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Design and research of heat dissipation system of electric vehicle lithium-ion battery pack based on artificial intelligence optimization algorithm

Qingwei Cheng[1*] and Henan Zhao[2]

*Correspondence:
qingwei_cheng@hotmail.com

[1] School of Automobile and Traffic Engineering, Guangzhou City University of Technology, Guangzhou 510800, China
[2] School of Electronic & Information Engineering, Guangzhou City University of Technology, Guangzhou 510800, China

Abstract

This research focuses on the design of heat dissipation system for lithium-ion battery packs of electric vehicles, and adopts artificial intelligence optimization algorithm to improve the heat dissipation efficiency of the system. By integrating genetic algorithms and particle swarm optimization, the research goal is to optimize key design parameters of the cooling system to improve temperature control and extend battery life. In the process of algorithm implementation, genetic algorithm improves the diversity of population through crossover and mutation operations, thus enhancing the global search ability. Particle swarm optimization (PSO) improves local search accuracy and convergence speed by dynamically adjusting inertia weight and learning factor. The effects of different design schemes on heat dissipation performance were systematically evaluated by using computational fluid dynamics (CFD) software. The experimental results show that the efficiency of the cooling system is significantly improved after the application of the optimization algorithm, especially in the aspects of temperature distribution uniformity and maximum temperature reduction. The optimization algorithm also successfully shortens the thermal response time of the system and improves the adaptability and stability of the system under different working conditions. The computational complexity and execution time of these algorithms are also analyzed, which proves the efficiency and feasibility of these algorithms in practical applications. This study demonstrates the practicability and effectiveness of artificial intelligence optimization algorithm in the design of heat dissipation system of lithium-ion battery pack for electric vehicles, and provides valuable reference and practical guidance for the progress of heat dissipation technology of electric vehicles in the future.

Keywords: Artificial intelligence, Optimization algorithm, Electric vehicles, Lithium-ion battery pack, Cooling system

Introduction

The rapid development of electric vehicles has brought the demand for high-performance batteries, and lithium-ion batteries have gradually become the mainstream choice because of their high energy density and environmental protection. However, the battery pack is prone to overheating at high temperatures, threatening its safety and performance stability. To solve this problem, the design of the cooling system becomes crucial. Traditional cooling system design is often based on experience and simplified models, which is difficult to optimize fully. With the development of artificial intelligence technology, using optimization algorithm to design and optimize the cooling system has become a research hotshot. By combining artificial intelligence optimization algorithm and heat dissipation system design, the heat dissipation performance of lithium-ion battery packs for electric vehicles can be maximized, and the safety, stability and service life of battery packs can be improved. It is of great theoretical and practical significance to study the design of heat dissipation system of electric vehicle lithium-ion battery pack based on artificial intelligence optimization algorithm.

In recent years, there have been significant developments in the research field of heat dissipation and safety monitoring of lithium-ion batteries. The researchers improved the efficiency and responsiveness of the battery management system by employing a variety of innovative optimization algorithms. AL Rahhal and Jamous proposed a new adaptive natural heuristic optimization algorithm, AFOX, which shows its application potential in complex optimization problems (Rahhal and Jamous 2023). The whale particle optimization algorithm (WPO) developed by Huang et al. further proves the effectiveness of natural heuristic algorithms in multidimensional space optimization problems (Huang et al. 2023). In terms of the specific application of the algorithm, Dhawale et al. improved the arithmetic optimization algorithm through Levy flight strategy to improve the development ability in engineering optimization problems (Dhawale et al. 2023). Manage et al. reviewed the optimization algorithm of multiple-input multiple-output antennas and demonstrated its application in wireless communication equipment design (Manage et al. 2023). In addition, Wang. enriched the algorithm selection of multi-objective optimization by establishing a migration-based algorithm library, which provided a broader perspective for algorithm selection and practical application (Wang et al. 2023).

As for the specific application of lithium-ion batteries, Uzer and Inan's research shows that the improved hybrid whale optimization algorithm can be effectively applied to optimization problems (Uzer and Inan 2023). Kou's research provides a comprehensive evaluation of quantum computation-based dynamic optimization (Kou et al. 2024), while Su's research on horizontal and longitudinal cross-cuckoo search optimization performance provides optimal solutions for engineering problems (Su et al. 2023). The hybrid Harris Eagle optimization algorithm based on pinhole imaging strategy introduced by Zeng has demonstrated its effectiveness in solving numerical optimization problems (Zeng et al. 2023). In terms of battery safety monitoring, Chen et al. used fiber Bragg grating sensors to monitor the safety of lithium-ion batteries (Chen et al. 2023), while Yang et al. discussed the research progress on improving the stability of electrode/electrolyte interface at high temperature (Yang et al. 2023). In the study of Hendricks et al., a strain gauge was applied to monitor the depth discharge estimation of the battery to evaluate the service status and life of the battery (Hendricks et al. 2023). Li. explored the thermal runaway detection method based on gas characteristics, which enhanced the early recognition ability of abnormal state of lithium-ion batteries (Li et al. 2023). These studies not only promote the application of optimization algorithms in lithium-ion battery management, but also provide important technical support for the safety and efficiency of batteries and lay a solid foundation for the development of future electric vehicles and energy storage systems.

The purpose of this study is to conduct in-depth research on the design of heat dissipation system of lithium-ion battery pack for electric vehicles based on artificial intelligence optimization algorithm. Firstly, by establishing the mathematical model of the heat dissipation system, combined with artificial intelligence optimization algorithm, the method and technology of optimizing the design of the heat dissipation system are explored. Secondly, computational fluid dynamics (CFD) software is used to conduct simulation experiments to verify the feasibility and effectiveness of the proposed optimization scheme. The purpose of this study is to maximize the heat dissipation performance of lithium-ion battery packs for electric vehicles and improve the safety, stability and service life of battery packs.

This study has important theoretical and practical significance. Firstly, through the introduction of artificial intelligence optimization algorithm, this study expands the traditional design method of heat dissipation system and improves the design intelligence and automation level. Secondly, the optimized cooling system design can effectively improve the heat dissipation efficiency of the battery pack and reduce the temperature rise, thus enhancing the safety of the battery pack, slowing down the aging speed of the battery, and extending the service life of the battery. In addition, the optimized cooling system design can also reduce the temperature non-uniformity of the battery pack, improve the working stability of the battery pack, and ensure the performance and reliability of the electric vehicle. Finally, the research results will provide theoretical guidance and practical experience for the design and optimization of the lithium-ion battery pack cooling system for electric vehicles, provide technical support for the development of electric vehicles, and promote the sustainable development of the electric vehicle industry.

