu et al. studied the use of intelligent algorithms for battery technology in electric vehicles and assessed the features, configuration, accuracy, benefits, and drawbacks of intelligent algorithms for battery state estimation (Hossain Lipu et al., 2021). Fig. 1 shows the increase in the utilization of machine learning in battery applications along the past nine years.

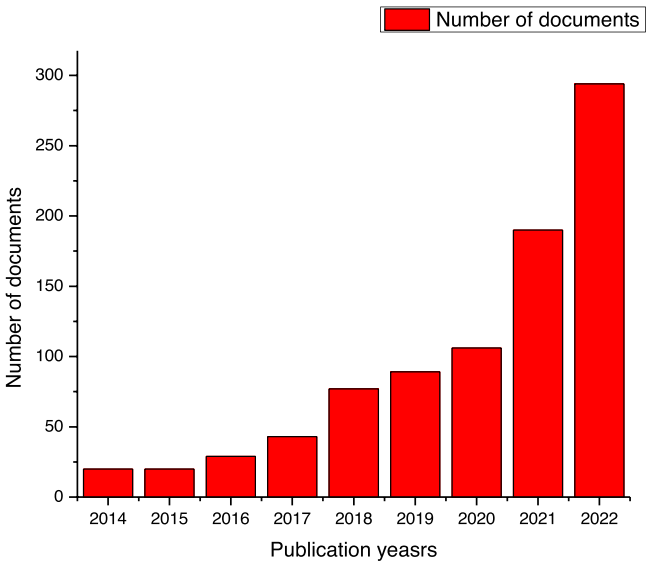


Fig. 1. Number of documents related to machine learning in battery applications on Dimensions AI.

Given the diversity of the fields of energy storage device and system design and machine learning are, a more thorough examination is required to give a more accurate picture and direction of the pertinent state-of-the-art research and development. In this work, we give a thorough overview of various machine learning algorithms that can be used for thermal performance and battery temperature prediction. Therefore, the goal of this work is to offer a fundamental manual for individuals in academia and business

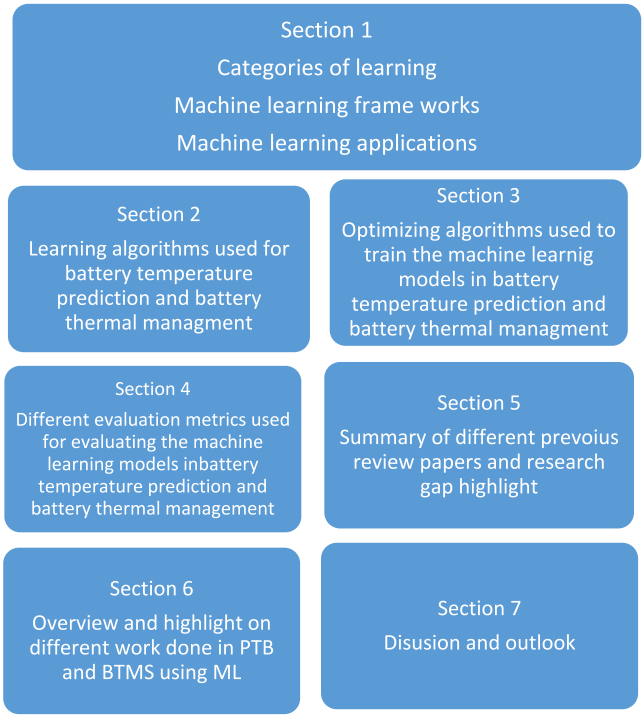


Fig. 2. Organization diagrammatic view.

who wish to learn, investigate, and create data-driven automated and intelligent systems based on machine learning techniques for BTP and BTMS applications.

The following is a list of this paper's main contributions:

- to give a thorough overview of machine learning algorithms that can be used in thermal management and temperature prediction for lithium batteries.
- To mention different frameworks and evaluation metrics used by researchers for BTP and BTMS.
- To provide an overview of how machine learning-based systems can be used to anticipate battery temperature prediction and manage battery heat.
- To highlight and summarize the applications, algorithms, and contribution done by research track.

The paper is organized as follows. Section 1 presents the definition of machine learning and different types of learning and their applications, moreover this section presents different frameworks used to build machine learning models in BTP and BTMS. Section 2 covers and discusses different learning algorithm used for BTP and BTMS. Section 3, mentions different optimization algorithms used for training machine learning models in BTP and BTMS. Section 4 mentions different evaluation matrices used by the research's to validate the ML model in BTP and BTMS. Section 5 recaps previous review papers concerning this topic and highlights different research gaps and mentions the purpose of this research paper. Section 6 highlights different recent work done in PTB and BTMS using ML. Section 7 summarizes the work done in this paper and give a brief discussion and outlook about the topic. The organization of the paper can be summarized in the Fig. 2.

1. Machin learning overview

Machine learning (ML) is a part of Artificial Intelligence (AI) in which it uses data, statistical methods and trained algorithms

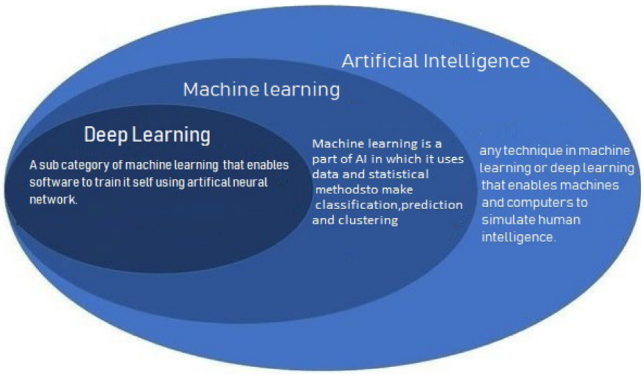


Fig. 3. Relation between artificial intelligence (AI), machine learning (ML) and deep learning (DL).

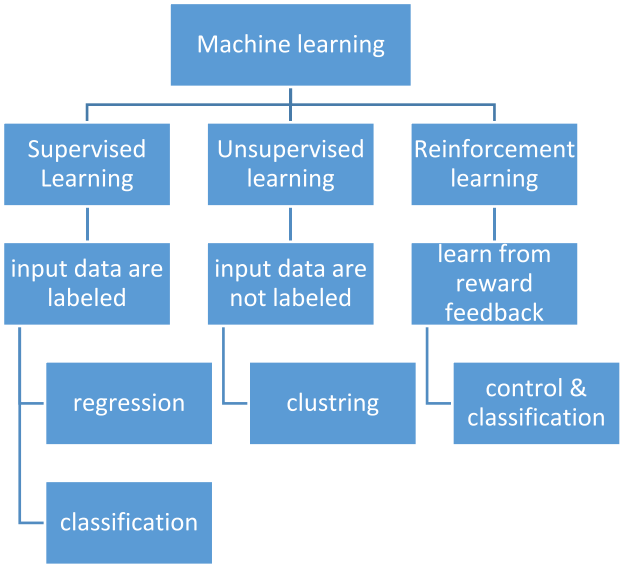


Fig. 4. Categories of learning schematic diagram.

to perform classification, prediction, or clustering. Arthur Samuel defined machine learning as a field of study that gives the computer the ability to learn without being explicitly programmed (Samuel, 2000). In 1998, Tom Mitchell defined machine learning as a computer program that is set to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measure by P, improves with experience E (Mitchell, 1997). Fig. 3 presents the definitions and relationships between artificial intelligence, machine learning, and deep learning.

1.1. Categories of learning

Machine learning can be classified into three categories supervised learning, unsupervised learning, and reinforcement learning (see Fig. 4).

1.1.1. Supervised learning

Supervised learning is considered a subcategory of machine learning were the algorithm is trained using a labeled dataset to predict the output. In supervised learning each training dataset consists of an input object and a desired correct output value. The supervised learning algorithm analyzes the dataset to generate an extrapolated function, which is then used for mapping the

new dataset (Mohri and R, 2012). For example a given number N of training datasets presented by (X1,Y1), (X2,Y2),…., (XN,YN) where X presents the input labeled by Y. The supervised algorithm analyzes the training dataset and derives a function F such that F(X) = Y. When a new input presented as X* is feed to the algorithm, the supervised learner uses the function F to predict an appropriate output label Y*. Usually supervised learning are used for classification and regression applications. Some commonly used supervised learning algorithms for temperature prediction and thermal management are Linear regression (Kumar et al., 2008), k-nearest neighbor's regression, random forest regression, decision tree regression (Tran et al., 2022), least square regression (Cochran and Reda, 2010), Bayes classifier (Jung and Pedram, 2010), artificial neural networks (Pourrahmani et al., 2019).

1.1.2. Un-supervised learning

Unsupervised learning is also subcategory of machine learning that utilizes unlabeled dataset to extrapolate a function that describes the unknown structure of the unlabeled dataset. For example a unlabeled number N of dataset presented by $X_1, X_2,\ldots, X_N$ are feed to the unsupervised algorithm. The algorithm attempts to find a relation or define boundaries to differentiate one set of data from other. Usually unsupervised learning is commonly used for clustering applications (Khanna et al., 2012).

1.1.3. Reinforcement learning

Reinforcement learning is subcategory of machine learning in which it uses trial and error to learn and achieve its goal in an uncertain environment. The interaction between the environment and the learning agent can be modeled using environment inputs set 'S' and a control actions set 'A' selected by the agent along with the reward function 'R' that is used to decide the action to take for a given condition. The model can be present as SxA →R. The main goal of reinforcement learning is to optimize the reward function by figuring out the following policy.

$$\pi\ (s) = a \tag{1}$$

where it decides action a for a certain state s (Sutton and Barto, 1998). The commonly used reinforcement learning algorithms in temperature and thermal management are Q learning (Shen et al., 2012), TD(λ)-learning (Lin et al., 2016).

1.2. Machine learning framework

Machine learning framework is considered any tool that simplifies the development of machine learning models without deeply understanding the used algorithms. Framework can be a platform, library, or any interface. All frameworks can be written using different languages such as python, java, R, C++. Or any other programming language. Most popular frameworks for temperature prediction and thermal management are:

(1) MATLAB deep learning toolbox: framework by MATLAB that enables to design and implement Artificial Neural Network(ANN). With deep learning toolbox, one can generate and build feedforward neural network (FFNN), convolutional neural network (CNN), long-short term memory (LSTM), and other networks to preform classification and regression tasks.
(2) MATLAB ANFIS toolbox: toolbox used for training and tuning a Sugeno-type neuro-fuzzy interface system. Moreover, with the help of fuzzy logic box MATLAB toolbox, one can use ANFIS commends and interactive application for training the system.
(3) MATLAB Neural Network toolbox: a toolbox made by Jingwei Too, that contains six different types of neural networks, which are easy to implement.
(4) Python TensorFlow: a free open source library that is compatible with python language. The library mainly focuses on training and inference of ANN.
(5) Python scikit-learn Machine: an integrated module with python that contains large varying machine learning algorithms (MLA) used for supervised and unsupervised learning problems. The module focuses on simplifying machine learning and introducing it to non-specialists.
(6) MATLAB Neural Net Time Series toolbox: toolbox that simplifies modeling and implementing dynamic neural networks at time-series applications. Using time series toolbox and app you can simply train three types of NN, nonlinear autoregressive with exogenous input (NARX), nonlinear autoregressive (NAR), and nonlinear input–output network.
(7) Python-keras: an open source library compatible with python for creating ANN. Keras apply best practices to simplify problems and minimize load.
(8) PyTorch: is an open source machine learning framework based on torch library. It is one of the preferred platforms for deep learning research.

There are lot of other frameworks used for ML such as MXNet, Caffe, H20, Theano, Shogun, Weka, Apache Singa, and many other that one can explore. Moreover, many other libraries such as Pandas, Numpy, and Jupyter Notebook can be used for data manipulation and analysis, array and matrices support, and arrange workflow respectively, to further facilitate ML problems.

1.3. Machine learning applications

There are numerous domains where ML can be implemented. Ranging From molecular dynamics (Li et al., 2015) to building financial (Heaton et al., 2017). In the domain of mechanical engineering, machine learning can be leveraged to enhance productivity and efficiency in manufacturing process. This can be achieved through using ML in quality control, reducing manufacturing time, lowering material waste and more (Liang et al., 2013). ML can also help in diagnosing faults in automobile gearboxes (Praveenkumar et al., 2014), can be used in wind speed applications (Mohandes et al., 2004), predicting wear, and material selection (Geetha and Bridjesh, 2020). several studies utilized machine learning tools to establish relationships between performance parameters within finite value ranges for prediction and thermal management. Dong Hyun lee et al. employed machine learning techniques to develop a condensation heat transfer model for passive cooling contaminant cooling system in advanced light water reactor (Lee et al., 2022).

Lee et al. (2021), Cho et al. (2022) and Bard et al. (2022) used machine learning tools to predict heat transfer coefficient and pressure drop coefficient for flow boiling and flow condensation in mini/micro channels for high heat dissipation and thermal management. Yang Ge et al. used reinforcement learning algorithm to perform a dynamic thermal management for multimedia applications (Ge and Qiu, 2011). Machine learning is also used to control thermal stresses, energy, and power consumption in electronics (Pagani et al., 2020; Acharya et al., 2021)

2. Learning algorithms for battery temperature prediction and thermal management

Learning algorithm is an essential part for applying machine learning in temperature prediction and thermal management of batteries. with the aid of these algorithms and fair amount of dataset, it becomes possible to establish a nonlinear mapping function to preform prediction and thermal management. This section provides a discussion and list of commonly used learning algorithms.

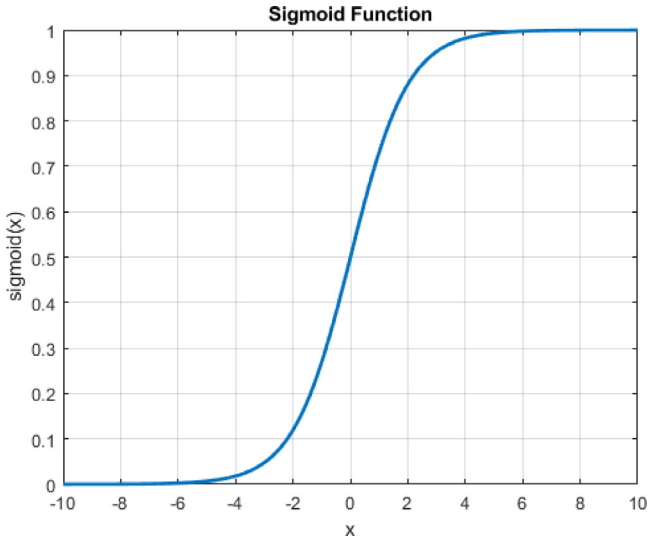


Fig. 5. Sigmoid function.

