A Low-power Battery Cooling using an Adaptive Liquid-cooled Battery Thermal Management System

Gengqiang Huang

A Thesis Submitted in Partial Fulfillment of Requirements for

degree of Doctor of Philosophy in Electrical and Computer Engineering

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ABSTRACT

Electric vehicles (EVs) are gaining popularity due to their environmental and economic benefits. However, their performance and safety depend on the thermal management of their power battery packs, which generate heat during operation. Excessive heat can degrade the battery capacity and lifespan, and even cause fire hazards. Therefore, this research aims to design a low-power battery cooling system using an adaptive liquid-cooled battery thermal management system. The main contributions of this research are: 1) developing a thermal model for the lithium-ion battery pack based on heat generation and dissipation mechanisms; 2) proposing an adaptive control strategy based on deep neural network (DNN) and dwarf mongoose's coati optimization algorithm (DMCOA) to regulate the battery temperature and minimize the energy consumption of the cooling system; and 3) validating the proposed model and strategy through simulations using AMESim and Matlab.

The proposed thermal model consists of two parts: a heat generation model based on the Bernardi heat generation rate model, which considers the internal resistance, entropy change, and reaction heat of the battery; and a heat dissipation model based on Newton's law of cooling, which considers the liquid flow rate, heat transfer coefficient, and fluid temperature in the cooling channels. The thermal model is applied to a single cell and then extended to the entire battery pack using the principle of energy conservation. The proposed adaptive control strategy uses the mass flow rate of the water pump as a control parameter and the battery temperature as a state variable. It employs a DNN to predict the vehicle speed fluctuations based on the driving cycle, and then uses a DMCOA to optimize the temperature cost function, which balances the battery temperature and energy consumption objectives.

To evaluate the performance of the proposed thermal model and control strategy, a simulation model of the battery's cooling system was built using AMESim, which was coupled with Matlab for data processing and optimization. The simulation results showed that the proposed thermal model could accurately capture the temperature dynamics of the battery pack under different operating conditions. The simulation results also showed that the proposed adaptive control strategy could effectively regulate the battery temperature within a safe range, while reducing the energy consumption of the cooling system by an average of 15% and 27% compared to conventional PID and MPC methods under predefined NEDC cycle conditions.

Keyword : Electric vehicles (EVs), Battery cooling, Adaptive control strategy, Thermal model

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Last but not least, I would like to dedicate this thesis to my family and friends, who have always been there for me with their love and support. They have encouraged me to follow my dreams and overcome the challenges that I faced along the way. They have also made my stay in Thailand more enjoyable and memorable. I could not have done this without them.

Gengqiang Huang

TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

Page

Chapter 1 Introduction

1.1 Research Background

The evolution of the automobile industry has rapidly advanced, bringing to the forefront critical challenges such as energy deficits and the looming oil crisis. Recognizing these challenges, global nations are aggressively advancing the new energy vehicle sector, ushering in the rise of electric vehicles (EVs) as the impending industry norm.

Among the various power sources contemplated for EVs, lithium-ion batteries emerge as the most promising due to their inherent advantages. However, they grapple with two major technical impediments: the first revolves around cost, lifespan, and range, while the second pertains to system reliability and safety.

For vehicular applications, battery configurations are stratified into three distinct tiers: cell, module, and pack (Wu et al., 2019b). A schematic representation of this grouping is delineated in Figure 1. To realize large-scale, high-capacity battery packs, myriad lithium-ion batteries are amalgamated in diverse configurations— series, parallel, or a fusion of both(Deng et al., 2019). This interconnection, during charge and discharge cycles, instigates a cascade of chemical reactions that invariably generate heat. This perpetual heat generation in the battery cells results in an incessant accumulation of thermal energy within battery packs. Absent timely heat dissipation, batteries stand vulnerable to leakage, deflation, and smoldering. Extreme scenarios even witness violent combustions and explosive events.

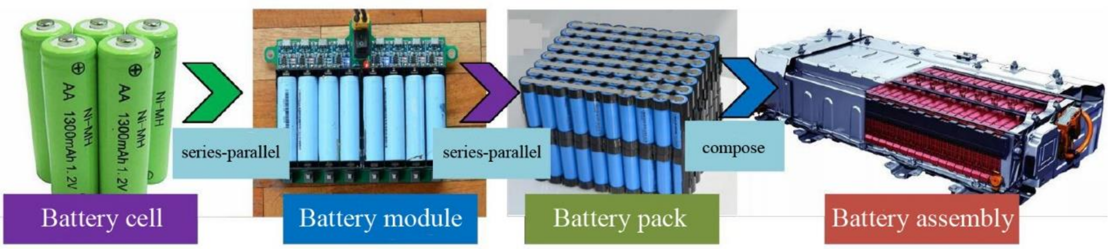

Figure 1 A Visual Breakdown of Power Battery Groupings(Lin et al., 2021)

Differing battery performance across varying temperature bands is tabulated in Table 1. A clear pattern emerges, underscoring that an optimal working temperature range for lithium-ion batteries lies between 15°C and 35°C, wherein they demonstrate elevated efficiency and operational normalcy(An et al., 2017; Tete et al., 2021; Wu et al., 2019b).

Table 1 Comparative Assessment of Battery Performance across Temperature Ranges(An et al., 2017; Tete et al., 2021; Wu et al., 2019a)

Classification	**Temperature Range**	**Charge**	**Discharge**	**Battery Performance**
Low Temperature	<0°C	Small current	Small current	Inefficient
Medium Temperature	0°C~15°C	Normal	Normal	Reduced efficiency
	15°C~35°C	Normal	Normal	Efficient working range
	35°C~40°C	Normal	Normal	Reduced efficiency
High Temperature	>45°C	Power reduction by half	Power reduction by half	Reduced service life and safety

Given these thermal sensitivities and constraints, the dire need for a robust battery thermal management system (BTMS) becomes evident, especially when no alterations are anticipated in battery or vehicle design structures. A BTMS functions as a guardian, ensuring that battery temperatures remain within acceptable brackets, enhancing both battery longevity and safety. Such systems are typically an amalgamation of the battery casing, heat transfer mediums, monitoring instruments, and other pivotal components (Jaguemont & Van Mierlo, 2020).

The arena of battery thermal management (BTM) has witnessed the emergence of myriad technologies. Liquid cooling technology, despite its ubiquity and distinct advantages, isn't devoid of challenges. Prominent among them is its proclivity to consume excessive energy to achieve desired cooling outcomes (Park & Ahn, 2020). This energy appetite inversely affects the travel range of EVs (German et al., 2019; Horrein et al., 2016; Reyes et al., 2016). Adding to the conundrum is the inherent nonlinearity and temporal variability in the cooling systems' parameters, especially during actual production phases. Traditional temperature regulation methods like PID, although tried-and-tested, grapple to achieve the desired efficiency, especially considering the evolving demands for better adaptability to environmental flux and expedited temperature regulation.

This research discerns a unique opportunity in the nexus of adaptive control and battery cooling. While adaptive control has found extensive application in battery charging and energy management systems and has even permeated sectors like air conditioning and industrial processes, its merger with battery cooling technology remains nascent. A significant potential lies in harnessing adaptive control for battery cooling to curtail energy consumption, addressing a distinct research lacuna.

1.2 Problem Description

The burgeoning ascent of electric vehicles (EVs) in contemporary transportation frameworks introduces a concomitant imperative: ensuring the durability and optimal functioning of lithium-ion batteries. At the crux of this imperative lies the judicious management of the thermal milieu these batteries operate within. Absent adept thermal management, not only does the battery's efficiency take a hit, but its overall lifespan also witnesses a decline, spiraling into potential safety risks. As such, delving deep into, modeling, and orchestrating the thermal dynamics of lithium-ion batteries becomes a non-negotiable priority.

This research elucidates and wrestles with the subsequent pressing inquiries:

i. **Model Precision:**

In what ways can one sculpt an exhaustive, precision-driven thermal blueprint for lithium-ion batteries? This model should be adept at foretelling battery responses across a spectrum of operational paradigms.

ii. **Thermal Regulation Mechanisms:**

Among the plethora of cooling stratagems available for lithium-ion batteries, which methodologies stand out in terms of practicality and efficiency? Furthermore, how do these stratagems recalibrate the battery's overarching performance and life expectancy?

iii. **Evaluative Paradigms:**

When venturing into the domain of battery thermal orchestration, how do conventional control paradigms measure up against their modern counterparts concerning efficacy and relevance?

1.3 Objectives

The primary aim of this research revolves around a comprehensive understanding of battery thermal management for electric vehicles, anchored in software-based simulations. The three cardinal objectives framing this exploration are:

i. Advanced Thermal Modeling:

Craft a software-driven thermal model for lithium-ion batteries, targeting the prediction and mitigation of thermal challenges, especially in high-temperature regions.

ii. Efficient Cooling Techniques:

Examine liquid-cooled battery thermal management systems, exploring their benefits, potential pitfalls, and efficacy in upholding optimal battery temperatures. Within this, develop a novel temperature control strategy tailored specifically for lithium-ion battery packs to amplify their operational efficiency, longevity, and safety.

iii. Holistic Comparative Evaluation:

Pit traditional thermal management frameworks against the newly proposed strategies to weigh their respective strengths, efficiencies, and practical applications.

1.4 Research Scope

This research is based on software simulations, rather than hardware experiments. This choice reflects the objectives to derive theoretical insights that can be applied to real-world situations, without requiring immediate empirical validations through hardware. This thesis belongs to the field of electrical control and focuses on the challenges of modeling and designing control strategies. The core of the research is the thermal management system model that uses liquid cooling methods for battery packs, along with an innovative temperature control strategy that is customized for these packs. The research intentionally avoids exploring the material chemistry of lithium-ion batteries. Although these batteries are the central subject of the research, the discussion remains faithful to the electrical and thermal control aspects, without a chemical perspective. A key factor that influences the design of the electric vehicle battery thermal management system in this research is its suitability and effectiveness in hot regions. This geo-thermal specificity affects the modeling assumptions, control strategies, and potential real-world implementations.

1.5 Benefits of the Research

i. Academic Advancements:

Augmentation of existing literature with innovative adaptive control methods tailored for EV battery thermal management and liquid cooling systems.

Comprehensive evaluation of diverse control methodologies, accentuating their efficiency and adaptability.

Validation and implementation of advanced algorithms, notably DMCOA and DNN, for precision-driven thermal management.

ii. Industrial Implications:

Enhanced battery lifespan and safety via the adaptive liquid-cooled thermal management system.

Promotion of scalable and reliable design frameworks adaptable to a myriad of operational conditions.

Pioneering the integration of DMCOA and DNN in liquid cooling systems, fostering both performance and energy efficiency.

iii. Societal Significance:

Acceleration of the transition to environmentally-friendly electric vehicles, mitigating environmental impacts.

Elevation of the electric vehicle driving experience, characterized by safety and extended range.

Stimulation of interdisciplinary collaboration, driving innovation in the realm of EV thermal management.

Chapter 2 Literature Reviews

This chapter is a literature review that provides a comprehensive overview of the existing research on the thermal model and management of lithium-ion batteries. The purpose of this chapter is to identify the main theories, methods, and challenges in this field, as well as to highlight the gaps and opportunities for further research.

This chapter is organized as follows:

Section 2.1 reviews the different types of thermal models of lithium-ion batteries, such as the electrochemical thermal coupling model, the electrothermal coupling model, and the thermal abuse model. These models are used to simulate and predict the temperature distribution and heat generation of batteries under various operating conditions and scenarios.

Section 2.2 discusses the battery thermal management technology, which is essential for ensuring the safety, performance, and lifespan of batteries. It covers the basic principles, components, and functions of battery thermal management systems, as well as the criteria and metrics for evaluating their effectiveness.

Section 2.3 focuses on the liquid-cooled battery thermal management system, which is one of the most widely used and advanced methods for cooling batteries. It describes the design, operation, and advantages of liquid-cooled systems, as well as the challenges and limitations that they face.

Section 2.4 explores the optimization strategy for battery cooling, which aims to improve the efficiency and reliability of battery thermal management systems. It presents some of the existing optimization methods and techniques, such as genetic algorithm, particle swarm optimization, and artificial neural network.

Section 2.5 summarizes the main findings and contributions of this chapter, as well as the research questions and objectives that will guide the next chapters of this thesis.

2.1 Thermal Model of Lithium-ion Batteries

The development of a thermal model for the battery pack serves as a foundational platform for examining the variables influencing the battery's thermal behavior and for strategizing its cooling design optimization. Since the 1990s, researchers have delved into various models pertinent to lithium-ion batteries, including the electrochemical-thermal coupling model, the electrothermal coupling model addressing internal current distribution, the thermal abuse model related to thermal runaway scenarios, as well as individual cell and overall battery thermal models. Each of these models possesses its distinctive applicability range and modeling precision(Siddique et al., 2018). The battery thermal models in the references are classified in Table 2. The specific introduction will be presented below.

Table 2 Classification of Battery Thermal Models

Model Types		**Application**
Electrochemical Thermal Coupling Model	Concentrated Heat Model	Suitable for the study of the factors affecting the thermal behavior of power batteries.
	1D Thermal Model	Mainly used to study the temperature distribution of lithium-ion batteries in the radial or axial direction.
	2D Thermal Model	Used to study the temperature distribution of the battery in a certain cross-section.
	3D Thermal Model	Usually used to study the internal temperature distribution of lithium-ion batteries.
Electrothermal Coupling Model		Mainly used to study the temperature field distribution inside the battery.
Thermal Abuse Model		Has positive significance for the design of battery cooling system and the prevention of thermal runaway.

2.1.1 Electrochemical Thermal Coupling Model

In the process of charge and discharge, complex chemical reactions will occur inside the lithium-ion battery, generating heat. The electrochemical thermal coupling model of lithium-ion battery combines the heat generated by chemical reaction and the heat generated by resistance in the battery to simulate the thermal behavior of the battery. According to the dimension, it can be divided into concentrated, one-dimensional, two-dimensional and three-dimensional thermal models.

(1) Concentrated Heat Model

The concentrated heat model regards the battery as a uniform heat generator and does not reflect the temperature distribution inside the battery. The calculation process of this model is simple, and it is suitable for the study of the factors affecting the thermal behavior of power batteries.

(Allafi et al., 2018) applied the centralized thermal model to real-time thermal management based on its simple structure and easy implementation. They considered the change of heat transfer coefficient under different cooling conditions and the time-varying of model parameters to improve the accuracy of the model. Compared with the battery test data, they verified the accuracy of the concentrated heat model and the effectiveness of the online parameter estimation method.

(Choi & Kang, 2014) compared the battery temperature changes of the concentrated heat model and the battery temperature changes under experimental conditions under different discharge rates for Sony 18650 battery. The thermal behavior deviation of these two groups of data is small at low discharge rate and large at high discharge rate. This is because under high discharge rate, the irreversible reaction heat generation in the high-temperature area inside the battery increases. However, Choi et al. Have not studied the heat dissipation of the battery, and the relationship between the heat transfer coefficient and the flow rate of the coolant has not been established.

(Cui et al., 2020) established the concentrated heat model of lithium ion battery, and identified the model parameters by solving the linear equation and fitting the least square nonlinear curve based on the experimental data. In the case of natural convection, forced air convection, regional liquid cooling and local heating, the accuracy of the model is evaluated, and the accuracy of the model is verified.

(Wang et al., 2014) studied the thermal behavior of each single cell in the battery pack, established a concentrated heat model and an empirical heat source model, and explored the influence of the arrangement of cylindrical lithium-ion batteries, the installation position of fans in the battery module and the ambient temperature on the heat dissipation of the battery, which has certain guiding significance for the development of the battery pack model.

(Li et al., 2013) established a concentrated heat model and predicted the maximum temperature in the battery module. The centralized heat model is simple, high precision and small calculation, and is widely used in the safety and thermal management system of electric vehicles. However, Li et al only estimated the maximum temperature in the battery module, and did not establish the thermal model of each cell in the battery module.

(2) 1D Thermal Model

Most lithium-ion batteries are wound, so the temperature difference in the radial or axial direction is large. The one-dimensional thermal model is mainly used to study the temperature distribution of lithium-ion batteries in the radial or axial direction.

(Al Hallaj et al., 1999) used a simplified one-dimensional battery thermal model to simulate the internal temperature distribution of the battery. For Sony 18650 battery, the temperature distribution of 10Ah and 100Ah cylindrical lithium-ion battery under different working conditions and cooling rate was simulated. The paper points out that the temperature distribution of the battery is uniform at a lower cooling rate, while the temperature gradient of the battery is obvious at a higher cooling rate.

(Greco et al., 2014) established a one-dimensional transient calculation model for columnar lithium-ion batteries and verified the validity of the established one-dimensional transient model.

(3) 2D Thermal Model

The two-dimensional thermal model is used to study the temperature distribution of the battery in a certain cross-section.

(He et al., 2014) constructed a serial battery pack, used computational fluid dynamics software to simulate the cross-sectional temperature distribution of the battery module, and verified the accuracy of the established two-dimensional thermal model based on the data of the battery temperature, air flow rate and pressure measured in the experiment. Then, they studied the energy consumption of the battery pack under different cooling air flow rates and different battery shell spacing. With the increase of wind speed, Energy consumption also increases.

(Liu et al., 2014) established a two-dimensional thermal model of lithium-ion battery and studied the effects of ambient temperature, charge and discharge rate and coolant flow rate on the temperature distribution of the battery pack. Under the condition of lower discharge rate, air cooling is better than liquid cooling, but under the condition of higher discharge rate, air cooling cannot meet the cooling demand.

(4) 3D Thermal Model

The three-dimensional thermal model is usually used to study the internal temperature distribution of lithium-ion batteries. It is mainly used to improve the battery design and has guiding significance for improving the battery processing technology.

Based on Bernardi's heat generation rate model, (Chen et al., 2005) established a three-dimensional layered model considering the influence of radiation heat dissipation and battery cell shell, compared the calculation accuracy and calculation amount of various simplified models, and analyzed the influence of discharge depth, discharge current and heat transfer coefficient on the thermal behavior of battery cell. (Basu et al., 2016) designed a new type of battery thermal management system based on liquid coolant. A three-dimensional electrochemical thermal coupling model was established for the fixed arrangement of lithium-ion batteries. The effects of coolant flow rate and discharge current under different working conditions on the temperature of the battery pack were studied. A battery temperature correlation model was established. The temperature of all the cells in the battery pack was predicted by measuring the temperature of the cells, and the experimental results were verified. This battery thermal model reduces the number of sensors used and the complexity of the battery management system.

2.1.2 Electrothermal Coupling Model

The difference between the electrothermal coupling model and the electrochemical thermal coupling model is that it does not consider the chemical reaction process inside the battery. It is mainly used to study the temperature field distribution inside the battery. In recent years, it has been widely used in the optimization design of the battery thermal management system of electric vehicles.

(Lin et al., 2014) proposed the electrothermal coupling model of cylindrical lithium-ion battery, including the equivalent circuit model and the heat generation model. They obtained the state of charge, terminal voltage, surface temperature and cell temperature of the battery under various working conditions. (Forgez et al., 2010) obtained the heat transfer coefficient and heat capacity of the battery by measuring the surface temperature and core temperature of the lithium-ion battery, and then established the electrothermal coupling model of the battery. The model can directly simulate the temperature change inside the battery from the measured battery current and voltage data.

2.1.3 Thermal Abuse Model

Under extreme conditions such as high temperature above 120 ℃ or collision of electric vehicles, reactions such as positive electrode decomposition and solid electrolyte interface facial mask decomposition will occur inside the lithium-ion battery, resulting in uncontrolled heat generation. The research of battery thermal abuse model has positive significance for the design of battery cooling system and the prevention of thermal runaway.

