A STUDY OF PROCESS PARAMETER MONITORING AND INTELLIGENT QUALITY ESTIMATION DURING RESISTANCE SPOT WELDING

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ABSTRACT

Resistance spot welding is one of the most widely used processes in sheet metal fabrication. Quality assurance of welding has been important to increase the productivity. In this study, weld quality estimation using primary circuit dynamic resistance applied to the in-process real-time systems. For quality estimation, factors relating to quality were extracted from the dynamic resistance, measured in the timer. The relationship between these factors and weld quality was determined through a artificial neural network model. This method has the advantage over the conventional one, such as obtaining the quality information without the use of extra devices.

KEYWORD

resistance spot welding, nugget formation, primary dynamic resistance, neural network, quality estimation

1. Introduction

Since its development, resistance spot welding has acquired an important place in the sheet metal fabrication industry. In order to produce structures of reliable strength with a minimal amount of parts and spots, the reliability of each spot is becoming increasingly critical. Generally, destructive and non-destructive methods using randomly extracted samples are being used in weld inspection. However, in current production systems, the quality of only some of the spots which have been extracted can be estimated through such traditional methods. Therefore, it is difficult to directly examine and fix a problem which has occurred in a welded part. In order to solve such problems, real-time weld quality estimation is necessary, and the development of an algorithm and the formation of a system is very important in accomplishing this task. There have been recent attempts to develop an artificial intelligence weld quality estimation system, which uses a fuzzy or neural network, and complements the shortcomings of extant estimation systems. It is predicted that the lack of perceptibility due to the process automation of such systems will be adequately supplemented.

After a few introductory researches [1], resistance spot weld quality was estimated based on several studies using electrical or mechanical measurement such as welding voltage and current, dynamic resistance, and the rate of electrode separation as monitoring variables [2-3]. Through analytical and experimental methods, various examinations of nugget formation were also performed [4-5]. Especially, Dickinson et al.[6] observed the relationship between the dynamic electrical factors and the formation of the weld nugget, based on the changes in pattern of the dynamic resistance. Also, researchers continued to examine weld quality using the above dynamic factors [7-8]. Recently research has also been done using the neural network on resistance spot welding also. Brown et al.[9] used this method to estimate the nugget diameter, which is closely related to weld strength. Dilthey et al.[10] used a similar method to estimate tensile shear strength.

However, although real time weld quality estimation is possible in such intelligence quality estimation systems, many limitations remain in field application. In this study, a system to monitor the dynamic resistance in the primary circuit of the welding machine without any additional measuring device was suggested. This parameter was applied to the weld quality estimation.

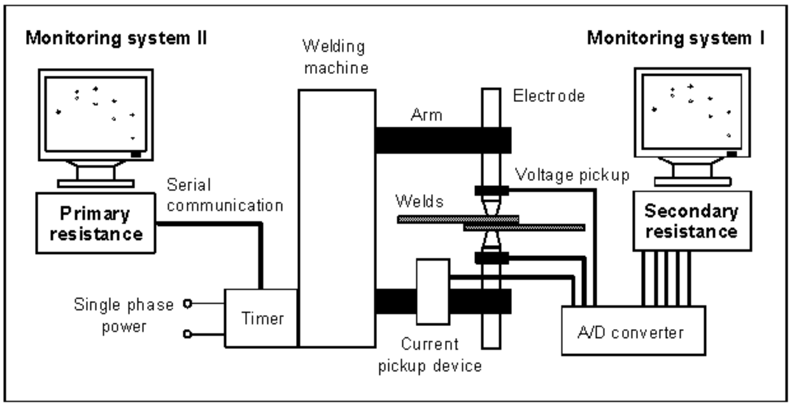

Fig. 1 Schematic diagram of the convensional secondary dynamic resistance (sys. I) and proposed primary dynamic resistance (sys. II) monitoring system

2. Primary Dynamic Resistance and its Monitoring

The nugget of resistance spot welding is formed in direct relation to many weld variables, such as electrode force, welding current, welding time, and material characteristics. Especially, the changes in dynamic resistance calculated based on these variables have been proven to be closely related to the formation of the weld nugget[6]. Although such dynamic resistance is generally monitored and used in the secondary circuit of the welding machine, many problems occur when this system is applied to an in-process system environment. To obtain the secondary dynamic resistance, not only are additional devices necessary to extract the voltage and current for each welding machine, but noise due to magnetic flux in the voltage-sensing circuit can be included.

