Crashworthiness Optimization of Longitudinal Beam Based on Artificial Neural Network and Genetic Algorithm

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Abstract: A new optimization method was applied to the crashworthiness optimization design of the longitudinal beam of a domestic vehicle using a combination of Uniform Design, Finite Element Method, Artificial Neural Network and Genetic Algorithm. The finite element model of the longitudinal beam was built in Hypermesh, and validated by a sled crash test. According to the requirement of crashworthiness of longitudinal beam, the energy absorption, weight and maximum impact force were chosen as the optimization objects, and the plate thickness of 4 parts of the longitudinal beam were chosen as the design variables. The variable samples were attained by uniform design, and then calculated by LS-DYNA. A nonlinear mapping was built from design variables to optimization objects with artificial neural network. The mapping was optimized by genetic algorithm to obtain a most appropriate thickness compounding that is presented in the paper. The methodology used in the study show good capability of multi-parameters optimization.

Keywords: longitudinal beam; crashworthiness; artificial neural network; genetic algorithm; optimization design

1. Introduction

In recent years, many kinds of optimization methods and approximate models have been used in research projects about vehicle structure crashworthiness.

Zhang et al. [1] used a method using a multi-objective optimization based on stepwise regression model which was applied for the optimization design of the reinforced members of a vehicle. Yamazaki et al. [2] did a research on crashworthiness optimization of tubular structure. The approximate model was built using response surface method in the design space, which was built by orthogonal design of experiment, and then optimized with usual mathematical programming technique. Shi et al. [3] did a research on the technology to search all local optimization design points in the feasible space. They also built an accurate approximate model by holographic neural network. Chen [4] developed a practical optimization method of structure crashworthiness using genetic algorithm with global search capacity, and the instability of finite element method were considered.

As we can conclude from the literature review, widely used orthogonal design of experiment whose factor levels are strictly limited could hardly build a design space for factors with multi-levels, but according to the authors opinion uniform design could disperse them evenly. Response surface model could approximate mapping of few parameters of low orders with high accuracy, but it also may lead to pseudo-fitting model when the basic function or the number of order is inappropriate in multi-parameters approximation. This problem can be solved using the artificial neural network that can achieve nonlinear approximation with any number of input parameters and output objects, which is the common requirement in engineering field.

Therefore, the authors used in the study a multi- parameters optimization method of vehicle body structure with uniform design, finite element method, artificial neural network and genetic algorithm, which was applied in optimization design of the longitudinal beam of a domestic vehicle regarding crashworthiness.

2. Optimization Method

The process of the optimization method proposed in the paper is shown in Figure 1. Major steps of this process are as follows:

(a) Determination of the optimization objects according to requirements of collision safety, and selecting optimal parameters and its range considering the limits of packaging, load conditions and manufacturing process of vehicle body parts.

(b) Dispersing the optimal parameters in the design space using uniform design. In order to improve the model accuracy, more artificial dispersed samples could be added appropriately.

(c) Simulation of dispersed samples with finite element method.

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(d) Training the neural network according to the calculating results of finite element method, evaluating the network by the mean square error. This error is optimized by changing the number of hidden layer units until it meets the established accuracy.

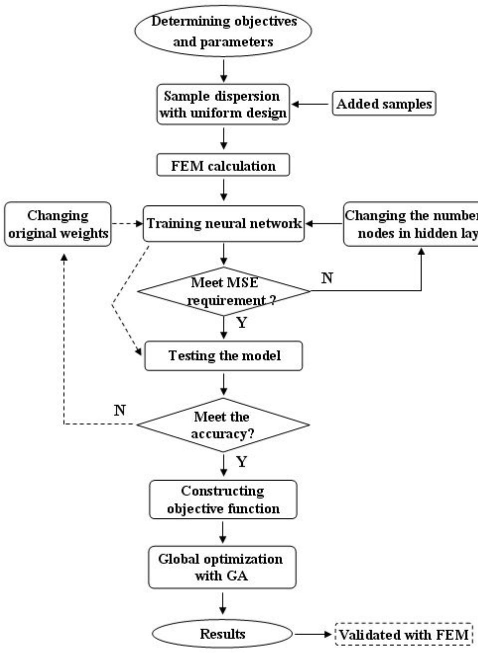

Figure 1. The process of optimization

(e) Testing the neural network model which meets the requirement of the mean square error, improving the accuracy from predictive to actual value by changing the initial weights until the network meets the requirement.