(Huang, 2020) studied the thermal runaway mechanism model of lithium-ion battery pack according to the thermal runaway in lithium-ion battery module. In this study, the heat generation ratio of each component of the battery was studied before the thermal runaway of the battery occurred, and the thermal runaway process of each cell in the battery pack was simulated under different battery capacity and ambient temperature.

To sum up, the electric vehicle power battery pack is composed of multiple cells in series and parallel. The internal thermal behavior of each cell in the battery pack is very complex. From the perspective of application, researchers pay more attention to the average temperature of each cell. In the cooling process of electric vehicle battery pack, the battery temperature generally does not reach the high temperature range above 120 °C. Therefore, the electrochemical thermal coupling model is more suitable for the thermal behavior calculation of electric vehicle battery pack than the electrothermal coupling model and the thermal abuse model. The modeling process of the multi-dimensional thermal model in the electrochemical thermal coupling model is complex, which needs to be solved by the computational fluid dynamics software, and the calculation time is long and the calculation amount is large. In the study of battery groups, the use of the concentrated heat model can reduce the computational burden, which is more conducive to analyzing the factors affecting the battery temperature, and can also better study the temperature change law of the single battery in the battery pack. Therefore, based on the analysis of the heat generation and heat dissipation mechanism of the battery pack, the concentrated heat model of the lithium-ion battery pack is established in this paper.

2.2 Battery Thermal Management Technology

A battery thermal management system (BTMS) is a system that controls the temperature of a battery pack, which consists of multiple battery cells connected in series or parallel. It is essential to prevent the batteries from the adverse effects caused by the rise in temperature and internal heat generation(Tete et al., 2021). Various cooling techniques, including air, liquid, phase-change materials, and thermoelectric devices, are employed by BTMS to facilitate heat dissipation from the battery to its surrounding environment. Moreover, BTMS systems incorporate sensors, controllers, and advanced algorithms to meticulously monitor and adjust the temperature of each cell or module within the battery pack. The design and optimization of a BTMS often depend on several factors, including battery type, dimensions, configuration, operating conditions, and specific thermal requisites.

Classification of BTMS primarily depends on power consumption, heat transfer medium, and the interaction between the battery surface and coolant(Kim et al., 2019; Wu et al., 2019a). Additionally, the arrangement of cells within a battery pack provides another basis for classification(Deng et al., 2019). Figure 2 offers a comprehensive breakdown of BTMS classifications. Subsequent sections will delve deeper into the specifics of the heat transfer medium classification.

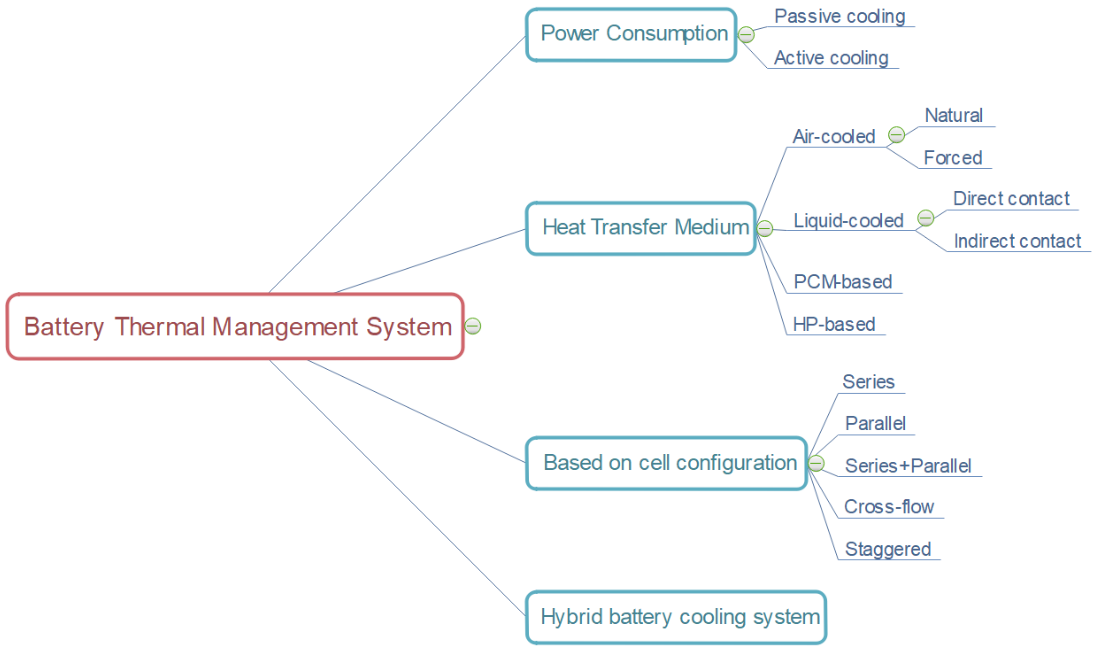

Figure 2 Classification of BTMS (modified from(Tete et al., 2021))

(1) Air-cooled BTMS

Air cooling refers to blowing cold air into the battery pack to dissipate heat from the power battery pack through convective cooling, as shown in Figure 3. Air is widely present and inexpensive, and will not affect various chemical reactions inside the battery(Chen et al., 2020).

According to the causes of air flow, it can be divided into natural cooling and forced cooling(Wu et al., 2019a). Natural cooling means that without using any external auxiliary energy, the system directly uses the natural wind formed when the vehicle moves to take away the heat of the battery. Forced cooling means that the system cools the battery by adding a fan to generate air flow rate.

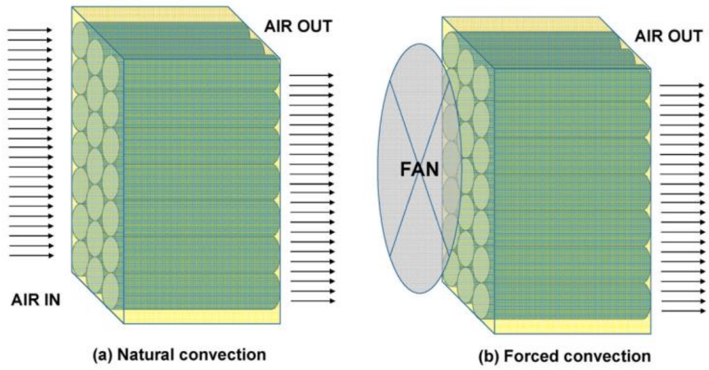

Figure 3 Air cooling strategies for Li-ion battery(Mali et al., 2021)

With the progressive increase in thermal load of automotive lithium-ion batteries, and considering their densely packed arrangement, natural convection cooling is inadequate to address their heat dissipation needs. While forced air cooling can moderately reduce the overall temperature of the battery pack, it inadvertently amplifies the temperature disparity among individual cells within the pack. This method of cooling necessitates auxiliary components such as fans or blowers, which demand supplementary energy from power sources. The installation of additional air ducts further complicates the structure, leading to an unduly intricate and bulky battery cooling system in electric vehicles.

2.2.2 Liquid-cooled BTMS

Liquid cooling refers to the process where a coolant with a high thermal conductivity and specific heat capacity is channeled into the battery pack via tubes and electronic water pumps. This facilitates cooling and temperature reduction of the battery pack, and subsequently, the heat from the battery pack is dissipated at the heat exchanger, as illustrated in Figure 4. Depending on whether the coolant directly contacts the battery, liquid cooling can be categorized into contact and non-contact cooling methods. For direct contact cooling, liquids with high thermal conductivity and insulation properties, such as mineral oil, are typically employed as coolants. However, substances like mineral oil have a relatively high viscosity, necessitating high-power pumps to circulate the coolant throughout the battery pack, thereby incurring additional energy consumption.

Non-contact cooling involves the flow of coolant through tubes, where heat exchange occurs indirectly between the battery and cooling components, such as cooling tubes and fins, resulting in high heat exchange efficiency. Liquid cooling is versatile; it meets the cooling needs of power batteries during low-current charging and discharging, as well as during high-current operations and under extreme conditions like summer temperatures, ensuring electric vehicles' cooling requirements are consistently met.

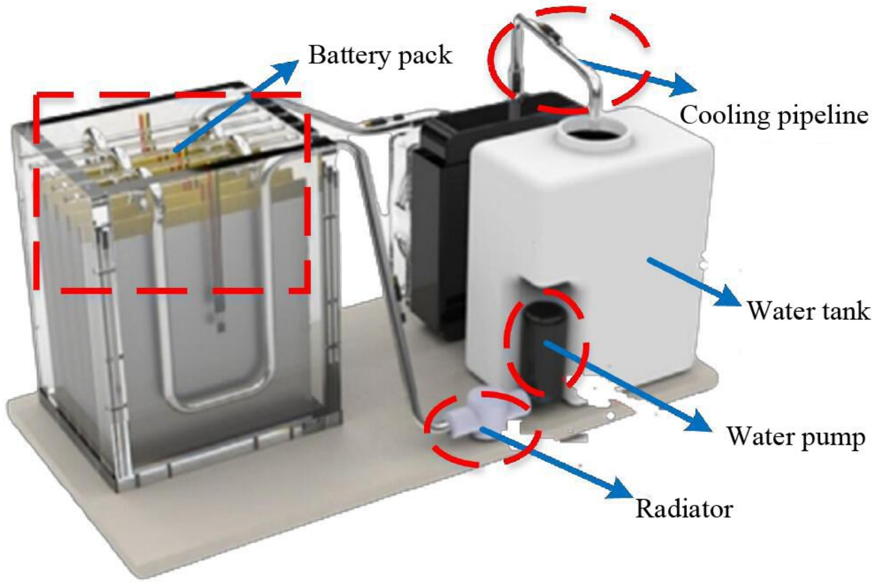

Figure 4 General structure of Liquid cooled BTMS(Yates et al., 2021)

2.2.3 PCM-based BTMS

Phase Change Materials (PCM) cooling involves placing power batteries within solid-phase change materials. Utilizing the solid-liquid phase transition of the PCM, heat is absorbed or released, thereby regulating the battery's temperature, as depicted in Figure 5. Paraffin is a commonly employed PCM. By filling the gaps between power batteries with paraffin, it acts as a thermal conduction medium. This not only efficiently addresses rapid temperature rises in batteries but also provides insulation for batteries in low-temperature environments.

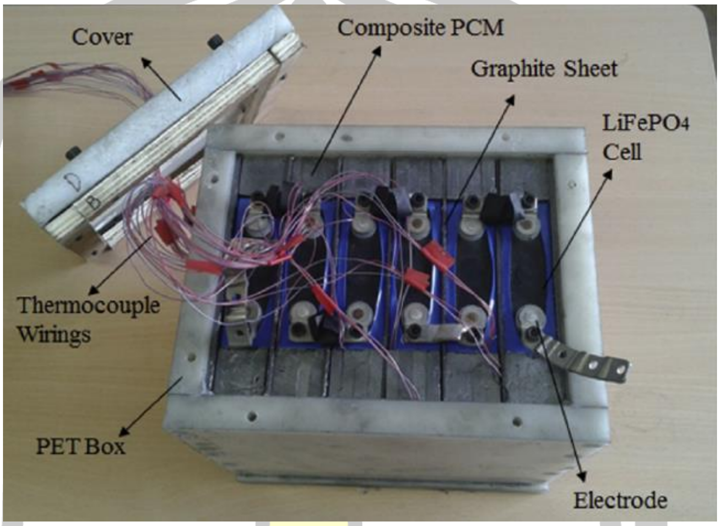

Figure 5 PCM-based BTMS(Lin et al., 2015)

2.2.4 HP-based BTMS

Heat pipe cooling leverages the thermal conductivity of heat pipes for cooling battery packs, as illustrated in Figure 6. Originally developed for aerospace applications, heat pipe technology is now broadly employed in various heat exchangers. Structurally, it can be divided into condensation, insulation, and evaporation sections. In the condensation section, the gaseous working fluid liquefies by dissipating heat to the external environment. In the evaporation section, the liquid working fluid vaporizes by absorbing heat. The insulation section does not engage in any heat exchange with the surroundings. It serves to transport heat from the evaporation section to the condensation section and segregates the heat source in the evaporation section from the cold source in the condensation section. Currently, the application of heat pipe technology in power battery thermal management systems is still in the early research stages.

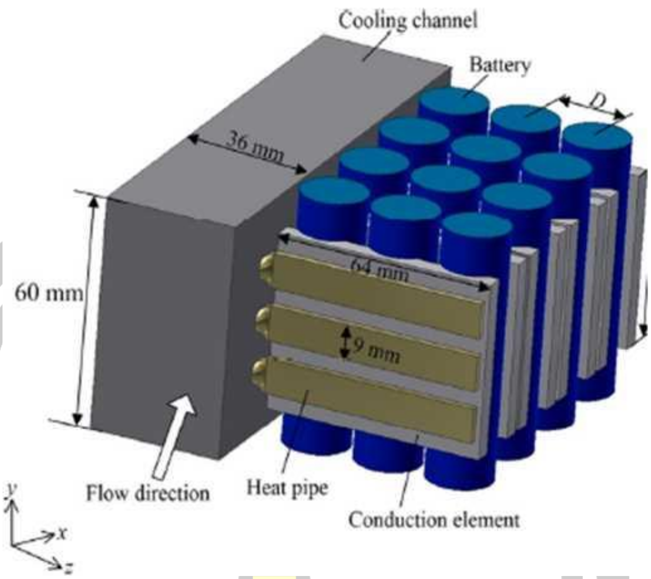

Figure 6 HP-based BTMS(Malik et al., 2017)

At present, PCM cooling and heat pipe cooling are still under investigation, while air cooling and liquid cooling are extensively deployed in electric vehicles. Table 3 presents a comparison of cooling effects between air and liquid cooling. It reveals that liquid cooling surpasses air cooling in terms of cooling speed, sealing characteristics, and resistance to environmental temperature effects.

Table 3 Comparison of Cooling Effects between Liquid Cooling and Air Cooling

Performance Metrics	**Air Cooling**	**Liquid Cooling**	**Advantages of Liquid Cooling**
Heat Transfer Rate (W/m • K)	0.0242	0.3892	15 times difference
Cooling Speed	Hours	Minutes	Higher cooling efficiency
Battery Pack Sealing	Unsealed	Sealed	Meets IP67 waterproof rating, dust prevention
Battery Temperature Inconsistency	Temperature difference >5℃	Temperature difference <2℃	Lower battery inconsistency, extends battery life, ensures safety
Impact of Ambient Temperature	Large	Small	Lower overheating risk with liquid-cooled battery pack
Regenerative Braking Heat	High temperature	Low temperature	Effectively prevents temperature rise
Fast Charging Cooling	Poor	Good	Fast charging generates a lot of heat; liquid cooling meets the cooling needs
Cost / Lifespan	Short lifespan	Long lifespan	Liquid cooling extends battery life, reducing costs

As battery cooling requirements progressively escalate, the cooling methodologies for power batteries in actual electric vehicles will gradually transition from air cooling to liquid cooling, as shown in Table 4. Liquid cooling stands out as the prevailing cooling method. This study will employ liquid cooling techniques for thermal management research on lithium-ion power batteries.

Table 4 Electric Vehicle Brands and Cooling Methods(Dober, 2023; PCmag, 2023)

Brand and Model	**Battery Type**	**Production Year**	**Production Country**	**Battery Capacity**	**Cooling Method**
Mercedes EQS	Li-ion	2021-present	Germany	108 kWh	Liquid cooling
Rivian R1T	Li-ion	2021-present	USA	105-180 kWh	Liquid cooling
Ford Mustang Mach-E	Li-ion	2020-present	USA	68-98 kWh	Liquid cooling
Audi e-tron	Li-ion	2018-present	Germany	71-95 kWh	Liquid cooling
Kia Niro EV	Li-ion	2018-present	South Korea	39-64 kWh	Air cooling
Hyundai Kona EV	Li-ion	2018-present	South Korea	39-64 kWh	Air cooling
Mercedes EQC	Li-ion	2019-present	Germany	80 kWh	Liquid cooling
Tesla Model 3	Li-ion	2017-present	USA	50-82 kWh	Liquid cooling
Hyundai Ioniq EV	Li-ion	2016-present	South Korea	28-38 kWh	Air cooling
Chevrolet Bolt EV	Li-ion	2016-present	USA	60-66 kWh	Liquid cooling
Tesla Model S	Li-ion	2012-present	USA	60-100 kWh	Liquid cooling
BMW i3	Li-ion	2013-present	Germany	33-42.2 kWh	Liquid cooling
Kia Soul EV	Li-ion	2014-present	South Korea	27-64 kWh	Air cooling
Ford Focus Electric	Li-ion	2011-2018	USA	23-34 kWh	Liquid cooling
Nissan Leaf	Li-ion	2010-present	Japan	24-62 kWh	Air cooling

2.3 Liquid-cooled Battery Thermal Management System

Presently, the liquid-cooled battery thermal management system is gradually maturing, yet there remains room for further improvements and enhancements.

(Jian et al., 2011) built an electric vehicle thermal management system based on AMESim simulation platform, and analyzed the heat dissipation of the thermal management system by using liquid and air heat dissipation forms, providing another feasible idea for the research and development of the battery thermal management system.

(Hao et al., 2012) designed a thermal management system based on liquid cooling and heating, which uses infrared instrument to detect the surface temperature of the battery pack, ensuring the temperature uniformity of the battery pack. At the same time, the simulation and experimental test of the battery cooling and heating system are carried out, and the experimental results are in good agreement with the simulation results.

(Kim et al., 2007) established a three-dimensional model without layering. They designed a scheme for the thermal management system of the battery pack of the cylindrical lithium-ion battery, evaluated the liquid cooling scheme and the air cooling scheme according to the cooling effect analysis of different coolants, and further analyzed the factors affecting the cooling effect of the battery. The results show that the shape design of the battery has a certain influence on the cooling effect of the battery.

(Weibing et al., 2013) established the cell model and designed four liquid cooling structures based on D. Bernardi model. Simulation analysis and structure optimization show that the battery pack can meet the requirements of temperature consistency.

(Shangan, 2013) used COMSOL software to simulate the lithium-ion battery cell, which can obtain the temperature characteristics of the battery under different conditions, and then simulated the influence of different cooling channels on the performance of the lithium-ion battery. The results show that the s-channel structure has a good cooling effect. Under the condition of high rate discharge, the temperature difference between the inside and outside of the battery is large. Increasing the mass flow rate can effectively reduce the temperature difference between the inside and outside of the battery and prolong the service life of the battery.

(Zhongjie & Guoqing, 2008) designed a thermal management system with the tube-in-tube liquid cooling mode for Ni MH batteries used in hybrid vehicles. The cooling system has good cooling effect and simple structure, which can ensure the temperature consistency of the battery and improve the power performance of the electric vehicle.

(Ke, 2011) obtained the charge and discharge characteristics and temperature of the battery through the test and analysis of the single battery, established the simulation model of the pure electric vehicle, and obtained the performance parameter curve of each battery under the NEDC condition. On this basis, he established a simulation model of the battery cooling system, analyzed the design rationality and cooling effect of the cooling system, and evaluated it. Li Xiangzhe et al. [48] tested the charge discharge and high-temperature forced cooling performance of battery packs with different heat dissipation structures, and obtained the internal temperature of each group of batteries and the battery temperature at different positions. The results show that the heat dissipation effect of the battery is better when the grid structure is adopted, and the temperature consistency meets the design requirements.

In summary, these studies underscore the importance and advantages of liquid-cooled battery thermal management systems. Researchers have explored a multitude of cooling structures and methods, consistently highlighting the efficiency of liquid-based systems in maintaining battery temperature consistency, extending battery life, and optimizing performance.

