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Robust Design for the Cooling Performance of the Battery Pack Fire Extinguishing System

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Abstract. The safety and reliability of electric vehicle battery packs depend on the cooling performance of the fire suppression system affected by uncertainty factors. In order to meet the battery pack fire extinguishing demand and ensure the battery pack fire safety, an optimization design method is proposed to improve the cooling performance robustness of the battery pack fire extinguishing system. A simulation-based multi-level robust optimization framework is developed including the adaptive surrogate model optimization, worst-case optimization, and final design parameter optimization to reduce the risk of maximum battery pack temperature and thermal runaway. Meanwhile, the adaptive surrogate model is used to build an accurate prediction model with a small number of samples, which reduces the simulation calculation workload, saves resources, and improves the optimization efficiency.

Keywords: Battery Pack Fire Extinguishing System, Cooling Performance, Robust design, Adaptive Surrogate Model
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1 INTRODUCTION

As the core component of an electric vehicle, the battery pack has the high fire safety requirement which is a challenge restricting the development of electric vehicles [14]. The cooling performance of the fire extinguishing system is critical to the safety and reliability of the battery pack in an electric vehicle, which is affected by various factors such as the ambient temperature and battery heat production rate [12]. For the battery pack fire extinguishing system to ensure the safety of electric vehicles, its performance should not be sensitive to changes in uncertainty parameters based on the safety principle, even in the worst case, the performance of the battery pack fire extinguishing system should still meet requirements of fire safety. However, in the current battery pack fire extinguishing systems, robustness of the system performance is rarely considered under the condition of uncertain parameter changes. In this case, the performance of the battery pack fire extinguishing system may fail to meet requirements of the fire extinguishing and cooling when uncertainty parameter changes, with serious consequences. Following three approaches are commonly used to reduce sensitivity of the system performance to uncertainty factors: analytical approach, experiment-based approach, and simulation-based approach [18].

The analytical approach is not suitable for complex systems without known mathematical relationships [3]. In the experiment-based approach, battery pack fire-extinguishing cooling experiments require a large number of experimental samples [5]. Simulation-based robust design methods use the Monte Carlo sampling method to simulate the effect of parameter variations on the product performance, which requires the sample probability distribution model and a lot of time in the process [4]. In a complex system with high input and output dimensions, the training sample size will be large and required training time is long. As variations of uncertainty factors have not been systematically studied, the worst case of the cooling performance of a fire extinguishing system should be considered in the design for safety.

To improve robustness of the cooling performance of the battery pack fire suppression system and reduce the maximum temperature of the battery pack, this study optimizes the cooling performance of the battery pack fire suppression system based on the worst-case method and the adaptive surrogate model. With limited samples, an accurate surrogate model is built to reduce the simulation computation effort and improve the optimization efficiency. The method is verified by comparing the cooling performance before and after optimization, as well as findings from established optimization methods.

Following parts of the paper are organized as follows. Section 2 provides a review of pertinent studies, and Section 3 explains the robust optimization of the battery pack fire extinguishing system's cooling performance. In Section 4, the research conclusion and further efforts are discussed.

2 LITERATURE REVIEW

The objective of this paper is to improve the robustness of the cooling performance of battery pack fire suppression systems for electric vehicles. The requirements and related designs of battery pack fire suppression cooling performance are reviewed, as well as the effects of uncertainty factors on them. Robust optimization methods based on the worst-case method and adaptive surrogate model are also reviewed to provide a reference for this paper.

2.1 Requirements for Cooling Performance of Battery Pack Fire Extinguishing System and Its Influencing Factors

Cooling is one of the most basic fire-fighting techniques as an excellent way of putting out battery fires, limiting thermal runaway propagation in battery packs, and preventing battery re-ignition [13]. Liu et al. tested a devised fire extinguishing system and found that the battery's peak temperature and high-temperature duration were greatly lowered compared to a scenario with no water mist cooling suppression [9]. Currently, most of the automatic battery fire extinguishing systems developed directly or indirectly drive the fire extinguishing agent to spray the battery monomer and extinguish the fire by cooling. In most situations, the extinguishing system is able to stop the spread of thermal runaway, but in a few circumstances, the battery re-ignition is a possibility. FM Global conducted a series of tests for the sprinkler fire suppression including fire suppression cooling tests using a water spray system on 18650 lithium-ion power batteries in a thermal runaway condition. The results showed that the extinguishing system could stop the spread of thermal runaway in most cases, but the possibility of re-ignition existed in a few cases [6]. As a result, the battery pack fire suppression system's powerful cooling performance is a critical need for battery fire safety.

