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

Lei Gao[a] • Feng Li*[a] • Peng Da Huo[a] • Chao Li[a] • Jie Xu**[b]

Abstract

As a widely recognized optimization method, BP neural network can provide scientific guidance for the formulation of reasonable process parameters. However, due to the randomness of its own weights and thresholds, the prediction accuracy remains to be further improved. The forming and manufacturing of heterogeneous welded sheet is a new extrusion connection method. There are many factors affecting the bonding quality, which brings trouble to the evaluation of bonding strength and quality. In this paper, orthogonal experiment, finite element simulation and process experiment were used to design and verify the key process parameters that affected the bonding strength of heterogeneous sheets. BP neural network and genetic algorithm neural network were used to predict the bonding strength. The results showed that the genetic algorithm neural network model has higher reliability, and the prediction accuracy was 99.5 %. Compared with the traditional BP neural network, the prediction 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 sheets extrusion manufacturing.

Key words Heterogeneous sheets; Extrusion bonding; Bonding strength; GA-BP neural network; Prediction accuracy

1. Introduction

Solid-state bonding of dissimilar metals [1-3] can connect different kinds of metals with different properties, so that it can play the advantages of different materials on the basis of the same whole, 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 processes of solid-state bonding of dissimilar metals, scholars from various countries have carried out research from the following aspects on how to evaluate the quality of welding:

The first was based on the process experiment and theoretical model derivation, and established the welding criterion that can predict the interfacial welding force. Researchers had successively proposed a number of welding criteria based on the normal pressure of the welding 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 was based on numerical simulation and intelligent algorithm, the welding pressure on the welding path was obtained by simulation optimization, so as to predict and evaluate the welding quality. In recent years, for this nonlinear mathematical model, 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 process. Compared with the above methods, modern intelligent algorithms were more suitable for the establishment of nonlinear

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mathematical models due to their outstanding self-learning and predictive capabilities, such as artificial neural network (ANN). There are many types of neural networks with self-learning and predictive capabilities. 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 includes genetic algorithm[16]（GA）, ant colony algorithm[17], particle swarm algorithm[18], pigeon-inspired optimization [19].

It is also one of the current research hotspots to realize the thickness-oriented bonding of heterogeneous sheets by extrusion. The bonding strength of the formed heterogeneous sheets directly affects the quality of the process. However, there is no traditional mathematical model to predict theoretically. BP artificial neural network establishes a mapping relationship between input and output. Starting from the existing experimental data, the network model is constructed, trained and tested, and finally the trained network model is used to predict and evaluate.

2. Methodology

As shown in Fig.1, this paper combined numerical simulation, neural network and process experiment to predict the bonding strength of heterogeneous sheet components. Firstly, the data were collected by numerical simulation. On this basis, the bonding strength prediction model of heterogeneous sheet components was established based on BP neural network. The sample data required in the algorithm were obtained from numerical simulation and process experiment. Secondly, GA was used to interfere with BP neural network which was optimized. The bonding strength prediction model of heterogeneous sheet components was established again by the optimized neural network. Finally, the ideal connection strength prediction curve was obtained, and then the process experiment was used to verify.

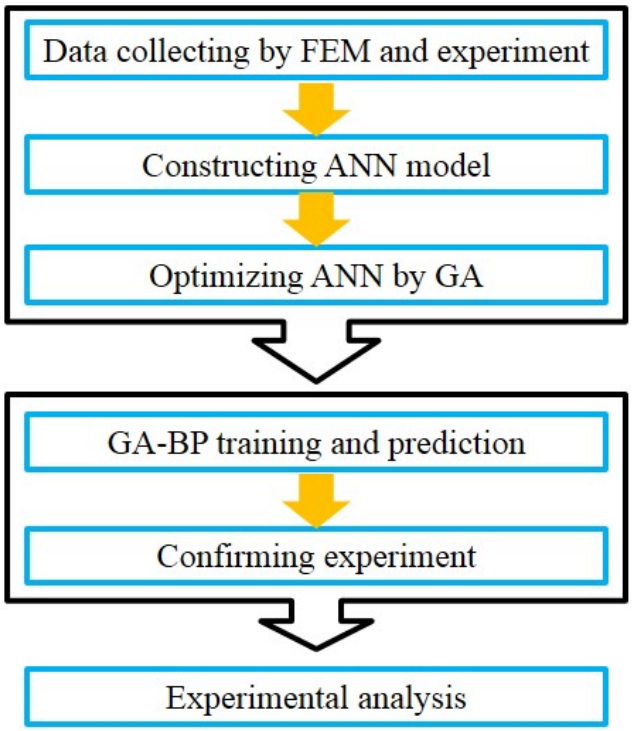

Fig. 1 Flow chart of this study

2.1 Processing principle

The principle of the extrusion forming process of the heterogeneous thickness-oriented welding sheets was to directly extrude the two semi-cylindrical billets after compounding. What is required was to ensure that the spatial relationship between the bonding surface of the two semi-cylindrical billets and the long side of the rectangular hole of the extrusion die was perpendicular to each other, as shown in Fig. 2

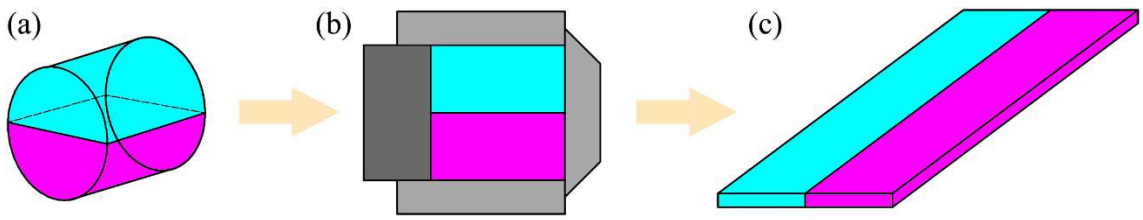

Fig. 2 Schematic diagram of process principle (a) Assembly (b) Extrusion (c) Forming

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 billets, which made the microstructure of the billet refined in the extrusion process. At the same time, the dissimilar metals could be stably bonded along the thickness direction. The performance was improved, and the composite effect was also achieved. The experimental materials were commercial AZ31 magnesium alloy and AA6061 aluminum alloy, and the size of semi-cylindrical billets were Φ40 mm × 30 mm. Before the experiment, the magnesium and aluminum alloy billets needed to be homogenized, and the homogenized annealing temperature and time of magnesium alloy were 420 °C and 12 h, and the aluminum alloy was 560 °C, 9h.

2.2 FE simulations

The commercial software Deform was used to carry out the finite element numerical simulation(FE) of the extrusion forming process of the heterogeneous bonded sheet, and a 1/2 axisymmetric finite element model was established as shown in Fig. 3. The interaction between the object and the surrounding environment was considered in the model. The ambient temperature was set to 20°C and the heat exchange coefficient between the experimental tooling die and the surrounding environment was 0.02 N/(s·mm·°C). The friction factors of magnesium, aluminum and rigid die were 0.7 and 0.3, respectively. Other relative parameters were given in other papers [20].

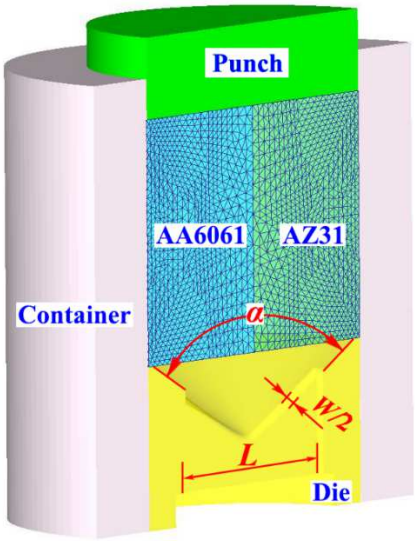

Fig. 3 FE geometric mode

For the diversity and consistency of the sample data, a series of finite element simulation of the process was carried out by changing the process parameters to prepare the data set for the training of the neural network model. Among them, the input variables of the training data set were extrusion temperature, extrusion ratio and angle of extrusion die. After the Deform post-processing operation, the normal pressure obtained was used as the output variable of the training data set.

2.3 Tension tests

The universal tensile testing machine was used to carry out the tensile test at room temperature on the extruded heterogeneous bonding composites, which obtained the tensile strength of the specimen. The tensile strength of the specimen was taken as the bonding strength of the heterogeneous bonding composites. The gauge of the tensile specimen is shown in Fig. 4. The loading speed of the testing machine was 1 mm / min. The data after the experiment were compared with the simulation results in Section 2.2 above to verify the reliability of the finite element model, and it was used as the test data set of the neural network.

