Prediction of Maximum Deformation of Single Nail Riveting Based on RBF Neural Network

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Abstract. The influencing factors of riveting deformation are more complicated, and the specific relationship between the amount of deformation and each factor is difficult to express with general expressions, which is a non-linear problem. Aiming at this problem, this study uses RBF neural network to establish a model of the relationship between the maximum deformation of single nail riveting and various factors. Then, 1000 sample sizes were designed using the LHS method, with 90\% of the sample size as training and 10\% as testing. Secondly, the secondary development of the finite element software is carried out by using Python language to realize parametric modeling and batch processing. Finally, using the RBF neural network model to predict the maximum deformation of a single nail riveting, the maximum relative error and the average relative error were 8.43\% and 2.948\%, respectively. The results show that the RBF neural network can be applied in the field of prediction of maximum deformation of riveting and has high prediction accuracy.

1. Introduction

Riveting is one of the most important connection methods in the field of aircraft assembly. It has the advantages of simple process, high connection strength and reliability [1]. The characteristics of the riveting process determine that each single nail riveting will produce a small amount of deformation, and gradually overlap during the multiple nail riveting process, eventually leading to the overall deformation of the assembly [2]. Therefore, the prediction research on the maximum deformation of riveting has certain guiding significance in engineering practice.

By means of experimental research and numerical simulation, domestic and foreign scholars have conducted a large number of studies on riveting deformation [3-5]. Zheng et al. proposed a mechanical model of equivalent riveting process to predict assembly deformation of riveted plates, and verified the effectiveness of the model by comparing numerical simulation and experimental measurement results [6]. Yang et al. proposed a local-global method to predict the deformation of aircraft plates during riveting by embedding rivet equivalent units into the global model [7]. Eckert et al. used a simplified model to predict assembly deformation caused by self-perforating riveting [8].

Most researchers use experimental research and numerical simulation methods to conduct in-depth research on riveting deformation from the riveting process parameters [9-11], but pay less attention to neural network in predicting the amount of riveting deformation. Although the riveting process is
relatively simple, the factors that affect the deformation of the riveting are more complicated. The specific relationship between the deformation and each factor is difficult to express with general expressions, which is a non-linear problem. The RBF neural network is used in both modeling and prediction. Has unique advantages [12,13]. The RBF neural network can approximate any non-linear function with arbitrary precision. It has the advantages of strong global approximation ability, avoiding falling into local optimum, compact topology, and fast convergence speed [14]. Therefore, this study uses RBF neural network for model prediction.

In this study, our goal is to build a reasonable RBF neural network model and accurately predict the maximum deformation of the riveting. Therefore, the rest of this article is organized as follows. The second part briefly describes the general structure of the RBF neural network model, and designs the RBF neural network model. The input variables are riveting geometric parameters, elastic mechanics parameters and process parameters, and the output variables are riveting maximum deformation. The third part introduces the parametric modeling process of riveting in detail, and uses Python to perform parametric modeling and batch processing operations. The fourth part introduces the training and testing results of RBF neural network, and proves that the method has higher accuracy in predicting the maximum deformation of riveting. The fifth part draws our conclusions.

2. Establishment of RBF neural network model

2.1. RBF neural network model

The basic RBF neural network, as shown in Figure 1, consists of three parts: the input layer, the hidden layer and the output layer. Each layer has different functions. The input layer directly connects the input variables. Referring to literature [15], the mapping function of the RBF neural network is as follows:

\[ f(x) = \sum_{j=0}^{n-1} w_j H_j(x) \]  \hspace{1cm} (1)

\[ H_j(x) = \exp \left( -\frac{(x-e_j)^2}{\delta_j^2} \right) \]  \hspace{1cm} (2)

where, \( x \) is the input vector, \( n \) is the number of hidden layer nodes, \( e_j \) is the core of hidden layer nodes, \( \delta_j \) is the basic width, \( w_j \) is the output weight. Gaussian function can directly reflect the characteristics of local response, and has the advantages of radial symmetry, good smoothness, and derivative of any order, etc. Therefore, this study chooses gaussian function as the basic function of hidden layer [16].

![Figure 1. RBF neural network model.](image)

2.2. RBF neural network model variable design
In the actual riveting process, the rivet and plate structure geometric parameters, elastic parameters and process parameters are random variables, need to be sampled. Since Latin hypercube sampling (LHS) method can extract relatively uniform test points in a predetermined sample space [17], LHS method is adopted in this study to generate 1000 test samples, and 90% of the sample size is randomly selected as the model fitting, and the remaining samples are taken as precision tests. The matrix expressions of the input vector $\mathbf{X}$ and output vector $\mathbf{Y}$ are shown in equations (3) and (4), where $n$ represents the number of input variables and $N$ represents the total number of samples.

$$
\mathbf{X} = \begin{bmatrix}
    x_{11} & x_{12} & \cdots & x_{1N} \\
    x_{21} & x_{22} & \cdots & x_{2N} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{L1} & x_{L2} & \cdots & x_{LN}
\end{bmatrix}
$$  \hspace{1cm} (3)

$$
\mathbf{Y} = \begin{bmatrix}
    y_1 \\
    y_2 \\
    \vdots \\
    y_N
\end{bmatrix}
$$  \hspace{1cm} (4)

In this study, the input variable is represented by $\mathbf{X} = \{x_1, x_2, \ldots, x_3\}$, and the output variable is represented by $\mathbf{Y} = \{y\}$. Before fitting the model, the input parameters and output parameters need to be dimensionless normalized, and the parameter size is transformed into the range of $[0,1]$.