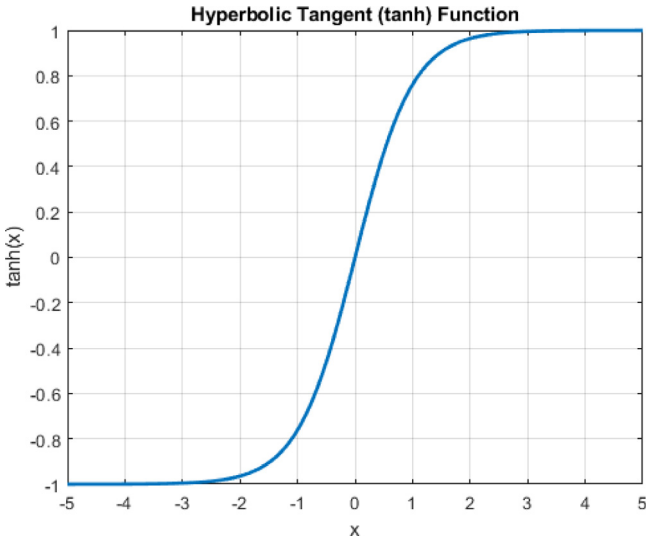


Fig. 6. Tanh function.

2.1. Artificial neural network

Artificial neural network (ANN) is a machine learning technique inspired from human brain structure. ANN are greatly known for function approximation and regression problems. In general, Artificial neural network is a web of interconnected entities called nodes, creating an input layer, one or more hidden layers and an output layer. Each node is connected to each other with a specific weight threshold. Each node has an activation function f(x) which is a fixed nonlinear function used to compute the output. The individual node is activated and pass by the data to the next layer node, only if the calculated output is above the threshold, otherwise no data is sent to the next layer node. The output value of Y of each neuron can be expressed as

$$Y = F\left(\sum_{i}^{2} P_i W_{ij} + b_j\right) \tag{2}$$

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.

Logistic function also known by sigmoid function can be presented as follows

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

As shown in Fig. 5, 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

$$\mathrm{f}(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{4}$$

The function can be presented in the Fig. 6. 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, otherwise it will output

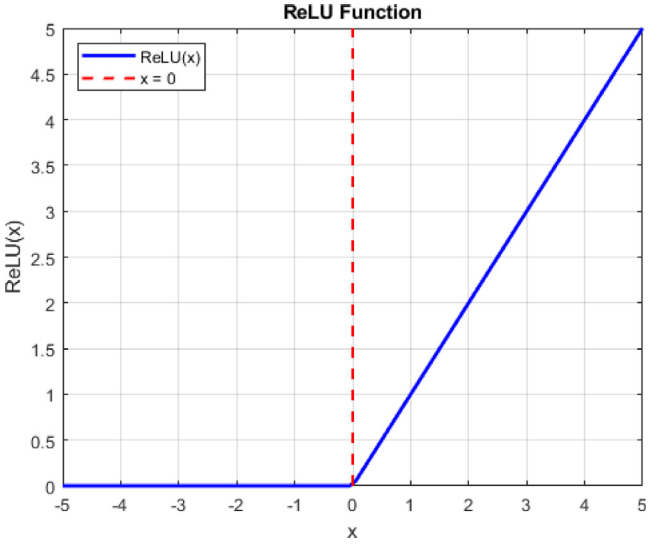


Fig. 7. ReLU function.

0. ReLU can be presented in form of the equation below.

$$ReLU\ (x) = \begin{cases} 0\ if\ x < 0 \\ x\ otherwise \end{cases} \tag{5}$$

The function is presented in the Fig. 7. The output of the function is zero when the value of x is negative and it is linear when it is positive.

The weight and the biases plays a big role in the prediction accuracy, so during the training process different optimizing algorithms can be used to reduce the network error by adjusting the network weight and biases constantly.

Artificial neural network can make accurate decisions without human intervention. ANN can be categorized into feed-forward, recurrent, modular, and convolutional neural networks.

Feed-forward neural network passes the data from the input layer to the output layer, while recurrent neural network fed back the data into the input at a specific point before proceeding forward to the output. In RNN, the weights are shared across time steps, and the outputs of each neuron are dependent on the previous ones, updating using the same formula. on the other

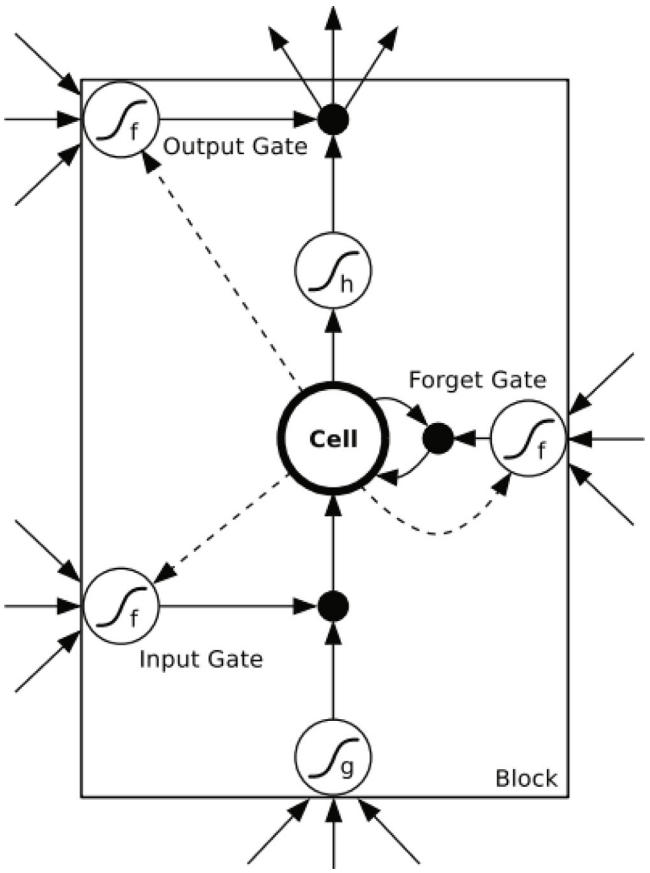


Fig. 8. LSTM memory block with a single cell (Graves, 2012).

hand, modular neural network consists of series of independent neural network. Each independent neural network operates on separate inputs to complete subtasks of the hole task that the network wants to preform, whereas, the convolutional neural network is similar to feed forward neural network but the connectivity pattern between the nodes is inspired by animal visual cortex (Abiodun et al., 2018).

2.1.1. Long-short term memory

Long-short term memory (LSTM) is an advanced type of conventional RNN which solves the problem of gradient exploding. LSTM stores the data for long period of time that RNN cannot do. The main architecture difference is that LSTM is made up of gated cells in the hidden layers. Each LSTM unit have three logistic sigmoid gates (forget gate, input gate, and output gate) and one tanh layer (see Fig. 8).

The only difference between an LSTM network and a typical RNN is that memory blocks are used instead of summation units in the hidden layer. The vanishing gradient issue is reduced by utilizing multiplicative gates that enables memory cells to retain and retrieve information over extended periods. With the input gate closed, the cell's activation is preserved and will not be overwritten by new inputs. Subsequently, the output gate can be opened later in the sequence to make the cell's activation available to the network. This feature allows the network to retain critical information from earlier sequences and use it to enhance its predictions (Graves, 2012).

The forget gate decides wither the information get forgotten or not, the forget gate can be expressed as

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{6}$$

where x is the input value, h is the hidden state value at previous time step, b is the bias, W and U are weight matrixes of the previous hidden layer and from the input to the hidden layer respectively. The substrates presented t, f, c and o in the below equations are the index of time step, forget gate, memory cell, and output gate respectively.

The input gate edits the information to be added by sigmoid function and new vector can be expressed as

$$\check{c}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{7}$$

were $\check{c}_t$ is cell input activation vector.

The cell state c_t is then updated by clearing the previous cell memory and adding new ones, were f is the forget gate activation function, and i is the input/update gates activation function.

$$c_t = f_t c_{t-1} + i_t \check{c}_t \tag{8}$$

Finally the output gate o_t determines the next hidden state with the previous information and the output h_t is calculated (Sherstinsky, 2020)

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{9}$$

$$h_t = o_t tanh(c_t) \tag{10}$$

2.1.2. Gated recurrent unit

Gated recurrent unit (RGU) is an equally effective method like LSTM to solve vanishing and exploding gradients. The main difference between GRU and LSTM is that GRU modulates the information flow instead of cell states using hidden states. GRU consists of two gates, the update gate which have a similar function to that of forget and input gates in LSTM. The update gate z_t, decides what amount of information to be added or forgotten and it can be express as shown in the equation below. The substrates t, z, and r presented in the equations below are the index of time, update gate, and reset gate respectively.

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1} + b_z\right) \tag{11}$$

were σ is the original sigmoid function, W,U, and b are parameter matrices and vector, and h is output vector

The other gate is the reset gate r_t, in which it decides which previous information passes to current state and it can be expressed as

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1} + b_r\right) \tag{12}$$

Lastly, the candidate activation $\check{h}_t$ and activation value h_t that are a sub part of the reset gate can be expressed as (Dey and Salem, 2017)

$$\check{h}_t = tanh(W_h x_t + U_h(r_t h_{t-1}) + b_h) \tag{13}$$

$$h_t = (1 - z_t)\, h_{t-1} + z_t \check{h}_t \tag{14}$$

2.1.3. Nonlinear autoregressive network with exogenous inputs

Nonlinear autoregressive network with exogenous input (NARX) is a recurrent neural network that is commonly used in time series application.

The autoregressive (AR) and exogenous inputs (X) parts make up the two primary parts of the NARX model. The X part models the effect of outside factors on the time series, while the AR part shows the temporal relationships between past and present time series values. NARX network can be practiced in different forms, it can be applied in closed form, open form, and open/closed-loop for multistep prediction. NARX can be used in many applications such as nonlinear filtering, and nonlinear dynamics system modeling, also it can be used for prediction. NARX predicts the future values of the time series by using the past values series. NARX maps the input and the output using a multilayer perceptron including time delay unit and output feedback in the input

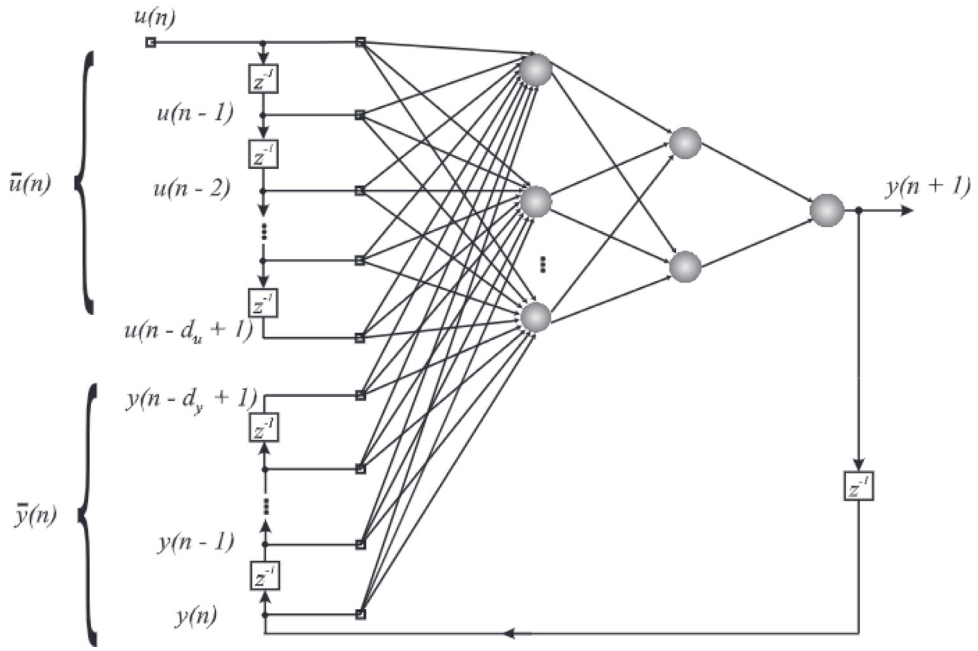


Fig. 9. Two hidden layer NARX network with du and dy delayed outputs (Menezes and Barreto, 2008).

layer (Liu et al., 2020) . The NARX model can be expressed as an equation presented below.

$$y(t) = f(y(t-1), y(t-2), \ldots, y\left(t-n_y\right), u(t-1), u(t-2), \ldots, u(t-n_u) \quad (15)$$

where $y(t)$ is the predicted output value, $u(t)$ is the input variable, n_y, n_u are the input and output time delay variable respectively (Yu et al., 2020). Eq. (15) can be written as vector form.

$$y(t) = f[y(t-1); u(t-1)] \quad (16)$$

where $(t-1)$, *and* $u(t-1)$ are the output and input regressor vectors respectively.

A typical multi-layer perceptron network, for instance, can approximate the nonlinear mapping function f, which is typically unknown. A NARX network is then used to describe the resulting connectionist design. The Fig. 9 shows a two hidden layer NARX network (Menezes and Barreto, 2008).

2.1.4. Temporal convolution network

Temporal convolution network (TCN) are suitable for time series data and have been recently proposed as a method that demonstrates superiority over CNN and RNN. The network combines 1 D fully convolutional network with causal convolutional. TCN network guarantees that the future information will not be affected by the past information, also it allows information to be transmitted as a cross layer manner (Chen et al., 2021).

2.1.5. Adaptive neuro-fuzzy inference system

ANFIS is a universal estimator technique used in machine learning. ANFIS captures the benefits of fuzzy logic principles and artificial neural network principle in one framework. ANFIS is very sensitive for type and number of membership functions, and it is considered efficient for input numbers above five. The network is mainly composed of five layer (see Fig. 10).

The first layer known as fuzzification layer where membership functions are assigned to the inputs, the second layer where fire strength rules are generated, the third layer is for normalizing, the fourth layer is responsible for defuzzification process of the

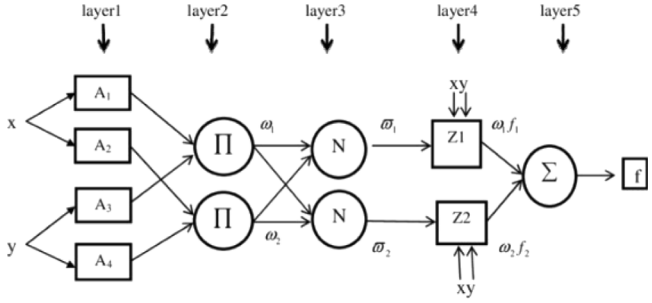


Fig. 10. Adaptive neuro-fuzzy inference system structure (Khoshnevisan et al., 2015).

normalized value, and the last layer is the output. This type of network accelerates learning and has high interpretation abilities, that can solve complex recurring problems. ANFIS uses different optimization algorithms during training to optimize its parameters such as gradient decent and Metaheuristic techniques (Jang, 1993).

