Geometry Optimization of Sheet Specimen for the Measurement Accuracy Improvement in the Hopkinson Bar Based on Intelligent Algorithm

QINGHUA WANG1,3, FENG XU2,3, BO YANG4, LIJIE FENG4, DEDONG HUANG2,3, CHEN WANG2,3, AND BIN WU2,3

1School of Aeronautics, Northwestern Polytechnical University, Xi’an 710072, China
2School of Astronautics, Northwestern Polytechnical University, Xi’an 710072, China
3Qingdao Research Institute, Northwestern Polytechnical University, Qingdao 266200, China
4Shanghai Spaceflight Precision Machinery Institute, Shanghai 201600, China

Corresponding author: Feng Xu (xufeng@nwpu.edu.cn)

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ABSTRACT At present, the split Hopkinson tensile bar (SHTB) is widely used to determine the dynamic tensile properties of materials under high strain rates, in which sheet specimen with dogbone-shaped structure is commonly adopted. However, the geometry dimensions of the specimen used in different literatures vary widely and no uniform criterion has been formulated. In order to obtain the optimal specimen geometry associated with the best measurement accuracy in SHTB experiments, the specimen geometry influence on the measurement accuracy of SHTB experiments is investigated by using the finite element (FE) method, and several key indicators which can characterize the measurement accuracy of specimen are proposed based on simulation analysis. Orthogonal tests are designed to generate training samples for BP (back propagation) neural network, and the complex and highly nonlinear mapping between the structure parameters and measurement accuracy indicators of specimen is fitted by BP and then utilized for the fitness function design of genetic algorithm (GA). Finally, the optimal geometry as well dimensions of the SHTB sheet specimen are determined using GA. Meantime, the finite element simulations are carried out in further to verify the effectiveness of the optimized geometry of specimen. The results of this investigation will provide a recommendation for specimen geometry design and a basis for data reliability analysis in SHTB experiments.

INDEX TERMS Split Hopkinson tensile bar, specimen geometry, measurement accuracy, BP neural network, genetic algorithm.

I. INTRODUCTION

The use of split Hopkinson bar (SHB) set-ups to investigate the dynamic mechanical properties of materials under high strain rates ($10^2$-10$^4$ s$^{-1}$) is getting more and more popular in materials science [1]–[4]. Although the SHB facilities are usually used for torsion [5], compression [6] and tension [7] test under high strain rate, tensile and compression test are still prevalent in the users. In 1960, early studies of split Hopkinson tensile bar (SHTB) were proposed by Harding et al. [8], then improved by Ogawa [9]. Up to now, the SHTB has been commonly used to determine the dynamic tensile stress-strain curve of various materials.

In 2002, dogbone-shaped sheet specimen was firstly adopted by Huh et al. [10] to study the dynamic tensile mechanical behaviors of sheet metals. Then using the sheet specimen to investigate the dynamic tensile behaviors of materials has been increasingly popular, and in recent years, the sheet specimen with glue connection has been widely used in literatures [11]–[15]. However, the specimens are widely divergent in geometry (shape and dimensions) without uniform standards, more importantly, it is confirmed that the geometry of specimen has a significant influence on the dynamic mechanical behavior determined by experiments. Actually, assumptions related to measurement accuracy such
as the stresses in specimen being uniaxial, the strains of specimen being homogeneous, there’s no deformation in transition zones and the specimen is in a state of stress equilibrium are largely influenced by the geometry dimensions of specimen [10], [16], therefore, the dynamic mechanical behavior determined in SHTB experiments is a combination of structure and material response. Indeed, the importance of the specimen geometry dimensions to the measurement accuracy of SHTB experiments has been realized from the early stage, for example, machining specimen to eliminate the eccentric loading [8], adopting the shorter gage section (about 6.0mm) to obtain the stress equilibrium in specimen and adjusting specimen geometry to accurately determine the dynamic mechanical behavior. Furthermore, some studies have been done to optimize the specimen structure parameters to achieve improved measurement accuracy in the SHTB test. Huh et al. [10] optimized the gage length and gage width of sheet specimen using orthogonal design of experiment, in his study, in order to optimize the gage length, specimens with diverse gage length of 2, 6, 8, 12, 18 and 24mm were simulated when the gage width is fixed to be 6mm, finally, a gage length ranging form 2 to 8mm has been proved to be acceptable. The similar simulated process is also carried out to determine the optimum gage width, here, it can be seen that the value range of the parameters adopted in Huh’s work is discrete and very limited, thus the optimization result is confined to be a suboptimal solution. Beside the gage length and width, the influence of transition radius on experimental measurement accuracy was investigated by Verleysen et al. [16], in which the accuracy of experiments can be acceptable only when the ratio of gage length to gage width is greater than 1.25 and the radius in the transition zone is small enough. In general, although the control variates method is easily executed, the optimal geometry of the specimen is hard to be obtained due to the limitation and dispersion of the value range, thus, a global optimization program is urgently needed to obtain the global optimal solution for the geometry of the sheet specimen in SHTB test method.