3. Parametric modeling for numerical simulation of riveting deformation

In order to simplify the modeling process and improve efficiency, first use Python to perform parametric modeling and batch operations on the numerical simulation of single-rivet deformation. In the parametric modeling process, parameterize the changed parameters, adopt fixed settings for the unchanged parameters, and then realize automatic parameterized modeling of numerical simulation. Then use the finite element software to obtain the numerical simulation results. The parametric modeling process of deformation numerical simulation as shown in Figure 2.

![Flow chart of parametric modeling for numerical simulation of riveting deformation](image-url)

**Figure 2.** Flow chart of parametric modeling for numerical simulation of riveting deformation.
3.1. Define the parameters

According to the characteristics of riveting process, the parametric modeling of single nail riveting deformation numerical simulation involves geometric parameters, elastic parameters and process parameters.

3.1.1. Geometric parameters. The simulation model of single-nail riveting is mainly composed of upper and lower plate, rivet and riveting tool, and its finite element model is shown in figure 3. The length and width of the upper and lower plates are the same, \( D_e \) and \( L \) are rivet diameter and length respectively, \( D_A \) and \( t_A \) are the aperture and thickness of the upper plate respectively, \( D_c \) and \( t_c \) are respectively the aperture and thickness of the lower plate, and the geometric parameters of each structure are shown in table 1 [18].

![Figure 3. Schematic diagram of rivet finite element model.](image)

**Table 1.** Geometric parameters and material parameters.

| Parameters   | Value | Parameters   | Value | Parameters   | Value | Parameters   | Value |
|--------------|-------|--------------|-------|--------------|-------|--------------|-------|
| \( D_e (mm) \) | 5.00  | \( t_A (mm) \) | 2.00  | \( E_r (GPa) \) | 72.60 | \( \mu_A \) | 0.33 |
| \( L (mm) \)  | 16.00 | \( D_c (mm) \) | 5.08  | \( \mu_r \) | 0.33  | \( \rho_r (g / cm^3) \) | 2.80 |
| \( D_A (mm) \) | 5.08  | \( t_c (mm) \) | 2.00  | \( E_A (GPa) \) | 70.00 | \( \rho_A (g / cm^3) \) | 2.80 |

3.1.2. Elastic mechanical parameter. The rivet and metal plate materials are 2A10-T4 and 7075-T651, respectively; the density is \( \rho_r \) and \( \rho_A \), the elastic modulus is \( E_r \) and \( E_A \), and the poisson ratio is \( \mu_r \) and \( \mu_A \), respectively, the parameter values are shown in table 1 [18].
3.1.3. The process parameters. In this study, the initial height of the rivet protruding from the plate surface is 6mm, so the maximum compression deformation of the rivet is \( S_{\text{max}} = 3.2 \text{mm} \). All friction coefficients in the riveting model are set to 0.18, and the coordinate definition and axis constraint are shown in Figure 3.

The riveting process is simulated in two steps, and the displacement load curves of loading and unloading. The loading time \( t_1 \) and unloading time \( t_2 \) were both 0.5ms.

3.2. Numerical simulation examples and analysis
The cloud diagrams of the stress variation during the riveting process and the displacement cloud diagrams of the panel after riveting are shown in Figures 4 and 5, respectively.

- In the first stage, the riveting tool began to contact the rivet and gradually tightened, and the rivet began to deform until the headless surface of the rivet touched the hole wall of the plate, as shown in Figure 4(a).
- In the second stage, the displacement of the riveting tool increased, and the contact between the rivet and the plate hole gradually increase the area until the rivet fills the plate hole, as shown in Figure 4(b).
- In the third stage, the displacement of the pressing tool increases again. The rivet between the pressing tool and the two plates gradually thickens and starts to contact the two plates. Surface, until the end of the rivet reaches the target position, the riveting tool stops moving, and the riveting die reaches the maximum displacement and deformation, as shown in Figure 4(c).
- In the fourth stage, the riveting tool starts to move in the opposite direction, the riveting tool returns to the initial position, and the riveting force gradually decreases. When it reaches zero, the rivet rebounds and the riveting process ends, as shown in Figure 4(d). The position where the riveting plate produces the largest amount of deformation is located at the edge of the riveting hole, as shown in Figure 5.

![Figure 4](image-url)
4. Analysis of model prediction results

RBF neural network model is used to predict the maximum deformation of single rivet joint. In order to evaluate the prediction accuracy, some statistical methods are often used, such as mean relative error (MRE), mean absolute percentage error (MAPE), mean square error (MSE) and root mean square error (RMSE). Among them, MAPE can better reflect the real situation of the absolute error value of prediction, and RMSE can well show the quality of data fitting [19].

The predicted value is then compared with the actual value calculated by the finite-element method, as shown in Figure 6(a). The predicted relative error chart, as shown in Figure 6(b). The maximum relative error, MAPE and RMSE are 8.43%, 2.948% and 0.00429, respectively. According to the prediction results, the RBF neural network model has a high prediction accuracy in the field of predicting the maximum deformation of single rivet joint, which can meet the actual engineering requirements.

5. Conclusion

In this study, the structural geometric parameters, elastic mechanical parameters and process parameters of rivet and plate are taken as input variables, and the maximum deformation of rivet is taken as output. RBF neural network is used to predict the maximum deformation of single rivet. The results of this study can be summarized as:

(1) The application of RBF neural network to the prediction field of riveting deformation is proposed. The results show that the methods have high prediction accuracy and MAPE value less than 5%.

(2) Based on the analysis of riveting deformation, parameterized modeling and batch processing are implemented using Python language, which simplifies and shortens the modeling cycle.

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