Development of an Intelligent On-Line Monitoring System Based on ANFIS Algorithm for Resistance Spot Welding Process

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Abstract
This paper presents an on-line quality assessment model based on Adaptive Neuro-Fuzzy Inference System (ANFIS).The ANFIS model is realized for identifying the RSW dynamical system based on given input output data. As a special neural network, ANFIS can approximate all nonlinear systems with less training data, quicker learning speed and higher precision.In this study, a system for monitoring various signals which provide real-time information of nugget formation and growth for RSW is established, and a series of experiments are conducted to research the correlation between these signals and weld quality. These signals include welding current, welding time and dynamic resistance. A set of dynamic resistance patterns are grouped based on their corresponding weld nugget quality, and were selected as the input data to train the proposed ANFIS model. Once the monitoring system had been trained, it was then tested to evaluate its efficiency and validity.The classifier based on ANFIS algorithm indicates the fast classification, showing a total success rate of 82.1 per cent for test data.
Keywords: ANFIS, dynamic resistance, resistance spot welding.

1. Introduction

Resistance spot welding (RSW) is one of the most widely used welding processes for sheet metal joining, especially in the automotive industry. One of the challenges facing RSW is inconsistencies in quality of the weld. This challenge can be addressed by implementing an on-line weld quality assessment. RSW is a thermo-electric process, in which the electrical energy is converted to heat, which is generated at the interface of the parts to be joined. This is accomplished by passing an electrical current through the parts for a precisely controlled time period and under a controlled pressure to form a molten nugget at the faying surface between the two sheets. Controlling an RSW system involves control of the amount of electrical energy which is delivered into the system. The advantages of spot welding are many and include the following: can be used to produce a high volume of work at high speeds that are reproducible at high quality [1], an economical process, adaptable to a wide variety of materials (including low carbon steel, coated steels, stainless steel, aluminum, nickel, titanium, and copper alloys) and thicknesses, a process with short cycle times, and a relatively robust process with some tolerance to fit-up variations. Owing to these clear advantages it is widely used in the appliance, electric and aviation industries. The automotive industry, for example, prefers spot welding for its simple and cheap operation. RSW is widely used in an automotive body assembly. There are thousands of spot welds on an automobile body [2] and improving their quality is an ongoing process in RSW research [3–5].

However, given the uncertainty associated with individual weld quality (attributed to factors such as tip wear, sheet metal surface debris, fluctuations in power supply etc.), it is a common practice in industry to add a significant number of redundant welds to gain confidence in the structural integrity of the welded assembly. In recent years, global competition for improved productivity and reduced non-value added activity is forcing companies such as the automotive industries to eliminate these redundant spot welds. In order to minimize the number of spot welds and still satisfy essential properties such as strength, an appropriate on-line weld quality assessment method needs to be established.

Cho and Rhee [6] showed that the process variables, which were monitored in the primary circuit of the welding machine, are used to obtain the variation of the dynamic resistance across electrodes. This allows the dynamic resistance monitoring system to be applied to the in-process. In addition, to test the reliability of such a system, an artificial intelligence algorithm was developed to estimate the weld quality using the primary dynamic resistance. The authors used uncoated steel welding to verify their model. They also used shear strength as weld quality metric.

Lee et al. [7] studied a quality assurance technique for resistance spot welding using a neuro-fuzzy algorithm. Four parameters from an electrode separation signal, in the case of non-expulsion, and dynamic resistance patterns, in the case of expulsion, were selected as the fuzzy input parameters. These parameters were determined using a neuro- learning algorithm and then used to construct a fuzzy inference system. They also used the displacement and the voltage signals as inputs to their model. Displacement signal is not very practical in industry due to the presence of backlash within the movements of the electrodes.

Podrzaj et al. [8] proposed a linear vector quantization (LVQ) neural network system to detect expulsion. The network was analyzed with different sensor combinations and different materials. The results showed that the LVQ neural network was able to detect the expulsion in different materials. They also identified welding force signal as the most important indicator for the expulsion occurrence, availability of force signal is limited to certain types of guns, and they are more expensive than other types of sensors.