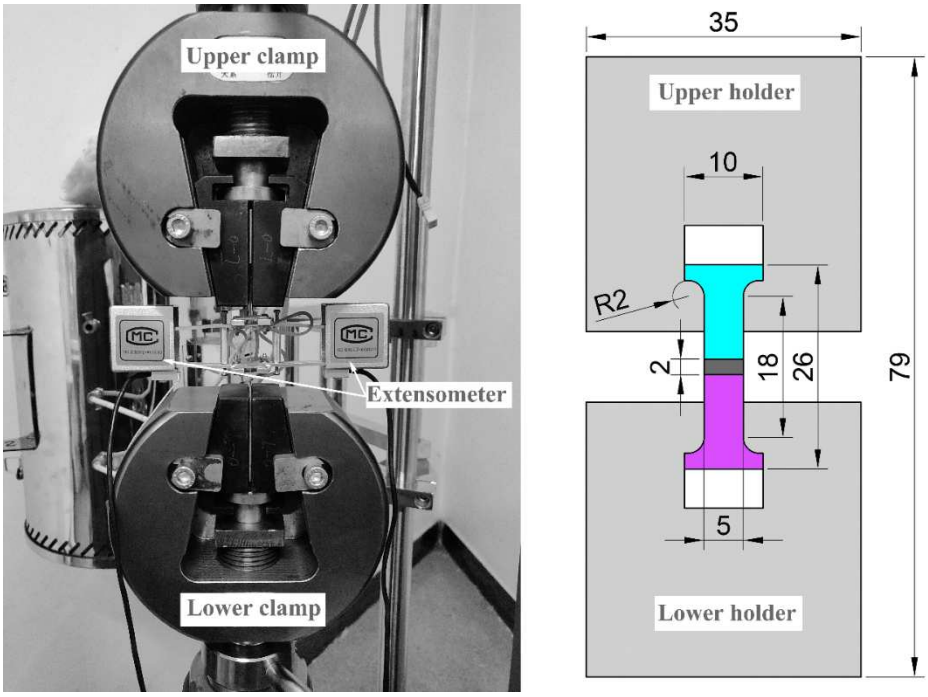

Fig. 4 Schematic drawing of tensile device

3 Prediction based on BP neural network model

The BP neural network model is a neural network with multiple forward propagation, which has the characteristics of forward signal propagation and backward error propagation [21]. The signal is transmitted from the input end to the output end through the weights and thresholds between the connected 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 was composed of input layer, hidden layer and output layer, as shown in Fig. 5. The network input layer was determined by the independent variables of the extrusion temperature T, extrusion ratio λ and the angle of extrusion die α, and the output layer was a single dependent variable of interface bonding strength. The number of hidden layers and the number of neurons are also one of the important factors that affected the accuracy of the model. If the number of neurons was too small, it would lead to insufficient training of the model, if the number was too large, it would over-fit, and the generalization ability of the model would be weakened. Therefore, appropriate hidden layer structure design was more important. Since this model is a three-dimensional single output with 16 sets of small samples, so we should not use a multilayer hidden layer network structure, and thought a single layer hidden layer network, namely three layer neural network structure model.

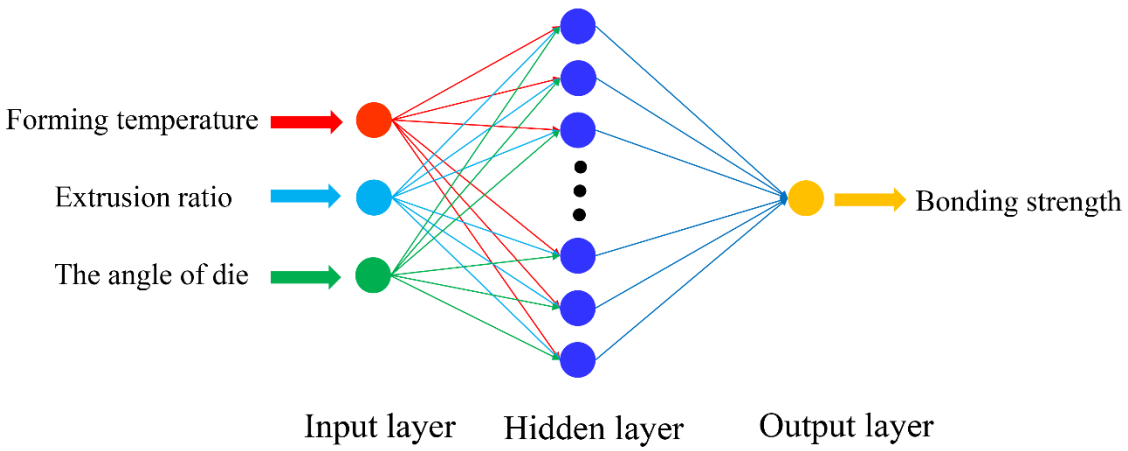

Fig. 5 Topological structure of BP neural network model

At present, there was no uniform criterion for determining 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 [22].Generally, it was determined by the empirical formula(1) :

$$l=\sqrt{n+m}+b \qquad (1)$$

Where: l is the number of neurons in the hidden layer, n and m are input and output layer variables, respectively, and b are a constant between 1 and 10. Among them, n=3 and m =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 Table1,

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	1×10^{-6}
learning rate	0.05
Maximum number of iterations	1000

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 extrusion temperature, extrusion ratio, the angle of extrusion die and bonding strength, the data needed to be normalized, which could avoid the influence of dimensional changes on BP network model. In this paper, all the input layer and output layer data were concentrated in the [0, 1] interval, the specific transformation formula (2) [23]was as follows :

$$X'=0.1+0.8\times\left(\frac{X-X_{\min}}{X_{\max}-X_{\min}}\right) \qquad (2)$$

Where: X is the original data of process parameters; X' is the normalized data of process parameters; $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of the data set.

For the performance evaluation of BP neural network, the determination coefficient of the data R^2 in the neural network training set and the mean square error of the test set MSE were usually used to evaluate. The greater the value R^2 was, the smaller the value MSE was, and the higher the model accuracy was. The definition of MSE (3) [24] was:

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(o_i-y_i)^2 \qquad (3)$$

Among them, n is the number of test set data; o_i is predicted output values for group i test sets; y_i is predicted the expected output value for the group i test set.

According to the above analysis, only the number of neurons was changed, and other parameters in Table 2 were kept unchanged. The model was trained, and then R^2 and MSE of each experiment was compared. In order to

avoid the fluctuation of neural network, each experiment needs to be repeated 20 times, and the minimum value was taken as the experimental result of this group. The results are shown in Fig. 6.

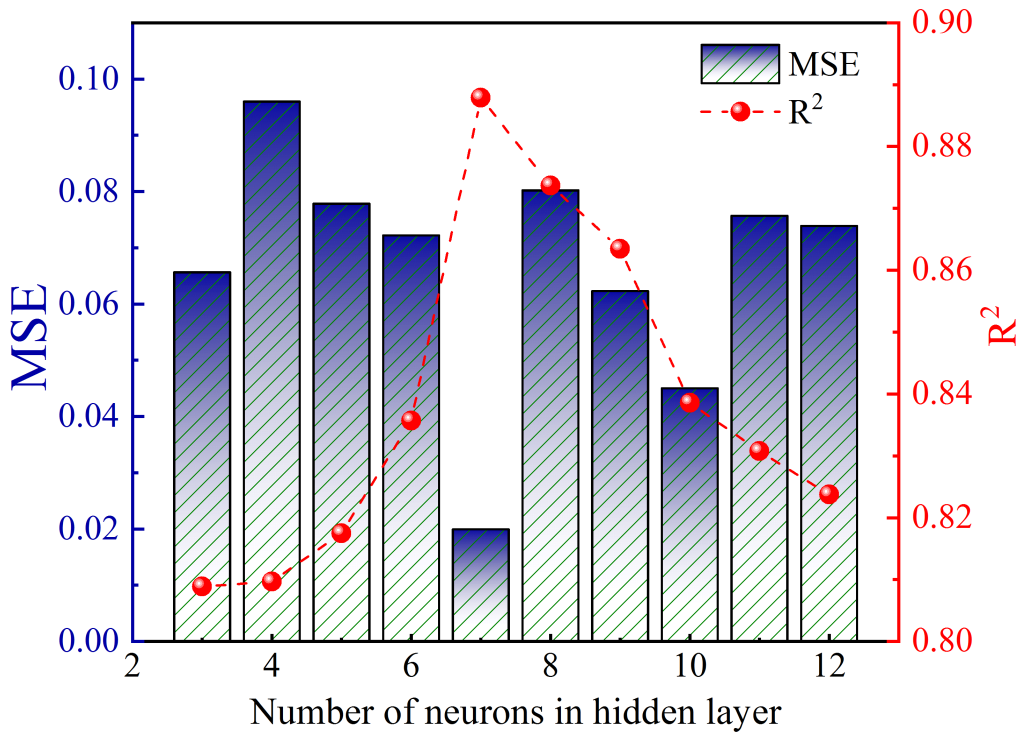

Fig.6 Test results of the number of neurons in the hidden layer

As the number of neurons continues to increased, R^2 continued to increase, and MSE continued to decrease. It could be clearly seen that when the number of neurons in the hidden layer was small, the training was insufficient, and when the number was too large, there was an over-fitting phenomenon. When the number of neurons in the hidden layer was 7, the training is the largest, and the error is also small. In summary, in the range of allowable error and fast convergence rate, this paper uses the single hidden layer seven neurons BP neural network model.