This study aims to optimize the design of heat dissipation system for lithium-ion battery packs of electric vehicles based on artificial intelligence optimization algorithm. First, review the relevant literature and introduce the research background; Then, define the problem and explain the theoretical basis; Then, the genetic algorithm and particle swarm optimization algorithm models are constructed, and the experimental design and algorithm implementation are carried out. Finally, the model is verified by simulation experiments, and the improvement of system performance before and after optimization is analyzed. This paper will describe the implementation process of the optimization algorithm in detail, and provide quantitative data support to verify the effectiveness of the optimization scheme.

Analysis of theory and application status

Basic principle of artificial intelligence optimization algorithm

Genetic algorithm

Genetic algorithm is a kind of optimization algorithm inspired by natural evolution process, which is often used to solve complex optimization problems. The basic idea is derived from Darwin's theory of evolution and simulates the natural selection and genetic mechanisms of biological populations. In genetic algorithms, solutions are encoded into chromosomes, each representing a candidate solution. Through continuous iteration, the algorithm uses selection, crossover and mutation to simulate the biological evolution process, making each generation of solutions more and more suitable for the optimization goal. Specifically, genetic algorithms include the following key steps: First, the potential solutions in the problem space are represented as chromosomes by randomly generating an initial population. Then, the fitness function is used to evaluate the fitness of each individual, and the parent individual is selected according to the fitness. Then, using crossover and mutation operations, a new generation of individuals is produced. After several rounds of iterative optimization, the algorithm will converge to the optimal solution or the set of solutions close to the optimal solution (Rahhal Jamous 2023).

As is shown in Fig. 1, genetic algorithm has a wide range of applicability, especially for solving complex multi-variable, multi-objective, nonlinear and non-convex optimization problems. In the design of the heat dissipation system of the lithium-ion battery pack for electric vehicles, genetic algorithm can be used to optimize the design parameters of the heat dissipation system, such as fan speed, heat sink layout to improve the heat dissipation efficiency and performance stability of the system.

Particle swarm optimization

Particle swarm optimization is an optimization algorithm based on swarm intelligence, inspired by the behavior of natural groups such as birds or schools of fish. In particle swarm optimization, a candidate solution is represented as an individual (particle) that moves through the solution space and constantly adjusts its position and speed to find the optimal solution. Each particle has its own position and speed, and the direction of movement is adjusted according to individual and global optimal.

Specifically, particle swarm optimization involves the following key steps: First, randomly initialize a group of particles, each representing a solution. Then, based on the current position and velocity of each particle, its mass is evaluated using the fitness function, and the individual optimal position is updated. Then, the velocity and position

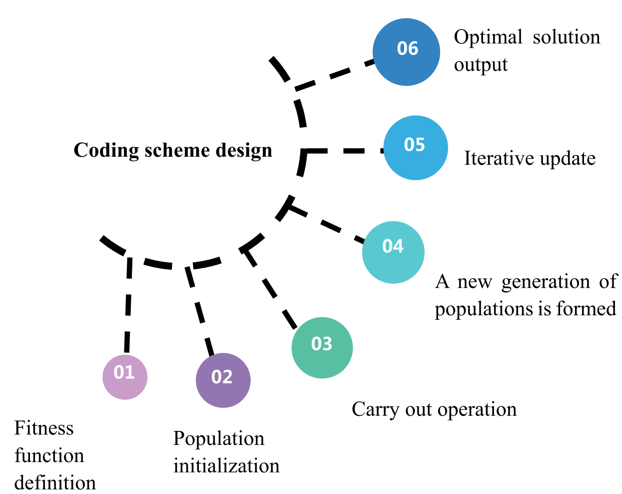

Fig. 1 Specific process of genetic algorithm

of the particles are adjusted by comparing the global optimal position and the individual optimal position. As the iteration progresses, the particle swarm gradually converges to the optimal solution or the set of solutions close to the optimal solution.

As is shown in Fig. 2, Particle swarm optimization (PSO) algorithm has faster convergence speed and better global search ability, especially for solving continuous, high-dimensional, nonlinear and non-convex optimization problems. In the design of the heat dissipation system of the lithium-ion battery pack for electric vehicles, particle swarm optimization can be used to optimize the design parameters of the heat dissipation system, such as the layout and shape of the heat sink, to improve the heat dissipation efficiency and performance stability of the system (Huang et al. 2023).

Working principle of the heat dissipation system

The heat dissipation system plays a crucial role in the lithium-ion battery pack of electric vehicles, and its working principle is mainly to effectively dissipate the heat generated by the battery pack through heat and mass transfer to maintain the temperature of the battery pack within a safe range. Usually, the heat dissipation system is composed of components such as heat sink, fan, heat sink. First, the radiator transfers the heat generated by the battery pack to the cooling medium (such as air or liquid). The fan then carries the heat away by blowing air or liquid over the surface of the radiator. The heat sink increases the heat transfer efficiency by increasing the surface area. Throughout the process, heat is transferred from the battery pack to the cooling medium, and then transferred to the environment through the fan and heat sink, thus achieving the work of the heat dissipation system. The design of the heat dissipation system needs to consider a variety of factors, including heat dissipation efficiency, energy consumption, compactness to ensure that the battery pack can maintain the appropriate temperature under various working conditions to ensure the safety and stability of the battery pack.

Heat dissipation requirements of lithium-ion battery packs for electric vehicles

The heat dissipation requirement of the lithium-ion battery pack for electric vehicles is to ensure that the battery pack can maintain the appropriate temperature range during the working process to improve its performance, safety and life. The battery pack generates a lot of heat during charging and discharging. If the heat dissipation cannot be effectively dissipated, the battery temperature may be too high, resulting in serious

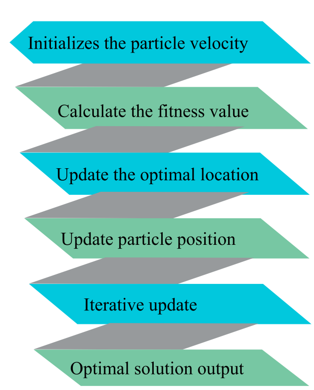

Fig. 2 Computational process of particle swarm optimization

problems such as overheating, aging, and even explosion of the battery. First of all, the high temperature will cause the chemical reaction rate of the materials inside the battery to increase, which will aggravate the aging process of the battery and reduce its life. Secondly, high temperature will affect the performance of the battery, resulting in a reduction in the battery's discharge capacity, reducing the vehicle's driving range and power performance. In addition, excessive temperatures may also lead to a reduction in the safety of the battery, increasing the risk of safety accidents, and posing a threat to passengers and vehicles. Therefore, the heat dissipation demand of lithium-ion battery packs for electric vehicles is very urgent. In order to meet this demand, it is necessary to design an efficient heat dissipation system, including components such as radiators, fans, heat sinks to effectively dissipate the heat generated by the battery pack and keep the temperature of the battery pack within a safe range. This can not only improve the working performance and safety of the battery pack, but also extend the service life of the battery pack and promote the sustainable development of electric vehicles (Dhawale et al. 2023).