Although cooling fire extinguishing is an effective method of dealing with battery fires, battery fires are typically unexpected and unpredictable, and the cooling performance of the battery fire extinguishing system will also fluctuate due to a variety of uncertainties. Liu et al. showed that the cooling performance of the fire extinguishing system is affected by the response time and pressure of the system, the longer the response time, the worse the cooling effect [9]. Zhong et al. conducted a series of combustion tests on ternary lithium batteries using a modified conical calorimeter to study the safety of lithium batteries. The results showed that the higher SOC leads the higher temperature and faster the exothermic rate of the battery during combustion, and the more difficult to perform cooling [19]. As a result, the cooling performance of the battery pack fire suppression system will change in response to uncertainty factors such as ambient temperature, pressure, and battery heat production rate. If the system cooling performance is not robust enough, it may not be able to meet cooling requirements of the battery fire suppression, resulting in serious battery fires and massive losses.

2.2 Cooling Design of Battery Pack Fire Extinguishing System

In terms of the emergency safety technology for lithium-ion batteries, fire extinguishing agent sprinkler systems are the most commonly used combustible fire safety equipment, with a focus on the use and design of cooling technologies. Yim proposed a method for battery self-extinguishing capability by incorporating temperature-responsive microcapsules containing an extinguishing agent to effectively improve safety, which can release the extinguishing system when the internal temperature of lithium-ion batteries rises through the heat absorption reaction [17]. The fire extinguishing system disclosed by Jung et al. includes a fire detection sensor, an extinguishing agent, and a control unit that injects the extinguishing agent into the battery pack to extinguish the fire during the early stages of a battery fire [7]. Kim and Yoon developed a safety device that can spray a fire-fighting agent to put out a battery pack fire or explosion [8].

The existing research, however, mainly focuses on improving the system accuracy in detecting fires and developing suitable extinguishing agents. There is a lack of research on the robustness of the cooling performance of battery extinguishing systems. According to the description in 2.1, the robustness of the battery extinguishing system cooling performance is very important. The ability to cool the battery to a safe state is the key to extinguish the battery and prevent re-ignition. As a result, we propose a robust design approach to improve the robustness of the battery fire suppression system cooling performance in order to ensure that the battery fire can be extinguished for the fire safety of the battery pack.

2.3 Robust Optimization Based on Worst-Case Approach and Adaptive Surrogate Model

When there is uncertainty in the input of practical engineering systems, the system output also has uncertainty, making it difficult to determine the optimal value of design parameters [17]. The goal of uncertainty robust optimization is to reduce the impact of such uncertainty on system effectiveness and stability. The requirement for robustness is generally determined by the engineering application scenario and the level of risk that can be assumed. There are two common approaches: a probabilistic approach can be used if a portion of products that do not meet requirements is acceptable, and a worst-case approach should be used if all products must meet the requirements [1].

It is impractical to find the worst case intuitively in complex engineering problems and nonlinear systems. How to find the global worst case with a small number of calculations is a challenge in this design approach. The surrogate model is a mathematical model proposed to reduce the cost of actual engineering computation time while improving the efficiency and accuracy of the optimization search [2]. To predict the target response values at unknown points, the model establishes a mapping between the input variables and target variables based on response relationships of known test sample points. The adaptive surrogate model-based optimization method can effectively address the aforementioned challenges by reducing the number of sample points required, improving computational efficiency, and design quality. The adaptive surrogate model-based optimization is divided into three stages: first, the design for experiment method is used to perform initial sampling; second, the approximate model is used to construct the surrogate model, and the surrogate model is reconstructed when newer points are added to the sample set; and finally, a sample update strategy is constructed for the surrogate model to obtain update points and add them to the sample set. The key of the adaptive surrogate model optimization method is to decide how to build an update strategy that will identify the optimal value quickly and feasibly. Furthermore, the adaptive surrogate model primarily adds more sample points in the region of interest to improve the accuracy of the surrogate model in that region [15]. Fig. 1 shows a block diagram of the adaptive surrogate-based model optimization.