The orthogonal experiment method and finite element simulation were used to obtain the sample data. Four factors affecting the welding force of heterogeneous welding sheet were selected: extrusion temperature, extrusion ratio and the angle of extrusion die. Four different levels of the above three factors were selected. The orthogonal experiment scheme is shown in table 2.

Table 2 Level factor table of orthogonal experiment

Input Parameters	Level1	Level 2	Level 3	Level 4
T	330	360	390	420
λ	12.07	16.10	24.15	48.30
α	80	100	120	140

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 output layer and the output layer, but too many samples will greatly increased the amount of calculation. By designing three factors four levels orthogonal table L_{16}（4^3）, BP neural network training samples as shown in table 3.

Table 3 Training samples of BP neural network

No.	T（°C）	λ	α（°）	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

The results of the six groups of experimental data after stretching experiment are shown in table 4. The data sample is used as the test set data of the neural network to test the learning ability of the neural network training model.

Table 4 Tensile data

No.	T（°C）	λ	α（°）	Bonding strength(MPa）
1	360	12.07	120	34.80
2	360	24.15	120	33.77
3	390	12.07	120	41.53
4	390	24.15	120	40.28
5	420	12.07	120	37.85
6	420	24.15	120	36.23

After the training of the BP neural network designed above, the prediction results and relative errors are shown in Fig. 7. The prediction accuracy of the model was determined by formula (4), and the average absolute relative error was determined by formula (5).

$$A = (1 - MAPE) \times 100\% \quad (4)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| \quad (5)$$

where A is the prediction accuracy, $MAPE$ is the average absolute relative error, n is the number of test samples, e_i is the prediction error of sample i, and y_i is the expected value of sample i.

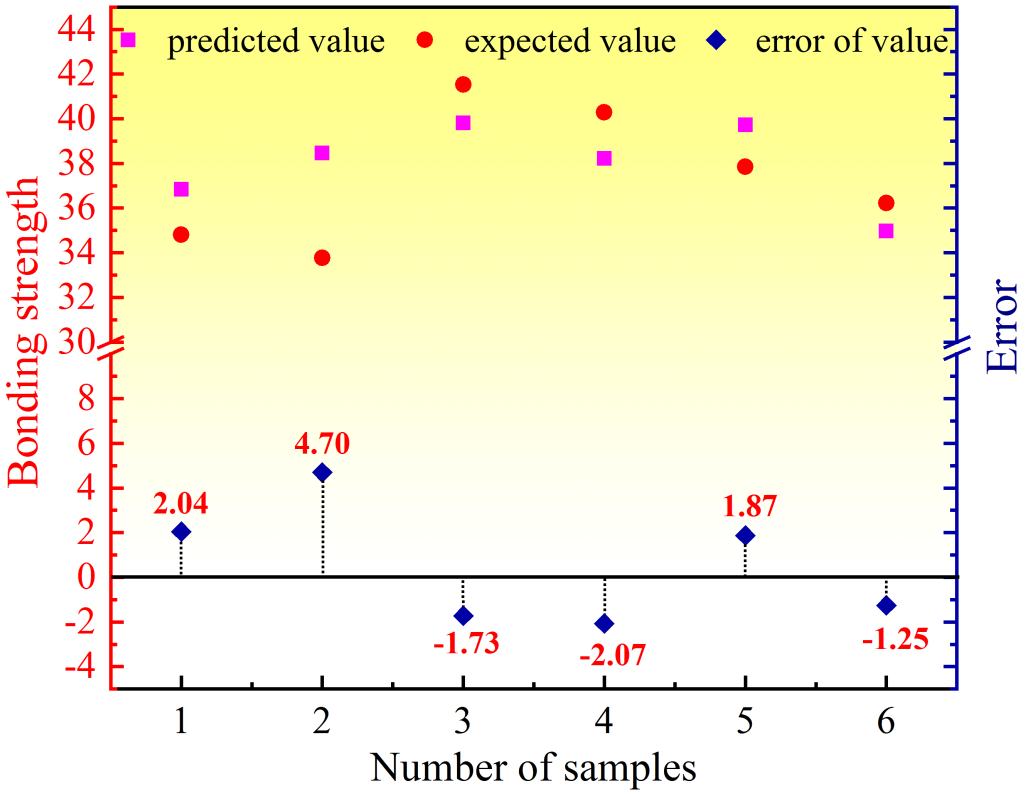

Fig. 7 BP result diagram and error diagram

The prediction accuracy of the bonding strength model obtained by BP neural network was 93.72 % and the average absolute relative error was 6.28 %. The accuracy was not high. The reason might be that the error fluctuation was large due to the large sample dispersion obtained from the finite element simulation and the BP neural network fell into the local optimal solution range in the training process. Therefore, it was difficult to meet the requirements of the process for the bonding strength, and it was necessary to optimize the BP neural network to further improve the prediction accuracy.

4 Prediction based on GA-BP neural network model

Genetic algorithm is an algorithm that simulates biological evolution and genetic mode, and searches the global optimum through parallel random search. This algorithm can not only optimize the individual, but also retain the parent information, after repeated genetic iterations until the optimal individual [25]. The weights and thresholds of BP neural network were optimized by genetic algorithm, which could effectively avoid the local optimum of BP neural network bonding strength model and improve the prediction accuracy. The specific optimization process is shown in Fig. 8,

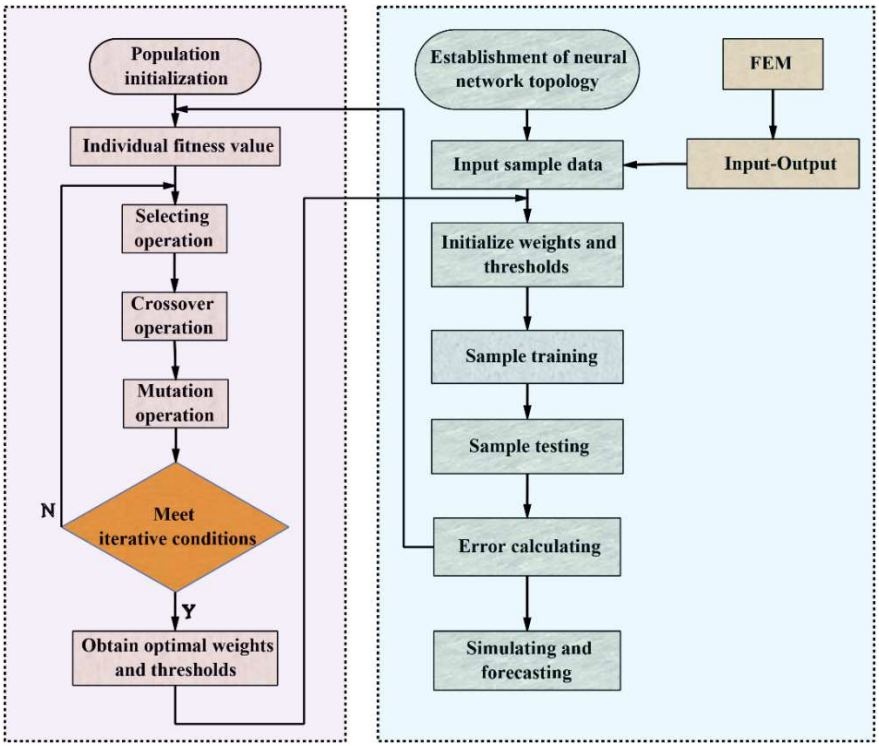

Fig. 8 GA-BP optimization flow chart

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 : Step1 , by determining the topological structure of BP neural network, the range of weights and thresholds was determined, and the initial chromosome of population was obtained by real number coding.; Step2, the random population is generated, and the larger fitness value was selected. Then the roulette method was used for selection, and then the crossover and mutation were carried out to generate a new generation of population.; Step3, repeating Step 1 and Step 2 until the end of the algorithm and decode the optimal individual 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 [26]. The size of the fitness could be used as the basis for the degree 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):

$$F = k\left[\sum_{i=1}^{n} abs(o_i - y_i)\right] \tag{6}$$

Where k is the relevant coefficient; n is the output layer node number of GA-BP model; o_i is the predicted output value of the i node; y_i is the expected output value of the i node.