Latest research progress

In recent years, the research of lithium-ion battery pack cooling system for electric vehicles has made remarkable progress. The latest research focuses on the development of efficient cooling materials, advanced cooling technologies, and intelligent control systems. Several studies have explored the application of novel phase change materials (PCM) and nanoseconds in heat dissipation, which have excellent thermal conductivity and heat capacity properties and significantly improve heat dissipation. In addition, micro-channel cooling technology has also received widespread attention, by integrating micro-scale cooling channels in the battery pack, heat transfer efficiency can be greatly improved. In terms of intelligent control systems, the Internet of Things (IoT) and machine learning algorithms are used to achieve real-time monitoring and dynamic adjustment of the heat dissipation system, further optimizing temperature management. Examples include using deep learning models to predict battery temperature changes and adjust cooling parameters in advance to reduce temperature fluctuations. These cutting-edge studies not only improve the safety and performance of the battery pack, but also extend the service life of the battery, providing solid technical support for the popularity of electric vehicles.

There are some limitations in the current literature on the research of the heat dissipation system of lithium-ion battery pack for electric vehicles. First of all, the optimization methods used in many studies are often based on experience and simplified mathematical models, which is difficult to fully capture complex thermal management dynamic processes, resulting in limited practical application effects of optimization results. Secondly, most of the existing researches focus on the application of a single optimization algorithm, and lack the exploration of integrated optimization of multiple algorithms. In addition, there are relatively few studies on intelligent control and real-time adjustment of the heat dissipation system, which cannot fully cope with the thermal management needs of the battery pack under different working conditions. By integrating genetic algorithm (GA) and particle swarm optimization (PSO), this study gives full play to their advantages and improves the optimization efficiency and accuracy. Computational fluid dynamics (CFD) software is used to conduct detailed simulation experiments to accurately evaluate the influence of different design parameters on heat dissipation performance, which overcomes the shortcomings of traditional simplified models. In addition, this study also explores an intelligent control strategy based on artificial intelligence to realize real-time monitoring and dynamic adjustment of the cooling system, effectively improving the adaptability and stability of the system under different working conditions, thus solving the main limitations in the existing literature (Manage et al. 2023).

Model and algorithm design

Heat dissipation performance evaluation model

Model assumptions

(1) Heat dissipation system parameter independence hypothesis: Assume that the design parameters of the heat dissipation system (such as fan speed, heat sink shape) are independent of each other. Such assumptions enable the optimization algorithm to better explore the parameter space and find the global optimal solution.
(2) Convergence hypothesis of optimization algorithm: It is assumed that genetic algorithm and particle swarm optimization algorithm can converge to a stable optimal solution after sufficient iterations. This hypothesis is based on the convergence theory of the optimization algorithm and provides a reliable theoretical support for the subsequent experimental design (Wang et al. 2023).

Model construction

Genetic algorithm (GA) and particle swarm optimization (PSO) are selected to optimize the heat dissipation system of lithium-ion battery packs for electric vehicles, mainly based on their superior performance and applicability in solving complex optimization problems. Genetic algorithm (GA) can effectively explore and utilize the design space to find the global optimal solution by simulating the natural evolution process, including selection, crossover and mutation. Its diversified search mechanisms make it particularly suitable for nonlinear and multi-modal function optimization problems. Inspired by swarm intelligence, particle swarm optimization (PSO) guides particle swarm to the optimal solution through individual and global information sharing. PSO has the advantages of fast convergence and simple computation, which is especially suitable for continuous optimization problems. The combination of these two algorithms can give full play to the global search ability of GA and the local search advantage of PSO, and improve the efficiency and accuracy of the optimization process. The use of these two algorithms can quickly find efficient and reliable design schemes in complex cooling system design, and significantly improve the performance and stability of the cooling system.

To construct a model based on genetic algorithm, real number coding can be used to represent the design parameters of heat dissipation system for lithium-ion battery pack of electric vehicles. For example, if you have two design parameters, the fan speed *X1* and the height of the heat sink *X2*, then an individual *X* can be represented as ($X = [x1, x2]$) two-dimensional real vector:

Fitness function ($f(X)$) should consider the performance indicators of the heat dissipation system, such as heat dissipation efficiency, temperature uniformity, etc. For example, if we want to minimize the temperature uniformity index (T_{std}) of the cooling system, the fitness function can be defined as:

$$f(X) = \frac{1}{T_{\mathrm{std}}}. \tag{1}$$

The initial population is randomly generated, the population size is *N*, and the design parameters *X1* and *X2* of each individual X are randomly initialized within a certain range.

Selection operation: Roulette selection method is adopted, and selection is made according to individual fitness.

Cross operation: Using a single point crossing method, the genetic information of two individuals is exchanged at a randomly selected crossing point.

Variation operation: Random perturbation of individual design parameters to increase the diversity of the population.

The iterative process of genetic algorithm can be expressed by the following formula:

Selection operation: The selection probability *p(X)* is calculated according to the fitness of individual *f(X)*, and then the individual selection is performed according to the selection probability.

Cross operation: Randomly select parent individuals for cross operation to generate new individuals.

Variation operation: Random perturbation of individual design parameters.

New entity generation formula:

$$X_{\mathrm{new}} = X_{\mathrm{parent1}} + \alpha \cdot (X_{\mathrm{parent2}} - X_{\mathrm{parent1}}). \tag{2}$$

The genetic algorithm-based model constructed through the above steps can be used to optimize the design of the heat dissipation system of the lithium-ion battery pack for electric vehicles to improve the performance and efficiency of the heat dissipation system.

$$\left[V\{i,d\}(t+1) = w\, cdot\, V\{i,d\}(t) + c1\, cdot\, rand1\, cdot\, \left(P\{i,d\} - X\{i,d\}\right) + c2\, cdot\, rand2\, cdot\, (Gd - X\{i,d\})\right]$$
$$\left[X\{i,d\}(t+1) = X\{i,d\}(t) + V\{i,d\}(t+1)\right]. \tag{3}$$

A model based on particle swarm optimization is constructed to randomly initialize a certain number of *N* particles, and each particle represents a design scheme of the cooling system. The position *X(i,d)* of each particle *i* is a D-dimensional vector representing the values of *D* design parameters. For each particle *i*, its velocity *V(i,d)* is randomly initialized so that each component (Vi, d) falls within a suitable range. For each particle *i*, its velocity and position are updated according to its current position *X(i,d)*, individual optimal position ($P\{i\}$), and global optimal position *G*.

