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Machine Learning Assisted Advanced Battery Thermal Management System: A State-of-the-art Review

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Abstract

With an increasingly wider application of the lithium-ion battery (LIB), specifically the drastic increase of electric vehicles in cosmopolitan cities, improving the thermal and fire resilience of LIB systems is inevitable. Thus, in-depth analysis and performance-based study on battery thermal management system (BTMs) design have arisen as a popular research topic in energy storage systems. Amongst the LIB system parameters, such as battery temperature distribution, battery heat generation rate, cooling medium properties, electrical properties, physical dimension design, etc., multi-factor design optimisation is one of the most difficult experimental tasks. Computational simulations deliver a holistic solution to the BTMs design, yet it demands an immense amount of computational power and time, which is often not practical for the design optimisation process. Therefore, machine learning (ML) models play a non-substitute role in the safety management of battery systems. ML models aid in temperature prediction and safety diagnosis, thereby assisting the early warning of battery fire and its mitigation. In this review article, we summarise extensive lists of literature on BTMs employing ML models and identify the current state-of-the-art research, which is expected to serve as a much-needed guideline and reference for future design optimisation. Following that, the application of various ML models in battery fire diagnosis and early warning is illustrated. Finally, the authors propose improved approaches to advanced battery safety management with ML. This review paper aims to bring new insights into the application of ML in the LIB thermal safety issue and BTMs design and anticipate boosting further advanced battery system design not limited to the thermal management system, as well as proposing potential digital twin modelling for BTMs.

Keywords: Battery thermal management; thermal runaway; mitigation; artificial neural networks; machine learning

Word Count: 6313 words.

Contents

Abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
BESS	Battery energy storage system
BTMs	Battery thermal management system
CFD	Computational fluid dynamics
CNN	Convolutional neural network
CPCM	Composite phase change material
DL	Deep learning
DOD	Depth of discharge
DRL	Deep reinforcement learning
EV	Electric vehicle
FEM	Finite element method
FF	Feed-forward
LC	Liquid cooling
LIB	Lithium-ion battery
LSTM	Long short-term memory
ML	Machine learning
MLP	Multi-Layer Perceptron
NN	Neural network
SOC	State of charge
SOH	State of health
SVR	Support vector regression
TM	Thermal management
TR	Thermal runaway

1. Introduction

1.1 Background

While greenhouse gas emissions and global warming remain the utmost concerning issues around the globe, countries worldwide have taken proactive countermeasures attempting to mitigate waste emissions, and it has become a global objective to advocate a cleaner future [1]. As accordingly, there is a seek for a secondary energy source for public transportation and logistic purposes. One example is the uprising blooming application of electric vehicles (EVs), which are powered by cleaner fuel sources. Rechargeable batteries, particularly lithium-ion batteries (LIBs) with high energy density, long life-span and high efficiency, have been used extensively in EVs and other energy storage solutions [2]. Nonetheless, the high energy density and thermal instability of LIBs bring key challenges to battery thermal safety, such as thermal management [3]. Furthermore, it is worth mentioning an extreme condition called battery thermal runaway (TR), which is a potential risk in the battery pack [4, 5]. In addition, battery TR propagation has become one of the greatest challenges for battery safety and often aggravates the thermal hazards through the domino effect during the TR propagation [6]. Figure 1.1 shows a series of chain reactions corresponding to the battery TR process, and the three-stage profile was presented by Wu et al. [7]. Researchers have conducted studies for the module design concerning fire protection and thermal insulation functions.

Given that LIBs are sensitive to working temperature [8-10], it is essential to ensure the battery works in a suitable temperature range to guarantee working efficiency and thermal safety [11]. Therefore, it is imperative to develop effective BTMs, which require a comprehensive system design with multi-factors considered.

1.2 Machine learning application and research gap

Benefited by the rapid development of numerical algorithms alongside data acquisition, ML has become more versatile and efficient with wide applications including electronic devices [12, 13], machinery [14, 15], and advanced materials [16-18]. The ML technique plays a substitutable role in system design and optimisation since it has strong functions in figuring out an optimal solution among multi-factors within a quite limited time [19]. This undoubtedly is not an easy task to fulfil via experiments and numerical simulation. Usually, the experiments can only aid in determining the optimal solution among some limited previously settings. Meanwhile, numerical simulations, such as computational fluid dynamics (CFD) simulations, demand intense computational power and time to deliver a single solution for one case scenario. Therefore, the implementation of ML techniques in the BTMs, to some extent, addresses this issue by being able to almost instantly provide an optimized parameter value provided with sufficient training of data. In addition, ML is expected to assist the temperature prediction in a certain time, enhancing the BTMs' function and giving an early warning before battery TR. For instance, according to time series data, the temperature change during the battery operation can be distinguished by the reversible heat and the irreversible heat, which is also linked to the charge/discharge current. To understand this, researchers attempted to implement ML models, such as artificial neural networks (ANN), convolutional neural networks (CNN), long short term memory (LSTM), deep reinforcement learning (DRL), etc., to assist the BTM system for enhanced battery thermal safety and resilience [13]. For example, Jaliliantabar et al. [20] developed an ANN model for the prediction of LIB temperature equipped with BTMs and proved the capability of ANN to predict battery temperature in various operating conditions of

BTMs. Kalkan et al. [21] built an ANN model, whose inputs involve the coolant flow rate, discharge rate, and coolant inlet temperature, for designing a novel serpentine tube cold late and mini channelled one. Jiang et al. [22] proposed a novel data-driven method for LIB fault diagnosis and TR warning based on state representation methodology.

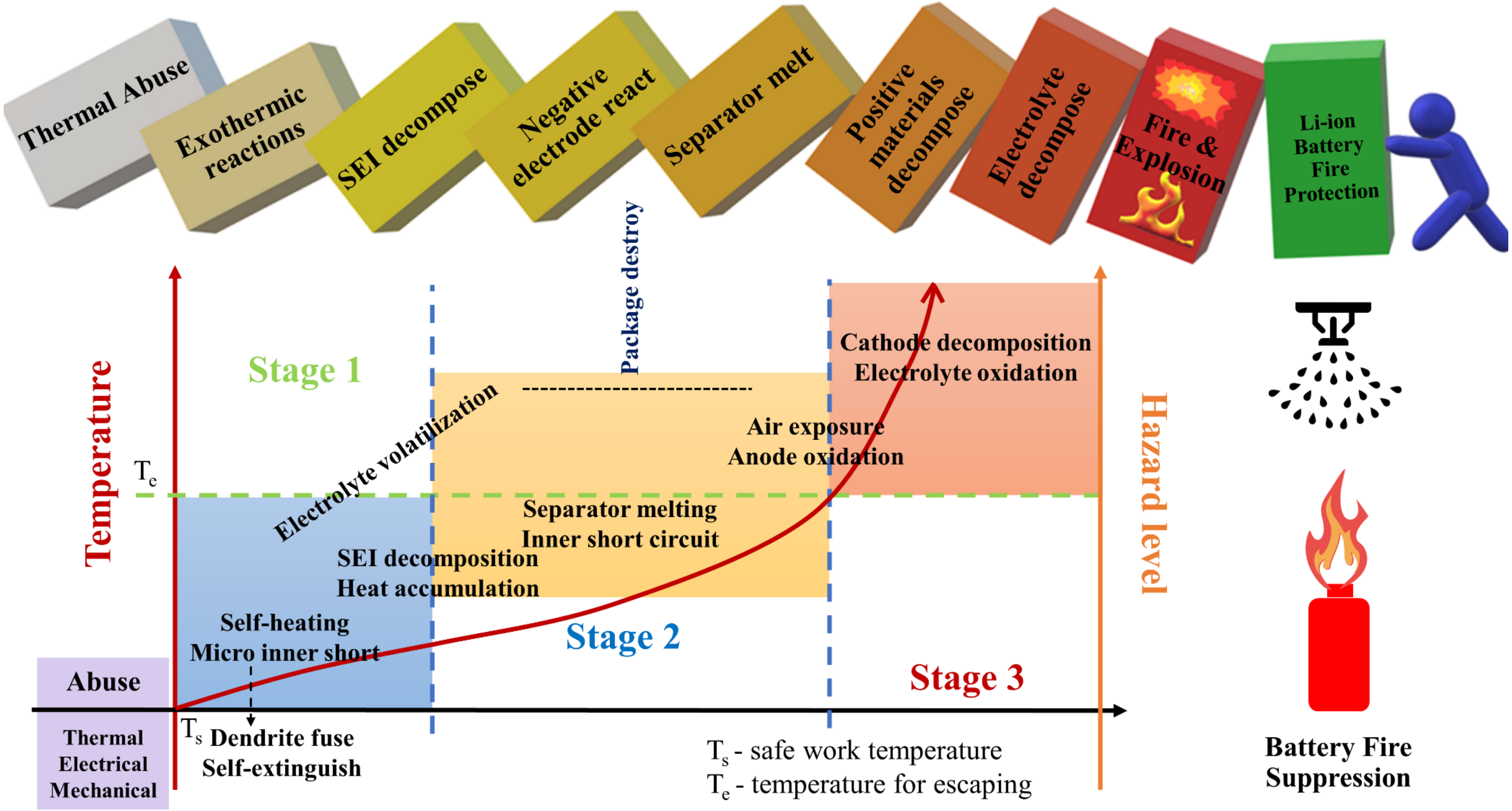


Figure 1.1. Domino effect of battery TR and the corresponding temperature profile along different stages.

Nevertheless, ML algorithms for BTMs remain an ongoing development and comprehensive studies with a vast amount of training database are both required to empower their industry applications. Furthermore, to the best of our knowledge, there is still little relevant review article summarizing the state-of-the-art literature using ML in the BTMs and battery fire prediction, which leads to a research gap in classifying ML models in thermal safety issues applications. In this review paper, by revealing past and current research works on ML-assisted battery systems, it delivers understandings, insights and future perspectives to accelerate the development of both intelligent BTMs optimization and safety design.

1.3 Contribution and structure

On the basis of the aforementioned research gap, the current work summarizes the state-of-the-art publications regarding the ML application in the battery thermal safety issue, including battery thermal management and battery fire. Also, the potential improvement directions with ML models applied in the battery are highlighted in the graphical abstract, including building and infrastructure, EVs and power stations, electrical transportation systems, portable devices, and rural region power supply hubs. In addition to the literature review, the authors have proposed some critical thinking in the potential combination of ML techniques with the battery system, particularly from the thermal safety perspective. The main contents of this paper are summarized as follows:

Section 2 briefly introduces ML, where the mostly ML models (such as ANN, CNN, and LSTM) used in the current related works are demonstrated in a certain category.

Section 3 summarizes the related literature using ML to solve problems, where the applications are generally divided into 3.1) battery temperature or thermal parameters prediction and 3.2) system optimization.

Following that, Section 4 lists the previous publications about battery fire (treated as the extreme state of thermal hazards) and ML applied in battery fire prediction.