With the help of Matlab toolbox, the main program of GA-BP algorithm and the subprograms of fitness, selection, crossover and mutation were written. The main parameters of 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 BP neural network was optimized by genetic algorithm. 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 BP neural network was, the greater the fitness value was, and the bonding strength corresponding to 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 of components for repeated training. The prediction results of bonding strength optimized by genetic algorithm are shown in Fig. 9.

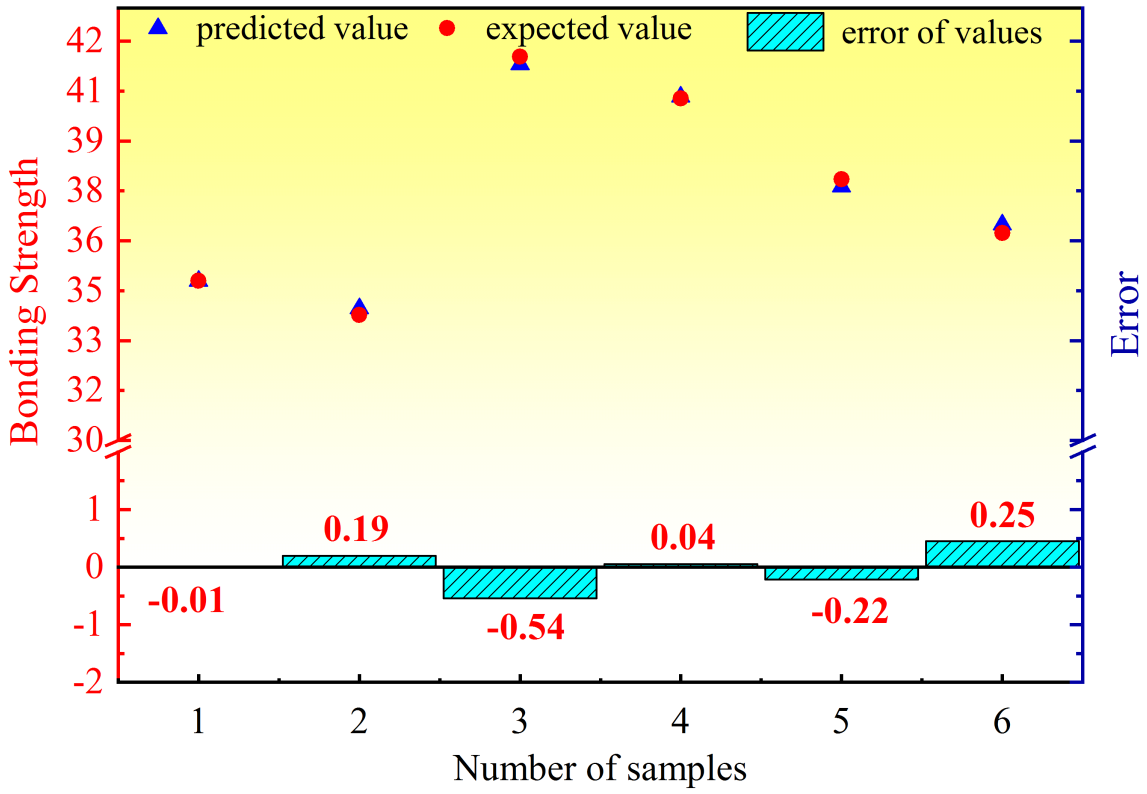

Fig. 9 GA-BP result diagram and error diagram

The GA-BP results and error diagram are shown in Fig.9. After calculation, the accuracy of the model reached 99.5 %, and the average absolute relative error was 0.5 %. It further improved the accuracy of the model and made the optimized model have more accurate prediction ability. The results show that the GA-BP network model can be used to predict the bonding strength of heterogeneous connections.

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 Fig. 7 and Fig. 9, respectively. The predicted values obtained by the GA-BP neural network were closer to the expected values, that is, the prediction accuracy of the GA-BP model is more accurate and more in line with the requirements of industrial production prediction. 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 of the orthogonal experiment design, and the finite element simulation was carried out. The results and the prediction results of the two models are shown in Fig. 10.

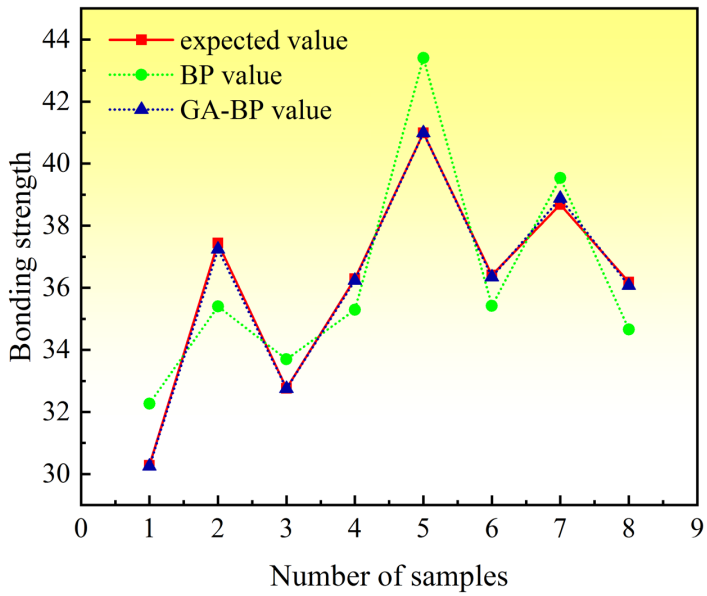

Fig. 10 comparison of generalization ability of two algorithms

In this paper, the prediction accuracy and generalization ability of BP neural network model and GA-BP neural network model were evaluated through root mean square error $RMSE$, Formula (7), absolute average deviation AAD, Formula (8).

$$RMSE = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(o_p - y_e)^2\right)} \quad (7)$$

$$AAD/\% = \left[\frac{1}{n}\sum_{i=1}^{n}\left(\left|o_p - y_e\right| / y_e\right)\right] \times 100\% \quad (8)$$

In the formula, o_p is the predicted value; y_e is the expected value; n is the number of samples. According to the above formula, the values of $RMSE$ and AAD of BP were 1.5828 and 4.11 %, and the values of $RMSE$ and AAD of GA-BP were 0.0821 and 0.22 %, respectively. The $RMSE$ and AAD obtained by GA-BP model were smaller, so the GA-BP model had stronger generalization ability and prediction accuracy for the prediction of bonding strength.

In order to compare the effects of the two models on the connection strength, the predicted process parameters with smaller error and larger connection strength obtained by the above models were used for process experiments. The process parameters of the BP model were as follows: the extrusion temperature was 390 °C, the extrusion ratio was 12.07, and the angle of extrusion die was 120°. Ultimately, the predicted value was 39.80 MPa, while the actual value was 41.53 MPa, and the error percentage was 2.5 %. The value of process parameters of GA-BP model was; extrusion temperature was 390 ° C, extrusion ratio was 24.15, the angle of extrusion die was 120 °, the predicted value was 40.33 MPa, and the actual value was 40.28 MPa, the error percentage was 0.12 %.

In this paper, the accuracy of GA-BP model verification was further verified from the microscopic point of view. The fracture morphology of tensile parts under the two models was obtained by scanning electron microscopy, as shown in Figure 11. From the view of morphology, both of them were layered structure, showing brittle behavior, which may be related to the formation of brittle intermetallic compound layers formed in the process behavior. The fracture morphology predicted by the BP model had an obvious block structure, as shown by the red arrow in Fig. 11(a), showing stress concentration, while the fracture morphology predicted by GA-BP was relatively smooth [27]. The results obtained by GA-BP model were more in line with the actual process and play the role of optimization and prediction.