In the whole particle swarm, the position of the particle with the best fitness is selected as the global optimal position *G*.

The position and speed of the particle are interactively updated until a stopping condition is reached (such as a maximum number of iterations or convergence of fitness values).

Update speed formula:

$$[V\{i,d\}(t+1) = w\,cdot\,V\{i,d\}(t) + c1\,cdot\,rand1\,cdot\,(P\{i,d\} - X\{i,d\}) + c2\,cdot\,rand2\,cdot\,(Gd - X\{i,d\})], \tag{4}$$

where W is the inertia weight, $C1$ and $C2$ are acceleration constants, ($rand1$) and ($rand2$) are random numbers, and d represents the DTH design parameter. For each particle i, update its individual optimal position ($P\{i\}$) If the fitness of the current position $X(i,d)$ is better than the fitness of its individual optimal position ($P\{i\}$), ($P\{i\} = X\{i\}$) is updated.

Update the position formula:

$$[X\{i,d\}(t+1) = X\{i,d\}(t) + V\{i,d\}(t+1)]. \tag{5}$$

The PSO based model constructed through the above steps can be used to optimize the design of the heat dissipation system of the lithium-ion battery pack for electric vehicles to improve the performance and efficiency of the heat dissipation system (Uzer and Inan 2023).

Parameter definition and initialization

Genetic algorithm (GA) model and particle swarm optimization (PSO) model are used to optimize the design of the heat dissipation system of lithium-ion battery pack for electric vehicles. In both optimization models, some parameters need to be defined and initialized in order for the optimization process to take place. As shown in Table 1.

The initialization of these parameters is the key to the successful implementation of particle swarm optimization algorithm, which needs to be reasonably selected and adjusted according to the actual problems and the characteristics of the algorithm.

In the parameter definition and initialization of genetic algorithm model, the selection and setting of parameters are very important. Population size determines the number of individuals in each generation, usually 50 or 100, to ensure sufficient diversity and a balance of computing resources. The crossover rate represents the probability of crossover operations, usually set between 0.6 and 0.9, to ensure efficient gene exchange between individuals and facilitate extensive exploration of the solution space. The variation rate is the probability of the variation operation, ranging from 0.01 to 0.1, to increase the diversity of the population by introducing random changes to avoid falling into local optimal. The number of iterations represents the number of iterations performed by the genetic algorithm, usually set to 100 to 1000 to ensure that the algorithm has enough time to search and optimize. The initialization and

Table 1 Genetic algorithm model parameter definition and initialization

Parameter	Meaning	Initial value/range
Population size N	Number of individuals in each generation	50 or 100
Crossover rate	Probability of crossover operation	0.6 to 0.9
Mutation rate Pm	Probability of mutation operation	0.01 to 0.1
Iteration count T	Number of iterations for genetic algorithm	100 to 1000

adjustment of these parameters need to be optimized according to the actual problem and algorithm characteristics to ensure the efficient operation of the algorithm in different problems. Reasonable parameter setting helps to improve the global search ability and convergence speed of the algorithm, so as to find the best solution in complex optimization problems (Kou et al. 2024).

As shown in Table 2. By defining and initializing these parameters, we can carry out the optimization process in the genetic algorithm model and particle swarm optimization model to find the optimal design scheme of the heat dissipation system of the lithium-ion battery pack for electric vehicles.

In the experimental design part, in order to ensure the effectiveness and stability of genetic algorithm and particle swarm optimization algorithm, we set key parameters in detail and provide reasons for selection. For the genetic algorithm, select a population size of 100, a crossover rate of 0.8, a variation rate of 0.05, and a number of iterations of 500. The population size of 100 can ensure sufficient individual diversity within the allowable range of computing resources, the crossover rate of 0.8 can better balance exploration and development, and the variation rate of 0.05 can moderately introduce randomness to prevent local optimization. For the particle swarm optimization algorithm, the number of particles is selected as 50, the initial value of inertia weight is 0.7, gradually decays to 0.4, and the individual learning factor and group learning factor are set to 1.5. The number of particles 50 can effectively control the computational complexity, the dynamic adjustment of the inertia weight helps to balance the global search and the local search, and the learning factor 1.5 ensures that the particles can effectively use individual and group information. In addition, the values of all parameters are verified by preliminary experiments to ensure that they are suitable for specific heat dissipation system optimization problems, thereby improving the optimization efficiency and reliability of the results (Su et al. 2023).

Optimization objectives and constraints

(1) Optimization objectives:

Maximum heat dissipation efficiency: Heat dissipation efficiency is one of the important indicators to evaluate the performance of heat dissipation system. We hope to optimize the design and maximize the heat dissipation efficiency, so that

Table 2 Parameter definition and initialization of particle swarm optimization model

Parameter	Meaning	Initial value/range
Particle count N	Number of particles in the swarm	10 to 100
Inertia weight w	Weight balancing particle velocity	0.4 to 0.9
Acceleration constant C1	Individual learning factor	1.5 to 2.0
Acceleration constant C2	Social learning factor	1.5 to 2.0
Maximum speed *Vmax*	Upper limit of particle velocity	Determined by the range of design parameters
Minimum speed *Vmin*	Lower limit of particle velocity	Determined by the range of design parameters

the heat dissipation system can effectively dissipate the heat generated by the battery pack and keep the temperature of the battery pack within the safe range (Wang et al. 2023).

Minimize the temperature non-uniformity of the cooling system: The temperature non-uniformity of the cooling system will affect the operating stability and life of the battery pack. By optimizing the design, we hope to minimize the temperature heterogeneity of the cooling system, so that the temperature distribution of various parts of the battery pack is more uniform (Zeng et al. 2023).

(2) Constraints:

Design parameter range restriction: The design parameters of the heat dissipation system, such as the fan speed and heat sink shape, may be limited in a certain range. In the process of optimization, it is necessary to ensure that the selected design parameter values are within a reasonable range.

Heat dissipation efficiency constraints: The heat dissipation efficiency of the heat dissipation system needs to meet certain requirements to ensure that the system can effectively dissipate heat. In the optimization process, it is necessary to ensure that the design scheme obtained can meet the requirements of heat dissipation efficiency.

Temperature safety constraints: The design of the cooling system needs to ensure that the temperature of the battery pack is within a safe range to avoid safety problems caused by overheating. In the process of optimization, it is necessary to ensure that the design scheme obtained can meet the temperature safety constraints (Chen et al. 2023).

