Multi-objective Optimization Design for Battery Pack of Electric Vehicle Based on Neural Network of Radial Basis Function (RBF)

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Abstract—As a carrier of EV batteries, battery pack is a key component that ensures stability, safety, and reliability of energy system for power batteries. In order to complete the requirement of light weight for EV, the battery pack shall have light weight as much as possible while meeting structural strength. This paper uses an Surrogate Models algorithm based on RBF neural network to solve the problem of multi-objective optimization for battery pack. It can be observed from LsDyna simulation results that the battery pack has declined 17.62\% in mass and 30.78\% in maximum deformation. Therefore, the proposed structure optimization model of battery pack hereof provides an effective design and optimization method for battery pack.

1. INTRODUCTION
Electric vehicle (EV) is more economical and environmental-friendly compared to traditional oil-powered automobile. In the future, it may completely substitute oil-powered automobile. The battery is a core EV component, while battery pack is a key component that ensures safety and reliability of batteries\,[1]. Moreover, structural strength and stiffness, space design and connection process of battery pack have important influences on the vehicle performance. Therefore, it is necessary in the design of battery pack to simulate extrusion for battery pack and module and reveal their conditions under strong extrusion force in the process of transportation, storage and utilization of power batteries and system, especially in the process of EV collision. No. 1 Modification List of GB/T 31467.3-2015 requires stopping extrusion or waiting for 10 min when extrusion force reaches 1 OOKN or extrusion deformation reaches 30\% of overall dimension at the extrusion direction. Besides, it also requires no fire and explosion for battery pack or system within one hour. Generally, simulation analysis and experimental test are necessary for EV battery pack in development phase. However, traditional simulation test method is featured with massive calculation data and long analysis cycle. Therefore, in order to improve efficiency of simulation analysis, a multi-objective optimization algorithm for battery pack based on RBF neural network is proposed to solve the problem of traditional low efficiency in simulation test. As a feedforward neural network and local approximation network built based on functional approximation theory, RBF neural network can obtain the unique optimal approximation value, of which output is calculated with linear weighting method. Because of few training steps and fast convergence, it is usually used in various engineering designs. Hence, it is proposed to use RBF neural network in multi-objective optimization design for battery pack. The multi-objective optimization means to achieve optimization of multiple objective functions, while it needs to fulfill both...
the strength and light weight requirement for battery pack in this paper [2]. However, these two objectives are opposite to a certain extent. That is to say, the larger the strength is, the larger the mass will be. As a result, an optimal solution is obtained only under national standard.

2. FINITE ELEMENT MODEL OF BATTERY PACK

The hard spot size is extracted from a known EV frame to get basic size of battery pack, quantity and distribution of fixed points, position and dimension of bolt hole between frame and body based on dimension and quantity of battery modules. After geometric modeling, model simplification, simulation of connection between components, and material attributes, the finite element model of battery pack is built in LsDyna simulation, as shown in Fig. 1.

![Finite element model of battery pack](image)

Figure 1. Finite element model of battery pack

The principal parameters of the model are shown in TABLE 1.

| Material of box | Total mass | Rated energy | Rated voltage | Rated capacity |
|----------------|------------|--------------|---------------|---------------|
| Q235           | 290.2kg    | 20.67kwh     | 313.2v        | 66Ah          |

| Unit mass control | Proportion |
|-------------------|------------|
| Warpage≤15        | 100%       |
| Length≥1          | 99%        |
| Aspect≤5          | 100%       |
| Jacobian≥0.6      | 99%        |
| Min angle(quads)≥40° | 100%     |
| Max angle(quads)≤140° | 100%    |
| Min angle(trias)≥20° | 100%     |
| Max angle(trias)≤120° | 100%     |

| % of trias        | 1.7%       |
| Tet collapse≥0.1  | 100%       |

Conditions of simulation experiment: A semi-cylinder with radius 75mm and length larger than height of tested object but within 1m is used to extrude the battery pack system respectively from X & Y-direction. It shall be waited for 10min when extrusion force reaches 200KN or extrusion level reaches 30% of overall dimension at extrusion direction.
3. BUILDING MULTI-OBJECTIVE OPTIMIZATION MODEL

3.1. Building multi-objective optimization model

The structural dimensions of battery pack $x_1$, $x_2$ & $x_3$ are shown in Fig. 2.