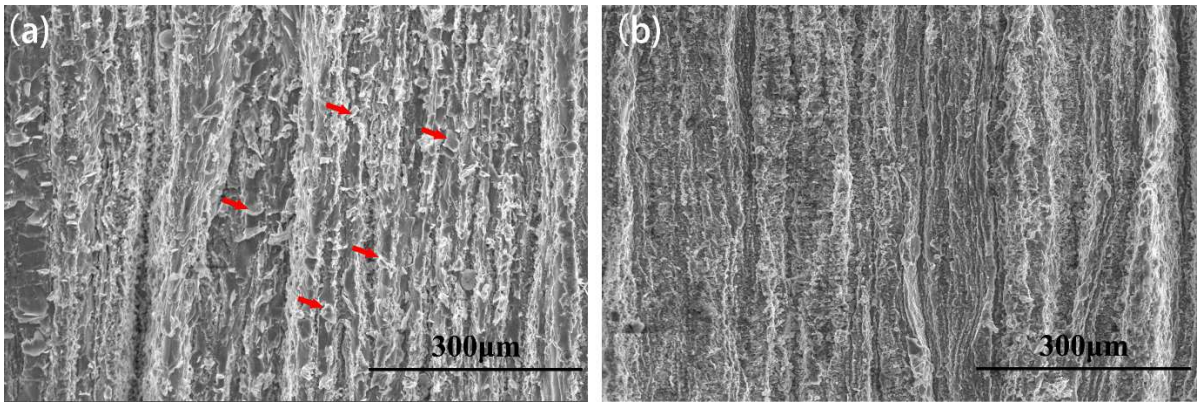

Fig.11 fracture morphology: (a)BP (b)GA-BP

6. Conclusion

In this paper, based on the extrusion process of heterogeneous light alloy thickness-oriented welding plate, the neural network model is constructed by finite element simulation and process experiment on the basis of orthogonal experiment design. According to the above results, the conclusions are as follows:

(1) A single hidden layer BP neural network structure with 7 neural units is established. Taking the bonding strength as the objective function, a BP neural network model suitable for the prediction of the bonding strength of heterogeneous connected composites is established. The genetic algorithm is used to optimize the random weights and thresholds of the BP neural network, to avoid the influence of the randomness of weights and thresholds and improve the prediction accuracy of the bonding strength of heterogeneous connected composites.

(2) The prediction results of BP model and GA-BP model are compared. It is found that the neural network model optimized by genetic algorithm has better prediction performance. The prediction accuracy increases from 93.72 % to 99.5 %, and the prediction error decreases from 6.28 % to 0.5 %, which proves that the model has good generalization ability.

(3) By comparing the actual process experiments and microscopic fracture morphology characterization of the BP model and the GA-BP model, the error percentages of the two models under the optimal parameters are 2.5 % and 0.12 %, respectively. Moreover, the microscopic scanning fracture of the GA-BP model is smoother, which directly verifies the reliability of the GA-BP model. It shows that the BP neural network optimized by genetic algorithm is feasible to predict the connection strength of heterogeneous connected composites.

Ethics declarations

Ethical Approval

Not applicable

Consent to Participate

Not applicable

Consent to Publish

Not applicable

Authors Coutributions

Lei Gao: conceptualization, methodology, writing-original draft preparation, experimental scheme design.
Li Feng: Writing- Reviewing and Editing.
Peng Da Huo, Chao Li, Jie Xu: Algorithm help

