

Title:

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

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Introduction:

Cooling performance of the fire extinguishing system is critical to the safety and reliability of the battery pack in an electric vehicle, which can be affected by various factors such as the environment temperature and battery heat production rate [3]. The minimal sensitivity to different factors is required in the robustness design of the battery pack. The following three approaches are usually used to reduce sensitivity of performance boundaries to uncertain factors: analytical approach, experiments-based approach, and simulation-based approach [5].

The analytical approach is not suitable for complex systems without known mathematical relationships [1]. In the experiments-based approach, battery pack fire-extinguishing cooling experiments require a large number of experimental samples. Simulation-based robust design methods use the Monte Carlo sampling method to simulate the effect of parameter variation on product performance, which requires the sample probability distribution model and a lot of time in process [2]. As variations of uncertain factors have not been systematically studied, the worst limit of the cooling performance of a fire extinguishing system should be considered in the design for safety. The cooling performance of the battery pack fire extinguishing system is optimized in this paper based on the worst-case method and adaptive surrogate model. An accurate surrogate model is established with fewer samples to minimize the maximum temperature of the battery pack and reduce the risk of thermal runaway of the battery. Meanwhile, the workload of simulation calculation is reduced, resources are saved and optimization efficiency is improved.

Main Idea:*Modeling of Battery Pack Fire Extinguishing System*

The structure of a fire extinguishing system in an electric vehicle battery pack is shown in Fig. 1. Related parameters affecting the cooling performance are to be optimized for the minimal influence of uncertain parameters. Design and uncertain parameters are summarized in Tabs. 1 and 2, respectively.

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.

Uncertain parameters are summarized in Tab. 2. Boundaries of the uncertain 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 by the heat flux on the battery surface, and the value range is $[41.5, 49.5]\text{W/m}^2$.
- 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°C and 50°C .
- 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.

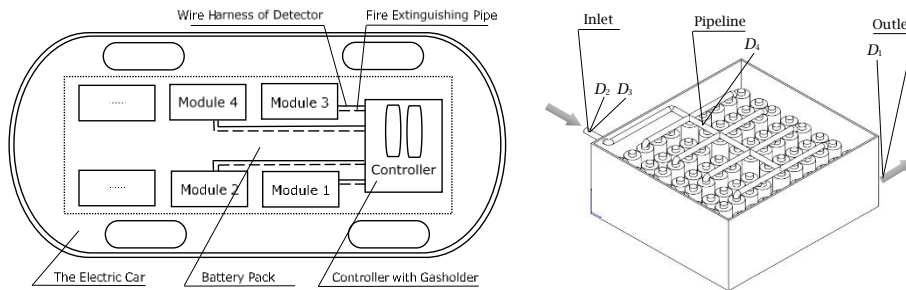


Fig. 1: Battery pack fire extinguishing system and simplified battery module.

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

Tab. 1: Design parameters of the fire extinguishing system.

Name	Symbol	Boundary	Unit
Surface heat flux of the normal battery	U_1	[41.5,49.5]	W/m^2
Surface heat flux of thermal the 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

Tab. 2: the related uncertain parameters of the cooling performance of the fire extinguishing system.

Evaluation of Cooling Performance Robustness

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 paper uses the upper bound (T_{UB}) of the maximum battery pack temperature after fire extinguishing and cooling to evaluate the performance of the fire extinguishing system. Lower value of T_{UB} provides the better cooling performance. T_{UB} should be under safety critical temperature point T_{NR} . The safety temperature is searched for 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.

Robust Optimization Process

360 initial 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 uncertain parameter set $\mathbf{U}=(U_1, U_2, U_3, U_4)$ are obtained as follows formula (1).

$$\begin{aligned} &\text{Find: Optimized input design parameter set } \mathbf{D} = D_1, D_2, D_3, D_4 \text{ and } \mathbf{U} = U_1, U_2, U_3, U_4, \\ &\text{Minimize : } T \\ &\text{Subject to: } T \leq T_{\text{NR}}, D_m \in [D_{\text{mL}}, D_{\text{mU}}], U_n \in [U_{\text{nL}}, U_{\text{nU}}]. \end{aligned} \quad (1)$$

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 uncertain 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 met: coefficient of determination $R^2 > 0.95$ [4].

