Quality Estimation System for Resistance Spot Welding of Stainless Steel

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Resistance spot welding (RSW), as one of the most widely used processes in sheet metal fabrication, is a complex electromechanical coupled nonlinear process, and weld quality is influenced by various process conditions, noise and errors. Therefore, inconsistent quality from weld to weld is a major problem for RSW process. However, so far there is no satisfactory non-destructive quality estimation method to evaluate the weld quality.

The objective of this study is to explore a quality estimation system for RSW. In order to build the quality estimation system, the relationship between various variables during RSW process and weld quality was studied by lots of experiments. Test results showed that the system built in this study could accurately estimate the weld quality and the maximum estimation error was only 5.6%.

KEY WORDS: resistance spot welding; weld quality estimation system; BP neural network.

1. Introduction

Resistance spot weld (RSW) has been an irreplaceable material joining process and has been widely used in many areas over the past decades, such as automotive, aerospace, railway car and electrical industries, due to its advantages of automation, high production efficiency and low cost. However, in the actual production, the fluctuation of weld quality is common even though using the same weld parameters. The main reason for the inconsistency is that the weld quality is influenced by the complex electromechanical coupled nonlinear process and various process conditions, noise and errors. In order to increase the reliability of each spot and to reduce the risk of part failure, a number of studies had been conducted in the past to perform destructive and nondestructive inspection of the welds.

In the previous studies, various electrical and mechanical variables, such as welding current, electrode voltage, dynamic resistance, and electrode displacement, have been researched to monitor and evaluate the quality of the RSW.^{1–5)} Dickinson *et al.*⁶⁾ observed the relationship between the dynamic resistance and the phenomena occurring during spot weld formation (surface breakdown, asperity collapse, heating of the work pieces, molten nugget formation, nugget growth, and mechanical collapse), based on the pattern changes of the dynamic resistance. Chien *et al.*⁷⁾ found force signal during welding process provided the

most information on nugget formation. C.T. Ji⁸⁾ characterized dynamic electrode displacement and force during RSW of aluminum alloy sheet and discussed possible strategies for process monitoring and control.

Recently, the artificial intelligence (AI) technique has been applied in the area of welding control and quality estimation, including RSW. Dilthey⁹⁾ used a neural network to estimate the tensile shear strength of the welds. Cho and Rhee¹⁰⁾ developed a AI quality estimation system of RSW by using Hopfield neural network, and the dynamic resistance, which included the information of nugget information, was applied to the system. Podrzaj¹¹⁾ used a LVQ (a linear vector quantization) neural network to detect the expulsion for different materials, and pointed that the electrode force signal was the most important indicator of the expulsion occurrence.

In this study, an AI weld quality estimation system for stainless steel was researched and established by using a BP neural network and various welding parameters and dynamic signals which provide important information of weld quality were applied to this system.

2. Experimental Procedures

The experiments were conducted on TDZ-3X100 three-phase secondary rectifying spot welder. Input voltage of the spot welder was $380 \pm 10\%$ V and the frequency of input voltage was 50 Hz. The electrodes used in this study were radius tips with 100 mm radius and 20 mm end face diameter. The material for electrode was Cu–Cr alloy. **Figure 1**

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Fig. 1. Shape and size of specimen (mm).

Fig. 2. Schematic diagram of the data acquisition system.

shows the specimen shape and size, and specimen material was SUS304 steel.

In order to monitor the weld quality of RSW, a data acquisition system,¹²⁾ shown in Fig. 2, was employed to collect various electrical and mechanical signals, including welding current, electrode voltage, dynamic resistance and electrode force. This system measured the welding current by a toroidal coil attached to the lower electrode, electrode voltage between two tips and electrode force by using a strain sensor, which produced an electric charge proportional to electrode force. The signal conditioning box included isolation amplifier for the voltage signal and integration for the current signal. The charge amplifier converted the charge signal from strain sensor into an output voltage proportional to the mechanical input quality. The sampling rate of A/D card was set at a rate of 10 kHz per channel. These signals acquired from A/D card were processed and analyzed by a software programmed by C++ language, and the dynamic resistance was then calculated from the electrode voltage and the welding current.

3. Quality Estimation System

In this study, back-propagation (BP) network was used to build weld quality estimation system. For the BP network, one input layer, one output layer and one to three hidden layers are very common and are widely employed in practical application. Yet one hidden layer seems sufficient to approximate any complex function.¹³⁾ In order to build a

neural network system, the input variables, output variables, and the number of hidden neurons should be determined properly.

3.1. Input Variables

The welding current, electrode force and welding time are the most important welding parameters for RSW and they directly influence the weld quality. The welding current signal provides information on the time of current starting and ending for each weld, in addition to the welding current level. In order to research the effect of welding current on the weld quality, spot welds were made with the welding current varying from 4.1 kA to 11 kA. During these processes, welding time (6 cycles) and electrode force (3.0 kN) were kept constant. The relationship between welding current and nugget diameter is shown in Fig. 3. It could be seen that when the welding current was below 10 kA, the nugget diameter increased with the welding current. After welding current exceeded 10 kA, excessive welding current induced a weld expulsion and the nugget diameter decreased accordingly.

Welding time is another important welding parameter and the relationship between welding time and nugget diameter is shown in Fig. 4, which is also the growth curve of nugget for the welding process using 7 kA welding current and 3.0 kN electrode force. It could be seen that the nugget appeared at 3 cycles and then grew quickly in the following welding time. With increasing of welding time there was no expulsion occurred.

