UDC 621.7.08:621.791.75

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MONITORING OF WELDING PROCESSES WITH APPLICATION OF ARTIFICIAL NEURAL NETWORKS

The paper presents a summary of methods of monitoring systems' development for the processes involving heating of filler material and/ or base metal by the electric current and with periodical shortages of the welding circuit. The processes investigated were MAG welding, underwater flux-cored welding and flash-butt welding. Details of experiments, primary data processing procedures based on statistical analysis methods are described, the aim of primary processing being obtaining of informative parameters of the welding processes. Details of neural network structure development, training and control sequences generation, nets training and adequacy check are presented as well. Comparison of determination of process variations (edge shifting, electrode outlet, variation of gap, variation of joint line – for arc welding methods; decreasing of open-circuit voltage and specimen travel speed – for flash-butt welding) is presented. The on-line monitoring systems based on neural networks developed for evaluation of process deviations are also 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 joints.

Keywords: MAG welding, underwater FCAW welding, flash-butt welding, process monitoring, detection of defects.

Introduction

Modern methods of non-destructive testing of welded joints often involve use of complex equipment and are rather labour-intensive. Their application reduces the overall productivity of welded structures' production. However even with these methods it is not reasonable from the economical point of view to control every single weld, especially in conditions of series manufacture. From the other hand, the requirements to the quality of all the joints within the production lot remain the same.

Currently research is performed to define the characteristics of quality of welded joints by energy parameters of welding with application of intellectual systems. Such systems decrease participation of human in the process of quality control thus reducing its cost and subjectivity. Evaluation of possibility of development of up-to-date systems of quality monitoring based on analysis of electric process parameters is a task to be solved. One of the ways seems to be an application of artificial intelligence systems.

For fusion and resistance welding processes some methods of development of quality monitoring systems were proposed. The relationship between parameters' deviations and possibility of typical defects' formation was defined as well for the processes mentioned [1, 2]. Such relationships make it possible to develop automated systems for welding process monitoring which simultaneously provide predicting of the weld quality.

For fusion welding processes it is possible to identify different disturbances by neural networks (this approach can be effectively used in case of on-site welding, for example, in underwater wet welding) [3, 4]. It is also possible to develop the quality control system based on Fuzzy Logic methods [5]. The same task can be solved using neural networks for pressure welding methods, for example, for flash-butt welding [6].

Objective

The objective of this work was to make a summary of principles of development and adequacy check of methods of welding processes' monitoring and prediction of quality of welded joints based on monitoring of electrical parameters of welding. Generally the tasks of welding processes' monitoring are classification-like which makes it possible to solve them using neural networks.

Details of experiments

Research was performed for three welding technologies: gas-shielded arc welding (MAG welding), underwater flux-cored arc wet welding (FCAW) and flash-butt welding (FBW). In all the processes mentioned the heating of filler material and/ or base metal are followed by partial or full periodical shortings of welding circuit. Such signal form is good for application of automated data processing methods. In MAG welding most of such shortages are accompanied by filler metal transfer to the welding pool while in underwater FCAW most of them do not provide the metal transfer. In FBW shortages are indicating processes of local contacts formation. Periodically they overheat and explode with energy release in the welding zone. This means that even though the signals are alike the effect of welding circuit shortages on the weld formation differs from method to method.

Base metal and filler material heating in all the processes mentioned can be evaluated by the energy input which is defined by the values of current and voltage. It should be mentioned that in case of FBW on the equipment with strict drives without feedback it is possible to apply single-factor measuring system [2].

Experiments were made to perform recording of electrical parameters: voltage (in the secondary circuit of the welding machine for FBW and arc voltage for arc welding methods) and welding current (for arc welding methods only). Measuring system included analog-digital converter E-140 (L-Card, Russia), voltage and current sensors (LEM, Switzerland) and the system for primary data collecting and processing developed by the authors. In all the experiments the sampling frequency was set at 10 kHz which is sufficient for signal recover for the welding methods investigated [7].

The development of monitoring system based on artificial intelligence algorithms involves the training procedure. During the training a set of reference patterns is to be analyzed by the system. To create the sets of reference patterns for the training and adequacy check of the neural networks several series of experiments in welding were done for every of the methods, including welding with its parameters set as it is recommended by literature and with deviations from these values. These deviations were based on continuous disturbances which often occur in welding production and which were big enough to cause the reducing of weld quality characteristics.

Experiments in MAG welding were performed using the ПС-250 power source, wire feeding mechanism LISA–14RB and A-1401 automatic welder. The base welding parameters were set at: welding current – 90 A (direct current, electrode positive), arc voltage – 19 V, welding speed – 18 m/hour (the speed was stabilized by the automated system). The specimens to be welded were produced from low-carbon steel 2 mm thick. For the continuous disturbances simulation special specimens were used as shown on Fig. 1: with variable gap, stick-out distance, weld line shifting and edge asymmetry.