2.2. Linear regression

Linear regression (LR) is the simplest type of machine learning algorithm based on supervised learning. This technique creates a linear relation between dependent variables (Y) and independent variables (X). This linear relation is referred as hypothesis function and can be presented as follows

$$Y = \theta_0 + \theta_1 X_1 + \theta_2 X_2 + \cdots + \theta_N X_N \quad (17)$$

where Y is the expected output(label), X is the input (training data-different parameters), θ_0 is the interception, θ_N is the coefficient of X.

The aim of linear regression ML technique is to determine the optimal values of θ_0 & θ_N to create a best fit line, which leads to accurate prediction of value Y based on data X in testing process. This fitting process is achieved by minimizing the cost function using optimization algorithms such as gradient descent,

Stochastic Gradient Descent, or other algorithms. The cost function in linear regression is the root mean square error between the predicted value and the true value of Y.

$$J = \frac{1}{n}{}^{n}_{1}\Sigma(preduction - Y)^2 \tag{18}$$

where J is the cost function (Maulud and Abdulazeez, 2020).

2.3. Gaussian process model

Gaussian process model is a supervised machine learning method, that employs Bayesian principle to give a statistical surface model response. This method is widely used in complex problems with high dimensionality, high non linearity and, sparse samples. The importance of Gaussian process lies in its ability to address the important goals related to design variables. Gaussian process can be expressed as follows

$$\hat{y}\left(X^*\right) = \mu + r^T R^{-1}(1 - I\mu) \tag{19}$$

where X^* is the prediction at a certain input, I is n $\times$ 1 vector of ones, μ is the mean prediction distribution, R and r are the correlation functions (Santner et al., 2003).

2.4. Support vector regression

Support vector regression (SVR) is a supervised learning algorithm inspired by support vector machines, which is primarily used for classification applications. The objective of SVR is to identify the best hyperplane fit in a N-dimensional space that collects the maximum number of points. in case of linear hypothesis, SVR separates the data into two sets, points that fall within a predefined limits of width $\epsilon > 0$ which are accepted, and other set of points that falls outside the predefined limits which are considered penalized as shown in Fig. 11.

$$H = (x \mapsto w.\Phi(xi) + b : w \in R^N, b \in R) \tag{20}$$

where Φ is the future mapping that corresponds to a positive definite symmetric k kernel function and w. $\Phi(xi)$ is the future mapping dot product. Training this model is done by optimizing the cost function presented below.

$$\frac{1}{2}|w|^2 + C\sum_{i=1}^{m}|y_i - (w.\Phi\,(xi)) + b|_\epsilon \tag{21}$$

where $|.|_\epsilon$ corresponds to ϵ-insensitive loss. The value of ϵ plays a big role in the accuracy of the model (Mohri et al., 2012).

2.5. K-nearest neighbors

K-nearest neighbors (KNN) is a supervised ML technique that can be employed for both regression and classifications tasks. KNN can easily capture the similarity between the dataset by calculating the distance. Various methods such as Euclidean, Manhattan, and Hamming distance can be utilized to calculate this distance. KNN can predict the label value Y, by finding the predetermined training object number that are near the new points. In other words, the new data is given a value based on how near it is to the training data based on the calculated distance. This technique is considered simple and straight forward as it does not need any optimization algorithm, it only requires tuning the k value (Bansal et al., 2022).

2.6. Random forest

Random forest (RF) is a popular supervised ML technique that can be used in classification and regression problems. RF consists of combined multiple trees. The given dataset is divided into subset and fed to the decisions trees to make its own decision. The final decision/prediction is taken on the majority voting results. No optimization algorithm is needed for RF (Rigatti, 2017).

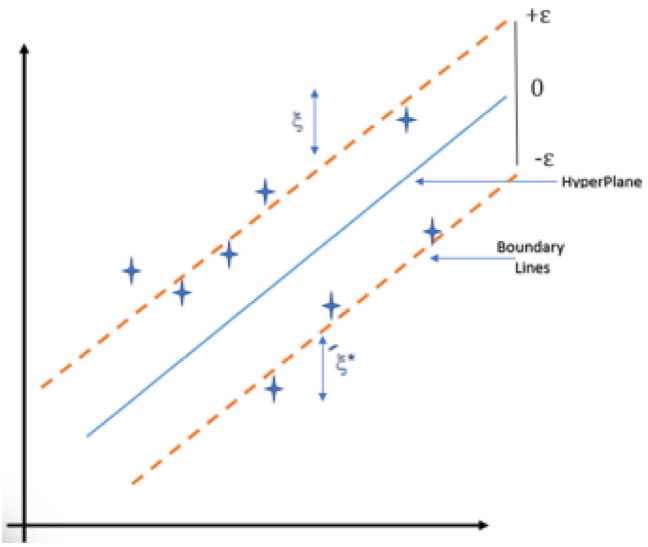


Fig. 11. Support regression vector (Pedamkar, 2023).

Table 1
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

2.7. Decision tree

Decision tree (DT) is a supervised machine learning algorithm that can perform prediction and classifications tasks. it can be visualized as a flow chart tree structure where each internal node preforms a test attribute, each branch represents the outcome of the test, and each leaf node corresponds to a class or to a prediction. This method is considered fast and can easily preform data fitting, with no need for optimizing algorithms (Jena et al., 2022).

All of the mentioned ML algorithms in Section 2, are used by researchers in battery temperature prediction and thermal management as shown in Table 1. However, the performance of these algorithms may vary depending on the data set, training algorithms, and other parameters. It is important to note that there is no one algorithm that is superior to others. The choice of algorithm depends on the specific application and data characteristics. Therefore, it is essential to try different algorithms, training algorithms, and parameters to identify the best fit for a particular application. Researchers should not rely solely on one algorithm but should instead experiment with various algorithms to ensure optimal results. The use of multiple algorithms will also provide better insights into the underlying data and the best ways to optimize the battery thermal management system.

To forecast battery temperature and to control thermal performance, researchers are increasingly using machine and deep learning approaches. Existing literature indicates that among

these techniques, ANN particularly LSTM, GRU, NARX, and FFNN, offer advantages in battery temperature prediction and thermal management. The advantage of using ANNs, specifically LSTM and GRU models, is their ability to handle time series data with long-term dependencies, which is particularly useful in predicting battery temperatures over extended periods. These models are also capable of learning from past data and adapting to changing conditions, which is critical in battery thermal management applications. On the other hand, NARX models allow for the inclusion of external variables that may affect battery temperature, such as ambient temperature, humidity, and charging and discharging currents. This additional information can improve the accuracy of temperature predictions and aid in thermal management. Finally, FFNN are suitable for predicting battery temperature at a single point in time, which can be useful in applications where real-time monitoring is required. However, they may not be as effective in predicting temperature trends over longer periods or in handling external variables (Lu et al., 2022).

3. Optimization training algorithms in battery temperature prediction and thermal management

ML algorithms should be trained to be able to solve the regression, classification, and clustering problem. Training is a process used in machine learning where a set of input data is feed to run through a machine learning algorithm. The machine learning technique analysis and correlates its output with the sample output and then uses this correlation results to modify the model. This process is iterative where the model output is modified each iteration to reduce the error and find the best solution. Some common ML algorithms such as linear regression, ANN needs an optimization algorithm. These algorithms minimize the cost function and determine the optimal weight and bias parameters. 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.

3.1. 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:

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J\left(\theta_i, \theta_j\right) \tag{22}$$

where θ_j is the weight, α is the learning rate of the gradient descent, $J\left(\theta_i, \theta_j\right)$ is the cost function, i & j are number index.

From the equation above gradient descent is the partial derivative with respect to its inputs and it can be expressed as a slope of a function. The sharper the slope, the higher the gradient and the learning. The model stops learning when the slop is zero.

Gradient descent is considered slow and computationally expensive over a large dataset, since it performs calculation over the hole dataset at each time step (Lemaréchal, 2012).

3.2. 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 (Bottou, 2012).

3.3. 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.

$$X_{t+1} = X_t - \left(J^T J + zD\right)^{-1} * J^T c \tag{23}$$

where X_k is weight vector, J is Jacobian matrix, D is unit matrix, 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, However, as the output value closes to the optimal solution the function starts to descend slowly. Newton method enhances the search near the optimal value in the gradient descent method in which it reduces time and accelerates convergence (Levenberg, 1944).

3.4. Root mean square propagation

RMSprop 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.

$$E\left[\nabla^2\right]_t = \gamma E\left[\nabla^2\right]_{t-1} + 0.1\nabla^2{}_t \tag{24}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E\left[\nabla^2\right]_t + \varepsilon}} \nabla_t \tag{25}$$

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, $E\left[\nabla^2\right]_t$ average moving of squared gradient, θ is set of hyper parameters or weights (Hinton, 2018).

3.5. 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 (Burden and Winkler, 2008).

3.6. 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 Guang-Bin (Huang et al., 2006). 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 (Wang et al., 2021b).

3.7. Genetic algorithm

Genetic algorithm (GA) is considered an evolutionary algorithm which is inspired from biological behavior and evolution of human creature. At each time step, the genetic algorithm randomly selects individuals from a population and make benefit of this parents to produce children for next generation. The repeated process of creating new generations ends up in evolving and reaching the optimal solution. Combining genetic algorithm with ANN has shown its ability in modeling complex nonlinear relationships (Arab et al., 2016).

3.8. ADAM

ADAM was firstly presented by Diederik Kingma and Jimmy Ba in 2015 a (Kingma and Ba, 2014). ADAM is an optimization algorithm that updates the network weights during training process instead of using classical stochastic gradient descent. Adam combines the benefits of Adaptive gradient algorithms(ADAGraf) and Root mean square propagation (RMSprop) in which it makes use of the first and second average moments of the gradients. It calculates the exponential weighted average of both gradients. This method is efficient and requires less memory for problems with large data. The mathematical equation for ADAM optimization can be presented as

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\frac{\delta L}{\delta W_t} \tag{26}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)\left(\frac{\delta L}{\delta w_t}\right)^2 \tag{27}$$

where m and v are aggregate of gradient and sum of square of gradients respectively at current and previous times, W is the weight at current time, $\frac{\delta L}{\delta W_t}$ is the derivative of the loss function with respect to the weight, β is the decay rate of the average moving parameters for the two methods,

To avoid oscillations near the local minima, the optimization computes the corrected bias $\widehat{m_t}$ *and* $\widehat{v_t}$

$$\widehat{m_t} = \frac{m_t}{1-\beta_1^t} \tag{28}$$

$$\widehat{v_t} = \frac{v_t}{1-\beta_2^t} \tag{29}$$

After correcting the normal weight parameters m_t *and* v_t, ADAM introduce those new parameters in the equation below

$$w_t = w_{t-1} - \widehat{m_t}\left(\frac{\alpha}{\sqrt{\widehat{V_T}+\epsilon}}\right) \tag{30}$$

Where α is step size, ϵ positive constant.

Based on the performance, ADAM gives low training cost and high performance than of ADAGrad, and RMSprop (Llugsi et al., 2021). Many other optimization algorithms are used in thermal management such as Polak Ribiere Conjugate Gradient, and Scaled Conjugate Gradient. In some studies, optimization algorithms are needed to optimize parameters. The most popular optimizing algorithm used in thermal management is particle swarm optimization. Moreover, this optimization can be combined with other algorithms such as search and rescue algorithm or fuzzy logics.

4. Evaluation metrics for batteries temperature prediction and thermal management models

To assist the performance of the ML model and its accuracy, it is important to define an evaluation metrics. Sometimes simple methods such as calculating the difference between the actual value and the predicted value is not enough for evaluating the model. Where a need of other measures to asset the model is needed. Sum squared error (SSE), mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE) are common and popular metrics used to assist the ML model in batteries temperature prediction and thermal management (Kartam and F, 1996). SSE is sum of the difference between the true and predicted value squared, MSE is SSE divided by number of observations, and MAE is the same as MSE but instead of squaring the difference an absolute value is done, and RMSE is the root square of MSE. Moreover, there are different metrics used such as R-squared (R^2), average absolute error(AAE), standard deviation error(SDE), explained variance, max error, and correlation.

5. Previous review papers on batteries temperature prediction and thermal management using machine learning

Several review papers on the subject have been published recently. These papers seek to offer an organized overview of the research done in this field, including the most recent developments and difficulties. Review articles are valuable because they can pinpoint knowledge gaps, research trends, and offer a critical evaluation of already conducted research. Review papers are essential for synthesizing and summarizing substantial quantities of research because they help scholars and practitioners understand the state-of-the-art in a certain topic. In this section different recent review papers will be summarized and discussed and compared to this study (Hull and Houston, 2020).

S. babu sanker et al. reviewed different research efforts on enhancing the thermal management of lithium batteries using PCM. In this study the authors give a complete insight on the design, working principles, chemistry, and thermal issues of lithium batteries. Moreover, the authors target different active and passive cooling technologies and focuses on cooling using PCM. Different thermal conductivity enhancers for PCM are also mentioned and discussed in this paper. At the end of the paper the authors address the importance of using ML in multiscale modeling for PCM based lithium batteries. Only few studies are mentioned and discussed in this study, and it is clear from the authors that ML plays a big role in enhancing the thermal management process. hence it is important to do more work and light on how ML can be used in the thermal management process (Babu Sanker and Baby, 2022).

Aykut can et al. reviewed the application and uses of nanofluid on soft computing for battery thermal management. In this paper, the authors discuss and mentions a wide introduction on lithium batteries, and different cooling techniques. Moreover, the authors give a fundamental introduction to Nano fluids and soft computing. in this review the authors focuses on the potential of using Nano fluids in batteries thermal management. The authors also highlight few work done with the help of ML and they stated that it is an excellent tool that should be considered in future studies (Can et al., 2022).

Ao Li et al. made a recent review on battery thermal management using ML. In this review paper, the authors summarize lists of literature on BTMs using ML models and identify the most recent state-of-the-art research. The use of different ML models in battery fire diagnosis and early warning is also demonstrated. moreover, the authors provide enhanced methods for managing advanced battery safety using ML (Li et al., 2023).

A state of art review about lithium battery thermal management using ML with exergy, and other factors is done by Sayed et al. In this study different active and passive cooling techniques for lithium-ion batteries using diverse energy, economic, environmental, and machine learning methodologies are covered (Parsa et al., 2023).

Table 2
Summary table for previous overview papers.