(f) Considering requirements and regulations of each object, gaining the objective function to be optimized by weighted combination of multiple targets.

(g) Global optimization of the objective function using genetic algorithm.

(h) Validation of the obtained optimal results by finite element method simulation.

3. Crashworthiness Optimization Design of Longitudinal Beam

3.1. Problem Description

In the car collision, impact kinetic energy should be absorbed by the front compartment of vehicle body to reduce the impact on passengers. The energy absorption capacity of longitudinal beam that is the main absorbing component in this compartment is the most important measurement of this structure. The maximum impact force on the longitudinal beam in the collision process is also an important factor to be considered. Lowering the maximum impact force can effectively reduce the maximum acceleration value of the vehicle in the collision, thus reducing the damage suffered by the passengers [5]. Vehicle lightening is one of the most fundamental ways to save energy and improve fuel economy. According to statistics, the fuel consumption can be reduced by 6% to 8% when 10% of vehicle weight is reduced [6]. Therefore, the energy absorption capacity, maximum impact force, and the weight of longitudinal beam are three main factors to be considered in structure optimization.

The model to be optimized is the front part of the longitudinal beam from a domestic vehicle, and its structure is shown in Figure 2.

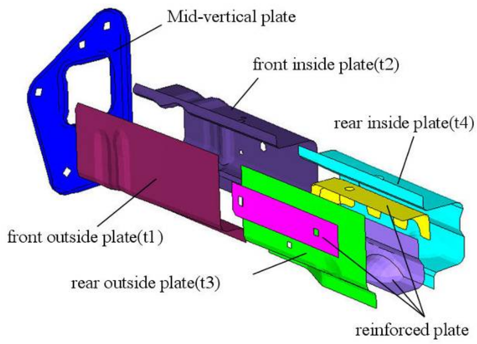

Figure 2. Structure of the longitudinal beam

The total length of the longitudinal beam is 470 mm, width transversal section is 76 mm and the height is 120 mm. The inside and outside plates are connected by flanging spot-weld, while front and rear parts by tailor-weld. The length of front part is 250 mm with thickness of 1.8 mm; the rear part's length is 220 mm with thickness of 2.2 mm. There are three plates on the rear part to enhance stiffness.

The size of longitudinal beam should fit suspension system and engine installation, therefore only the sheet thickness, material, and some minor details of this structure could be optimized. Several laboratory tests performed in connection to the study show that changing the thickness of the metal sheet influences the deformation modes, energy absorption and maximum impact force strongly.

The authors attempt to obtain a most optimal combination of plate thickness of the longitudinal beam's four main parts considering the requirements of energy absorption, maximum impact force and weight.

3.2. FE Model Used in the Study

The finite element model of longitudinal beam used in optimization mounted on the sled was built in Hypermesh according to the real sled. The whole model was meshed with 4 or 3 nodes shell elements. The element basic size of sled is 50 mm, and 5 mm of longitudinal beam. The material of front part of the beam is B340/DP590, and the rear part is SAPH440. The tailor-weld is simulated with coinciding nodes, and the flanging spot-weld of inside and outside plates is simulated by solid spot-weld elements with the size of 6.5×6.5 mm according to its actual number and locations. Considering that the sled has no deformation in the collision, the rigid material type MAT20 was chosen. The contact between rigid wall and longitudinal beam was defined with a friction coefficient of 0.6. The automatic single surface was chosen as the contact type of longitudinal beam, friction coefficient is 0.2. Mass elements were added to simulate the counterweight and data acquisition device to make the total weight and the location of centre of gravity of simulated model consistent with real test equipment. Because the total energy of the model is very large due to high speed of 50 km/h therefore two assisting energy absorption tubes were added on both sides of the longitudinal beam to avoid the sled hitting the rigid wall when the beam was completely crushed or instability of the sled. The gravity acceleration in all simulations is set to 9.8 m/s^2. The test equipment and finite element model is shown in Figure 3.