Finally, in the conclusion section, the authors draw conclusions and potential contributions of this review paper based on the current development. Besides, the authors propose some novel ideas on the way forward for future applications, hoping to give guidance and references for further probe into this field. Last but not least, we anticipate this review article can give more references for researchers in designing and/or optimizing future BTMs. The booming artificial intelligence technology can further boost the development of BTMs.

2. Machine learning overview

As the world is rapidly transiting towards electrification and automation, artificial intelligence (AI) systems are increasingly integrated into our daily lives (telecommunication networks, infrastructures, transportation systems, etc.). Concurrently, our current age is deemed a digital world, and various data types are ubiquitous. Implementing AI, particularly ML approaches, is the key to intelligently analysing the data and constructing correlative smart applications. With the revolutional developments of computer science and processing power over the last decades, ML algorithms have been widely applied in different fields, such as building [23, 24], chemistry [25], manufacturing [26], agriculture [27, 28], etc. ML is a computer program that learns from experiences concerning some class of tasks and performance measures if its performance at tasks improves with the experiences [29]. Figure 2.1 shows the schematic of ML. Samples train the machine, and then when input comes to the machine, the machine's structure and/or parameters are updated by the new samples. The approximated output will be generated afterwards. Also, many previous reviews of ML have been done [30-32]. Normally, ML techniques are categorised into four major types: Supervised learning, Unsupervised learning, Semi-supervised learning, and Reinforcement learning [33], shown in Figure 2.2.

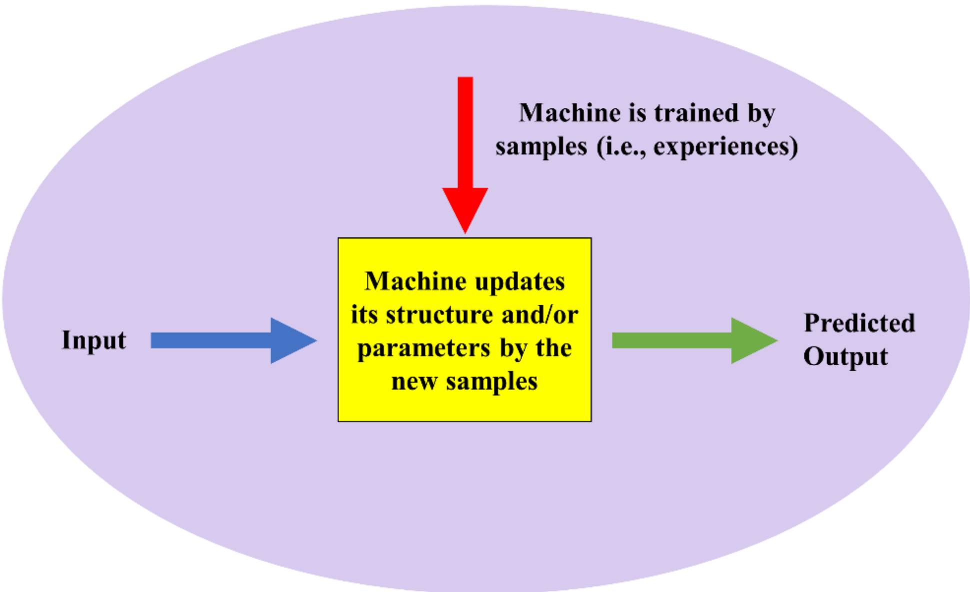


Figure 2.1. Schematic of ML methods.

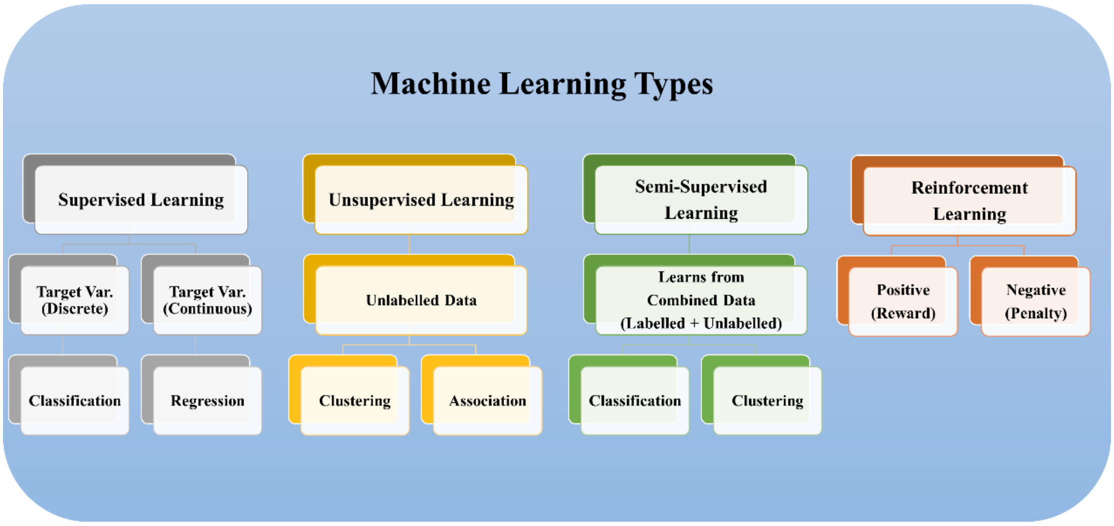


Figure 2.2. Major types of ML techniques [33].

This review mainly focuses on the ML applied in the battery thermal safety issues field. The applied algorithm depends on many factors, including the problem to be addressed, the number of variables, the chosen model, and so force. In line with the overall reviewed papers, the ML algorithms in this review are summarised in three components: ANN, deep learning (DL) and other methods. In this section, we briefly outline the ML algorithms used in the battery thermal safety issues and provide the potential of the applied ML models to improve the intelligence and capabilities of BTMS applications.

2.1 Artificial neural network (ANN)

Artificial neural networks, normally called neural networks (NNs), are computing systems inspired by the biological neural networks that form animal brains. ANN has rapidly developed as a common tool to model a broad range of engineering systems due to its capability to learn and adapt to find potential correlations among different properties. ANN-based models are empirical. However, they can contribute to practical, accurate solutions for accurately or imprecisely formulated problems and phenomena only identified with experimental data and field observations. ANNs have been used in various applications, including modelling, classification, pattern recognition, multivariate data analysis, etc. Owing to the high precision and outstanding data noisy tolerance, ANN has been successfully utilised in studying battery-related topics, such as the state of charge estimation, state of health assessment, battery temperature prediction, BTMs optimization, etc.

ANN is a non-program, adaptive, brain-style information processing that functions through network transformation and dynamic behaviour [34]. An ANN model has five main components: inputs, summation functions, weights, activation functions, and outputs, which the early researchers propose to model the operation of the artificial neurons. The working process of a typical ANN model is straightforward. Inputs of ANN were received by an artificial processing neuron and were combined to generate a net input. The neuron passes that through a threshold gate and transmits the output to another neuron or the environment.

The artificial neuron in the hidden layer works as a biological neuron in the brain. To form a directed and weighted graph, the network is shaped by linking the output of specific neurons to the input of other neurons. A learning process can adapt the activation functions and weights. The learning rule or training approach controls the certain learning process. The activation function of a node governs the output of that node, or "neuron," provided input or set of inputs. The activation function presents a functional relationship between the input and output layers. Step activation, threshold, sigmoid, and hyperbolic tangent are frequently applied activation functions.

ANN approaches are applied in the control or modelling of systems with unknown or complex internal structures by achieving the advantage of learning and the stability of facing minor disturbances. This section focuses on multilayer perceptron and support vector regression applied for BTMs.

2.1.1 Multilayer perceptron (MLP)

Multilayer Perceptron (MLP) is known by its architecture, which is also a feed-forward ANN [33]. A typical MLP contains at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input layer, each node of other layers is a neuron that utilizes a nonlinear activation function to connect. MLP utilizes a supervised learning technique called back-propagation for training. Its multiple layers and nonlinear activation separate MLP with a linear perceptron, which can distinguish data that is not linearly separable. A hidden layer is a layer located between the input and output of the ANN model, in which artificial neurons apply a set of weights to the inputs and direct them through an activation function as the output. Hidden layers of ANN allow for a neural network's function to be taken apart for specific data transformations. For example, images and documents are treated as initial inputs from external data. The ultimate outcomes, such as recognizing objects in a snap, complete the task.

2.1.2 Support vector regression (SVR)

Support Vector Regression (SVR) is popularly and widely applied for classification problems in ML. SVR is an analytical approach to investigating the relationship between one or more predictor parameters and a real-valued (continuous) dependent variable [35]. As a significant branch of support vector machine (SVM), SVR only has one kind of sample point [36]. Compared to SVM, SVR is less popular, but it is an effective tool for estimating real-value functions. SVR uses kernel functions to outline the nonlinear regression problem for nonlinear problems. The optimal hyperplane it pursues is not to maximize the separation length between two or more types of sample points like SVM but to minimize the total variation between sample points and hyperplane. And the sample points can be separated by an optimal hyperplane in high-dimensional spaces. For example, for a linear situation of SVM, the points outside the middle shaded tube region affect the cost insofar as the deviations are penalized linearly [37].

2.2 Deep learning (DL)

Deep learning (DL) is a subfield of ML, typically a neural network with three or more layers of neurons, as shown in Figure 2.3. DL attempts to replicate the behaviour of the human brain, allowing numerical models with multiple layers to learn multiple levels of large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers contribute to optimising and refining accuracy.

Compared to traditional neural networks, DL shows a better performance in everyday products and service cases with large datasets, such as voice-enabled TV remotes and credit card fraud detection. Observing patterns in the data allows a DL model to cluster inputs appropriately. Therefore, a DL model would require more data points to improve its accuracy. Furthermore, DL has some limitations: data amount, computational power, and training time. Typical types of DL related to BTMs in this review are listed as follows.

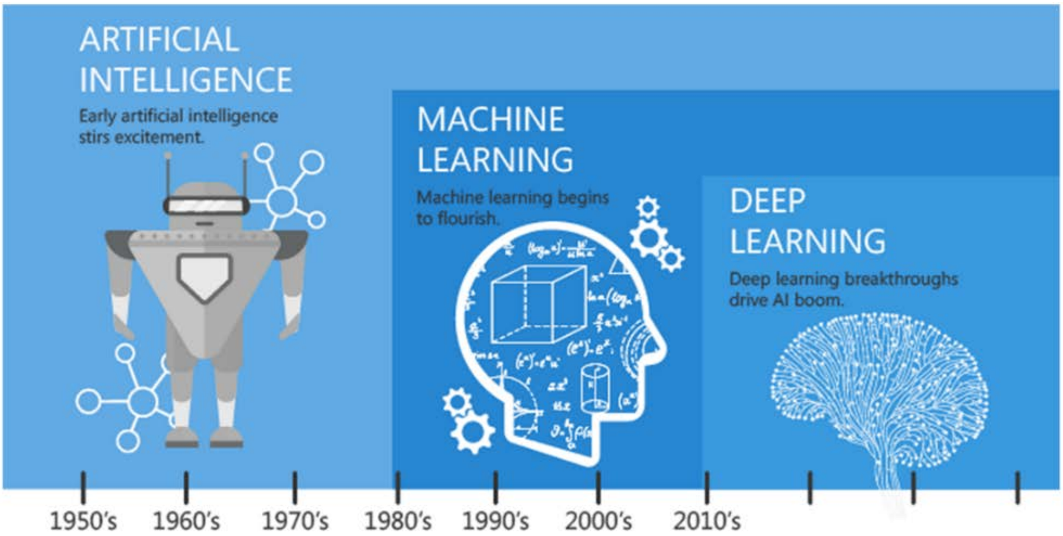


Figure 2.3. Relationship among AI, ML and DL [38].