2.4 Optimization Strategy for Battery Cooling

The research on cooling optimization strategy is mainly to adjust the temperature of the power battery, so as to avoid the excessive temperature rise of the battery caused by the untimely heat dissipation under the condition of large current discharge, or the energy waste caused by the excessive heat dissipation under the condition of small current discharge.

At present, battery cooling strategies are mainly divided into two types, active cooling and passive cooling. Passive cooling refers to cooling the battery completely depending on the temperature difference between the surrounding environment and the battery under the condition of natural convection. Passive cooling has poor ability to adjust the battery temperature. Active cooling method refers to cooling air driven by fan or cooling liquid driven by water pump to dissipate heat of battery. It has strong heat dissipation ability and has been widely concerned by researchers in recent years.

(Ji et al., 2013) proposed an manual cooling strategy to balance the temperature distribution of the battery, improve the inconsistency of the temperature of the battery pack by adjusting the flow rate of the coolant, and keep all the batteries in the battery pack in a suitable temperature range during operation. On the basis of active cooling strategy, (He & Ma, 2015) added reciprocating cycle cooling to heat the battery pack, reducing the temperature inconsistency and the required coolant flow in the battery pack. Compared with passive temperature cooling and unidirectional flow cooling, the temperature inconsistency in the battery pack is reduced from 4.2 ℃ to 1.0 ℃, and the coolant consumption is reduced by 38%.

(Wang & Ma, 2017) proposed a two-way flow cooling battery thermal management structure. The comparison between unidirectional flow cooling and constant cycle reciprocating flow cooling shows that reciprocating flow cooling can reduce the temperature inconsistency of the battery pack and reduce the maximum temperature rise of the battery pack.

The battery active cooling strategy also has some shortcomings: (1) It does not form a closed-loop control, so the cooling process of the battery needs to manually control the opening and closing of the cooling system. (2) When the battery temperature reaches the target range, if the cooling system is still on, it is easy to cause excessive battery cooling and unnecessary energy waste. Therefore, hysteresis control method, finite state machine method and PID method are proposed.

The hysteresis control (Wang et al., 2016) is also called switching control. When the battery temperature is higher than the set temperature threshold, turn on the electronic water pump or fan to dissipate heat from the battery. When the temperature of the battery is lower than the set temperature threshold, turn off the electronic water pump or fan to stop the heat dissipation. In this way, the battery is cooled cyclically, but frequent opening and closing of cooling devices will damage the cooling equipment, which also increases the loss of the cooling system and the cost of the cooling system.

The finite state machine method(Kim et al., 2014)sets more temperature thresholds, and adopts different strategies at different temperature thresholds. When the battery temperature is high, it can quickly cool down, and when the battery temperature is low, it can save the energy consumed by the cooling device.

The traditional PID method(Qingfeng et al., 2014) can adjust the cooling capacity of the system in real time based on the difference between the target temperature of the battery and the actual temperature, which not only avoids the loss of the system caused by the frequent switching of cooling devices, but also reduces the waste of cooling energy.

However, due to the nonlinear characteristics of the power battery liquid cooling system, the traditional hysteresis control, finite state machine and PID methods can not meet the requirements of the system. In particular, the setting of temperature threshold and the setting of PID parameters depend on human experience, and the cooling system will not achieve the goal of regulating the temperature of the battery. Therefore, some intelligent algorithms are also gradually applied to the battery cooling system to regulate the battery temperature and reduce the cooling energy consumption, such as fuzzy PID algorithm, genetic algorithm, neural network control, model predictive control (MPC) method, etc.

The method based on fuzzy control is to set fuzzy rules according to experience. The advantage is that it does not depend on the mathematical model of the controlled object. It combines fuzzy control with PID method and uses fuzzy method to realize the self-tuning of PID proportional, integral and differential parameters. The disadvantage is that when the fuzzy rules are insufficient or the rules are wrong, the effective battery temperature regulation effect will not be achieved(Gao et al., 2018; Murashko et al., 2014; Yan et al., 2021). The battery cooling system is characterized by time-varying parameters and hysteresis. In order to adjust the heat dissipation of the battery in time and achieve the purpose of saving the energy of the cooling system, the dynamic planning method(Zhu, Lu, Zhang, Sun, et al., 2018) is proposed to adjust the temperature of the battery pack and minimize the cooling energy while ensuring the temperature of the battery pack within the appropriate range. However, the dynamic planning algorithm is complex and requires high hardware requirements, the calculation time is long and the calculation amount is large.

Genetic algorithm and neural network method have been applied in the optimization of battery liquid cooling system because of their strong self-learning ability.

For the air-cooled battery thermal management system, (Kai & Shuangfeng, 2018) adopted the method of combining the flow resistance network model and genetic algorithm to optimize the angle of the inlet and outlet deflectors of the system, so as to make the air flow velocity in the cooling channel of the system uniform, thereby reducing the maximum temperature and temperature difference of the battery pack. The flow resistance network model reduces the calculation amount of the velocity field, thus shortens the optimization time. After optimization, the maximum temperature and the maximum temperature difference of the battery pack are significantly reduced. (Mousavi et al., 2011) studied the parameters affecting the air cooling performance of lithium-ion batteries for electric vehicles, and analyzed the factors such as cooling air flow rate and battery diameter by using genetic algorithm. Under the condition that the cooling air flow rate is constant, the cooling performance is better by increasing the battery diameter. (Liu & Zhang, 2020)combined the adaptive neural network and model predictive control method to further reduce the temperature inconsistency of the battery pack and improve the cycle life of the battery on the basis of ensuring that the battery temperature is within the appropriate range and energy saving. (Chen et al., 2021) adopted the ranking genetic algorithm and selected the cooling air intake as the control variable to optimize BTMS with the goal of reducing energy consumption, minimum temperature inconsistency and minimum temperature deviation on the basis of not increasing the temperature inconsistency of the low power battery pack and reducing the energy consumption of the liquid cooling system. Compared with the original BTMS, the energy consumption of the optimized BTMS is reduced by 16.7%, and the maximum temperature is reduced by 3.4K.

The battery cooling system should not only adjust the temperature of the battery to a suitable range, but also reduce the energy consumption of the cooling system and the inconsistency of the temperature of the battery pack. Model predictive control (MPC) is widely used in battery cooling system because of its ability to deal with multi constraint problems. (Masoudi & Azad, 2017) designed the controller of the battery thermal management system based on the nonlinear model predictive control method, but did not consider the cooling energy consumption of the thermal management system. (Lopez-Sanz et al., 2017)Based on the nonlinear model predictive control method, taking the cooling energy consumption as the cost function, realized the minimum energy consumption in the cooling process, but did not consider the influence of the parameter uncertainty of the liquid cooling system.(Xie et al., 2020) proposed an intelligent model predictive control (IMPC) strategy to optimize and control the battery thermal management system composed of water pump, cooling plate and radiator. Under NEDC condition, the energy consumption of IMPC is reduced by 24.5% and 14.1% respectively compared with switch controller and model predictive control.

(Zhu, Lu, Zhang, & Mi, 2018) proposed a robust predictive optimization strategy for hybrid electric vehicle battery thermal management system based on finite set model. Because the thermal model of the battery thermal management system is highly nonlinear and time-varying, extended state observer (ESO) is used to estimate and predict the state of the system to compensate for the parameter uncertainty of the system. Under UDDS condition, based on Toyota Prius hybrid electric vehicle, hardware in the loop verification of the proposed strategy is carried out. Under 50% parameter uncertainty, the proposed robust predictive optimization strategy for battery thermal management can not only make the battery pack in the hybrid electric vehicle run at the optimal temperature, but also save 30% energy.

(Amini et al., 2020)proposed a hierarchical model predictive control (MPC) strategy to reduce the energy consumption of the battery thermal management system through real-time prediction and multi-time scale and multi-level optimization. Compared with the traditional battery thermal management strategy, the proposed robust hierarchical model predictive control method can save 5.4% of battery energy consumption in the case of long-term vehicle speed prediction uncertainty.

(Tao et al., 2015) studied a battery thermal management system based on the dynamic thermoelectric model of cylindrical battery and designed a nonlinear backstepping controller to regulate the temperature of cooling fluid, so as to stabilize the temperature of the battery. Compared with the traditional controller, the nonlinear backstepping controller not only improves the performance of temperature tracking and cooling system power saving.

Table 5 categorizes the above references based on optimization strategies and displays their respective strengths and weaknesses.

Table 5 Comparison of Different Optimization Strategies for Battery Cooling System

Year	Author(s)	Optimization Strategy	Strengths	Weaknesses
2013	Ji et al.	Manual Cooling	Balances temperature distribution by adjusting coolant flow rate.	Manual control required; risk of excessive cooling.
2015	He & Ma; Wang & Ma (2017)	Reciprocating & Two-Way Flow Cooling	Reduces temperature inconsistency; potential coolant consumption reduction.	Manual control, risk of excessive cooling.
2015	Tao et al.	Dynamic Thermoelectric Model	Nonlinear backstepping controller improves temperature tracking and energy saving.	Comparative data with traditional controller not mentioned.
2014-2021	Kim et al.; Qingfeng et al.; Murashko et al.; Gao et al.; Yan et al.	PID & Fuzzy Control Methods	Real-time adjustments, self-tuning PID parameters, doesn't depend on mathematical models.	Dependent on human experience for parameter and threshold settings; accuracy of fuzzy rules.
2016	Wang et al.	Hysteresis Control	Cools the battery cyclically depending on set temperature thresholds.	Frequent on/off can damage equipment and increase costs.
2017-2020	Masoudi & Azad; Lopez-Sanz et al.; Xie et al.; Zhu, Lu, Zhang, & Mi; Amini et al.	Model Predictive Control (MPC) Variants	Multi-constraint handling, real-time prediction, multi-level optimization, potential energy savings.	Some versions neglect cooling energy consumption or parameter uncertainty; computational complexity.
2021-2022	Zhu, Lu, Zhang, Sun, et al.; Kai & Shuangfeng; Liu & Zhang; Chen et al.	Genetic Algorithm & Neural Network Methods	Optimizes various system parameters; self-learning; reduces max temp and inconsistency.	Some focus on specific types of battery packs; algorithm complexity and computational time.

Based on the extensive research review on Liquid cooled Battery Thermal Management System, existing methodologies predominantly focus on a combination of active cooling strategies, traditional control systems, and intelligent algorithms to optimize the battery temperature. The most explored methods include active cooling strategies like reciprocating cycle cooling, control methods such as Hysteresis control, Finite State Machine, and PID. Additionally, intelligent algorithms, including fuzzy PID, genetic algorithms, neural networks, and model predictive control, have also been put into play.

The trajectory of battery thermal management research has been both comprehensive and insightful, contributing a depth of understanding while highlighting certain gaps that the field needed to address. A central strength of the existing research lies in its detailed exploration into active cooling strategies, ranging from hysteresis control and finite state machines to more intricate methodologies such as genetic algorithms and neural networks. These foundational studies, through their various approaches, have shed light on the multifaceted nature of battery thermal management, emphasizing the significance of temperature regulation, energy consumption optimization, and system adaptability.

While the diversity of these methodologies is commendable, several persistent shortcomings have emerged. A primary limitation centers on the reactive nature of many existing strategies. Many methods were non-predictive, resulting in systems that, while effective, often lagged behind rapidly changing operational conditions. Additionally, while these methods were diligent in temperature regulation, they occasionally either overcompensated, leading to wasted energy, or undercompensated, potentially harming the battery's longevity and efficiency.

However, these recognized limitations have also been the bedrock upon which newer methodologies, like the one presented in this study, have been formulated. Drawing inspiration and knowledge from these foundational studies, the current research introduces an adaptive control strategy dubbed DNN DMCOA. Harnessing the power of Deep Neural Networks, this strategy innovatively brings predictive capabilities to the fore, allowing for more proactive and efficient thermal management. It's this forward-looking nature, coupled with the Dwarf Mongoose's Coati Optimization Algorithm, that ensures optimal battery pack temperature consistency while minimizing energy consumption.

In synthesizing the rich tapestry of existing research with the advanced capabilities of contemporary techniques, this study carves out its distinct advantage. It builds on the strengths and learns from the limitations of preceding works, positioning itself at the forefront of battery thermal management solutions. Through such a symbiotic relationship between past insights and present innovations, the DNN-DMCOA strategy emerges as a promising beacon in the ongoing journey of optimizing battery performance and longevity.

2.5 Summary

This chapter delves deep into the rich tapestry of literature surrounding the thermal management of lithium-ion batteries, offering a holistic perspective on the progression of methodologies and strategies over time.

In section 2.1, a focus on the thermal models of lithium-ion batteries is presented. The intricacies of the Electrical Thermal Coupling Model, Electrical Coupling Model, and the Thermal Abuse Model offer a robust understanding of the multifaceted nature of battery thermal behaviors. These models lay down the foundation, emphasizing the complex interplay between electrical and thermal properties in batteries and the potential hazards associated with them.

Section 2.2 widens the lens to the broader spectrum of Battery Thermal Management Technology. The exploration ranges from basic techniques to more advanced strategies, reinforcing the significance of temperature regulation and energy optimization in the longevity and performance of batteries.

A more specialized investigation is undertaken in section 2.3, focusing on the Liquid-cooled Battery Thermal Management System (BTMS). The segment brings to light various active cooling strategies, control systems, and intelligent algorithms, all converging towards a singular goal - optimal battery temperature regulation. The detailed exploration of methodologies, ranging from traditional control systems to more nuanced algorithms like genetic algorithms and neural networks, showcases the evolving landscape of BTMS research.

Section 2.4 elevates the discussion to the realm of optimization strategies for battery cooling. While appreciating the comprehensive nature of previous research, this segment also pinpoints the reactive nature of many existing strategies. The introduction of the innovative DNN DMCOA strategy, a harmonious blend of Deep Neural Networks and the Dwarf Mongoose's Coati Optimization Algorithm, offers a glimpse into the future - a future where predictive and proactive thermal management reigns supreme.

In summation, the literature review in this chapter paints a picture of a field in constant evolution. From foundational thermal models to cutting-edge optimization strategies, the journey of battery thermal management has been both insightful and transformative. With a firm base in past research and an eye on future innovations, the chapter aptly sets the stage for the discussions and methodologies that follow.

Chapter 3 Research Methodology

This chapter is a research methodology that describes and justifies the data collection and analysis methods used in this research. The purpose of this chapter is to explain how this study was designed and conducted, and how the reliability and validity of the results were ensured.

This chapter is organized as follows:

Section 3.1 presents the proposed methodology for this research, which consists of two main parts: modeling of liquid-cooled battery thermal management system, and an adaptive control strategy based on deep neural network (DNN) and Dwarf Mongoose-based Coati Optimization Algorithm (DMCOA). This section explains the theoretical basis, assumptions, and steps of each part, as well as the expected outcomes and benefits.

Section 3.2 introduces the research equipment and tools that were used in this study, such as the simulation software, data management and analysis software, and hardware devices. This section describes the features, functions, and advantages of each tool, as well as how they were applied in the research process.

Section 3.3 reports the research analysis that was performed to evaluate the performance and effectiveness of the proposed methodology. This section presents the results of three types of analysis: reliability analysis of thermal model for battery pack, accuracy analysis of vehicle speed prediction, and performance analysis of the proposed adaptive control strategy.

Section 3.4 summarizes the main points and contributions of this chapter.

3.1 Proposed Methodology

3.1.1 Modeling of Liquid-cooled Battery Thermal Management System

Before studying the control strategy of the battery cooling system, the researcher need to study and analyze the heat generation principle inside the battery and the dynamics and heat transfer principle during the battery heat dissipation process, and establish equations for the heat generation and heat dissipation of the battery. By designing the structure of the battery cooling pipeline and utilizing the energy transfer relationship between the battery pack and the coolant, a thermal management system model for the battery pack based on liquid cooling is established, providing a foundation for studying the temperature control strategy of the battery pack.

3.1.1.1 Establishment of Battery Heat Generation Model

(1) The Working Principle of Lithium-ion Batteries

Although there are many differences in the structure of different lithium-ion batteries, the core part of lithium-ion batteries mainly consists of three parts: positive electrode, negative electrode, and core, as shown in Figure 7. Among them, the core is composed of cells, electrolytes, current collectors, separators, etc. These battery materials determine various aspects of the electrochemical performance of the battery.

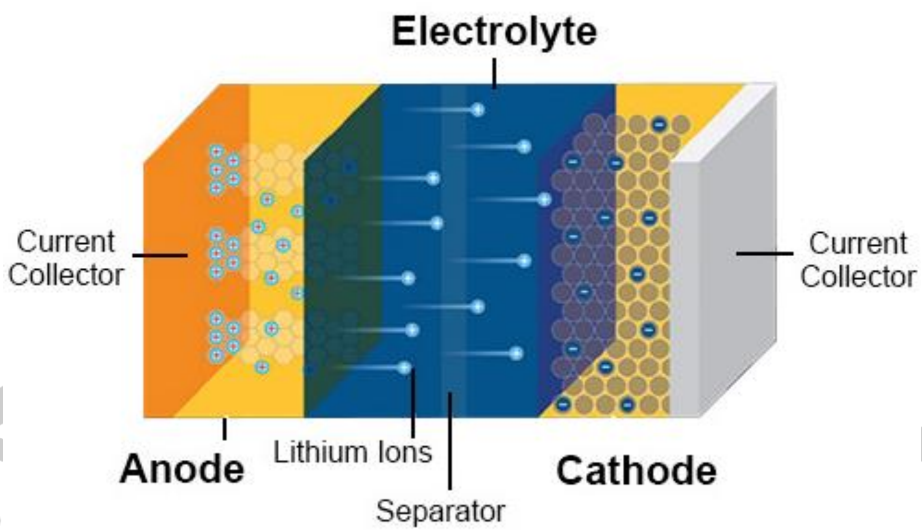

Figure 7 Structure of Lithium-ion Cell(Scrosati & Garche, 2010)

The chemical reaction during the charging and discharging process of a battery can be regarded as a reciprocal process. When the battery is in the discharging process, lithium ions detach from the positive electrode material, pass through the electrolyte and separator, and reach the negative electrode of the battery. At the same time, during the process of lithium ion detachment, electrons that cannot pass through the electrolyte are collected and transferred to the negative electrode of the battery through an external circuit. They react with lithium ions that have already passed through the electrolyte and separator to form lithium compounds that are embedded in the negative electrode material. The charging process is opposite to the discharge process, forming a reciprocal process, which is the working principle of lithium-ion batteries(Xiao & Choe, 2015).

For lithium iron phosphate batteries, the internal charging and discharging chemical reactions occur as follows

Positive electrode reaction:

$$LiFePO_4 \xrightarrow{\text{charge}} Li_{1-x} + xLi^+ + xe^- \tag{1}$$

$$Li_{1-x} + xLi^+ + xe^- \xrightarrow{\text{discharge}} LiFePO_4 \tag{2}$$

Negative electrode reaction:

$$xLi^+ + xe^- + 6C \xrightarrow{\text{charge}} Li_x\mathrm{C}_6 \tag{3}$$

$$Li_xC_6 \xrightarrow{\text{discharge}} xLi^+ + xe^- + 6C \tag{4}$$

(2) Heat Generation Model for Lithium-ion Batteries

During the working process of lithium-ion batteries, the heat generation mainly includes the following four aspects:

(1) Internal thermal resistance Q_i

The internal resistance of a battery can be divided into two parts: ohmic internal resistance and polarization internal resistance. They together form the thermal internal resistance of the battery, and the polarization internal resistance in the battery can be divided into electrochemical polarization internal resistance and concentration difference polarization internal resistance. When current passes through the battery, internal resistance heat is generated due to the presence of various internal resistances:

$$Q_i = I^2R \tag{5}$$

R is the total internal resistance of the battery, and I is the total operating current of the battery.