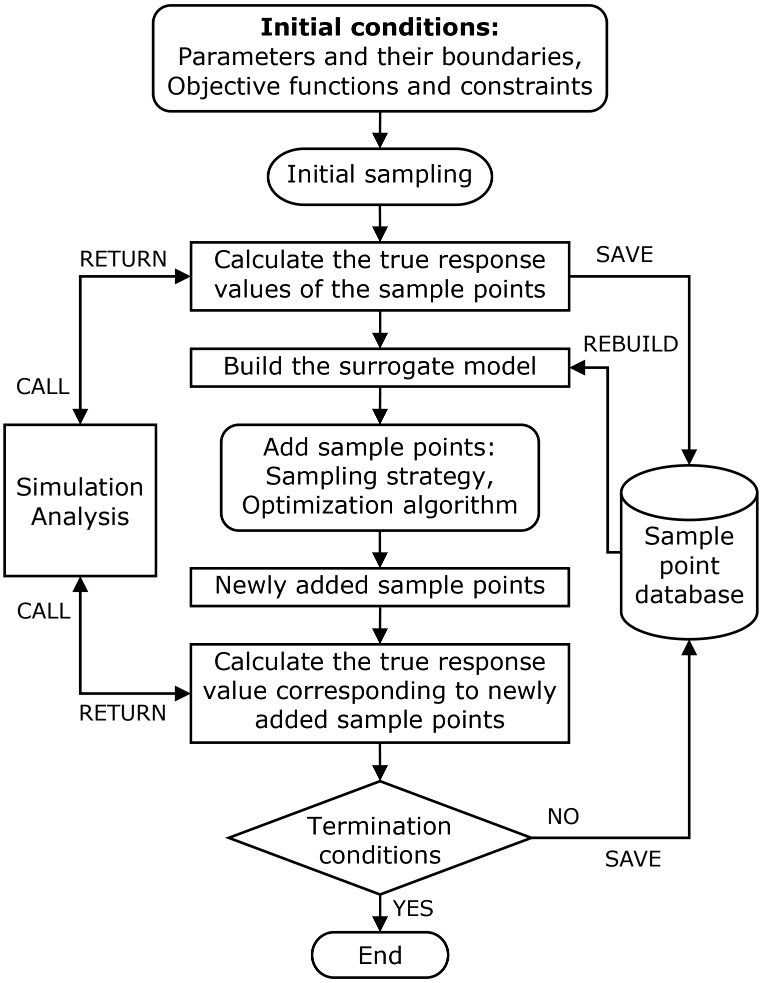

Figure 1: Robust optimization based on adaptive surrogate model.

3 ROBUST OPTIMIZATION OF COOLING PERFORMANCE OF FIRE EXTINGUISHING SYSTEM

3.1 Modeling of Battery Pack Fire Extinguishing System

The structure of a fire extinguishing system in an electric vehicle battery pack is shown in Fig. 2. Related parameters affecting the cooling performance are to be optimized for the minimal influence of uncertainty parameters.

The stored liquid carbon dioxide fire extinguishing agent is vaporized into the low-temperature carbon dioxide gas due to the pressure drop during battery fire extinguishing and cooling. After being adjusted by the shunt, they enter the battery thermal runaway module from the system pipe at the given inlet flow rate and inlet pressure and are ejected from the jet valve port above the battery. Air in the battery module container is discharged from the safety valve port. The outlet boundary condition is that the outlet pressure is equal to the atmospheric pressure. Design parameters are summarized in Tab. 1.