2.2.1 Convolutional neural networks (CNNs)

Convolutional neural networks (CNNs) are applied primarily in image and video recognition, classification, natural language processing, etc. CNN can take advantage of the two-dimensional structure of the input data for detecting features and patterns and achieving tasks like object detection or recognition. Many successful applications of CNN models in the field. For example, a CNN firstly bested a human in an object recognition challenge in 2015.

2.2.2 Long short-term memory (LSTM)

Long short-term memory (LSTM) is a recurrent neural networks (RNNs) architecture, which is typically applied in natural language and speech recognition as it leverages sequential or time-series data. LSTM can overcome the training difficulty caused by the exploding/vanishing gradient problem. The learning advantage of LSTM impacted several fields from both a practical and theoretical viewpoint, so it became a state-of-the-art model [39]. Figure 2.4 shows the architecture of a typical LSTM block, including gates, inputs and outputs. The output of the block will be connected back to the block input and all of the gates for the calculation. Also, researchers keep studying the possibilities to improve the performance of the typical LSTM.

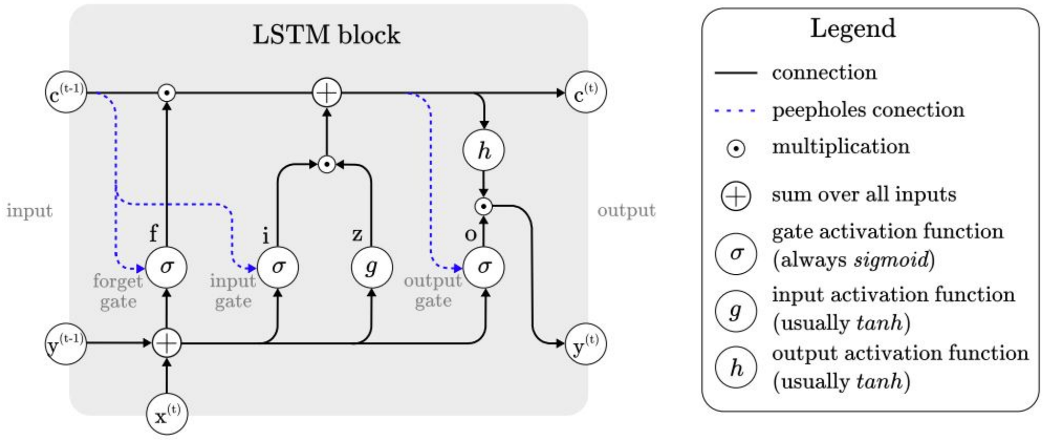


Figure 2.4. The architecture of a typical vanilla LSTM block [39].

2.3 Other machine learning methods

Due to the battery itself combining electrical, chemical and mechanical parameters, many different perspectives should be involved, such as voltage, temperature, State of Charge (SOC), Depth of Discharge (DOD), resistance, cycle life, State of Health (SOH), etc. Therefore, besides the prementioned ML techniques, some other ML algorithms are still applied in battery thermal and safety research. In addition, the combined ML methods will be listed in the next section.

2.3.1 k-nearest neighbours algorithm (KNN)

k-Nearest neighbours (KNN) is an uncomplicated algorithm that allocates new data based on a similarity measure (e.g., distance functions) with the input data, also known as a 'lazy' learning model. KNN has been applied in some analysis fields, such as statistical estimation and pattern recognition. The concept behind nearest neighbour methods is to catch a pre-determined number of training objects closest to the new point and utilise them to predict its label. KNN is quite robust to noisy training data, and accuracy depends on the data quality. The number of cases can be a user-defined constant, which can also vary locally depending on the density of points.

2.3.2 Gaussian process regression (GPR)

Gaussian process defines a distribution over functions and inferences taking place directly in the space of functions. Gaussian processes often have characteristics that can be changed by setting certain parameters. The algorithm is applied to estimate the SOH and SOC of LIBs. Also, the GPR model has a straightforward parameterization. The model parameters can be computed by maximizing a marginal loglikelihood function, which is easy to implement and flexible to use, in contrast to commonly used grid-searching trial-and-error methods used to optimize the SVM [40].

2.3.3 Digital twin (DT)

With the wave of the digital economy, the application of the Internet of Things (IoT), cloud computing, big data and other technologies have become a future trend in battery management and production [41]. To overcome the increase of battery cell number, algorithm complexity, and new functionalities, digital twin (DT) was built to improve the computation and data storage capabilities, where all battery-relevant data can be measured and transmitted seamlessly to the cloud platform [42]. DT uses massive twin data and real-time coupling to achieve simulation, prediction, diagnosis, etc., while ML can be matched with intelligent algorithms for multiple needs [43]. DT can improve accuracy and responsiveness of different functions with ML algorithms.

To sum up, in the field of battery research, ML has emerged as a potential modelling method and has already been applied in many perspectives of this area. Figure 2.5 shows the trend of applying ML methods in battery research continually increases. It shows that ML has a great potential in battery fire (BF) and BTMs. Meanwhile, it has specific advantages in fast and accurate real-time battery state predictions. In this section, we summarise the most used ML methods for battery thermal and safety issue.

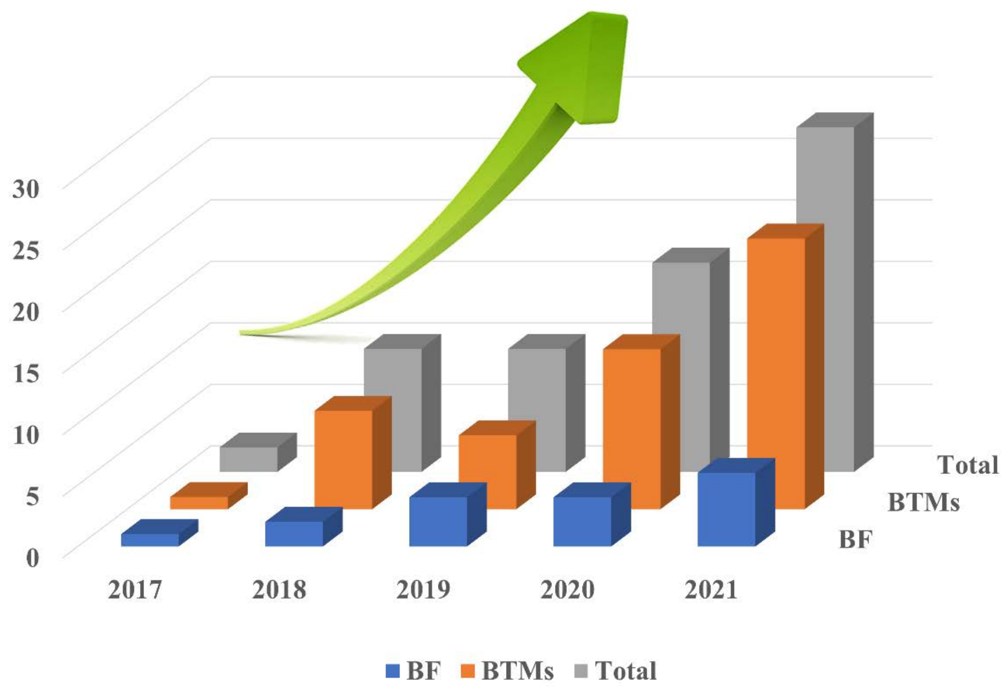


Figure 2.5. Publication amount trend of ML applied in battery in recent years.

3. Machine learning and battery thermal management

As mentioned in Section 1, it is imperative to design ideal BTMs due to the strict temperature requirement of LIBs. Currently, there are numerous studies concerning BTMs emerging fast, which employ air cooling, liquid cooling, phase change material cooling, etc. Among them, many parameters must be determined or optimized before establishing an effective BTMs. These parameters optimization include air velocity in the forced air cooling [44, 45], the ambient temperature in the forced air cooling [46], the flow rate of the liquid [47, 48] and cooling liquid temperature [49, 50]. However, it is not an easy task to optimize so many parameters via experiments or simulations only. For one thing, most experimental studies adopt the method of determining the most optimum one among many options. For another, even though the numerical studies mostly follow this pattern, whose results are indeed superior but operated under a recommended range. Rare studies proposed the most optimum values applying the optimization progress with ML methods [51], which are considered a superior tool in optimizing and predicting parameters [52-54].

3.1 Heat generation and temperature prediction/Thermal data prediction

Kleiner et al. [55] developed a lumped thermal model with a novel neural network and proposed a direct comparison of a physics-based and a data-driven thermal battery module for the first time. In their study, the temperature estimation of both modelling approaches is in good agreement with the reference temperatures for multiple locations.

Afzal et al. [56] compared single layer NN with deep NN to figure out an optimized number of hidden layers to predict Nu coupling with neurons and activations functions (See Figure 3.1). They concluded that the deep NN provided a much better prediction than the single layer NN model.

