Research on Reverse Engineering of Mechanical Characteristic Parameters of Materials in Collision Simulation

Zechen Fan*
Qingdao Taihong track equipment Co., Ltd, Shandong Qingdao 266000, China

*Corresponding author email: zhang.xiaohui@qdtaihong.cn

Abstract. The setting of material mechanical characteristic parameters in collision simulation has a great influence on the accuracy of simulation results. Taking the energy absorbing box as the research object, based on the inverse method of energy absorption box test data, finite element simulation, test design and genetic algorithm, the mechanical characteristic parameters of energy absorption box materials are optimized and the initial peak force and the platform force of the force displacement curve obtained from the quasi-static compression test are taken as the evaluation criteria. According to the price standard, the optimized reverse parameters are applied to the simulation model for calculation, and the simulation data are compared with the test data. The results show that the force displacement curve obtained by the simulation model is basically consistent with the overall change trend of the force displacement curve obtained by the test, and the error between the simulation data and the test data is small.

Keywords: Simulation of energy absorbing box; Material mechanics characteristic parameters; Reverse optimization.

1. Introduction
At present, Material parameters can be obtained by test method and reverse method\cite{1}. The real structure and test method are used in the actual test. The direct test needs to set the test conditions according to the impact attitude under three-dimensional conditions, and also needs to connect the energy absorption device with the test equipment. In the process of collision, the relative velocity of collision is very large, and the collision time is very short, which makes the energy absorbing device produce plastic deformation and large deformation, and the plastic deformation is uneven, and the test is destructive, so the whole process of the experiment needs to be monitored. In this case, it is not only expensive to directly measure the material parameters, but also difficult to operate, and the reliability of the test is difficult Guarantee. In recent years, thanks to the great improvement of computer performance, with the help of the existing mature finite element simulation software, many scholars through the combination of experiment, simulation and optimization algorithm to reverse optimize the material parameters. The material parameters measured by the reverse method\cite{2}, not only can shorten the time of obtaining the material parameters, but also has high accuracy of obtaining the material parameters, less consumption of human and financial resources, easy to reuse and high operability, which makes up for the shortcomings of direct experimental research. Therefore, taking the force displacement curve of the energy absorbing box measured by the quasi-static compression test as a reference, the mechanical characteristic parameters of the energy absorbing box material are designed, and then the mechanical characteristic parameters of the energy absorbing box simulation material are determined by the inverse method of the combination of approximate model and genetic algorithm.
In the process of collision simulation, reverse optimization of various material parameters has always been the focus of many scholars. Liu\cite{3} proposed a reverse method based on the combination of tube side pressure experiment, numerical simulation, regression analysis and genetic algorithm to determine the compression stress-strain relationship of thin-walled tube. In this method, based on the numerical simulation and regression analysis, the explicit expression between the macro deformation and the material parameters is established, and then the genetic algorithm is used to reverse the material parameters until convergence. The prediction accuracy and efficiency of this method are higher than that of the traditional reverse method through comparison with the experiment. Gao Hui\cite{4} et al. Used the average impact force data under different impact speeds in the crash test of energy absorbing tubes commonly used in vehicle crashworthiness design and combined with genetic algorithm to get the plastic hardening parameters and strain rate parameters of high-strength steel, which greatly reduce the experimental cost and improve the calculation efficiency. Zhang Yong\cite{5} et al. Based on the force displacement curve in the collision experiment of high strength steel DP800 energy absorbing beam, combined the small population genetic algorithm with the sequential response surface approximation model, and calculated the parameters of its JC model. This paper takes the force displacement curve measured by the quasi-static compression test of the energy absorbing box as a reference, takes the characteristic value on the mechanical characteristic curve of the energy absorbing box as a variable, carries out the inverse optimization of the material mechanical characteristic parameters of the base material, and obtains the mechanical characteristic parameters of the energy absorbing box imitating the real material with high accuracy.

2. Establishment of Simulation Model of Energy Absorbing Box

According to the actual test size of the energy absorbing box, three-dimensional modeling is carried out in software, and finite element mesh is divided whole finite element model is divided by four node shell element mesh. The calculation accuracy is considered according to the actual model, and the size of the model mesh is set as 8mm. The finite element mesh is completed and imported into the PAM crash software. Set the solution condition and constraint loading according to the actual test condition of energy absorption box compression, and the simulation finite element model of energy absorption box is shown in Figure 1. Then the finite element model of the energy absorbing box is simulated.

![Figure 1. The finite element model of energy absorbing box.](image)

3. Evaluation Criterion

In order to judge the validity and accuracy of simulation results more effectively, referring to the discussion of relevant literature\cite{6-8}, two parameters of initial peak force and platform force of energy absorption box compression are used as evaluation criteria. The definitions of initial peak force and platform force are as follows:

1. The initial peak force is the initial maximum peak force in the initial compression stage of the colliding energy absorbing box. That is, the peak force of the first wave peak is reached in the force stroke curve.