(2) Reaction heat Q_j

The reaction heat of a battery is the heat generated by the electrochemical reaction inside the battery, which increases with the temperature of the battery.

(3) Polarization heat Q_k

During the charging and discharging process of a battery, the current will flow through the entire battery. At this time, the electrodes in the battery will deviate from the original electrode potential, causing polarization of the battery. Therefore, the heat generated by battery polarization is called battery polarization heat.

(4) Side reaction heat Q_t

During battery charging and discharging, the electrolyte separates from each other, leading to various side reactions and battery self discharge, resulting in battery side reaction heat.

Therefore, the total heat production of the battery can be described as

$$Q_p = Q_i + Q_j + Q_k + Q_t \tag{6}$$

For the heat generation part of the battery, based on the Bernadi heat generation rate model of the power battery(Bernardi et al., 1985), assuming that the internal heat source of the lithium-ion battery is stable and uniformly generates heat, considering both the internal resistance of the battery and the entropy increase principle of chemical reactions, the polarization heat and reaction heat of the battery are considered as reversible reaction heat, and the heat generation rate of the battery can be obtained:

$$Q_p = I(E_{oc} - U) - IT_b \frac{dE_{oc}}{dT_b} + Q_k + Q_t \tag{7}$$

E_{oc} is the open circuit voltage of the battery. U is the working voltage of the battery. T_b is the temperature of the battery. I is the total operating current of the battery.

Due to the presence of internal resistance in the battery, the difference between the open circuit voltage and the working voltage represented by E_{oc} can be equivalently replaced by the product of current and internal resistance IR. Therefore, equation (7) can be expressed as

$$Q_p = I^2R - IT_b\frac{dE_{oc}}{dT_b} + Q_k + Q_t \tag{8}$$

In the above equation, the first part on the right represents the internal resistance heat of the battery, the second part represents the internal reaction heat of the battery, the third part represents the polarization heat of the battery, and the fourth part represents the side reaction heat of the battery.

When the battery is charged and discharged normally, if the temperature difference along the thickness direction of the battery is very small or the battery is very thin, the polarization reaction heat and side reaction heat of the battery can be ignored. Assuming that the internal current density of lithium-ion batteries is consistent and the heat generation is uniform, the heat generation rate of lithium-ion batteries mentioned above can be simplified as

$$Q_p = I^2R - IT_b\frac{dE_{oc}}{dT_b} \tag{9}$$

The two parameters that have the greatest impact on the internal resistance R of a battery are the discharge depth and temperature of the battery. When the lithium-ion battery is at a temperature of 20 ℃~40 ℃ and the discharge rate is above 10%, the change in the internal resistance value of the battery is not significant. Therefore, the internal resistance of the battery can be considered as a constant, set as $a_1 = 2m\Omega$ (Zhang et al., 2014). And $T_b\frac{dE_{oc}}{dT_b}$ is related to the electrochemical reaction of the battery. For the same type of battery, this value can be considered a constant, set to $a_2 = 11.6mV$ (Zhang et al., 2014). By determining these two parameters, the function of the heat generation rate of the single battery and the operating current can be obtained as

$$Q_p = a_1I^2 - a_2I \tag{10}$$

3.1.1.2 Establishment of Battery Heat Dissipation Model

(1) Design of Liquid-cooled Heat Exchange Structure

The research of the cooling structure for the battery pack in this study can be roughly divided into two parts: the battery and the heat exchange structure around the battery. Firstly, for the selection of coolant, the preferred solution is a 50% concentration of ethylene glycol water solution(Wang et al., 2018). This solution has a high boiling point, low evaporation loss during use, low freezing point, and good safety. It is not only suitable for cold areas, but also for high load and high temperature work requirements. Secondly, establish the physical structure and heat exchange structure of the battery pack. Assuming that the fluid inside the cooling pipeline is uniformly distributed and flows in the pipeline, the specific heat transfer structure is: heat dissipation pipeline - battery - heat dissipation pipeline. The battery is cooled by the thermal convection between the coolant in the heat dissipation pipes on both sides of the battery and the battery. The specific liquid flow heat transfer structure of the battery pack is shown in Figure 8.

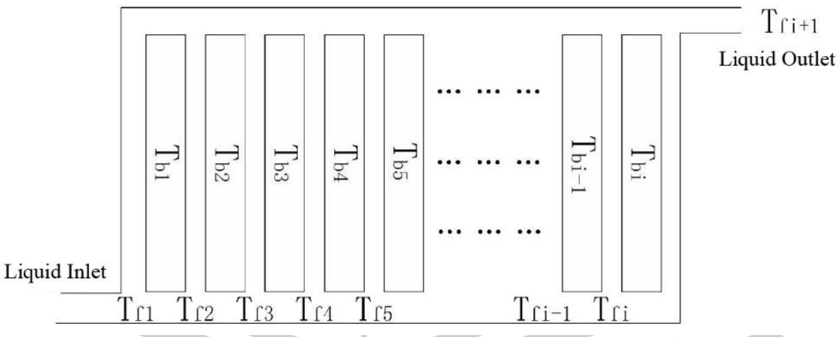

Figure 8 Structure of the liquid flow heat exchange pipeline

The battery cell is a square shaped thin sheet, which uses aluminum pipes with good heat transfer efficiency to form the main heat transfer channels for the heat dissipation fluid and each power battery. The heat dissipation structure diagram on both sides of the single battery is shown in Figure 9.

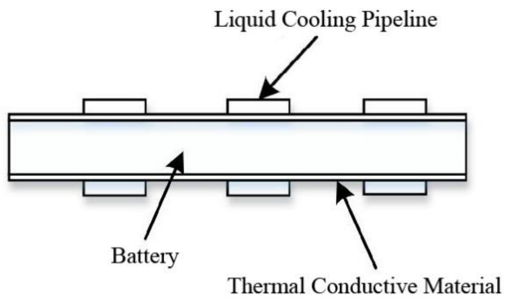

Figure 9 Heat dissipation structure on both sides of the battery

(2) Heat Dissipation Model for Lithium-ion Batteries

The occurrence of heat transfer process is due to the temperature difference between different objects or different parts of the same object, and this process is automatic. Heat transfer problems can be divided into three basic modes: heat conduction, heat convection, and heat radiation.

The basic characteristic of heat conduction is that the relative positions between heat transfer objects do not change, and the transfer of heat depends on the thermal motion of microscopic particles between the constituent objects. For example, the heat transfer process of using a cold plate to cool a battery belongs to the heat conduction process.

The heat transfer process that corresponds to heat conduction and generates relative displacement due to macroscopic motion between objects is called thermal convection. Because thermal convection can only occur in fluids, while heat conduction can only occur in solids, generally speaking, the heat transfer mode in fluids is the coexistence of thermal conduction and thermal convection. For example, the cooling liquid carries the heat from the battery to the heat exchanger, but the main heat transfer mode is thermal convection, which in contrast transfers very little heat.

Although there is direct or indirect contact between objects, heat transfer occurs, which is called thermal radiation. For the liquid cooled heat management system studied in this study, the battery is mainly cooled by the convective heat transfer between the battery and the coolant in the cooling channel. The circulating flow of the coolant in the pipeline takes away some of the heat generated by the battery. The heat dissipation method used in this study is relatively small in magnitude through thermal radiation and conduction, so this study only considers thermal convection heat transfer. According to Newton's cooling law, it can be obtained that the total heat lost during convective heat transfer between the battery and the coolant is:

$$Q_s = hA(T_b - T_f) \tag{11}$$

Q_s is the heat dissipation capacity of the battery, h is the convective heat transfer coefficient between the fluid and solid contact surface. If the heat transfer ability of the liquid is strong, the heat transfer coefficient is relatively high, A is the convective heat transfer area, and T_f is the coolant temperature.

Newton's cooling law only defines the convective heat transfer coefficient h in fluid heat transfer, and does not reveal the internal relationship between it and the relevant physical quantities that affect it. In fact, there are many factors that affect convective heat transfer, and various convective heat transfer phenomena are formed due to differences in fluid dynamics, fluid flow state, fluid phase transition, and heat transfer surface geometry. However, the convective heat transfer coefficient h varies greatly under different conditions. For the calculation of heat transfer in cooling pipelines, the convective heat transfer coefficient can be obtained using Nusselt number Nu, and Nu can be used to represent the numerical relationship between convective heat transfer coefficient and fluid thermal conductivity. This article uses a square tube to dissipate heat from the battery. For the convective heat transfer relationship inside the square tube, the relationship between the convective heat transfer coefficient h between the battery and the coolant and Nusselt number Nu is:

$$h = \frac{Nu\lambda}{d} \tag{12}$$

$$Nu = 0.023\mathrm{Re}_f^{0.8}\,\mathrm{Pr}_f^{0.4}\left(\frac{\eta_f}{\eta_b}\right)^{0.11} \tag{13}$$

$$\mathrm{Re} = \frac{ud}{v_f} \tag{14}$$

λ is the thermal conductivity of the fluid, Nu is the Nusselt number of the fluid inside the pipe, d is the equivalent diameter of the fluid pipeline, $d = 2ab/(a + b)$, a is the width of the square pipe, b is the height of the square pipe, Re is the Reynolds number of the fluid inside the pipe, Pr is the Prandtl number of the fluid inside the pipe, η_f and η_b are the fluid dynamic viscosity calculated based on the average temperature and wall temperature of the fluid, u is the average velocity of the fluid inside the pipe, and v_f is the kinematic viscosity of the fluid inside the pipe.

The relationship between the convective heat transfer coefficient h between the battery and the coolant and the coolant flow rate u in the square tube can be obtained from equations (12) to (14) as follows:

$$h = \frac{0.023\mathrm{Pr}_f^{0.4}\eta_f^{0.11}\lambda}{\eta_b^{0.11}v_f^{0.8}d^{0.2}} \cdot u^{0.8} \tag{15}$$

The thermophysical parameters Pr, v_f and η_f of the coolant can be obtained by looking up the average temperature of the fluid inside the tube. η_b can be obtained by looking up the temperature of the fluid near the pipe wall. In addition, the fixed dimensions a and b of the square tube will not change during battery operation, so the convective heat transfer coefficient h is mainly a function of the coolant flow rate u.

Let

$$e = \frac{0.023\mathrm{Pr}_f^{0.4}\eta_f^{0.11}\lambda A}{\eta_b^{0.11}v_f^{0.8}d^{0.2}} \tag{16}$$

Put equations (15) and (16) into equation (11), and the total heat lost by the battery in the battery heat dissipation model is:

$$Q_s = e \cdot \left(T_b - T_f\right) \cdot u^{0.8} \tag{17}$$

3.1.1.3 Establishment of a Thermal Model for Battery Pack Based on Liquid Cooled Heat Dissipation Structure

(1) Thermal Model of Battery Cell

The battery thermal model is a thermal model derived from the mathematical description of the heat generation process and heat dissipation process of the battery using certain physical laws. According to the law of conservation of energy, for a battery in a charging and discharging state, the accumulated heat of the battery is equal to the total heat generated by various electrochemical reactions inside the battery minus the total heat dissipated by the heat exchange between the battery and the coolant:

$$dQ_b = dQ_p - dQ_s \tag{18}$$

dQ_b is the heat accumulated by the battery per unit time, dQ_p is the total heat generated by the battery per unit time, and dQ_s is the total heat dissipation between the battery and the coolant per unit time.

The heat accumulated by the battery per unit time dQ_b can be calculated based on the change in temperature of the battery per unit time as follows:

$$dQ_b = c_b m_b dT_b \tag{19}$$

dT_b is the change in temperature of the battery per unit time. m_b is the battery mass, and c_b is the specific heat capacity of the battery.

According to equations (10) and (17), the heat generated inside the battery per unit time and the heat transferred to the coolant by the battery per unit time can be obtained:

$$dQ_p = (a_2 I^2 - a_1 I)dt \tag{20}$$

$$dQ_s = \left(e \cdot \left(T_b - T_f\right) \cdot u^{0.8}\right)dt \tag{21}$$

Put equations (19) to (21) into equations (18), then the thermal model of battery cell is:

$$\dot{T}_b = \frac{eu^{0.8}}{c_b m_b} T_b + \frac{a_1 I^2 - a_2 I - eT_f u^{0.8}}{c_b m_b} \tag{22}$$

(2) Thermal Model of Battery Pack

In the heat dissipation structure of the liquid cooled battery pack thermal management system in this study, the cooling pipeline of the battery has been designed, as shown in Figure 8. Therefore, the coolant temperature $T_{f,1}$ at the inlet of the battery pack is a measurable quantity, while the coolant temperature $T_{f,n}$ near each battery in the battery pack is not measurable. For battery packs, after each battery is cooled, its corresponding coolant temperature will increase. And whenever a battery is cooled, the temperature of the coolant that converges to the outlet of a single battery cooling pipeline gradually increases with the number of batteries in the battery pack. Finally, the coolant temperature at the outlet of the battery cooling pipeline becomes increasingly high, which affects the temperature of the battery. So the temperature of the coolant in the pipeline will gradually increase, leading to a higher temperature of the battery. So the established battery pack model can only represent the temperature distribution in the battery pack by establishing the thermal models of the first and last batteries.

For each battery in the battery pack, the thermal conductivity, fluid Nusselt number, fluid Reynolds number, fluid Prandtl number, fluid dynamic viscosity, and fluid kinematic viscosity near each cell are different. According to equation (22), the thermal model of the i-th cell is:

$$\dot{T}_{b,i} = f_1(u) \cdot T_{b,i} + f_2(u) \cdot T_{f,i} + a_3 \tag{23}$$

$$f_1(u) = \frac{eu^{0.8}}{c_b m_b} \tag{24}$$

$$f_2(u) = -\frac{eu^{0.8}}{c_b m_b} \tag{25}$$

$$a_3 = \frac{a_1 I^2 - a_2 I}{c_b m_b} \tag{26}$$

$T_{b,i}$ is the temperature of the i-th battery in the battery pack, $T_{f,i}$ is the temperature of the coolant in the pipeline near the i-th battery, $i = 1,2,\dots,n$. Due to the fact that the temperature of the coolant at the inlet of the cooling pipeline can be measured by a temperature sensor, $T_{f,1}$ can be approximated as the temperature of the coolant fluid at the inlet of the cooling pipeline in the thermal model of the first battery established. From equation (23), the thermal model of the first battery can be obtained as:

$$\dot{T_{b,1}} = f_1(u) \cdot T_{b,1} + f_2(u) \cdot T_{f,1} + a_3 \tag{27}$$

Due to the inability to know the cooling temperature near each battery in equation (23), the last battery thermal model of the battery pack is solved by considering the heat conservation of the entire battery pack. According to the law of conservation of energy, the sum of the heat dissipated by each battery in a battery pack is equal to the sum of the heat absorbed by the cooling fluid in the cooling pipeline of the battery pack from the inlet to the outlet.

$$dQ_1 = dQ_2 \tag{28}$$

According to the law of heat transfer, the total amount of heat absorbed by the cooling fluid in the cooling pipeline of a battery pack per unit time from the inlet to the outlet is:

$$dQ_1 = c_f m_f \Delta T_f = c_f \cdot (\rho_f abu) \cdot (T_{f,n+1} - T_{f,1})dt \tag{29}$$

c_f the specific heat capacity of the coolant, and ρ_f is the density of the coolant.

The sum of the heat dissipated by each cell in the battery pack per unit time is:

$$\begin{aligned} dQ_2 &= dQ_{s,1} + dQ_{s,2} + \cdots + dQ_{s,n} \\ &= e \cdot u^{0.8} \cdot [(T_{b,1} - T_{f,1}) + (T_{b,2} - T_{f,2}) + \cdots + (T_{b,n} - T_{f,n})]dt \end{aligned} \tag{30}$$

Among them, $dQ_{s,1}, dQ_{s,2} \ldots, dQ_{s,n}$ represent the heat dissipated into the coolant from the 1st battery to the i-th battery, $T_{b,1}, T_{b,2} \ldots, T_{b,n}$ represent the temperature from the 1st battery to the i-th battery, and $T_{f,1}, T_{f,2} \ldots, T_{f,n}$ represent the temperature of the coolant near the i-th battery. Due to the increase in the number of cooled batteries, the cooling fluid in the battery pack pipeline shows an equal amplitude increase, which also leads to an equal amplitude increase in the temperature of each cell in the battery pack.

Assuming that

$$\begin{aligned} T_{b,i} &= T_{b,1} + \frac{i-1}{n-1}\left(T_{b,n} - T_{b,1}\right) \\ T_{f,i} &= T_{f,1} + \frac{i-1}{n-1}\left(T_{f,n} - T_{f,1}\right) \end{aligned} \tag{31}$$

By combining equations (21) and (28)~(31), the following equation can be obtained:

$$dQ_{s,n} = \left[\frac{0.023c_f\rho_f abeu}{c_f\rho_f abu^{0.2}+(n-1)\cdot e}T_{b,n} - \frac{(n-1)\cdot e^2\cdot u^{0.8}}{2c_f\rho_f abu^{0.2}+(n-1)\cdot e}T_{b,1} - \frac{2c_f\rho_f abue-(n-1)\cdot e^2\cdot u^{0.8}}{2c_f\rho_f abu^{0.2}+(n-1)\cdot e}T_{f,1}\right]dt \tag{302}$$

By placing equations (28), (17), and (18) into equation (16), the thermal model of the last cell per unit time can be obtained as:

$$\dot{T}_{b,n} = f_3(u)T_{b,n} + f_4(u)T_{b,1} + f_5(u)T_{f,1} + a_3 \tag{313}$$

$$f_3(u) = \frac{-0.023c_f\rho_f abeu}{c_f\rho_f abu^{0.2}c_b m_b+(n-1)\cdot ec_b m_b} \tag{324}$$

$$f_4(u) = \frac{(n-1)\cdot e^2\cdot u^{0.8}}{2c_f\rho_f abu^{0.2}c_b m_b+(n-1)\cdot ec_b m_b} \tag{335}$$

$$f_5(u) = \frac{2c_f\rho_f abue-(n-1)\cdot e^2\cdot u^{0.8}}{2c_f\rho_f abu^{0.2}c_b m_b+(n-1)\cdot ec_b m_b} \tag{346}$$

Although the liquid flow rate in the liquid cooling and thermal management system leads to the nonlinearity of the thermal model of the battery pack, it also makes the temperature of the battery pack controllable, and provides relevant reference methods for the control research of battery temperature. When the initial temperature of battery charging and discharging, the current during battery operation, and the fluid flow rate in the pipeline are known, the temperature of the first and last batteries can be calculated based on the thermal model of the battery pack. For the numerical values of various fluid parameters of the coolant in this chapter, Table 6 shows the specific relationship between temperature and various parameters (Tang et al., 2020).

Table 6 the specific relationship between temperature and various parameters

Temperature (K)	**Kinematic Viscosity** $(\times 10^{-6} m^2/s)$	**Dynamic Viscosity** $(\times 10^{-6} kg/ms)$	**Prandtl Number** -	**Density** (kg/m^3)	**Specific Heat Capacity** $(J/kg \cdot K)$	**Thermal Conductivity** $(W/m \cdot K)$
283	4.8116	5.1098	40.088	1062	3268	0.41656
288	4.1952	4.4429	34.572	1059	3277	0.42122
293	3.6604	3.8659	29.856	1056	3287	0.42568
298	3.1969	3.3671	25.825	1053	3297	0.42996
303	2.7954	2.9363	22.378	1050	3307	0.43404
308	2.448	2.5645	19.432	1047	3318	0.42795
313	2.1477	2.2439	16.913	1044	3329	0.44169
318	1.8883	1.9676	14.76	1042	3340	0.44525

3.1.2 An adaptive Control Strategy Based on DNN-DMCOA

In this research, a liquid-cooling method is employed for heat dissipation in the battery pack, leveraging the flow of water in the cold plate to remove the heat produced by the battery pack. In practice, the entire cooling process experiences a certain latency, leading to a delayed response in temperature changes and causing the battery pack's temperature characteristics to be nonlinear.