![Battery pack structure](image)

Optimization objective:
Because the structure of battery pack has significant influences on safety of battery, responses of three important components, & as shown below are calculated to evaluate structural safety. Meanwhile, in order to obtain light-weight vehicle, component mass shall be controlled to a low level. However, their strength and mass are opposite under known material attributes. In consequence, the multi-objective optimization algorithm shall be used to calculate optimal solution meeting process requirements as below:

$$\begin{align*}
\text{Minimize } & f(x_1, x_2), m(x_1, x_2) \\
\text{s.t. } & 1.5\text{mm} \ll x_1 \ll 3\text{mm} \\
& 2.5\text{mm} \ll x_2 \ll 4\text{mm} \\
& 0.5\text{mm} \ll x_3 \ll 2\text{mm}
\end{align*}$$

Optimization objective: Minimum deformation of battery pack f and minimum mass of design structure m.

3.2. Building Surrogate Models based on RBF

Despite high precision and easy modeling, traditional optimization method by direct search is time-consuming. Here the Surrogate Models is used. A certain number of sample points are obtained through experimental design, and then used to build an Surrogate Models with optimization software after Lsdyana calculation. When error analysis is made to verify accuracy of the obtained Surrogate Models, optimization design is implemented with a certain algorithm to get optimal result.

RBF neural network has similar structure with BP neural network, faster convergence rate and approximation to any non-linear function. It has three structures as shown in Fig. 3, including input layer, hidden layer and output layer. The node on input layer sends input signal to hidden layer on which node has local response to input signal and Gaussian function is usually used here. Besides, node on output layer is usually a linear function. The transformation from input layer space to hidden layer space is non-linear, but it is linear from hidden layer space to output layer space [3].
It is necessary to set two parameters in order to build an Surrogate Models based on RBF neural network, of which one is the basis function. With various forms, the basis function is an action function of node on hidden layer of RBF neural network. This paper selects radial basis function which uses Euclidean distance between target point and sample point as independent variable, being a typical Surrogate Models. It is featured with high flexibility and efficiency, and simple structure.

The activation function of RBF neural network can be expressed as:

$$ f(x) = \sum_{i=1}^{h} w_{ij} \exp \left( - \frac{1}{2\sigma^2} \| x_p - c_i \|^2 \right) $$

where, “$x_p$” is the pth input sample; “$c_i$” is the ith center point; “$h$” is the number of nodes on hidden layer; and “$n$” is the number of output samples or categories. The obtained output from RBF neural network is:

$$ y_j = \sum_{i=1}^{h} w_{ij} \exp \left( - \frac{1}{2\sigma^2} \| x_p - c_i \|^2 \right) j = 1,2,\ldots,n $$

Definitely, the loss function with least squares can be expressed as:

$$ \sigma = \frac{1}{p} \sum_{j} \| d_j - y_j c_i \|^2 $$

The other parameter is smoothing filter which is used for releasing RBF requirement of passing through each data point approximately. It aims to eliminate noise. This filter works in Euclidean space with normalized domain $[0,1]$ where the cluster is executed. Besides, its allowable maximum is 0.1. From the view of mathematics, there are at most 10 sample points for clustering in each input. Therefore, the smoothing filter is taken with value 0.1.

The initial sample points are selected through design of experiments (DOE). As a method based on probability theory and statistical theory, DOE effectively and properly selects finite sample points in design space to reflect features of this space [4]. The selected 30 scientific sample points that have uniform distribution are shown in Fig.4.
The accuracy test is executed for Surrogate Models, in which R² and average error rate e are used as indexes. It can be observed from results in TABLE 2 that accuracy is high, i.e. the closer R gets to 1, the better.