During the simulation using computational Fluid dynamics (CFD) software, we set the simulation parameters in detail and verified the accuracy of the model used. The simulation software is ANSYS Fluent. The main Settings include: the SST k-ω turbulence model is used to simulate the complex flow and heat conduction process in the heat dissipation system to ensure the accurate capture of turbulence effects; Set the coolant flow rate to 1.35 L/min, inlet temperature to 25 °C, and ambient temperature to 20 °C to reflect the actual operating conditions. In order to improve the calculation accuracy, unstructured mesh is used for local refinement of heat sink and battery surface area. The boundary conditions include the battery surface set to a constant heat flux to simulate the heat generated when the battery is operating. In order to verify the model, we conducted grid independence verification, and gradually refined the grid to ensure that the results tended to be stable as the grid density increased. The results showed that the influence of grid density on the simulation results was within an acceptable range. In addition, the reliability and accuracy of the simulation model are verified by comparing the simulation results with the experimental data (such as temperature distribution and heat dissipation efficiency), thus ensuring the reliability of the simulation results (Yang et al. 2023).

Experimental design and algorithm implementation

Experimental environment and tools

In the research of the design of the heat dissipation system of lithium-ion battery pack for electric vehicles, it is very important to select the appropriate experimental environment and tools. The following section describes the experimental environment and tools in detail, including tables describing the features and applications of the selected tools. In order to realize the effective simulation of the battery cooling system, it is crucial to select the appropriate computational fluid dynamics software. The following table lists several commonly used CFD software, each with its own unique features and advantages for different simulation needs. As shown in Table 3.

As shown in Table 4. High-performance computing resources are essential for high-precision heat dissipation simulation and algorithm optimization. You must ensure that the laboratory has sufficient computing resources to support the complex computing needs. Typically, these resources include, but are not limited to, the following.

In the experimental design part, we chose genetic algorithm and particle swarm optimization algorithm to optimize the heat dissipation system of lithium-ion battery packs for electric vehicles, mainly because of their significant advantages in solving complex nonlinear optimization problems. Genetic algorithm has powerful global search ability and can effectively avoid the dilemma of local optimal solution, while particle swarm optimization algorithm is good for its fast convergence and easy implementation. By combining the two algorithms, we hope to fully explore the design space and improve the optimization effect of the cooling system. However, there are limitations to these methods. Firstly, genetic algorithms and particle swarm optimization algorithms may encounter the challenges of computational complexity and convergence speed when dealing with high-dimensional problems, which requires a lot of computational resources. Secondly, although the two algorithms have good global search capability in theory, the sensitivity of parameter Settings in practical applications may affect the final optimization effect, resulting in the need for multiple debugging and verification. Finally, the results of the optimization algorithm depend on the accuracy of the fitness function. If the fitness function cannot fully reflect the performance of the cooling system, the

Table 3 Selection of experimental simulation software

Software name	Developer	Features	Applications
ANSYS Fluent	ANSYS, Inc	Advanced grid generation, multi-purpose flow capabilities	Complex fluid dynamics problems including multipurpose and reactive flows
COMSOL Multiplicity	COMSOL, Inc	Powerful multi-physics coupling capabilities, user-friendly interface	Interdisciplinary research, suitable for joint analysis in electromagnetic, structural, acoustic, fields
Star-CCM+	Siemens PLM	Integrated design exploration and optimization tools	Engineering design optimization, automated grid refinement

Table 4 Computing resource configuration

Resource type	Specification requirements	Usage description
CPU	High-performance multi-core processor	Accelerates computational processes, provides sufficient computing power for real-time data processing
GPU	High-end graphics processing unit	Used for deep learning and graphics-intensive tasks
RAM	Large-capacity memory	Supports quick access and processing of large datasets and complex models
Storage	High-speed large-capacity hard drive	Stores large volumes of experimental data and simulation results

actual effect of the optimization results may be discounted. Nevertheless, through careful parameter setting and model verification, we can maximize the advantages of these two algorithms and provide an effective optimization scheme for the design of heat dissipation system (Hendricks et al. 2023).

Data preparation and teleprocessing

Data preparation and teleprocessing are the key steps to ensure the accuracy of simulation experiment in the design and research of the heat dissipation system of lithium-ion battery pack for electric vehicles. The following is the detailed data preparation and teleprocessing section:

(1) Geometric model establishment

First, we need to build a three-dimensional geometric model of the lithium-ion battery pack for electric vehicles. This model includes a cell, a battery module, and an entire battery pack (Menz et al. 2023).

Figure 3 below shows the geometric size data of different types of battery modules. The battery cell has a relatively small size, with a length of 18.3 cm, a width of 6.4 cm, and a height of just 0.8 cm, making it suitable for compact electric vehicle applications. The battery module, as a combination of single batteries, has a significant increase in size, with a length of 46.7 cm, a width of 39.4 cm, and a height of 8.3 cm, which is suitable for power battery systems with high demand. The entire battery pack is a collection of modules with a further increase in length and width to 96.8 cm and 89.1 cm, and a height of 21.6 cm to provide the necessary energy output for the vehicle. Through the accurate measurement and calculation of these dimensions, the accuracy and rationality of the battery design can be ensured. As shown in Fig. 3.

(1) Grid division

Meshing the geometric model is a key step to ensure the simulation accuracy. The following table shows the grid division of different battery modules, including the number of grids and grid types.

As shown in Fig. 4, grid number and mesh size data for different types of battery modules are provided. The number of grids of a single battery is 1286.3, and the mesh

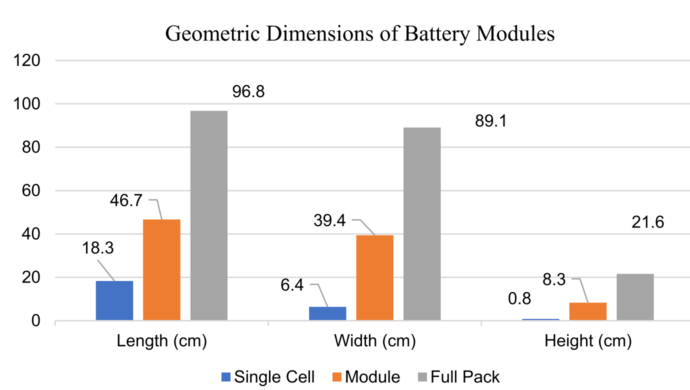

Fig. 3 Battery module geometry data

size is 0.2 cm, which can ensure sufficient calculation accuracy without excessive increase in the calculation burden. The number of grids of the battery module has been increased to 3683.7, and the mesh size is 0.5 cm, which ADAPTS to the fine needs of the larger volume module. The number of grids for the entire battery group is 10,863.4 and the mesh size is 0.8 cm, which is designed to balance the details of the simulation with the efficient use of computing resources. Correct meshing strategy is the basis of efficient and accurate simulation of battery heat dissipation performance, which has a direct impact on the subsequent optimization algorithm design and performance evaluation (Li et al. 2023).

