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Artificial neural networks in steel-mushy aluminum pressing bonding ①

ZHANG Peng(张 鹏)[1], DU Yun-hui(杜云慧)[1], REN Xue-ping(任学平)[2],
LIU Han-wu(刘汉武)[3], CUI Jian-zhong(崔建忠)[3], BA Li-min(巴立民)[4]

1. Department of Mechanical Engineering, Tsinghua University, Beijing 100084, P.R.China;
2. Department of Metal Forming, University of Science and Technology Beijing, Beijing 100083, P.R.China;
3. Department of Metal Forming, Northeastern University, Shenyang 110006, P.R.China;
4. Anshan Automobile Fittings Factory, Anshan 114014, P.R.China

Abstract: Artificial neural networks were successfully used to research the modeling of aluminum solid fraction, preheat temperature of steel plate, preheat temperature of dies, free diffusing time before pressing and the interfacial shear strength in steel-mushy aluminum pressing bonding. Further more, the optimum bonding parameters for the largest interfacial shear strength were also optimized with a genetic algorithm.

Key words: artificial neural networks; steel-mushy aluminum bonding; genetic algorithm **Document code:** A

1 INTRODUCTION

For steel-aluminum bonding, if aluminum solid fraction is 100 %, it is steel-aluminum solid to solid bonding; if aluminum solid fraction is 0, it is steel-aluminum solid to liquid bonding; if aluminum solid fraction is within 0 ~ 100 %, the bonding is steel-mushy aluminum bonding. For steel-aluminum solid to solid bonding, it is mechanically occluded together with only a little physical bonding[1], so the interfacial mechanical property is generally bad. For steel-aluminum solid to liquid bonding, it is metallurgical bonding that is the firmest one[2]. However, at the interface, the higher bonding temperature can very easily result in Fe-Al brittle compound (Fe_2Al_5 and $FeAl_3$) layer that embrittles the interface to a certain extent[3], so the interfacial mechanical property does not reach its own level. For steel-mushy aluminum bonding, if the bonding parameters are suitable, the layer structure of Fe-Al brittle compound at the interface can be changed into net structure[4], that is, the embrittlement of the Fe-Al brittle compound layer at the interface can be removed, so the interfacial strength of the bonding plate should be much better.

In steel-mushy aluminum pressing bonding, the bonding parameters mainly include aluminum solid fraction, preheat temperature of steel plate, preheat temperature of dies and free diffusing time before pressing. These parameters have very complex influence on interfacial structure and shear strength. The too much bigger aluminum solid fraction, the more Fe-Al solid solution at the interface and the more weak bonding, the lower interfacial shear strength; however, the too much smaller aluminum solid fraction, the more Fe-Al brittle compound at the interface and the bigger embrittlement of the interface, the lower interfacial shear strength either. Similarly, the too much lower preheat temperature of steel plate and dies and the too much longer free diffusing time before pressing, the less diffusing of aluminum atoms, the more Fe-Al solid solution at the interface and the more weak bonding, the lower interfacial shear strength; the too much higher preheat temperature of steel plate and dies and the too much shorter free diffusing time before pressing, the more diffusing of aluminum atoms, the more Fe-Al brittle compound at the interface and the bigger embrittlement of the interface, the lower interfacial shear strength either. Further more, these influences of bonding parameters effect one another. Therefore, there exist complicated nonlinear relationship between the bonding parameters and the interfacial shear strength in steel-mushy aluminum pressing bonding, and this relationship is rather difficult or can not be determined by conventional regression method.

In this paper, a model of steel-mushy aluminum pressing bonding by using neural networks is maken according to the experimental data and also the optimum technology with a genetic algorithm is set up successfully.

2 MATERIALS AND EXPERIMENTAL PROCEDURES

The experimental materials were 1.2 mm thick 08Al-steel plate and industry pure aluminum

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(99.99 %). The treatments such as defatting, descaling must be conducted to the steel plate surface in order to get fresh surface to contact with aluminum mushy. The industry pure aluminum mushy was prepared by means of electromagnetic stirring method. The steel-mushy aluminum pressing bonding experiments were carried out on the bonding equipment (as shown in Fig.1). The pressing equipment was model 100 hydraulic press. First, put the steel plate (being preheated at some required temperature) into the lower die (being preheated at some required temperature). Second, delivered the aluminum mushy (being of some required solid fraction) onto the steel plate surface in the lower die through the mushy transfer. Third, covered the upper die (being preheated at the same required temperature as that of the lower die) and descended the press head (after some required time to result in the free diffusing of aluminum atoms) to conduct the pressing bonding for 2 min. The pressure was 50 MPa, and the deviation was ± 0.1 MPa. The preheat temperature deviation of experimental material and tools was ±1 ℃. In the course of the bonding, gas shield must be conducted in order to prevent the fresh surface of steel plate and the aluminum mushy from oxidization. The thickness of the solid aluminum layer of bonding plate was 4.0 mm. After the pressing bonding experiments, the testing samples of interfacial shear strength were made by using spark erosion. The interfacial shear strength of sample (being prepared for treatment by using artificial neural networks) was measured (Table 1) on universal material testing machine.