In this study, a global optimization program based on BP (back propagation)-GA (genetic algorithm) mixed algorithms is proposed for SHTB sheet specimen optimization. A reference geometry of the specimen is firstly determined according to the different but representative geometries used in the published papers [11]–[15]. Then several key indicators characterizing the measurement accuracy of specimen are proposed on the basis of the finite element analysis (FEA) from the reference specimen. Orthogonal test with 6 factors and 5 levels is designed to generate different specimen geometries and the indicators reflecting the measurement accuracy of the various geometries are then obtained by FEA analysis. The BP neural network is used for fitting the non-linear mapping between the specimen structure parameters and indicators of measurement accuracy and then the reasonable fitness function is constructed based on the fitted non-linear mapping. Finally, adopting the constructed fitness function, genetic algorithm is utilized to search the optimal parameters of specimen geometry in the global scope.

II. SPLIT HOPKINSON TENSILE BAR SYSTEM

A. PRINCIPLE AND ASSUMPTIONS

A schematic diagram of the split Hopkinson tensile bar device is given in FIGURE 1. The device is mainly composed of three parts, namely the input bar, the transmission bar as well the striker tube, and the tensile specimen is sandwiched between the input bar and transmission bar. During the dynamic tensile experiment, a striker tube is driven by the high-pressure air in air gun to impact the front end of input bar. After that, a tensile wave namely the incident wave is generated in the input bar and propagates towards the specimen. When the incident wave reaches the interface between specimen and input bar, part of the incident wave continues to propagate along the transmission bar in the form of a tensile wave after passing through the specimen, and the other part of the incident wave is reflected back to the input bar in the form of a compressive wave and propagates along the input bar in the opposite direction of incident wave. The strains of incident, reflected and transmitted waves, $\varepsilon_i(t)$, $\varepsilon_r(t)$ and $\varepsilon_t(t)$ respectively, are measured by the strain gauges attached to the bars. The stress, strain and strain rate of the specimen during the dynamic tensile loading can be derived using the following equations [19]:

$$
\sigma_s = \frac{AE}{A_s} \varepsilon_t
$$

$$
\varepsilon_s = -\frac{2C_0}{L_s} \int_0^t \varepsilon_r \, d\tau
$$

$$
\dot{\varepsilon}_s = -\frac{2C_0}{L_s} \varepsilon_r
$$

where $A$ is the cross section area of specimen and $A_s$ is the cross section area of the bars, $L_s$ is the gage length of the specimen, $E$ is the elastic modulus of the bars and $C_0$ is the wave speed of the elastic wave in the bars.

Several basic and crucial assumptions have to be satisfied in the derivation of Equation (1) [16], [17], [19], [22], [23]:

![FIGURE 1. Schematic representation of a typical split Hopkinson tensile bar.](image-url)
i) The specimen is in a state of stress equilibrium, namely the stress values at the specimen interfaces with the input bar and transmission bar are equal. ii) The deformations occurring in the gage section of specimen are homogeneous. iii) The stress in the gage section of specimen is one-dimensional and the direction is along the axis. iv) The deformations in the transition zones of specimen is negligible. The satisfaction of the above basic assumptions is a prerequisite for the validity and accuracy of SHTB tests.

![Glue zone and transition zone](image)

**FIGURE 2.** Geometry for the specimen commonly used in Hopkinson tensile test.

### B. SHEET SPECIMEN AND REFERENCE SPECIMEN

FIGURE 2 illustrates the geometry for the sheet specimen commonly used in Hopkinson tensile test. As can be seen, the specimen can be divided into three parts in structure: the central zone, the transition zone and the glue zone. The central zone is the so-called gage section of specimen, the transition zones are used for the connection between central zone and glue zones, while the glue zones are used for the adhesive connection between bars and specimen.

Reference dimensions for the specimen are determined according to the diverse geometries used in [11]–[15]: $L_1$, $W_1$ are respectively the length and width of the central zone, $L_2$, $W_2$ are respectively the length and width of the glue zone, $R$ is the radius of the quarter circle in transition zone and $T$ is the specimen thickness, the above parameters $L_1$, $W_1$, $L_2$, $W_2$, $T$ and $R$ will be taken into consideration in the geometry optimization of specimen. Table 1 gives the reference dimensions for the specimen structure parameters.