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Competing Interests

Not applicable

Availability of data and materials

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

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Figures

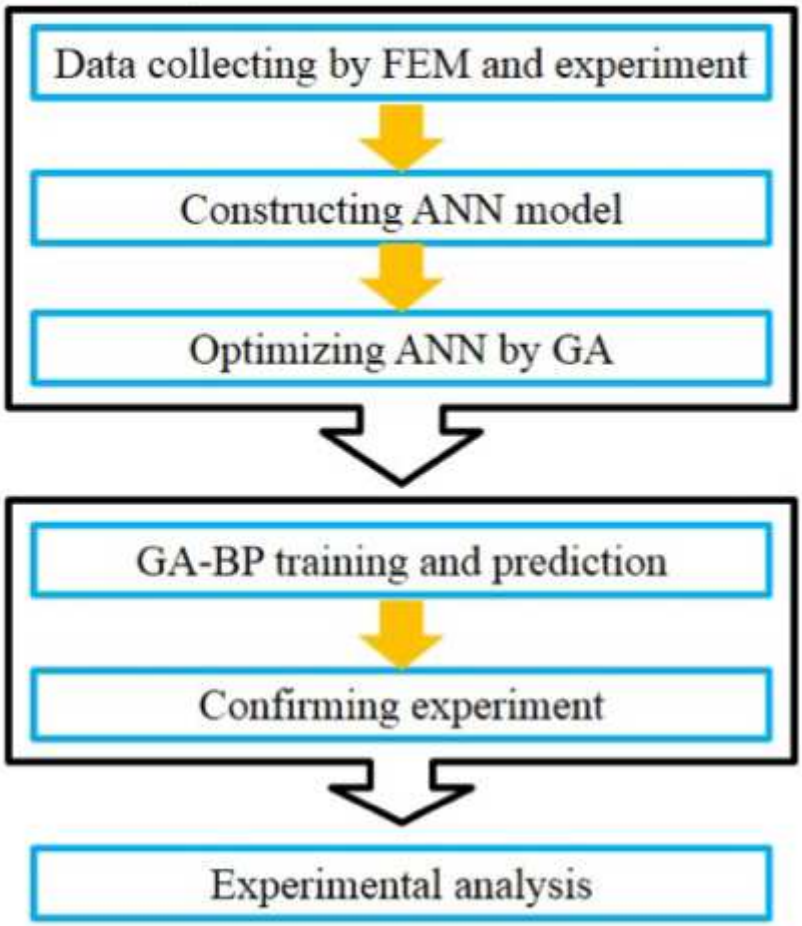

Figure 1

Flow chart of this study

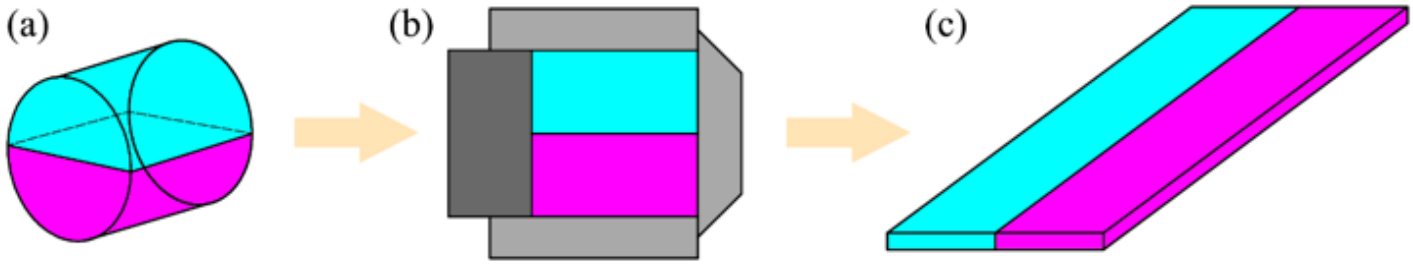

Figure 2

Schematic diagram of process principle (a) Assembly (b) Extrusion (c) Forming