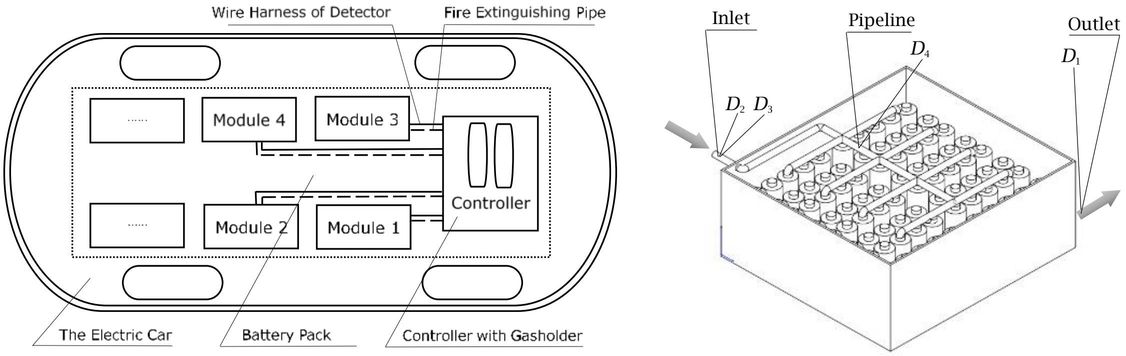

Figure 2: Battery pack fire extinguishing system and simplified battery module.

Name	*Symbol*	*Boundary*	*Unit*
Inner diameter of the safety valve	D_1	[10,15]	mm
Inlet flow rate of the fire extinguishing surrogate	D_2	[70,100]	m/s
Inlet pressure of the fire extinguishing surrogate	D_3	[5.5,6.5]	mPa
Inner diameter of the fire extinguishing system pipeline	D_4	2/2.5/3	mm

Table 1: Design parameters of the fire extinguishing system.

Uncertainty parameters are summarized in Tab. 2. Boundaries of the uncertainty parameters are considered as follows:

- Surface heat flux of the normal battery: According to experimental studies, the volume heat rate of lithium-ion monomers ranges from 7895.33W/m^3 to 10079.6W/m^3. The heat generated by the battery is expressed as the heat flux on the surface of the battery, and its value is taken to be in the range of [41.5, 49.5] W/m^2 under the principle of safety consideration;
- Surface heat flux of the thermal runaway battery: The surface heat flux of thermal runaway battery is expressed as 40 times of the surface heat flux of normal battery;
- Ambient temperature: In actual conditions, the normal operating temperature of EV battery pack is between -20℃ and 50℃; and
- Ambient pressure: The actual ambient pressure is not fixed, and the change of atmospheric pressure is related to uncertain factors such as height, location and gas movement.

Name	*Symbol*	*Boundary*	*Unit*
Surface heat flux of the normal battery	U_1	[41.5,49.5]	W/m^2
Surface heat flux of the thermal runaway battery	U_2	[1620,1980]	W/m^2
Ambient temperature	U_3	[253,323]	k
Ambient pressure	U_4	[0.091,0.111]	mPa

Table 2: Design parameters of the fire extinguishing system.

3.2 Evaluation of Cooling Performance Robustness

Design parameters and uncertainty parameters of the battery fire extinguishing system affect the cooling performance of the system, and the change of system performance index can be simulated according to the system model by determining the value range of system design parameters and uncertainty parameters. The maximum temperature (T) is used to measure the cooling performance of the fire extinguishing system and evaluate the potential risk of thermal runaway behavior of battery cells. Based on the worst-case method and safety principle, this research uses the upper bound (T_{UB}) of the maximum temperature of the battery pack after fire extinguishing and cooling to evaluate the cooling performance of the fire extinguishing system. Lower value (T_{UB}) provides the better cooling performance. T_{UB} should be under safety critical temperature point T_{NR}. The safety temperature is the critical point at which the thermal runaway reaction and reignition of the battery will not occur, which is determined by the occurrence condition of the decomposition reaction of the battery.

3.3 Robust Optimization Process

3.3.1 Constructing multi-level optimization function and optimization framework

Initial 360 sample design points are randomly selected using the Latin hypercube sampling method. The response value of each sample point is searched by simulation to build the system input and output sample database. Initial sample data are used to build an initial surrogate model of the system. In order to minimize the maximum temperature(T) after fire extinguishing and cooling, corresponding design parameter set $\mathbf{D}$=(D_1,D_2,D_3,D_4) and uncertainty parameter set $\mathbf{U}$=(U_1,U_2,U_3,U_4) are obtained as follows.