The present work aims at combining the important aspects of fuzzy logic control and artificial neural networks to come up with an adaptive neuro-fuzzy system that will be used to provide real-time quality assessment in RSW process. Such framework makes fuzzy logic control (FLC) more systematic and less relying on expert knowledge.

2. Methodology and Experimental Design

The welding experiments were carried out on a LECCO ANNETTONI Resistance spot welding machine from COSTRUZIONI ELETTROMECCANICHE. Co. Ltd., Italy. The specifications of the machine are shown in table 1

Table 1. Resistance Spot Welding Machine Specification

Single phase input 50/60 Hz	u_1	400 V.
Max. welding power	S_{max}	23 KVA.
Secondary voltage 50/60 Hz	U_{20}	2.4 - 2.7 V.
Secondary short circuited current	$I2cc$	10.2 KA
Max. welding current	I_{max}	8.2 KA
Electrode force	F_{max}	220N

Experiments were conducted and the effects of various parameters, such as the welding time and the welding current on the quality of the weld produced were investigated. The welding currents were varied from 6 to 10 kA with an interval of 1 kA for a fixed welding force of 2200 N. A series of spot welding experiments were repeated for different values of the welding time 8, 9, 10, 11 and 12 cycles.

The materials used in the experiments are commercially available mild carbon steel sheets of 0.85 mm widely used in the fabrication industry.

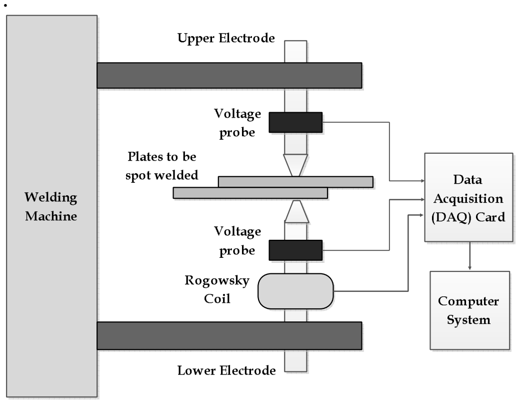

Figure 1. Schematic of RSW machine setup.

2.1 Determination of weld quality based on peel test

To check the effect of welding current and welding time on quality of the weld produced, destructive testing were carried out.

Two metal stacks are used for tests with the AC resistance spot welding machine; mild steel with 0.8mm thickness. Small coupons of size 25mm X 300mm with 6 welds in each (first weld as anchor weld) were used as test specimen. 10 small coupons with 5 welds each (total 50 welds each batch without anchor weld counted) were peeled and the maximum and minimum nugget diameters were measured and averaged. This measurement of weld size is typically used as an indication of weld quality, i.e. whether the weld is fit for its intended purpose.

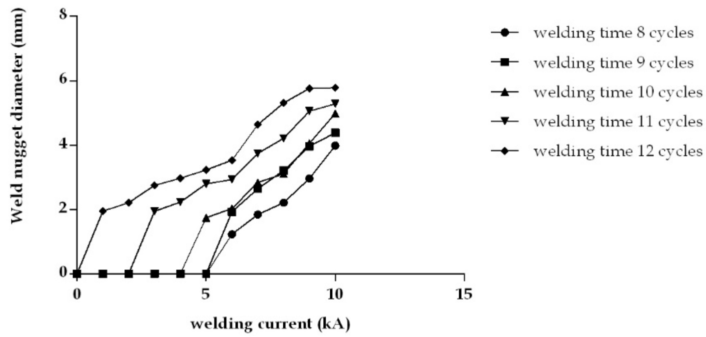

Figure 1: Illustrates the practical representation of the weld current vs. the diameter of the weld nugget

2.2 Classification of welding qualities according to dynamic resistance patterns

A weld monitoring system was designed to record two important welding parameters during the welding process. The welding parameters which were monitored are current and voltage as they contribute to Joule heating, or the formation of a weld nugget. A Rogowski coil, with current measurement range of 5A to 100kA and a differential voltage probe, rated to measure differential and common mode voltage were used for secondary welding current and voltage measurements, respectively.

