Spot Welding Quality Assessment System Based on Improved BP Neural Network

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ABSTRACT. Resistance spot welding has the characteristics of high production efficiency, easy automatic production, and suitable for welding of thin-walled parts. It is widely used in automobile, aerospace and other fields. The quality of solder joints will directly determine the safety and stability of the equipment or system. However, resistance spot welding still has problems such as high cost of purchasing equipment, poor versatility, and low detection accuracy. Therefore, this paper proposes a resistance spot welding quality evaluation method based on an improved BP neural network algorithm to realize the quality of solder joints. real-time monitoring. By proposing an improved BP neural network algorithm, a detection platform for the quality characteristic parameters of resistance spot welding was built, and the actual welding test was carried out. The sampling and training of the characteristic parameters were completed through the detection platform of the resistance spot welding quality characteristic parameters, and the neural network model was obtained. The remaining sampling points are used as the test set, which proves that the accuracy of the predicted solder joint quality is as high as 93%. It is verified that the proposed resistance spot welding quality evaluation system has the advantages of improving the measurement accuracy, reducing the cost and enhancing the versatility.

Keywords: Improved BP neural network algorithm, Resistance spot welding, Spot welding quality

1. Introduction. The resistance spot welding process is widely used in the production of aviation, automobile manufacturing and other industries. It has the characteristics of energy concentration, high production efficiency, and easy automation [1]. The mainstream research method of spot welding quality assessment technology is to test some parameters in the welding process and use the established fixed model to predict the welding spot, but the model cannot be updated with the production process. Another research hotspot is the spot welding quality control system, which mainly detects a certain parameter of the welding process and adds feedback control to make this parameter meet the industry standard value, thereby achieving the purpose of controlling the spot welding quality. The research results of domestic and foreign researchers indicate that, without changing the number of welding cycles and electrode pressure, the size of the nugget in the welding area and the effective value of the welding current have a great correlation and have nothing to do with the peak value of the welding current. Real-time collection of relevant welding parameters during the resistance spot welding process, such as welding current, electrode voltage, dynamic resistance and welding machine working power and other related signals, also including electrode pressure, indentation depth, electrode displacement, acoustic emission signal, infrared radiation, electromagnetic radiation and other physical parameters [2, 3, 4].

At present, although the measurement technology of various parameters has basically matured, there are not many studies on how to establish the relationship between these parameters and the quality of solder joints. Chen et al. [5] developed a state monitoring system for resistance spot welding equipment based on LabVIEW. By extracting the dynamic resistance information during the working process of the resistance spot welding machine and proposing a five-number summary threshold setting method, the normal solder joints and unfused joints were extracted. The dynamic resistance curve characteristics of solder joints and spatter solder joints, and the signal characteristics of solder joints with unfused and spattered solder joints are obvious, thereby realizing the evaluation of the quality of solder joints [6, 7, 8, 9]. Chen et al. [10] developed a set of resistance spot welding quality inspection system based on nonlinear C-scan ultrasonic imaging technology, using ultrasonic imaging method to measure the diameter of the nugget and identify the internal defects of the nugget, and analyzed the A-scan characteristics and internal defects of different types of nuggets. C-scan feature image [11, 12, 13, 14]. To sum up, the current research is often only aimed at monitoring a certain physical quantity or some physical quantities in the welding process, and establishing the relationship between the physical quantity and the quality of the solder joints through simple fitting techniques. However, resistance welding is an extremely complex physical process, so only detecting a single parameter will inevitably introduce errors [15]. The existing research methods do not take into account the complex physical process in the nonlinear process, so an efficient and accurate resistance spot welding quality evaluation system is urgently needed, which simultaneously considers multiple characteristic parameters and existing nonlinear factors.