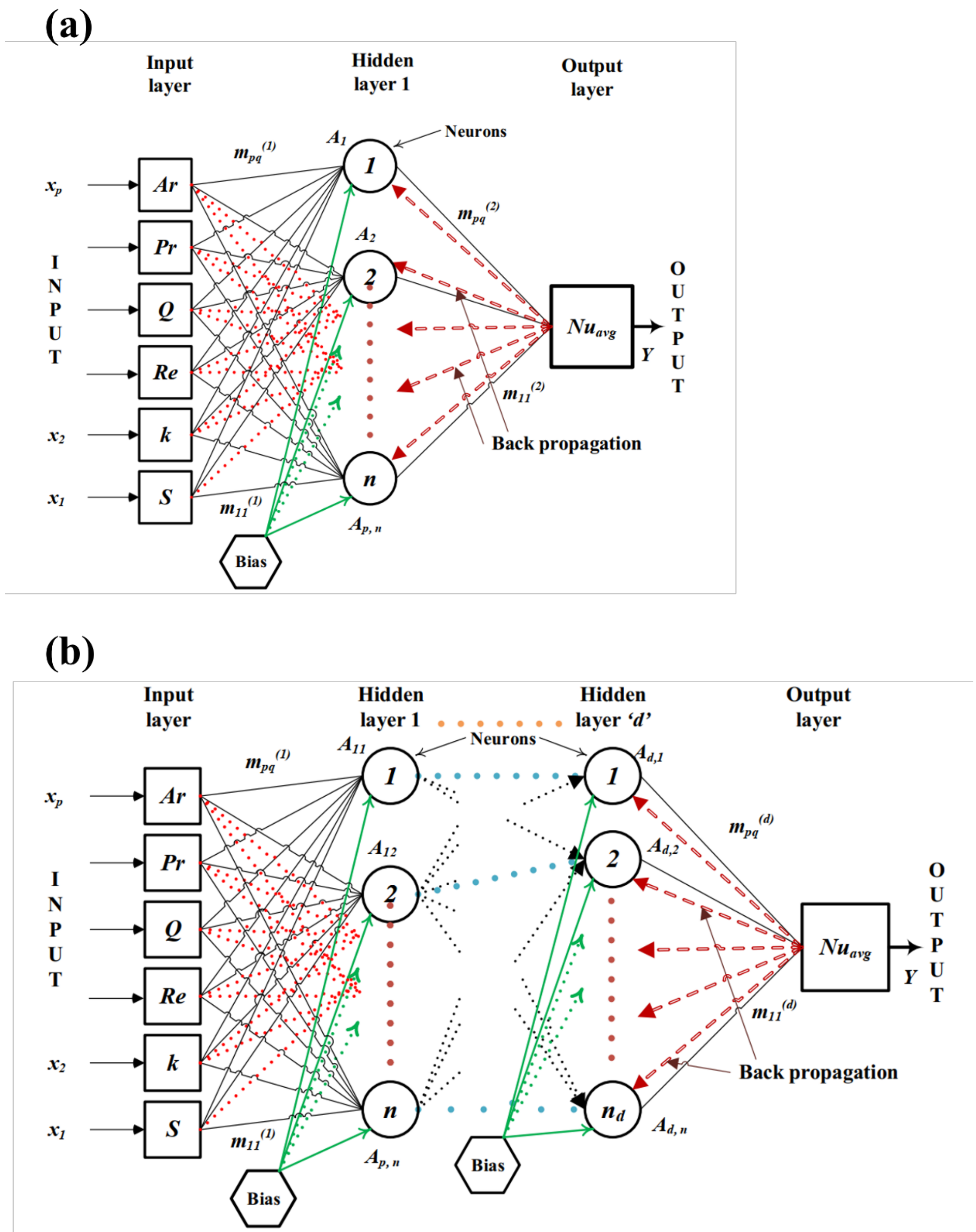


Figure 3.1. (a) single hidden later NN tested for different neuron numbers, (b) deep hidden layer NN tested for the different neuron numbers and deep hidden layers' d'.

Kleiner et al. [57] proposed a novel simplified modelling approach for predicting the jelly roll temperature of large format prismatic cells based on ANN. Arora et al. [58] also proposed a new computational model based on ANN for estimating battery heat generation rate with cell nominal capacity as one of its key inputs, along with ambient temperature, discharge rate and depth of discharge. Their trained ANN accurately simulates the thermal behaviour of LiFePO4 pouch cells of the nominal capacities from 8 to 20 Ah under varied conditions.

Except for ANN, CNN and LSTM are also popular ML models for evaluating the effectiveness of the BTMs. To highlight the accuracy and application prospect of CNNs to substitute complex, time-consuming FEM modelling, Kolodziejczyk et al. [59] first modelled CPCM microstructures with FEM, whose image dataset is subsequently used to train CNN models. After that, the CNN was used to predict the temperature evolution of the CPCM-based BTMs during charging/discharging currents, as shown in Figure 3.2. Wang et al. [60] applied CNN and virtual thermal sensors to predict a ternary battery internal temperature and highlighted this method needs no knowledge of battery thermal properties, heat generation or thermal boundary conditions. Besides, Zhu et al. [61] used time-series data to train the LSTM model and found that battery temperature fluctuation can be efficiently predicted over a long period, serving as a battery temperature prognostic. Huang et al. [62] propose a deep reinforcement learning model to optimize the battery energy management strategy considering battery thermal effects. By comparing the numerical results to two conventional reinforcement learning algorithms, the proposed method demonstrates a more than 6.7% energy reduction, which saves the cost for training and makes the data sets close to the practical scenario.

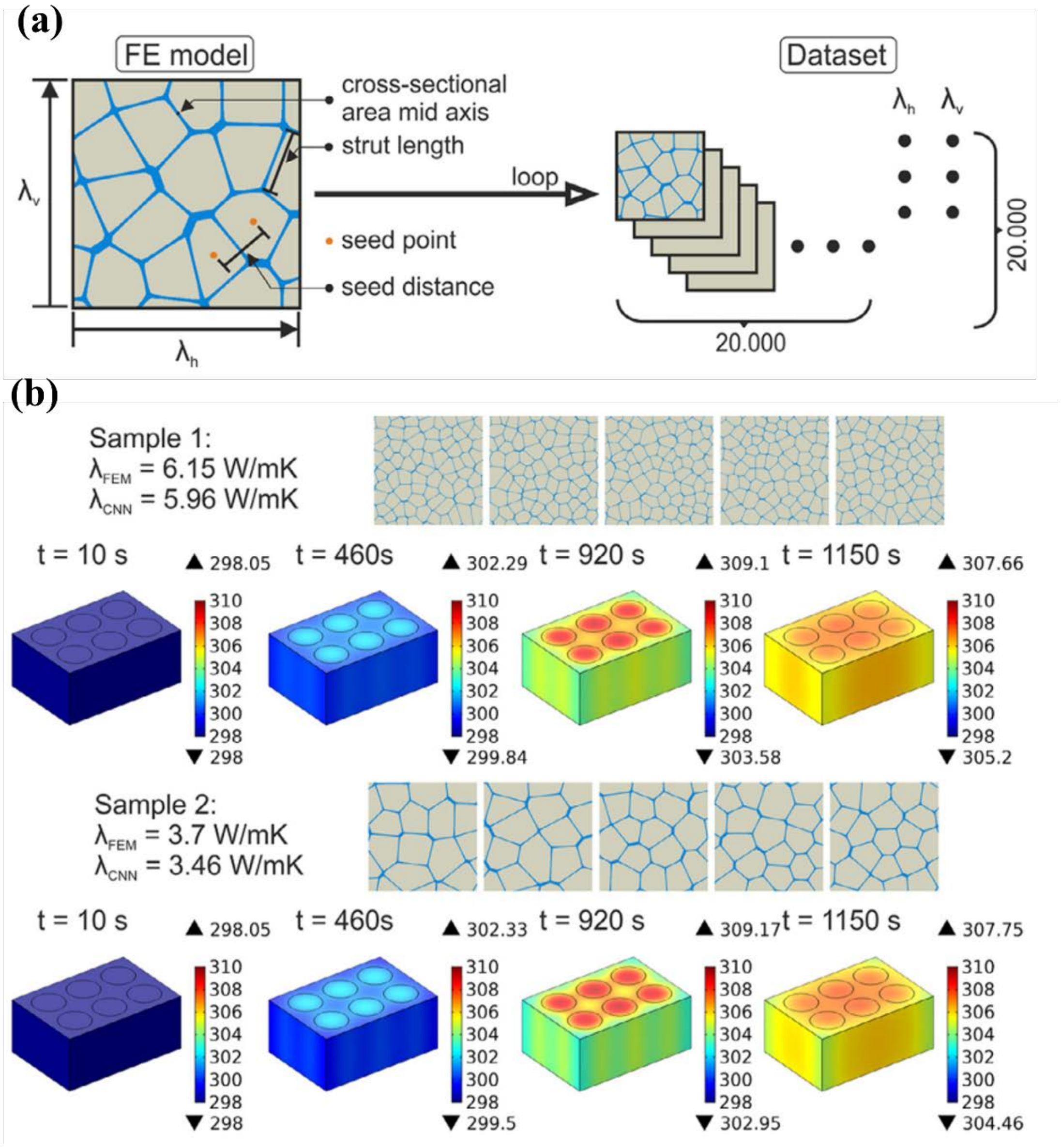


Figure 3.2. (a) the developed modelling strategy for creating the dataset of composite PCMs, (b) two CPCM samples with their cross section images and time evolution of surface temperature [59].

3.2 System optimization with machine learning

ML is a smart tool to assist multi-factor design [52]. For example, ANN can be applied to describe the relationship between BTMs parameters [63, 64] and provides a time-saving and efficient method for optimal design.

3.2.1 Multi-factor design

Mokashi et al. [65] applied ANN model to analyse the heat removal from the battery pack using a different flowing fluid with an average Nusselt number. In their work, three different types of multi-layered FF networks with back-propagation were developed, i.e. the multiple back propagation (MBP) 1-3 (Figure 3.3(d-f)). The multiple back-propagation algorithms assist the regression analysis of the average Nusselt number.