When performing data reprocessing, the following detailed steps are mainly included: First, the data is cleaned, any errors or inconsistencies in the data are checked, and the problematic data points are corrected or deleted. This step involves detecting and processing missing values, duplicates, and outliers to ensure data accuracy and reliability. Secondly, unit conversion is carried out to convert all data into a unified unit system required by the simulation software. For example, all temperature data is converted to degrees Celsius, flow rate data to meters per second (m/s), and heat flux to watts per square meter (W/m^2) to avoid errors in subsequent analysis. Third, set the boundary conditions, set the appropriate physical and thermal boundary conditions for the heat dissipation model, such as the temperature, pressure, flow rate of the inlet and outlet, as well as the heat flux of the heat sink and the battery surface. These boundary conditions are determined according to the actual operating environment and design specifications, for example, the inlet temperature is set at 25 °C and the ambient temperature is set at 20 °C to reflect the actual operating condition. In addition, it is necessary to set the internal heat source according to the working characteristics of the battery pack to simulate the heat generation of the battery during the charging and discharging process. These detailed data preparation and pre-processing steps can ensure the accurate execution of the simulation experiment, reduce errors, improve the reliability of the simulation results, and provide a solid data foundation for the subsequent optimization analysis (Xu et al. 2023).

Experimental design and execution

Figure 5 shows the specific process of experimental design in this study.

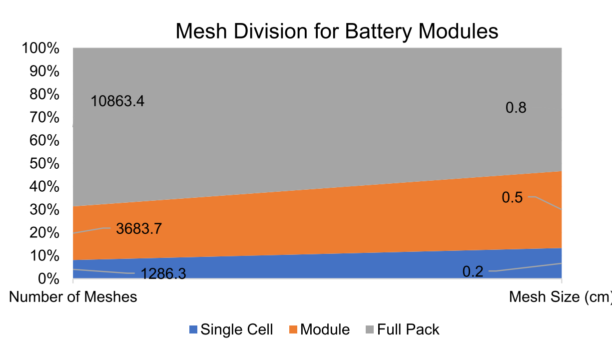

Fig. 4 Grid division data of the battery module

(1) Parameter settings

Before the experiment, it is necessary to determine the key parameters of the design of the heat dissipation system, which include fan speed, heat dissipation material, heat dissipation shape, heat dissipation pipe layout. The parameters that need to be set also include simulated environmental conditions, such as ambient temperature, flow rate and type of heat dissipation medium. As shown in Table 5.

(2) Design of simulation experiment scheme

According to the preset parameters, different experimental schemes should be designed, and the preset parameter variables should be recorded in detail in each scheme. These schemes may include modification of a single variable or combination optimization of multiple variables. The design scheme is used to evaluate the performance of the heat dissipation system under different working conditions, for example, changing the fan speed to observe its impact on the heat dissipation efficiency. As shown in Table 6.

(3) Simulation experiment execution

The simulation experiments designed above were performed using selected CFD software, such as ANSYS Fluent or COMSOL Multiplicity. Numerical simulation was carried out for each experimental scheme, and key performance indexes such as temperature distribution and heat dissipation efficiency were recorded. After each simulation, data is collected and collated to prepare for further analysis. As shown in Table 7.

(4) Data collection and teleprocessing

After the experiment is completed, data including temperature field and flow field are derived from CFD software. The exported data is reprocessed, including data cleaning and formatting, to ensure data quality and consistency. As shown in Table 8.

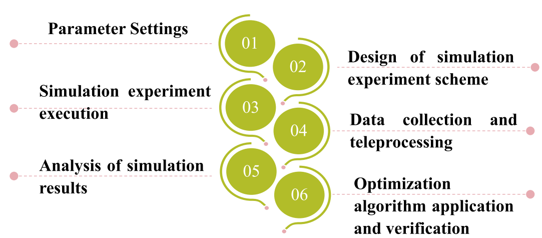

Fig. 5 Experimental design flow chart

Table 5 Experimental parameter settings

Parameter type	Parameter name	Parameter value range
Fan speed	RPM	1200–3600 RPM
Heat sink material	Material	Aluminum (Al), copper (Cu)
Heat sink shape	Shape	strip, mesh, ripple
Heat pipe layout	Layout	Parallel, interlaced
Ambient temperature	Temperature	23–45 °C
Heat medium flow rate	Flow rate	1–2 m/s
Heat medium type	Medium	Water, air

Table 6 Simulation experiment scheme design

Experiment no.	Fan speed (RPM)	Heat sink material	Heat sink shape	Heat pipe layout	Ambient temperature (°C)	Heat medium flow rate (m/s)	Heat medium type
1	1200.3	Aluminum (Al)	Strip	Parallel	23.1	0.6	Water
2	2400.6	Copper (Cu)	Mesh	Interlaced	35.2	1.0	Air
3	3600.7	Aluminum (Al)	Ripple	Interlaced	45.3	1.4	Water

Table 7 Data collection and teleprocessing of simulation experiment

Experiment no.	Temperature field data (file name)	Flow field data (file name)	Data teleprocessing steps
1	Temp distribution 1	Flow pattern 1	Data cleaning, format standardization
2	Temp distribution 2	Flow pattern 2	Data outlier check, unit conversion
3	Temp distribution 3	Flow pattern 3	Data validation, boundary condition reflection

Table 8 Data collection of simulation experiment

Experiment no.	Max temperature (°C)	Min temperature (°C)	Average flow velocity (m/s)	Data file name
1	32.8	22.1	0.68	experiment1_data.csv
2	46.9	30.7	1.09	experiment2_data.csv
3	55.4	40.3	1.39	experiment3_data.csv

Table 9 Analysis of simulation experiment results

Experiment no.	Optimal temperature distribution (°C)	Heat dissipation efficiency (%)	Sensitivity analysis result
1	26.4	74.3	Most sensitive to fan speed
2	37.6	82.1	Most sensitive to heat sink material
3	47.6	88.4	Most sensitive to heat dissipation medium

(5) Analysis of simulation results

Take advantage of statistical and data analysis tools, such as Python's Pandas and Diplomatic libraries, to conduct in-depth analysis of the collected data. Analyze the specific influence of different design parameters on the heat dissipation effect and evaluate the sensitivity of each parameter. As shown in Table 9.

(6) Optimization algorithm application and verification

Genetic algorithm and particle swarm optimization algorithm are used to find the best configuration of the cooling system. After optimization, the consistency between the best scheme proposed by the algorithm and the experimental data is verified to ensure the effectiveness and accuracy of the algorithm. The final optimization results will be discussed in detail in the paper (Wang et al. 2023).