2. Principle of BP Neural Network. Neural network technology is a kind of data information analysis and processing system developed by simulating the working mechanism and thinking nature of the human brain. Artificial neural network has great advantages in solving problems in nonlinear and uncertain systems, so it is gradually applied to all walks of life, and it also has its unique advantages in weld inspection, defect identification, nugget size prediction and quality assessment. BP neural network takes a single neuron as a unit. A single neuron is shown in Figure 1, which is a general neuron model with n input, net is the basis function, and f is the activation function [16, 17, 18].



FIGURE 1. Universal neuron model

A BP neural network consists of an input layer, an intermediate layer (one or more layers), and an output layer, and each layer contains multiple neurons. The learning process of BP neural network includes forward propagation and back propagation. The structure of the BP neural network model is shown in Figure 2.

3. Construction of testing platform for resistance spot welding quality characteristic parameters. In the spot welding process, various improper factors can cause defects that exceed the welding quality standards. Solder joint defects are generally divided into internal defects and external defects. Internal defects mainly include unfused and partially fused welding areas, shrinkage cavities, cracks, over-burning, etc. External defects mainly include surface burns of solder joints, workpiece burn-through and splashing, deep indentation and lift-off, etc [19].

By analyzing the defects and formation mechanism of solder joints, the characteristic parameters most closely related to the quality of solder joints are determined as welding current, electrode voltage and electrode pressure. The test and calibration of the self-made Rogowski coils were completed, and the current sensor detection circuit was completed



FIGURE 2. The BP Neural Network Model

to realize the welding current detection of resistance spot welding; the corresponding detection circuit was designed by using the MPX5700AP absolute pressure sensor to realize the detection of resistance spot welding electrode pressure; The HCNR201 optocoupler implements resistance spot welding electrode voltage detection. The data acquisition circuit is designed and the acquisition program is written to complete the acquisition of characteristic parameter signals. The establishment of the detection platform for the quality characteristic parameters of resistance spot welding is realized, and the input data is provided for the BP neural network algorithm [20, 21, 17].



FIGURE 3. The sensor of MPX5700AP



FIGURE 4. the peripheral circuit diagram of MPX5700AP

This article uses MPX5700AP absolute pressure sensor produced by Freescale, which is an advanced monolithic silicon pressure sensor. The actual object is shown in Figure 3. The power supply voltage is DC5V, the measuring range of air pressure is 0-7kpa, and the gas pressure entering the sensor interface It is proportional to the sensor output voltage, the full-scale output voltage is 5V, the normal operating temperature range is 0 to 85 degrees Celsius, the response time is 1ms, and the measurement accuracy is $\pm 2.5\%$. Pin 1 is the signal output Vout, pin 2 is the sensor power supply ground GND, and pin 3 is the positive Vs of the sensor power supply. Collect electrode pressure by constructing peripheral circuit. The circuit diagram is shown in Figure 4, where IPS is a pressure sensor [22, 23, 24].



FIGURE 5. Voltage signal detection circuit

The main circuit is mainly composed of a linear optocoupler HCNR201 and two operational amplifiers, as shown in Figure 5, where Vin+ and Vin- are the signal input terminals, and the main function of the resistor R1 is to limit the bias current of the primary operational amplifier, and the capacitance C is mainly responsible for smoothing the signal in the circuit. Under the condition that the input signal remains unchanged, R3 can change the luminous intensity of the LED.

4. Experimental process and result analysis.

4.1. Construction of Welding Experiment Platform. The resistance spot welding machine used in the experiment is a suspended spot welding machine produced by Tianjin Qisuo High-tech Co., Ltd., the model is DNT3-200. The DNT3 series spot welding machine is mainly composed of a single-phase AC power frequency spot welding mechanism and resistance points of different powers. Welding machine control cabinet composition. The physical object is shown in Figure 6. The model of the spot welding machine control cabinet is LK-22DMO5, the rated working voltage is AC380V, the secondary no-load voltage of the welding transformer is 26V, and the secondary maximum peak current is 14000A. The clamping action of the welding tongs is driven by the cylinder. When the compressed air pressure charged into the cylinder is 5bar (0.5Mpa), the electrode clamping force of the welding tongs is about 3000N. The working process of the spot welding machine is closed-loop controlled by the logic control unit, and the welding current is kept constant during the welding process through feedback. There are three control modes: constant current mode, constant voltage mode and constant phase mode. There are protective measures on the secondary side of the main engine to protect the personal safety of the operator.



