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MONITORING OF RESISTANCE SPOT WELDING PROCESS WITH DECREASED SPOT-TO-SPOT DISTANCE

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Abstract. *Resistance spot welding is a welding process with high level of automation and high productivity. This rises a number of tasks related to development of quality evaluation and process monitoring systems operating in real-time mode which would allow to detect non-compliant joints during the process run of shortly after it is finished. The more complex task is to make such system as much universal as possible. In case of resistance spot welding aside from the base metal characteristics, parts' design and welding parameter the spot-to-spot distance effects significantly the joint formation. The authors made efforts to develop the system for monitoring the parameters of resistance spot welding with varying distance between spots. The on-line monitoring system based on artificial neural networks was developed for evaluation of process deviations. This system is believed to be adequate for determination of process violations resulting in disturbances of welding parameter and can be used for prediction of possible defects in the welded spots even with variations of distance between them.*

Keywords: *Stance Spot Welding, Dynamic Resistance, Neural Network, Classification of Joints*

1. INTRODUCTION

Resistance spot welding is widely used in modern industry to produce metal structures. The process of resistance spot welding itself requires rather high level of automation due to very short process time, limited access to the weld zone (this also limits the possibilities for operational control), high (up to melting point) temperatures, etc. Usually the structures are designed so that several spots should be welded on them their location being defined by the designer to ensure the overall strength and other mechanical properties required. Sometimes this leads to spots' location being different from the standard requirements (Gost 15878-70, 1980).

Monitoring of resistance spot welding processes may be organized upon opened or closed circuit, each having its own advantages and disadvantages for different conditions of welding (Steinmeier, 2010). The type of feedback should be considered as well: the main parameters can be current, voltage, power. Each of them has its own limitations, so the final choice is always being made as a kind of compromise. It should be also mentioned that up-to-date means of quality assurance for resistance spot welding usually are designed to stabilize the joints' quality while the monitoring of process dynamics still remains uncovered. This leads to obligatory use of destructive testing methods in every production-run, though defects still can occur in final products.

Recent research has proven that monitoring of dynamical resistance could be a good tool for quality evaluation in resistance spot welding (Livshits, 1997). It can be used to track the amount of heat generated in weld zone and in this way to predict the characteristics of the welded spot (Bai *et al.* 2008). The method works in real-time mode which is also a huge advantage. Though the spot-to-spot distance will effect dynamics of its changes during the welding process which makes it hard to develop a universal monitoring system which could operate effectively despite distance between welded spots.

The objective of this work was to develop methods of quality evaluation of welded joints produced by resistance spot welding with decreased distance between them by means of monitoring of dynamical resistance.

2. EXPERIMENTS' DETAILS

The specimens to be welded were produced from low-carbon steel 0,8 mm thick, their dimensions being 40×100 mm. Welding was performed on MT-1215 resistance spot welding machine with PKC-801 welding timer (both are products of "Kakhovka plant of electric welding equipment", Ukraine). To avoid edge effects during welding the welded spots were located on the longitudinal symmetry axis, the outside ones being placed on the distance 20 mm from the specimen edge.

According to requirements Gost 15878-70 (1980). for metal thickness 0,8 mm the distance between spots should be 20 mm with minimum diameter 6 mm. Experiments were performed for optimal spot-to-spot distance and for several reduced ones: 15 mm, 10 mm, 6 mm (spots are located next to one another) and 3 mm (spots overlap one another on half of their diameter).

For every distance three series of experiments were performed. In the first one (the base set) welding parameters were set up so that despite decrease of spot-to-spot distance the welded spots obtained were 6 mm dia, their values were chosen according to recommendations (Smirnov, 2000). The other two were designed to simulate violation of welding technology which led to incomplete fusion and metal spitting. Incomplete fusion was obtained by reducing the welding current and metal spitting – by reducing the pressure together with decrease of the preliminary compression time.

Measuring system included analog-digital converter E-140 (L-Card, Russia), voltage and current sensors and the system for primary data collecting and processing developed by the authors. In all the experiments the sampling frequency was set at 50 kHz which is sufficient for signal recover for the welding methods investigated (Chvertko, Pirumov, Shevchenko, 2013). The current sensor used was Rogowski loop which is a common one for resistance welding equipment. The voltage measurement was performed between two electrode-holders (the signal obtained included the welding zone and two electrodes).

The measuring system was designed according to the following requirements:

- the equipment used should be uniform, with no special adjustments to use it for resistance spot welding process;
- no special training should be required to work with the system designed;
- the equipment should be able to work in conditions of resistance spot welding: short welding time, high energy applied to the parts to be welded, high level of electromagnetic disturbances, etc.;
- data processing should be considered due to huge amount of data recorded, including intermediate operations (integration, filtration, etc.).