**TABLE 1.** Reference dimensions for the structure parameters of specimen.

| Parameters | $L_1$ | $L_2$ | $W_1$ | $W_2$ | $T$ | $R$ |
|------------|-------|-------|-------|-------|-----|-----|
| Dimensions (mm) | 8.0   | 18.0  | 4.0   | 14.0  | 0.8 | 3.0 |

### III. NUMERICAL SIMULATIONS

#### A. FINITE ELEMENT MODEL

In this paper, the finite element software ABAQUS (Explicit) is used to numerically simulate the Hopkinson tensile experiment, the stress and strain state of specimen during the dynamic tensile loading will be analyzed based on the numerical calculation.

The diameter of the Hopkinson bars is 20mm; the length of the input bar, the transmission bar and the striker tube are 1800mm, 1000mm and 300mm, respectively. Owing to the symmetry of full model, in order to improve the efficiency of numerical calculation a quarter-symmetric model, as shown in FIGURE 3, is used in simulation. The mesh of specimen and its connection area is refined to improve the accuracy of calculation. Since the other areas only serve in the generation or transmission of stress waves, the division of the mesh in these areas is relatively coarser. In addition, the element type of Hex cell is set to C3D8R and the element type of Tet cell is set to C3D4.

A tied surface to surface contact was applied at bar-glue layer and glue layer-specimen. It should be noted that the influence of the glue layer can be ignored, since the glue layer is thin enough in actual test. A frictionless surface to surface contact was applied at anvil-striker tube. Symmetrical boundary conditions were applied to the sections of Hopkinson bars, specimen, glue layers and striker tube respectively. A velocity field was predefined for the striker tube in the direction of impact, and the velocity was controlled at the same time to maintain the strain rates of the specimens within 1000/s-1500/s.

#### B. MATERIAL MODEL

In FEA simulation work, the specimen is considered to be made of AA (aluminum alloy) 7075-T6, the glue layer is considered to be made of bi-component epoxy adhesive, the input bar and transmission bar as well the striker tube are considered to be made of 45# steel. Based on the fact that only elastic deformation occurs in the tensile bars and striker tube during the dynamic loading, the material model of the bars and striker tube is assigned as a linear elastic model in the numerical simulation. Similarly, the epoxy adhesive is considered to be strong enough to fix the specimen to the bars firmly and assumed that only elastic deformation occurs in the glue layers as well, so the material model of the glue layers is also assigned as a linear elastic model. However, not only elastic deformation but plastic deformation occurs in the specimen during the dynamic tensile loading, thus the material model of the specimen is assigned as a simplified Johnson-Cook material model. The mechanical properties for the Johnson-Cook parameters of AA 7075-T6 and other used materials are shown in Table 2 [20], [21].

#### C. INDICATORS OF MEASUREMENT ACCURACY OF SPECIMEN

In this section, simulation results of the specimen with the reference dimensions have been analyzed based on the assumptions in II-A. In order to achieve more accurate measurement in Hopkinson tests, the following requirements for the specimen have to be satisfied. Firstly, the specimen is supposed to reach dynamic stress equilibrium as soon as possible [17]. Secondly, the stress in specimen is one-dimensional and axial [22]. Thirdly, the deformations of specimen are uniform [16]. What’s more, the deformation of transition zones is negligible relative to the deformation of total specimen [23]. Four indicators which can characterize the measurement...
TABLE 2. Johnson-Cook model and other mechanical parameters for the materials adopted in FE calculation.

| Mechanical parameters | Young’s Modulus (GPa) | Density (kg/m³) | Poisson’s ratio | Parameters in J-C model |
|------------------------|-----------------------|-----------------|----------------|------------------------|
| Epoxy adhesive         | 1.990                 | 1800.0          | 0.360          | n          | C  | A(MPa) | B(MPa) |
| 45# steel              | 211.0                 | 7800.0          | 0.300          | -          | -  | -      | -      |
| AA7075                 | 71.0                  | 2750.0          | 0.330          | 0.381      | 0.033 | 473    | 210    |

accuracy of specimen are proposed based on the above analysis and the numerical simulation of the reference specimen.

- **Duration to reach stress equilibrium (DRSE)**
  FIGURE 4 gives a quarter meshed model for the sheet specimen with adhesive connection. In order to facilitate the following analysis and explanation, a path is selected along the axis of central section namely the gage section, as shown in FIGURE 4.

  Whether the specimen has reached the stress equilibrium can be determined by the relative deviation of the axial stress at the front and back end of specimen, and it can be considered that the specimen has reached stress equilibrium when the relative deviation of axial stress is less than 5%. Therefore, the indicator duration to reach stress equilibrium is defined to characterize an interval from the moment when the incident wave reaches the front end of gage section to the moment when the relative deviation of axial stress is less than 5%.