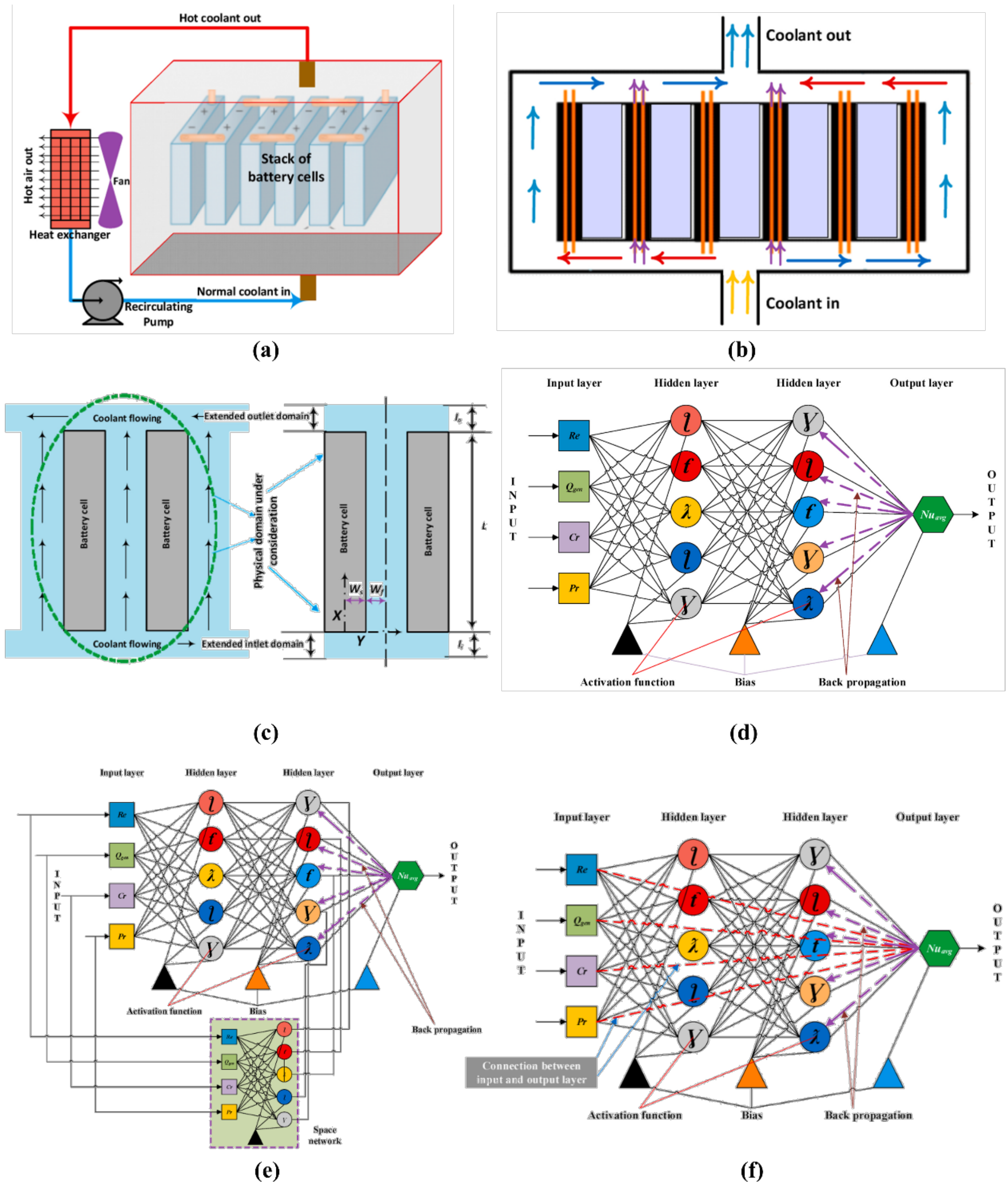
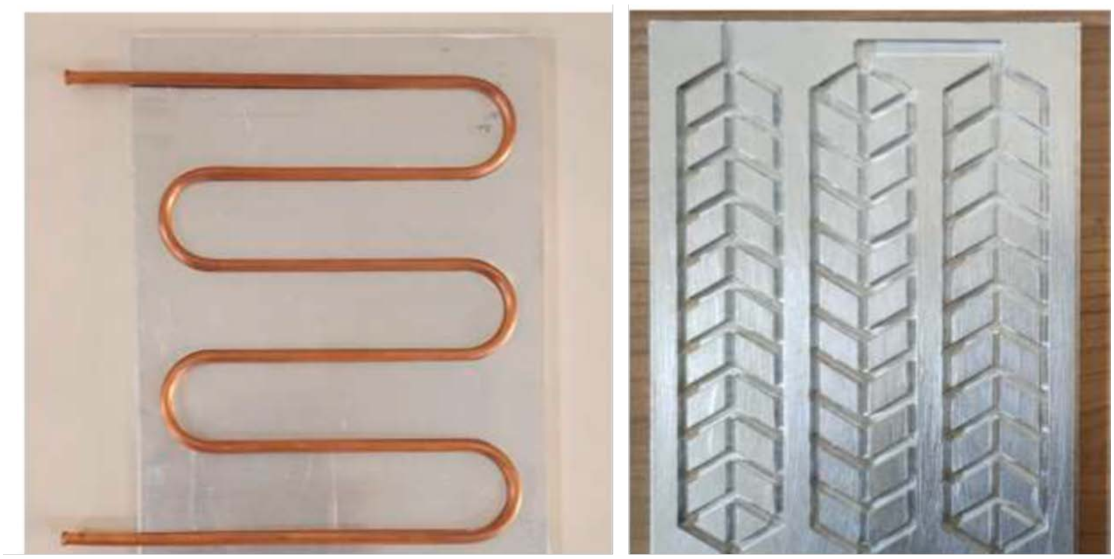


Figure 3.3. (a) 3 D and (b) 2 D diagrams of the BTMs, (c) computational domain of the conjugate problem, (d) MBP 1, (e) MBP 2, and (f) MBP 3 [65].

Lin et al. [63] utilize an ANN network combined with a genetic algorithm to optimize the thermal performance of air-PCM BTMs regarding the inlet air velocity, inlet air temperature, PCM thickness, and battery unit spacing and discharge rate. Their results showed that the PCM thickness and battery unit spacing affect the battery temperature. The optimal parameter combinations help slow the temperature rise and delay the PCM phase transition.

Xu et al. [66] proposed a novel digital twin virtual model-based BTMs parameter optimization (including microchannel plate width or cell internal spacing d1, side spacing d2, microchannel height l and coolant flow rate V). Finally, they developed a new type of microchannel liquid cooling BTMs, which has a better cooling effect but smaller volume. Similarly, Talele et al. [67] applied ANN to investigate the delay effect caused by the battery pack to resist the set limit of the threshold temperature range, where a multi-objective optimization strategy is proposed between the battery pack delay effect for selected paraffin wax and RT-18 PCM against its given C-rate. Kalkan et al. [21] applied ANN when developing a cold plate (Figure 3.4), including some key parameters like coolant flow rate, the inlet temperature of coolant and discharge rate.



(a) **(b)**

Figure 3.4. Section views of (a) serpentine tube cold plate (STCP) and (b) mini channel cold plate (MCCP) [21].

Genetic programming (GP) models are also popular in system optimization. For example, Su et al. [68] applied genetic programming (GP) when optimizing the inlet coolant temperature in the BTMs. The GP model process is illustrated in Figure 3.5.

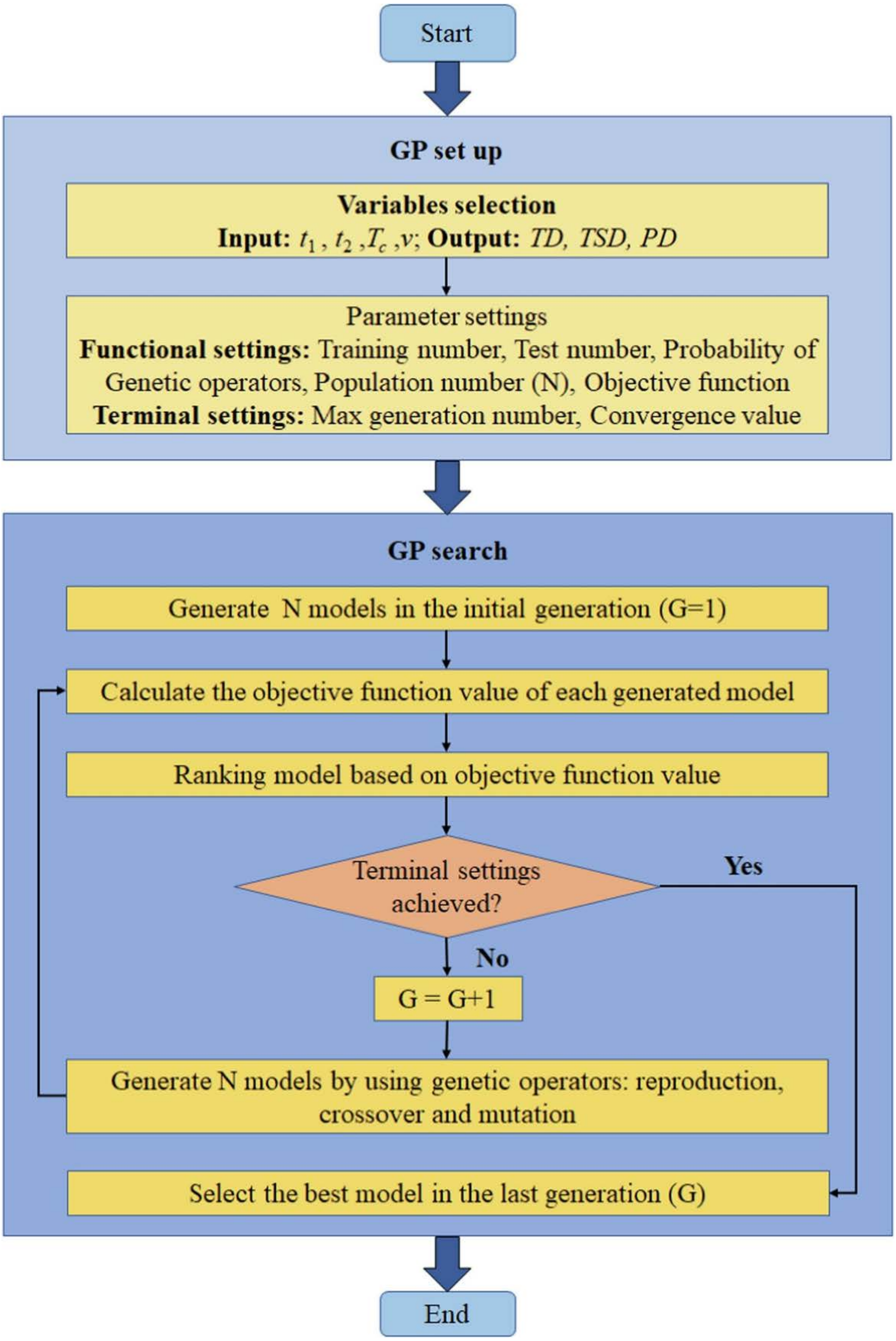


Figure 3.5. Illustration of the GP process [68].

There are also some newly developed models by the researchers to investigate the specific scenarios. Shi et al. [69] developed a fully connected deep network to optimize the air cooling model regarding different shell structure features, including various numbers, positions, and sizes of the additional outlet in the U-type cooling BTMs.

Besides, SVR models can also be applied to predict battery temperature changes. For example, Tang et al. [70] used the system coefficient performance-support vector regression (PSO-SVR) model to investigate the influence of ambient temperature, air flow rate of the external heat exchanger and compressor speed on performances of the liquid-cooled BTMs and proved the PSO-SVR model can be used as a new method to fit the complex nonlinear relationship among the system COP.

3.2.2 Cooling efficiency determination

Except for the simultaneous design of multi-factor optimization in the BTMs, there is also an important but seldom investigated issue, namely the coordination among (fast) charging, effective cooling and energy efficiency. This task can be extremely tough to realize via limited experiments, while machining learning models can help. Chen et al. [71] proposed the NN model to assist in combining fast-charging process scheduling with thermal management and figure out a trade between the charging speed, cooling efficiency and energy consumption, as shown in Figure 3.6. In their study, the regression model could predict three target values for all of the combinations among a wide range of charging current rates (0.5C, 1C, 1.5C, 2C and 2.5 C) at three different charging stages and a range of coolant rates (0.0006, 0.0012 and 0.0018 kgs^{-1}). The maximum temperature and temperature standard deviation (TSD) were lower than 33.35 and 0.8 °C. Similarly, Park et al. [72] first proposed an optimal TM strategy and then used an ANN-based model to reduce the total energy consumption while maintaining the battery temperature within an acceptable range.

In this section, the related literature with the applications of ML techniques to solve problems of battery thermal prediction and system optimization are reviewed. Table 3.1 summarises the reviewed research works that applied ML techniques for BTMs, and it is concluded that ANN is applied the most in this area. At the same time, other methods, including CNN, SVR, and LSTM, also have the potential to enhance BTMs.