3 MODELING WITH ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) has been widely used to realize modeling, estimation, prediction, diagnosis and adaptive control in complex nonlinear system[5~10]. The back-propagation (BP) network is a multilayer feedforward and full-connected neural networks. It has strong associative memory and generalization capabilities, and it can approximate any nonlinear continuous function with an arbitrary precision. A three layered feed-forward neural networks with 4 neurons in the input layer, 2 in the hidden layer and 1 in the output layer was used in this paper (Fig.2). Layer Ⅰ was input layer which used linear elements Z_1, Z_2, Z_3 and Z_4 to represent the values of aluminum solid fraction, preheat temperature of steel plate, preheat temperature of dies and free diffusing time before pressing, respectively. Layer Ⅱ was hidden layer which used nonlinear elements. The input of element J was N_j which was the sum of the outputs of layer Ⅰ after timing weight respectively, and the output of element J was Y_j which was the result of the nonlinear function of N_j named as $f(x)$. Layer Ⅲ was output layer which used only one nonlinear element whose input N was the sum of the outputs of layer Ⅱ (Y_j) after timing weight respectively, and the output, also the output of ANN, was the interfacial shear strength of the steel-mushy aluminum pressing bonding plate (H) which was the result of the nonlinear function of N named as $f(x)$. V_{ji} was the connection weight between the input layer and the hidden layer. W_j, the weight between the hidden layer and the output layer.

The learning algorithm could be summarized as follows:

Step 1 Select the learning rate $\eta = 0.1$, momentum coefficient $\alpha = 0.1$ and $Z_5 = Y_3 = -1$.

Step 2 Take a group of random numbers within $(-0.5, 0.5)$ as the initial values of V_{ji} and W_j.

Step 3 Compute the outputs of all neurons layer by layer, starting with the input layer as following.

$$\text{net}_j = \sum_{i=1}^{5} V_{ji} Z_i, \quad j = 1, 2 \tag{1}$$

$$Y_j = f(\text{net}_j) \tag{2}$$

$$\text{net} = \sum_{j=1}^{3} W_j Y_j \tag{3}$$

$$H = f(\text{net}) \tag{4}$$

$$f(x) = (1 - e^{-x})/(1 + e^{x}) \tag{5}$$

where V_{j5} and W_3 offered the thresholds for the

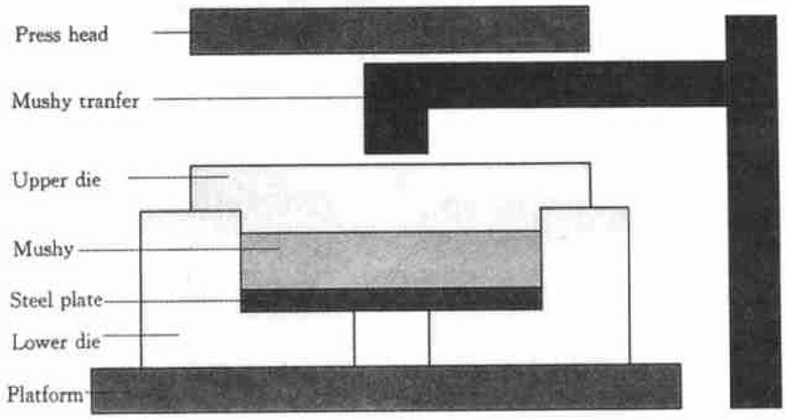

Fig.1 Schematic diagram of steel-mushy aluminum pressing bonding equipment

Table 1 ANN training and predication points

Sample	Aluminum solid fraction / %	Temperature of steel plate / ℃	Temperature of dies / ℃	Free diffusing time / s	Interfacial shear strength / MPa		Relative error / %
					Desired D	Output H	
1	15	300	150	10	57.3	56.9	0.7
2	15	300	250	25	45.5	45.8	0.7
3	20	300	150	15	64.4	66.1	1.6
4	20	300	100	15	52.4	53.1	1.3
5	25	300	150	10	65.3	62.7	4.0
6	25	200	150	15	43.9	44.6	1.6
7	30	400	250	15	66.9	66.8	0.5
8	30	300	150	10	64.9	65.1	0.3
9	35	300	200	15	69.8	70.6	1.1
10	35	400	150	10	67.4	68.3	1.3
11	40	100	100	15	54.1	54.3	0.4
12	40	300	150	15	60.5	61.2	1.2
13	40	300	150	10	68.1	69.8	2.5
14	45	300	150	15	62.3	63.2	1.4
15	45	300	250	10	57.0	56.4	1.1
16	50	100	100	20	37.9	37.1	2.1
17	50	300	150	10	58.4	57.8	1.0
18	50	500	200	10	36.1	36.7	1.7
19	55	300	150	15	50.7	50.4	0.6
20	55	100	150	10	35.8	35.2	1.7
21	60	100	100	15	22.4	22.1	1.3
22	60	100	100	10	25.7	25.3	1.6
23	60	300	150	10	49.5	47.2	4.6
24	60	500	200	20	38.8	38.4	1.0
25*	20	200	100	10	45.4	45.6	0.4
26*	30	200	200	15	56.9	57.2	0.5
27*	40	400	150	10	68.8	68.3	1.0
28*	50	300	100	20	45.7	45.6	0.2