  FIGURE 5 shows the time-varying curve of relative deviation for the reference specimen. As can be seen, the relative deviation decreases with time, and it takes 22.81µs for the reference specimen to reach stress equilibrium.

- **Level of non-axial stress (LNS)**
  When the axial stress at the center point of specimen reaches the maximum value, the stress distribution on the path is shown in FIGURE 6, and non-axial refers to the direction of \(W_1\) (see FIGURE 2).

  As can be seen, the non-axial stress is obviously lower than the axial stress, and the non-axial stress on sides is greater than that in the middle. The ratios of non-axial to axial stress at various points on the path is shown in FIGURE 7, In order to characterize the relative level of the non-axial stress,
the average of ratios is taken as the indicator level of non-axial, and the level of non-axial stress for the reference specimen is 0.0249.

- **Deformation homogeneity (DH)**

Axial strain in the reference specimen after the loading of tensile wave is shown in FIGURE 8, as can be seen, the deformations of the reference specimen are not uniform.

![FIGURE 8. Axial strain of the specimen after loading.](image)

### FIGURE 8. Axial strain of the specimen after loading.

The distribution of axial strains on the path is shown in FIGURE 9, as can be seen, the distribution is non-homogeneous as well. The variance of the axial strains on the path can characterize the uniformity of the specimen deformation to a certain extent, therefore, it is used as an indicator to characterize the measurement accuracy of specimen which is called deformation homogeneity, and the deformation homogeneity for the reference specimen is 0.0018.

![FIGURE 9. Distribution of axial strain on the path.](image)

### FIGURE 9. Distribution of axial strain on the path.

- **Deformation contribution of transition zones (DCTZ)**

The deformation of the gage section, the transition zones, and the total specimen as well as the relative deformation of transition zones to the total specimen are listed in Table 3, and that all the deformations were measured at the same moment when tensile loading completed.

Although the deformation of transition zones is relatively much smaller than that of central section, it happened. What’s more, situation would be worse when the axial stress at the center of specimen reaches the maximum value, the relative deformation of the transition zones to the total specimen would increase to 3.5%.

According to the simulations results and analysis above, none of the assumptions in II-A can be satisfied in the actual Hopkinson tensile tests, while indicators such as deformation homogeneity, duration to reach stress equilibrium, deforming contribution of transition zones and level of non-axial stress can be defined to measure the measurement accuracy of the specimen. And the smaller the value of the indicators is, the more accurate the experiment results are. Reducing all the indicators is the primary objective of this optimization work.

### TABLE 3. Deformation of each section of specimen and the relative deformation of transition zones.

| Deformation (mm) | Relative deformation |
|------------------|----------------------|
| Transition zones | 0.007                |
| Gage section     | 1.012                |
| Total specimen   | 1.019                |
|                  | 0.69%                |

### IV. OPTIMATION PROGRAM

The purpose of the optimization is to obtain the combination of the optimal structural parameters of specimen and then improve the measurement accuracy of Hopkinson tensile tests. The relationship between the structure parameters and the indicators of measurement accuracy of specimen is complex and highly non-linear. Thus, establishing a mapping, namely a function, between the specimen structure parameters and indicators of measurement accuracy has become the key to this optimization.

A BP neural network is outstanding in self-adapting, self-learning as well as nonlinear modeling and forecasting abilities, and the powerful nonlinear fitting ability is one of the advantages of BP neural network. Reference [24] The samples selected by orthogonal test design are representative and evenly distributed, and to a great degree, they can represent the attributes of the population. Reference [25] Therefore, orthogonal test design method is used in this study to generate the samples for BP learning and the BP would construct the nonlinear mapping relationship between the specimen structural parameters and indicators of measurement accuracy after learning the sample data.

Meantime, genetic algorithm, widely used in different fields, is an evolutionary algorithm fit for complex and non-linear problems. Reference [26] Compared with the traditional optimization algorithms, genetic algorithm makes it easier to achieve global optimization by the way population to population searching, and the fitness function of GA which can determine the fitness of individuals is designed based on the trained BP in this paper. The flowchart of the global optimization program combining BP with GA is shown in FIGURE 10.

