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Predicting effects of diffusion welding parameters on welded joint properties by artificial neural network ①

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[Abstract] The static model for metal matrix composites in diffusion welding was established by means of artificial neural network method. The model presents the relationship between weld joint properties and welding parameters such as welding temperature, welding pressure and welding time. Through simulating the diffusion welding process of SiC_w/6061Al composite, the effects of welding parameters on the strength of welded joint was studied and optimal technical parameters was obtained. It is proved that this method has good fault-tolerant ability and versatility and can overcome the shortage of the general experiment. The established static model is in good agreement with the actual welding process, so it becomes a new path for studying the weldability of new material.

[Key words] artificial neural network; diffusion welding; composite
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1 INTRODUCTION

Metal matrix composites (MMCs), due to their outstanding properties such as high specific strength, specific modulus, size stability, high temperature-resistant and cosmic-ray resistant, are widely used in aerospace, aviation and electron fields, and become the major developing and studying direction of composites. However, the bad weldability of MMCs resulted from its special microstructure is the main obstacle for its application. The weldability of SiC_w/6061Al composite was studied systematically in previous paper[1]. It was found that the microstructure and performances of the welded joint are highly sensitive to welding parameters. The welding process of MMC, which concerns not only the diffusion of the matrix atom but also the change of the interface between matrix and reinforcement, is very complicated and different from that of monolithic matrix metal. In the temperature range between liquidus and solidus of the composite, the matrix metal melt in welded joint will diffuse and infiltrate to the reinforcement. In addition, the oxide film also affects the performances of the welded joint. It is necessary to establish the mathematical model for MMCs in diffusion welding to reveal the relationship between welding parameters and welded joint properties. With characteristics as self-study, self-adapting and non-linear dynamic handling, artificial neural network (ANN) is fit for modeling and predicting the performances of the non-linear system[2~4]. In the present work the static model of welding process for the new composite was established by artificial neural network method on the basis of previous studies, and the welding process was simulated to explore the new path for studying on weldability of new material.

2 ESTABLISHMENT OF STATIC MODEL

2.1 Experimental

SiC_w/6061Al composite was made by squeeze casting. Its tensile strength is 280 MPa and solidus is 570 ℃. The mean diameter of SiC whisker reinforcements was 0.5 μm, and its volume fraction was 18% ~ 20%. By wire cutting, the welding specimens with size of 5 mm × 10 mm × 30 mm were got. Diffusion welding by electric resistance heating was conducted in the vacuum chamber (1.3×10^{-3} Pa), where the temperature was measured by thermocouple and remained constant throughout the welding process.

The strength of welded joint could be thought as the main quality of diffusion welded joint for SiC_w/6061Al composite, so establishing the static model for the composite is to present the relationship between the strength and the welding parameters.

2.2 Establishment of static model

In order to establish the static model of SiC_w/6061Al composite in diffusion welding, 35 groups of

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experiment were made. The experimental result aggregation was divided into learning and testing sample sub-aggregations. The testing sample sub-aggregation was input after the network had been trained by learning sample sub-aggregation. The predicted data and testing results are listed in Table 1.

In BP network model, the input layer had three nodes which represented welding temperature (θ), welding pressure (p) and welding time (t), respectively; the middle layer had five nodes and output layer had a node which represented the strength of diffusion welded joint for SiC_w/6061Al composite.

The data from group 1 to 23 in Table 1 was used as learning parameters. The non-linear function was adopted as transfer function. The rate of learning was 0.5 and momentum factor was 0.4. The convergence curve of the mean square error (MRS) for training normalization is shown in Fig. 1. It can be seen that MRS decreases with increasing training times; after training for 5000 times, MRS tends to be stable. In the meantime, the maximum relative error of output results is 7.20%, average relative error is 3.92% and the mean square error is 2.73%, so the training network can be regarded as convergent one and the model can meet the requirements.

2.3 Verification of model

The data of groups 24 to 35 in Table 1 was taken as testing parameters. It is found that the maximum relative error of verification sample is 4.90%, the av-

Table 1 Comparison of predicted tensile strength with experimental results

Experimental group	Welding temperature / ℃	Welding pressure / MPa	Welding time / min	Welded joint strength/MPa		Relative error / %
				Experimental	Predicted	
1	620	5	5	270	263.6	2.37
2	620	5	15	274	277.8	1.38
3	620	5	45	285	276.5	2.90
4	620	5	60	281	271.9	3.20
5	620	5	30	287	287.6	0.20
6	610	5	30	271	271.5	0.18
7	600	5	30	269	259.7	3.40
8	590	5	30	240	238.1	0.79
9	580	5	30	224	214.4	4.20
10	570	5	30	183	186.1	1.60
11	560	5	30	154	164.0	6.40
12	540	5	30	99	96.5	2.50
13	520	5	30	78	81.3	4.20
14	500	5	30	72	79.3	10.10
15	480	5	30	63	62.7	0.47
16	460	5	30	54	57.9	7.20
17	440	5	30	48	46.9	2.20
18	420	5	30	46	44.6	3.00
19	400	5	30	37	37.1	0.27
20	600	2	30	130	122.7	5.60
21	600	3	30	211	211.5	0.23
22	600	4	30	241	241.9	0.37
23	600	6	30	280	265.3	5.20
24	600	7	30	288	273.7	4.90
25	620	6	30	283	277.2	2.04
26	620	4	30	271	271.8	0.29
27	620	3	30	228	231.1	1.35
28	620	2	30	139	136.8	1.58
29	620	1	30	104	109.1	4.90
30	615	5	30	280	274.7	1.89
31	605	5	30	270	266.3	1.37
32	595	5	30	269	259.7	3.45
33	585	5	30	225	226.1	0.48
34	575	5	30	213	214.3	0.61
35	565	5	30	160	165.2	3.25