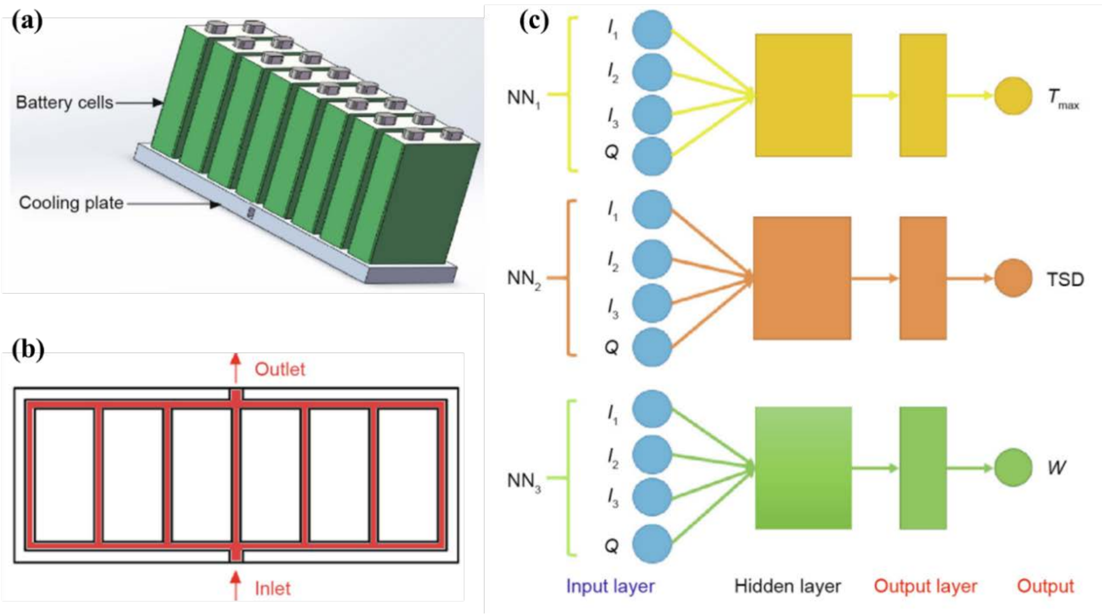


Figure 3.6. Diagram of (a) LC-based BTMs (b) mini-channel-based cooling plate, (c) proposed NN model [71].

Table 3.1 Summary of the ML applied in the battery thermal management design and thermal data prediction.

ML approach	Target object	Reference
ANN	PCM design	[20]
	Cold-plate design	[21]
	Optimization of battery pack enclosure	[53]
	Battery pack configuration	[54]
	Temperature prediction	[57]
	PCM-based BTMs design	[63]
	PCM delay	[67]
	BTMs design	[72]
	Energy efficiency optimization	[73]
	Surface temperature	[74]
	Liquid cooling based BTMs	[75]
	Thermal coupled equivalent circuit model	[76]
	Heat generation rates	[77]
MLP	Liquid cooling	[71]
CNN	PCM design in thermal management	[59]
LSTM	Thermal effects and temperature changes	[61]
DRL	Battery temperature and energy consumption	[62]
SVR	Liquid-cooled battery thermal management	[70]

4. Battery safety and machine learning

Batteries, as complex materials systems, pose unique challenges for the application of ML [78]. In recent decades, LIBs have been widely used in our daily life, such as electric vehicles (EVs), battery energy storage systems (BESSs), and small portable devices. Many battery fire accidents happen now and then. Ghiji et al. [79] demonstrated more than 300 fires or fire-related incidents with 40 fatalities reported over the past two decades. Although a shift to data-driven, ML-based battery safety research has started, new initiatives in academia and industry are still needed to exploit its potential fully.

4.1 Battery safety

LIBs with high energy density materials are sensitive to abusive conditions and have relatively low thermal stability [80-82], leading to safety problems, such as TR and its propagation [83, 84]. These papers have reviewed and summarised many representative incidents of LIBs failure accidents [85, 86]. Due to the typical explosive components of a battery, such as plastic packing, separator and electrolyte, LIB accidents happen in various applications, from mobile telephones to EVs and even aeroplanes. Based on these reviews, the various abusive conditions, such as over-heating, over-charged, short circuit and mechanical shock, have been studied, and it is easy to conclude that thermal abuse is the root cause of battery TR [6]. Moreover, the abuse conditions can be categorized into three sections: mechanical abuse, electrical abuse and thermal abuse, whose common features are smoke, fire and explosion, as shown in Figure 4.1 (a).

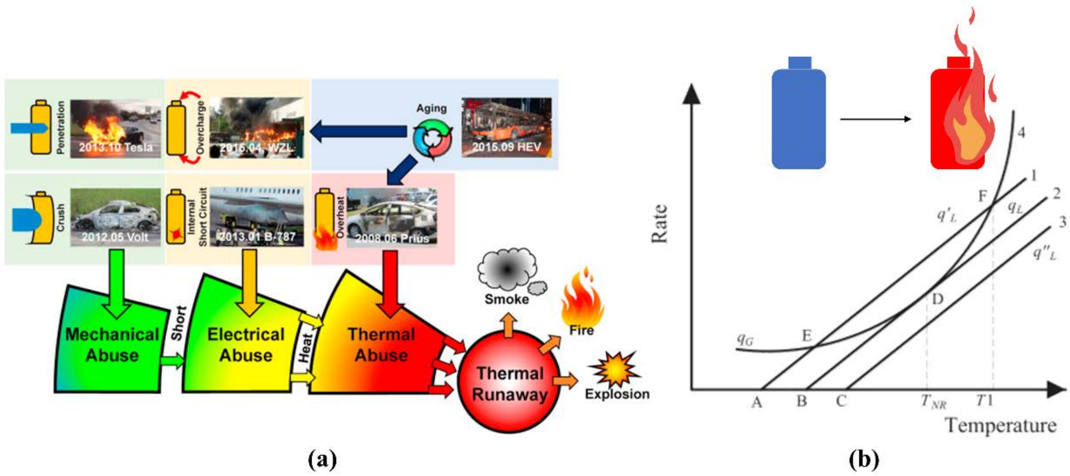


Figure 4.1. (a) Accidents related to LIB failure and correlated abuse conditions [6]; (b) Thermal digraph of a reaction and heat loss from a vessel at three ambient temperatures, where B is at the critical temperature [87].

As for the necessary components of combustion, fuel, oxygen, and an ignition source consist of the combustion triangle. For LIB fire, these three parts are also necessary.

The main fuel is the electrolyte, which is made of organic solvent and inorganic salt. Furthermore, LIBs are separated from the air in a normal situation without an explosion or fire danger as a closed system. However, due to the TR, the positive electrode decomposes and releases O_2, which is one of the contributions to the combustion triangle and chemical reactions at the negative electrode. Meanwhile, all these decompositions are exothermic processes that serve as the ignition source. Consequently, the LIB is under fire hazard risks.

As shown in Figure 4.1 (b), the TR process can be described as follows: with the increase of the battery temperature and more exothermic chemical reactions happening, more heat was generated. The curved line 4 stands for the generated heat owing to an exothermic reaction, while the straight lines stand for the heat removal, which is a linear function at various coolant temperatures. The Straight line 2 has one tangent point D with curved line 4. This point is a critical point, as heat removal equals heat generation; thus, this critical equilibrium temperature is named the 'Temperature of No Return'. The temperature B is called the self-accelerating decomposition temperature. If the TR happens, once the temperature is over the critical point, all the exothermic chemical reactions will contribute to the self-heating and will not return. Then the temperature and pressure in the LIB are cumulated until it exceeds the battery endurance. The fire and explosion are inescapable, and the whole process can be described as the Domino effect of the reaction chain. For the sake of fire protection, it is important to take measures to break the Domino chain to avoid TR and fire hazards.

The battery TR is similar to a series of chain reactions, which can be described as the domino effect, shown in Figure 1.1. Under the common battery working conditions, the battery temperature is no more than 40 °C, which is relatively low. Still, the abuse situations, such as short circuit, overcharge, applying reverse polarity or exposure to extreme temperature, will lead to a sharp increase in the temperature. In a situation with a temperature exceeding 66.5 °C, more reactions trigger, generating more heat to quicken up self-heating reactions. After that, the reaction will not return when the temperature is over 75 °C. Along with more chain reactions, the generated gas and heat are cumulated. Once the inner environment pressure exceeds the battery endurance, the explosion is inevitable, and the battery components are easily ignited and thus leading to a LIB fire.

Kriston et al. [88] investigated the impact of TR initiation conditions on the severity of TR of Graphite—NMC (111) cells. Seven hundred eighty various TR events are simulated, and the output is studied by ML techniques such as principal component analysis and clustering.

Similarly, Li et al. [89] employed a high-accuracy finite element model of a pouch cell to generate over 2,500 simulations and analysed the data with ML methods, shown in Figure 4.2. The safety envelope was visualized with two types of phase diagrams, a classifier that predicts with a fast speed on the short circuit or safe to a given loading condition and a regressor that quantitatively tells the amount of deformation needed to develop a short. The safety envelope provides important guidelines for the design of EVs and batteries. The regression model provided the ranges of the safe and electric short circuit ranges, and also predict the quantity of intrusion, force, and energy absorption to which the short circuit happens.

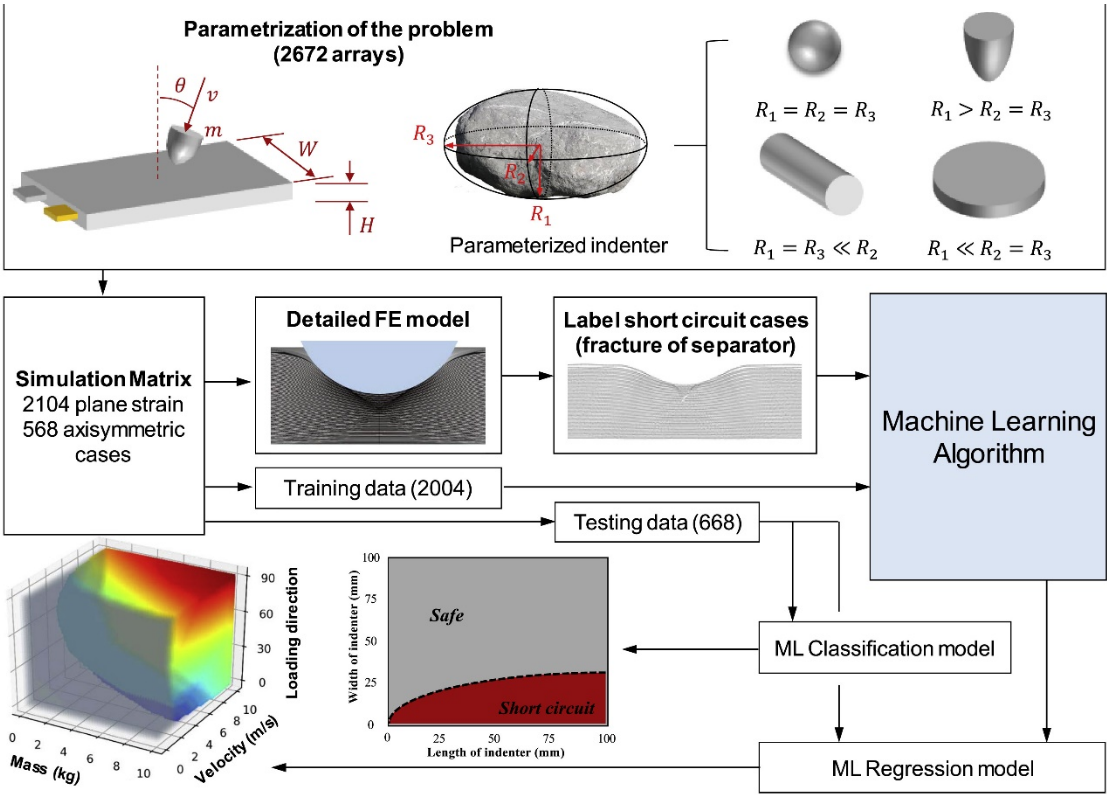


Figure 4.2. Flowchart of the Data-Driven Safety Envelope Using ML Algorithm [89].