### A. SAMPLE DATABASE BASED ON ORTHOGONAL TEST DESIGN

Six structure parameters in this paper need to be optimized, and according to the design rules, orthogonal table on specimen structure parameters with six factors and five levels is designed, as listed in Table 4. Meantime, the indicators of measurement accuracy corresponding to the specimens

### TABLE 4. Orthogonal table of specimen structure parameters.

| Parameter | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 |
|-----------|---------|---------|---------|---------|---------|
| A         | 1       | 2       | 3       | 4       | 5       |
| B         | A       | B       | C       | D       | E       |
| C         | A       | B       | C       | D       | E       |
| D         | A       | B       | C       | D       | E       |
| E         | A       | B       | C       | D       | E       |

### FIGURE 10. Flowchart of the global optimization program.
TABLE 4. Orthogonal test design and the indicators of the corresponding specimen.

| Orthogonal test | Structural parameters/mm | LNS  | DRSE/μs | DCTZ | DH  |
|-----------------|--------------------------|------|---------|------|-----|
| 01              | 6.0                      | 16.0 | 3.0     | 13.0 | 0.4 | 2.0 | 0.0287 | 18.00 | 0.0090 | 0.0020 |
| 02              | 6.0                      | 17.0 | 3.5     | 14.0 | 0.6 | 2.5 | 0.0328 | 18.00 | 0.0086 | 0.0025 |
| 03              | 6.0                      | 18.0 | 4.0     | 15.0 | 0.8 | 3.0 | 0.0348 | 18.61 | 0.0061 | 0.0023 |
| 04              | 6.0                      | 19.0 | 4.5     | 16.0 | 1.0 | 3.5 | 0.0353 | 18.85 | 0.0107 | 0.0021 |
| 05              | 6.0                      | 20.0 | 5.0     | 17.0 | 1.2 | 4.0 | 0.0339 | 20.80 | 0.0107 | 0.0030 |
| 06              | 7.0                      | 17.0 | 3.0     | 15.0 | 1.2 | 3.5 | 0.0188 | 21.45 | 0.0084 | 0.0016 |
| 07              | 7.0                      | 18.0 | 3.5     | 16.0 | 0.4 | 4.0 | 0.0194 | 21.00 | 0.0248 | 0.0015 |
| 08              | 7.0                      | 19.0 | 4.0     | 17.0 | 0.6 | 2.0 | 0.0353 | 21.00 | 0.0046 | 0.0031 |
| 09              | 7.0                      | 20.0 | 4.5     | 13.0 | 0.8 | 2.5 | 0.0373 | 21.50 | 0.0070 | 0.0029 |
| 10              | 7.0                      | 16.0 | 5.0     | 14.0 | 1.0 | 3.0 | 0.0380 | 22.00 | 0.0067 | 0.0031 |
| 11              | 8.0                      | 18.0 | 3.0     | 17.0 | 1.0 | 2.5 | 0.0191 | 22.50 | 0.0164 | 0.0015 |
| 12              | 8.0                      | 19.0 | 3.5     | 17.0 | 1.2 | 4.0 | 0.0215 | 23.00 | 0.0189 | 0.0015 |
| 13              | 8.0                      | 20.0 | 4.0     | 14.0 | 0.4 | 3.5 | 0.0228 | 22.79 | 0.0141 | 0.0016 |
| 14              | 8.0                      | 16.0 | 4.5     | 15.0 | 0.6 | 4.0 | 0.0244 | 22.81 | 0.0173 | 0.0018 |
| 15              | 8.0                      | 17.0 | 5.0     | 16.0 | 0.8 | 2.0 | 0.0436 | 22.81 | 0.0044 | 0.0032 |
| 16              | 9.0                      | 19.0 | 3.0     | 14.0 | 0.8 | 4.0 | 0.0133 | 24.00 | 0.0208 | 0.0011 |
| 17              | 9.0                      | 20.0 | 3.5     | 15.0 | 1.0 | 2.0 | 0.0265 | 23.50 | 0.0056 | 0.0017 |
| 18              | 9.0                      | 16.0 | 4.0     | 16.0 | 1.2 | 2.5 | 0.0249 | 24.00 | 0.0048 | 0.0018 |
| 19              | 9.0                      | 17.0 | 4.5     | 17.0 | 0.4 | 3.0 | 0.0270 | 23.41 | 0.0082 | 0.0019 |
| 20              | 9.0                      | 18.0 | 5.0     | 13.0 | 0.8 | 3.5 | 0.0289 | 24.00 | 0.0082 | 0.0020 |
| 21              | 10.0                     | 20.0 | 3.0     | 16.0 | 0.6 | 3.0 | 0.0140 | 25.20 | 0.0072 | 0.0012 |
| 22              | 10.0                     | 16.0 | 3.5     | 17.0 | 0.8 | 3.5 | 0.0164 | 25.20 | 0.0093 | 0.0013 |
| 23              | 10.0                     | 17.0 | 4.0     | 13.0 | 1.0 | 4.0 | 0.0179 | 25.00 | 0.0139 | 0.0012 |
| 24              | 10.0                     | 18.0 | 4.5     | 14.0 | 1.2 | 2.0 | 0.0318 | 25.01 | 0.0024 | 0.0021 |
| 25              | 10.0                     | 19.0 | 5.0     | 15.0 | 0.4 | 2.5 | 0.0310 | 24.00 | 0.0051 | 0.0022 |

with various structures are obtained by FE and also be listed in Table 4.