To achieve optimal temperature control, this study utilizes Deep Neural Networks (DNN) to predict the vehicle's driving speed in advance. Based on these predictions, adjustments are made to the subsequent cooling process promptly. Besides aiming for temperature control, another objective of this research is to address the energy consumption of the system, making this endeavor a multi-objective optimization problem. Drawing from the preceding literature review, this study employs the Coati optimization algorithm based on the Dwarf Mongoose (DMCOA) for problem-solving.

The diagram of the proposed adaptive control strategy is shown in Figure 10. The system consists of two main parts: an adaptive control module and a Liquid-cooled BTMS basic module, where the adaptive control module includes a DNN predictor and a DMCOA optimizer. The Liquid cooled BTMS basic module has been explained in the previous section.

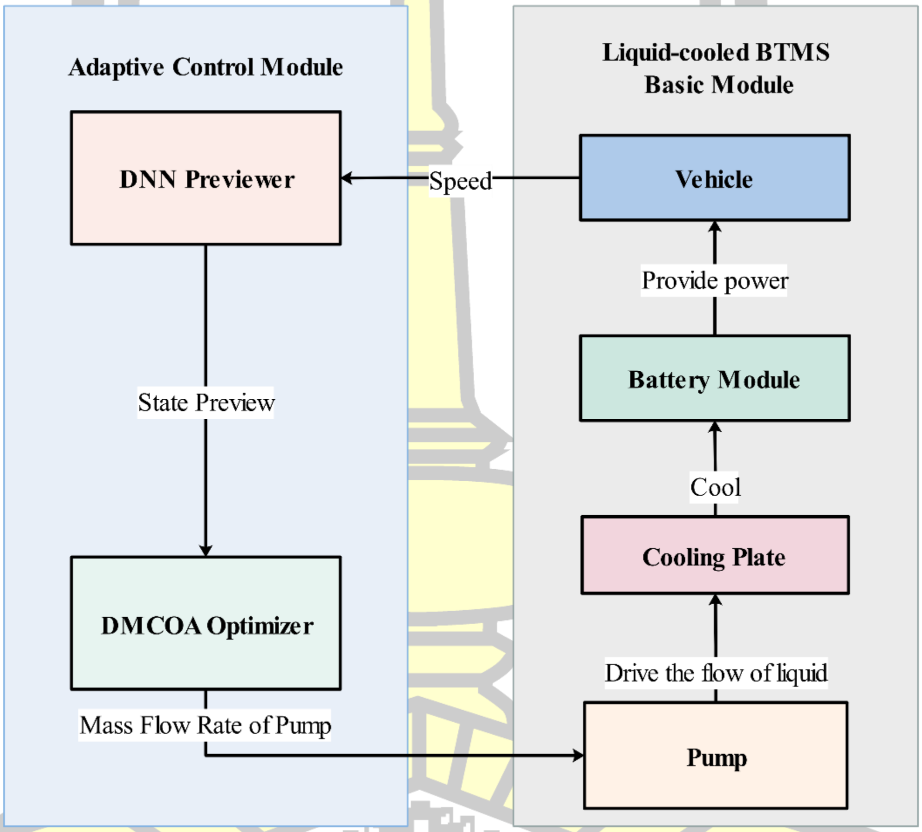

Figure 10 Diagram of the Proposed Adaptive Control Strategy for Liquid-cooled BTMS

3.1.2.1 Vehicle Speed Prediction Based on DNN

A DNN is a type of machine learning model inspired by the structure of the human brain. It consists of multiple interconnected layers of artificial neurons, designed to process and learn from complex patterns in data. Each layer in a DNN transforms input data progressively, extracting hierarchical features at increasing levels of abstraction. The basic structure of DNN is shown in Figure 11, where I1 is the input layer, H1 and H2 are called as hidden layer and O1 is called as output layer.

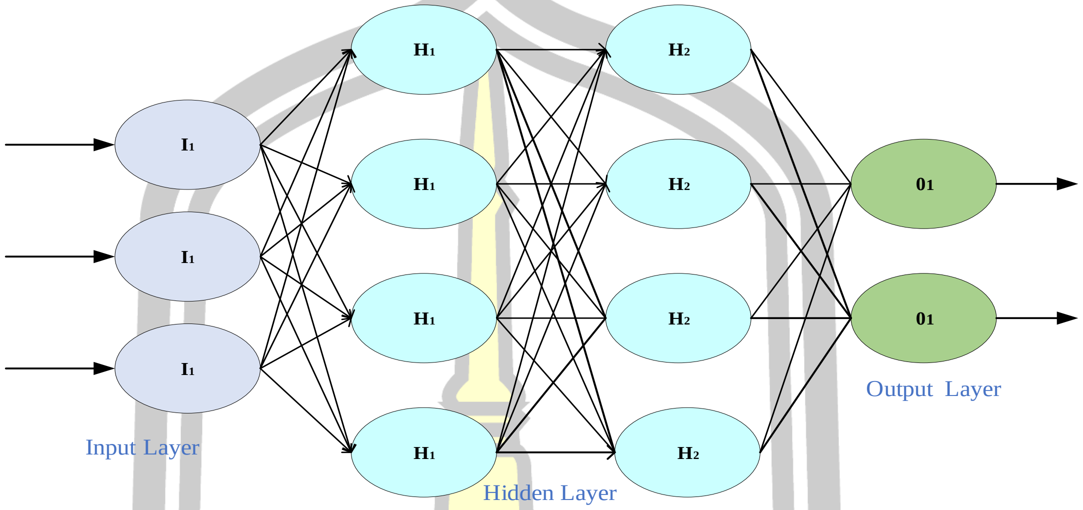

Figure 11 Structure of Deep Neural Network

The term deep in DNN refers to the depth of the interconnected layers. DNNs have been highly successful in tasks, such as image and speech recognition, natural language processing, and more, owing to their ability to automatically learn and represent intricate patterns within data. The research aims to evaluate the potential of EV parameters and Vehicle-to-Infrastructure (V2I) data in enhancing vehicle velocity prediction.

In this research, a sensor-equipped vehicle gathers drive inputs during its journey as the first step. Utilizing these data as input, DNN involve in the prediction of the vehicle velocity. The proposed prediction model yields result for diverse prediction windows. These outcomes are subsequently scrutinized to determine the most optimal velocity of the EV. The architecture of DNN predictor, as depicted in Figure 12, features an input layer of 20 neurons. This ensemble encapsulates historical parameters such as velocity, mean velocity (with and without idling conditions), mean acceleration, and mean deceleration observed over the preceding 60 seconds. With a prediction interval of 2 seconds, the output layer, comprising 30 neurons, forecasts vehicle velocity over the next 60 seconds. The training procedure can draw velocity data from WLTC and NED driving cycles.

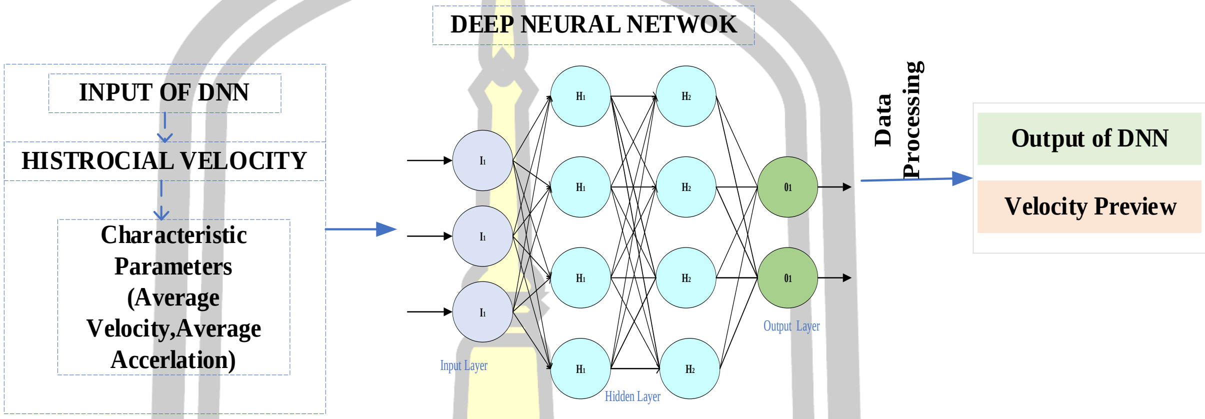

Figure 12 The Architecture of DNN predictor

The velocity data is partitioned into distinct sets for training, validation, and testing. In this schema, 70% of the data fuels the network's training, 15% validates the model's performance, and the remaining 15% evaluates the predictive precision, effectively mitigating overfitting risks.

3.1.2.2 Multi-objective Optimization Based on DMCOA

The consumption of energy in BTMS depend on the target temperatures of the battery. A lower target temperature increases the consuming more energy of BTMS. Hence, it is important to maintain a balanced target temperature that can save energy with minimal cost expenditure.

As explained in the previous section, the DNN predictor can predict the vehicle speed for the next 60 seconds. In this section, the DMCOA optimizer takes the predicted vehicle speed from the DNN to make decisions about the liquid-cooling process in the battery. Since the battery's temperature characteristics are nonlinear and the cooling process has a latency, timely predictions about vehicle speed can help make real-time adjustments to the cooling process. This ensures optimal temperature control and energy consumption.

So the objective of the DMCOA optimization is twofold:

1) Temperature Control: Ensure that the battery temperature is maintained within optimal limits to maximize battery lifespan.

2) Energy Efficiency: Minimize the energy consumption of the Battery Thermal Management System (BTMS).

$$min_x F(x) = \omega_1 \times T(x) + \omega_2 \times E(x) \tag{357}$$

$F(x)$ is the objective function to be minimized. $T(x)$ represents the deviation of battery temperature from its optimal value. $E(x)$ represents the energy consumption of the BTMS. ω_1 and ω_2 are weights indicating the relative importance of temperature control and energy consumption, respectively.

For effective battery management, certain constraints must be adhered to:

1) Temperature Range: The battery temperature must be maintained within a certain range for safety and efficiency.

$$T_{min} \leq T(x) \leq T_{max} \tag{368}$$

T_{min} and T_{max} are the minimum and maximum allowable battery temperatures, respectively.

2) Energy Consumption: The BTMS shouldn't consume more energy than available or allocated.

$$E(x) \leq E_{max} \tag{379}$$

E_{max} is the maximum allowable energy consumption by the BTMS.

The optimization algorithm, DMCOA in this case, will seek to minimize this cost function $F(x)$. This task is accomplished through the usage of the proposed hybrid DMCOA algorithm, which is an integration of the characteristic features of both Dwarf Mongoose and Coatis.

The principles of the coatis when attacking the iguanas, and their behavior when confronting and escaping from predators are the intelligent processes in COA.

The simulation of these natural coatis' behaviours is the fundamental inspiration in designing the proposed COA approach(Baş & Yildizdan, 2023; Dehghani et al., 2023). The advantage of using COA is the effective application of it in high dimensional complex problems. Also, the method is capable of providing a better balance between both the exploration and the exploitation phases. The absence of control parameters is an additional advantage as there is no need to tune any parameter. The DMO algorithm models the adaptive behaviour of dwarf mongooses, encompassing factors like prey size, social structure (alphas, scouts, babysitters), and a semi-nomadic lifestyle. This adaptation is supported by the alpha group, scouts, and babysitters, collectively exploring a territory suitable for the entire group(Agushaka et al., 2022). Foraging and scouting occur concurrently, and as the alphas forage, they scout for new mounds. The decision to move is based on the average sleeping mound value, preventing over-exploitation and ensuring territory exploration.

The optimization of several error parameters using COA is explained in this section in detail.

Step 1:Initialization: In the implementation of the COA, the coati's location in the search space is initialized randomly using equation (40).

$$C_{i,j}^{P1} = c_{i,j} + rand.(iguana_j - I.c_{i,j}),\ for\ i = 1,2,.....,[N/2]\ and\ j = 1,2,.......,d \tag{40}$$

Where, the j^{th} decision variable is $c_{i,j}$, $rand$ represents the random value between $[0,1]$, the maximum and minimum limit of the j^{th} decision variable is $\max_j$ and $\min_j$. N illustrates the number of coatis. And $C_{i,j}^{P1}$ denotes the coati adaptive step size, $N/2$ is a half index of the number of coatis. The following equation (41) uses the matrix which denotes the mathematical expression of coatis' population.

$$C = \begin{bmatrix} C_1 \\ \vdots \\ C_i \\ \vdots \\ C_N \end{bmatrix}_{N\times d} = \begin{bmatrix} c_{1,1} & .. & c_{1,j} & .. & c_{1,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_{i,1} & .. & c_{1,j} & .. & c_{i,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_{N,1} & .. & c_{N,j} & .. & c_{i,d} \end{bmatrix}_{N\times d} \tag{41}$$

Step 2: Objective Function: The objective function is evaluated by the location of candidate solution in every parameter as determined in equation (42).

$$O = \min(F) \tag{42}$$

Where, the objective function is addressed as O, with the minimization of the cost function needed to expand the battery life time considering the battery target temperature.

Step 3: Position Update: The updating process is carried out in 2 stages namely, exploration and exploitation phase.

i) Phase 1: Exploration stage (Hunting and attacking plan on iguana)

In this stage, the population's optimal member is signified as the iguana's position. Also, it is considered as some of the coatis climb the tree and other coatis wait for the iguana to fall to the ground. Equation (43) expresses the coati's position rising from the tree.

$$C_{i,j}^{P1} = c_{i,j} + rand.(iguana_j - I.c_{i,i}),\ fori = 1,2,.....,[N/2]\ and\ j = 1,2,......., d \tag{43}$$

The iguana is placed in a random position when it falls to the ground. According to this random position, simulations using equations (44) and (45) is done for coatis on the ground moving towards the search space.

$$iguana_J^G = \min_j + rand.(\max_j - \min_j),\ j = 1,2,......, d \tag{44}$$

$$for\ i = [N/2]+1, [N/2]+2, ..., N \quad and \quad j = 1,2,......, m \tag{45}$$

Where $iguana_J^G$ represents the iguana position located from the top nodes, N is the Number of active propagated nodes in the Active optimal member layer. The conditions in equation (46) represents that the updated position, which is suitable only if it improves the objective function value.

$$c_i = \begin{Bmatrix} c_i^{p1} + D_i + ph_i * peep, O_i^{p1} < O_i \\ C_{i,} \qquad\qquad else \end{Bmatrix} \tag{46}$$

At this instance, the alpha phase of the DMO algorithm is integrated into COA, in such a way to inherit the advantages of both the algorithms, where iguana_j denotes the position of iguana in the search domain that is considered as the optimal member's position in the iguana_j in the j^{th}dimension . c_i^{p1} is the Coati crossover probability at the first phase, D_i is the Coati Recombination Rate, ph_i is the Hybridization rate, O_i^{p1} is the Coati Solution stability at first phase , C_i is the integration of the coati variables, i is the initialization variables.

i) Phase 2: Exploitation stage (Fleeing from predators)

In this stage, the optimal position in the search space is modelled according to the coati's natural behaviour of fleeing from predators (exploitation ability in local search). A random position is created adjacent to each coati's position for the simulation of this behaviour as represented in equations (47) and (48).

$$\min_j^{local} = \min_j / t, \max_j^{local} = \max_j / t \text{ , where } t = 1,2,\ldots\ldots T \qquad (47)$$

Where, $\min_j^{local}$ is the minimum variable declared for optimization, $\max_j$ are the maximum variables at boundary handling, t is the coati time per iteration, T is the coati time for convergence.

$$C_i^{P2} : c_{i,j}^{P2} = c_{i,j} + (1-2rand).(\min_j^{local} + rand.(\max_j^{local} - \min_j^{local})) \text{ for } i = 1,2,\ldots..N, j = 1,2,\ldots.d. \qquad (48)$$

Similarly, the conditions in equation (49) represents that the newly updated position in phase 2.

$$c_i = \begin{cases} c_i^{p2} + D_i + ph_i * peep, O_i^{p2} < O_i \\ C_{i,} \qquad \text{else} \end{cases} \qquad (49)$$

In the exploitation phase, the position of DMO is updated with the position of COA. The addition of the alpha phase of the DMO into COA enhances the convergence characteristics of the proposed DMCOA approach. Here, the updated position evaluated for the coati is C_i^{P2} and its dimension is $c_{i,j}^{P2}$. The objective function value is represented as O_i^{P2}. $\max_j^{local}$ and $\min_j^{local}$ signifies the decision variable's local maximum and minimum limit. t represents the iteration number and $rand$ is the random value between [0,1], c_i^{p2} is the Coati crossover probability at the second phase, d is the dynamic adaptions. The Pseudocode of proposed DMCOA Algorithm is given in Algorithm 1, and the flowchart is shown in Figure 13.

Algorithm 1. Pseudocode of proposed DMCOA algorithm

Step 1	**Start**	
Step 2	**Population and parameter initialization**	
Step 3	**Initialize,** m	
Step 4	**Initialize the position of all coatis by Eq (40)**	
Step 5	**Fix parameters of N and d. Fix** $i = t - 1$.	
Step 6	**For i>N/2**	
Step 7		Determine the fitness
Step 8		Calculate C_i^{P1} using equation (43)
Step 9		Update C_i using equation (46)
Step 10		Create location of the iguana at random using equation (44)
Step 11		Re-calculate C_i^{P1} using equation (43)
Step 12		Revise C_i using equation (46)
Step 13		**For i<N**
Step 14		Set Iter=1
Step 15		Calculate C_i^{p2} using equation (48)
Step 16		Update C_i using equation (49)
Step 17		Keep the optimal candidate solution found so far
Step 18		Determine new fitness of C_i^{P1} and C_i^{p2}
Step 19		Terminate if the optimal solution of the fitness function is determined using DMCOA
Step 20	**End for**	
Step 21	**Return** optimum solution	

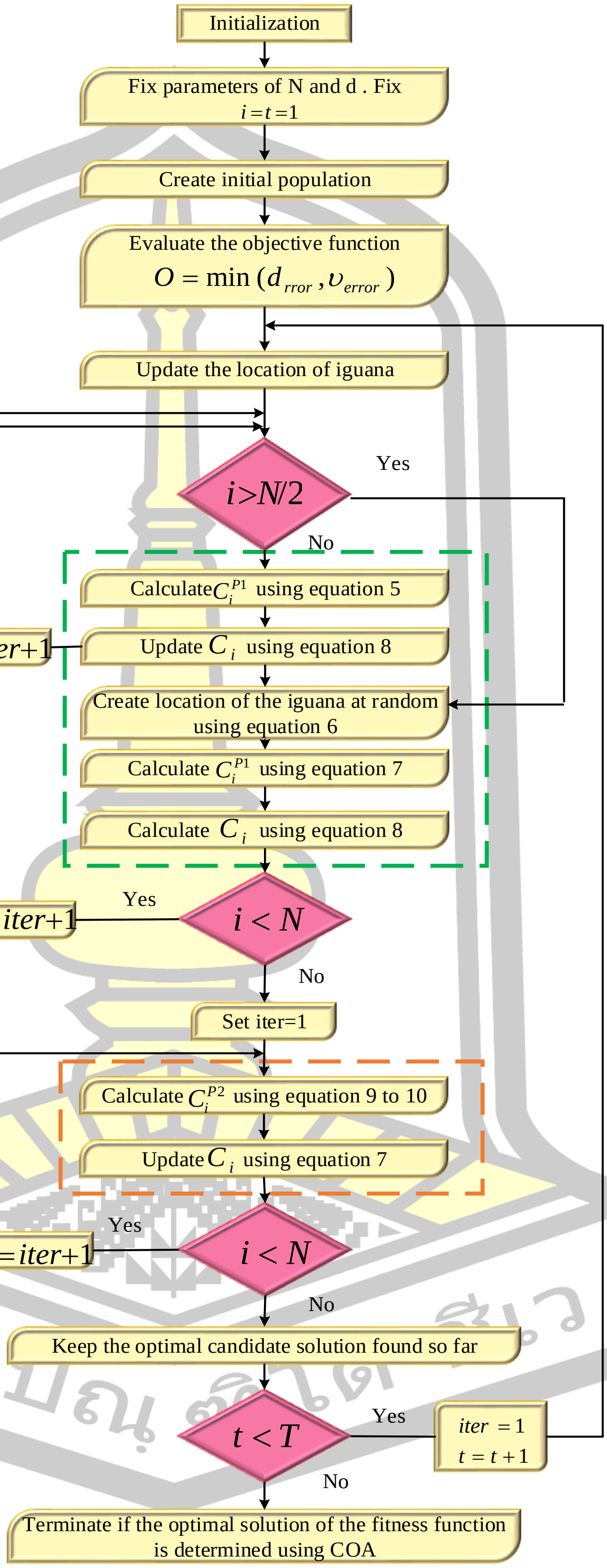

Figure 13 Flowchart of DMCOA

3.2 Research Equipment and Tools

3.2.1 Simulation Software

a. AMEsim

Overview: Advanced Modeling Environment for Simulating complex systems, AMEsim is renowned for its proficiency in modeling the intricate fluid power systems. AMEsim offers a comprehensive library of pre-defined components to facilitate the construction of accurate system-level models.

