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Accurate prediction model of bead geometry in crimping butt of the laser brazing using generalized regression neural network

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Accurate prediction model of bead geometry in crimping butt of the laser brazing using generalized regression neural network

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Abstract. There are few researches that concentrate on the prediction of the bead geometry for laser brazing with crimping butt. This paper addressed the accurate prediction of the bead profile by developing a generalized regression neural network (GRNN) algorithm. Firstly GRNN model was developed and trained to decrease the prediction error that may be influenced by the sample size. Then the prediction accuracy was demonstrated by comparing with other articles and back propagation artificial neural network (BPNN) algorithm. Eventually the reliability and stability of GRNN model were discussed from the points of average relative error (ARE), mean square error (MSE) and root mean square error (RMSE), while the maximum ARE and MSE were 6.94% and 0.0303 that were clearly less than those (14.28% and 0.0832) predicted by BPNN. Obviously, it was proved that the prediction accuracy was improved at least 2 times, and the stability was also increased much more.

1. Introduction

In recent years, the research on the bead geometry (BG) has gradually become a hot issue in the welding field because the mechanical properties and distortion can be reflected by BG [1, 2]. From the point of prediction and optimization of the bead geometry (POBG), the research methods of BG mainly include the intelligent algorithm and the mathematic model, which both are detailed as follows.

Especially, artificial neural network (ANN) is one of the most widely intelligent algorithms that have been applied in POBG problems. Back propagation artificial neural network (BPNN) was used to forecast penetration depth, weld-seam width of thermoplastics and the four BG sizes of the crimping butt [3-5]. Shojaeefard, et al. built ANN model to simulate the correlation between the friction stir welding parameters and mechanical properties [6]. Singh, et al. developed a model using ANN and genetic algorithm (GA) to study BG and hardness profile [7]. Omajene, et al. applied ANN to optimize BG welding process parameters of the underwater wet welding and the influence of the water environment [8]. In general, it was the composite application of BPNN and GA that was used more widely in POBG field [5, 9-11]. In addition, some other intelligent algorithms, such as simulated annealing algorithm, adaptive neuro-fuzzy inference system, and hybrid artificial bee colony with

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sequential kriging algorithm, were also used in POBG [12-14]. On the other hand, mathematical model was usually developed to research POBG based on different welding methods. Response surface methodology (RSM) was used to build math model to optimize the important process parameters while BG was selected as one of several output goals [15-17]. Lin et al established the grey relational analysis model to demonstrate the influences of process parameters on BG in gas metal arc welding [18]. Magudeeswaran et al used analysis of variance to optimize welding parameters of tungsten inert gas welding [19, 20].

However, there are few researches about POBG problem of laser brazing, especially scarcely any using GRNN to crimping butt. As shown in figure 1, a typical laser brazing system consists of fiber laser, welding robot, wire feeder machine, laser welding header, workbench and so forth, while the BG of crimping butt is composed of the efficient length of connection on the left side (ELL), top width of bead (WT), the efficient length of connection on the right side (ELR) and bottom width of bead (WB) [5]. In this paper, generalized regression neural network (GRNN) algorithm is used to predict BG of the crimping butt of the laser brazing, and the prediction accuracy is analyzed by comparing with other articles and BPNN model.