From the electrochemical perspective, Seo et al. [90] demonstrated a method for detecting the internal short circuit in the LIB using CNN, which is used to classify the degree of the internal short circuit faults. The proposed method shows classification results with high accuracy of 96.0% and consequently contributes to detecting the internal short circuit in the early battery state.

Furthermore, Petrich et al. [91] used MLP to detect cracks in the anode of a LIB after the TR. The classifier studies pairs of particles and distinguishes three causes for their separation: breakage during the TR, image segmentation and disjointness in the pristine cell. For the dataset of the hand-labelled data from a real electrode, an overall accuracy of 73% is achieved.

4.2 Hazard prediction

Due to the wide applications of LIBs, the safety and reliability of LIBs are crucial for people's lives. Yet, our capability to predict failure through online and offline diagnostics still has space to improve [72]. LIBs hazardous failure is rare, but the consequences are relatively severe. LIBs can be treated as highly complex and nonlinear systems. Worse, similar battery cells or packs may perform differently towards identical mechanical, electrical, or thermal stimuli, limiting the performance of classical deterministic numerical approaches. For supporting decisions in design and control, a probabilistic method can be applied to quantify uncertainty. For example, Figure 4.3 demonstrates an overview of data from battery cells can be applied to interpret and perhaps to enhance the prediction accuracy by data-driven techniques, where spatial surface temperature profiles can also be monitored as a thermal data input.

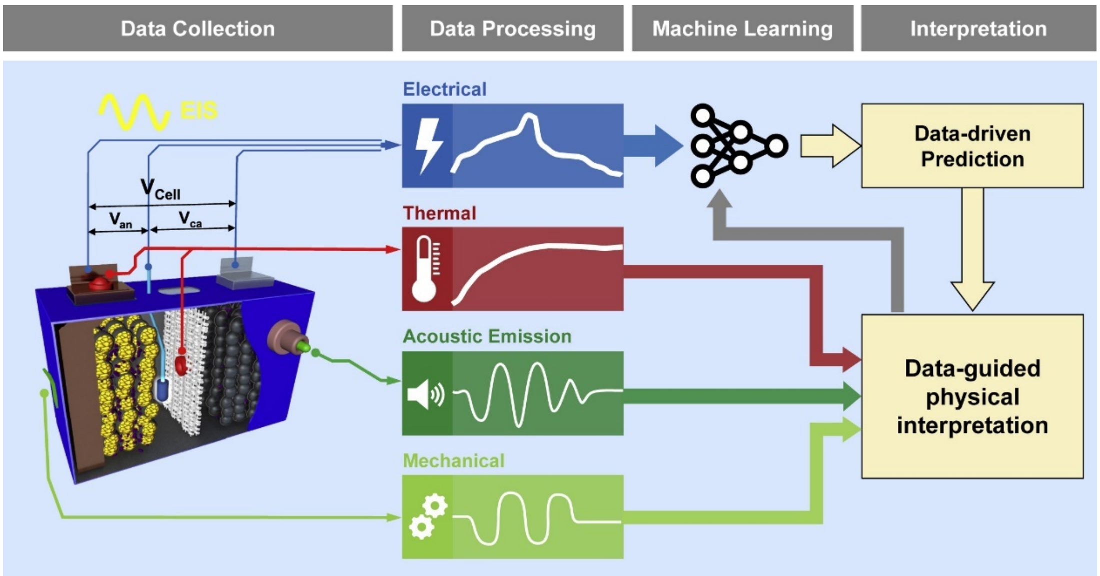


Figure 4.3. Record-keeping the related data of LIB for data-driven prediction and physical interpretations [92].

ML algorithms are well fitted for predicting nonlinear systems like lithium-ion cells. ML is typically agnostic to underlying physics even if the algorithms predict accurately. It thus demonstrates limited value in informing researchers and engineers on design opportunities to improve the cells' performance. Still, training and validation of models are challenging for safety applications since large amounts of failure data are essential. Battery researchers have a high interest in conquering these challenges. This perspective offers suggestions on the potential ways of study to manage precise predictions of the hazards of cell failure while obtaining some physical insights into the predicted behaviours.

Lee et al. [93] mapped partial charging data into a distinct statistical entity called the likelihood vector, as shown in Figure 4.4. Then the likelihood vectors are computed by referring to possibility distribution functions of experimental voltage and current simulating different degradation/abuse conditions for LIBs. Compared with the brute-force training method utilizing partial charging curves to train MLP classifier models, training assisted by likelihood vectors leads to improvements in test set classification accuracy by 26-85%, according to the size of neural networks. Furthermore, by monitoring the failure index calculated from the cumulated list of detections made, it is experimentally presented that the TR and resultant fatal explosion event of lithium pouch cell under operando dent test can be predicted before the event occurs.

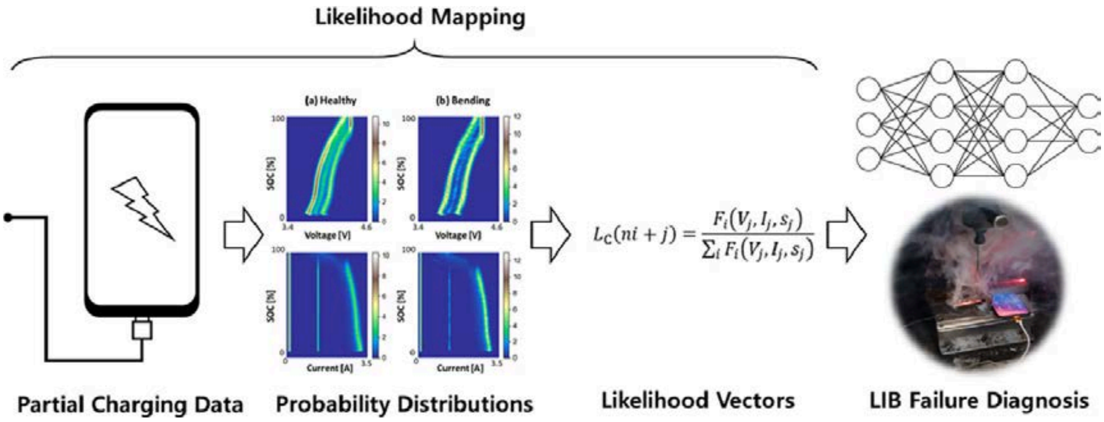


Figure 4.4. Schematic diagram explaining artificial neural network enhanced by likelihood mapping approach [93].

Besides, Jiang et al. [22] propose a novel data-driven method for LIB pack fault diagnosis and TR warning based on state representation methodology. The results show that the proposed method can perform not only the accurate identification of the faulty cells and accurate determination of the voltage fault type but also the early detection of faults and early warning of TR. Also, Ding et al. [94] proposed a novel data-driven approach to perform multistep ahead forecast accurately for battery TR state at cell-level by applying meta TR forecasting neural network (Meta-TRFNN). Both simulated and real-world samples were tested, demonstrating the forecasting ability of Meta-TRFNN, the benefit of embracing high-dimensional thermal images, and the efficacy of the meta-learning framework.

Additionally, Yang et al. [95] applied an extreme learning machine (ELM)-based thermal (ELMT) model to depict battery temperature behaviour under an external short circuit, where a lumped-state thermal model was chosen to replace the activation function of conventional ELMs. Compared the ELMT model with a multi-lumped-state thermal (MLT) model parameterized by the genetic algorithm using the experimental data from various sets of battery cells, it is demonstrated that the ELMT model can achieve higher computational efficiency than the MLT model and better fitting and prediction accuracy.

Moreover, Ojo et al. [96] introduced an LSTM-based NN model in conjunction with the newly developed stretch-forward technique and residual monitor to detect these faults. The experimental results showed that this approach could estimate the surface temperature of the cell, which means that it achieved a good predictive accuracy and fault detection performance. Da Li et al. [97] proposed an enabling TR prognosis model based on abnormal heat generation, which combines the long short-term memory neural network (LSTM) and the convolutional neural network (CNN), shown in Figure 4.5. The verification results conclude that the presented scheme exhibits accurate 48-time-step battery temperature prediction with a mean-relative error of 0.28% for all four seasons, which verifies its robustness and adaptability. Also, the proposed model can realize a 27-min-ahead TR prognosis, including 19 mins ahead by abnormal heat generation (AHG) diagnosis method and 8 mins in advance by CNN-LSTM.

Furthermore, Garg et al. [98] proposed an intelligent system framework based on DT to provide access to real-time big data cloud storage and address some serious issues, such as switching malfunction, heat generation, changing temperature rise, SOC/SOH estimation, etc. Based on the proposed system, the hardware and software design for the reconfiguration battery system can be further integrated.

This section lists previous publications about battery fire and ML applied in battery fire prediction. It can be concluded that increasing ML methods are applied and developed in battery safety issues from many perspectives, such as TR, internal or external short circuits, temperature prediction, failure diagnosis, etc. Table 4.1 summarises the related research works that applied ML to improve battery thermal performance and enhance battery fire safety.