Purpose: Precisely emulate the physical characteristics of the battery cooling system for accurate simulations.

Capabilities:

i. Access to a broad library of components suitable for creating multidisciplinary system models.

ii. Perform dynamic simulations to capture system performance over time.

Data Output: AMEsim's embedded data logging tools save critical simulation data like fluid flow rates, pressures, and temperature variations, exportable to MATLAB.

b. Matlab/Simulink

Overview: MATLAB offers an intricate environment for algorithm development, data processing, and visualization, whereas Simulink aids in simulating multidomain dynamic systems.

Purpose: Design and test control algorithms (PID, MPC, DNN, DMCOA,) and interface with AMEsim models.

Capabilities:

i. Detailed algorithm design and simulation.

ii. Integration with AMEsim system models.

Data Integration: Matlab/Simulink can import data from AMEsim for further processing. It also facilitates the application of advanced control algorithms, such as MPC, and DMCOA-DNN methods, to the data.

3.2.2 Data Management and Analysis

MATLAB Data Analysis Toolbox

Overview: This toolbox is an integrated suite of tools in MATLAB that offers advanced data processing capabilities.

Purpose: Post-simulation data is critical. This toolbox is essential to process this data, extract meaningful statistics, and facilitate a more in-depth understanding of the results.

Capabilities:

i. Advanced statistical tools.
ii. Data visualization and preprocessing.

Data Collection: Further processes the raw data from AMEsim and Simulink, facilitating insightful results presentation.

The diagram shown as Figure 14 visualizes the main tools used in the research. AMEsim interacts directly with Matlab/Simulink, which in turn is connected to the MATLAB Data Analysis Toolbox for data processing and visualization.

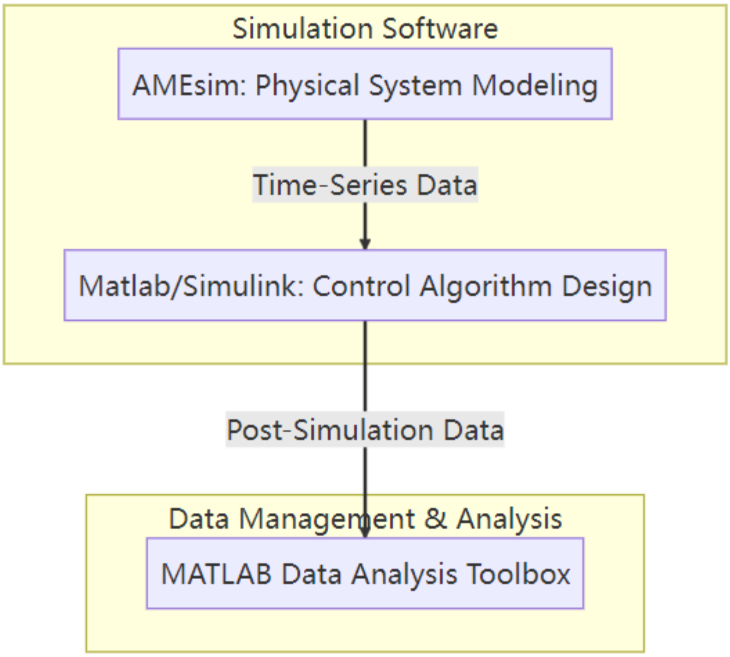

Figure 14 The diagram of research tools

3.3 Research Analysis

3.3.1 Reliability Analysis of Thermal Model for Battery Pack

In order to verify the reliability of the thermal model of the battery pack, this study sets different battery operating conditions in the simulation. On the one hand, by solving the thermal model of the battery pack in Matlab, the temperature change curve of the battery pack can be obtained through equations (27) and (33). On the other hand, to verify the accuracy of the model, a battery pack model was established in AMESim, and the battery temperature change curve obtained in AMESim was used as the actual measurement value. Compare two sets of curve data to verify the accuracy of the model.

During the model validation process, three sets of battery pack current and coolant flow rate simulation experiments were set, with current sizes set at 2C and 3C, and coolant flow rates set at 0.01m/s and 0.02m/s, respectively, to validate and analyze the thermal model of the battery pack.

3.3.2 Accuracy Analysis of Vehicle Speed Prediction

To analyze the accuracy of vehicle speed prediction based on DNN in this research, the WLTC and NEDC driving cycles are employed. NEDC and WLTC are two different driving cycles that are used to test the performance and emissions of vehicles. They are designed to simulate typical driving patterns and conditions in Europe and around the world, respectively. Choosing these two operating conditions when verifying the accuracy of electric vehicle speed prediction can help to evaluate how well the prediction model can handle different scenarios and parameters, such as speed, acceleration, deceleration, road grade, traffic flow, and ambient temperature.

The NEDC operating condition consists of four repeated urban driving cycles (UDC) and one extra-urban driving cycle (EUDC). The total duration of the NEDC cycle is 1180 seconds, which includes 780 seconds of UDC and 400 seconds of EUDC(J.D.Power., 2020). The NEDC cycle is characterized by low speeds, gentle accelerations and decelerations, and a high proportion of urban driving. The NEDC cycle is representative of the driving behavior and conditions in Europe before 1990s(Li et al., 2021).

The WLTC operating condition is a newer and more realistic driving cycle that was introduced in 2017 to replace the NEDC cycle. The WLTC cycle is based on real-world driving data collected from different regions and road types. The WLTC cycle consists of four parts: low, medium, high, and extra high. The total duration of the WLTC cycle is 1800 seconds, which includes 589 seconds of low, 433 seconds of medium, 455 seconds of high, and 323 seconds of extra high(J.D.Power., 2020). The WLTC cycle is characterized by higher speeds, more dynamic accelerations and decelerations, and a better balance between urban and non-urban driving. The WLTC cycle is representative of the current and future driving behavior and conditions in Europe and other regions(Li et al., 2021).

3.3.3 Performance Analysis of the Proposed Adaptive Control Strategy

As discussed in Section 2.4, the PID controller is the most common and simplest control method used in the thermal management system of electric vehicle batteries. On the other hand, MPC represents a more recent and effective line of research. This study compares the methodology proposed herein with the PID and MPC. Both of these methods were evaluated under the NEDC driving cycle, prompting this study to adopt the same driving conditions. Given that the NEDC lasts only 1180 seconds, our analysis utilizes five cycles of the NEDC to fulfill the performance evaluation requirements.

Subsequently, initial values for battery temperature, coolant temperature, State of Charge (SOC), and State of Health (SOH) are established. The performance analysis of the proposed adaptive control strategy is then carried out under NEDC driving conditions.

Comparative analysis is conducted focusing on the following four metrics: (1) Pump mass flow rate, (2) Battery temperature, (3) Battery's State of Health (SOH), and (4) Energy consumption.

3.4 Summary

In this chapter, the intricate approaches employed for the study are meticulously delineated. This chapter serves as the backbone, elucidating the strategic pathway for advancing the understanding and application of liquid-cooled battery thermal management systems.

The chapter commences with the conceptualization of the proposed methodology. It embarks on a journey of establishing a deep comprehension of the thermal dynamics of liquid-cooled batteries. The multi-tiered approach begins with the formulation of the battery's heat generation model, progresses to the heat dissipation model, and culminates in a comprehensive thermal model for the battery pack. Each sub-model offers a detailed insight, ensuring that the entire battery thermal ecosystem is well-understood and effectively represented.

In an endeavor to bridge the theoretical models with actionable control strategies, the chapter introduces the adaptive control mechanism founded on the synergy between Deep Neural Networks (DNN) and Dwarf Mongoose-based Coati Optimization Algorithm (DMCOA). This section is pivotal, signifying the blend of predictive intelligence (via DNN) and optimization excellence (via DMCOA). Together, they present a solution that anticipates vehicular speeds and dynamically optimizes the battery cooling operations, pushing the boundaries of efficiency and responsiveness.

Recognizing the indispensability of modern research tools, the chapter delves into the essential equipment and software that drive the simulations and data analyses. The highlighted role of AMEsim and Matlab/Simulink accentuates their capabilities in crafting accurate system-level models and fostering algorithmic interplay. These tools, complemented by the MATLAB Data Analysis Toolbox, empower the research with the prowess to simulate, capture, analyze, and visualize the multifaceted data produced.

Venturing further into the analytical realm, the methodology chapter undertakes rigorous evaluations across three dimensions. It seeks to ascertain the reliability of the formulated thermal model by juxtaposing simulated temperature curves from Matlab and AMESim. This validation is pivotal, ensuring that the theoretical constructs align with simulated realities. In the pursuit of holistic evaluation, the chapter assesses the DNN's prowess in predicting vehicle speeds using benchmarked WLTC and NEDC driving cycles. Lastly, the spotlight shifts to the performance of the proposed adaptive control strategy. By contrasting its efficacy against conventional PID and MPC techniques, the research underlines its potential advancements in battery temperature regulation, health monitoring, and energy conservation.

In summation, this chapter is the methodological compass of this doctoral thesis. It charts the strategies, tools, and analyses that together propel the study from foundational modeling to transformative solutions in the realm of electric vehicle battery management.

Chapter 4 Results and Discussion

This chapter is a results and discussion chapter that presents and interprets the findings of this research. The purpose of this chapter is to answer the research questions and hypotheses, and to evaluate the performance and effectiveness of the proposed methodology.

This chapter is organized as follows:

Section 4.1 reports the results of reliability verification for the battery pack's thermal model, which was developed and simulated on AMESim software. This section compares the simulation results with the experimental data and calculates the error and deviation values to assess the accuracy and validity of the model.

Section 4.2 reports the results of vehicle speed prediction accuracy, which was achieved by using a deep neural network (DNN) model. This section presents the predicted and actual vehicle speed curves for different driving scenarios and the curves to measure the prediction accuracy.

Section 4.3 reports the comparison results of the proposed adaptive control strategy with proportional-integral-derivative (PID) and model predictive control (MPC) strategies, which were applied to optimize the liquid-cooled battery thermal management system. This section compares the three strategies in terms of mass flow rate, battery temperature, state of health (SOH), and energy consumption, using various indicators such as maximum temperature difference, temperature uniformity, cooling efficiency, and cooling power.

Section 4.4 summarizes the main findings and contributions of this chapter, as well as the research questions and hypotheses that were answered or supported by this research.

4.1 Results of Reliability verification for Battery Pack's Thermal Model

4.1.1 Simulation Model on AMESim

(1) Pipeline in Liquid Cooling System

The pipeline model of the battery pack liquid cooling system was built in this research based on the cooling system library module and the thermal hydraulic library module in AMESim software. The establishment of the model requires setting the parameters of the coolant in the pipeline and various components of the battery pack. The coolant for the power battery pack is selected as ethylene glycol solution, which is a 50% mixture of ethylene glycol aqueous solution. The parameters of various liquid thermal characteristics are set in the AMESim simulation software. The setting of battery parameters for the power battery pack in this research requires setting. Firstly, it is necessary to select the battery model, determine the density of the battery material, and then set its density, size, specific heat capacity, and thermal conductivity based on actual battery parameters. The specific values of the battery are shown in Table 7. In addition, all the heat exchange components in the cooling pipeline model are made of aluminum metal materials.

The lithium-ion battery selected in this article is the A123 square flake lithium-ion power battery. The experimental battery pack consists of 14 square sheet lithium iron phosphate batteries, with a single cell voltage of 3.2V and a capacity of 10Ah. The specific parameters of the battery are shown in Table 7. By constructing heat transfer modules related to batteries and coolant, the heat transfer structure of the battery pack in AMESim is aligned with the heat transfer structure designed in this research.

Table 7 Battery Parameters (Yan et al., 2021)

Rated Voltage	3.2 V
Capacity	10 Ah
Density	1653 kg/m^3
Specific Heat Capacity	1350 J/kgK
Thermal Conductivity	0.6 W/mK
Length	200mm
Width	160 mm
Height	7.8 mm

Firstly, the battery pack of an electric vehicle will transmit current to the vehicle system to make it work, and at the same time, the battery temperature will increase. The circulating flow of coolant in the pipeline will transport heat outward through the constructed liquid cooled pipeline. The heat dissipation model of the experimental battery module is shown in Figure 15.

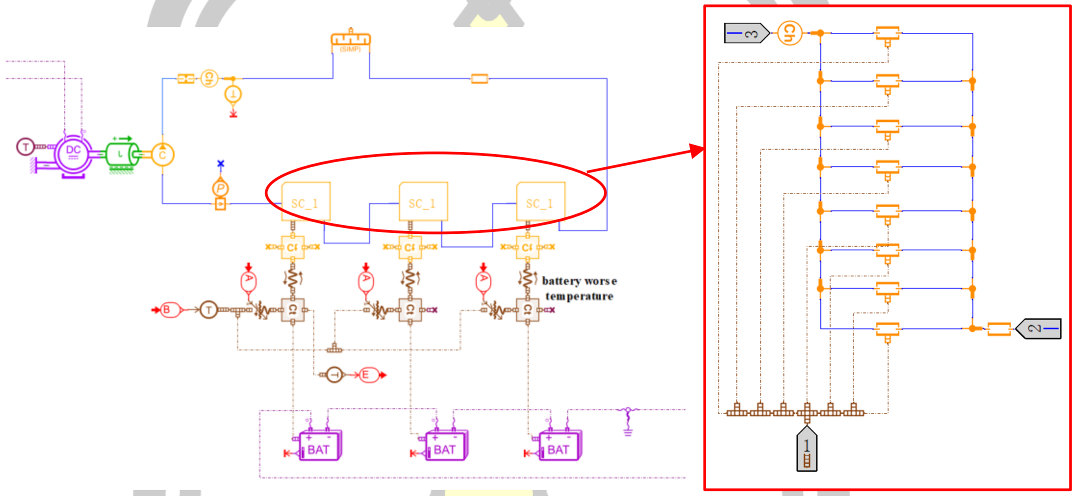

Figure 15 Pipeline Model Diagram of Liquid Cooling System

(2) Vehicle System

The AMESim software itself contains a car system model, which was selected for this study. This module can provide working current to the liquid cooled pipeline module of the battery pack. By setting the operating conditions of this model and the parameters of the entire electric vehicle, the required battery pack current, control signals, battery pack power, and other related signals can be transmitted to the liquid cooling pipeline system and other system submodules. The driving conditions of electric vehicles can indirectly affect the working status of the battery pack in the electric vehicle battery liquid cooling pipeline model, such as battery pack power, battery heat production, and so on. The vehicle operating conditions can be divided into many different cycle conditions according to different road regions, specifically including Worldwide harmonized Light vehicles Test Cycle(WLTC), New European Driving Cycle(NEDC), Japanese 10-15 Mode Test Cycle(JC08), Environmental Protection Agency Test Cycle(EPA), and so on. This research selects NEDC standard operating conditions of first driving at low speed and then driving at high speed for simulation verification. The parameters of the vehicle system model in this study are shown in Table 8. The model of vehicle system in AMESim is shown in Figure 16.

Table 8 Vehicle Parameters (Yan et al., 2021)

Vehicle Mass	1.53t
Frontal Area	2.49 m^2
Axle Load Distribution	50:50
Wheel Diameter	15m
Tread Width	185mm
Tire Aspect Ratio	60%

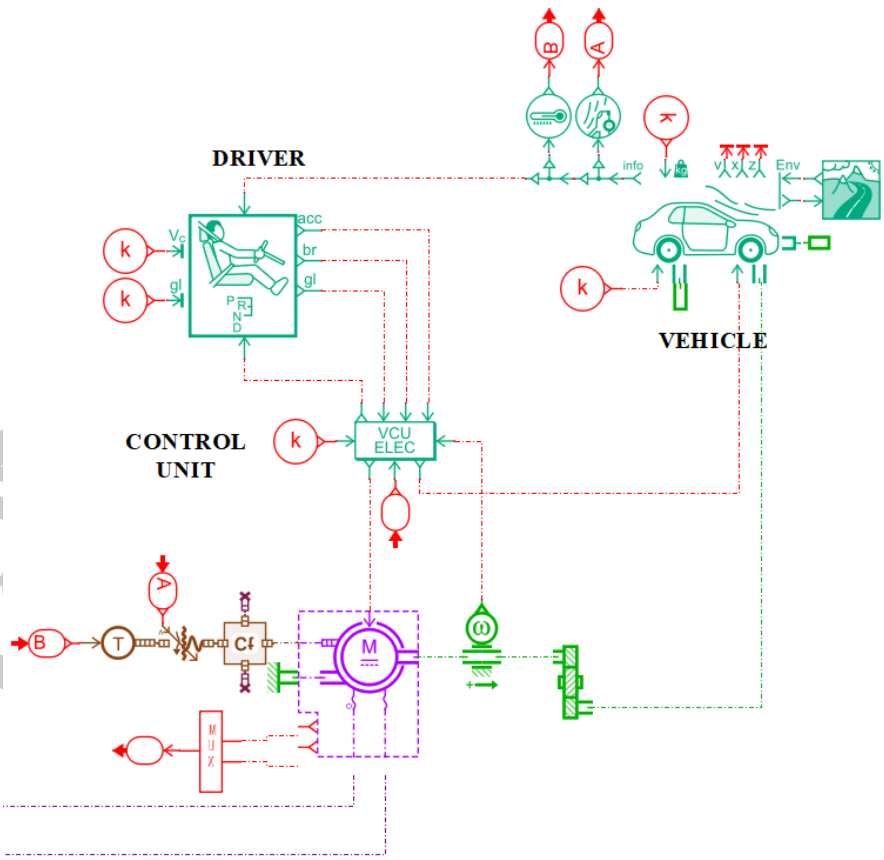

Figure 16 Model of Vehicle System

(3) Air conditioning System

The establishment of a model for the air conditioning circuit system requires the use of relevant submodules in the air conditioning library and two-phase flow library in the AMESim simulation software. The main components include compressors, condensers, expansion valves, gas-liquid separators, and heat exchangers. For the air conditioning circuit system model built in this article, in order to accurately reflect the temperature changes of the battery in the liquid cooling pipeline model of the battery pack without affecting the normal operation of the condenser, certain input quantities of the condenser are used as fixed values.