2. The platform force is the average value of the force displacement curve in the stage of platform force. Because it is difficult to determine the value range of the platform collision force stage, resulting in the inability to obtain an absolutely accurate mean platform force. There are different methods for the value of the platform force in each literature. In this paper, the data from the first
trough position after the maximum peak force to the last trough position of the final compaction point is used as the value range of the platform force stage to calculate the platform force, as shown in Figure 2.

According to the above criteria, the initial peak force of the compression test of the energy absorbing box is 325 kN, and the platform force is 190.35 kN.

4. Reverse Calculation of Mechanical Characteristic Parameters of Materials

4.1. Design of Experiment

The stress-strain characteristics of metal materials in the plastic deformation stage are non-linear. In the simulation process, the non-linear mechanical characteristics of materials can be described by two parameters, elastic limit and tangent modulus, the accuracy of these two parameters has a great impact on the accuracy of the simulation results. Therefore, this paper takes these two parameters as optimization objectives. In the Pam-crash software, the nonlinear mechanical parameters of materials are defined by curve input, and the elastic limit and tangent modulus of materials are determined by defining two characteristic points.

As shown in Figure 3, the value of the material mechanics characteristic curve in Pam-crash software represents the elastic limit of the material, and the value of $\sigma_1$ represents the elastic limit of the material, and the slope of the curve represents the tangent modulus of the material. Intuitively, defining the characteristic curve requires the abscissa and ordinate values of two points, four variables in total, but in reality, the abscissa value of the characteristic value 1 point is the starting point of the curve, and its abscissa value is always zero, so $\sigma_2 = 0$. For the characteristic value 2 point, if the abscissa of two points is defined as constant, then only the value of $\varepsilon_2$ is given, the whole curve can be determined, that is, at this time, the optimization variables are reduced from four to two. Therefore, define $\varepsilon_1 = 0$, $\varepsilon_2 = 0.225$ as constant, and define $\sigma_1$ and $\sigma_2$ as variables. Since the base material is low carbon steel. According to its actual mechanical property range, set the value range of...
\( \sigma_1 \) as 0.2-0.3, and \( \sigma_2 \) as 0.4-0.5.

Considering the fitting accuracy of the approximate model and the calculation time and other factors, take 10 sample points within the stress value range, calculate the corresponding response value of the sample points, and record 10 sample points and the corresponding response value in Table 1.

\[
\text{Table 1. Latin hypercube design.}
\]

| Sample points | \( \sigma_1 \) | \( \sigma_2 \) | The initial peak force(KN) | The platform force(KN) |
|---------------|----------------|----------------|--------------------------|-----------------------|
| 1             | 0.2            | 0.4            | 272                      | 150.17                |
| 2             | 0.21           | 0.41           | 283                      | 153                   |
| 3             | 0.22           | 0.43           | 294                      | 160.19                |
| 4             | 0.23           | 0.47           | 305                      | 167.61                |
| 5             | 0.24           | 0.5            | 318                      | 174.86                |
| 6             | 0.26           | 0.42           | 321                      | 164.55                |
| 7             | 0.27           | 0.44           | 331                      | 172.91                |
| 8             | 0.28           | 0.48           | 341                      | 183.41                |
| 9             | 0.29           | 0.46           | 348                      | 181.04                |
| 10            | 0.30           | 0.49           | 366                      | 193.99                |

4.2. Radial Basis Function Model

The radial basis function model is constructed by interpolation. The overall data interpolation is required for the reverse optimization. Therefore, the inverse multiple quadratic basis function is selected as the radial basis core function. The radial basis function is in the form of:

\[
f(x) = \sum_{j=1}^{n} \lambda_j \varphi(r_{ij})
\]

\[
\varphi(r) = (r^2 + c^2)^{-\frac{1}{2}}
\]

\[
r_{ij} = \left\| x_i - x_j \right\|_2 = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}
\]

Where: \( n \) is the number of sample points; \( \lambda_i (i = 1, 2, \cdots, m) \) is the regression coefficient; \( \varphi(r_{ij}) \) is the inverse multiple quadratic basis function; \( r_{ij} \) is the Euclidean distance.

Take the sample points into equation (2) and get the following equation:

\[
B\beta = F
\]

Where: \( \beta = [\lambda_1 \lambda_2 \cdots \lambda_n]^T \); \( F = [y_1 \ y_2 \ y_3 \ \cdots \ y_n]^T \); \( B_{ij} = \varphi(r_{ij}) \); \( i, j = (1, 2, 3, \cdots n) \)

The regression coefficient \( \lambda_i \) and the radial basis function model are obtained.