Due to complex data processing needed it was decided to use digital system instead of analog one. Such system is easily operated and can be used to store huge data arrays and to process them rather quickly. Data recording was performed using L-Graph v.2.0 programme, data processing was performed with MatLab R2013b. Signals were filtered using digital Butterworth filter.

After welding of specimens with different spot-to-spot distances and different sets of welding parameters destructive tests were performed by making welded spots' macrosections (Fig. 1).

a b c

Figure 1. Welded spots: a – good quality; b – incomplete fusion; c – metal spitting

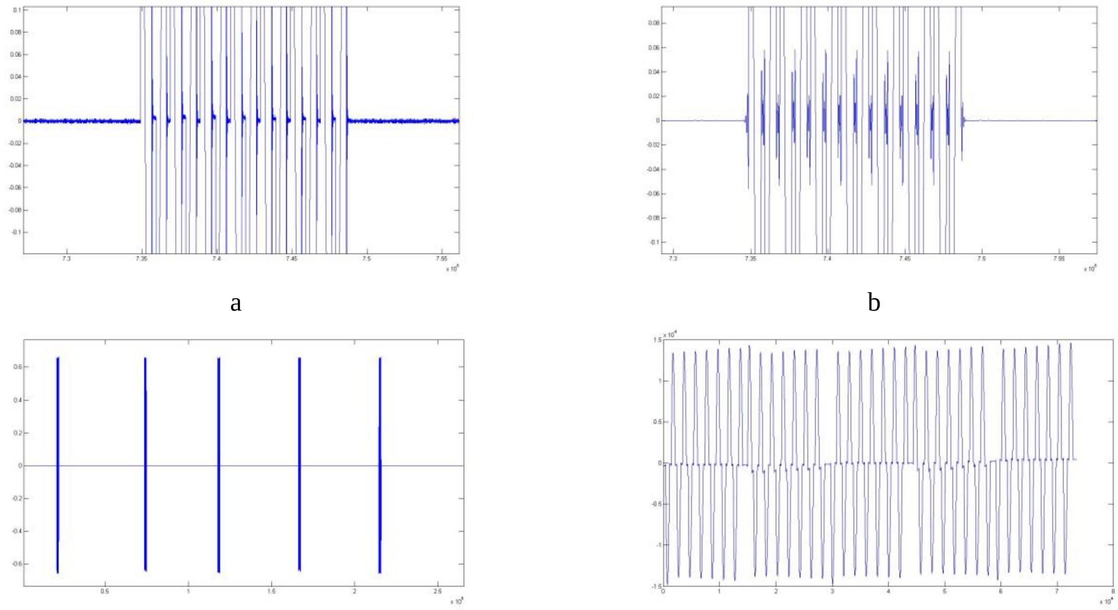
3. DATA PROCESSING

Data obtained via measuring current and voltage had to be processed to form arrays of values of dynamical resistance which could be adequately analyzed by means of artificial intellect. Neural networks are widely used for monitoring different welding processes Chvertko, Pirumov, Shevchenko (2014) which makes it rational to apply the in this case as well. The main requirements to the data to be analyzed with neural networks are (Osovskiy, 2002):

- two data arrays should be developed: the training sequence used for network training and control one used to check the network operation;
- the training sequence should contain as many possible patterns of welded spots' formation as possible;
- data placement in the training sequence should not be aligned with any kind of relationship;
- data in training sequence should be normalized to avoid changes of welding parameters to effect the classification; the information should be taken from the signal form, not its value (Khaikin, 2006).

According to requirements listed it was decided to used integrated by the time equal to half of main power period values of electrode-to-electrode dynamical resistance.

Additionally a script was developed to identify the time intervals corresponding to joint heating and removal of pauses between them as far as when welding machine is operated by human such pauses may significantly vary in time. Signals on different stages of processing are given on Fig. 2.

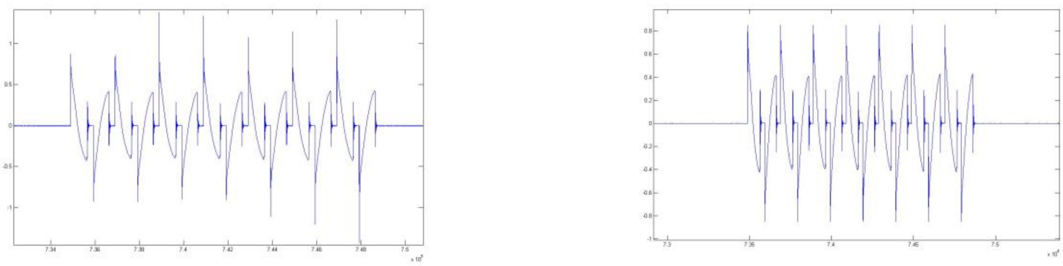


a b

c d

Figure 2. Signal processing: a – as recorded; b – filtered signal; c – before pauses' removal; d – with pauses removed