**TABLE 2 ACCURACY TEST INDEX FOR SURROGATE MODEL**

| Objectives | R²  | e    |
|------------|-----|------|
| m          | 0.99| 0.0025|
| f          | 0.99| 0.0033|

3.3. Calculation with NSGA-II algorithm

NSGA-II algorithm is used to achieve multi-objective optimization for process parameters and obtain the intermediate solution between above two optimization objectives[5]. The parameter setting for NSGA-II algorithm is shown in TABLE 3. The mathematical relationship between mass and deformation of three components of battery pack is provided by RBF neural network in the process of multi-objective optimization.

**TABLE 3 NSGA-II PARAMETER SETTING**

| Option                   | Value |
|--------------------------|-------|
| Population Size          | 12    |
| Number of Generation     | 100   |
| Crossover Probability    | 0.9   |
| Crossover Distribution   | 10.0  |
| Mutation Distribution    | 20.0  |

All intermediate solutions calculated with NSGA-II algorithm are non-inferior solutions. That is to say, there is not any solution that is superior to above solutions on these two optimization objectives. The Fig. 5 shows Pareto Optimal Front that consists of above non-inferior solutions. For multi-objective problem, there is optimal solution set only instead of unique optimal solution. It can be observed from Pareto Optimal Front that decreasing component mass may result in increased deformation of battery pack. Therefore, Pareto Optimal Front tends to incline towards the lower right. Generally, the comprehensive optimal solution of above two optimization objectives (i.e. intermediate non-inferior solution) will be selected as applicable process parameters.
Based on practical demands in engineering, it is considered that mass and safety are equally important, so that the optimal scheme is to calculate minimum weighted sum between the mass $m$ and the minimum deformation $f$ and then compare the result with actual data. The error and performance improvement are shown in TABLE 4. It can be seen that the mass declines 17.62% and the maximum deformation decreases 30.78%.

| Model         | Parameters | Predicted value | Real value | Error  |
|---------------|------------|-----------------|------------|--------|
| Baseline scheme | $x_1$      | /               | 3          |        |
|               | $x_2$      | /               | 2          |        |
|               | $x_3$      | /               | 1.5        |        |
|               | $m$        | /               | 5.51       |        |
|               | $f$        | /               | 200.12     |        |
| Optimal scheme | $x_1$      | /               | 1.58       |        |
|               | $x_2$      | /               | 2.82       |        |
|               | $x_3$      | /               | 0.66       |        |
|               | $m$        | 4.55            | 4.539      | 0.24%  |
|               | $f$        | 136.89          | 138.53     | 1.20%  |

Through comparing results of extrusion and simulation experiment for battery pack model before and after optimization shown in Fig. 6 & Fig. 7, it can be observed clearly that deformation of battery pack after optimization is greatly smaller than the one before optimization, so that the multi-objective optimization task can be completed better with this optimization strategy.
Figure 7. Deformation in extrusion test after optimization

4. CONCLUSIONS
This paper has used the Surrogate Models algorithm based on RBF neural network to solve the problem of multi-objective optimization. The cost of traditional optimization method by direct search is high because of its massive calculations and long consumption time. Therefore, the Surrogate Models is used for optimization in order to decrease calculation time and optimization cost. In consideration of modeling stability, prediction accuracy and stability, RBF neural network is considered as an applicable Surrogate Models under experimental conditions in this paper, because it can describe internal correlation between component mass and extrusion & deformation of battery pack with high accuracy and stability. According to simulation results, it can achieve the multi-objective optimization including light weight and strength of battery pack better with RBF neural network and NSGA-II algorithm. In addition, design parameters of battery pack can be selected from Pareto Optimal Front based on different engineering applications.

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