The signals from the DAQ system were then sampled by the monitoring system developed using LabVIEW based software, see Figure1which illustrates a schematic diagram of the experimental apparatus for the measurement and the implementation of sensors for the welding process.

Before any measurements were made, the current sensor was calibrated. Measurements of welding current and welding voltage were taken simultaneously in order to determine the Dynamic Resistance (DR) during the RSW process. The DR is obtained indirectly, using Ohm's law, by measuring the welding voltage across the electrodes as close as possible to the sheets.

Five samples are used for each condition. Therefore, a total of 125 data including the size of the weld nugget diameters with 50 data respectively are obtained as the experimental results. Figure 2-6 shows the changes in dynamic resistance patterns for various welding currents from 6 to 10 kA, with a fixed welding force of 2200N.

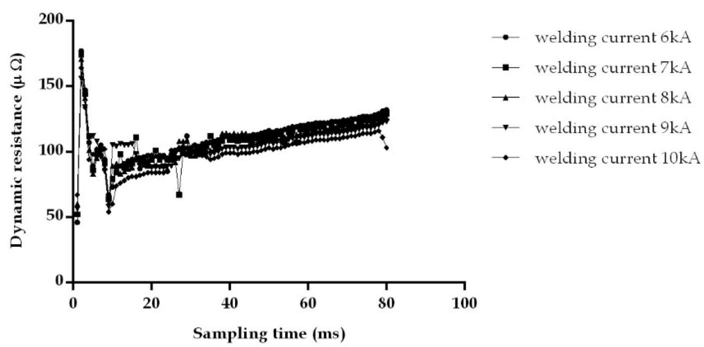

Figure 2. Illustrates the dynamic resistance patterns for a welding time of 8 cycles

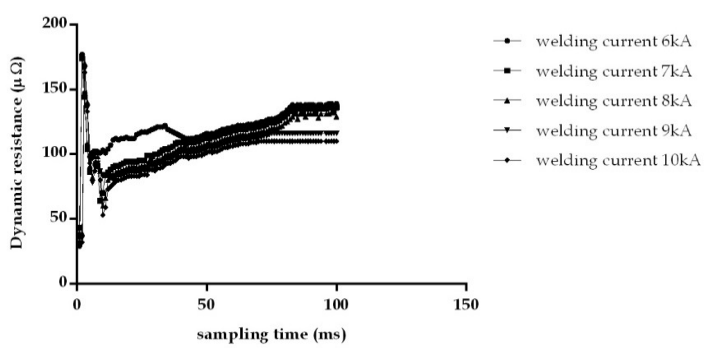

Figure 3. Illustrates the dynamic resistance patterns for a welding time of 9 cycles

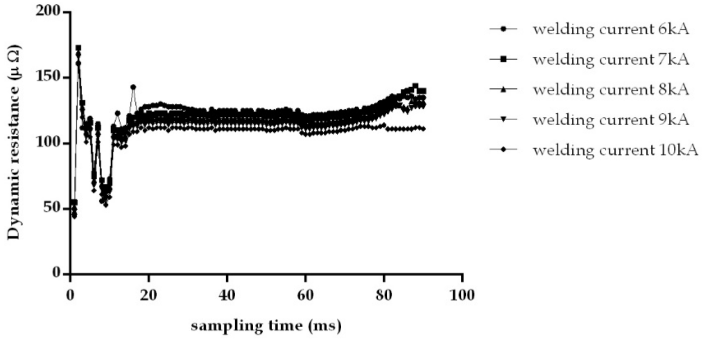

Figure 4. Illustrates the dynamic resistance patterns for a welding time of 10 cycles

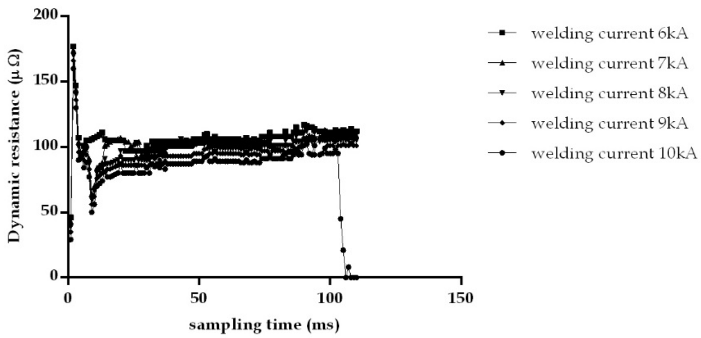

Figure 5. Illustrates the dynamic resistance patterns for a welding time of 11 cycles