B. CREATE BP NEURAL NETWORK

A neural network model with 3 layers, the so-called input, output and hidden layer is utilized in the present study to fit the non-liner mapping. And according to the characteristics of the non-linear mapping to be fitted, there should be 6 neurons in input layer matched to the 6 structure parameters of specimen, and 4 neurons in output layer matched to the 4 indicators of measurement accuracy of specimen, in addition, the number of neurons in the hidden layer is determined to be 8. The transfer function of hidden layer and output layer are set to the tangent sigmoid function tansig and the linear function purelin, respectively. The completed neural network model was trained with the training function trainlm, which based on the Levenberg-Marquardt algorithms.

Suppose $X$ is the structural parameter matrix of specimen and $Y$ is the accuracy indicators matrix of specimen, as shown in the following equations (2) and (3). Where $L_1, L_2, W_1, W_2, T, R$ are the structure parameters of specimen in FIGURE 2, $DH, DRSE, DCTZ, LNS$ are the indicators of measurement accuracy deformation homogeneous, duration to reach stress equilibrium, deformation contribution of transition zones and level of non-axial stress respectively. After training, qualified neural network will have the ability to map from $X$ to $Y$, in other words, it can predict $Y$ from $X$ correctly.

$$X^T = \begin{bmatrix} L_1 & L_2 & W_1 & W_2 & T & R \end{bmatrix}$$

$$Y^T = \begin{bmatrix} DH & DRSE & DCTZ & LNS \end{bmatrix}$$

C. COMBINE GA WITH BP NEURAL NETWORK

The fitness function of GA designed based on the non-linear mapping fitted by BP is shown in equation (4). $I_1, I_2, I_3, I_4$ are the indicators of measurement accuracy of specimen mapped from a random structure parameters matrix $[l_1, l_2, w_1, w_2, t, r]$, and $I_{1k}, I_{2k}, I_{3k}, I_{4k}$ are the corresponding indicators in Table 4, $m = 25$, $\text{ObjV}$ is the function value of fitness function, namely the fitness of individuals.

$$\text{ObjV} = \frac{1}{m} \sum_{k=1}^{m} I_{1k} i / m + \frac{1}{m} \sum_{k=1}^{m} I_{2k} i / m + \frac{1}{m} \sum_{k=1}^{m} I_{3k} i / m + \frac{1}{m} \sum_{k=1}^{m} I_{4k} i / m$$

FIGURE 10. Flowchart of the optimization program.
It can be seen that the overall level of the accuracy indicators is reflected in the objective function, and the influence of different indicators put equal weight on the value of the objective function.

In this paper, GA was programmed with the Sheffield genetic algorithm toolbox inserted in MATLAB, and the important parameters of GA are shown in following Table 5. Fitness of individuals was allocated by the function rank according to the values of the objective function. The larger the objective value of an individual is, the smaller the fitness is.

### D. OPTIMIZATION RESULTS AND ANALYSIS

The training process for BP neural network is actually to adjust and determine the threshold as well the weights between different layers, however there’s certain randomness in this process even the same samples are learned by the network. So, it’s necessary to verify the validity of the neural network before using it to determine the objective values of individuals. Thus, as shown in Table 6, 3 groups of testing simulations were set to verify the network, the parameters of the testing specimens were recombined randomly from the parameters data in Table 4.

Suppose $X_t$ ($6 \times 3$) is the input matrix of BP neural network, and the elements in $X_t$ are the structural parameters of the testing specimens shown in Table 6. The output matrix $Y_t$ ($4 \times 3$), elements in which are the accuracy indicators of testing specimens, can be mapped from $X_t$ by BP. Then, the prediction accuracy of the trained BP can be verified by comparing the elements in $Y_t$ with the corresponding indicators data in Table 6, which were obtained by numerical simulations. The comparison result is listed Table 7. The maximum error of indicators between simulation and mapping is 19.6%, the mean error is 7.7%. The maximum error of objective values between simulation and mapping is 5.0% and the mean error is 4.7%. It can be considered that the trained neural network is valid and it can forecast the indicators of specimens correctly.

![FIGURE 11. Evolution of GA.](image-url)
generation no longer decreases. The individual with the highest measurement accuracy is eventually evolved and its structure parameters are given in the following equation (5) (mm).

\[
\begin{bmatrix}
L_1 & L_2 & W_1 & W_2 & T & R
\end{bmatrix}^T =
\begin{bmatrix}
9.8 & 19.4 & 3.9 & 16 & 1.1 & 2.9
\end{bmatrix}^T \tag{5}
\]

FIGURE 12. Geometry dimensions of the optimized specimen.