For a certain set of design parameters, there are different response values of cooling performance evaluation indexes when the value of uncertain 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 is searched. In this paper, the upper bound of 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, the worst case corresponding to each design parameter is searched as follows formula (2).

$$\begin{aligned} &\text{Find: The } T_{\text{UB}}^i \text{ for design parameter set } \mathbf{D}^i = D_1^i, D_2^i, D_3^i, D_4^i, \\ &\text{Maximize : } T^i \\ &\text{Subject to: } T^i \leq T_{\text{NR}}, D_m^i \in [D_{\text{mL}}, D_{\text{mU}}], U_n^i \in [U_{\text{nL}}, U_{\text{nU}}]. \end{aligned} \quad (2)$$

where T^i is the response value of cooling performance evaluation index corresponding to the i^{th} design parameters set. T_{UB}^i 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 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 formula (3).

$$\begin{aligned} &\text{Find: Optimized design parameter set } \mathbf{D} = D_1, D_2, D_3, D_4, \\ &\text{Minimize : } T_{\text{UB}} \\ &\text{Subject to: } T_{\text{UB}} \leq T_{\text{NR}}, D_m \in [D_{\text{mL}}, D_{\text{mU}}]. \end{aligned} \quad (3)$$

Variables to satisfy constraints and objective functions are searched by optimization for design parameters. Fig. 2 is a multi-level robust optimization process for the cooling performance of the fire extinguishing system considering the variation of uncertain parameters.

Optimization methods for comparison

Deterministic optimization: Design parameters are optimized without considering uncertain parameters. The ranges of the design parameters are referred to Tab. 1. In this study, 400 sets of design parameters are extracted and simulated to generate their relevant temperature. On this basis, a surrogate model is built for searching the optimal values of design parameters.

Traditional non-deterministic optimization: Design parameters are optimized considering uncertain parameters. The ranges of design parameters and uncertain parameters are referred to Tab.

1 and Tab. 2. In this study, 400 sets of design parameters and uncertain parameters are extracted and simulated for building the surrogate model to search the optimal values of design parameters.

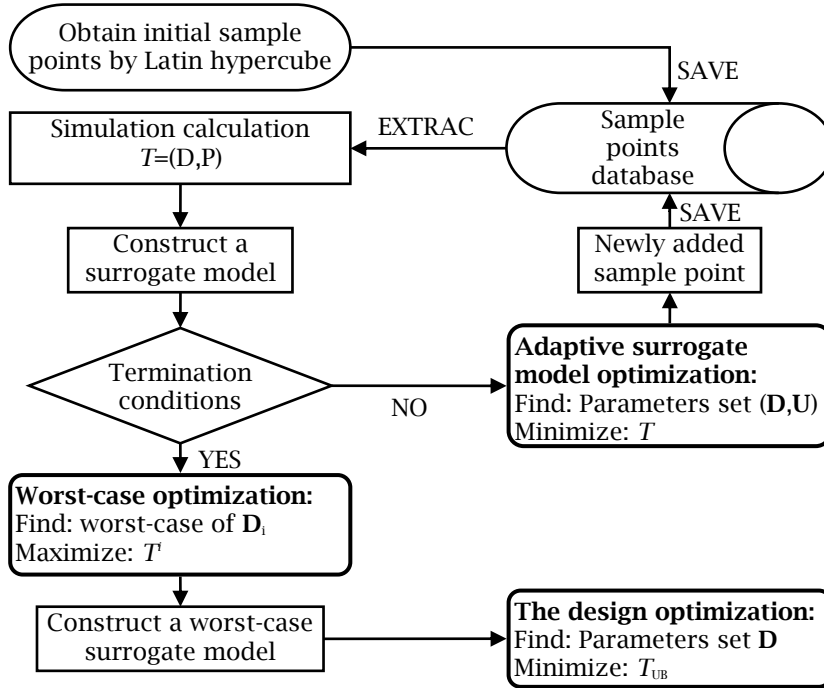


Fig. 2: Multi-level robust optimization considering variation of uncertain parameters