The air conditioning system model built in AMESim is shown in Figure 17.

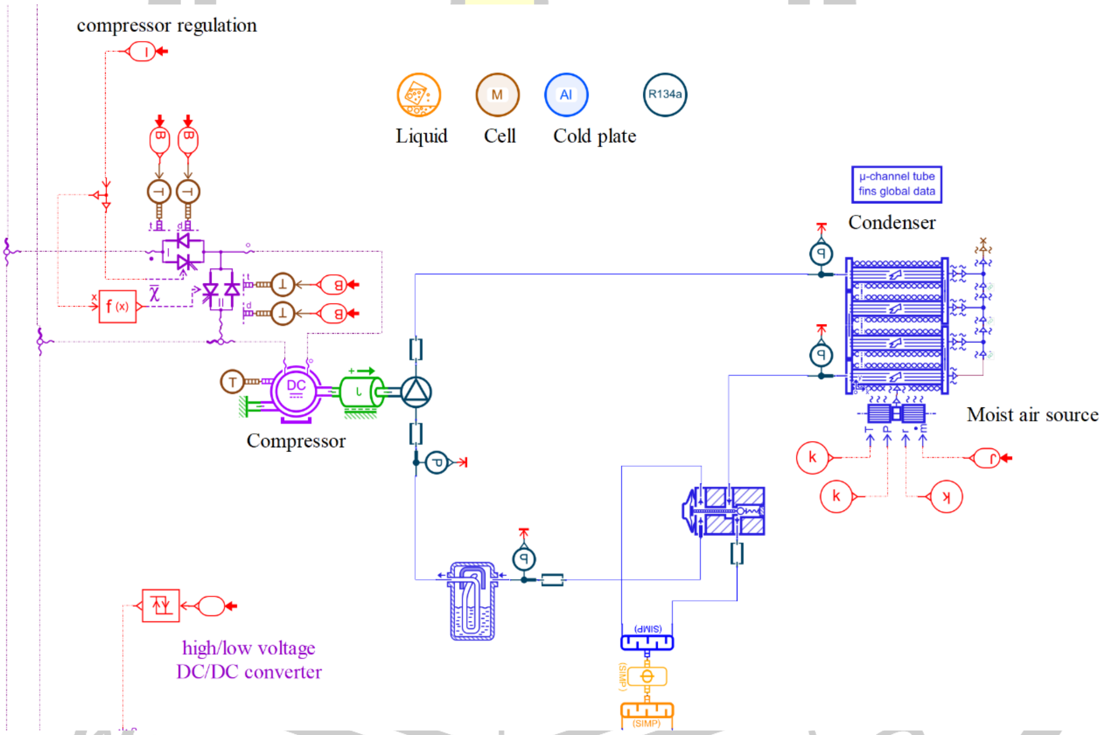

Figure 17 Model of Air conditioning System

(4) The overall simulation model of Liquid-cooled Battery Thermal Management System

The overall simulation model of Liquid-cooled Battery Thermal Management System on AMESim is shown in Figure 18.

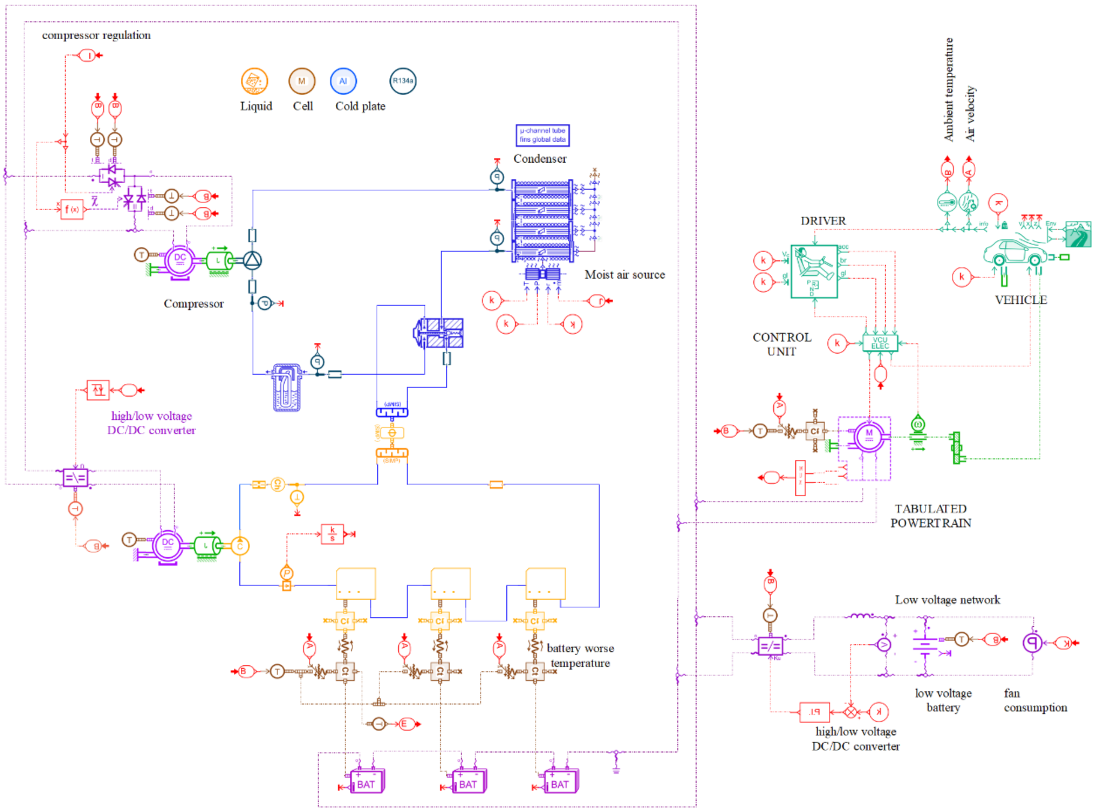

Figure 18 Simulation Model of Liquid-cooled Battery Thermal Management System on AMESim

4.1.2 Results of Verification Reliability

During the experiment, the battery was in normal operation and the system pipeline temperature was set to a constant value to reduce the impact of the external environment on the heat dissipation of the battery pack. The initial temperature of the battery was set to 25 ℃, and two constant current currents were set to 2C and 3C, respectively. 2C means that the current is equal to two times the capacity of the device in ampere-hours, and 3C means that the current is equal to three times the capacity of the device in ampere-hours. The two coolant flow rates were 0.01m/s and 0.02m/s. The simulation and actual battery pack temperatures were compared, as shown in Figures 19 to 21.

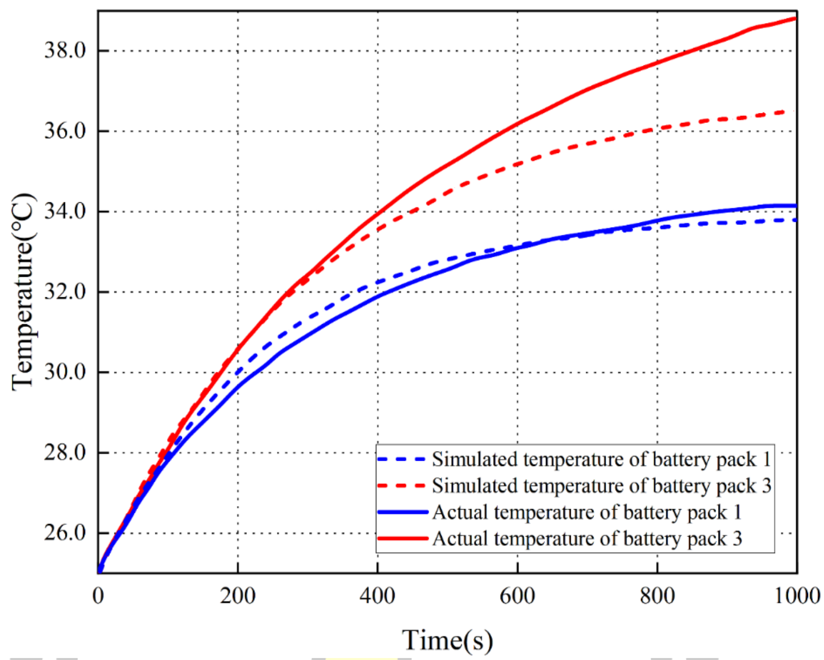

Figure 19 Comparison results of battery temperature change curves under 3C constant current discharge and flow rate of 0.01m/s

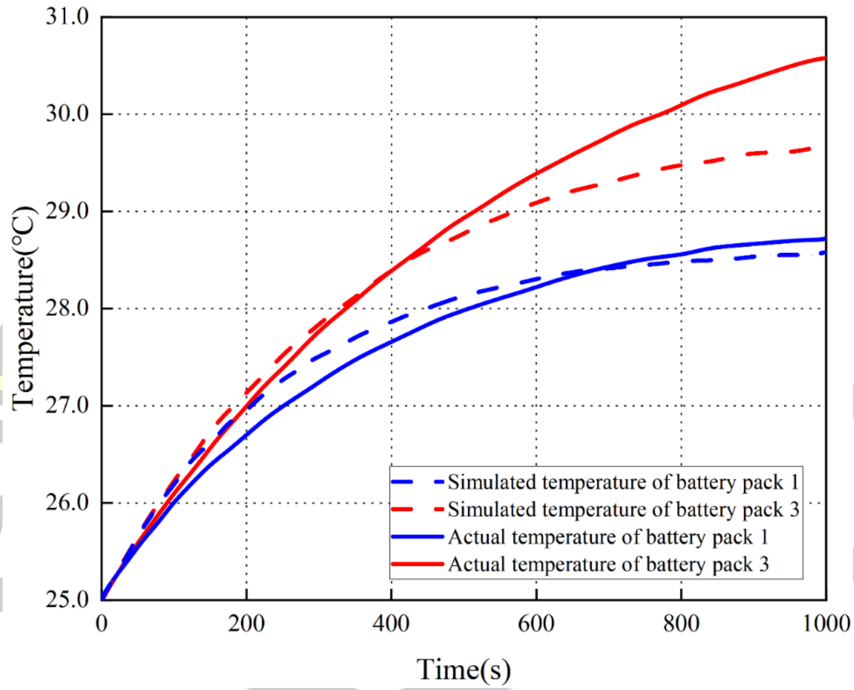

Figure 20 Comparison results of battery temperature change curves under 2C constant current discharge and flow rate of 0.01m/s

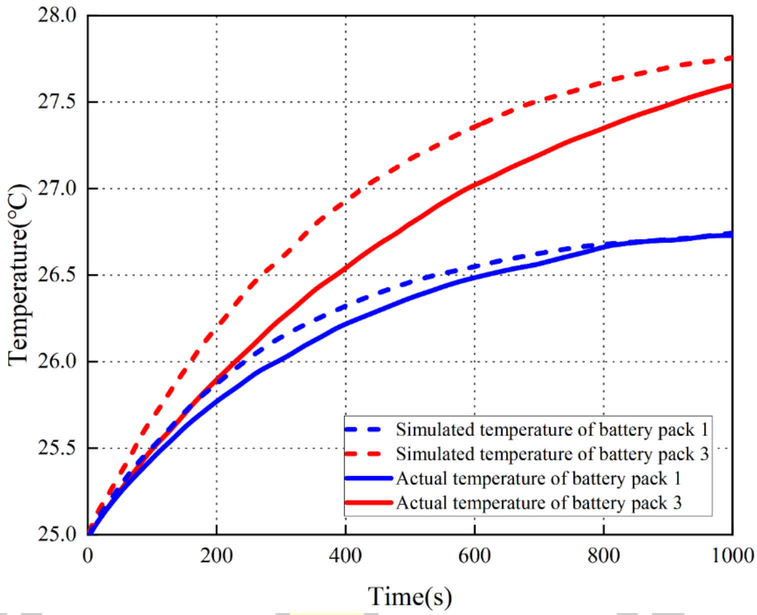

Figure 21 Comparison results of battery temperature change curves under 3C constant current discharge and flow rate of 0.02m/s

From Figures 19 to 21, it can be seen that under different constant current discharge conditions and coolant flow rates, the temperature of the battery pack gradually increases and finally reaches equilibrium. The output curves of the thermal model of the battery pack can track the actual values well, and ensure that the temperature error is within 0.3°C, which can meet the accuracy requirements and can be used for the design of subsequent temperature controllers.

4.2 Results of Vehicle Speed Prediction Accuracy

The WLTC and NEDC driving cycles were employed to evaluate the predictive accuracy of the DNN in this research. Figure 22 and Figure 23 depict the anticipated velocities over intervals of 10 s to 60 s. For NEDC, the discrepancy between the predicted and actual speeds is 0.21 s, whereas for WLTC, it stands at 0.19 s. These results align with findings from (Yufang et al., 2020). Due to the negligible size of this lag, it isn't explicitly shown in Figure 22 and Figure 23. The forecasted vehicle velocities closely mirror the actual ones, with regression values recorded at 0.889 and 0.884 for NEDC and WLTC respectively. These findings suggest that the Vehicle Speed Prediction based on DNN, provides a reliable estimation of speed progression over time.

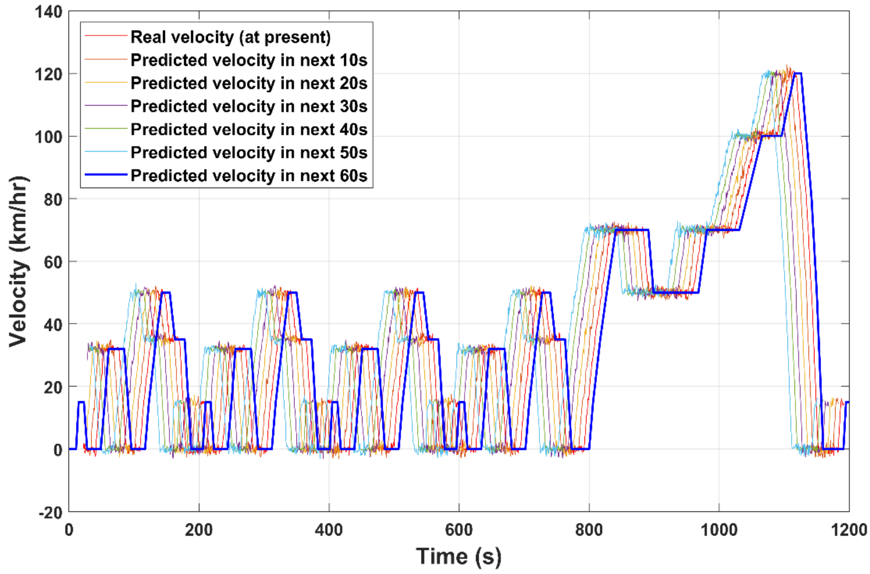

Figure 22 Results of vehicle speed prediction under NEDC driving condition

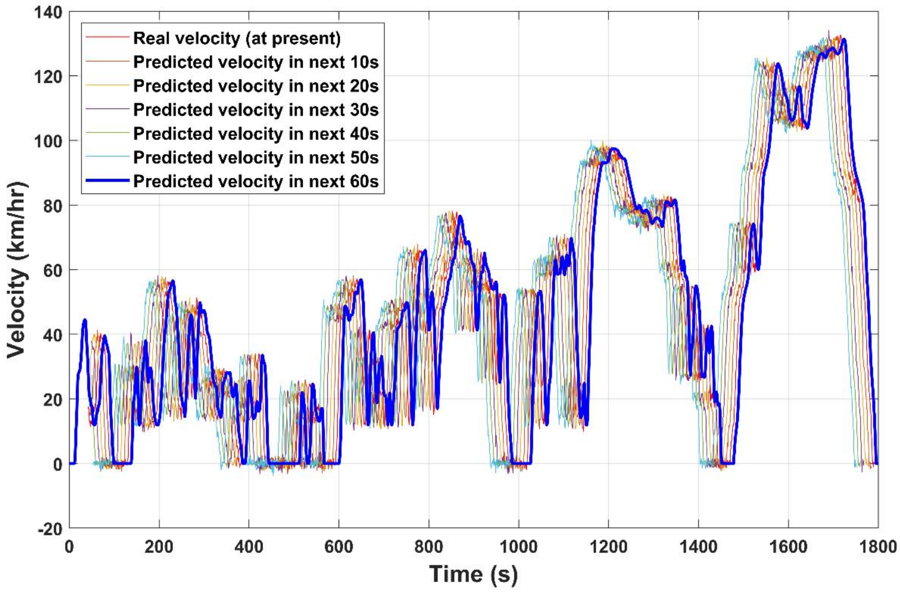

Figure 23 Results of vehicle speed prediction under WLTC driving condition

4.3 Comparison Results of the Proposed Adaptive Control Strategy with PID and MPC

As explained in section 3.3.3, the simulation in this section is based on five cycles of the vehicle driving under NEDC conditions, with the vehicle speed shown in Figure 24. The initial temperature of the coolant is 20℃, the initial SOC and SOH of the battery are both 100%, and the target temperature of the battery is set to 25℃.

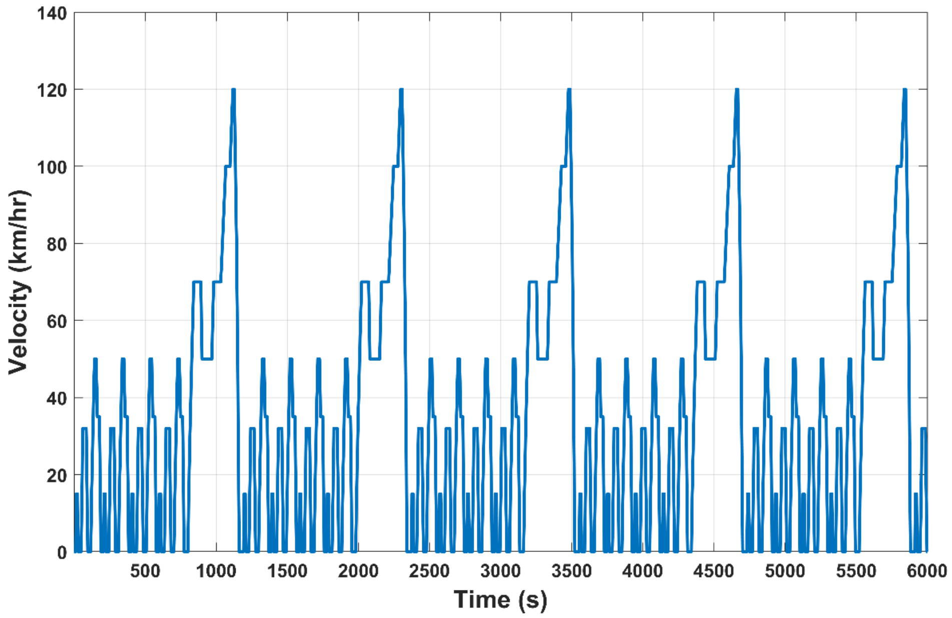

Figure 24 Speed curve of EV under NEDC's 5 cycle driving conditions

Based on the speed predicted by DNN, BTMS can predict the heat generation of the battery in advance, so the mass flow rate of the pump has been adjusted. For example, there is a high-speed zone between 1977 s and 2355 s, which leads to changes in the heat generation rate of the battery, as shown in Figure 25.