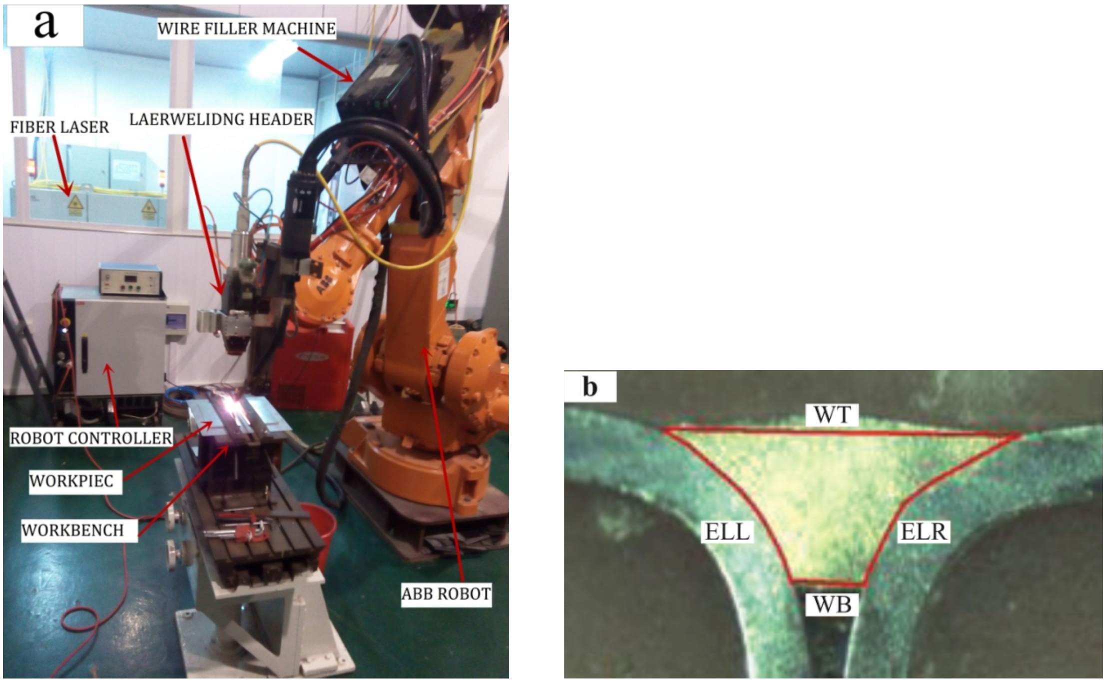

Figure 1. A typical laser brazing system: (a) laser brazing setup and (b) a typical crimping butt.

2. Prediction methodology

2.1. Generalized regression neural network

GRNN is a kind of radial basis function (RBF) networks with a highly parallel structure, which was developed in 1991 by Specht [21], and has been widely used to achieve prediction and estimation results in many fields such as plant disease, power load, the maintenance cost of construction equipment, intermittent flow and so on [22-25]. The basic function of GRNN is nonlinear regression surface dominated by independent variable $\mathbf{X}$, given the dependent variable y. The procedure of GRNN can be given by equation (1) [24]

$$\hat{\mathbf{Y}}(\mathbf{X}) = E(y \mid \mathbf{X}) = \frac{\int_{-\infty}^{\infty} y f(\mathbf{X}, y)dy}{\int_{-\infty}^{\infty} f(\mathbf{X}, y)dy} \tag{1}$$

where $\hat{\mathbf{Y}}(\mathbf{X})$ is the expected value of the output y, $\mathbf{X}=[x_1,x_2,\ldots,x_n]^T$ is a n dimensional input vector, $f(\mathbf{X},y)$ is the joint probability density function of $\mathbf{X}$ and y.

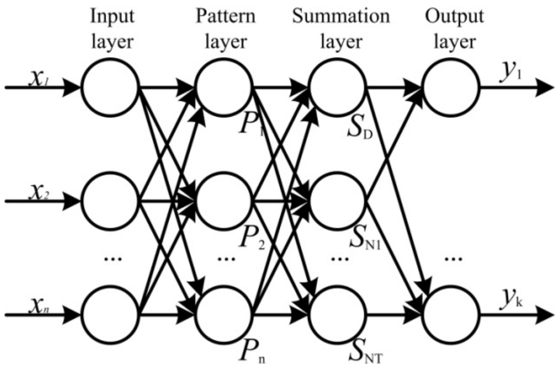

Figure 2. GRNN block diagram [21].