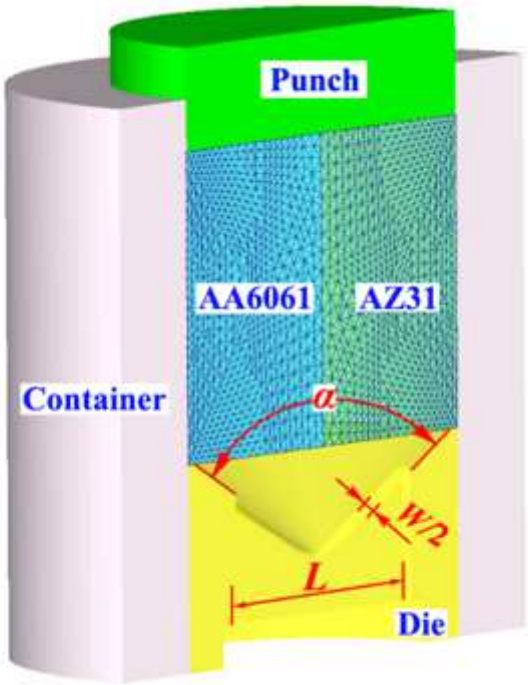

Figure 3

FE geometric mode

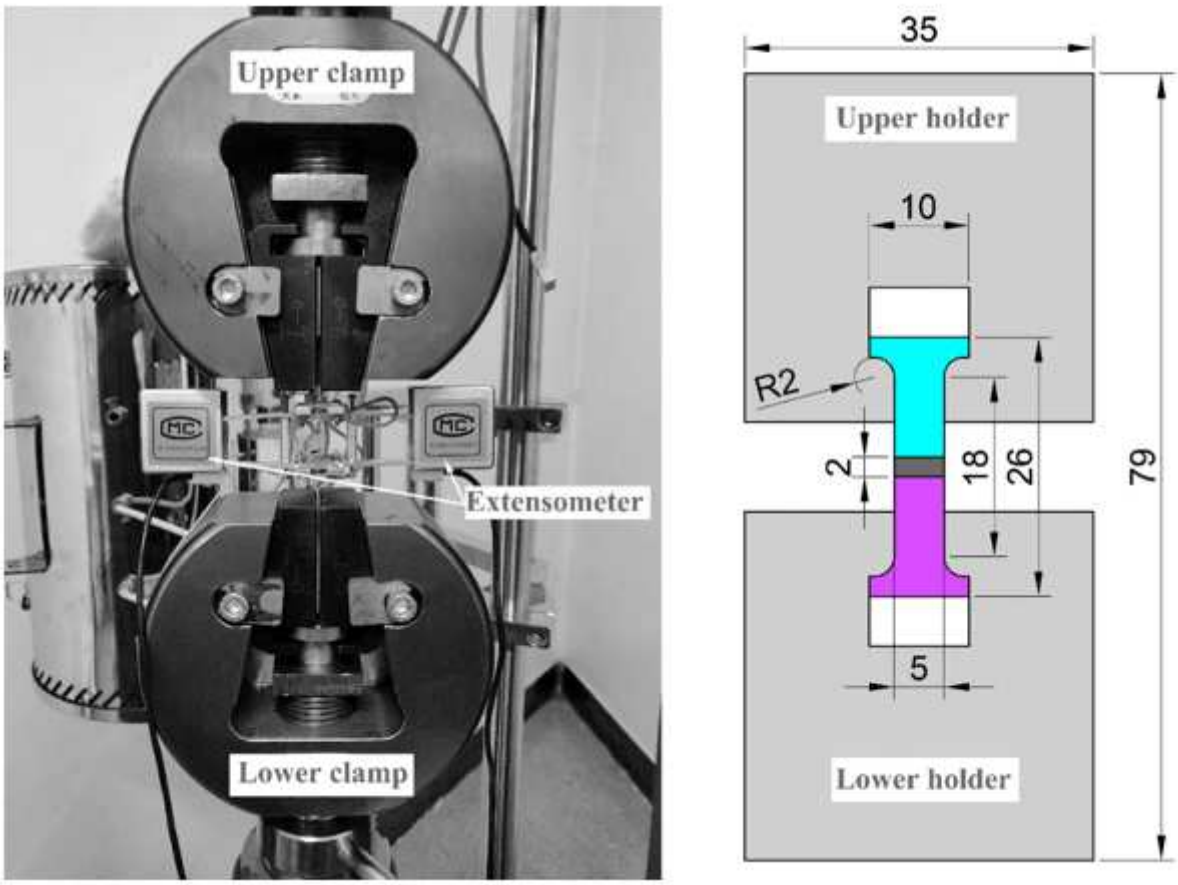

Figure 4

Schematic drawing of tensile device

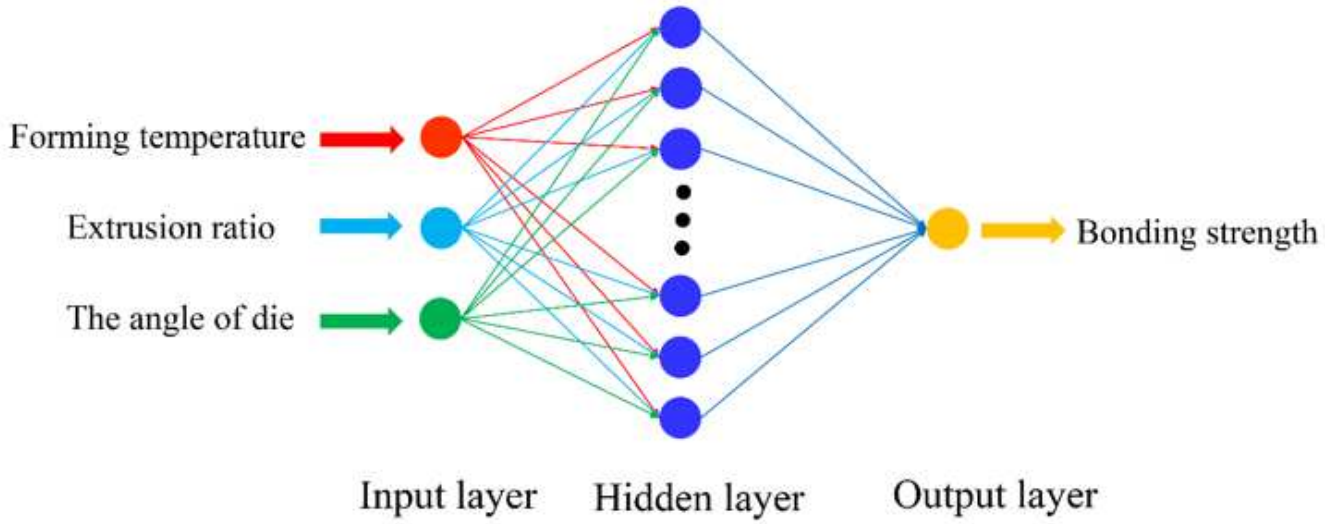

Figure 5

Topological structure of BP neural network model

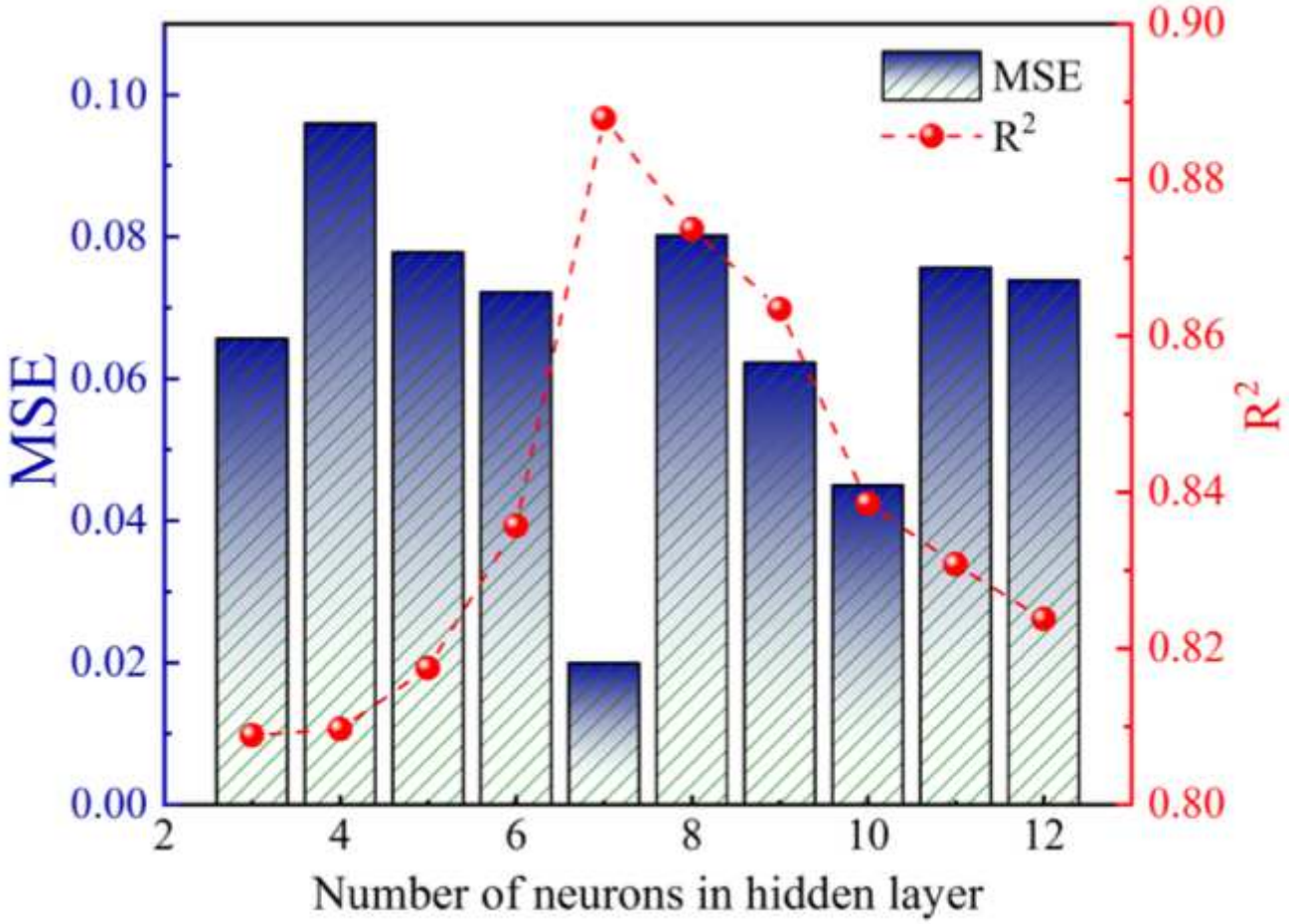

Figure 6

Test results of the number of neurons in the hidden layer

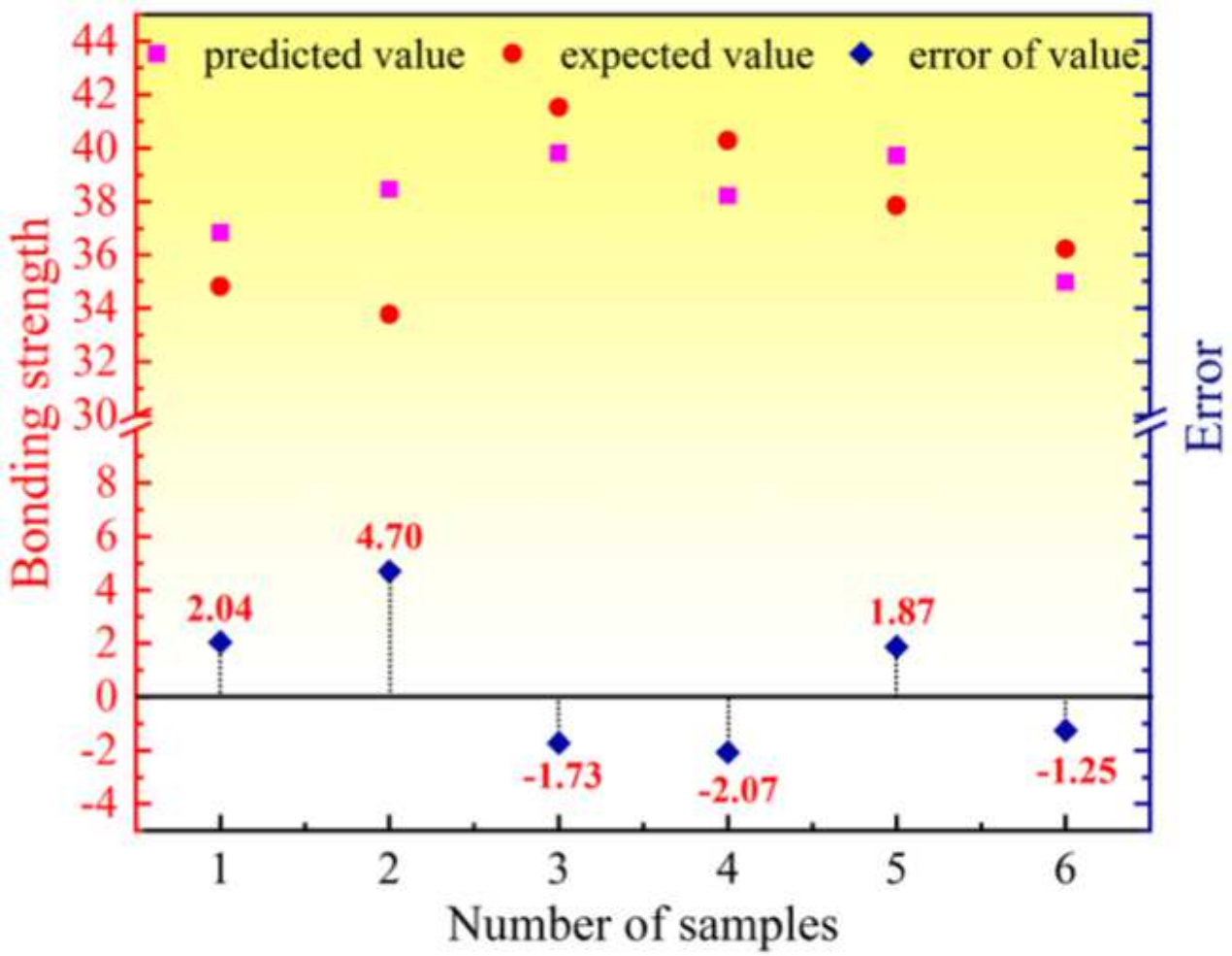