Author	Work summary	Research gap
Babu Sanker and Baby (2022)	This paper provides a whole explanation on the lithium batteries design, operation, chemical composition, and thermal issues. The benefits of using active and passive cooling technology are emphasized. with a particular emphasis on PCM-based cooling. The paper also provides full details on PCM classification, selection, manufacturing and methods of enhancing their thermal conductivity	Recently, multi-scale modeling of PCM-based Li-ion battery thermal management has also been modeled using machine learning techniques. The use of artificial neural networks or other modeling tools for the prediction of various battery thermal management system parameters is currently rare in the literature, and the application of optimization approaches is even rarer.
Can et al. (2022)	This paper reviews different applications for nanofluids and soft computing for lithium thermal management. In this paper the authors introduce lithium batteries and different cooling techniques. Moreover, the authors gives a fundamental background on Nano fluids and soft computing and then focuses on different work done on thermal management using Nano fluid and soft computing	The authors stated that Multiparametric and multiphysics modeling of BTMS design can be done using deep learning and other cutting-edge machine learning techniques and they may consider it in future work.
Li et al. (2023)	In this review study, the authors identify the most recent state-of-the-art research and summarize lists of literature on BTMs using ML models. It is also shown how several ML models may be used for early detection and diagnosis of battery fires. The authors also offer improved strategies for applying ML to manage advanced battery safety.	The authors stated that the ML has high potential and can be integrated in BTMs in different ways. Also, they stated that there is large room for improvement and hug research gaps to be explored.
Parsa et al. (2023)	This current review discusses numerous active and passive cooling techniques for lithium-ion batteries using diverse energy, economic, environmental, and machine learning strategies. In addition, applications of data-driven and machine learning to the thermal control of Li-ion batteries and how they affect this context are discussed	The authors stated that ML showed a vital role in lithium thermal management. Also they discovered that some algorithms produce findings that are more accurate than others. In this context the authors suggested future research to compare the outcomes of various algorithms.
Sukkam et al. (2022)	This study shows a description of how BTMS is used in the development of electric vehicles, as well as how machine learning techniques are used to forecast and improve BTMS performance based on fast-charging protocols.	The authors addressed few references for ML in BTMS and focused more on using ML for fast charging.
Ghalkhani and Habibi (2022)	The authors examined the application of ML in BTMs for electric cars. The authors of this study discusses the most recent developments in battery design, thermal management, and the application of artificial intelligence to battery management systems. The authors came to the conclusion that employing AI-based predictive algorithms in BMS can both enhance reliable real-time data processing for electric car applications.	The authors stated that the ability of ML technology to estimate battery SOH is crucial. Therefore, the focus of the research's outlook for future research should be on integrating improved battery models and algorithms onto the cloud-based BMS and the challenges of doing so onboard.

Natthida et al. reviewed the application of ML in batteries thermal management inside electric cars. The authors saw that ML is becoming an important tool for researching and improving fast-charging battery technology. Were ML was successfully used to design ten-minute fast-charging protocols that used to specify the battery's current and voltage inputs (Sukkam et al., 2022).

Mayram et al. also reviewed the use of ML in BTMs for electric vehicles. In this study the authors present the most recent technological advancements in battery design, thermal management, and the use of AI in battery management systems. the authors concluded that reliable real-time data processing for electric car applications can both be improved by applying AI-based predictive algorithms in BMS (Ghalkhani and Habibi, 2022). Table 2 provides a comprehensive summary of recent reviews and highlights the identified research gaps.

The purpose of this review paper is to provide a simplified background on machine learning and different algorithms, with a focus on their applications in lithium battery thermal management and temperature prediction. While previous studies have emphasized the importance of machine learning in this field, most review papers only touch on a few studies and did not delve into the specific structures and algorithms used. As this is a relatively new topic for many researchers, there is a need for more comprehensive and accessible reviews that can help researchers apply machine learning tools in their studies and improve their outcomes. By summarizing the different works done in battery temperature prediction and battery thermal management, and providing a deep understanding of the structures of the models used, this review paper aims to bridge this gap in the literature. The benefits of this review paper over previous ones lie in its comprehensive and accessible nature, which will enable researchers to gain a deeper understanding of machine learning algorithms and their applications in battery thermal management.

6. Application of machine learning in battries temprature prediction and thermal managmenet

Energy storage devices are becoming an essential part due to the increasing amount of renewable energy resources. their importance lies in improving the power quality, stability and reliability of the system, increasing the market value by varying generation sources, increasing the value and reliability of renewable energy sources, and by reducing the cost of investments (Rufer, 2017). Batteries are a type of energy storage devices that can support solar and wind energy production by storing the excess energy produced and can be used in electric vehicles. Despite rapid improvements in battery technology, addressing battery degradation remains a significant concern (Scrosati and Garche, 2010). Batteries are less attractive when its energy storage capacity drops. 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 (Hasan et al., 2017). 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 (Motloch et al., 2002). Cell temperature distribution also plays a big factor in lifespan of the battery. To maximize the lifetime of the battery it is needed to limit the cell temperature difference to below 5 °C (Park and Jaura, 2003;

Mahamud and Park, 2011). Different studies showed that the overall capacity and lifespan is reduced when the cell experiences a high non-uniform temperature distribution (Ratnakumar et al., 2003; Semerie, 2000). Therefore, it is important to accurately predict temperature of battery cell and apply an optimized thermal management to maintain battery life and reduce the cooling cost. Machine learning is one of the favorable technique compared to complex mathematical equations, physics based equations and empirical equations. The advantage of machine learning is that it accelerates the understanding of new material with less computational efforts.

6.1. Temperature prediction

Since introduction of battery in electric vehicles and other applications, battery life and temperature has been an important subject of investigation. There are different approaches for temperature prediction. Electrochemical modeling which is a physics based model that requires a moderate amount of data and understanding of physical and chemical laws is considered a one type. This type of model is considered the most accurate, yet the most complex, while the semi-empirical model which is a performance based model is less complex and less accurate of that of electrochemical model. However, a new method for predicting the temperature is data-driven model. Data driven model is considered a black box model that can only be observed from its inputs and outputs without any knowledge of its internal workings (Hosen et al., 2021). 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 (Tran et al., 2022).

Since battery temperature depends on many parameters and variables, ANN are often considered better approach than traditional ML algorithms such as decision tree. ANN are considered more flexible than other machine learning, were they can handle complex and large-scale datasets, moreover they are more capable to find the complex non-linear relationships between input and output data.

Kaizheng Fang et al. used ANN instead of internal physical–chemical reactions complicated models to predict the surface temperature of nickel-metal hydride battery during charging state under different ambient conditions. From previous experiments, the authors concluded that surface temperature is mainly effected by the charging current, charging time and ambient temperature. A feed-forward artificial neural network (FFNN) with back-propagation is used in the study to predict the surface temperature of the battery. The artificial neural network constructed by the authors is made up of 3 layers. 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 (Fang et al., 2012). In same content, Chen et al. 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 (Chen et al., 2013).

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.

Also Tea-Ryong park et al. used ANN with multi-physics simulation data to predict the temperature of a thermal battery. This data is used along with other parameters in a proposed optimization procedure to find the best optimized heat and weight for the thermal battery (Park et al., 2021).

This study shows that ANN can be integrated with multi-physics simulation for better temperature prediction and control.

Occupying temperature sensor in every battery cell to measure its temperature is not feasible, and also, the sensors are limited to surface temperature measurement. A lot of sensorless mathematical models are done, but they require large computational effort to solve complicated differential equation. Marco Strobel et al. saw that the best way to predict the temperature of lithium ion cell is by using electrochemical impedance spectroscopy (EIS) data with the help of ANN. the authors modeled a FFNN consisting of three layers with tangent activation function using MATLAB toolbox. An experimental investigation is done on 36 different Samsung INR18650-15L1 1500 mAh Lithium ion battery cells at different SOC and temperatures to collect the data. 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 (Ströbel et al., 2021).

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. Jiang YuHeng et al. used recurrent neural network (RNN) with

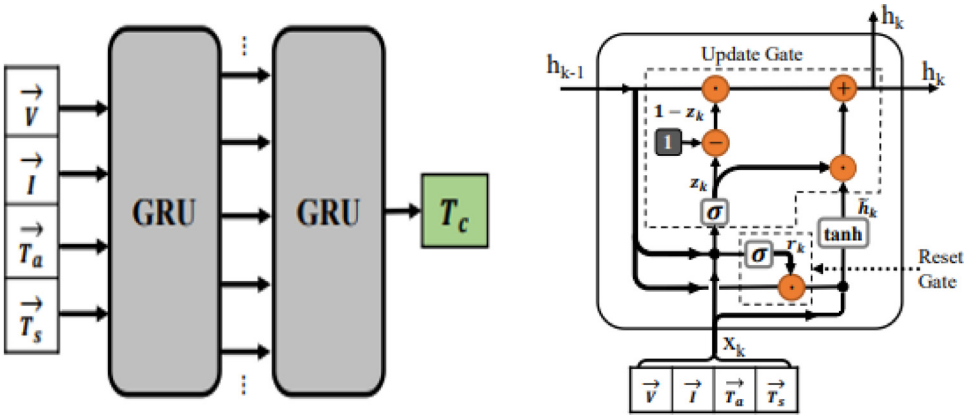


Fig. 12. GRU-RNN and GRU internal structure (Ojo et al., 2020).

back-propagation to estimate Li-ion battery temperature during discharging under different ambient temperatures to ensure high efficiency and safety. During the study the authors examined the performance of two different types of recurrent neural network, the long-short term memory(LSTM) and the gated recurrent unit neural network (GRU). For both types of network, voltage and current are the input signals, and the temperature difference is the output. Number of neurons in the hidden layer is five and three for LSTM-RNN and GRU-RNN respectively. The dataset used to train, validate and test the network are acquired from prognostic center of excellence of NASA. These data are collected from 18 650 li-ion under different conditions, including charging and discharging at different ambient conditions. The dataset is made up of eight discharging cycles. The first seven discharging cycles data are used for training and validation, while the last discharging cycle is used for testing. The two models were trained using LM algorithms on MATLAB 2018b software with a specific initial learning rates of five and ten for LSTM-RNN and GRU-RNN respectively. Results showed that both types of RNN were capable to accurately predict the battery temperature. The maximum absolute error for the two types were approximately 0.75 and the correlation coefficient between predicted and measured temperature was greater than 0.95. Although both networks proved their capability to predict the battery temperature, GRU-RNN was seen to be more sensitive to the initial hyper-parameters (number of neurons, learning rate, number of iterations) which makes LSTM-RNN more robust and favorable (Jiang et al., 2021). In another research, the authors used long-short term memory network (LSTM) to predict the temperature of a battery cell at a certain time. The research demonstrated new thermal and temperature models and a guide for new battery management system (Zhu et al., 2021). Olaoluwa Ojo et al. proposed a gated recurrent unit neural network (GRU-RNN) to estimate the core temperature of a lithium ion battery from input voltage, current, ambient and surface temperatures data as shown in Fig. 12. The proposed model is composed of two GRU-RNN layers. Each GRU-RNN layer is made up of update and rest gate with sigmoid and tangent functions. The two GRU-RNN layers are fully connected with each other, so that they reduce the hidden state of the last GRU layer to one neuron output which is the estimated core temperature. Number of neurons used in the first and second GRU-RNN are 256 and 128 respectively.

The dataset was collected experimentally using two 2.5 Ah lithium iron phosphate batteries running at cycle current profile with constant charging and discharging cycles. The dataset is done on five different current profiles all starting from 80% SOC and ranging from 1C to 6C. 80% of the training dataset was used for training and the 20% left was used for validation. However, only one batch of data is only used for the testing process. The model was built using a keras neural network library with python and tensor flow interface. The proposed model was trained using Root mean square propagation (RMSprop) on two Nvidia Tesla P100 GPU and Compute Canada system with a learning rate of 0.0001. Results showed that the model was well trained and was able to accurately predict the core temperature of the battery. The model was also found to preform good over cycling and on other batteries of the same type (Ojo et al., 2020). In different study, the authors investigated the effect of using first derivative artificial feature extraction with LSTM-RNN on the temperature prediction accuracy for lithium ion batteries. The authors proposed three different network architecture named as model A, B, and C. Model A is a base network consisting of three layers with voltage and current as inputs and temperature as an output. Model B is the same as Model A, but a separately trained first derivative layer is introduced after the input layer. Model C is same as model B but the inputs are feed to the first derivative layer and to the hidden layer at the same time to benefit from both approaches of model A and B. Results showed that by using model C the temperature prediction accuracy increased by 0.01 for the training data compared to the base model (Kopp et al., 2022). To achieve better temperature prediction, the authors used elitist preservation genetic algorithm with long short term memory network (LSTM). in this study an optimal segmentation strategy and improved loss function was introduced to find the optimal segment lengths and enhances temperature prediction at upper and lower limits respectively. The proposed method reduced the prediction error by 12% compared to the performance of long short term model (Jiang et al., 2022b). To secure thermal safety of lithium ion battery, Marui Li, proposed a multi-step ahead thermal warning network based on core temperature based on LSTM network, this network uses real time data to predict the core temperature and based on the prediction the network determines whether to send an early warning or not (Li et al., 2021b).

According to the studies LSTM and GRU has almost the same performance in predicting battery temperature, however, in some studies LSTM is shown to be more powerful than GRU and proven to be more stable. However, LSTM is considered more complexed than GRU, and more computationally expensive. On the other side, GRU are easier to train and have less parameters to optimize. It is concluded that If the task requires the network to capture long-term dependencies in sequential data and computational resources are not a constraint, LSTM may be a better choice. If computational resources are limited or the task does not require the network to capture long-term dependencies, GRU may be a more efficient and effective choice.

Another approach to predict BT is to use CNN. CNN are designed to automatically detect and extract features from images

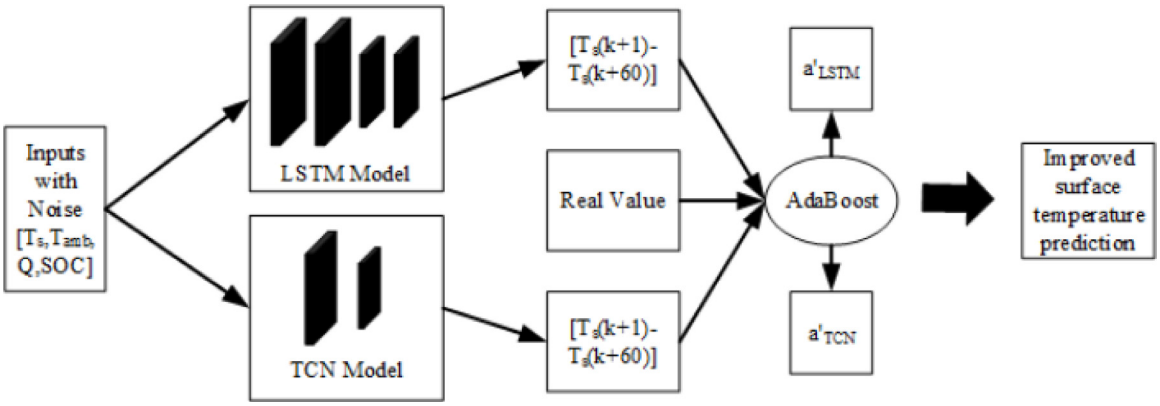


Fig. 13. Schematic model of temporal convolutional-recurrent model (Li et al., 2021a).

by using convolutional layers that apply a set of learnable filters to the input image. The output of these filters is then passed through pooling layers, which down sample the image to reduce its dimensionality, and finally through fully connected layers, which produce the final classification output.