$$\begin{aligned}&\text{Find: Optimized input design parameter set } \mathbf{D}= \ D_1, D_2, D_3, D_4 \ \text{ and } \mathbf{U}= \ U_1, U_2, U_3, U_4 \ ,\\&\text{Minimize}: T\\&\text{Subject to: } T \le T_{\mathrm{NR}}, D_m \in \left[D_{m\mathrm{L}}, D_{m\mathrm{U}}\right], U_n \in \left[U_{n\mathrm{L}}, U_{n\mathrm{U}}\right].\end{aligned} \tag{1}$$

where D_{mL} and D_{mU} represent lower and upper boundaries of the allowable interval of the m^{th} design parameter in the design parameter set respectively; U_{nL} and U_{nU} represent lower and upper boundaries of the allowable interval of the n^{th} design parameter in the uncertainty parameter group. The real response value of the optimized design point is obtained through simulation, which is added to the sample database as a group of new sample data to update the surrogate model of the system. In this process, new sample data are constantly obtained, and the surrogate model is updated iteratively until the termination condition is satisfied: coefficient determination $R^2 > 0.95$[15].

For a certain set of design parameters, there are different response values of cooling performance evaluation indexes when the value of uncertainty parameters is different. Based on the principle of safety, the cooling performance should meet requirements of fire extinguishing in the worst case. Therefore, the worst limit of cooling performance corresponding to each design parameter set is searched. In this paper, the maximum temperature of the battery pack after fire extinguishing cooling is used as the response value of the cooling performance evaluation index. The maximum response value corresponding to each set of design parameters is its worst case. In order to maximize the response value of cooling performance evaluation index corresponding to each design parameter set, the worst case corresponding to each design parameter is searched as follows.

$$\begin{aligned}&\text{Find: The } T_{\mathrm{UB}}^i \text{ for design parameter set } \mathbf{D}^i = \ D_1^i, D_2^i, D_3^i, D_4^i \ ,\\&\text{Maximize}: T^i\\&\text{Subject to: } T^i \le T_{\mathrm{NR}}, D_m^i \in \left[D_{m\mathrm{L}}, D_{m\mathrm{U}}\right], U_n^i \in \left[U_{n\mathrm{L}}, U_{n\mathrm{U}}\right].\end{aligned} \tag{2}$$

where T^i is the response value of cooling performance evaluation index corresponding to the i^{th} design parameters set. T^i_{UB} is the upper bound of the response value of the cooling performance corresponding to the i^{th} design parameters set, namely, the maximum value of T^i.

Based on the worst case corresponding to each design parameter set, the worst-case surrogate model of the system is established. The higher upper bound T_{UB} of the maximum temperature after cooling performance represents the higher thermal runaway risk of a battery. For minimizing T_{UB}, a set of design parameters is searched for the system sufficiently robust and response value of the performance index in the worst case within an acceptable safety range as follows.

$$\begin{aligned} &\text{Find: Optimized design parameter set } \mathbf{D} = D_1, D_2, D_3, D_4 \ , \\ &\text{Minimize}: T_{\text{UB}} \\ &\text{Subject to: } T_{\text{UB}} \le T_{\text{NR}}, D_m \in \left[D_{m\text{L}}, D_{m\text{U}}\right]. \end{aligned} \tag{3}$$

Variables to satisfy constraints and objective functions are searched by optimization for design parameters. Fig.3 is a multi-level robust optimization process for the cooling performance of the fire extinguishing system considering the variation of uncertainty parameters.