The welding machine is comprised of a relatively simple electrical circuit made up of SCR(Silicon Controlled Rectifier), resistance, coil, and transformer, the simplified equivalent circuit of which can be expressed as in Fig. 2. The secondary elements of this circuit can be presented as a reflected impedance expressed with transformation ratio a, and rewrote into elements which correspond to the current of the primary circuit. Because the voltage drop due to the inductive reactance is included in the weld voltage monitored in the primary circuit, this element must be effectively eliminated in order to measure the voltage drop due to pure resistance. The weld voltage V_p monitored in the primary circuit can be divided into two kinds of voltage drops due to the resistance and the inductive reactance, as shown in equation (1).

$$V_p = V_R + V_L = R\,I_p + L\frac{dI_p}{dt} \qquad (1)$$

The voltage drop V_L due to the inductive reactance is proportionate to the rate of change of current. Thus, at the moment the rate of change of current reaches zero can be used to calculate the voltage drop element V_R due to only the resistance, regardless of the inductive reactance. This value is divided by the current I_p which is monitored from the primary circuit, to calculate the total resistance R. This value can be expressed in the added value of the resistance of the primary circuit R_p and the resistances R_s and R_L, which have been shifted from the secondary circuit. By using this equation (2), the resistance variation across the electrodes R_L can be converted with the dynamic resistance monitored in the primary circuit.

$$R = R_p + a^2 (R_s + R_L) \qquad (2)$$

In this study, the microprocessor of the welding machine timer was used to formulate the above mentioned algorithm, and the dynamic resistance values were stored in the timer's memory upon completion of the welding. More detailed monitoring method was introduced at the author's earlier study. [11]

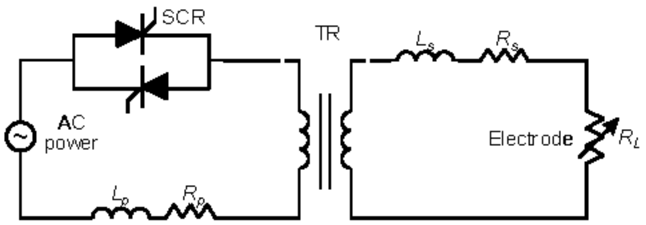

Fig. 2 Equivalent welding machine circuit including practical transformer

3. Primary Dynamic Resistance and Pattern Extraction

In order to examine the reliability of the proposed primary dynamic resistance monitoring system, the dynamic resistance monitored in the welding machine timer and that monitored across electrodes were plotted on the same plane. Fig. 3 shows the results of low carbon cold rolled steel welding and with welding current between 5kA and 11kA, the electrode force at 2.45kN, and 10 cycles. As seen in the figure, the two dynamic resistances show good linearity and the maximum absolute error is 8.5078 μΩ, and the RMS error is 2.0882 μΩ.

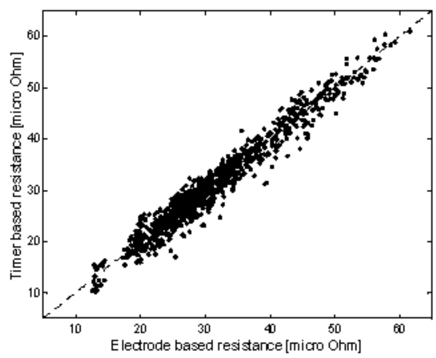

Fig. 3 Relationship between the dynamic resistance monitored in the welding machine timer and that monitored across the electrodes

Fig. 4 is the result of the primary dynamic resistance of a positive cycle under a welding current of 8kA. It can be observed that the resistance increases during the initial welding process due to heating of the faying surface. In the forth cycle the peak point, which is known as the beta peak [11], is reached. At this point, the increase in resistivity due to an increase in temperature forms an equilibrium with the increase in the cross-sectional area available for current flow and the decrease in resistance caused by the shortening of the current path due to plastic deformation of mechanical collapse. After this point the dynamic resistance decreases, as in a typical dynamic resistance pattern.