Mengyi wang et al. proposed a CNN to predict the internal temperature of ternary polymer lithium ion battery pack with the help of virtual thermal sensors. A total of 81 376 data set is collected from 128 uniform all distributed sensors inside and outside the battery pack during seven discharge cycles for training validating and testing the network. The CNN consists of 18 different layers modeled on python. The CNN was capable to predict the internal temperature of the battery pack by feeding the measured external temperature to the network. Results showed that the network was able to accurately predict the internal temperature with mean square error of 0.047. Also the proposed network had many advantages while compared to linear regression method on terms prediction accuracy (Wang et al., 2021a).

From this study, CNN is shown to perform better than linear regression in terms of MSE, MAE, and R2 evaluation, while it shows a lower performance in terms of max error.

In some cases, the data measurement can be noisy, and it may affect the temperature prediction results. to overcome this issue Marui Li et al. proposed an allied temporal convolutional-recurrent diagnosis network. This network combines the advantage of LSTM in time series processing and temporal convolution network (TCN) in handling sequential tasks to accurately predicted the surface temperature of 10 Ah prismatic LiFePO4-Graphite battery. The two models are combined with each other with the help of AdaBoost algorithm. The authors simulated the lithium ion battery using ANSYS Fluent software to calculate the input values of the network which are terminal voltage, current, SOC, internal resistance and temperature. using MATLAB noise is generated and introduced to the input values.

This inputs are feed to the two networks to predict the temperature and then the resulted temperatures with the real value are feed to the AdaBoost algorithm to predict a more accurate surface temperature as shown in Fig. 13. results showed that the mean square error has a reduction of 0.02 compared to the LSTM (Li et al., 2021a).

Temporal convolutional networks are known by its ability to highly process parallel long sequence. Combining TCN with LSTM can combine the advantages of both LSTM and TCN to further reduce the error and enhance the performance compared to using LSTM alone.

Ruixin Yang et al. studied the thermal behavior of lithium ion battery under external short cut using extreme learning machine thermal model. The authors replaced the activation function of the extreme learning machine with a lumped-state thermal model to predict the temperature of the battery (see Fig. 14).

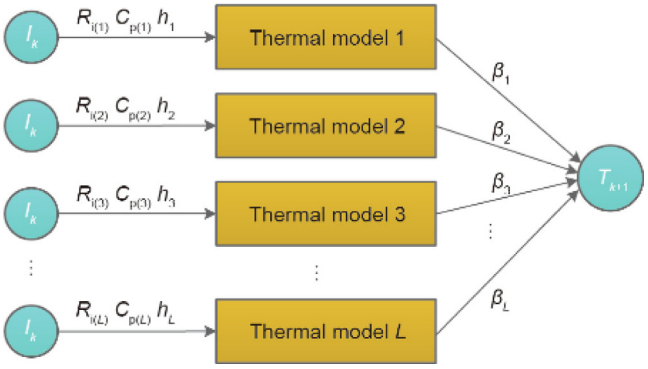


Fig. 14. Schematic model of extreme learning machine model (Yang et al., 2021a).

The data used for constructing and evaluating the network are collected experimentally. The study was carried Under external voltage circuit and initial state of charge (20%, 40% and 80%) and at different ambient temperatures of −10 °C, 10 °C 20 °C and 40 °C. the network was feed with current data to calculate the temperature as an output. To show the effectiveness of the proposed model, the authors compared the extreme learning machine thermal model with multi-lumped-state-thermal model parametrized by genetic algorithm. Results showed that the proposed model has higher computational efficiency and accuracy where the average root mean square error result under new dataset is 3.97 for the proposed model and 6.11 for the multi-lumped-state-thermal model (Yang et al., 2021a). In similar work, with the help of extreme learning machine and physics based models the authors were able to estimate online temperature distribution of a lithium ion battery (Liu and Li, 2015) . another research is done to investigate the properties of lithium ion battery pack under one cell short circuit under charging and discharging process, using artificial neural network, the authors was able to predict the short circuited current using only voltage information. Furthermore, with the help of a 3D electro-thermal coupling model and the predicted short circuited current, the authors were able to estimate the maximum temperature increase, internal and surface temperature (Yang et al., 2020). The application of batteries is growing and the ability to predict longer usage time is needed. To estimate long term battery surface temperature, voltage, and power, Xiaopeng Tang et al. proposed using extreme learning machine model as shown in Fig. 15. The usage of extreme learning machine enhances the performance, then of that of normal back propagation feed forward neural network. The data was gathered experimentally from 2.1 Ah sony US18650VTC4 at three different

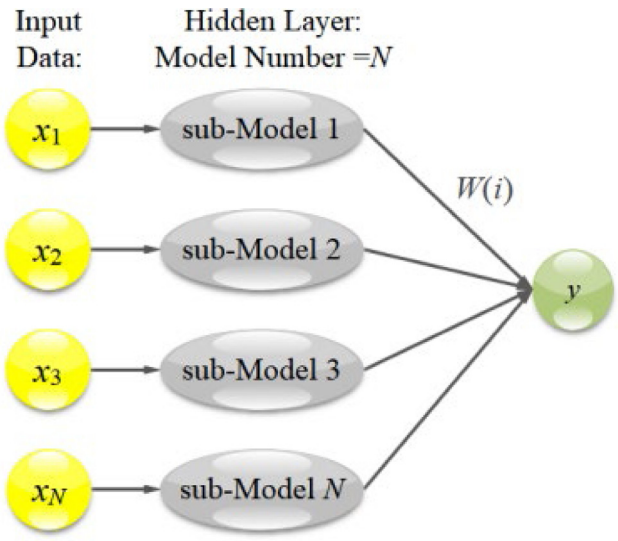


Fig. 15. Schematic model of extreme learning machine model with sub temperature models (Tang et al., 2018).

ambient temperatures to be compared with the data predicted from the model proposed. The network is made up of three layers with a single hidden layer using MATLAB software. to better enhance the performance of the network, the activation function in the hidden layer is replaced by set of temperature models. The battery temperature model is a rough first order temperature model considering heat generation, dissipation, and time delay.

The authors used recursive least square method to obtain the weight matrix for the temperature models that is used along with current profile collected experimentally to predict the future temperature (Tang et al., 2018).

Extreme learning is considered as a FFNN with a single hidden layer. its advantages compared to other types of NN lays in its fast processing. Extreme learning does not require any training algorithms to adjust the weights instead it uses simple linear regression algorithm to change the weights with a single step. Extreme learning has been shown to be particularly effective for tasks that require high-speed processing of large datasets

Temperature estimation performance of many battery models are still limited and only can co-estimate small ranges of temperatures. To address this problem, Fei Feng et al. developed electrochemical–thermal neural network model for state of charge and temperature prediction (see Fig. 16).

Two mathematical models are integrated with artificial neural network. an electrochemical and thermal sub models are used to calculate the voltage and temperature of the battery cell. the voltage is then corrected using a feed-forward neural network. The correction of the voltage values highly effect the values calculated by the thermal model. The network is constructed from four layers with two hidden layers. The inputs parameters for the network are current, cell temperature, and voltage. The hidden layers are made up of 5 neurons each with sigmoid activation function. An experimental setup is done to collect the surface and core temperatures, voltage and current. Two prismatic A123AMP20 battery cells are connected in parallel for the experiment. thermocouples are connected on the surface and between the batteries to measure the surface and core temperatures. The data set is collected under two cities and two high ways driving cycles at $-20\ ^{\circ}$C, $10\ ^{\circ}$C, $30\ ^{\circ}$C and $50\ ^{\circ}$C for training the network and $-10\ ^{\circ}$C, $20\ ^{\circ}$C, $40\ ^{\circ}$C for validation. Based on root mean square error, results showed that the electrochemical–thermal–neural network was able better predict the voltage and the core temperature than of that calculated by the mathematical models alone (Feng et al., 2020). NARX is a type of neural network that is similar to other RNNs, but with some important differences. One of the key advantages of NARX is its ability to handle multiple inputs and outputs simultaneously. NARX can also incorporate exogenous variables, which are variables that are not part of the time series but may have an impact on the data.

To hourly forecast a lithium ion battery cell temperature for more than 24 h, Md Mehedi Hasan et al. proposed an exogenous input nonlinear autoregressive network that accepts a real time values (current and temperature) coming from outside the model along with an output feedback with a certain delay. series–parallel and parallel architectures NARX architectures are used to train and estimate cell temperature. the data used for training validating and testing were collected over one year of charging and discharging the battery at different ambient temperatures. The total dataset consists of 516,960 samples. After doing a sensitivity study to choose the best number of neurons and time delay, the authors concluded the optimal values of 10 neurons and 20 min respectively (see Fig. 17).

Results showed the proposed model can accurately predict the temperature of the cell with only two inputs (current and ambient temperature) (Hasan et al., 2020).

In similar context, Jan Kleiner et al. implemented and compared two different models forward feed neural network and a novel NARX A data-driven network, to predict the internal thermal behavior of a prismatic 25 Ah Li-ion cell in a dynamic application. Both neural networks consist of input, hidden, and output layers. And both have the same input and training data which are the current, voltage, state of charge, heat generated, cooling temperature. Further inputs, the feedforward neural network needs an extra input in order to still provide the necessary information about one current temperature in the jelly roll. the temperature is measured by a sensor as an additional input. However, the NARX does not need additional temperature sensor, since the output of an of the previous time steps is stored and fed back to the input layer. The hidden layer consists of 3 neurons with sigmoid activation function, and the output to predict the temperature of the belly. The voltage, state of charge, and heat generated are calculated using electrical and heat generated models respectively. The training data was divided into three subsets 70% as training, 15% for validation, and 15% for testing. Results showed that both ANN networks are capable of predicting the temperature in accuracy rang of 1k for 10 h (Kleiner et al., 2021b). Mohammad Jamshidi et al. proposed a dynamic artificial neural network to estimate the thermal behavior of lithium ion battery. A nonlinear exogenous model was built on MATLAB and trained by Levenberg–Marquardt backpropagation algorithm. The data set was collected from the NASA research group and split into 70% 15% 15% for training validating and testing respectively. Two networks were tested by the authors, the first network called ANN1 with 10 hidden neurons and 2 min time delay, and the second network called ANN2 with 14 hidden neurons and 5 min time delay. the first network ANN1 showed a good prediction result in which the correlation value is 0.967 between all outputs and targets (Behdad Jamshidi and Rostami, 2017). To advance monitor and predict the thermal state of battery cell, the authors proposed a combined novel artificial neural network with NARX network and physics based methods in the same work frame (Kleiner et al., 2021a).

NARX is considered almost the same like LSTM, and GRU but with more complex structure that requires more computational power. The advantage of using NARX is its capability to accept exogenous variables that may highly effect the output. however, the NARX is very sensitive and it may easily overfit on small or noisy data sets.

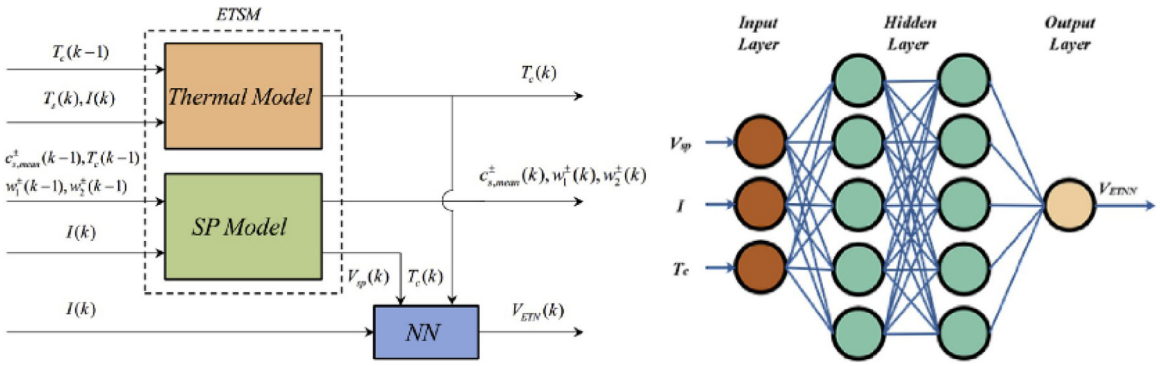


Fig. 16. Mathematical model and ANN network connection (Feng et al., 2020).

Parameter	Description
Problem	Nonlinear auto-regressive time-series network with external input (NARX)
Training Algorithm	Levenberg-Marquardt
Input	Charging-Discharging Current and Ambient Temperature
Output	Battery Cell Temperature
Data Division	Training (80%), Validation (10%) and Testing (10%)
Hidden layer size	10 neurons
Feedback Delay	20 minutes

Fig. 17. NARX network training parameters (Hasan et al., 2020).