Dynamical resistance is calculated by dividing recorded values of voltage and current. As far as Rogowski loop was used as a current sensor additional signal preparation was needed. First of all, the signal has a very sharp edge which results in loss of data during recording (maximum value isn't always registered, see Fig. 3, a). To compensate this a script was developed to seek the maximum value of signal in every half-period time interval and to replace it with maximum one, now equal to all periods recorded (see Fig. 3, b). Results of dynamical resistance calculations and forming data arrays for further analysis by neural networks are given on Fig. 4.



a b

Figure 3. Signal from Rogowski loop: a – as measured; b – after augmenter

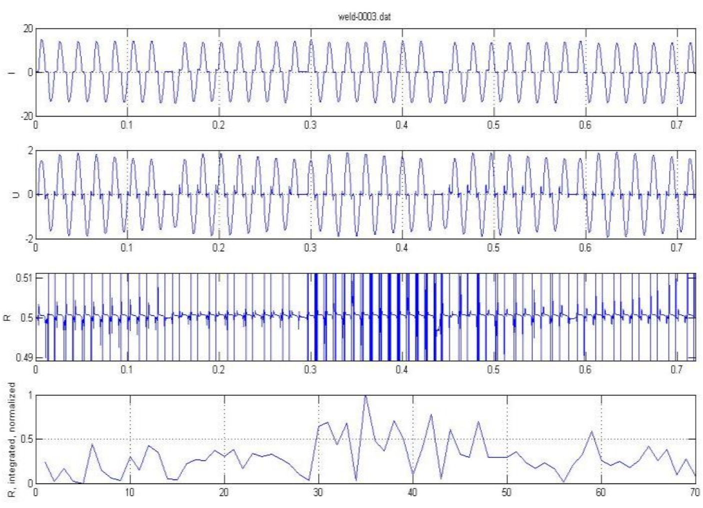


Figure 4. Calculation results

4. APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR QUALITY EVALUATION

Neural networks can be used to find and analyze implicit relations between data arrays. In our case the main task of network was to classify data according to disturbances in welding process despite distance between spots and divide them into three classes: good quality, incomplete fusion and metal spitting.

Two networks were chosen to perform this task: Radial Basis Functions network (RBF) and Probability Neural Network (PNN). Both types of networks provide classification of data array based upon its adjacency with other arrays taking into account peculiarities of distribution of previously analyzed arrays.

Network training was performed using two training sequences: one containing information about 96 spots, another – 167. Lesser one (symmetric sequence) contained equal number of every spot class signals, bigger one (non-symmetric) was built as symmetric sequence plus additional arrays from 'good quality' class joints. This was done due to PNN network application: when training sequence contains equal number of each class data, these networks in their further work will 'think' that probability of obtaining good and non-compliant joints is equal as well.

The quality of network training was performed by the effectiveness factor [10]. After the network training the elements used for it were presented to the network input and the number of right responds was calculated. The precision of training sequence analysis was calculated from Eq. (1):

$$T_T = \frac{B}{R} \tag{1}$$

where B – number of right responds, R – total number of blocks for training.

For both networks T_T was equal to 1.

The evaluation of effectiveness of the neural networks developed was performed by presenting to their inputs data matrices which were not used for training (the control sequence). Effectiveness of the neural network application was calculated from Eq. (2) (Dyakonov and Kruglov, 2010):

$$E = \frac{T_C}{T_T} \tag{2}$$

where T_C – precision of control sequence processing. As far as for all the networks $T_T = 1$, $E = T_C$.

Overall effectiveness of spots' classification (different distances mixed in one array) was as follows:

1. RBF network, non-symmetric sequence (167 signals):
   - frq1 = 0,9737 – good quality;
   - frq2 = 0,5247 – incomplete fusion;
   - frq3 = 0,8261 – metal spitting;
2. RBF network, symmetric sequence (96 signals):
   - frq1 = 0,6667;
   - frq2 = 0,4106;
   - frq3 = 0,7232;
3. PNN network, non-symmetric sequence (167 signals):
   - frq1 = 0,8131;
   - frq2 = 0,5323;
   - frq3 = 0,8575;
4. PNN network, symmetric sequence (96 signals):
   - frq1 = 0,6667;
   - frq2 = 0,4523;
   - frq3 = 0,8667.