As shown in figure 2, the GRNN is composed of four layers (input layer, pattern layer, summation layer and output layer). The input layer is distribution layer, which provides the information of input vector $\mathbf{X}$ to the second layer. The pattern layer possesses the nonlinear transformation from input space to pattern space after the data fed back to the pattern layer from the input layer using the input neurons. The pattern neurons can memorize the map between the input neurons and the proper response of pattern layer, and the number of neurons equals to the number of input variables. The transfer function of pattern neurons is Gaussian function of p_i as shown equation (2) [22]. The pattern neuron outputs are passed on to the third layer.

$$p_i=\exp\left[-\frac{(\mathbf{X}-\mathbf{X}_i)^T(\mathbf{X}-\mathbf{X}_i)}{2\sigma^2}\right] \quad i=1,2,\ldots,n \tag{2}$$

where $\mathbf{X}_i$ is a specific learning sample of the neuron i, σ indicates the smoothing parameter.

Then, two kinds of calculation methods are used in summation layer. Just as shown in equation (3) [21], one is simple summation S_D that is applied to compute the arithmetic sum of the second layer outputs, and the interconnection weight is 1. The other is weighted summation S_{Nj} that is calculated as seen in equation (4) [21], while the interconnection weight between the *i* th neuron of the pattern layer and the *j* th neuron of the summation layer is the *j* th unit of the *i* th ouputY_i.

$$S_D=\sum_{i=1}^{n}P_i \tag{3}$$

$$S_{Nj}=\sum_{i=1}^{n}y_{ij}P_i \quad j=1,2,\ldots,k \tag{4}$$

Finally, the summations of neurons are fed into the output layer, and the j th output shown as equation (5) [21] corresponds with the j th unit of the estimation result $\hat{\mathbf{Y}}(\mathbf{X})$. It is noted that the number of neurons in the output layer is equal to the k -dimension of output vector $\mathbf{Y}$.

$$y_j=\frac{S_{Nj}}{S_D} \quad j=1,2,\ldots,k \tag{5}$$

Through the above simple description of the GRNN basic principle, it is easy to find that there is only one tunable parameter (the smoothing value, σ) of GRNN model. The parameter σ is very important for GRNN model in process of the prediction, and determines the generalization capability of the GRNN. Generally, the prediction results of this network are closer to the sample data with a smaller σ . Meanwhile, the approximation process from the GRNN prediction network to the sample data presents much smoother when the σ value turns bigger.

2.2. The prediction of laser brazing BG using GRNN

GRNN has the capacity to solve the complex nonlinear problems due to its advantages of good fault tolerant performance, high robustness and good ability to deal with the unstable data. Through article surveys, it can be found that some abnormal errors were occasional and even the individual error unexpectedly reached to 247.75% during BG prediction procedure using ANN [5, 26, 27]. In this article, the GRNN model was developed and trained considering cross-validation method to decrease the prediction error that may be influenced by the sample size [28], and the σ parameter was achieved through cycle structure to search the best value. Considering the characteristics of the crimping butt of the laser brazing, the prediction procedure is planned in detail as below:

- Preparation work. The task at this stage is to identify the inputs, outputs, train set and test set. The inputs include welding speed (WS, 0.8 m/min-1.6 m/min), wire feed rate (WF, 2.6 m/min-3.4 m/min) and gap (GAP, 0 mm-0.8 mm). The outputs consist of ELL, ELR, WT and WB. About two-thirds of experiment data are selected as train set and the rest are as test set.

Table 1. Divisions of experiment data to train set and test set.