The electrode force ensures the applied force and the dynamic value of electrode force is changing during weld stage. The change of dynamic electrode force is caused by thermal expansion and the yielding of the weld area at high temperature, so dynamic electrode force is also important for monitoring weld quality.¹²⁾ Figure 5 shows the typical signal for dynamic electrode force during the welding process when using 7.5 kA welding current, 3.0 kN electrode force and 6 cycles welding time. In this study, lots of experiments were conducted to research the relationship between dynamic electrode force and nugget diameter. Figure 6 shows the relationship between the increased value of dynamic electrode force (f) and nugget diameter. The correlation coefficient between the value of f and nugget diameter was obtained by using correlation analysis, and the value of correlation coefficient was -0.862 . The results showed that the increased value of dynamic electrode force (f) during welding process had strong correlation with nugget diameter and could serve as an input variable for the estimation system of weld quality.

The dynamic resistance signal, which was researched in the previous study,¹⁴⁾ responds well to the variations of process conditions, such as edge weld, poor fit-up and axial misalignment, and provides plenty of weld quality information. Figure 7 shows the typical signal for dynamic resistance during the welding process when using 7.5 kA welding current, 3.0 kN electrode force and 6 cycles welding time. Based on results of experiments and correlation analysis, the endpoint value of dynamic resistance curve(r) also had strong correlation with nugget diameter. The correlation coefficient between the value of r and nugget diameter was -0.841 . Therefore, the endpoint value of

Fig. 3. Relationship between welding current and nugget diameter.

Fig. 4. Relationship between welding time and nugget diameter.

Fig. 5. Typical signal of dynamic electrode force during welding process.

dynamic resistance curve (r) could be used to estimate the weld quality.

In conclusion, welding current, welding time, increased value of dynamic electrode force (f) and endpoint value of dynamic resistance curve could be used as the input variables for the estimation system of weld quality.

Fig. 6. Relationship between increased value of dynamic electrode force (f) and nugget diameter.

Fig. 7. Typical signal of dynamic resistance during welding process.

3.2. Output Variable

Nugget size has good correlation to the strength of resistance spot welds (tensile, tensile-shear and impact strength) and is widely used as a weld quality measure in industry. In this study, nugget diameter was used as the output variable for the estimation system of weld quality.

3.3. Number of Hidden Neurons

The number of hidden neurons has great influence on the performance of neural network. Too few hidden neurons will induce low network accuracy, and too many hidden neurons will also lead to various problems, such as overfitting, long training time and bad generalization. Therefore, proper hidden neurons number is very important to decrease the neural network error, raise the convergence speed and avoid the local minimum. An empirical formula as below is usually used to determine the initial value of hidden neurons number.

$$m = \sqrt{n + l} + \alpha \dots\dots\dots (1)$$

Where m, n, l represent the values of hidden neurons, input neurons and output neurons respectively, and α is a

Fig. 8. Error curve of neural network during training. (Online version in color.)

Fig. 9. Comparison between the measured nugget diameter and diameter estimated by the neural network.

constant between 1 and 10. In this study, there were 4 input variables and 1 output variable, so here $n=4$, $l=1$ and 3 was used as the initial value for hidden neurons (m). Through training the network with the same testing samples and different hidden neurons number, the hidden neurons number was chosen for the weld quality estimation system when the network error is minimum. Finally, 5 was determined as the hidden neurons number.

3.4. Quality Estimation System

Therefore, a $4 \times 5 \times 1$ structure BP neural network was used to estimate weld quality in this study. Before training the neural network, the training parameters, including maximum training epochs (epochs), expected training error (goal), learning rate (Lr), were set as below:

```
net.trainParam.lr=0.01
net.trainParam.epochs=5 000
net.trainParam.goal=1e-3
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Figure 8 shows the curve of Mean Square Error during training and it could be seen that the estimation Mean

Table 1. Part of test results of neural network.

No.	Measured nugget diameters/mm	Estimated nugget diameters/mm	Deviation (mm)	Relative error (%)
1	2.5	2.4490	0.0510	2.04
2	2.8	2.7650	0.0350	1.25
3	3	3.1680	0.1680	5.60
4	3.3	3.4435	0.1435	4.35
5	4	4.0255	0.0255	0.64
6	4.8	4.7093	0.0907	1.89
7	5	5.2780	0.2780	5.56
8	5.2	5.1825	0.0175	0.34
9	5.5	5.5061	0.0061	0.11
10	6.2	6.2665	0.0665	1.07

Square Error reached expected value and the convergence speed of this neural network was very fast.

The reliability of the estimation system was tested by using a set of samples. Figure 9 shows the comparison between the measured nugget diameter and diameter estimated by the neural network, and part of test results could be seen in Table 1. The results showed that the neural network built in this study could accurately estimate the weld nugget diameter. The estimation deviation was less than 0.3 mm and the maximum estimation error was only 5.6%.

4. Conclusions

- (1) In this study, the increased value of dynamic electrode force (f) during welding process was proved to have strong correlation with nugget diameter by experiments.
- (2) Welding current, welding time, increased value of dynamic electrode force (f) and endpoint value of dynamic resistance curve were used as the input variables for the estimation system of weld quality.
- (3) The weld quality estimation system for RSW was researched and a BP neural network was used to build the estimation system. Test results showed that the system built in this study could accurately estimate the weld quality and the maximum error was only 5.6%.

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