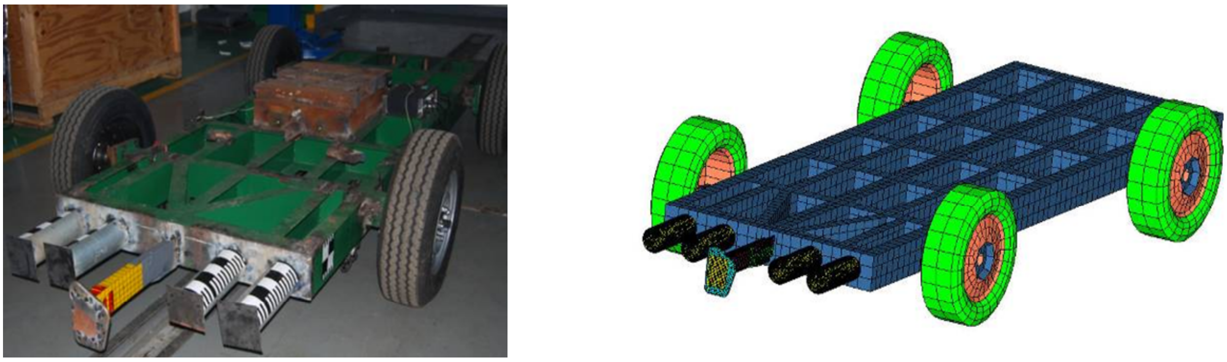

Figure 3. Rail-sled test and simulation model

In order to validate the finite element model, a test of the longitudinal beam mounted on the sled was performed in the Laboratory of Automotive Safety Crash in Hunan University under completely the same boundary conditions.

The comparison of deformation between test and simulation after collision is shown in Figure 4.

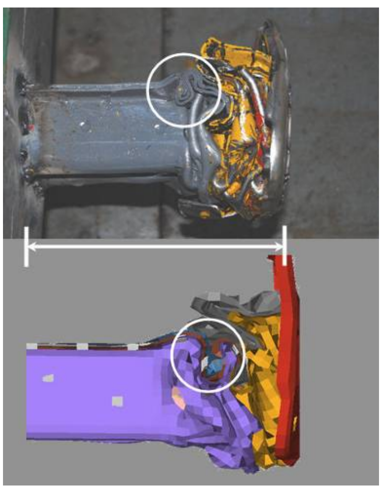

Figure 4. Deformation comparison between test and simulation

It shows that the similarity of deformation mode and final form between test and simulation is quite high.

Generally, the acceleration time history curve is used to verifying the accuracy of FE model. The model is considered to be correct when the difference between test and simulation is within 20% [7]. The acceleration time history curves of sled test and simulation are shown in Figure 5.

The coincidence of the two curves is very high with the same collision duration, almost the same number of peaks and little difference between them. Therefore the model was approved for our study.

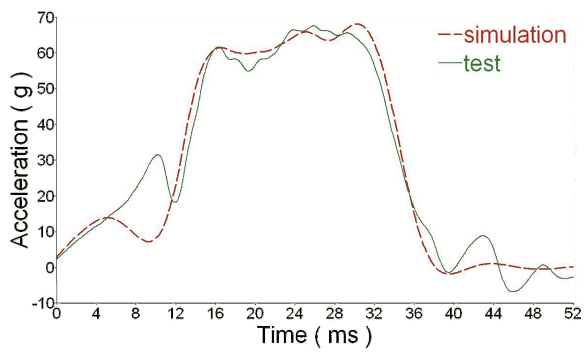

Figure 5. Acceleration curves of test and simulation

3.3. Optimization Design Space

According to the problem description in the paragraph 3.1, the energy absorption (E), weight (m) and maximum impact force (F) were chosen as the optimization objects, and the thickness of front outside plate (t1), front inside plate (t2), rear outside plate (t3), rear inside plate (t4) were chosen as the variables for optimization, see Figure 2 for details.

The range of variables determined by engineering practice is shown in Table 1.

Table 1. Range of optimal variables

variables	t1 [mm]	t2 [mm]	t3 [mm]	t4 [mm]
upper	1.2	1.2	1.6	1.6
lower	2.4	2.4	2.8	2.8

3.4. Acquisition of Training Samples

Uniform design was used to disperse the samples with multi-levels. Uniform design [8] was first proposed by Chinese mathematicians Fang and Wang in 1978. This method is efficient to solve problems with multi-variables and multi-levels and commonly used in recent years. The experimental points are uniformly dispersed within the design space; therefore a more comprehensive understanding of the object could be obtained.