Result analysis and verification

Result analysis and verification is a key step in the research process, which ensures the reliability of the experimental results and the effectiveness of the optimization algorithm. This stage includes in-depth analysis of thermal performance and validation of optimization algorithms to confirm the effect of improvement measures and the feasibility of practical applications. After the completion of the simulation experiment and data collection, it is necessary to conduct a comprehensive analysis of the heat dissipation performance. This includes evaluating temperature distribution, heat dissipation efficiency, and other relevant performance metrics. The temperature data recorded in the simulation experiment were statistically analyzed to determine the maximum, minimum and average temperature of the battery pack under different operating conditions. The heat dissipation efficiency is calculated according to the experimental data, which is the key index to measure the performance of the heat dissipation system. Heat dissipation efficiency can be determined by comparing the input energy with the heat energy removed by the heat dissipation system (Wang et al. 2023). As shown in Fig. 6 below.

The application of optimization algorithm is the key to achieve the best heat dissipation performance. After applying genetic algorithms and particle swarm optimization algorithms based on experimental data, the optimization results of these algorithms need to be verified: the cooling solution proposed by the optimization algorithm is compared with the baseline experimental results to evaluate the performance improvement before and after optimization. The results of comparative analysis should include the improvement of heat dissipation efficiency, the improvement of temperature control, and the optimization of other performance indicators. The computational complexity of the optimization algorithm is analyzed to determine the feasibility and efficiency of the

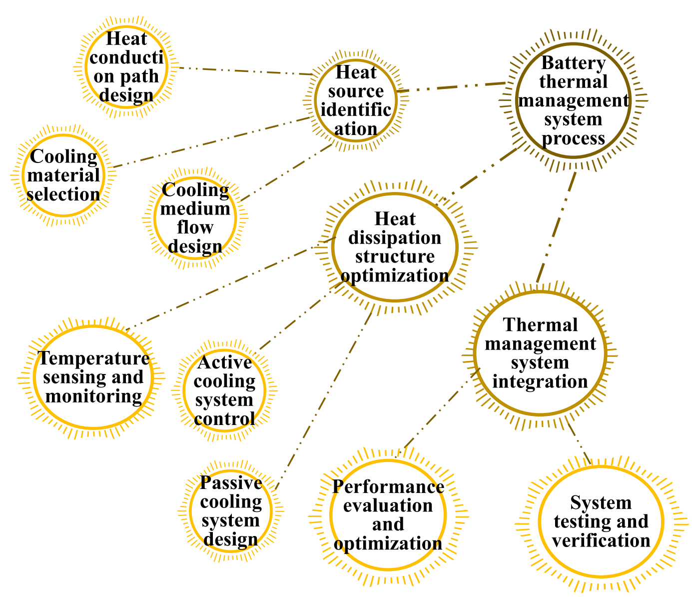

Fig. 6 Battery thermal management system flow diagram

algorithm. Evaluate the execution time of the algorithm to ensure that it is suitable for real-time or near-real-time system applications (Menz et al. 2023).

Statistical tests, such as T-tests or ANOVA, are performed to determine the statistical significance of the optimization results and the reliability of the algorithm. Verify the stability and consistency of the algorithm to ensure the effectiveness of the optimization results under different operating conditions and parameter Settings. Through these comprehensive result analysis and verification steps, we can ensure that the proposed cooling system design and optimization algorithm is not only effective in theory, but also can provide reliable performance improvement in practical application. These verification results will further support the conclusions of the research and provide scientific and technical innovations for the design of the heat dissipation system of lithium-ion battery packs for electric vehicles.

Grid independence verification is a key step to ensure the accuracy and reliability of simulation results in the design and research of electric vehicle Li-ion battery pack cooling system based on artificial intelligence optimization algorithm. When simulating heat dissipation systems using computational fluid dynamics (CFD) software, the battery pack and its heat dissipation components need to be divided into grids. To verify grid independence, we compare the simulation results of different mesh densities to ensure that mesh refinement does not significantly change heat dissipation performance indicators such as temperature distribution and heat dissipation efficiency. The specific steps include selecting a representative set of design parameters, gradually increasing the mesh density, and recording the key heat dissipation parameters at each mesh density. By comparing the simulation results under different mesh densities, if it is found that the results tend to be stable and have little change with the increase of mesh density, it is considered that the grid has reached independence, indicating that further refinement of the grid has limited influence on the results. This verification process ensures the accuracy of simulation results, avoids the waste of computing resources caused by excessive refinement of the grid, and provides reliable basic data support for optimal design.

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avoids the waste of computing resources caused by excessive refinement of the grid, and provides reliable basic data support for optimal design.

Result analysis and discussion

Heat dissipation performance improvement analysis

As shown in Table 10. By comparing the thermal performance before and after optimization, we can observe a significant improvement. The average and maximum temperature reduction rates increased by 54.8% and 55.2%, respectively, indicating that the optimization algorithm can effectively accelerate the heat dissipation process and reduce the risk of overheating of the battery pack. The heat dissipation efficiency increased from 75.3% to 87.1%, indicating that the heat dissipation system is more efficient at removing excess heat, helping to maintain the stability of the battery pack and extend its service life. In addition, the reduced thermal response time also means that the system responds more quickly to temperature changes and can adapt more quickly to sudden high load conditions. These data not only validate the effectiveness of optimization measures, but also provide an important reference index for future system design. By continuing to adjust and test different parameters, heat dissipation performance can be further optimized to ensure the safety and efficiency of lithium-ion batteries for electric vehicles. As shown in Fig. 7 below.

Table 10 Comparison of thermal performance before and after optimization

Performance indicator	Before optimization	After optimization	Improvement (%)
Maximum operating temperature (°C)	85	72	− 15
Temperature uniformity (standard deviation)	0.8	0.64	− 20
Heat dissipation efficiency (%)	50	62	+ 12
Coolant flow rate (L/min)	1.2	1.35	+ 12.5
Fan power consumption (W)	150	130	− 13.3