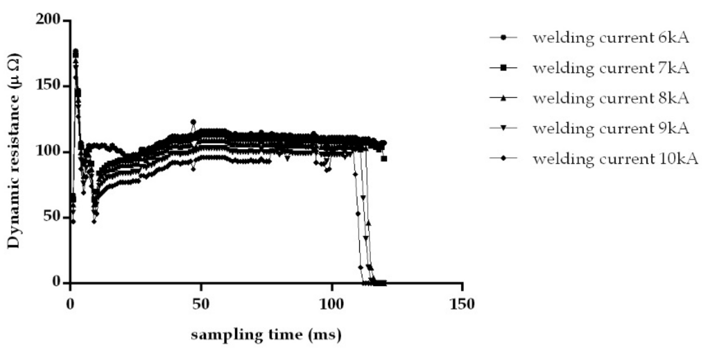

Figure 6. Illustrates the dynamic resistance patterns for a welding time of 12 cycles

2.3 Classification of the standard welding quality classes

First of all, in order to evaluate the welding qualities by classification of the dynamic resistance patterns, sample patterns classified into weld quality classes are required.

Experimental data obtained composing of 125 sets of the dynamic resistance patterns for the classification of welding quality classes are used to generate three sets of the standard patterns for each class. These sample patterns are classified into three types of standard welding quality class according to the peel test criterion. The three welding classes are: cold (C), normal (N) and expulsion welding. Class 1 (C) welding state represents poor weld quality with a small weld nugget diameter due to insufficient heat, and class 2 (N) represents better weld quality with an acceptable weld nugget diameter due to the adequate heat. Finally class 3 (E) belongs to poor weld quality due to the excessive heat. Therefore, the welding state with class 2(N) should be aimed at for the best welding quality in this RSW process.

3 Classification by ANFIS

3.1 Design of Adaptive Neural Fuzzy Inference System

The purpose of this study is to evaluate the welding quality in real time by monitoring and classifying the dynamic resistance patterns generated from RSW process. For the classification methods, the ANFIS method is proposed. This classification method is evaluated using the total success rate attained by the welding quality classes.

ANFIS model is realized for identifying the RSW dynamical system based on given input output data. As a special neural network, ANFIS can approximate all nonlinear systems with less training data, quicker learning speed and higher precision.

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge [9].

To present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered:
Rule 1: If (x is A_1) and (y is B_1) then $(f_1 = p_1x + q_1y + r_1)$
Rule 2: If (x is A_2) and (y is B_2) then $(f_2 = p_2x + q_2y + r_2)$
where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig. 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

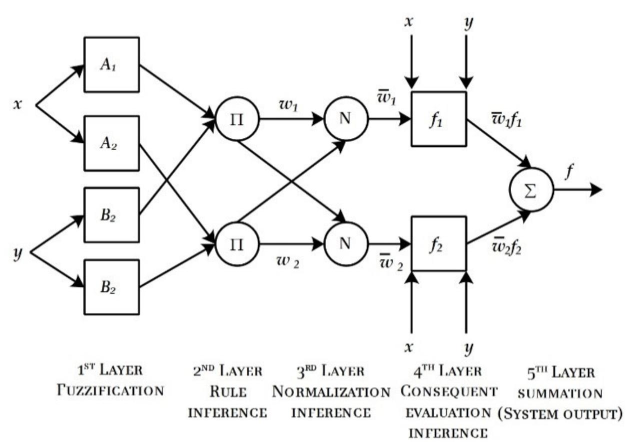

Figure 2: ANFIS architecture

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of theinputs, which are given by:

$$O_i^1 = \mu A_i(x) \qquad i = 1,2$$
$$O_i^1 = \mu B_{i-2}(y) \qquad i = 3,4$$

Where$\mu A_i(x)$, $\mu B_{i-2}(y)$ can adopt any fuzzy membership function.
In the second layer, the nodes are fixed nodes. They are labeled with *P*, indicating that they perform as a simple multiplier.
The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu A_i(x)\mu B_i(y) \qquad i = 1,2$$