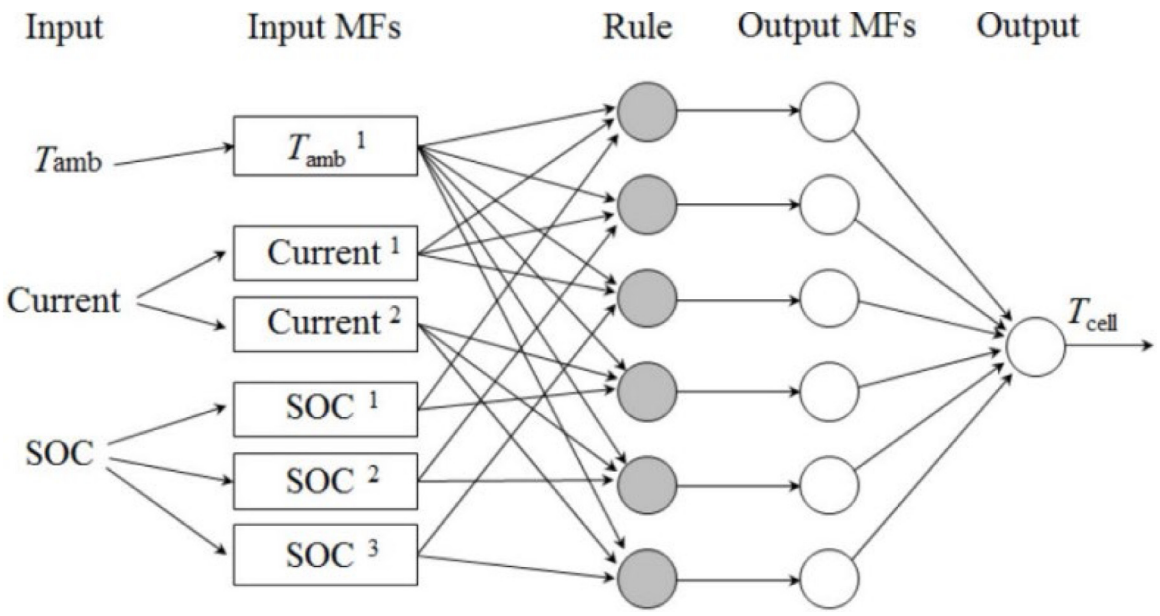


Fig. 18. Adaptive neuro-fuzzy inference system (Fan et al., 2018).

An adaptive neuro-fuzzy inference system data driven was proposed by Bin Fan, et al. to predict the battery temperature at different current, state of charge and ambient temperatures.

The authors started their study by collecting large amount of data experimentally on lithium ion battery at 0°C 5°C 10°C 15 °C and 20°C and at current rate of C/2, 1C, and 2C. the data collected was cleaned and separated into training and validation datasets. After the authors loaded the training dataset and specified initial structure of the model and trained it. after training the results were validated and compared with the experimental one. The authors changed the structure of the network until the experimental results matched the predicted ones.

Fig. 18 shows the studied network that is made up of five layers. The second and fourth layers are made up of Gaussian curve and linear type respectively. A hybrid combination of back-propagation and least squares method is used as a training optimization algorithm. Results showed that the proposed model was able to accurately predict the temperature under different conditions (Fan et al., 2018).

Comparing ANFIS to NARX and GRU, there are several additional drawbacks. ANFIS may not be appropriate for time-series data or issues requiring memory or feedback loops because it is a feedforward network. ANFIS could not be as efficient as other neural network architectures for tasks requiring high accuracy. Table 3 offers a consolidated summary of the studies related

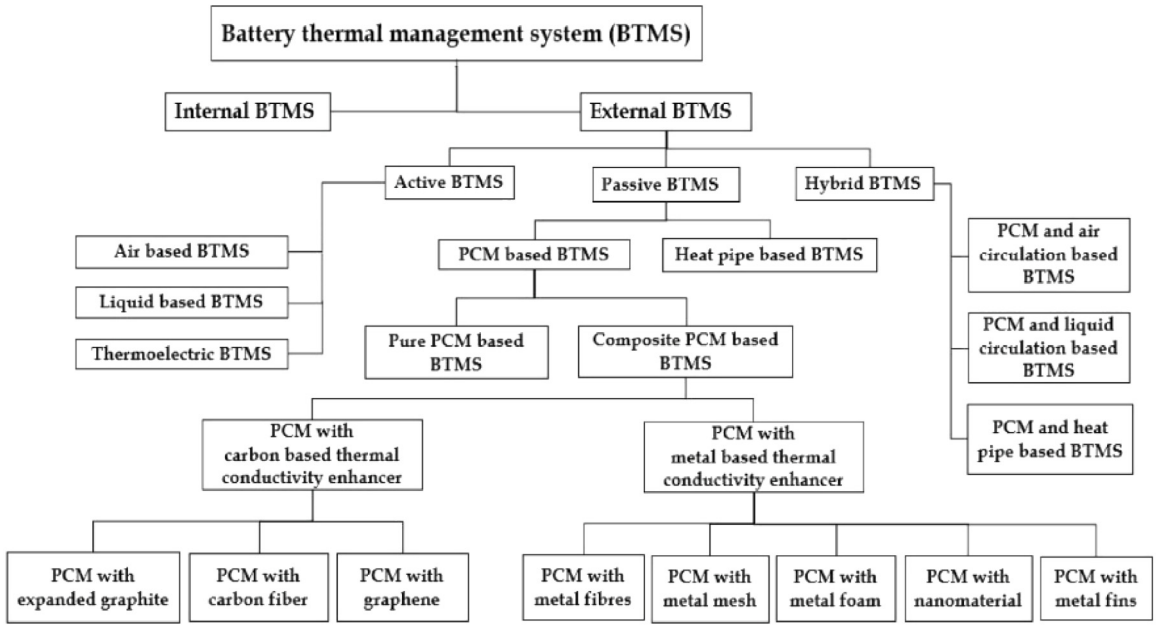


Fig. 19. Different BTMS classification (Patel and Rathod, 2020).

to battery temperature prediction, including key data and their respective contributions.

6.2. Thermal management

Almost all cell materials experience a decline in performance and stability within an abnormal temperature range. Due to the influence of ambient factors and heat generation resulting from chemical reactions during charging and discharging, batteries, especially lithium batteries, are susceptible to temperature variations. Consequently, it is usually unavoidable to encounter temperature changes. Hence, an efficient battery thermal management system is required to maintain the appropriate temperature range, minimize temperature gradients, and mitigate the adverse effects of temperature. Table 4 provides a comprehensive summary of the research discussed in this section regarding battery thermal management through machine learning, including essential data and highlighting their respective contributions.

Fig. 19 shows different BTMS that can be used to control the temperature of the batteries. Felix et al. studied the thermal management system of 6 Li-ion battery cells of type 4680 inside a rectangular layout composite phase change material with the assist of machine learning. In this study the authors used electrochemical model, finite element model, and convolutional neural network to simulate the performance of the lithium ion battery and predict the thermal conductivity of the composite phase change material. The battery pack is a typical Li-ion battery consisting of two electrodes, two current collectors, and a separator. The study assumes that the anode and the cathode are made up of meso-carbon micro-bead graphite and lithium cobalt oxide (LiCoO2) respectively. The electrochemical response of the batteries is simulated using Newman's two dimensional electrochemical model. And for the simplicity, the heat generation is only assumed from three main sources which are the reaction current over potential, ionic ohmic heat inside the active materials and electrolyte phase, and the heat from entropy change in the active material. To save time and effort, different 2-D structure dataset of CPCM made up of paraffin and copper metal with different densities and pore sizes were prepared using Voronoi method on python software to be feed in the CNN. Different studies talked about creating and predicting the composite properties using machine learning (Gu et al., 2018; Abueidda et al., 2019). The total dataset generated for CPCM is 200 00 image of 442 × 442 pixels of varying densities of 7.4% to 10.5% with nominal cell size of 9–22 ppi. The CNN consists of six total layer with two dense layers. The network was constructed using PyTorch framework with a total of 434 111 learnable weight parameters. The authors used adam optimizer to update the weights and solve the problem. Results showed that the proposed CNN architecture can accurately predict the thermal conductivity of the CPCM with mean absolute error of 5%. This results were compared to ResNet 18 network which showed similar results (Kolodziejczyk et al., 2021).

The CNN technique, trained on a dataset of CPCM images offers significant time and effort savings in predicting the thermal conductivity compared to traditional methods, which rely on complex mathematical models and extensive experimentation. This simplified procedure enables effective optimization of battery thermal management systems, which boosts production and accelerates advancement in the area.

Wen Yang et al. proposed a novel battery thermal management system consisting of honeycomb shape with hexagonal cooling plate bionic liquid channel and phase change material (see Fig. 20).

The authors used CFD and second order equivalent circuit model to investigate the thermal performance. Moreover, with the help of ANN, the authors were able to predict the appropriate inlet flow rate to maintain and stabilize the temperature of the cells at varying driving cycles and ambient temperature conditions (Yang et al., 2021b). To achieve a reliable BTMS with low cost and light weight and to maintain the battery temperature in reasonable range, shahid ali khan et al. proposed a U shape water cooling system for prismatic battery cell. the authors at first numerically investigated the important parameters that effects the temperature. after the numerical study it is shown that the temperature is highly effected by fluid flow rate, channel size, discharge rate, ambient temperature, and fluid medium. To optimize those values, the author proposed a neural network based regression based on Gaussian process. results showed it is possible to reduce the temperature battery cell by 21% and weight by 45% compared to conventional liquid cooled BTMS (Khan et al., 2022). Mehrdad Mesgarpour et al. combined physics informed neural network with visual tracking commercial software to predict

Table 3
Temperature prediction overview summary..

Reference	Application	Machine learning algorithm	Training algorithm	Input data	Battery type	Framework	Contribution
Tran et al. (2022)	Compare the performance of four different machine learning algorithms for battery temperature prediction	Linear regression, k-nearest neighbors Decision tree Random forest	Gradient descent	AT C I Past I & V	Prismatic 25 Ah Lithium ion battery cell	Python scikit-learn Machine	Best fit algorithm for the studied case is the decision tree regressor, where it scored the best value of 0.99 R-squared.
Fang et al. (2012)	Predicate battery surface temperature during charging state under different ambient conditions	Feed-forward artificial neural network (FFNN)	Levenberg–Marquardt algorithm	I AT t	Cylindrical 8 Ah Ni-MH battery	MATLAB	Applied ANN instead of complicated internal physical–chemical reactions models to predict the surface temperature
Chen et al. (2013)	Predicate battery surface temperature	Feed-forward artificial neural network (FFNN)	Levenberg–Marquardt algorithm	–	Lithium ion	–	Introduce ANN to predict surface temperature.
Ströbel et al. (2021)	Predict T, SOC, & SOH using EIS and ANN	Feed-forward artificial neural network (FFNN)	Bayesian regularization Levenberg–Marquardt algorithm	Real & imaginary parts of impedance	Cylindrical 1.5 Ah Samsung INR18650-15L1 Cylindrical 3 Ah Sony US18650V TC6 Prismatic 2.35 Ah Panasonic NCA 103450	MATLAB Neural Network toolbox	The model only needs one single EIS spectrum to predict the temperature of the battery cell
Jiang et al. (2021)	LSTM-RNN & GRU-RNN battery temperature prediction accuracy comparison	Long-short term memory (LSTM) Gated recurrent unit neural network (GRU)	Gradient descent	V I	18650 Li-ion battery	MATLAB 2018b	Both learning algorithms were capable to predict battery temperature, but it is shown that LSTM-RNN is less sensitive and more favorable.
Zhu et al. (2021)	Data driven analyze the heat type (reversible or irreversible) and predict temperature change.	Long-short term memory (LSTM)	Forward and backward passes Adam optimizer	T	LiFePO4/graphite lithium-ion	Python Pandas Numpy Keras Tensorflow Sklearn	The proposed model can predict later temperature change helping battery system to adjust and manage
Ojo et al. (2020)	Battery temperature prediction using GRU-RNN under different current profiles	Gated recurrent unit neural network (GRU)	Root mean square propagation	V I ST AT	2.5 Ah lithium iron phosphate battery	Python Keras Tensorflow	Propose a new model composed of two interconnected GRU-RNN layers to accurately predict the temperature over different cycling and on other batteries of the same type.
Kopp et al. (2022)	Three architecture NN models were investigated for best battery temperature prediction	Long-short term memory (LSTM) with first derivative	ADAM optimizer algorithm	U I	1.5 Ah Samsung (INR18650-15L1) lithium ion	–	Investigate the effect of first derivative artificial feature extraction with LSTM on temperature prediction results
Jiang et al. (2022b)	Temperature prediction for battery storage plant	Elitist preservation genetic algorithm with long short term memory network (LSTM)	ADAM optimizer algorithm	P SOC V C T	Battery energy storage plant	–	Developed an optimal segmentation strategy and improved the loss function to accurately predict the temperature of storage plant

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Table 3 (*continued*).

Reference	Application	Machine learning algorithm	Training algorithm	Input data	Battery type	Framework	Contribution
Li et al. (2021b)	Multi-step ahead thermal warning network based on core temperature, to secure thermal safety of lithium ion battery	Long-short term memory (LSTM)	ADAM optimizer algorithm	ST SOC AT Q	Lithium-ion	MATLAB	The network can predict the core temperature in the next 10 s from 20 s measurement data and can also sent early warning signal
Wang et al. (2021a)	Predicate the internal temperature of battery pack with the help of virtual thermal sensors and ANN	CNN Linear regression	Batch Normalization	ST	Ternary polymer lithium ion battery	Python	CNN is more accurate in temperature prediction of that linear regression
Li et al. (2021a)	Predict battery temperature by using two different ANN	LSTM and temporal convolution network(TCN)	AdaBoost algorithm	V I SOC T R	10 Ah prismatic LiFePO4-Graphite battery	ANSYSfluent MATLAB	Predicate an accurate temperature using noisy signals
Yang et al. (2021a)	Thermal behavior of lithium ion battery under external short cut using extreme	Single hidden neural network	Extreme learning	I	2.45 Ah Lithium ion	Matlab 2013b	Compared extreme learning machine thermal model with multi-lumped-state-thermal model parametrized by genetic algorithm. Results showed that the proposed model has higher computational efficiency and accuracy
Liu and Li (2015)	Real time temperature distribution prediction across the battery	Single hidden neural network FFNN	Extreme learning Levenberg–Marquardt algorithm	I	Lithium ion	Neural Network toolbox in MATLAB	Compared the proposed extreme learning model with FFNN. Results showed extreme learning model is more accurate.
Yang et al. (2020)	Predict current and temperature of battery pack under one cell short circuit during charging and discharging process	FFNN	Gradient descent	V	Lithium battery pack	COMSOL	Used 3D electro-thermal model with the help of ANN to predict the temperature
Tang et al. (2018)	Estimate long term battery surface temperature, voltage, and power.	Single hidden neural network	Extreme learning	I	2.1 Ah sony US18650VTC4 battery	MATLAB	Joule heat is taken into consideration
Feng et al. (2020)	Electrochemical-thermal neural network model for state of charge and temperature prediction.	FFNN	–	I V T	Prismatic A123AMP20 battery cell	MATLAB NN toolbox	Electrochemical-thermal-neural network was able better predict the voltage and the core temperature than of that calculated by the mathematical models alone
Hasan et al. (2020)	Use exogenous input nonlinear autoregressive network that accepts a real time values to predicate temperature of the battery	NARX	Levenberg–Marquardt algorithm	I AT	Lithium-polymer battery	MAT-LAB/Neural Net Time Series toolbox	Hourly forecast a lithium ion battery cell temperature for more than 24 h

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Table 3 (*continued*).