FIGURE 12 illustrates the optimal geometry and dimensions for the sheet specimen after optimization. As shown in FIGURE 13, the indicator duration to reach stress equilibrium gets longer after optimization and increased to be 24.75 µs.

FIGURE 13. Relative deviation of axial stress over time for the optimized specimen.

When the axial stress at the center of the optimized specimen reaches the maximum value, ratios of non-axial stress to axial stress distributing along the path is given in FIGURE 14, and the average ratio, namely level of non-axial stress is 0.0220.

Axial strain in the optimized specimen after the loading of tensile wave is shown in FIGURE 15, and FIGURE 16 gives the axial strains distribution on the path, and the indicator deformation homogeneity of the optimized specimen is 0.0015.

The deformation of the gage section, the transition zones, the total specimen and the relative deformation of the transition zones to the total specimen are listed in Table 8. As shown, the indicator deforming contribution of transition zones for the optimized specimen is 0.38%.

TABLE 8. Deformation of each section for the optimized specimen and the relative deformation of transition zones to total specimen.

| Deformation / mm | Relative deformation |
|------------------|----------------------|
| Transition zones | 0.00481              |
| Gage section     | 1.26870              |
| Total specimen   | 1.27351              |
|                  | 0.38%                |

The comparison of the indicators before and after optimization is listed in Table 9. It can be seen that the indicator duration the reach stress equilibrium has increased slightly, while the other indicators has significantly decreased, and the indicator level for the optimized specimen has decreased overall, that means the measurement accuracy of the specimen after optimization is improved.

TABLE 9. Indicators comparison between the reference and the optimized specimen.

| Accuracy Indicators | Optimized geometry | Reference geometry | Increase or decrease |
|---------------------|--------------------|--------------------|----------------------|
| DRSE                | 24.75              | 22.81              | 8.5%↑                |
| LNS                 | 0.0220             | 0.0249             | 11.6%↓               |
| DH                  | 0.0015             | 0.0018             | 16.7%↓               |
| DCTZ                | 0.38%              | 0.69%              | 44.9%↓               |
of transition zones is used to characterize the measurement accuracy of the specimens. What’s more, FE analysis shows that the above indicators have a great influence on the accuracy of the experimental results.

2) The optimal specimen geometry (shown in FIGURE. 12) is obtained, although the indicator duration to reach stress equilibrium increased by 8.5% compared to the reference specimen, other indicators such as level of non-axial stress, deformation homogeneity, deformation contribution of transition zones reduced by 11.6%, 16.7%, 44.9% respectively. In overall perspective, the measurement accuracy of the optimized specimen is significantly improved.

3) The intelligent algorithm was used to optimize the geometry dimensions of the specimen with different structure. After optimization, the measurement accuracy of the optimized specimen is significantly improved. The used optimization method is proved to be valid and adaptable broadly.

TABLE 10. Indicators comparison between the optimized geometry and the geometry used in [13].

| Accuracy indicators | Optimized geometry | Geometry used in [13] | Increase or decrease |
|---------------------|--------------------|-----------------------|----------------------|
| DRSE                | 24.75              | 29.10                 | 17.6%                |
| LNS                 | 0.0220             | 0.0322                | 46.4%                |
| DH                  | 0.0015             | 0.0017                | 16.7%                |
| DCTZ                | 0.38%              | 0.53%                 | 39.5%                |

TABLE 11. Indicators comparison between the optimized geometry and the geometry used in [14].

| Accuracy indicators | Optimized geometry | Geometry used in [14] | Increase or decrease |
|---------------------|--------------------|-----------------------|----------------------|
| DRSE                | 24.75              | 17.12                 | 30.4%                |
| LNS                 | 0.0220             | 0.0401                | 82.3%                |
| DH                  | 0.0015             | 0.0024                | 60%                  |
| DCTZ                | 0.38%              | 0.41%                 | 7.9%                 |

TABLE 12. Indicators comparison between the optimized geometry and the geometry used in [15].

| Accuracy indicators | Optimized geometry | Geometry used in [15] | Increase or decrease |
|---------------------|--------------------|-----------------------|----------------------|
| DRSE                | 24.75              | 18.03                 | 27.2%                |
| LNS                 | 0.0220             | 0.0378                | 71.8%                |
| DH                  | 0.0015             | 0.0022                | 46.7%                |
| DCTZ                | 0.38%              | 0.72%                 | 89.5%                |

Similarly, in order to further verify the validity of the optimized specimen geometry, three additional sets of verification tests were performed. Table 10, 11 and 12 give the comparison of indicators of measurement accuracy between the optimized geometry and the geometries used in [13], [14] and [15], respectively. On the whole, the value of the indicators of measurement accuracy decreased significantly, the measurement accuracy of the specimen is improved after optimization.