FIGURE 6. The control cabinet and welding tongs of the welding machine

4.2. Measurement and analysis of experimental data. Welding current refers to the current flowing in the secondary circuit when the resistance spot welding machine is working, that is, the sum of the currents flowing through the welding spot area. The welding current of the resistance spot welding machine is of the order of magnitude, generally several thousand to tens of thousands of amperes. Welding current is the most important parameter in the spot welding process parameters, and has a crucial influence on the mechanical properties of the welding spot. The calculated effective value of the welding current and the state of the solder joints for each welding test piece are shown in Table 1.

TABLE 1. Measurement of welding current

								Current	Set	Devia-
	1#	2#	3#	4#	5#	6#	7#	average	current	tion
								/A	value/A	01011
Test1	3053.1	3033.1	3044.9	3045.1	3036.7	3065.6	3040.1	3045.5	3000	1.52%
Test2	3490.1	3527.8	3536.2	3519.5	3515.3	3520.3	3521.7	3518.7	3500	0.53%
Test3	3997.4	4001.6	3968.1	3968.1	3947.1	4015.6	4010.7	3986.9	4000	-0.33%
Test4	4412.5	4425.1	4450.2	4425.1	4441.8	4437.6	4470.4	4437.5	4500	-1.39%
Test5	4982.7	4957.5	4961.7	4961.7	4965.9	4961.7	4980.6	4967.4	5000	-0.66%
Test6	5456.4	5485.8	5477.4	5439.7	5460.6	5490.3	5530.9	5477.3	5500	-0.41%
Test7	5896.7	5967.9	5921.8	5926.1	5993.1	5980.6	5989.6	5953.7	6000	-0.77%
Test8	6559.1	6588.4	6580.1	6533.9	6567.5	6554.9	6540.4	6560.6	6500	0.93%
Test9	7062.2	7087.4	7049.6	7045.4	7011.9	7016.1	$7020,\!6$	7045.4	7000	0.65%
Test10	7941.2	7927	7973.2	7955.7	7984.4	7920.7	7954.9	7951.0	8000	-0.61%

Through the spot welding experiment of the test piece, the welding current signals during the processing of all the solder joints were obtained. It can be seen that: with the increase of the welding current, the solder joints experienced non-nugget \rightarrow normal solder joints \rightarrow splashing, The size of the nugget gradually increases, the indentation starts from nothing, and the solder joint starts to sputter seriously from 7000A.

4.3. Implementation and Verification of Evaluation System. Divide the sampled solder joint data obtained above into training group and test group, and use the input data (welding current, electrode voltage and electrode pressure results) and output data (tensile strength data) of the training group to train the proposed improved BP neural network model. The input data of the test group is substituted into the obtained neural network model, and the results obtained from the model are compared with the real output data of the test group to verify the accuracy of the proposed overall evaluation scheme for solder joint quality.



FIGURE 7. Welding current curve

The structure of the BP artificial neural network model is shown in Figure 8. The three different types of signals of welding current, electrode voltage and electrode pressure have a total of 4200 data (the sampling interval is 1ms, and the 7 cycles are 1400ms), which are used as the input of the BP neural network; The shear resistance of the solder joint is only one, as the output of the BP neural network; the number of nodes in the hidden layer is 65.