NO.	Welding parameters			Bead geometry			
	WS m/min	WF m/min	GAP mm	ELL mm	ELR mm	WT mm	WB mm
Train set							
1	0.8	2.6	0.0	3.43	2.48	4.12	0.61
2	1.0	3.4	0.0	2.61	1.86	3.82	0.83
3	1.4	3.0	0.0	2.1	1.33	3.5	1.09
4	1.6	2.8	0.0	2.23	1.01	3.44	1.25
5	1.0	2.6	0.2	2.38	2.29	3.84	3.11
6	1.2	3.4	0.2	2.46	1.68	3.64	1.11
7	1.6	3.0	0.2	1.92	1.443	3.31	1.12
8	1.0	2.8	0.4	2.56	1.93	3.71	0.96
9	1.4	3.4	0.4	2.07	1.81	3.37	1.27
10	1.6	3.2	0.4	2.16	1.12	3.26	1.24
11	1.0	3.0	0.6	2.88	1.93	4.0	0.93
12	1.2	2.8	0.6	2.59	1.72	3.63	1.28
13	1.6	3.4	0.6	2.39	2.07	2.41	0.86
14	0.8	3.4	0.8	3.1	2.26	3.8	1.25
15	1.2	3.0	0.8	3.02	2.94	3.65	1.01
16	1.4	2.8	0.8	2.37	1.76	3.62	1.3
Test set							
17	1.2	3.2	0.0	2.36	1.33	3.42	1.03
18	0.8	2.8	0.2	2.55	2.07	3.61	0.95
19	1.4	3.2	0.2	1.92	1.6	3.41	1.12
20	0.8	3.0	0.4	2.37	1.79	4.07	1.26
21	1.2	2.6	0.4	2.73	2.53	3.7	0.85
22	0.8	3.2	0.6	3.32	1.98	4.2	1.03
23	1.4	2.6	0.6	1.91	0.92	3.24	1.41
24	1.0	3.2	0.8	2.62	1.86	3.88	1.24
25	1.6	2.6	0.8	2.4	1.24	3.5	1.35

- Training the GRNN network. Firstly, the best smooth parameter σ can be determined using cross-validation method with a cycle structure, and then GRNN network is developed and trained by invoking the best smooth parameter and train set.
- Prediction through GRNN testing. Each output of the test set would be fed to GRNN network that has been trained, and finally the prediction results and errors can be obtained by comparing them with the experiment data.

3. Results and discussion

3.1. The division of data set

The welding experiment of galvanized thin double phase steel 590 (DP590) with thickness about 0.8mm was designed as a 3-factor, 5-level problem using Taguchi L_{25} method. The welding parameters were WS, WF and GAP, and the output goals were acquired as ELL, ELR, WT and WB [5]. The train set and test set were randomly decided as table 1.

3.2. The prediction results by GRNN

The program of GRNN model was run in the MATLAB2013a. Just as shown in table 1, 16 groups of experiment data were selected to create and train the network, and the rest 9 sets of data were used to conduct the validity of the GRNN model. The error (Err) of each prediction result was calculated by equation (6), while $y_{\exp}(i)$ is the i th actual result, and $y_{pre}(i)$ is the i th prediction result. As shown in table 2, the prediction results of GRNN and errors were listed as specific as possible.

$$Err = \frac{y_{\exp}(i) - y_{pre}(i)}{y_{\exp}(i)} \times 100\% \qquad i = 1, 2, \ldots, 9 \tag{6}$$

Table 2. Forecast results and errors of BG by GRNN model.

NO	ELL			ELR			WT			WB		
	Result	Err (%)	σ	Result	Err (%)	σ	Result	Err (%)	σ	Result	Err (%)	σ
17	2.344	0.683	1.0	1.425	-7.157	0.7	3.433	-0.383	0.9	1.083	-5.119	0.8
18	2.498	2.049	1.2	2.108	-1.851	1.1	3.719	-3.011	1.1	0.872	8.192	0.3
19	2.071	-7.875	0.7	1.603	-0.192	0.8	3.392	0.533	1.1	1.134	1.489	0.5
20	2.386	-0.685	0.1	1.734	3.110	0.7	3.967	2.544	0.9	1.211	3.901	2.0
21	2.628	3.750	2.0	2.125	16.017	1.0	3.672	0.750	1.3	0.790	7.058	2.0
22	3.034	8.623	0.1	1.951	1.474	1.4	3.979	5.267	0.8	0.960	6.796	0.1
23	2.253	-17.963	0.1	0.982	-6.685	0.8	3.421	-5.587	0.8	1.447	-2.605	2.0
24	2.667	-1.779	0.8	1.895	-1.871	0.9	3.903	-0.580	1.0	1.185	4.428	2.0
25	2.493	-3.866	1.4	1.539	-24.078	0.5	3.530	-0.859	0.9	1.230	3.718	0.5

