Accurate prediction of the extrusion forming bonding reliability for heterogeneous welded sheets based on GA-BP neural network

Lei Gao 1 · Feng Li 1 · Peng Da Huo 1 · Chao Li 1 · Jie Xu 2

Received: 7 April 2021 / Accepted: 23 July 2021 / Published online: 31 July 2021
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Abstract
Extrusion connection is a new method of forming and manufacturing heterogeneous welded sheets. The factors that affected the bonding quality are the forming temperature, the extrusion ratio, and the guiding angle of the die, which has brought trouble to the evaluation of bonding strength and quality. A method to establish a predicted model for the bonding strength of welded sheets by integrating finite element simulations, process experiments, and artificial neural networks was developed. Finite element simulations were used to verify the process experiments and provided training data sets for the artificial neural networks. The BP neural network was used to predict the bonding strength. Due to the randomness of the weight and threshold of the BP neural network, its predicted accuracy needs to be improved, in which genetic algorithms were used to optimize consequently. The results showed that the genetic algorithm neural network model had higher reliability, and the predicted accuracy was 99.5%. Compared with the traditional BP neural network, the predicted accuracy was improved by 5.78%, and the error was reduced to 0.5%. It has good generalization ability and provides a new way for intelligent reliability evaluation of high performance heterogeneous welded sheets via extrusion.

Keywords Heterogeneous welded sheets · Extrusion connection · Bonding strength · GA-BP neural network · Predicted accuracy

1 Introduction
Solid-state bonding processes of dissimilar metals [1–3] can connect different kinds of metals with different properties, so that it can play the respective advantages of each component material in the composite products, such as friction stir welding [4], diffusion welding [5], cumulative extrusion [6], cumulative rolling [7], and so on. With the continuous further research on the various solid-state bonding processes of dissimilar metals, scholars from various countries have carried out researches from the following aspects on how to evaluate the welded quality.

The first method was based on the process experiments and theoretical model derivations, and the welding criterion that can predict the interfacial welding force was established. Researchers had successively proposed a series of welding criteria based on the normal pressure of the welded surface, such as the maximum pressure criterion (P criterion) [8], the pressure-time criterion (Q criterion) [9], the pressure-time-flow velocity criterion (K criterion) [10], and the J criterion [11], which were all based on various physical parameters on the welding path to determine whether the welding was carried out.

The second method was based on numerical simulations and intelligent algorithms, and the welded pressure on the welding path was obtained by simulations and optimizations so as to predict and evaluate the welded quality. In recent years, for this nonlinear mathematical model, the Taguchi method [12], response surface method [13], grey relational analysis method [14], etc., have been widely used in parameter optimization and prediction of solid-phase bonding processes. Compared with the above methods, modern intelligent algorithms were more suitable for the establishment of nonlinear mathematical models due to their outstanding self-learning and predictive capabilities, such as artificial neural

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1 School of Materials Science and Chemical Engineering, Harbin University of Science and Technology, Harbin 150040, China
2 Key Laboratory of Micro-systems and Micro-structures Manufacturing of Ministry of Education, Harbin Institute of Technology, Harbin 150001, China

Feng Li
fli@hrbust.edu.cn

Jie Xu
xjhit@hit.edu.cn

https://doi.org/10.1007/s00170-021-07797-7 / Published online: 31 July 2021

The International Journal of Advanced Manufacturing Technology (2021) 117:765–774
network (ANN). From previous studies, it had been found that the BP algorithm was often used for neural network training due to its fast response speed and high accuracy. However, due to the randomness of the BP algorithm's own parameters, the solution space is easy to fall into the local optimal range [15], and other auxiliary algorithms are usually needed to optimize and solve the problem. Common intelligent algorithms included genetic algorithm (GA) [16], ant colony algorithm [17], particle swarm algorithm [18], and pigeon-inspired optimization [19].

The heterogeneous thickness-oriented welded sheets fabricated by direct extrusion was a new process proposed by this research group, whose bonding strength directly affected the quality of the process. However, there is no traditional mathematical model to predict it theoretically. Due to many factors that affected the process, such as forming temperature, extrusion ratio, the guiding angle of die, and so on, BP artificial neural network was used to establish a mapping relationship between those process parameters and bonding strength. Combining process experiments and finite element simulations, the network model was constructed, and the network model was trained and tested, which was used to predict and evaluate subsequently. Finally, a genetic algorithm was used to optimize BP neural network to improve the prediction accuracy.