Figure 7

BP result diagram and error diagram

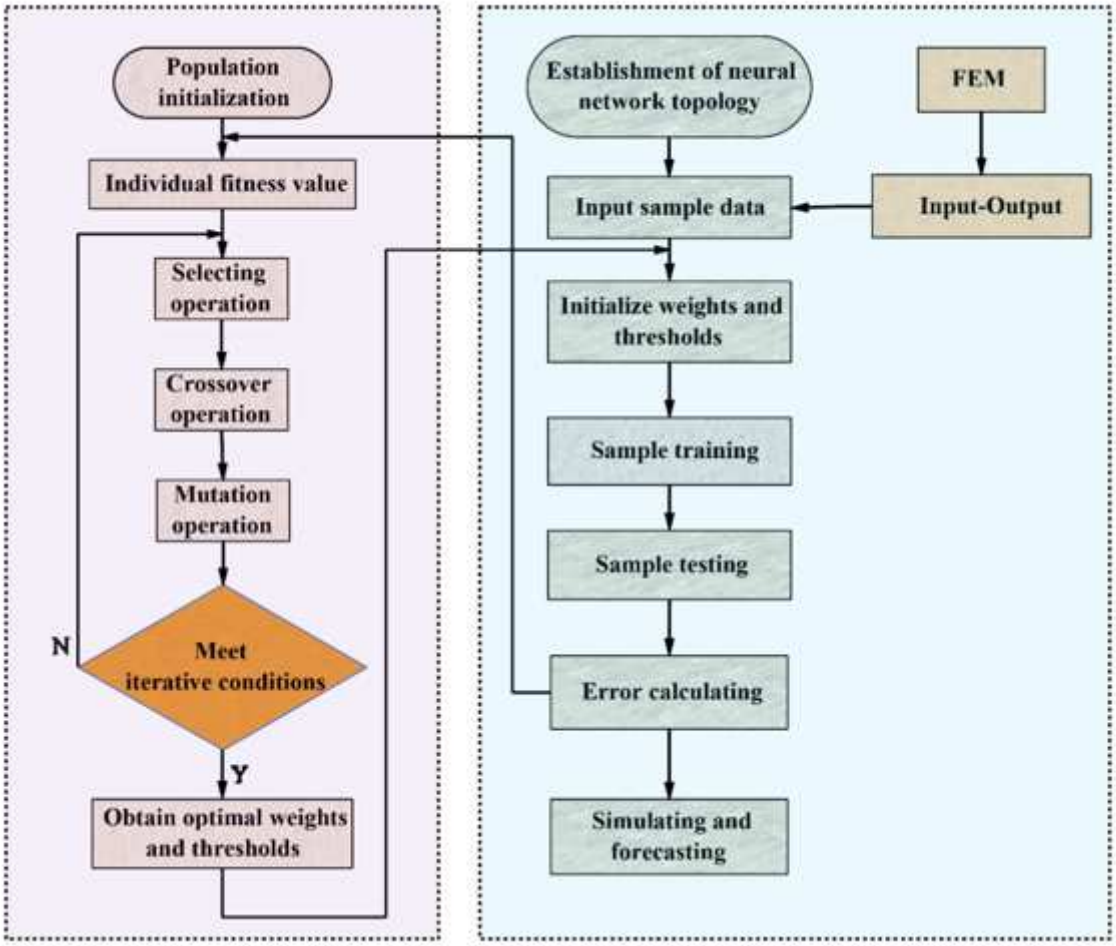

Figure 8

GA-BP optimization flow chart

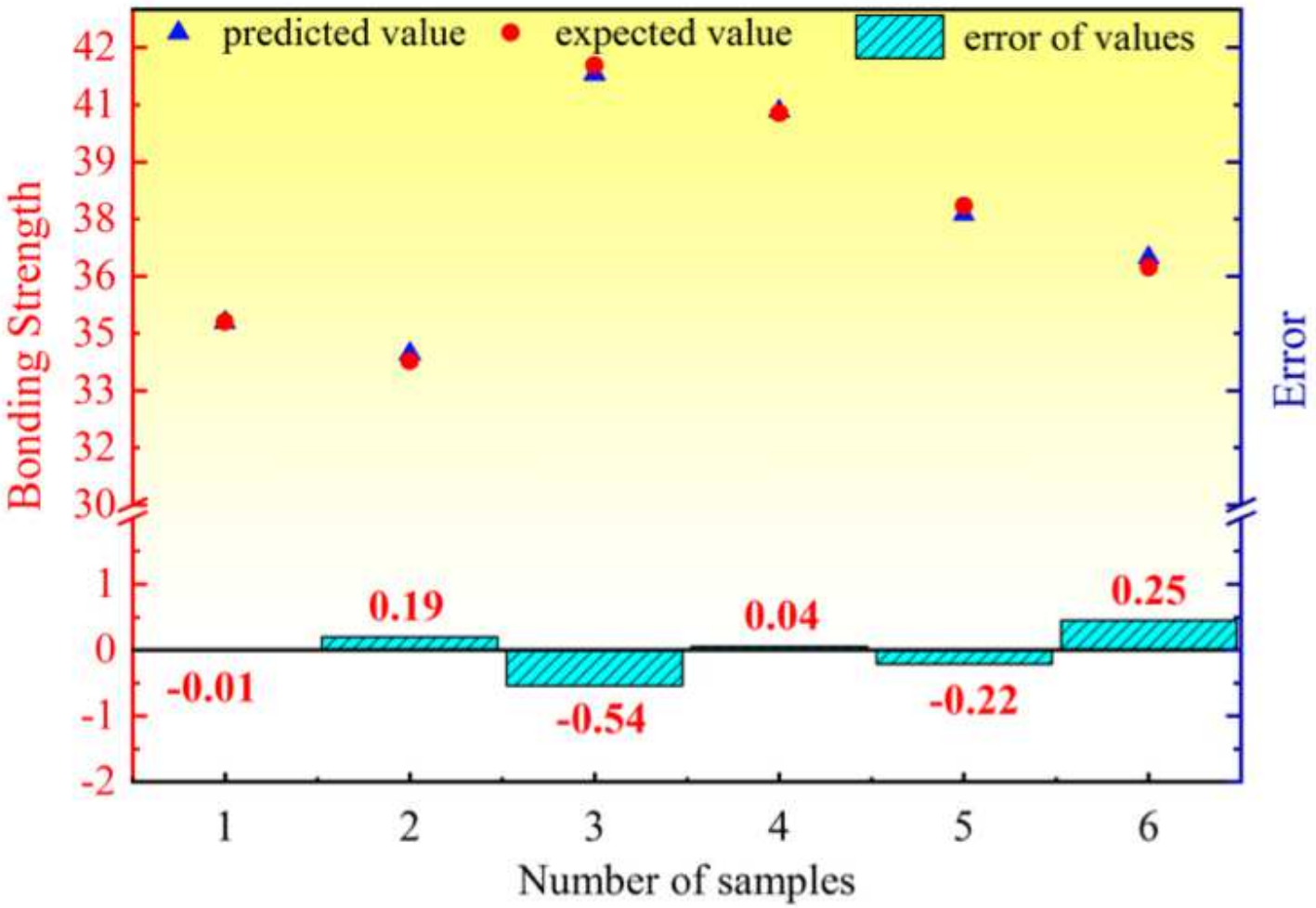

Figure 9

GA-BP result diagram and error diagram

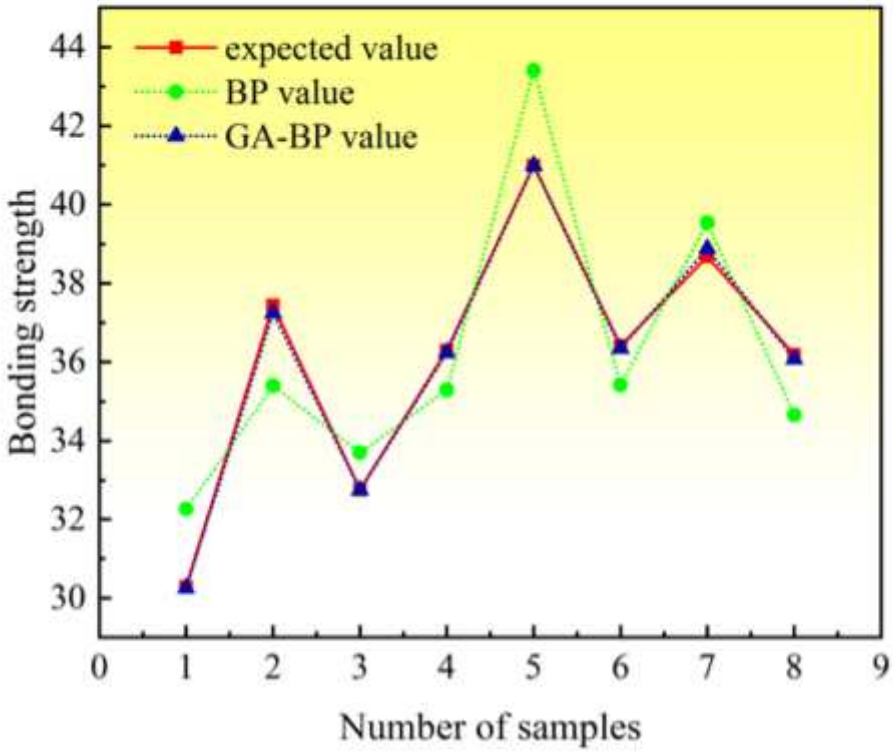

Figure 10

comparison of generalization ability of two algorithms

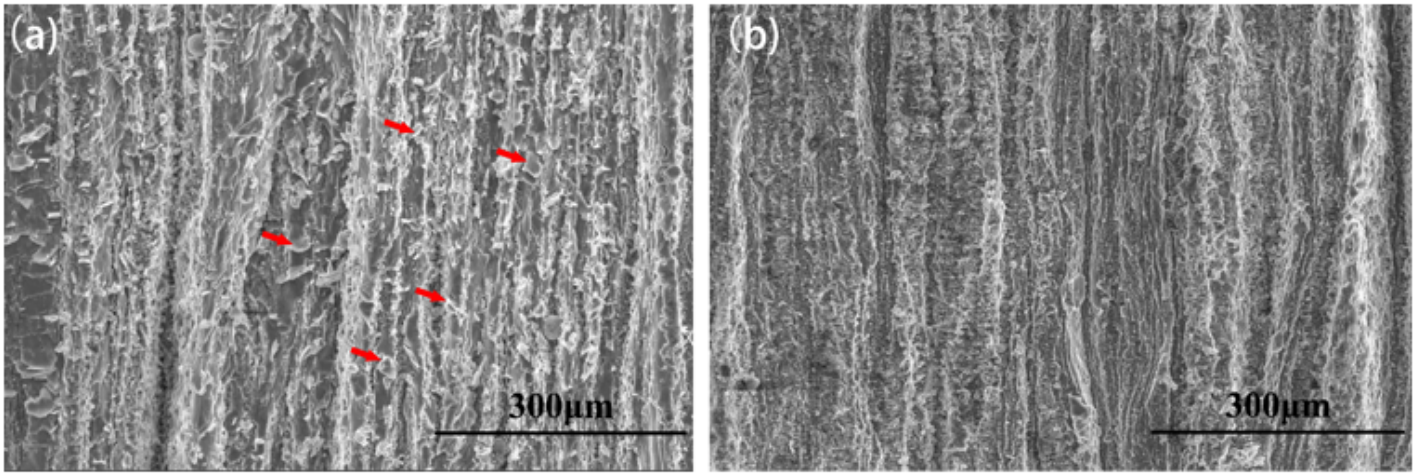

Figure 11

fracture morphology: (a)BP (b)GA-BP