The uniform design disperses samples through a carefully designed table. Each uniform design table has a code named $U_n(q^s)$ or $U_n*(q^s)$, where U means uniform design, n is the number of tests, q is the number of each factor's levels, s is the columns of the table. $U_n(q^s)$ and $U_n*(q^s)$ are two different type of uniform design table, Generally $U_n*(q^s)$ has better uniformity, which should be chosen firstly, but $U_n(q^s)$ could arrange more factors. When the number of factors is too large to be arranged in $U_n*(q^s)$, the $U_n(q^s)$ can be used. Each uniform design table has an additional table, which indicates how we choose the appropriate columns and the deviation of the test program formed by those columns.

In order to examine the various factors fully within the scope of design space, 25 levels of each factor were taken into simulation. We choose the uniform design table of $U_{25}*(25^{11})$, deviation of the uniform design is D = 0.1210.

After dispersing the samples, the finite element models of each test were built with Hypermesh and simulated with LS-DYNA. The experimental design program and simulation results are shown in Table 2.

Aim to provide the neural network a sufficient number of training samples to ensure precision, 40 samples were artificially added from additional simulations with LS-DYNA of randomly selected samples. Due to the limited space, no details would be listed here. The 50 samples in all the 65 groups were used to train the network, and the remaining 15 samples were used to test the accuracy of the network.

3.5. Training and Testing of the Neural Network

Artificial Neural Network (ANN) is a kind of network system, which is interconnected with a large number of simple units [9]. Neural network has many network models, such as BP network, RBF network and so on. The BP network used in the study is a multi-layer network using Widrow-Hoff learning algorithm and nonlinear differentiable transfer function. It is suitable for prediction, pattern recognition and nonlinear function approximation.

Table 2. Experimental design and simulation results

	t1 [mm]	t2 [mm]	t3 [mm]	t4 [mm]	*F* [kN]	*E* [kJ]	*m* [kg]
1	1.4	1.5	2.0	2.8	94.45	34.90	3.04
2	1.65	1.85	2.45	2.75	131.33	36.89	3.33
3	1.9	2.2	1.6	2.7	180.18	35.41	3.32
4	2.15	1.25	2.05	2.65	118.99	33.75	3.13
5	2.4	1.6	2.5	2.6	148.77	36.90	3.42
6	1.35	1.95	1.65	2.55	141.84	34.47	3.02
7	1.6	2.3	2.1	2.5	195.12	39.01	3.31
8	1.85	1.35	2.55	2.45	123.46	35.35	3.13
9	2.1	1.7	1.7	2.4	137.43	34.68	3.11
10	2.35	2.05	2.15	2.35	161.62	36.56	3.4
11	1.3	2.4	2.6	2.3	177.48	38.55	3.31
12	1.55	1.45	1.75	2.25	110.37	30.82	2.82
13	1.8	1.8	2.2	2.2	140.61	35.45	3.11
14	2.05	2.15	2.65	2.15	159.37	37.43	3.4
15	2.3	1.2	1.8	2.1	129.2	29.54	2.91
16	1.25	1.55	2.25	2.05	99.86	30.60	2.82
17	1.5	1.9	2.7	2.0	131.75	35.57	3.11
18	1.75	2.25	1.85	1.95	175.46	29.63	3.1
19	2.0	1.3	2.3	1.9	132.61	32.46	2.91
20	2.25	1.65	2.75	1.85	143.7	34.18	3.2
21	1.2	2.0	1.9	1.8	150.66	29.58	2.8
22	1.45	2.35	2.35	1.75	152.64	31.08	3.09
23	1.7	1.4	2.8	1.7	125.97	31.62	2.9
24	1.95	1.75	1.95	1.65	160.44	23.33	2.89
25	2.2	2.1	2.4	1.6	138.07	29.52	3.18

BP net work consists of the input layer, hidden layer, output layer and weights of node connection between the layers. Input layer accepts the input signals that are weighted and passes them to the hidden layer, and then hidden layer nodes weighted and removed these signals' threshold and pass them to the output layer. The transfer function of hidden layer is *tansig*, and *purelin* of output layer. To ensure the convergence of the simulation, the sample data is normalized so that all input and output data is in [0, 1].