2 Methodology

As shown in Fig. 1, numerical simulations, neural networks, and process experiments are combined to predict the bonding strength of heterogeneous sheets. Firstly, the data were collected by numerical simulations and the bonding strength prediction model of heterogeneous sheets was established based on BP neural network. The sample data required in the algorithm were obtained from numerical simulations and process experiments. Secondly, GA was used to interfere with BP neural network which would be optimized subsequently. The bonding strength prediction model of heterogeneous sheets was established again by the optimized neural network. Finally, the ideal bonding strength predicted curve was obtained, and then the process experiments were used to verify.

2.1 Processing principle

Two semi-cylindrical-shaped billets after compounding were directly extruded to heterogeneous thickness-oriented welded sheets via extrusion. But what is required was to ensure that the spatial relationship between the bonding surface of the two semi-cylindrical-shaped billets and the sizing band of the die was parallel to each other, as shown in Fig. 2.

This process could cause the shear behavior of the velocity difference between the internal bonding surface and the external edge of the two semi-cylindrical-shaped billets, which made the microstructure of billets refined in the extrusion process. At the same time, the dissimilar metals could be stably welded along the thickness direction. The experimental materials were commercial AZ31 magnesium alloys and AA6061 aluminum alloys, and the size of semi-cylindrical-shaped billets was Ф40 mm × 30 mm. Before the experiment, the magnesium and aluminum alloy billets needed to be homogenized.

2.2 FE simulations

The commercial software DEFORM was used to carry out the finite element numerical (FE) simulation of the extrusion process, and axisymmetric model was established as shown in Fig. 3. Firstly, the workpieces were assumed to be an elastic-plastic body and the tooling die was a rigid body. The geometric model was divided into a four-node tetrahedron with the minimum mesh length of 1.5 mm and the maximum mesh length of 4 mm. Then, the interaction between the object and the surrounding environment were considered in the model. The ambient temperature was set to 20 °C. The heat exchange coefficient between the workpieces and the tooling die was 11 N/(s·mm·°C), and that between the tooling die and the surrounding environment was 0.02 N/(s·mm·°C). Finally, the sticking condition friction model was used for the two semi-cylindrical-shaped billets, and the shear friction model was used for the billets and the tooling die. Moreover, the friction factors of between magnesium and aluminum alloy billets and tooling die were 0.7 and 0.3, respectively [11, 20]. Other relative parameters were given in other papers [21].

For the diversity and consistency of the sample data, a series of finite element simulations were carried out by
changing the process parameters, which can provide the data
set for the training of the neural network model. Among them,
the input variables of the training data set were extrusion tem-
perature \( T \), extrusion ratio \( \lambda \), and guiding angle of the die \( \alpha \).

2.3 Tension tests

The universal tensile testing machine was used to carry out the
tensile test at room temperature on the extruded heterogeneous
welded sheets, and the tensile strength of the specimen could
be obtained, which was taken as the bonding strength of the
heterogeneous welded sheets. The gauge of the tensile speci-
men is shown in Fig. 4(b). The loading speed of the testing
machine was 1 mm/min. The data after the experiments were
compared with the simulated results in Section 2.2 above to
verify the reliability of the finite element model. Moreover, it
was found that the bonding strength obtained from the tensile
test in Section 2.2 was approximately equal to the maximum
normal pressure between the two billets obtained from the FE
post-processing operation. Therefore, the normal pressure
obtained by DEFORM software can be used as the output
variable of the training data set.

3 Prediction based on BP neural network model

The BP neural network model is a neural network with mul-
tiple forward propagation, which has the characteristics of
signal forward propagation and error backward propagation
[22]. The signal is transmitted from the input end to the output
end through the weights and thresholds between the connect-
ed neurons, and the weights and thresholds are adjusted by
error feedback, so that the error becomes smaller and smaller
and the expected effect is achieved.

BP neural network is composed of input layer, hidden lay-
er, and output layer, as shown in Fig. 5. The network input
layer was determined by the independent variables of the
forming temperature \( T \), extrusion ratio \( \lambda \), and the guiding
angle of die \( \alpha \), and the output layer was a single dependent
variable of bonding strength. The number of hidden layers and
the number of neurons were also one of the important factors
that affected the accuracy of the model. If the number of neu-
rons was too small, the training of the model would be insuf-
icient; if the number was too large, it would overfit and the
generalization ability of the model would be weakened.
Therefore, appropriate hidden layer structure design was more
important. Since this model was a three-dimensional single
output with 30 sets of small samples, a single layer hidden
layer network should be used without multilayer hidden layer,
namely, three-layer neural network structure model.