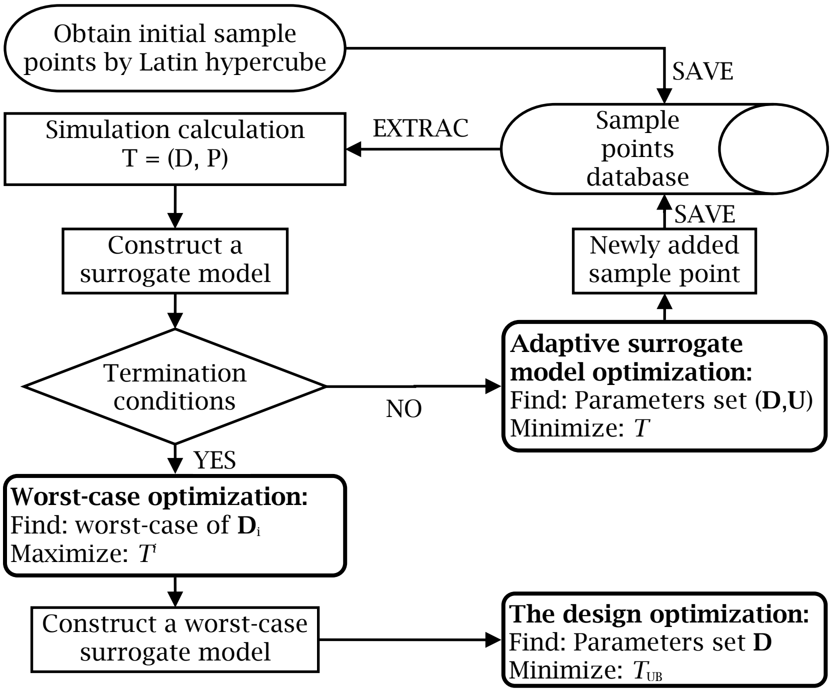

Figure 3: Multi-level robust optimization considering variation of uncertainty parameters.

3.3.2 Constructing finite element model and simulation setup

Since there is no obvious linear mathematical function relationship between input parameters and response indicators of this system, it cannot be solved using mathematical calculations. Therefore, the uncertainty problem needs to be transformed into a series of deterministic problems by means of sample test design and simulation. The process of fire extinguishing system simulation and multi-objective optimization is outlined below.

This work selects one module of simplified battery pack fire extinguishing cooling system as the research object to create a CFD simulation model of the finite element based on the design scheme of modular fire extinguishing system of the battery pack and requirement for the simplified calculation. The number of meshes generated is over two million in order to improve the calculation accuracy. The mesh division for the fluid domain of the battery module is shown in Fig. 4. The mesh is imported into the fluid simulation analysis software Fluent for fluid-solid coupling heat dissipation analysis when the mesh division of the CFD model is completed. The energy equation is used in further calculations to incorporate the heat exchange.

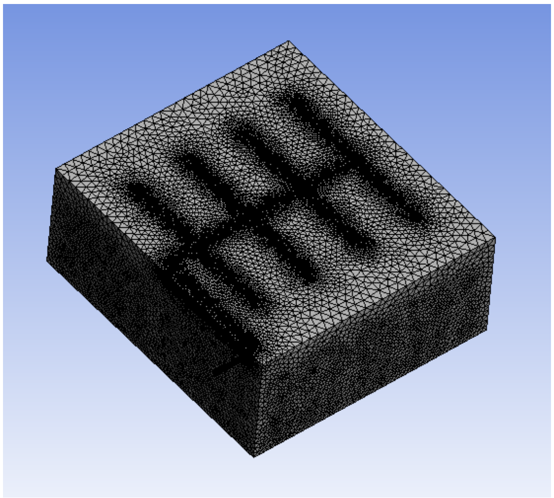

Figure 4: Finite element meshing.

The cell is regarded as a uniform heat generator; the fire extinguishing agent is defined as carbon dioxide. The heat flow density on the surface of the cell is used to represent the heat generation rate of the cell monomer, which is set according to parameters in Tab. 2. In the battery pack fire extinguishing cooling model, the fire extinguishing agent inlet is set as the velocity inlet boundary condition, and the initial flow rate is set. The fire extinguishing agent outlet is set as the pressure outlet boundary condition, and the backpressure is ambient air pressure. The fire extinguishing agent and battery are fluid-solid coupling surfaces. According to the Reynolds number calculation method, the flow state of the fire extinguishing agent is set as the turbulent flow. The process selects the pressure-based solver, chooses the "SIMPLE" format for the solution algorithm, and sets the initialization method as "Standard Initialization".

3.3.3 Multi-level robust optimization calculation

The Latin hypercube design method is used to extract test sample points, which can effectively fit the nonlinear response problem by uniformly sampling the pre-defined sample space and considering various influencing factors of input parameters and diverse combinations among these factors. 360 sets of design point samples are extracted. Values of cooling performance optimization indexes corresponding to 360 sets of design point samples are calculated in ANSYS software using the fluent module.