* Testing sample

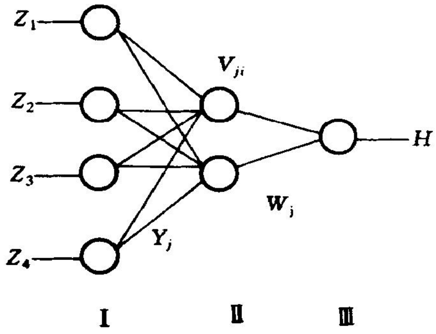

Fig.2 Back-propagation structure of artificial neural networks

neurons in hidden layer and output layer because the output values of Z_5 and Y_3 were constant and equaled to -1.

Step 4 Compute system error

$$E = \frac{1}{2p}\sum_{n=1}^{p}(D_n - H_n)^2 \tag{6}$$

where p represents the total number of patterns, H is the ANN outputs and D the desired outputs (the experimental data of interfacial shear strength).

Step 5 If E is small enough or learning iteration is big enough, stop learning.

Step 6 Compute learning errors for all neurons layer by layer

$$\delta_H = (D - H) f'(\text{net}) \tag{7}$$

$$\delta_j = W_j \delta_H f'(\text{net}_j), \quad j = 1, 2 \tag{8}$$

Step 7 Update weights along negative gradient of E

$$W_j(t+1) = W_j(t) + \eta\delta_H Y_j + \alpha[W_j(t) - W_j(t-1)] \quad (9)$$

$$V_{ji}(t+1) = V_{ji}(t) + \eta\delta_j Z_i + \alpha[V_{ji}(t) - V_{ji}(t-1)] \quad (10)$$

Step 8 Repeat by going to Step 3.

Randomly select 24 samples to train the ANN and the remaining 4 samples to verify the generalization capability of the ANN. After 87600 iterations, the outputs H of the ANN are close enough to the desired outputs D, not only for training samples but also for testing samples. The results are shown in Table 1. The maximum of relative error is 4.6 %. This fact shows that the ANN is good enough.

4 OPTIMIZING WITH GENETIC ALGORITHM

After modeling the relationship between H and (Z_1, Z_2, Z_3, Z_4) by using ANN, a nonlinear function containing 4 variables, $H = (Z_1, Z_2, Z_3, Z_4)$ has been obtained. The aim of this paper is to find a proper group (Z_1, Z_2, Z_3, Z_4) to maximize H, this is a nonlinear optimization problem. The gradient methods generally used encounter one difficulty, i.e., they often result in a local maximum.

A genetic algorithm could overcome the difficulty that gradient methods encountered since it is a kind of optimization algorithm based on the law of evolution of living things, i.e., survival of the fittest, natural selection, inheritance and variation. Considering a nonlinear optimization problem in n dimensions:

$$C = f(x_1, x_2, \cdots, x_n) \quad (11)$$

Randomly select m points within n dimensions to construct the population, C was used to evaluate every individual, superior and inferior. The genetic algorithm was summarized as follows:

(1) Compute C_i ($i = 1, 2, \cdots, m$) for every point Half of the population would survive, the surviving probability is proportional to the corresponding value of C_i for the ith individual.

(2) Crossbreed Copy the $m/2$ surviving individuals firstly and pair them randomly, then exchange part elements of every pair randomly to generate new individuals.

(3) Mutation Select several individuals randomly in the population, and mutate some elements in the selected individuals (add a small random number).

(4) A new generation has been generated Return to (1) and start to breed next generation. In this way the whole population would move to the area which corresponds to high C values. At last, some individual is close enough to the maximum of f.

For our example, $m = 28$, $n = 4$. After the genetic algorithm being worked over 9 000 iterations, the optimization point is (34 %, 324 ℃, 216 ℃, 16 s), i.e., the optimum parameters are 34 % for the value of aluminum solid fraction, 324 ℃ for that of preheat temperature of steel plate, 216 ℃ for that of preheat temperature of dies, 16 s for that of free diffusing time before pressing, and the corresponding H, namely, the maximum interfacial shear strength of the steel-mushy aluminum pressing bonding plate is 70.8 MPa. This optimum technology has been verified through further experiments.

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