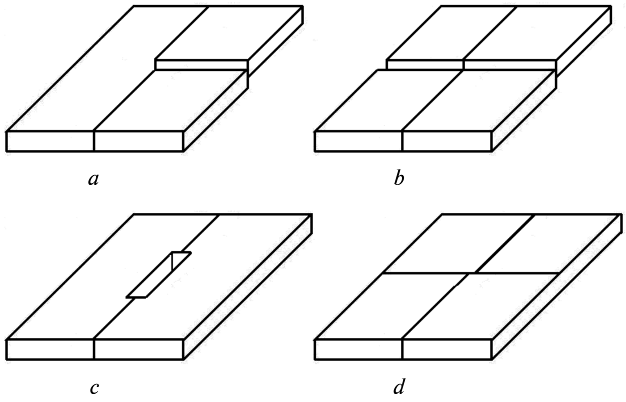

Fig. 1. Specimens for arc welding with continuous disturbances: *a* – edge asymmetry; *b* – stick-out distance variation; *c* – gap variation; *d* – weld line shifting

Experiments in underwater FCAW were performed using АСУМ–400 automated welder, the specialized system for welded joint moving, high-pressure chamber (for simulation of depth of submersion). The ППС-АН2 flux-cored wire (developed for underwater welding) was used.

The base underwater wet welding parameters were set at: welding current – 200 A (direct current, electrode positive), arc voltage – 30 V, welding speed – 8 m/hour. The specimens were made of low-carbon steel 10 mm thick, only the root runs were welded. The continuous disturbances were simulated in the same way as for MAG welding.

Experiments in FBW were performed on the МСО-606 welding machine with strict electric-mechanical drive without feedback. The rods made of low-carbon semi-killed steel 14 mm dia were welded. The base welding parameters were set at: open circuit voltage – 4,87 V, average speed – 6,5 mm/s, adjusting length – 25 mm, average upsetting speed 10 mm/s, tolerance for flashing 10 mm and for upsetting 4 mm, time of upsetting with current on – 0,04 s.

Continuous disturbances were simulated by changing of main process parameters: open circuit voltage, speed and adjusting length, only one parameter was changed per time. When the corresponding disturbances were "active" the welding parameter were set at: open circuit voltage – 4.17 V, speed – 3 mm/s, adjusting length – 50 mm. As far as in FBW the weld itself is formed during the upsetting stage, but its quality is significantly determined by the base metal heating during the flashing, the upsetting parameters were kept intact for all the experiments.

Development of welding monitoring systems

Welding process monitoring should be based on continuous analysis of electrical parameters and identification of possible disturbances continuously or immediately after the process is finished. Identification of such disturbances can be performed as classification of oscillograms' fragments for the parameters to be analyzed or as pattern recognition. The LVQ (Learning Vector Quantization) neural network was applied to solve these tasks.

Preparation of data for network training. After welding and measuring of its parameters the data arrays were obtained for MAG welding (Fig. 2), underwater FCAW (Fig. 3) and FBW (Fig. 4), all of them being quite of big size. The preliminary data processing and reduction was needed to make it possible to apply the LVQ networks.

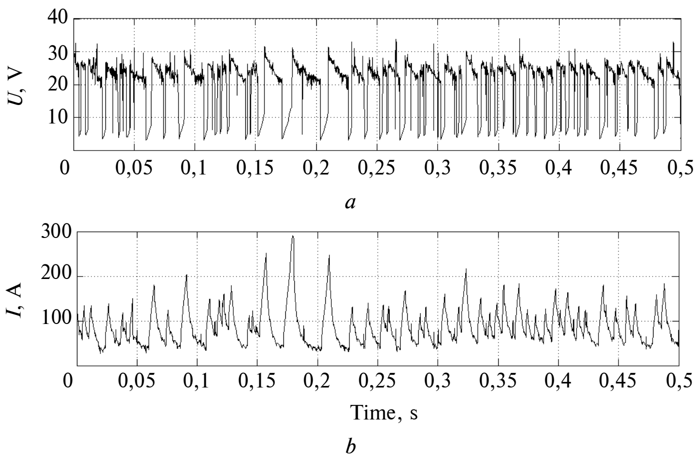

Fig. 2. Fragments of arc voltage (*a*) and welding current (*b*) patterns for MAG welding

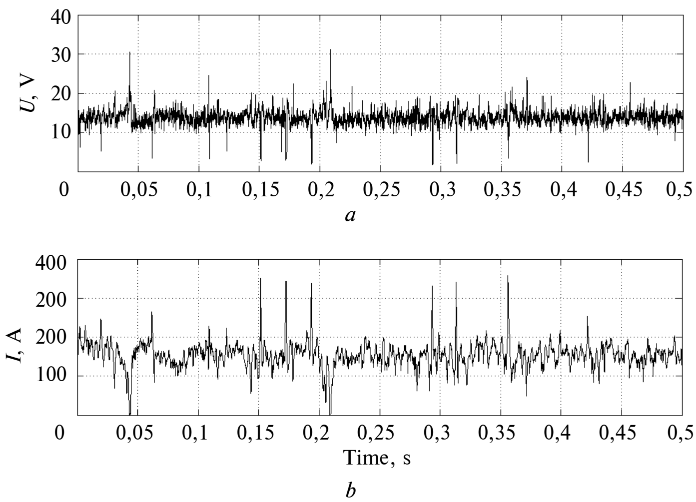

Fig. 3. Fragments of arc voltage (*a*) and welding current (*b*) patterns for underwater FCA welding