Reference	Application	Machine learning algorithm	Training algorithm	Input data	Battery type	Framework	Contribution
Kleiner et al. (2021b)	Predict the internal thermal behavior using ANN	NARX FFNN	Levenberg–Marquardt algorithm	I V SOC Q T	25 Ah lithium ion battery	MATLAB Deep Learning Toolbox.	Compared two different models forward feed neural network and a novel NARX A data-driven network, results showed both networks were able to predict temperature in accuracy rang of 1k for 10 h
Behdad Jamshidi and Rostami (2017)	Dynamic artificial neural network to estimate the thermal behavior of battery	NARX	Levenberg–Marquardt algorithm	Discharge load voltage	Lithium ion battery	MATLAB	Compared different NARX structures, results showed its better to use 10 hidden neurons and 2 min time delay than of using 14 hidden neurons and 5 min delay
Kleiner et al. (2021a)	Predict the thermal state of battery cell using NARX network with physics based methods	NARX	Levenberg–Marquardt algorithm	I T SOC	25 Ah lithium ion battery	MATLAB Deep Learning Toolbox.	A comparison between physics based and data driven models, NARX shows slightly advantages on physics based model
Fan et al. (2018)	Predict the battery temperature at different current, state of charge and ambient temperatures.	ANFIS	A hybrid combination of back-propagation and least squares method	AT SOC I	LiFePO4 battery	MATLAB ANFIS toolbox	Results showed that the proposed model was able to accurately predict the temperature under different conditions

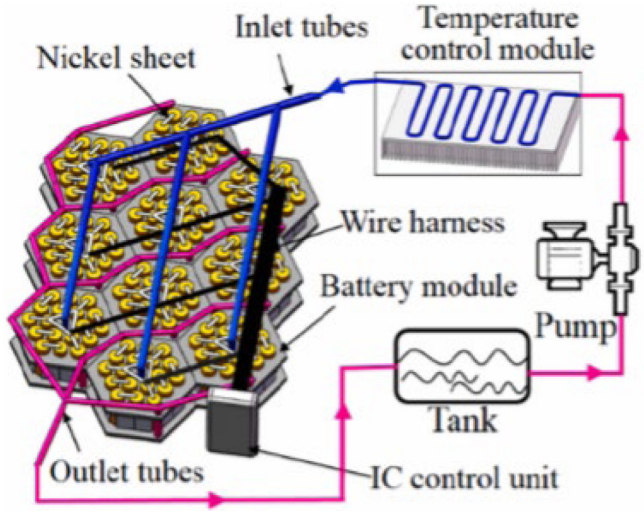


Fig. 20. Honeycomb with phase change material cooled by bionic fluid cooling plate (Yang et al., 2021b).

the thermal behavior of a battery package. The authors suggest that this algorithm reduces coding complexity and computational cost. Results showed that the combination of PCM with cooling fluid can effectively reduce the temperature moreover, increasing the cooling water velocity can reduce the average temperature by 20.97% (Mesgarpour et al., 2022).

ANN can be used in various approaches in lithium batteries thermal management, in which they make accurate predictions, optimize system parameters, cut down on computing expenses, and provide lightweight, affordable solutions.

Ozge yetik et al. used ANN to study the thermal effect of different bus bars materials on 10 series prismatic lithium ion battery. The bus bars tested in this study are silver, nickel and steel (see Fig. 21).

The ANN proposed by the authors is a FFNN consisting of 3 layers with only one hidden layer containing 16 neurons. The bus bars material, capacity rate, ambient air temperature and velocity inlet and time are considered the important inputs to predict the maximum temperature of the base bar material in which it keeps the battery cooled. The ANN was modeled using MATLAB software, and the dataset was generated using ANSYS simulation with varying the parameters between 1.5–2–2.5 C, 1–2 m/s and 295–300 k. The total generated dataset number is 3708 were 80% of this data are used for training and the other 20% are used for estimation. In this study, the authors also investigated the ANN performance using different optimizing techniques which are BR, LM, CGP, and SCG and different number of neurons in the hidden layer. Results showed that the best bus bar for cooling is silver, and the best structure optimizing algorithm is 16 neuron BR were the R2 value was 0.995 (Yetik and Karakoc, 2021).

ANN showed that it can be used as evaluation process to measure the accuracy of the data obtained by study in short time. The effectiveness of ANN in producing accurate results depends on the choice of training algorithm and the number of neurons in the network. To obtain optimal performance for a specific application, it is important to explore and evaluate different algorithms and parameters.

Wei li et al. studied the thermal effect and pressure drop of serpentine and u shape channel on a 40 cylindrical lithium type 18 650 system batteries with the help of machine learning.

Table 4
Battery thermal management overview summary..

Reference	Application	Machine learning algorithm	Training algorithm	Input Data	Battery type	Framework	Contribution
Kolodziejczyk et al. (2021)	Prediction of thermal conductivity of CPCM	CNN	ADAM	20 000 of 442 × 442 pixels foam image	(LiCoO2)	PyTorch	A new way in creating dataset and ability to predict the temperature rise of battery surrounded by CPCM
Yetik and Karakoc (2021)	Predict the temperature of different material bus bar used for cooling	ANN	BR, LM, CGP, and SCG	BBM, C, AT, AV, and t	Prismatic lithium battery	MATLAB	Silver bus bar is the best to be used for cooling compared to steel and nickel. Also BR is proved to have a better performance than LM, CGP, and SCG
Li et al. (2021c)	Optimization of liquid cooling battery thermal system	Radial basis function, response surface model, and Gaussian model	–	T WV thickness	40 cylindrical lithium type 18 650 system batteries	–	The best ML algorithm for optimizing the output in this study is Gaussian model
Tang et al. (2021)	Predicting the cooling capacity and the coefficient performance of a water cooled coupled with heat pump for electric vehicles battery	Support vector regression	Particle swarm algorithm	CS, AT AFV	Lithium batteries	–	A new method to fit the complex nonlinear relationship between different factors such as COP, cooling capacity and other influencing factors for liquid cooling battery management system based on heat pump.
Park and Kim (2020)	Optimizing the thermal management system in electric vehicle through sub interconnected NARX and multiple inputs	NARX	LM	P T CFR I T VS	Lithium batteries	Matlab and IBM ILOG CPLEX Optimize	Power consumption reduced by 48.5% and maintaining temperature of the battery
Li et al. (2022b)	Optimizing the battery thermal management configuration using computational fluid dynamics and ANN	ANN	LM	BC AT AFV	Lithium battery	MATLAB	The optimal configuration for the current battery setup is 0.02 m X-direction gap and a 0.01 m Y-direction gap.
Wan (2021)	Optimize the battery spacing of lithium battery using tunicate swarm combined with search and rescue algorithm	Tunicate swarm combined with search and rescue algorithm	–	Maximum temperature and temperature difference	Lithium battery	MATLAB	The TSSR results is more effective compared with other approaches
Immonen et al. (2020)	Temperature optimization of retrofit air cooled battery system	Random forests	–	N binary design variables	SebNet battery system	MATLAB	It is possible to relatively drop the temperature with small values of a retrofit device using baffle plates
Li et al. (2022a)	Battery configuration optimization based on forced and natural air cooling	ANN	LM	BC AP AFD	Lithium hexafluo-rophosphate	MATLAB	Forced cooling is better than natural cooling the optimized proposed model can reduce the maximum temperature by 1.94%

(*continued on next page*)

Table 4 (*continued*).

Reference	Application	Machine learning algorithm	Training algorithm	Input Data	Battery type	Framework	Contribution
Yang et al. (2021b)	Thermal performance of honeycomb battery thermal management system with mini bionic liquid channel and PCM	ANN	LM	I AT AFR	Cylindrical Lithium Ion	–	The ANN was used to stabilize temperature of the system by predicting appropriate flow rate at varying cycling and ambient temperature conditions
Khan et al. (2022)	Design of u shape water cooled BTMS in electric vehicles	Neural network-based on Gaussian process	–	FFD, CFR CD, AT, FM	8 Ah lithium ion prismatic battery cell.	–	Cost and weight optimization of BTMS while maintaining the temperature of the system
Liu and Zhang (2020)	Self-adaptive control system for battery air cooling	Neural network-based (NN-based) controller	–	HF Bias T Average T	Lithium battery	–	based on the temperature bias and operating mode, the system generate an appropriate mass flow rate
Arora et al. (2017)	Estimation of heat generation rate of a lithium battery using ANN	FFNN	LM	C DOD T DR Bias term	8 Ah LifePO4 pouch lithium battery	MATLAB	Predicate heat generation using a simple ANN with no complex multi-physics models
Mesgarpour et al. (2022)	The thermal behavior performance of a water cold and PCM battery pack system using new prediction model	Pattern based neural network	Error back-propagation	CS CT t HF	A lithium-ion battery pack	Tensor flow & python	Reduce computational cost and code complexity by integrating physics informed neural network with visual tracking real time monitor
Shahsavar et al. (2022)	Entropy analysis of a cylindrical battery in influence of fins and PCM	Gradient Boosting Decision Tree	–	Fin tip Flow time	18650 lithium-ion battery	Python Scikit-learn	Proposed a new gradient based ensemble machine learning approach
Afzal et al. (2021a)	Computationally optimizing ANN with four different activation functions for BTMS	ANN	LM	AR Pr HF Re k BC	Lithium-ion battery pack	–	Optimizing the best single ANN and deep ANN based on activation function and number of neurons for Nusselt number prediction

The batteries in this study are considered isotropic from the inside and considered as a constant heat source of value 42,200 W/m3. The heat capacity is constant and independent of time. The radiation and convection heat transfer are neglected from the inside. Heat from the batteries are transferred to the cold aluminum plate cooled with water through direct contact (see Fig. 22).

A CFD simulation using ANSYS software is done by the author to compare between the u shape and the serpentine shape scheme taking into account design variables input such as cooling plate thickness, cooling plate wall thickness, inlet water temperature, and water flowrate. it is found that both have the same cooling effect, but serpentine scheme has higher pressure drop then u shape scheme. To optimize the output values (temperature difference, pressure drop, and temperature standard deviation.) (TD, TSD, PD), the authors generated a total of 100-point dataset using Latin hypercube sampling and used machine learning model. The author investigated the performance of three different machine learning models which are radial basis function and response surface model, and Gaussian model to see which can predict the real values of the output parameters. Using the root mean square error, median absolute deviation and r square, Gaussian model showed the best fit for the problem. Results showed by using machine learning to TD, TSD, PD are optimized were TD increased by 2.88%, TSD decreases by 2.05% and PD decreased by 24.18% by decreasing the velocity of the cooling water by 26.67% (Li et al., 2021c). In similar context, Xingwang Tang et al. used machine learning to analyze and study the performance of liquid cooled battery thermal management system for electric vehicles. The thermal management system is a couple of liquid cool and heat pump air conditioning system. In this study, the authors used support vector regression to predict the cooling capacity and the coefficient performance of the system. To better achieve prediction results, the author introduced particle swarm algorithm to optimize the penalty coefficient, kernel function parameter, and insensitive loss coefficient which are the three important hyper parameters of the support vector regression. Results showed that when using particle swarm algorithm with support vector regression, the prediction results of cooling capacity and system COP improved by 2.1% and 2.8% respectively. the authors stats that this machine learning method used can accurately predict the performance of the system without the need of long term experiments and money (Tang et al., 2021). Jonghyun et al. optimized the thermal management system of an EV that effects the battery temperature and reduces power consumption using supervised learning strategy and artificial neural network.

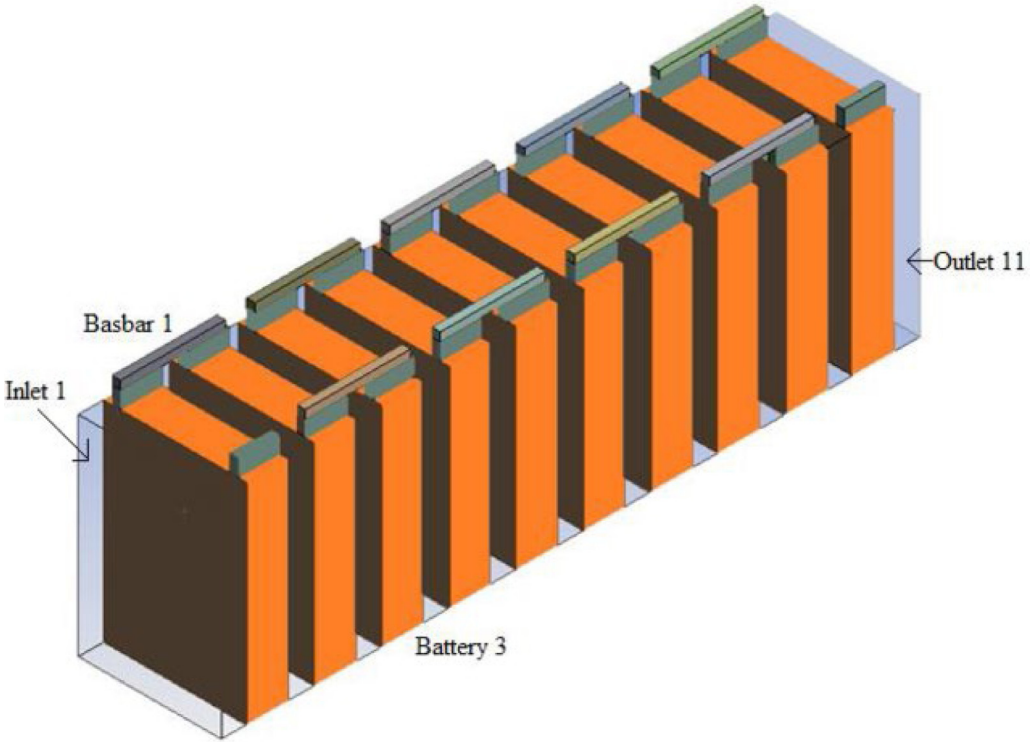


Fig. 21. Bus bars battery system (Yetik and Karakoc, 2021).

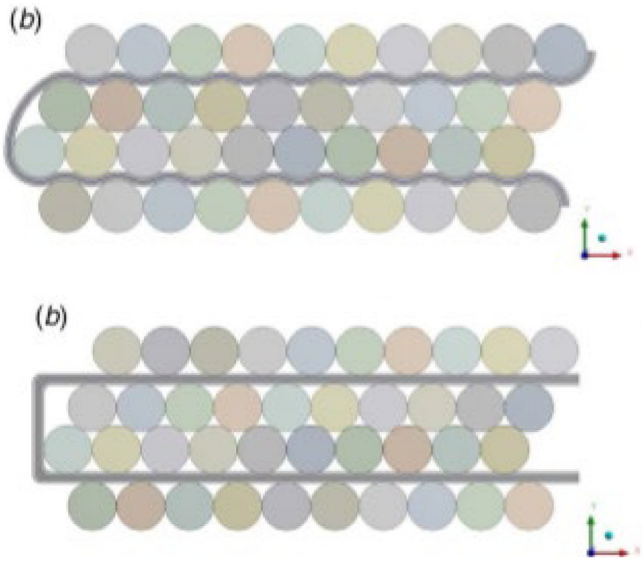


Fig. 22. Serpentine and u shape channel (Li et al., 2021c).

two different thermal cooling system configurations are studied by the authors as shown in Fig. 23.