4.3. Optimization Algorithm Selection and Calculation

There are two variables in the inverse optimization, so it is a multi-objective optimization problem, which leads to the increase of the optimization complexity. Because NSGA-II algorithm has a new hierarchical fast non-dominated sorting method, which can reduce the optimization complexity. Moreover, niche technology and elitist strategy are also adopted, which can make it possible to keep the diversity of the population at the same time, and in the process of continuous iteration, it ensures that the population evolves in a better direction and converges to the approximate optimal solution quickly. Therefore, NSGA - II algorithm is used for the optimization calculation.
NSGA-II algorithm carries out optimization inverse calculation. When the optimization result is close enough to the experimental data, $\sigma_1 = 0.27, \; \sigma_2 = 0.49$, the initial peak force is 330KN, and the platform force is 185.32KN. The error between the optimization result and the experimental result is compared. As shown in Table 2.

**Table 2.** Comparison between optimization results and experimental result.

|                       | The initial peak force (KN) | The platform force (KN) |
|-----------------------|-----------------------------|------------------------|
| Reverse optimization  | 330                         | 185.32                 |
| Test result           | 325                         | 190.35                 |
| Error value           | 1.54%                       | 2.64%                  |

It can be seen from the table that the error of initial peak force and the platform force between the optimization results and test results is small. It shows that the precision of reverse optimization is high.

**5. Verification of Mechanical Characteristic Parameters of Materials**

The mechanical characteristic parameters obtained from the optimization calculation are input into the simulation model of the energy absorbing box in order to carry out the simulation calculation. And the simulation data is used to be compared with the test data to verify the effectiveness of the parameters obtained from the reverse optimization.

The error comparison between simulation data and test data is shown in Table 3, and the change trend of force-displacement curve and test force-displacement curve of simulation model is shown in Figure 4.

**Table 3.** Comparison between simulation results and test results

|                       | The initial peak force (KN) | The platform force (KN) |
|-----------------------|-----------------------------|------------------------|
| Simulation result     | 328                         | 187.56                 |
| Test result           | 325                         | 190.35                 |
| Error value           | 0.92%                       | 0.53%                  |

**Figure 4.** Force stroke curve of simulation and test.
In Table 3, it can be seen that the error of initial peak force and the platform force are less than 1%. In Figure 4, it can be seen that of reverse optimized force displacement curve is basically the same as that of test force displacement curve. Compare the total energy absorption curve from simulation calculation results with that from test results, as shown in Figure 5, it can be seen that the total energy absorption of both The overall trend of the displacement curve is the same, the total energy absorption at the compaction site is close, the accuracy of the finite element simulation model is better, and the material parameters obtained from the reverse optimization are effective.

6. Conclusion
The mechanical characteristic parameters of the base material of the energy absorbing box are obtained by using the inverse optimization method which combines the test data of the energy absorbing box, the finite element simulation, the test design and the genetic algorithm. The optimized material parameters are taken as the input to carry out the compression simulation of the energy absorbing box. The initial peak force and the platform force of the comparative test and the simulated force displacement curve are compared, which proves that the parameters obtained are sufficient Precision, the reverse method of material parameters can get effective matrix material parameters to a certain extent, saving cost.

References
[1] Liu Jing, Li Lanyun. Plastic stress–strain relationship of thick-walled titanium alloy tube under compressive stress state[J]. Chinese Journal of non ferrous metals, 2016,26 (10): 2093-2101.
[2] Qiao Liang, song Xiaoxin, Xie Yanmin, Wang Jie, Wang Xinbao. Reverse and optimization of sheet forming parameters based on PSO—RBF Surrogate Model [J]. China Mechanical Engineering, 2014,25 (19): 2680-2685.
[3] J. Liu,H. Yang,H.W. Li,H. Li,S. Zhu. A new hybrid identification method for determining the material parameters of thin-walled tube under compressive stress state[J]. Materials and Design,2013,44.
[4] Gao Hui, Li Guangyao, Han Xu. Inverse identification of material parameters based on crash simulation and genetic algorithm [J]. China Mechanical Engineering, 2008 (22): 2714-2717.
[5] Zhang Yong, Lu Yong. Inverse method for material parameters estimation for high strength steel based on successive response surface method [J]. China Mechanical Engineering, 2010,21 (18): 2255-2259.
[6] Chen Yousong, sun Wanpeng, Research on energy-absorption characteristics of anti-collision beam with energy absorbing box based on low-speed frontal collision [J]. Modern manufacturing engineering, 2018 (03): 53-58.
[7] Xu Ping,Chi Kai. Energy distribution analysis and multi-objective optimization of a single tapered thin-walled square tubes with diaphragms [J]. Journal of Railway Science and Engineering, 2019,16(01): 185-191.
[8] Tang Chunqiu, Yuan Youli. Research on Anti-Bending Behavior of Thin-Walled Beam Based on Latin Hypercube Sampling [J]. Automotive technology, 2017 (05): 30-35.