At present, there are no uniform criterions to determine the
number of neurons in the hidden layer. The common methods
for determining the number of neurons in the hidden layer
were trial and error method, direct stereotype method and
growth method [23]. Generally, it was determined by the em-
pirical formula (1):

\[
l = \sqrt{p + q + b}
\]

where \( l \) is the number of neurons in the hidden layer, \( p \) and \( q \)
are input and output layer variables, respectively, and \( b \) is a
constant between 1 and 10. Among them, \( p = 3 \) and \( q = 1 \), so it
could be preliminarily determined that the number of neurons is in the interval [3, 12].

The initial settings of the neural network are shown in Table 1.

MATLAB neural network toolbox was used to write programs for neural network training. Due to the different unit dimensions of forming process parameters such as forming temperature, extrusion ratio, the guiding angle of die, and bonding strength, the data needed to be normalized, which could avoid the influence of dimensional changes on the BP network model. For this reason, all the input layer and output layer data were concentrated in the interval [0, 1], and the specific transformation formula (2) [24] was as follows:

\[
X' = 0.1 + 0.8 \times \left( \frac{X - X_{\min}}{X_{\max} - X_{\min}} \right)
\]  

(2)

where \(X\) is the original data of process parameters, \(X'\) is the normalized data of process parameters, and \(X_{\max}\) and \(X_{\min}\) are the maximum and minimum values of the data set.

For the performance evaluation of the BP neural network, the determined coefficient (\(R^2\)) of the data \(R^2\) in the neural network training set and the mean square error (MSE) of the test set MSE were usually used to evaluate. The greater \(R^2\) was, the smaller MSE was, and the higher the model accuracy was. The definition of MSE (3) [25] was

\[
\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (a_i - y_i)^2
\]

(3)

According to the above analysis, only the number of neurons was changed and other parameters in Table 2 were kept unchanged, then the models were trained and \(R^2\) and MSE of
In order to avoid the fluctuation of the neural network, each experiment needed to be repeated 20 times, and the average value was taken as the experimental result of this group. The results are shown in Fig. 6.

As the number of neurons continued to be increased, $R^2$ it increased first and then decreased, while MSE was in a fluctuating state. It could be clearly seen that when the number of neurons in the hidden layer was 7, $R^2$ was the largest, and the error was also small. In summary, in the range of allowable error and fast convergence rate, the single hidden layer and seven neurons BP neural network model would be adopted.

The orthogonal experiments and finite element simulations were used to obtain the sample data. Three factors such as forming temperature, extrusion ratio, and the guiding angle of the die were considered, which affected the welding force of heterogeneous welded sheets. And each factor had four different levels. The scheme of the orthogonal experiments is shown in Table 2.

The number of training samples was also very important for the establishment of the neural network. The more samples were, the closer the BP neural network was to the mapping relationship between the input layer and the output layer. But too many samples would greatly increase the amount of calculation. The orthogonal table $L_{16}(4^3)$ with three factors and four levels are designed as shown in Table 3.

The results of the six groups of tensile experimental data are shown in Table 4. The data sample was acted as the test set data of the neural network, which tested the learning ability of the neural network training model.

After the training of the BP neural network designed above, the predicted results and relative errors are shown in Fig. 7.

\[
A = \left(1 - \frac{\text{MAE}}{}\right) \times 100\%	ag{4}
\]

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - y_i \right|	ag{5}
\]

where $A$ is the predicted accuracy.

The predicted accuracy of the bonding strength model obtained by the BP neural network was 93.72%, and the mean absolute error was 6.28%. The reason for the low accuracy might be that the error fluctuation was large due to the large sample dispersion obtained from the finite element simulations, and the BP neural network fell into the local optimal

### Table 1 BP neural network algorithm parameters

| Parameters | Values |
|------------|--------|
| Activation transfer functions (input layer to hidden layer) | tansig |
| Activation transfer functions (hidden layer to output layer) | purelin |
| Training functions | trainlm |
| Target error | $1 \times 10^{-6}$ |
| Learning rate | 0.05 |
| Maximum number of iterations | 1000 |

### Table 2 Level factor table of orthogonal experiment

| Input parameters | Level 1 | Level 2 | Level 3 | Level 4 |
|------------------|---------|---------|---------|---------|
| $T$ (°C)         | 330     | 360     | 390     | 420     |
| $\lambda$       | 12.07   | 16.10   | 24.15   | 48.30   |
| $\alpha$ (°)    | 80      | 100     | 120     | 140     |