FIGURE 8. Artificial neural network structure

In order to select the optimal training method for the designed network model, 60 data samples were randomly selected as the training set of the network model, and the remaining 10 samples were used as the test set of the network model. Without any modification of the parameters of the neural network model, gradient descent with adaptive learning rate (trainingda), gradient descent with momentum (trainingdm), gradient descent algorithm (trainingd) and the default Levenberg- The Marquardt training method (trainlm) trains the neural network model separately, counts the network output results, calculates the relative error of the model output results, and takes the mean of the error as the main reference. As can be seen from Table 2, the average relative error of the training results of the gradient descent method with adaptive learning rate is 1.98%, and the accuracy rate is the highest.

Among the four pictures shown in Figure 9, the picture in the upper left corner is the result obtained by the network trained by the gradient descent method with adaptive learning rate, and the picture in the lower left corner is the result obtained by the network trained by the gradient descent method with momentum, the picture on the upper right is the result of the network trained by the gradient descent algorithm, and the picture

	, · 1	D 1 / '	· · 1	D 1 /	1	D 1 /	1	D 1 /
target	traingda	Relative	traingdm	Relative	traingd	Relative	trainIm	Relative
value	output	error	output	error	output	error	output	error
3902	3825.8	1.95%	3914.0	0.31%	3732.2	4.35%	3773.4	3.30%
3758	3814.5	1.50%	3625.8	3.52%	3564.4	5.15%	3643.0	3.06%
3420	3492.8	2.13%	3524.0	3.04%	3422.9	0.08%	3243.6	5.16%
3812	3667.7	3.78%	3726.1	2.25%	3792.9	0.50%	3828.5	0.43%
3828	3760.3	1.77%	3862.9	0.91%	3813.6	0.38%	3807.4	0.54%
3600	3522.6	2.15%	3625.8	0.72%	3573.0	0.75%	3543.0	1.58%
3680	3752.0	1.96%	3625.5	1.48%	3658.5	0.58%	3560.5	3.25%
3200	3224.6	0.77%	3367.8	5.24%	3494.5	9.20%	3018.2	5.68%
3340	3352.7	0.38%	3421.9	2.45%	3445.5	3.16%	3556.4	6.48%
2280	2356.9	3.37%	2127.0	6.71%	2683.2	17.6%	2245.7	1.51%
	Error	1.98%	Error	2 66%	Error	1 1 2 07	Error	3.10%
	average		average	2.0070	average	4.1070	average	

TABLE 2. Comparison of different training methods

on the lower right corner is the result obtained by the network trained by Levenberg-Marquardt, the abscissa in each figure is the sample number, and the ordinate is the shear resistance of the solder joint Value, unit Newton, R2 is the coefficient of determination, a coefficient calculated according to the error of the output result and the number of samples, the closer the value is to 1, the better the performance of the network, The coefficient of determination of the network trained by the gradient descent method with adaptive learning rate is the closest to 1. It can be seen that the performance is the best, and the relative error with the output data in Table 2 is the smallest. It can be seen that the network model designed in this paper uses the adaptive learning rate. The network performance trained by the gradient descent method is optimal.



FIGURE 9. Comparative Results of different training methods

Conclusion. (1) Since resistance spot welding is a very complex nonlinear process, an improved BP neural network algorithm based on genetic algorithm is proposed, and the intelligent optimization link of genetic algorithm is used to replace the original gradient descent method to determine the neural network. Reduce the error existing in the traditional BP neural network in the process of dealing with nonlinear problems.

(2) Using MPX5700AP absolute pressure sensor to complete the welding current detection link of resistance spot welding. The characteristic parameter detection link and the data acquisition link are connected to the welding experiment, the construction of the characteristic parameter detection platform is completed, and the detection of the welding current signal is completed when there is no splash in the welding point.

(3) The genetic algorithm is used to train the BP neural network model, the input data of the test group is substituted into the obtained neural network model, the results obtained from the model are compared with the real output data of the test group, and the average value of the relative error of the prediction results is 3.34%, which proves the accuracy of the proposed resistance spot welding quality evaluation system.

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