Which are the so-called firing strengths of the rules.
In the third layer, the nodes are also fixed nodes. They are labeled with *N*, indicating that they play a normalization role to the firing strengths from the previous layer.
The outputs of this layer can be represented as:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad i = 1, 2$$

Which are the so-called normalized firing strengths.
In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \overline{w_i}f_i = \overline{w_i}(p_ix + q_iy + r_i) \qquad i = 1, 2$$

In the fifth layer, there is only one single fixed node labeled with *S*. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i$$

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely$\{p_i + q_i + r_i\}$, to make the ANFIS output match the training data [10].

3.2 Pattern recognition by ANFIS algorithm

The mapping of the measured dynamic resistance patterns to their corresponding weld quality class is implemented by the ANFIS method. Figure 7 shows the block diagram of the proposed approach for an adaptive control system.

The dynamic resistance patterns obtained from the experiment are mapped to an appropriate class of the three welding quality classes which are cold welds (C), normal welds (N) and expulsion welds (E).

In order to reduce the dimensionality of the ANFIS input, the actual resistance vector was replaced with a set of representative features, including:

- Maximum value of the input resistance vector.
- Minimum value of the input resistance vector.
- Mean value of the input resistance vector.
- Standard deviation value of the input resistance vector.
- Range value of the input resistance vector.
- RMS value of the input resistance vector.

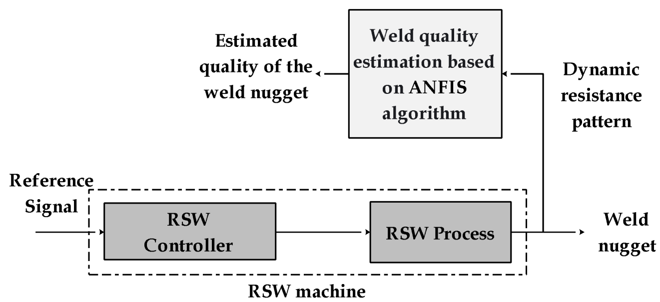

Figure 7. Proposed approach for on-line quality estimation.

The ANFIS model was trained on 12, 22, and 16 patterns of the secondary resistance vector for cold, normal, and expulsion welds, respectively.

3.3 Evaluation of pattern classification algorithm

Evaluation results on the classification of the standard patterns by the standard welding quality classes are summarized in Table 2. The dynamic resistance patterns in the welding quality classes 1 (Cold welds), 2 (Normal welds) and 3 (Expulsion welds) are exactly classified into the standard dynamic resistance patterns 1, 2 and 3 respectively.

Table 2 Classification results based on the proposed ANFIS model

		No. of samples in the following weld quality class			
Weld quality class	No. of samples	C	N	E	No. of samples subjected to confusion
Cold welds (C)	12	10	2	0	2
Normal welds (N)	22	3	18	1	4
Expulsion welds (E)	16	0	3	13	3

Thus, as shown in Table 2, the total success rate is 82.1 per cent, which is not high but is feasible for use in a real industrial application. Therefore, it is clear that the standard dynamic resistance patterns can be used for on-line monitoring and evaluation of their welding qualities, considering the characteristics of standard patterns. The false alarm rate for cold welds was lowest in comparison with normal welds.

4 Conclusion

In this study, a model for weld quality monitoring to predict quality of the weld nugget in a RSW process was developed and was validated through the experimental work. An adaptive neuro-fuzzy inference system was designed for nugget quality classification that employs the easily accessible dynamic resistance profile as input. The goal is to make an on-line distinction between normal welds, cold welds, and expulsion welds. The results from applying the ANFIS algorithm trained using very limited data collected during the stabilization process are very promising and it can be customized for implementation in a practical on-line quality monitoring systems for resistance spot-welding machines.

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