### Table 3 Training samples of BP neural network

| No. | $T$ (°C) | $\lambda$ | $\alpha$ (°) | Bonding strength (MPa) |
|-----|----------|-----------|--------------|------------------------|
| 1   | 330      | 12.07     | 80           | 30.27                  |
| 2   | 330      | 16.10     | 100          | 33.91                  |
| 3   | 330      | 24.15     | 120          | 37.44                  |
| 4   | 330      | 48.30     | 140          | 35.97                  |
| 5   | 360      | 12.07     | 100          | 33.27                  |
| 6   | 360      | 16.10     | 80           | 32.76                  |
| 7   | 360      | 24.15     | 140          | 36.84                  |
| 8   | 360      | 48.30     | 120          | 36.29                  |
| 9   | 390      | 12.07     | 120          | 40.99                  |
| 10  | 390      | 16.10     | 140          | 37.72                  |
| 11  | 390      | 24.15     | 80           | 38.84                  |
| 12  | 390      | 48.30     | 100          | 36.41                  |
| 13  | 420      | 12.07     | 140          | 31.96                  |
| 14  | 420      | 16.10     | 120          | 38.68                  |
| 15  | 420      | 24.15     | 100          | 36.18                  |
| 16  | 420      | 48.30     | 80           | 35.17                  |
solution range in the training process. Therefore, it was difficult to meet the requirements of the process for the bonding strength, and the BP neural network needed to be optimized to further improve the predicted accuracy.

4 Prediction based on GA-BP neural network model

A genetic algorithm is an algorithm that simulates biological evolution and genetic mode and searches the global optimum through parallel random search. This algorithm could not only optimize the individual but also retain the parent information, which repeated genetic iterations until the optimal individual [26]. The weights and thresholds of the BP neural network were optimized by a genetic algorithm, which could effectively avoid the local optimum of bonding strength model established by the BP neural network and improve the predicted accuracy. The specific optimization process is shown in Fig. 8.

The essence of genetic algorithm was to optimize the weights and thresholds of BP neural network. The main steps of genetic algorithm to optimize BP neural network were as follows: Step 1, the range of weights and thresholds was defined by determining the topological structure of BP neural network, and the initial chromosome of population was obtained by real number coding; Step 2, the random population was generated, and the larger fitness value was selected subsequently. Then the roulette method was used for selection, and the crossover and mutation were carried out to generate a new generation of population; Step 3, step 1, and step 2 were repeated until the end of the algorithm and the optimal individuals were decoded to obtain the optimal weights and thresholds assigned to BP neural network for training.

When the fitness function was written by the genetic algorithm, the sum of the absolute value of the error of the BP neural network was usually taken as the fitness of the individual population [27]. The size of the fitness could be used as the criterion of genetic difficulty of individual offspring. That is, it was easy to inherit when the fitness was large. Generally, the fitness value is shown in formula (6):

\[ F = k \left[ \sum_{i=1}^{n} \text{abs}(o_i-y_i) \right] \]  

where \( k \) is the relevant coefficient.

With the help of the MATLAB toolbox, the main program of the GA-BP algorithm and the subprograms of fitness, selection, crossover, and mutation were written. The main parameters of the genetic algorithm were set as follows: population size was 40, iteration number was 100, crossover probability was 0.7, and mutation probability was 0.1. The training set and test set data in Section 3 were still used. Through the selection, crossover, mutation, fitness calculation, and other optimization operations of samples, the smaller the error of the BP neural network was, the greater the fitness value was. And the larger fitness value was retained until the optimal weights and thresholds were obtained. The optimal weights and thresholds were put into the BP neural network for repeated training. The predicted results of bonding strength optimized by the genetic algorithm are shown in Fig. 9.

As can be calculated from Fig. 9 that the accuracy of the model reached 99.5% and the mean absolute error was 0.5%. It further improved the accuracy of the model and made the optimized model have a more accurate predicted ability. The results showed that the GA-BP neural network model can be used to predict the bonding strength of heterogeneous welded sheets.

5 Results and discussion

Under the same training data and test data, the results and errors of the traditional BP neural network and the above GA-BP neural network are shown in the analysis results of Figs. 7 and 9, respectively. The predicted values obtained by the GA-BP neural network were closer to the expected values.
that is, the predicted accuracy of the GA-BP model was more accurate and more in line with the requirements of industrial production. In order to further compare the generalization ability of the traditional BP neural network and the BP neural network optimized by GA, eight groups of process parameters were randomly generated by MATLAB within the range of process parameters designed by the orthogonal experiments, and the finite element simulations were carried out subsequently. The results are shown in Fig. 10.