3.3. Discussion about the results

Figure 3 showed the comparison analysis among experiment values, BPNN predictions and GRNN predictions. The results of the ELL of the crimping butt were shown in figure 3(a), and the maximum prediction errors of the BPNN and GRNN were 38.34% and 17.96%. Figure 3(b) showed that the maximum prediction errors of the ELR through BPNN and GRNN were 60.35% and 24.08%. As shown in figures 3(c) and 3(d), the maximum prediction errors of the WT using BPNN and GRNN were 9.10% and 5.27%, and these of the WB were 22.16% and 8.19%. Thus the maximum errors of ELL, ELR, WT and WB reduced half or even more. In addition, comparing the prediction results of bead profile with other articles [5, 26, 27], as shown in table 3, the maximum error (24.08%) was obviously less than that of other articles (60.35%, 247.75% and 29.125%). The prediction error of BG occasionally exceeds 20% (1 out of 36 outputs, and only about 2.78%), still the prediction precision of this article was clearly better than that of other papers (11.11%, 11.67% and 25%) and hence GRNN was able to accurately predict bead profile of the crimping butt.

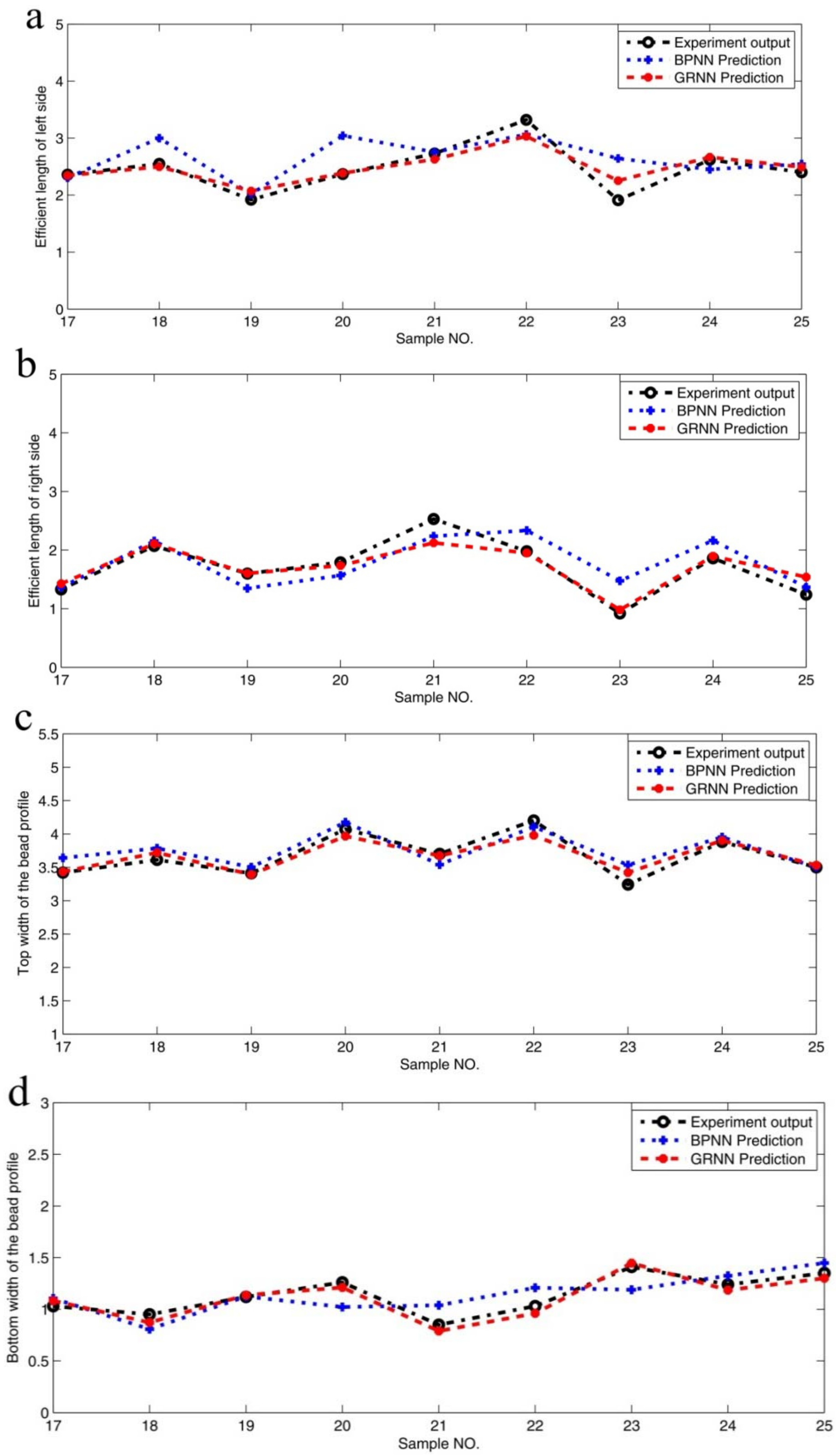

Figure 3. Comparison of results using BPNN and GRNN: (a) ELL, (b) ELR, (c) WT and (d) WB.

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Table 3. Comparison of the prediction accuracy with other articles using ANN.

Comparison	Method	Maximum Error (%)	Number of exceeded 20%	
			Number	Percentage (%)
Present	GRNN	**24.08**	1/36	**2.78**
Ref. 5	BPNN	60.35	4/36	11.11
Ref. 28	BPNN	247.75	7/60	11.67
Ref. 29	BPNN	29.125	3/12	25.00

The reliability and stability of the prediction results can be weighed by average relative error (ARE, equation (7)), mean square error (MSE, equation (8)) and root mean square error (RMSE, equation (9)). Through comparing prediction results from the point of ARE and MSE in table 4, ARE values of crimping butt using GRNN model were 5.25%, 6.94%, 2.61% and 4.81%, while these results calculated by BPNN were 10.45%, 14.28%, 3.64% and 12.53%. The MSE of each BG dimensions of the crimping butt through GRNN (0.0275, 0.0303, 0.0119 and 0.0030) were all better than these predicted by BPNN. Meanwhile, as