erage relative error is 2.51%, and mean square error is 1.87%. The data of groups 24 to 35 in Table 1 agree with the model well, which proves the model is effective. In the meantime, the comparison of output results with experimental ones is shown in Fig. 2, which proves further the network has good commonality. It indicates the model can be used as the static model for $SiC_w/6061Al$ composite in diffusion welding.

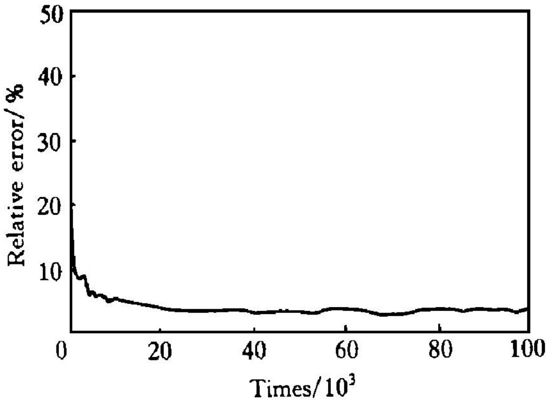

Fig. 1 Convergence curve of model during training

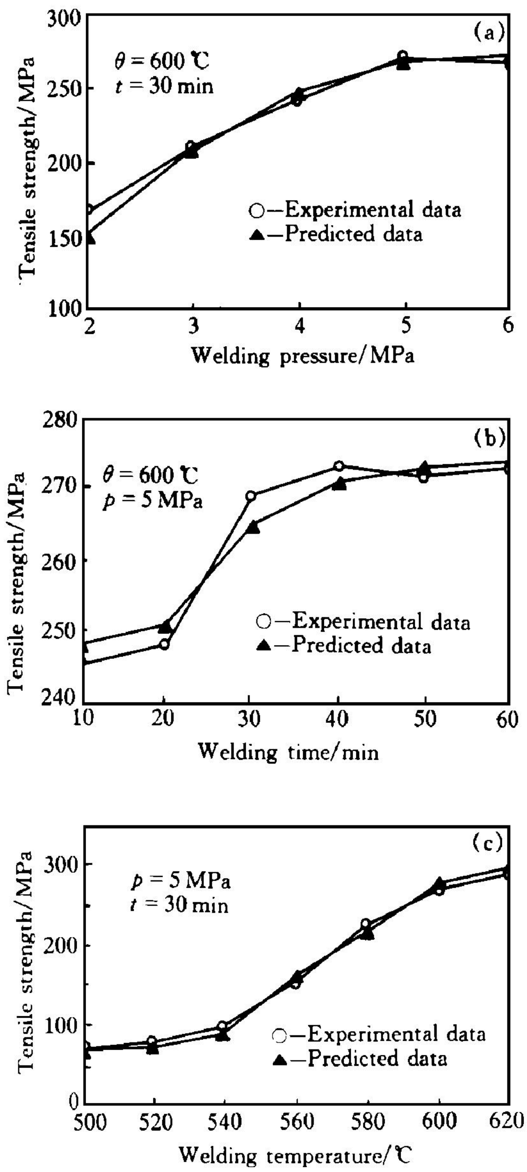

Fig. 2 Effects of welding parameters on tensile strength of welded joints

3 SIMULATION OF DISSUSION WELDING PROCESS

The diffusion welding process of $SiC_w/6061Al$ composite is simulated by the model, the results are shown in Fig. 3. It is found that the temperature (θ), pressure (p) and time (t) of welding determine the strength of welded joint and the effect of welding temperature is the most evident.

For example, when the diffusion welding was carried out at a temperature lower than the solidus of the composite at $p = 5$ MPa and $t = 30$ min, the strength of welded joint increases with increasing temperature, and the maximal strength reaches 134 MPa (48% of the matrix strength). When the welding temperature changes about 10 ℃ between the solidus and 606 ℃, the strength of welding joint changes obviously. When the welding temperature is above 606 ℃, the strength of welded joint increases smoothly with increasing temperature, and the maximum strength is 270~280 MPa (about 90%~100% of the matrix strength. Otherwise, at the beginning of welding, the strength of welded joint increases as the welding process goes on. When the welding time exceeds 30 min, the strength tends to be stable. However, at the adjacent temperature of solidus, the strength increases with time, which perhaps results from that the holding time during welding is too long and the matrix metal melt on the bonding interface infilitrates into the interface. The relationship between welding parameters and welded joint strength reflected by the model agrees well with the experimental results given in previous paper[1].