V. CONCLUSION
The finite element method was used to simulate the SHTB experiments. Dimensions of the reference geometry were defined based on the different geometries used in literatures. Indicators of measurement accuracy of specimen were proposed based on the simulation results of the reference specimen. Orthogonal test and reasonable fitness function were designed. Non-linear mapping between the structure parameters and indicators of measurement accuracy of specimen was fitted by BP neural network and the optimal geometry of the specimen was obtained with GA. The following conclusions were summarized.

1) None of the assumptions that the specimen is in stress equilibrium state, the stress in the specimen is axial, the deformation of the specimen is homogeneous and there’s no deformation in transition zones is satisfied in practice. However, indicators such as duration to reach stress equilibrium, level of non-axial stress, deformation homogeneity as well as deforming contribution of transition zones is used to characterize the measurement accuracy of the specimens. What’s more, FE analysis shows that the above indicators have a great influence on the accuracy of the experimental results.

2) The optimal specimen geometry (shown in FIGURE. 12) is obtained, although the indicator duration to reach stress equilibrium increased by 8.5% compared to the reference specimen, other indicators such as level of non-axial stress, deformation homogeneity, deformation contribution of transition zones reduced by 11.6%, 16.7%, 44.9% respectively. In overall perspective, the measurement accuracy of the optimized specimen is significantly improved.

3) The intelligent algorithm was used to optimize the geometry dimensions of the specimen with different structure. After optimization, the measurement accuracy of the optimized specimen is significantly improved. The used optimization method is proved to be valid and adaptable broadly.

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QINGHUA WANG received the B.E. degree in electrical engineering and automation from the Shandong University of Technology, China, in 2017, and the M.E. degree in aircraft design from the School of Astronautic, Northwestern Polytechnical University, China, in 2020, where he is currently pursuing the D.E. degree in mechanical engineering and automation with the School of Astronautics. His current research interests include optimal design of aircraft structural design and development of aircraft quality characteristics test systems.

QINGHUA WANG received the B.E. degree in electrical engineering and automation from the Shandong University of Technology, China, in 2017, and the M.E. degree in aircraft design from the School of Astronautic, Northwestern Polytechnical University, China, in 2020, where he is currently pursuing the D.E. degree in mechanical engineering and automation with the School of Astronautics. His current research interests include optimal design of aircraft structural design and development of aircraft quality characteristics test systems.

FENG XU received the B.Sc. degree in information and computing science from the Xi’an University of Technology, China, in 2008, and the M.Sc. degree in computational mathematics and the D.E. degree in solid mechanics from Northwestern Polytechnical University, China, in 2011 and 2016, respectively. He is currently an Assistant Professor with the School of Astronautics, Northwestern Polytechnical University. His current research interests include intelligent composites and structures, shock and vibration, and structural health monitoring.

BO YANG received the B.E. degree in electrical engineering and automation from the Harbin Institute of Technology, Weihai, China, in 2011, and the M.E. degree in electrical engineering and automation from the Harbin Institute of Technology, China, in 2013. He is currently with the Shanghai Spaceflight Precision Machinery Institute, China. His main research interest includes aerospace structural design.

LUJIE FENG received the B.E. and M.E. degrees in MEMS and nanotechnology from Northwestern Polytechnical University, China, in 2007 and 2010, respectively. He is currently with the Shanghai Spaceflight Precision Machinery Institute, China. His main research interest includes aerospace structural design.

DEDONG HUANG received the B.E. degree in mechanical design and manufacturing and automation from Sichuan University, China, in 2004, and the M.E. and D.E. degrees in aircraft design from Northwestern Polytechnical University, China, in 2009 and 2013, respectively. He is currently an Assistant Professor with the School of Astronautics, Northwestern Polytechnical University. His current research interests include optimal design of aircraft structure/control coupling and development of aircraft quality characteristics test systems.

CHEN WANG received the B.E. degree in aircraft design from Northwestern Polytechnical University, China, in 1989. He is currently an Associate Professor with the School of Astronautics, Northwestern Polytechnical University. His current research interests include environmental experiment technology and missile structural design.

BIN WU received the B.E. degree in aircraft design from Northwestern Polytechnical University, China, in 1989. He is currently an Associate Professor with the School of Astronautics, Northwestern Polytechnical University. His current research interests include environmental experiment technology and missile structural design.

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