shown in table 4, evaluation indicator of RMSE for GRNN model is clearly better than that of BPNN model. The prediction accuracy and stability of bead geometry of the crimping butt using GRNN model were apparently better than that by BPNN model, especially the WB group. In short, the GRNN model we had developed was credible and stable, and would be used in the further welding process optimization and actual manufacturing.

$$ARE = \frac{1}{n}\sum_{i=1}^{n}\frac{y_{\exp}(i) - y_{pre}(i)}{y_{\exp}(i)} \times 100\% \tag{7}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[y_{\exp}(i) - y_{pre}(i)\right]^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[y_{\exp}(i) - y_{pre}(i)\right]^2} \tag{9}$$

Table 4. Calculation of ARE, MSE and RMSE of the BPNN and GRNN models.

Bead shape	BPNN model			GRNN model		
	ARE (%)	MSE	RMSE	ARE (%)	MSE	RMSE
ELL	10.45	0.1467	0.3830	5.25	0.0275	0.1658
ELR	14.28	0.0832	0.2884	6.94	0.0303	0.1741
WT	3.64	0.0249	0.1550	2.16	0.0119	0.1091
WB	12.53	0.0240	0.1549	4.81	0.0030	0.0548

4. Conclusions

In this paper, considering welding parameters (WS, WF and GAP) and the output goals (ELL, ELR, WT and WB), GRNN model was created and trained considering cross-validation method to decrease the prediction error that may be influenced by the sample size. The prediction accuracy was demonstrated by comparison with other articles and BPNN model. Meanwhile, the reliability and stability were discussed from the point of ARE, MSE and RMSE. Eventually, three conclusions can be drawn: (1) The GRNN model can be used to accurately predict the bead shape of crimping butt, while the average errors of ELL, ELR, WT and WB (5.25%, 6.94% 2.16% and 4.81%) were all apparently less than these using BPNN model (10.45%, 14.28%, 3.64% and 12.53%); (2) The reliability and accuracy of prediction results by GRNN model were obviously better than that of other articles and BPNN model from the point of ARE, MSE, RMSE, and maximum error and so forth; (3) The GRNN model is reliable and stable in predicting bead shape of the crimping butt, and would be used to direct the further welding process optimization and actual manufacturing.

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