Otherwise, by the static model, the optimal welding parameters at which the maximum strength of welded joint can be obtained are simulated, as shown in Table 2. It is shown that considerably good agreement is obtained, the maximum error is only 3.1%.

In general, the predicted results for $SiC_w/6061Al$ MMC in diffusion welding by the static model reveals the intrinsic relationship among diffusion welding parameters of the composite, and shows the change condition in welding process. It is indicated that the static model for MMC during diffusion weld

Table 2 Optimal welding parameters and corresponding welded joint strength

p /MPa	θ /℃	t /min	σ_b/MPa		Relative error/%
			Predicted	Experimental	
3	620	40	234	230	1.7
4	620	45	273	275	0.7
5	615	30	284	275	3.1

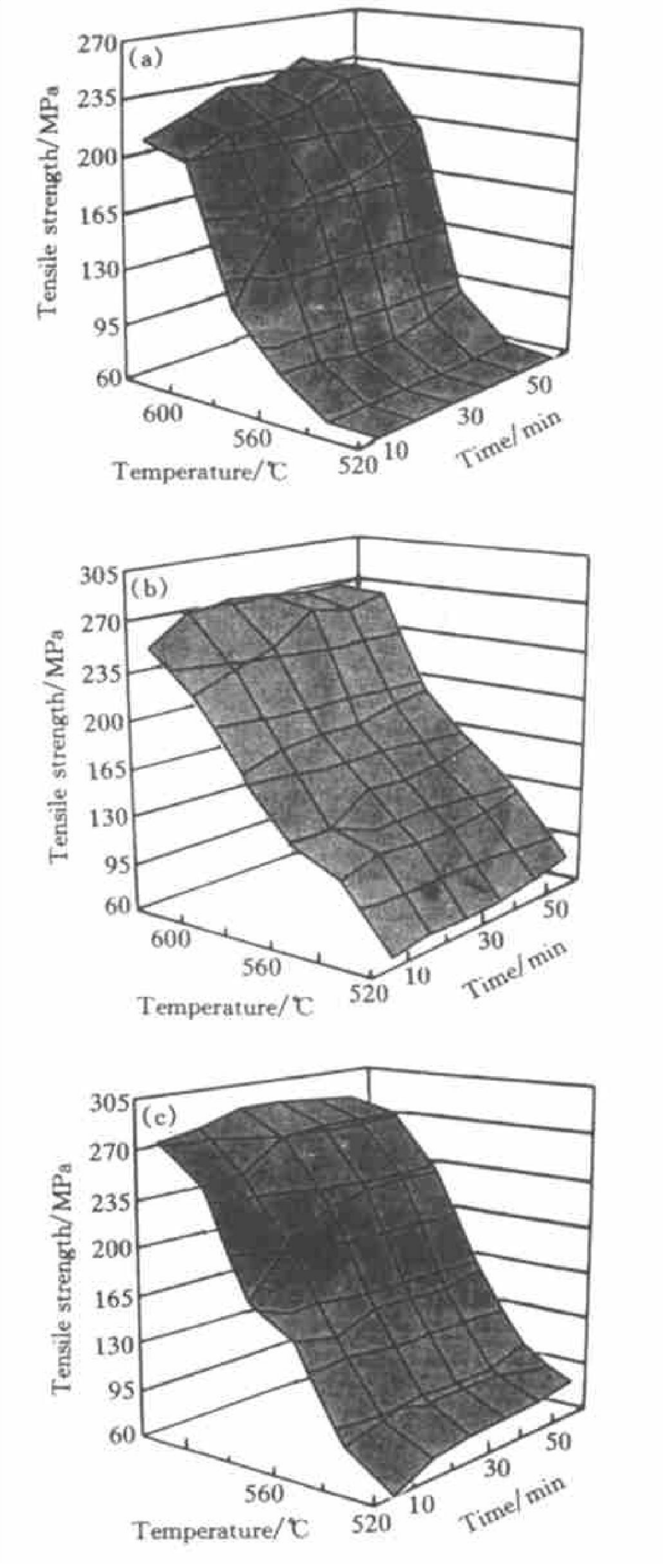

Fig. 3 Simulation curve of model

(a) $\bar{p}$ = 3 MPa; (b) $\bar{p}$ = 4 MPa; (c) $\bar{p}$ = 5 MPa

ing can overcome the confinements of the experiment and lower precision of convention curve fitting. And the model can play an important role in selecting diffusion welding parameters for new materials in practical production.

4 CONCLUSIONS

1) The static model predicting the properties of welded joint for composite $SiC_w/6061Al$ in diffusion welding is established successfully, and the model has higher precision and stronger fault-tolerance.

2) The optimal welding parameters obtained in simulating welding process by the model agree well with the experimental results, which indicates that establishing static model for diffusion welding by AAN is an effective path for studying of weldability on new material.

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