Detalized data on every spot-to-spot distance are given on Fig. 5. It is clear that neural network application for classification of joints has a probabilistic nature and its precision is less then 100 %. Anyway, they can be used to detect the joints for which additional testing methods should be applied. For example, symmetric RBF network has shown good results in identifying spots with good quality (more then 84 %) while non-symmetric RBF network's results prove it to be useful to detect non-compliant joints. The fact that PNN networks has shown good results for some classes means that there is a certain relationship between those data and they can be classified (Dyakonov and Kruglov, 2010).

Effectiveness can be improved by re-forming the training sequences and application of additional preliminary data processing. Also deep neural networks operating on special computer clusters seem to be useful in this case because of their huge number of links.

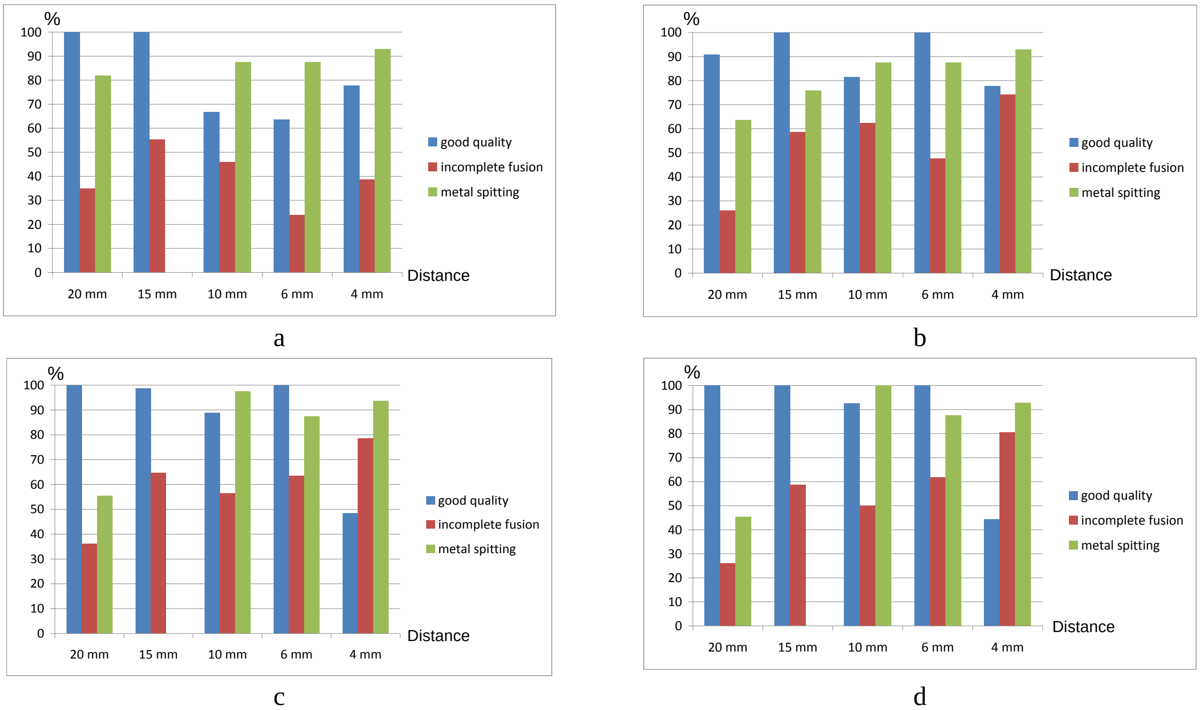


Figure 5. Effectiveness of neural networks' operation: PNN with symmetric (a) and non-symmetric (b) sequences, RBF with symmetric (c) and non-symmetric (d) sequences

5. CONCLUSIONS

1. Electrode-to-electrode resistance appears to be one of the key characteristics which defy the conditions of heating in resistance spot welding and, respectively, affect the joint formation. Dynamics of this resistance changes can be used to evaluate the quality of welded spots. This dynamic depends not only on welding parameters, but on the spot-to-spot distance as well.

2. Artificial neural networks can be used for quality estimation in resistance spot welding with varying spot-to-spot distance. Analysis of effectiveness of their operation has shown that PNN network with non-symmetric training sequence can be used to define joints of good quality when distance between spots is decreased (its effectiveness being 81 %). If the spot-to-spot distance is bigger the best results can be obtained using RBF network with non-symmetric training sequence (97 %). Non-compliant joints can also be detected: PNN with symmetric training sequence has shown high effectiveness for metal spitting (81 – 92 %, differs with distance increase) while RBF network with symmetric sequence is good for detecting incomplete fusion (up to 78 %).

3. The final choice of network type and training sequence should be made taking into account tasks from quality assurance program. For example, the task could be to divide all the joints into two groups (compliant and non-compliant), to identify the joints with incomplete fusion only, etc.

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7. RESPONSIBILITY NOTICE