There are four input parameters in the optimization design, namely $X_{4\times1}$= [t1, t2, t3, t4]^T, and three output parameters namely $A_{3\times1}$=[$E(X)$, $M(X)$, $F(X)$]^T. A BP network model was built with three layers, namely 4×n×3, where n is the number of hidden layer nodes. There is no theoretical guidance of the number of hidden layer nodes, but we can obtain the number with minimum network mean square error (MSE) by a group of testing calculation. The MSE of the neural network is an important criterion to measure the accuracy of the network which is defined as *Eq* (1) below:

$$MSE = \sqrt{\frac{1}{NP}\sum_{j=1}^{N}\sum_{i=1}^{P}(t_{ij}-o_{ij})^2} \qquad (1)$$

Where

N — training set of samples

P — number of network output units

t_{ij} — true value of output from i unit when input sample is j

o_{ij} — predictive value of output from i unit when input sample is j

The change of MSE is shown as Figure 6 when the number of hidden layer nodes changes from 7 to 18.

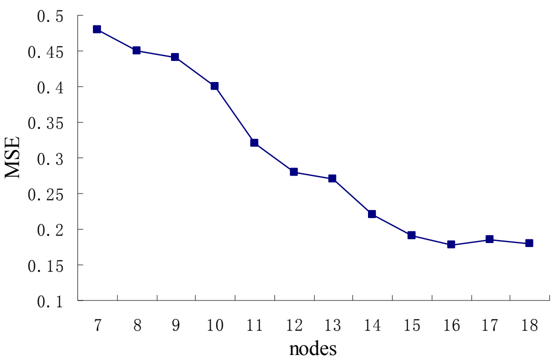

Figure 6. Change of MSE with number of hidden nodes

The MSE reaches a minimum value of 0.178 when the number of hidden layer nodes is sixteen; therefore we built a 4×16×3 BP neural network.

Using the neural network toolbox in Matlab, the network was trained by calling the train function with collected samples. The network was tested with 15 samples, and training it again by changing the initial nodes weight until the network meets precision requirement. The final test results from the training of neural network in comparison to those from LS-DYNA simulations are shown in Figure 7. It should be mentioned here that all the values on vertical axis had been normalized already.

It can be seen from the test results that the neural network model prediction and the finite element calculation results are consistent in trend. The difference between prediction and calculation are very small, where the difference in energy absorption is 4.5%, maximum impact force is 6.3%, and weight is 1.3%. Considering the instability of finite element method, the accuracy requirement of the model had been met. A 3×1 implicit function matrix A has been obtained, namely A=*sim*(net, X).

Then the corresponding optimization objects are $E(X)$=[1, 0, 0]A, $M(X)$=[0, 1, 0]A, $F(X)$=[0, 0, 1]A.

3.6. Constructing the Objective Function

Multi-objective problem was simplified to a single objective problem by weighted method. The objective function $O(X)$ was constructed as shown in *Eq*. (2):

$$O(X) = \lambda_1 E(X) + \lambda_2 M(X) + \lambda_3 F(X) \qquad (2)$$

where X is the design variable, namely the thickness of four parts in the longitudinal beam; $E(X)$ is the energy absorption; $M(X)$ is the weight; $F(X)$ is the maximum impact force; λ_1, λ_2 and λ_3 is the weight coefficient of each object.