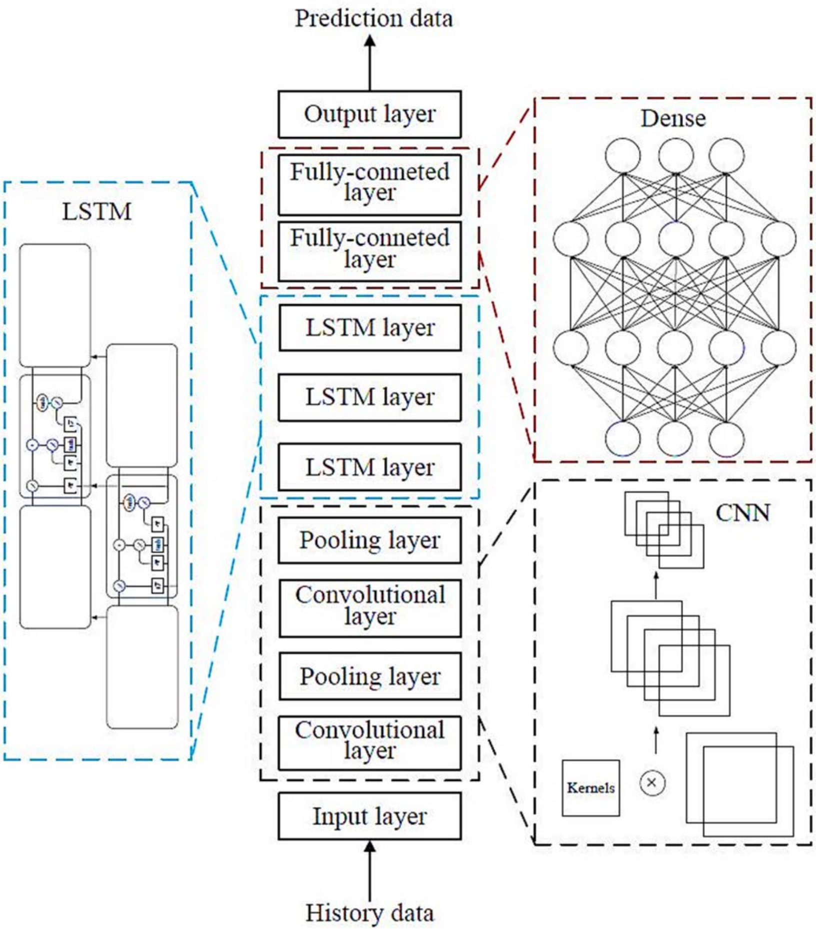


Figure 4.5. Configuration of the proposed battery TR prognosis method based on the CNN-LSTM [97].

Table 4.1 Summary of the ML applied in battery fire safety research.

ML approach	Achievement	Reference
K-means clustering	TR initiation conditions	[88]
Decision tree; SVM; ANN	Mechanical loading conditions	[89]
CNN	Internal short circuit	[90]
MLP	Crack detection	[91]
MLP	Failures diagnose	[93]

Meta-TRFNN	Forecast TR	[94]
ANN	External short circuit	[95]
LSTM	Temperature prediction	[96]
LSTM & CNN	Temperature prediction; TR prognosis	[97]
DT	Heat generation; charging temperature	[98]

4.3 Hazard mitigation and safety control

Safety is the utmost priority in LIB applications in energy storage systems. Recent accidents with different failure mechanisms undermine the industry's confidence in using LIBs. To our knowledge, the TR mechanism has been studied using a time sequence map. The state transition in the time sequence map explains the potential mechanisms for all types of observations in TR tests. Effective hazard mitigation approaches have been investigated by understanding the TR mechanisms. Battery failures and TR hazards can be properly alleviated by researchers applying safety control actions under various practical scenarios, such as material, cell and system levels.

Mitigation strategies are fulfilled by cutting off a specific transformation flow between the states in the time sequence map. Figure 4.6 outlines the battery TR mechanisms and the thought of time sequence regulation. The safety design of battery systems aims to lower the possibility of abuse, eliminate abuse once it happens, and build TR alert systems at the earliest stage. A competent mitigation strategy that helps avoid the occurrence of TR is founded on the mechanisms of abuse conditions. Charging and temperature control are critical for battery safety and the TR system. The mitigation strategies work at different levels and guarantee the global safety of an electric energy storage system using LIBs.

ML techniques have already been used in fire modelling [99], safety assessment [100] and fire prediction [101]. Yamanaka et al. [102] introduced a framework for performing multi-objective optimization using ML methods at a reasonable computational cost. An analysis of the relationship between descriptors and predictors confirms a high correlation between fire spread and negative electrode active material diameter. Battery fire safety applied ML methods for mitigation and control is a potential direction that should be encouraged for future direction.

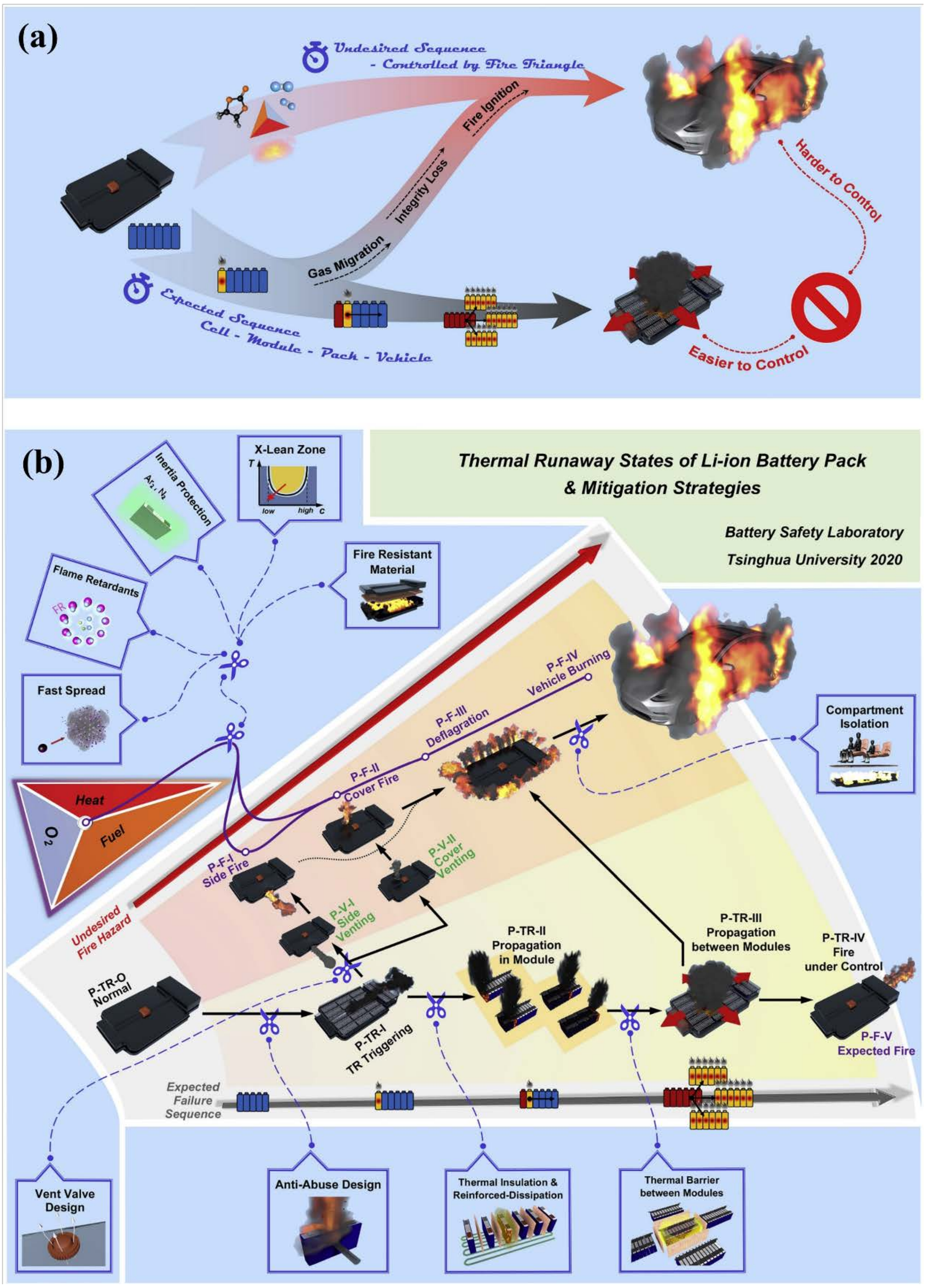


Figure 4.6. TR states of LIB pack and correlated mitigation strategies [103].

5. Conclusions and prospect

5.1 Summary

Owing to the global interest in clean energy, electrification and net zero emissions, there is a rapid usage increase of battery systems with LIB systems being one of the largest applications. With overwhelming public expectations and more complex application scenarios, LIBs are experiencing unprecedented challenges including concerns regarding thermal resilience, fire and explosion risks. This review article aims at bringing new insights into the further application of ML in the field of battery thermal safety. The emphasis has been made on three mostly used ML models including ANN, CNN, and LSTM. This paper reviewed two major topics: battery thermal management and battery system safety. The following are the conclusive summaries that were drawn based on our literature review:

ANN, CNN and LSTM are three major ML models used in state-of-the-art publications for battery thermal stability and resilience studies. Due to multivariate analysis function, high precision, and excellent data noisy tolerance, ANN is advantageous for parameters optimization contributing to better and highly efficient BTMs design. CNN is utilized for pattern recognition in the scenarios with thermal images involved in BTMs. LSTM leverages sequential or times series data and can be served a role in temperature prediction, monitoring, and early fire diagnostics and prevention.

It is reasonable that these models have their respective areas of expertise. Their results, however, can follow the same rule; namely, the input data dramatically influence the training process and output. This indicates that data input is significantly important in the ML process. Due to its high noise tolerance, ANN is more suitable for the experimental data with noise data. While for the numerical data, dimensionality and training time are two crucial factors in choosing. When it comes to the temperature prediction or thermal hazards diagnosis with time series, LSTM is the first option to establish models, but vanishing gradients may appear owing to long series. Furthermore, DT technique, as a relatively new technology, is also applied in battery safety and BTMs. It shows great potential for computation power, data storage capability, and reliability of real-time simulation and responsiveness.

In general, these models have been used in the thermal safety issue, but further development is imperative with a more flexible combination and more advanced models.

5.2 Moving ahead

While the industry applications for LIB are still relatively new, there is a large room for improvement and unrevealed explorations in technology, such as thermally stable components, smart material design, safety monitoring BTMs, battery system safety design model, thermal management system, battery safety evaluation system, etc. Meanwhile, ML technologies can be applied and aligned with those directions effectively and flexibly. While we are developing new energy materials with high energy density, fast electric cycle speed, and excellent longevity, the safety perspective, if not more important, is crucial as well. We expect researchers to collaborate and develop future LIBs or BTMs with guaranteed overall safety performance. The potential directions of ML applied in BTMs are listed as follows: a) ML techniques, such as ANN, CNN, LSTM, SVR, DT, and so force, can be further investigated for LIB and BTMs optimal design, risk prediction, fault diagnosis, and hazard mitigation; b) Multi physics numerical simulations can be coupled to build more performance-oriented datasets for ML training; c) Other potential ML methods can be included for improving LIB safety research with various data types and amounts; d) ML techniques can be further applied to other energy storage systems for improving the performance and mitigating the potential risks.

Credit author statement

Ao Li: Conceptualization, Methodology, Writing – Original Draft, Visualization, Validation. **Jingwen Weng:** Conceptualization, Methodology, Writing – Original Draft, Formal analysis, Data Curation. **Anthony Chun Yin Yuen:** Investigation, Writing – Review & Editing, Visualization, Project administration. **Wei Wang:** Software, Validation. **Hengrui Liu:** Investigation, Resources. **Eric Wai Ming Lee:** Data Curation, Supervision. **Jian Wang:** Supervision, Funding acquisition. **Sanghoon Kook**: Conceptualization, Writing – Review & Editing. **Guan Heng Yeoh:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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