The optimization search method uses the particle swarm optimization algorithm, which is a population-based search optimization technique based on the basic principle of mimicking the social behavior of a flock of birds [11]. To solve the premature convergence problem of the particle swarm algorithm, Shi and Eberhart added a parameter called inertia weight ω to the algorithm [10]. ω is defined for adjusting the balance between global and local search as a function that decreases linearly with time. In the inertia weight particle swarm algorithm, the velocity of the particles is updated as follows.

$$
\begin{aligned}
v_{ab} &= \omega v_{ab} + c_1 r_{1ab} \;\; pbest_{ab} - x_{ab} \;\; + c_2 r_{2ab} \;\; gbest_{ab} - x_{ab} \\
x_{ab} &= x_{ab} + v_{ab}
\end{aligned}
\tag{4}
$$

where a denotes a dimension of the variable, a=1,2, … , d, d denotes the dimensionality of the problem. a represents each particle in the population (i=1,2, … ,μ). x_a and v_a represent the position and velocity variables of the *ith* particle, respectively. $pbest_a$ is the best position of the *ith* particle and $gbest_a$ is the best position of the whole population. c_1 and c_2 are acceleration coefficients, and r_{1a} and r_{2a} are randomly generated numbers in the range [0,1].

There are three commonly used nonlinear fitting approximation models for complex systems with multidimensional variables: radial basis function approximation model, Kriging approximation model, and backpropagation neural network approximation model. In order to make the prediction results accurate, this paper uses the input and output data of 360 sets of initial sample design points obtained from simulation to train the above three approximation models to construct the surrogate model of the battery pack fire extinguishing system respectively. By comparing the prediction accuracy of the three models, it is found that the accuracy of the surrogate model constructed by using the BP neural network approximation model is higher for the optimization problem of the battery pack fire suppression system in this paper. The minimum response surface sample update strategy can be applied to different types of surrogate models, and it directly uses the optimal solution of the surrogate model to update the surrogate model.

In summary, the proposed uncertainty robust optimization process is as follows:

- Data samples are designed using the Latin hypercube experimental design method for the four design parameters and four uncertainty parameters, respectively. 360 sets of design point samples are used;
- The simulation analysis is carried out in ANSYS software using the Fluent module to obtain 360 sets of system response values corresponding to 360 sets of design point samples;
- According to obtained input and output sample data, the initial BP neural network surrogate model of the fire extinguishing system is constructed. The particle swarm algorithm is used to find the optimum, and sample points are added according to the minimum response surface sample update strategy. When the prediction accuracy of the surrogate model reaches the requirement, the operation of adding sample points is stopped;
- The worst limit of the cooling performance corresponding to each design parameter group **D** is calculated based on the surrogate model obtained in the previous step. The Worst-Case data set is generated;
- The Worst-Case dataset is used to construct a worst-case surrogate model of the fire suppression system. The model and the particle swarm algorithm are used to search for the optimized design parameter group **D** that minimizes the maximum battery pack temperature;
- The effectiveness of this optimization method is decided by comparing evaluation index values of the cooling performance of the battery pack fire suppression system before and after the optimization and by comparing results of other optimization methods.

3.3.4 Optimization methods for comparison

The following two optimizations are performed for a comparison with the proposed method.

Deterministic optimization method: Under the assumption that the uncertainty parameters do not change, design parameters are optimized. The range of the design parameters is referred to Tab. 1, and values of uncertainty parameters are the average of values of uncertainty parameters in Tab. 2. For the design parameters, hypercubic sampling of 400 groups is used, and the simulation generates the relevant index response values, builds the BP neural network surrogate model, and searches for the best design parameters using the particle swarm algorithm.

Traditional simulation-based optimization method: Under considering uncertainty parameters, design parameters are optimized. Tab. 1 lists the design parameter ranges, while Tab. 2 lists the uncertainty parameter ranges. The corresponding index response values are obtained by simulation, a BP neural network surrogate model is developed, and a particle swarm technique is utilized to seek the ideal design parameters while considering uncertainty parameter changes.