In this study, four factors that represent the variations of dynamic resistance in such dynamic resistance pattern are extracted, and used in weld quality estimation. First, in order to reflect the geometric type of the dynamic resistance, the beta peak location L_{btp}, which is related to the nugget birth timing, and the speed of increase of the dynamic resistance R_{slope}, which is related to the nugget growth rate, are selected. Next, the maximum dynamic resistance R_{max} is selected to examine whether the heating is adequate for nugget generation. Standard deviation of dynamic resistance R_{std} is used in order to examine the resistance variations. The geometric definition of each factor is shown in Fig. 4.

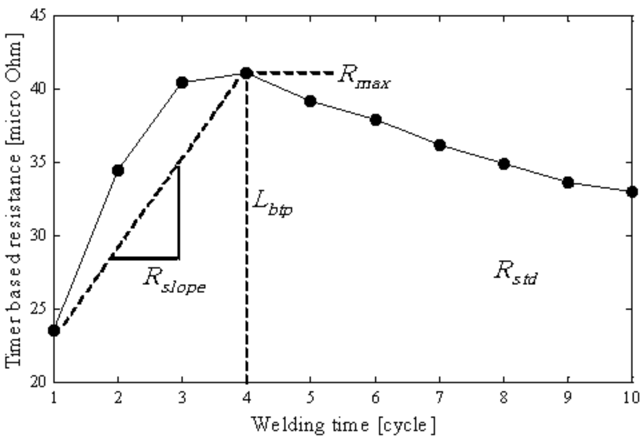

Fig. 4 Primary dynamic resistance pattern and feature extraction

4. The Neural Network and Quality Inspection

In order to effectively use the factors extracted from the primary dynamic resistance the multi-layer artificial neural network, which has been trained by the error back propagation method, is used to estimate the strength of the welds. The ultimate strength, obtained through the tensile-shear strength test, is established as the object of comparison for weld strength. The four estimation indexes mentioned earlier are selected as the input parameters of the neural network, and two hidden layers, each containing 10 nodes, are used to construct a $4\times10\times10\times1$ structure neural network as shown Fig. 5. It is then used in the estimation of weld strength. First, the 40 pieces of data used in training are used to examine the performance of the quality estimation model. Fig. 6 shows the relationship between the measured strength, which is used in training, and the strength estimated through the neural network after training. According to Fig. 6, the model shows good linearity between the two strengths, and the RMS error has a fairly low value of 0.0398kN. Such results stem from the conversance criteria of 0.001 during the training of the neural network. At the network, the learning rate is 0.3, the momentum parameter is 0.7, and the maximum iteration number is 10,000.