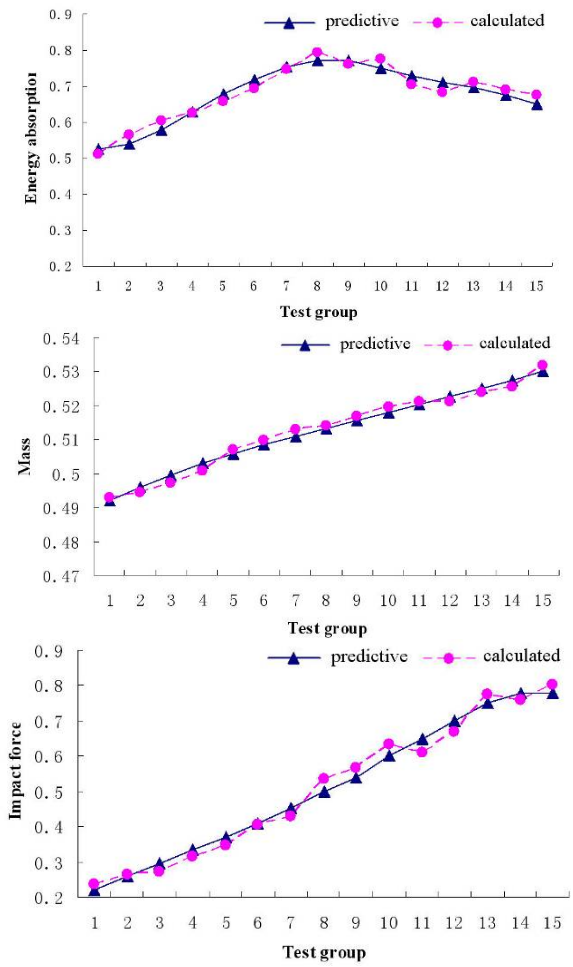

Figure 7. Test results of the neural network

The objective function described with matrix form in Matlab is shown as *Eq*. (3):

$$O_{1\times1} = [\lambda_1, \lambda_2, \lambda_3]A_{3\times1} \qquad (3)$$

The energy absorption of original design was 34.54 kJ, and it should be increased in the optimal design, therefore it is required that E ≥ 34.54 kJ.

The results of several tests performed in connection to the study show that the peak acceleration during the collision is generally less than 25 g, and the weight of sled with all equipments is 1024 kg. According to the Newton' second law, it can be calculated that the maximum impact force should satisfy: $F_{max} \leq 250$kN.

The aim of optimization is to increase the energy absorption as much as possible in the case of limited increase of the weight and impact force. Considering all of the factors, $\lambda_1 = 0.7$, $\lambda_2 = -0.2$, $\lambda_3 = -0.1$ was selected.

Therefore the optimization problem can be described as follows:

$$
\begin{aligned}
&Max && O = [0.7, -0.2, -0.1]A \\
&s.t. && F(X) \leq 250 \\
& && E(X) \geq 34.54 \\
& && 1.2 \leq t1 \leq 2.4 \\
& && 1.2 \leq t2 \leq 2.4 \\
& && 1.6 \leq t3 \leq 2.8 \\
& && 1.6 \leq t4 \leq 2.8
\end{aligned}
$$

3.7. Global Optimization with Genetic Algorithm

Genetic Algorithm (GA) is an adaptive global probabilistic search algorithm deriving from biological science in genetics and evolutionary processes of the natural environment [10]. Practical application shows that GA is a good global optimal search algorithm which has a strong search capabilities and the ability to solve problems. It also has features of simple and robust, and is suitable for parallel processing, which don't need gradient calculation process.

The objective function was optimized using genetic algorithm toolbox in Matlab. The design variables were coded with real number. The initial population size is M=50, crossover probability is P_c=0.8, mutation probability is P_m=0.01, and the number of generations is 2000. In the optimization we used the objective function itself as the fitness function.

The optimal solution of design variables obtained by GA are *t1* = 1.587, *t2* = 2.212, *t3* = 2.077, *t4* = 2.573. In practical engineering applications, we can take *t1* = 1.6 mm, *t2* = 2.2 mm, *t3* = 2.0 mm, *t4* = 2.6 mm.

The thicknesses selected above were used in final LS-DYNA simulation to verify the effect of optimization (opt). These results are compared with results from simulation of original design (org) are shown in Table 3.

Table 3. Comparison between original and optimal design

	t1 [mm]	t2 [mm]	t3 [mm]	t4 [mm]	E [kJ]	m [kg]	F [kN]
org	1.8	1.8	2.2	2.2	34.54	3.11	164.72
opt	1.6	2.2	2.0	2.6	38.74	3.28	170.3
Imp	-	-	-	-	+12.2%	+5.5%	+3.4%

It can be seen from the comparison results that the energy absorption of the optimal design has significantly increased with limited increase of the weight and maximum impact force. The optimization purpose was achieved.

In engineering practice, the object and its importance in study is usually not certain, the methodology used in the study can easily be applied for various needs of optimization. These needs can be expressed easily by modification of the weight coefficients of the objective function.

4. Conclusions

The design optimization of crashworthiness of the longitudinal beam was evaluated by combination of uniform design, finite element method, artificial neural network and genetic algorithm. The optimal combination of plate thicknesses of four parts was obtained. The advantages of this methodology are: uniform design can disperse multilevel samples, neural network model can gain the nonlinear mapping from multi-parameter to multi- target, and the genetic algorithm can take global optimization to established neural network model. Compared to traditional optimization methods, this method is more consistent with the requirements in engineering field; It can be used for multi-parameter optimization of automotive structure.

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