Robust Optimization Result

Optimized results of design parameters are shown in Tab. 3 and Fig. 3. The results are compared with results from two traditional parameter optimization methods. 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 paper considers the change of uncertain parameters in the robust optimization according to the worst case. Comparing with the traditional uncertain 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 simulation or experimental tests 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 non-deterministic optimization method.

	Symbol	Initial value	Deterministic optimization	Traditional non-deterministic 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
The upper bound of T	T_{UB}	363.34	351.07	348.28	342.78

Tab. 3: Comparison of optimization results

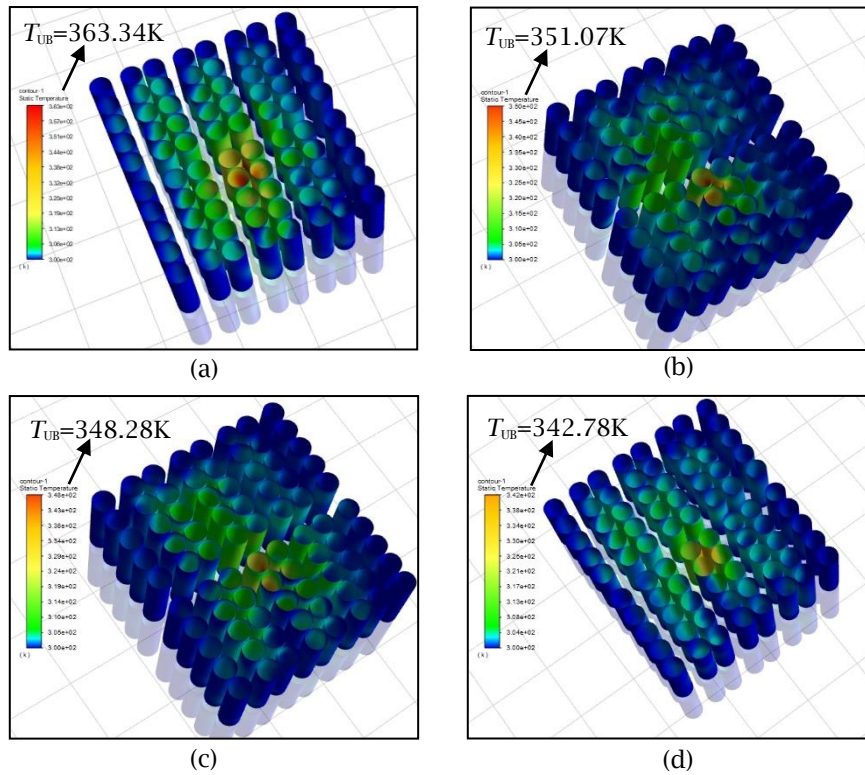


Fig. 3: Comparison of temperature distribution after cooling: (a) Initial design parameters, (b) Traditional optimization, (c) Traditional non-deterministic optimization, (d) Proposed optimization.

Conclusions:

In order to improve the robustness and safety of battery packs, a novel robust optimization method is proposed to minimize the upper bound of the worst-case cooling performance response value of the fire suppression system. An adaptive surrogate model is developed to construct an accurate surrogate model with fewer samples, which improves the optimization efficiency and also predicts more accurately the optimal solution for the design parameter set of the fire suppression system. The effectiveness of the proposed method is verified by comparing with the traditional robust optimization method.

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