The predicted accuracy and generalization ability of the BP neural network model and GA-BP neural network model were evaluated through the root mean square error (RMSE), formula (7), and the mean absolute error (MAE).

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (o_i - y_i)^2}
\]  
(7)

Fig. 8 The optimization flowchart of GA-BP neural network

Fig. 9 The diagram of predicted results and errors in GA-BP neural network model

Fig. 10 Comparison of generalization ability of two algorithms
It can be calculated that the values of RMSE and MAE of BP neural network model were 1.5828 and 4.11\%, and the values of RMSE and MAE of GA-BP neural network model were 0.0821 and 0.22\%, respectively. RMSE and MAE obtained by GA-BP neural network model were smaller, so the GA-BP neural network model had stronger generalization ability and predicted accuracy for the prediction of bonding strength.

In order to compare the effects on the bonding strength of the two models, the predicted process parameters with smaller error and larger bonding strength obtained by the above models were used for process experiments. The process parameters of the BP neural network model were as follows: the forming temperature was 390 °C, the extrusion ratio was 12.07, and the guiding angle of the die was 120 °C. Ultimately, the predicted value was 39.80 MPa while the actual value was 41.53 MPa, and the error percentage was 2.5\%.

Correspondingly, the value of process parameters of the GA-BP model was: forming temperature was 390 °C, extrusion ratio was 24.15, and the guiding angle of the die was 120 °C. And the predicted value was 40.33 MPa while the actual value was 40.28 MPa, and the error percentage was 0.12\%. Moreover, the results of bonding strengths between this process and the same type of solid-phase bonding process are shown in Fig. 11 [28–31], which shows the feasibility of the process and the GA-BP model.

In order to further verify the accuracy of the GA-BP neural network model, the fracture morphologies of tensile samples under the two models were obtained by scanning electron microscopy (SEM), as shown in Fig. 12. From the view of morphology, both of them were layered structure, showing brittle behavior, which may be related to brittle intermetallic compound layers formed in the process. The fracture morphology predicted by the BP neural network model had a block structure, as shown by the red arrow in Fig. 12(a), which had obvious cracks of the intermetallic compound. While the fracture morphology predicted by GA-BP neural network model was relatively smooth in Fig. 12(b) [28, 29, 32, 33]. The results obtained by GA-BP neural network model were more in line with the actual process and played the role of optimization and prediction.

6 Conclusion

It was based on the extrusion process of heterogeneous light alloy thickness-oriented welded sheets, so the neural network models were constructed by finite element simulations and process experiments. According to the above results, the conclusions are as follows:

1. A single hidden layer BP neural network structure with 7 neural units was established, in which the forming temperature, extrusion ratio, and the guiding angle of die were taken as input variables and the bonding strength of heterogeneous welded sheets was taken as output variables. The genetic algorithm was used to optimize the random weights and thresholds of the BP neural network, which...
could improve the predicted accuracy of the bonding strength of heterogeneous welded sheets.

2. The predicted results of BP neural network model and GA-BP neural network model were compared. It was found that the GA-BP neural network model had better predicted performance. The predicted accuracy increased from 93.72 to 99.5%, and the predicted error decreased from 6.28 to 0.5%, which proved that the GA-BP neural network model had good generalization ability.

3. By comparing the actual process experiments and fracture morphology characterization of the BP neural network model and the GA-BP neural network model, the error percentages of the two models under the optimal parameters were 2.5% and 0.12%, respectively. Moreover, the scanning fracture morphology of the GA-BP neural network model was smoother, which indirectly verified the reliability of the GA-BP neural network model. It showed that the BP neural network optimized by genetic algorithm was feasible to predict the bonding strength of heterogeneous welded sheets.

**Nomenclature**

- \( n \): The number of test set samples;
- \( o_i \): Predicted output value of the \( i \)th test set sample;
- \( y_i \): Expected output value of the \( i \)th test set sample

**Author contribution**

Lei Gao: conceptualization, methodology, writing-original draft preparation, and experimental scheme design. Li Feng: writing, reviewing, and editing. Peng Da Huo, Chao Li, and Jie Xu: algorithm help.

**Funding**

This paper was supported by the Key Laboratory of Microsystems and Micro-structures Manufacturing, Ministry of Education, Harbin Institute of Technology (2020KM005), and the Fundamental Research Foundation for Universities of Heilongjiang Province (LGYC2018JQ011).

**Data availability**

The data obtained in the framework of this study are available to the journal upon request.

**Declarations**

**Ethics approval**

Not applicable.

**Consent to participate**

Not applicable.

**Consent for publication**

Not applicable.

**Competing interests**

The authors declare no competing interests.

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