3.4 Robust Optimization Result

Optimized results of design parameters are shown in Tab. 3 and Fig. 5. Results of two conventional parameter optimization methods are compared using F_{UB}^{i} , the upper limit of the cooling performance response value corresponding to the optimized design parameter set, as a comparison index for optimization. It is observed that the optimized design parameter by using the proposed method reduces the maximum temperature of the battery pack after cooling, which improves the robustness and safety of the battery pack. At the same time, comparing with the deterministic optimization, this research considers the change of uncertainty parameters in the robust optimization according to the worst case. Comparing with the traditional uncertainty optimization, this paper adopts the iterative cycle of self-adapting updating sample points to constantly reconstruct the surrogate model, which makes the model reach the required prediction accuracy quickly, reduces the required number of samples, and improves the optimization efficiency. When the number of simulations or experiments is the same, the prediction accuracy of this surrogate model is higher, and the prediction of the optimal solution for the system design parameter set is more accurate than the traditional simulation-based uncertainty optimization method.

	Symbol	*Initial value*	*Deterministic optimization*	*Traditional simulation-based optimization*	*The proposed optimization*
Design parameters	D_1	12	14.88	11.75	12.57
	D_2	80	86.05	83.24	91.6
	D_3	6.0	5.729	6.383	6.370
	D_4	2.5	3	3	3
Comparison index	T_{UB}^{i}	363.34	351.07	348.28	342.78
Prediction accuracy	R^2	-	-	0.9216	0.9513

Table 3: Comparison of optimization results.

4 CONCLUSIONS

This paper presented a robust optimization method based on the worst-case method and adaptive surrogate model to optimize the worst-case limit of the cooling performance of the battery pack fire suppression system, ensuring that the battery can be cooled to a safe temperature and improving the fire safety of the battery pack. An accurate surrogate model is constructed with fewer samples to improve the optimization efficiency and predict the optimal solution of the fire suppression system design parameter set accurately. The effectiveness of the proposed method is verified by comparing it with traditional robust optimization methods.

Future work will consider more metrics to evaluate the cooling performance of the fire suppression system, such as the time required for cooling, so that the cooling of the battery pack fire suppression system can be fully and robustly optimized for the safety of the battery pack.

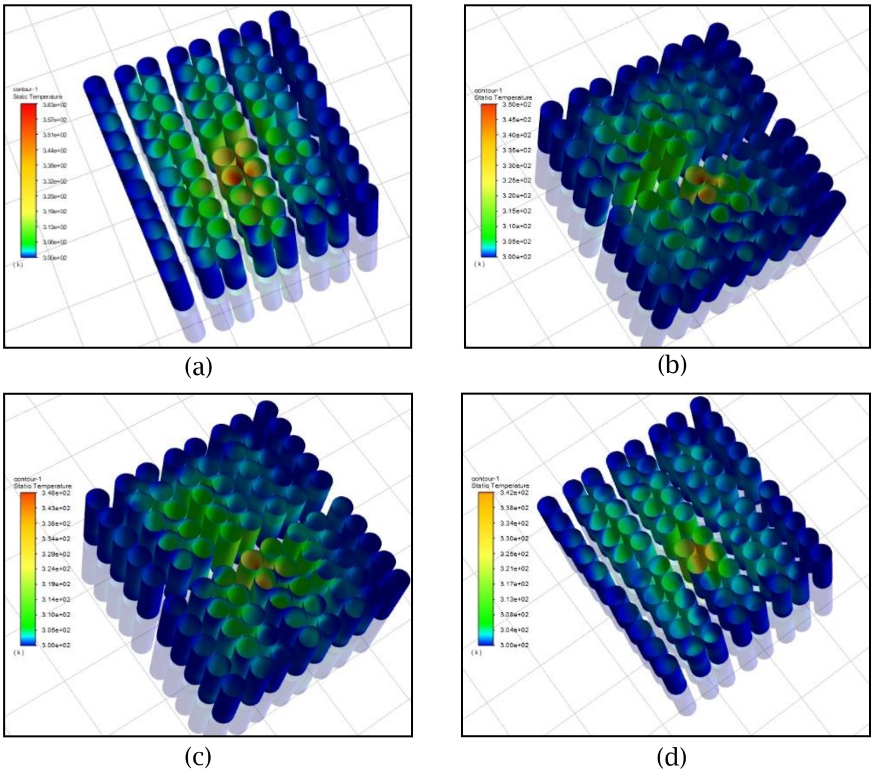

Figure 5: Comparison of temperature distribution after cooling: (a) Initial design parameters, (b) Deterministic optimization, (c) Traditional simulation-based optimization, (d) Proposed optimization.

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