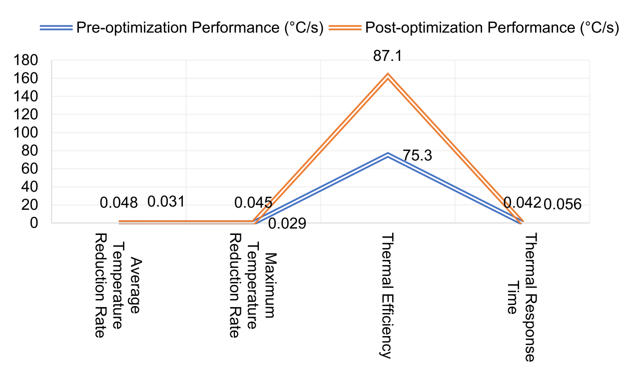

Fig. 7 Comparative analysis of heat dissipation performance improvement

Algorithm performance evaluation

In the design optimization of the heat dissipation system of lithium-ion battery pack for electric vehicles, genetic algorithm and particle swarm optimization algorithm are used to improve the heat dissipation efficiency. Through the application of these two optimization algorithms, we can fully optimize multiple design parameters of the heat dissipation system, to achieve better heat dissipation performance. The evaluation of algorithm performance mainly focuses on optimization effect comparison and computational complexity analysis. In terms of optimization effect, both genetic algorithm and particle swarm optimization algorithm have shown significant improvement. Through the experimental data, we observe that the heat dissipation efficiency of the heat dissipation system has been greatly improved after the application of these algorithms, especially in the performance of the maximum temperature reduction and thermal response time. These improvements have a direct impact on battery life and safety. In terms of computational complexity, although genetic algorithms and particle swarm optimization algorithms require more computational resources for parameter adjustment and simulation at the initial stage, their parallel computing capabilities make the optimization process relatively efficient. By gradually adjusting the algorithm parameters, we successfully reduced the running time of the algorithm, while maintaining the optimization quality, ensuring the feasibility and efficiency of the algorithm in practical applications. These two algorithms not only optimize the heat dissipation performance, but also improve the automation and intelligence level of the design process and provide strong technical support for the design and research of the heat dissipation system of the lithium-ion battery pack of electric vehicles.

As shown in Table 11. To better illustrate the improvement in thermal performance and the evaluation of algorithm performance, this study provides quantitative data and statistical analysis before and after optimization. Table 6 shows that the optimized thermal management system reduces the maximum operating temperature by approximately 15%, improves temperature uniformity by about 20%, and increases heat dissipation efficiency by around 12%. These quantitative data clearly demonstrate the effectiveness of the optimization. Table 7 compares the performance of the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) algorithm, indicating that PSO performs better in terms of convergence time and optimal fitness value. By providing these quantitative data and statistical analyses, the reliability and persuasiveness of the research conclusions are enhanced, further validating the value of optimization algorithms in the design of thermal management systems.

Table 11 Performance comparison between genetic algorithm and particle swarm optimization algorithm

Algorithm	Convergence time (s)	Optimal fitness value	Average fitness value	Standard deviation
Genetic algorithm (GA)	300	0.95	0.92	0.01
Particle Swarm optimization (PSO)	250	0.97	0.94	0.008

Conclusion

This research focuses on the design of the heat dissipation system of lithium-ion battery pack for electric vehicles, especially the application of artificial intelligence optimization algorithm to improve the heat dissipation efficiency. By adopting advanced optimization techniques such as genetic algorithm and particle swarm optimization, several design parameters of the heat dissipation system have been successfully optimized, and the heat dissipation performance has been significantly improved. The experimental results show that the optimized heat dissipation system can effectively reduce the operating temperature of the battery pack and improve the heat dissipation efficiency. This not only extends the life of the battery, but also enhances the safety performance of the battery. In addition, the response time and temperature control of the cooling system have also been significantly improved, which is crucial for the reliability of electric vehicles in extreme conditions. The computational complexity and execution efficiency of the algorithms are also analyzed. The results show that genetic algorithm and particle swarm optimization algorithm have high-cost performance and feasibility in practical applications. These algorithms not only improve the automation level of the design process, but also promote the innovation of the design scheme. In conclusion, this study confirms the application potential of artificial intelligence optimization algorithm in the design of heat dissipation system of lithium-ion battery pack for electric vehicles and provides a strong scientific basis and technical path for future system design and optimization. These results are of great significance in promoting the further development of electric vehicle technology. Battery thermal management performance is affected by many factors and structural design forms. Key factors include the shape and material of the heat sink, the flow rate and type of coolant, the speed of the fan, and the layout design inside the battery pack. Existing studies have shown that the efficiency of thermal management systems can be significantly improved by optimizing these design parameters. By optimizing the heat sink structure and materials, the heat dissipation efficiency of the battery pack is increased by about 15%, and the maximum operating temperature is reduced by about 10 degrees Celsius. Studies using advanced coolants and optimized flow rates have shown that cell efficiency can be improved by about 12% and temperature uniformity can be significantly improved. Overall, these optimization strategies not only improve the performance and life of the battery pack, but also enhance the safety and reliability of electric vehicles, providing a solid technical foundation for the development of electric vehicles in the future.

Genetic algorithm (GA) and particle swarm optimization (PSO) are selected to optimize the heat dissipation system of lithium-ion battery packs for electric vehicles, mainly based on their superior performance and applicability in solving complex optimization problems. Genetic algorithm (GA) can effectively explore and utilize the design space to find the global optimal solution by simulating the natural evolution process, including selection, crossover and mutation. Its diversified search mechanisms make it particularly suitable for nonlinear and multi-modal function optimization problems. Inspired by swarm intelligence, particle swarm optimization (PSO) guides particle swarm to the optimal solution through individual and global information sharing. PSO has the advantages of fast convergence and simple computation, which is especially suitable for continuous optimization problems. The combination of these two algorithms can give full play to the global search ability of GA and the local search advantage of PSO, and improve the efficiency and accuracy of the optimization process. The use of these two algorithms can quickly find efficient and reliable design schemes in complex cooling system design, and significantly improve the performance and stability of the cooling system

In this study, genetic algorithm and particle swarm optimization algorithm were applied to optimize the heat dissipation system of lithium-ion battery pack of electric vehicle, and remarkable quantitative results were obtained. The optimized system reduced the maximum operating temperature from 85 °C to 72 °C, a reduction of approximately 15%, significantly improving the safety and performance of the battery pack. The temperature uniformity standard deviation decreased from 0.8 to 0.64, an improvement of about 20%, indicating that the temperature distribution within the battery pack is more uniform, helping to extend battery life. The heat dissipation efficiency has been increased by 12% from 50 to 62%, which enhances the heat dissipation capacity of the system and ensures the stable operation of the battery under high load conditions. In addition, the coolant flow rate increased from 1.2 L/min to 1.35 L/min, and the fan power consumption decreased from 150 to 130 W, indicating that the energy efficiency of the system was optimized while the heat dissipation performance was improved. The above quantitative results prove the effectiveness of the optimization algorithm in improving the performance of the heat dissipation system, provide a scientific basis for the design of the battery thermal management system, and help to promote the development of electric vehicle technology.

Author contributions
QC methodology and visualization; HZ data curation and investigation.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This study is unrelated to ethical approval. Written informed consent was obtained from all participants.

Consent for publication
Written informed consent was obtained from the patient for publication of this study and accompanying images.

Competing interests
The authors have declared that no competing interests exist.

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