It has been shown that the integration of machine learning with optimization and physics-based models allows for the development of hybrid models that are capable of accurately and efficiently capturing the intricate interactions and dynamics of thermal management systems in which improves its performance.

The temperature of the battery is controlled by dividing the thermal management system into three sub systems with outputs coolant flow rate, coolant inlet battery temperature. battery temperature respectively. Each subsystem is modeled using nonlinear auto regressive network with exogenous inputs. The artificial neural network inputs are dynamically taken from different sensing technologies and feedback system that can be classified by control inputs, environmental inputs, and feedback inputs. The artificial neural networks of the sub systems are interconnected with each other in a specific order based on the physical configuration of the thermal management system. Were the output of the first subsystem is fed into the second and third subsystems. And the output of the second subsystem is fed to the third subsystem. The third subsystem gives us the battery temperature (see Fig. 24).

To avoid over fitting the authors proposed a simple procedure to find the hyper parameters (number of hidden layers and number of hidden neurons) of each subsystem artificial neural network. The first subsystem consists of one hidden layer with 16 neurons, the second subsystem consists of two hidden layers, while The third subsystem consists of one hidden layer with 18 neurons. The interconnected artificial neural network is presented using a set of explicit piecewise linear equations which can be directly integrated into the constraints of an optimization problem. Results showed that by using artificial neural network the power consumption is reduced by 48.5% for the integrated mode and the battery temperature was maintained regulated and maintained within acceptable ranges (Park and Kim, 2020). By using the ANN-based model, variations in battery temperature can be accurately estimated based on changes in system operation under different driving conditions.

Orhan Kalkan et al. used ANN to predict the thermal performance of a new designed cold plate made for pouch lithium batteries in electric vehicle. The ANN model input are depth of discharge, coolant flow rate, discharge rate, and coolant inlet temperature. Results showed that the ANN model can successfully predict the surface temperature with 10% error band range and 0.997 r value (Kalkan et al., 2022). To address safe and homogeneous control of battery thermal system, Mikel Arrinda et al. used surrogate BTMS control model that consists of classification

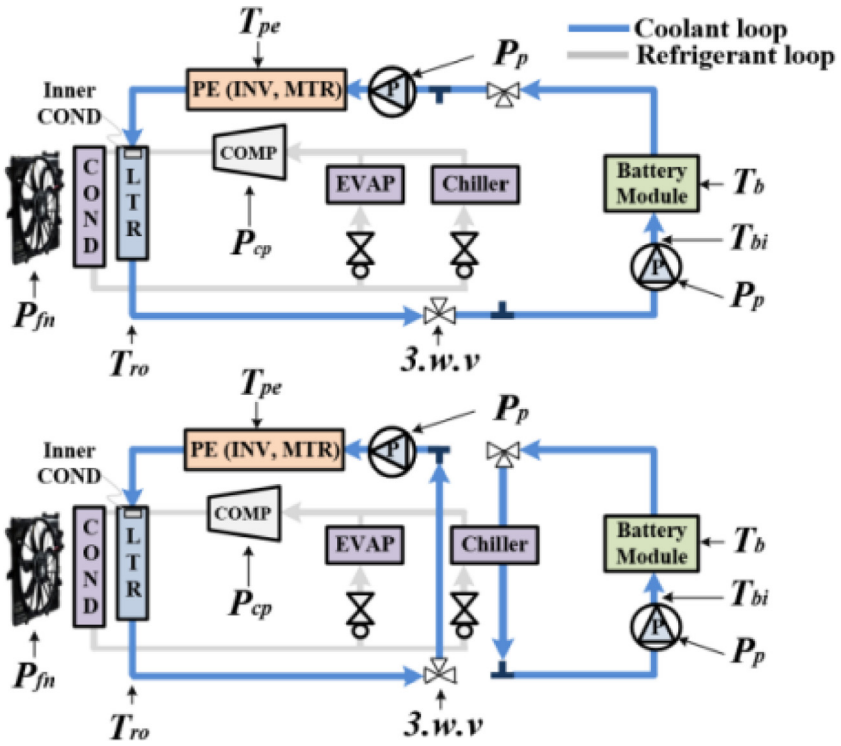


Fig. 23. Two thermal cooling system configurations (Park and Kim, 2020).

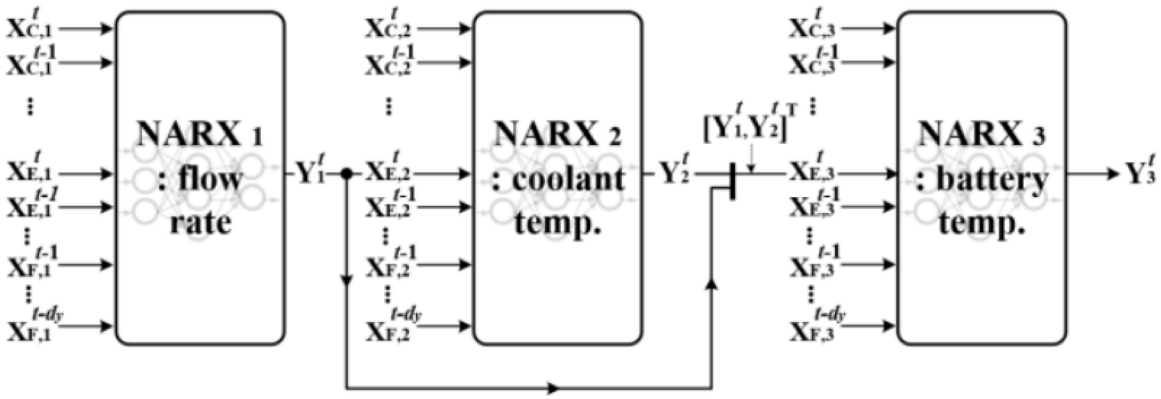


Fig. 24. Proposed model (Park and Kim, 2020).

machine learning model to define the best cooling–heating power of an actuator according to temperature measurements (Arrinda et al., 2022). To avoid high temperature of a battery module, Ziming Xu et al. proposed microchannel liquid cooling BTMS. The authors used Gaussian process regression and CFD to optimize the proposed process for best cooling capacity of the system (Xu et al., 2022). Eero Immonen et al. used machine learning and CFD to improve an existing air cooled battery thermal management system by means of passive components such as baffle plates. The authors utilized CFD for fluid flow and heat transfer modeling moreover, they used random forests learning for cause and effect assessment of binary design variables. Results showed that it is possible to reduce the temperature of a retrofit device, however, the temperature reduction is very relatively small (Immonen et al., 2020).

Yuanzhi liu studied the thermal performance of J-type air cooled system using a neural network based model predictive control strategy. The structural design of the system plays a big role in the thermal performance and temperature uniformity between the cells. This study talks about two approaches for developing more advanced air cooled system. Regarding system structural design and control strategy. The study introduces J type structural configuration, which is a combination between U type and Z type configurations. The system consists from one air inlet at the bottom of the system and two outlets at the top of the system. two control valves are assembled at the outlets to control the flow by adjusting the opening degree. The two control valves are controlled using model predictive control strategy using neural network. The lithium battery is modeled based on simple first order equivalent circuit. the battery is assumed to be homogeneous with a uniform internal heat generation calculated from the electrochemical model. The conductive coefficient and convection coefficient is set be 7 W/m k and 20 W/m^2 k. After optimizing the structure of the j type system using surrogate based optimization algorithm. A large number of transit CFD simulation are conducted to build a data for the neural network. The neural network is feed by the transit simulation from the CFD for the 3 predefined modes in which the mass flow rate input

is reversed as the output of the neural network. The purpose of the controller is to generate a suitable mass flow rate based on the temperature bias, operating mode and defined temperature trajectory. Results showed that neural network control with switching mode was able to regulate the maximum temperature and balance temperature uniformity within 1.5k under varying working conditions (Liu and Zhang, 2020).

Ao li et al. integrated computational fluid dynamics and ANN to optimize the design of battery thermal management system. In this study the authors proposed a three dimensional electro-thermal model coupled to CFD to calculate and generate the temperature distribution dataset at different battery configuration, input air velocity and temperatures. the generated dataset is then validated experimentally and then feed to an FFNN of three layers to predict the optimal configuration and cooling efficiency based on temperature. The ANN was trained and optimized using LM and the overall R fitness is shown to be 0.99 (Li et al., 2022b). In another study, Ao li et al. used ANN coupled with CFD to optimize the configuration of a battery system while investigating the effect of natural and forced cooling effect. The ANN builds a relation between the cell spacing and ambient cooling properties. It is found that ambient pressure has a major effect in temperature drop in forced cooling. The optimal design proposed by the authors can decrease the maximum temperature by 1.94% (Li et al., 2022a). In another work, Chaoyai Wan, used tunicate swarm combined with search and rescue algorithm to optimize the battery space in thermal management system. By means of physics models, CFD and MATLAB a 1520 different battery spacing is generated and feed to the optimizing algorithm to predict the best configuration based on maximum temperature and temperature difference (Wan, 2021). Machine learning are integrated with CFD models to simplify and enhance the work in BTM.

to easily predict heat generation of a lithium battery without using multi-physics models, shashank Arora et al. constructed an experimental setup consisting from power supply, programmable charging system, programmable electronic load, programmable air bath, data acquisition system with custom designed battery calorimeter to collect different dataset consisting of nominal capacity, ambient temperature, discharge rate, depth of discharge, and heat generation for a LifePO4 lithium battery. These datasets are used to train an ANN optimized using LM algorithm. Results showed that the optimal configuration for the ANN is a three layers with one hidden layer consisting of six neurons were it can successfully predict the heat generation of pouch cell of varying capacities from 8 Ah to 20 Ah (Arora et al., 2017). Kailong liu et al.. proposed a new model that combines a well-trained RBF with extended Kalman filter to estimate the internal temperature of a lithium ion thermal management battery. two-stage stepwise identification algorithms used to adopt the most significant inputs which are Battery current, terminal voltage, surface temperature moreover, in the forward selection stage FRA is used to obtain the optimal number of neuron. Results showed the proposed model outperforms the other approaches and can extend to other type of batteries (Liu et al., 2018). Kim et al. used characteristics related to fan speed and heat generation rate to accurately forecast the present temperature of several cylindrical lithium batteries (Kim et al., 2013). An experimental battery system's temperature, SOC, and voltage were predicted using an ANN model by Panchal et al. (2018). Amin Shahsavar et al. studied the entropy generation of a cylindrical lithium battery surrounded by three tip fins and PCM with the help of machine learning. Results showed that the best tip clearance for this application is 0.5 mm in which It performs a higher heat transfer and a lower PCM melting time. For an accurate prediction of liquid fraction, and thermal entropy generation rates the authors proposed using gradient boosting decision tree based on flow time and tip parameters. The r value of the model was recorded to be 0.99 (Shahsavar et al., 2022).

Heat generation inside the battery can be effectively be predicted by using machine learning techniques.

Temperature of the battery and its thermal management depends on many parameters such as heat generation, conductivity ratio, Reynolds number, Prandtl number, Nusselt number, coefficient of friction, and many other parameters. lots of studies focused on optimizing these parameters using machine learning and optimizing algorithm. Asif Afzal et al. used Cuckoo search and artificial bee colony algorithm to optimize the maximum temperature, Nusselt number, and friction coefficient by using different cooling fluids of different categories. Results showed that the best cooling fluid is thermal oils and Nano fluids for battery thermal management (Afzal et al., 2021c). In another study for Asif Afzal et al. addressed optimizing the same mentioned parameters using genetic and particle swarm algorithms combined with fuzzy logics. Results showed that genetic algorithm is more suitable for heat transfer application than of particle swarm algorithms (Afzal and Ramis, 2020). In similar context, Mokashi et al. (2021) analyzed Nusselt number for a BTMS using feed forward networks. To study the effect of high and low Prandtl number of different coolants on BTMS, the authors used response surface methodology and particle swarm optimization algorithm to optimize the maximum temperature (Afzal et al., 2021b). For better prediction of Nusselt number which is mainly effected by flow velocity, coolant type, heat generation, thermal conductivity, battery length to width ratio, and spacing between battery packs, Asif Afzal et al. proposed ANN. In this study the authors focuses on computationally optimizing the proposed ANN while using four different activation function (Afzal et al., 2021a).

7. Discusion and outlook

This research offers a thorough analysis of the application of ML for battery temperature prediction and thermal management mainly for lithium batteries. A summary of research papers that adopted ML algorithms in BTP and BTMS is exhibited. This work provides the readers with the foundational knowledge required to adopt ML algorithms in their future work. Researchers tested different ML models and used different input data samples to predict temperature and thermally control the battery system. However, tested models were limited to specific types of batteries and, in some cases, were effected by other unconsidered input parameters. Another thing to think about is choosing the model hyper parameters that will affect the outcomes such as training and optimization strategies, network design, regularization techniques, selection of activation functions, and others.

A summary of the main review findings is mentioned below:

- Machine learning provides strong information-processing algorithms that can model, optimize, predict, and control battery applications. There is no perfect ML technique for battery temperature prediction and thermal management. The effectiveness of any given method is highly dependent on a variety of factors, including the size and quality of the data, the complexity of the inputs and outputs, the training algorithm and parameters used, and the evaluation metrics employed. Therefore, it is crucial to explore and experiment different techniques, algorithms, and evaluation metrics, to identify the most suitable ML technique.
- According to the literature, deep learning techniques such as artificial neural networks, are being more preferable by researchers than traditional machine learning techniques such as linear regression, support vector machine in battery temperature prediction. Exploring traditional ML techniques might provide more in-depth knowledge for the most effective model.

- NARX, LSTM, and GRU neural networks outperform FFNN and ANFIS in the application of BTP and BTM. This is due to their ability to effectively handle time series data, which is a critical requirement in this domain.
- The integration of machine learning with optimization algorithms and physics models allows for the development of hybrid models that improve the performance of thermal management systems.
- There is no specific evaluation metrics for the model, instead various metrics need to be computed allowing the author to determine the most suitable one among all.
- Battery temperature can be reduced by more than 25% by using an appropriate cooling technology integrated with machine learning.
- Researchers in the domain of energy storage are benefiting from machine learning interface and new promising direction for batteries technology.

Declaration of competing interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Data availability

Data will be made available on request.

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