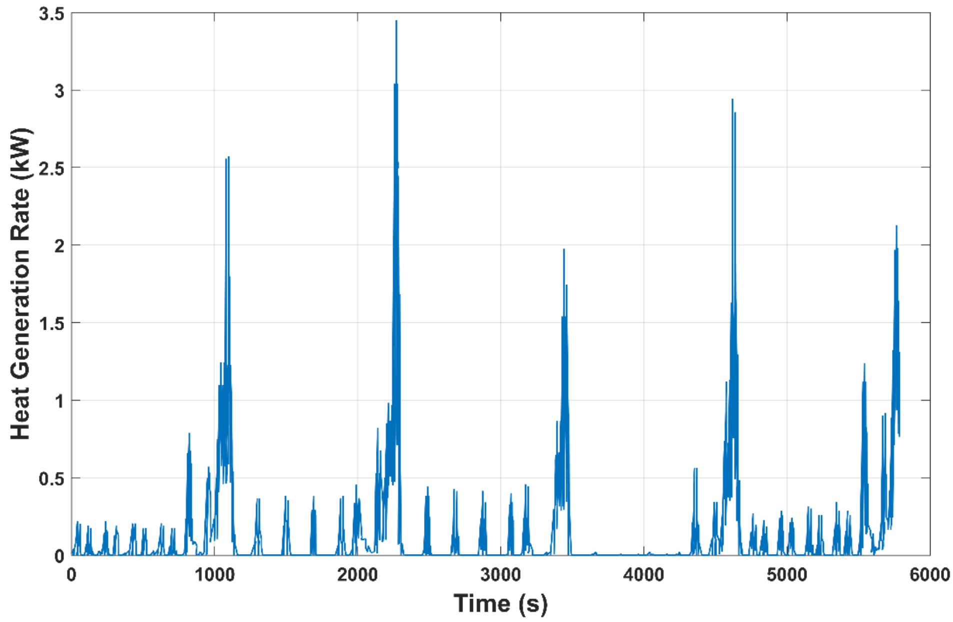

Figure 25 Heat Generation Rate of Battery Pack

4.3.1 Comparison Results of Mass Flow Rate

Figure 26 illustrates the pump's mass flow rate under diverse control strategies. Under PID control, the pump operates at a mass flow rate of 700 g/s to stabilize the battery temperature. This extended operation results in notable energy consumption.

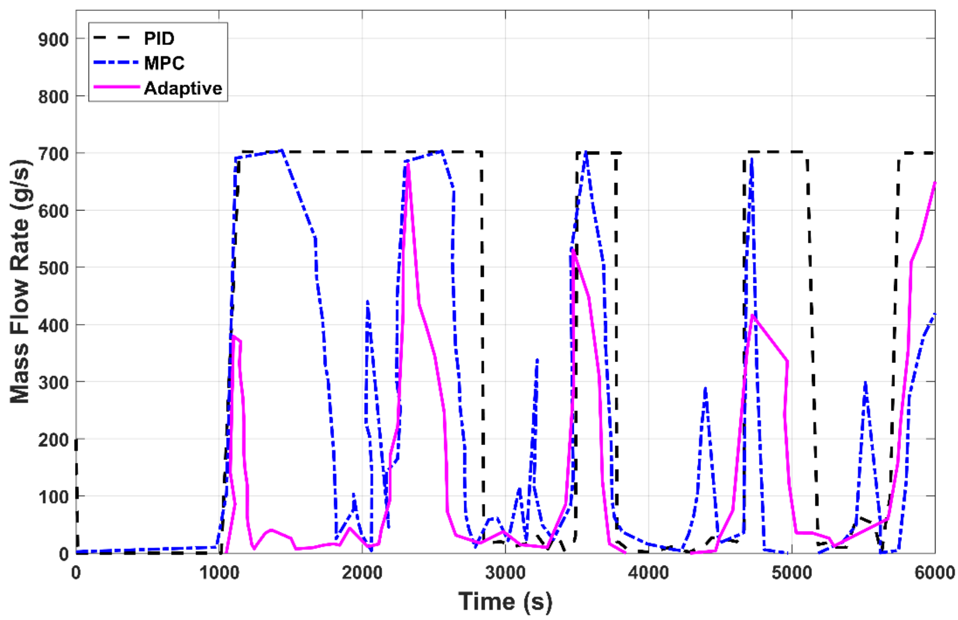

Figure 26 Comparison of Mass flow Rate of the Pump

Conversely, the adaptive strategy proposed employs a DNN to forecast the battery's heat generation, determining the requisite mass flow rate for an adequately large pump. In contrast, the MPC method does not provide battery temperature predictions, adjusting the coolant's mass flow rate based solely on the current battery temperature.

Furthermore, during the intervals of 3204 to 3307 seconds and 3412 to 3501 seconds, the vehicle experienced accelerations. Its speed amplified from 0.4 m/s to 18.95 m/s in the first interval and from 14.02 m/s to 34.16 m/s in the latter. The respective average heating rates for these stages were 181.2 W and 581.6 W.

Within these phases, the adaptive control strategy led to a modest temperature rise during the initial acceleration but a more substantial one during the latter phase. The pump's mass flow rate was minimal in the first phase and escalated in the second. In slower speed domains, this adaptive strategy benefits the electric pump by preemptively predicting battery temperature, enabling the system to decide on flow rate adjustments.

In order to regulate battery temperature, the MPC method markedly ramps up the pump's mass flow rate during the first acceleration to lower battery temperature, and incrementally does so in the second phase. While this strategy results in minimal battery temperature shifts, it incurs higher energy costs due to the pump's varied speed.

In summation, Figure 26 demonstrates that the adaptive strategy optimizes the pump's mass flow rate more efficiently than alternative approaches, presenting minimal rate fluctuations. Consequently, it is more energy-efficient than other strategies.

4.3.2 Comparison Results of Battery Temperature and SOH

In Figure 27, the battery temperature is benchmarked against a target value of 25 ℃, comparing the proposed method with the other two methods. The data suggests that the battery temperature using the proposed approach remains lower than that observed with current methods. This underscores the effectiveness of our model in proficiently controlling battery temperature.

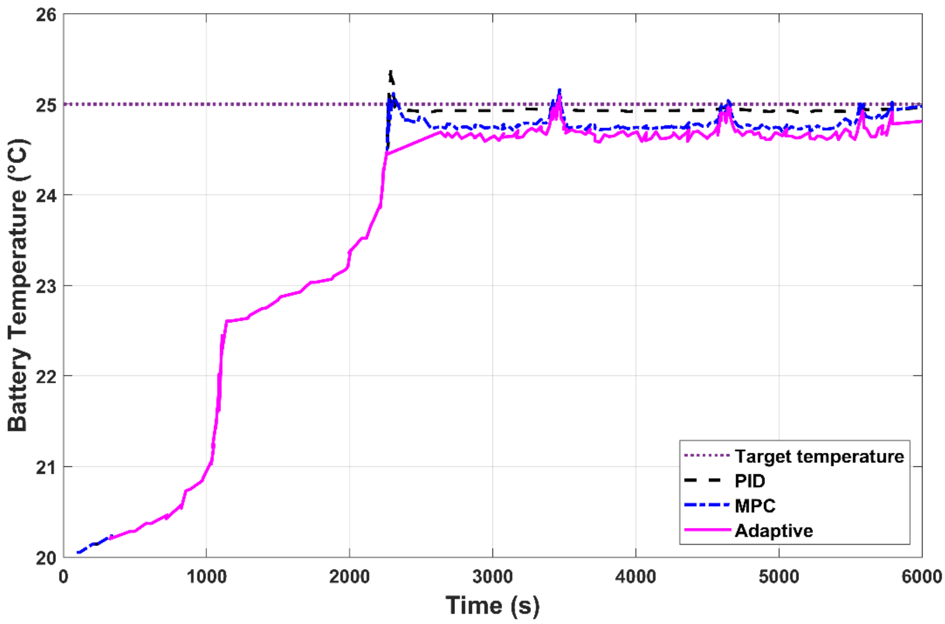

Figure 27 Comparison of Battery Temperature

Figure 28 presents the battery State of Health (SOH) at the conclusion of the NEDC cycle for three methods: PID, MPC, and the proposed adaptive technique. The SOH values are 98.517%, 98.771%, and 98.825% for PID, MPC, and the adaptive method, respectively. From this data, it's evident that the adaptive method offers superior SOH regulation compared to the other methods, suggesting potential benefits for extending battery lifespan.

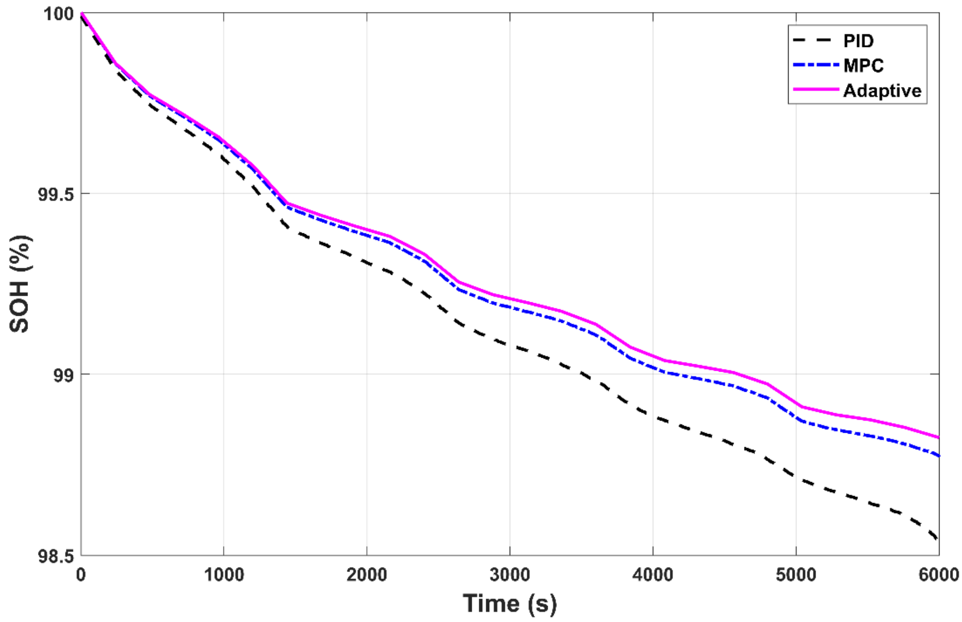

Figure 28 Comparison of Battery SOH

4.3.3 Comparison Results of Energy Consumption

Figure 29 illustrates the energy consumption of systems employing PID, MPC, and the proposed adaptive method. The PID consumes more energy than other control strategies, primarily because the pump operates at a high mass flow rate of 700 g/s for extended periods. Throughout the entire process, the adaptive method consistently records the lowest energy consumption. At the end of the driving cycle, the energy consumption of the adaptive, MPC and PIC method stand at 77.918 kJ, 101.673 kJ and 185.098 kJ, respectively. During the entire process, compared with the MPC and PID methods, the adaptive method reduced energy consumption by an average of 15% and 27%, respectively. Consequently, the proposed adaptive method not only offers energy savings but also strikes a balance between the energy consumption of the BTMS and battery lifespan.

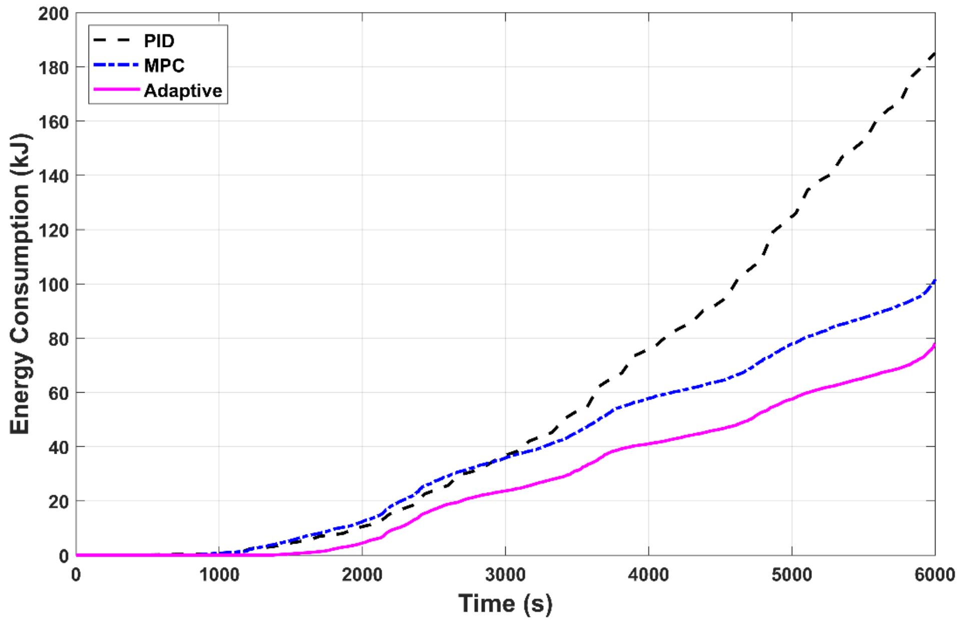

Figure 29 Comparison of Energy Consumption

4.4 Summary

This chapter has methodically delved into the results obtained from the research methods articulated in Chapter 3. An iterative progression from validation of the battery pack's thermal model to in-depth comparisons between various control strategies ensures a comprehensive understanding of the work presented.

Reliability Verification of Battery Pack's Thermal Model: The research commenced with a thorough reliability verification of the battery pack's thermal model. Using AMESim, the simulation model has provided a foundation for all subsequent experiments. The outcome accentuated the robustness and reliability of the chosen thermal model, instilling confidence in the ensuing research steps.

Vehicle Speed Prediction Accuracy: Utilizing the DNN, the research emphasized the prediction accuracy for vehicle speeds over various intervals. The congruence between predicted and actual speeds was impressively accurate, with discrepancies merely amounting to fractions of a second. This validated the capability of the DNN in effectively forecasting vehicle velocities, laying the groundwork for the subsequent adaptive control strategy.

Adaptive Control Strategy vs. PID & MPC:

i. Mass Flow Rate: The comparative study underscored the adaptive method's prowess. Unlike the PID control that constantly operated at a high mass flow rate, or the MPC which responded primarily to current battery temperature, the adaptive strategy used DNN predictions to make pre-emptive adjustments.

ii. Battery Temperature & SOH: The results here were indicative of the superior battery management capabilities of the adaptive method. Not only did it maintain an optimal temperature, but it also promised extended battery lifespan as evidenced by the highest SOH value.

iii. Energy Consumption: Among the triumvirate of methods, the adaptive strategy proved to be the most energy-efficient. Continuous operation of the pump in the PID method led to the highest energy consumption, whereas the adaptive method was found to be the most frugal, presenting significant energy savings over the other two strategies.

In summation, this chapter provides empirical evidence supporting the adaptive control strategy's potential to revolutionize battery thermal management systems (BTMS). Leveraging the power of deep neural networks (DNN), the proposed strategy promises not only efficient energy consumption but also optimal battery health and performance. These findings, rooted in the rigorous research methodology of Chapter 3, offer a solid foundation for the implications and recommendations that follow in subsequent chapters of this thesis.

Chapter 5 Conclusions

This chapter is a conclusion chapter that summarizes the main findings, contributions, and implications of this research. The purpose of this chapter is to reflect on the research process and outcomes, and to provide suggestions for future work or recommendations.

This chapter is organized as follows:

Section 5.1 presents the key findings of this research, which are derived from the results and discussion chapters. This section answers the research questions and hypotheses, and explains how the proposed methodology achieved the research aims.

Section 5.2 discusses the practical implications of this research, which are relevant for the field of battery thermal management and beyond.

Section 5.3 acknowledges the limitations of this study, which are related to the research design, methods, data, and analysis.

Section 5.4 proposes future work or recommendations based on this research, which are aimed at advancing the knowledge or practice in this field.

5.1 Key Findings

Thermal Model's Reliability:

Employing the simulation platform AMESim, the validity of the battery pack's thermal model was exhaustively established. The model demonstrated both its precision and an intricate capacity to emulate real-world thermal scenarios, marking a significant stride in thermal modeling endeavors.

DNN's Predictive Precision in Speed Forecasting:

The Deep Neural Network (DNN) was not only proficient but also illustrated an exceptional adeptness in predicting vehicle speeds with minimal discrepancies. This precision emphasizes DNN's potential for robust real-time vehicular applications, especially in fast-paced dynamic environments.

DMCOA's Novel Contribution:

The introduction and successful integration of the Dwarf Mongoose based Coati Optimization Algorithm unveiled a cornerstone for modern BTMS designs. DMCOA's adaptability and potent search mechanism augmented the efficiency metrics of the entire BTMS, proving its pivotal role in the successful outcomes witnessed.

Comparative Excellence of the Adaptive Control Strategy:

In a detailed comparative analysis with conventional methodologies like PID and MPC:

The adaptive strategy, richly enhanced by DMCOA, emerged as a paragon of excellence, optimizing mass flow rate while maximizing energy-saving attributes.

Through meticulous management of battery temperatures, the strategy favorably influenced the State of Health (SOH) of the battery, potentially revolutionizing battery longevity considerations.

In the realm of energy efficiency, the proposed methodology recorded unparalleled outcomes, substantiating its potential to redefine BTMS designs for a sustainable future.

5.2 Practical Implications

DMCOA-Induced Industry Evolution: Merging DNNs and DMCOA in BTMS design might usher in a new era for the automobile industry. This seamless integration could redefine how EVs are conceptualized, ensuring a harmonious balance between performance and longevity.

Consumer Advantages: Enhanced battery health, amalgamated with stellar energy efficiency, translates into a two-fold advantage for consumers: an extended battery lifespan and a significant reduction in associated maintenance costs, promising a more cost-effective EV ownership experience.

Setting New Industry Norms: The groundbreaking efficacy of the DMCOA-enhanced adaptive control strategy has the potential to redefine industry benchmarks, setting a higher standard for future BTMS designs.

5.3 Limitations of the Study

Model Specificity: Although the thermal model exhibited remarkable accuracy, its performance is intrinsically tied to the datasets used. Consequently, there remains a possibility that it might not encompass all conceivable real-world scenarios.

DNN's Singular Focus: Despite DNN's commendable capabilities, its sole reliance might overshadow potential benefits that alternative or more advanced neural architectures could bring to the table.

Simulatory Restrictions: The study, while exhaustive, leaned heavily on simulations. This approach, though pragmatically sound, might inadvertently bypass the nuanced challenges that real-world driving conditions present.

DMCOA's Potential Unknowns: As with any novel optimization algorithm, there's always an avenue of uncertainty. With DMCOA, there may remain latent behaviors or attributes that could surface under specific scenarios, warranting further exploration.

5.4 Future Work or Recommendations

Diversifying Neural Networks: Delving into a plethora of neural architectures might yield augmented predictive insights, further enhancing the BTMS's adaptability and response metrics.

Real-world Validations: Shifting the research lens towards tangible on-road assessments could offer a more granular perspective on the DMCOA-enriched strategy's applicability and efficacy in real-world conditions.

Expanding Data Horizons: To bolster the model's versatility and generalizability, future endeavors could incorporate a broader spectrum of datasets, capturing a more diverse array of vehicular dynamics.

Further DMCOA Refinements: While DMCOA has made an indelible mark, it still offers avenues for refinement. Continuous iterations, fortified by diverse scenarios, can hone its optimization capabilities further, ensuring it remains at the forefront of optimization methodologies.

To encapsulate, this doctoral exploration, stationed at the confluence of pioneering engineering methodologies and innovative algorithmic practices, seeks to redefine the landscape of electric vehicles. The insights garnered, both revelatory and instructive, shed light on the vast terrains yet to be traversed, directing the domain towards enhanced efficiency, environmental sustainability, and novel conceptualizations.

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