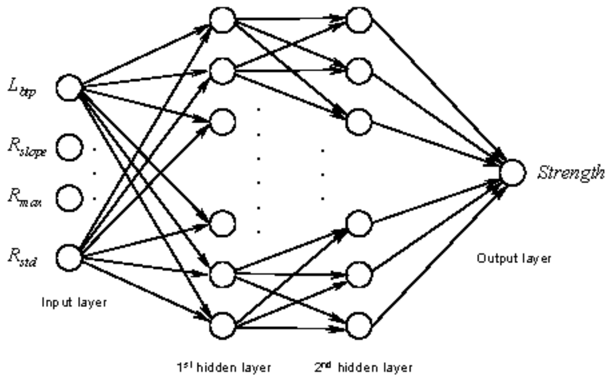

Fig. 5 The neural network architecture

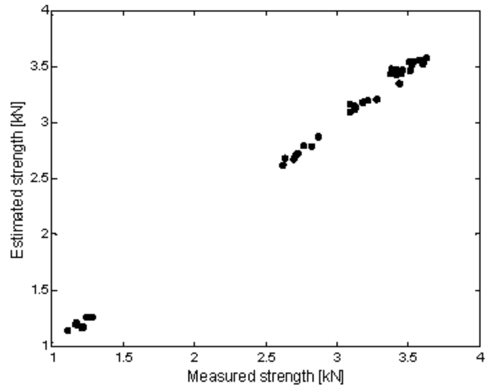

Fig. 6 Relationship between measured strength and strength estimated by neural network

To test the reliability of the neural network model, the experimental results which are obtained from 10 tests under the same conditions as the data used for training, are used to compare the measured strength with the strength estimated by the neural network, as shown in Fig. 7. The RMS error is 0.0924kN, which is slightly higher than the error of the strength used in training, but the maximum absolute error and percent relative error are 0.1487kN on the fifth test and 8.7228% on the second test. Thus proving the neural network is effective in estimating the strength of the welds.

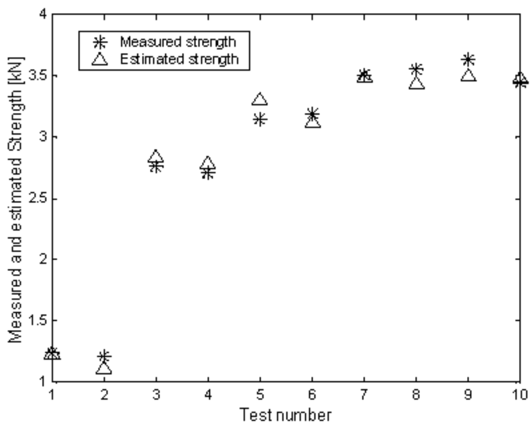

Fig. 7 Estimated strength tested by neural network model

5. Conclusion

In order to obtain information regarding the birth and growth of a fusion nugget in resistance spot welding, the dynamic resistance was monitored as a process parameter. In previous studies, the welding current and voltage monitored in the secondary circuit were used to calculate the dynamic resistance. However, this method is not adaptable to in-process systems. Therefore, in this study, a primary circuit of the welding machine, or a welding machine timer is used with a microprocessor to monitor the primary dynamic resistance. First, the welding machine circuit is analyzed in order to express the secondary electrical elements transferred to the primary side as reflected impedances. This is used to monitor the resistance variation of the secondary circuit using the process variables measured in the primary circuit. Especially, the characteristics of the inductive reactance are utilized to calculate the dynamic resistance using the instantaneous value obtained at the moment when the current reaches its peak. This made it possible to effectively eliminate inductive noise caused by the transformer coil. In order to examine the reliability of the primary dynamic resistance, the dynamic resistance which is converted using the primary dynamic resistance is compared to that which is monitored across the electrodes of the welding gun. The mean RMS error is only 2 μΩ, and the two data coincided in linearity. This is also used with the neural network in strength estimation, in order to effectively use the primary dynamic resistance. First, four factors which can decide the mechanical properties are extracted and used as input variables for the neural network. These are the beta peak location L_{btp}, the speed of increase of the dynamic resistance R_{slope}, the maximum dynamic resistance R_{max}, and standard deviation of dynamic resistance R_{std}. Then, the tensile-shear strengths of the welds are outputted. The trained network shows an RMS error of 0.0398kN for the training data, and 0.0942kN for the test data, showing good performance. By using this dynamic resistance monitoring system and weld quality assurance algorithm, real weld quality estimation can be possible without attaching any extra monitoring devices to the secondary circuit of the welding machine. Also, the dynamic resistance can be used as a control object, making it possible to manufacture a spot welding machine in which the welding quality can be controlled in real time.

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