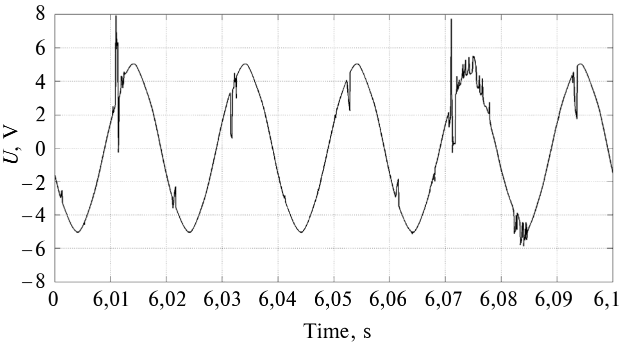

Fig. 4. Fragment of secondary circuit voltage pattern for flash-butt welding

For *MAG welding* several parameters should be analyzed simultaneously to take into account the process features. The following values were chosen as the input signals for the neural network: standard deviations of arc voltage σ_U^2 and welding current σ_I^2 (indicate stability of the electrical parameter during the period of time), mean values of arc voltage μ_U and welding current μ_I (indicate deviations of the parameter from the pre-set value) and the mean duration of shortages t_{sc} (indicates the filler material transfer stability) [1]. The mean duration of shortages was calculated by the oscillogram of voltage.

To calculate the parameters mentioned the oscillograms were split into sections with duration 0.1 s (equal to the minimum duration of the disturbance which can cause a defect formation) [8]. The final matrix for every experiment contained 5 variables, its dimensions were $R\times5$, where $R = T/1000$ (for sampling frequency 10 kHz) — number of blocks, T — overall number of values recorded.

For *underwater FCAW* the data matrix was obtained using the algorithm similar to the one developed for MAG welding. The matrix included mean values and standard deviations of arc voltage and welding current as well as the density of shortages for each section (the oscillogram of voltage was used to calculate it). The final matrix dimensions were $R\times5$, where $R = T/1000$.

Choice of different parameters of shortages for MAG welding and underwater FCAW was based on described above features of filler metal transfer. As far as during underwater FCAW mostly the globular metal transfer with occasional shortages occurs, it should be analyzed by the density of shortages D_{sc}.

In case of *the FBW* the high-frequency component of the voltage was obtained by means of application of digital Butterworth filter with pulsed final characteristic and frequency band 100 Hz and higher. To simplify the automated data analysis the signal was afterwards turned into unidirectional form and integrated by sections equal to 0.2 s (10 periods of mains frequency) being the minimum disturbance duration which can cause a defect formation [6]. All data arrays were reduced to the same dimension, the last element in each array being the first signal value after the current was turned off. The final array dimension was 80×1.

To prevent the effect of variations of the preset welding parameters and of stochastic measurement errors on the results of data analysis the normalization procedure was applied. The calculations were performed according to the following equation:

$$b(i) = \frac{a(i) - a_{\min}}{a_{\max} - a_{\min}}, \quad (1)$$

where $a(i)$ – initial value, the one to be normalized; $a_{\max}, a_{\min}$ – respectively maximum and minimum values in the data array; $b(i)$ – normalized value.

As a result matrices were obtained for every welding method with the minimum value equal to 0 and maximum equal to 1 in each of them.

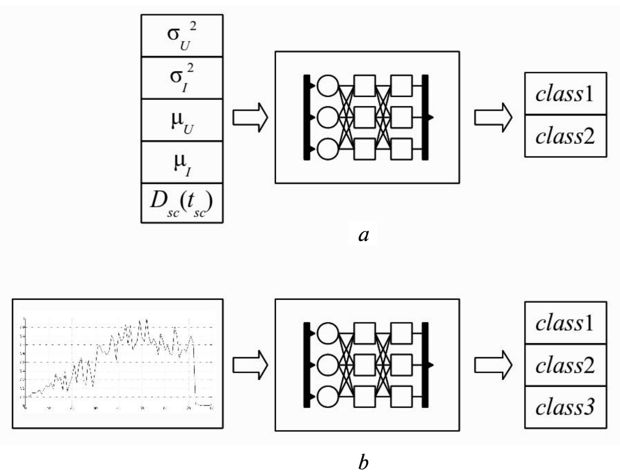

Fig. 5. Application of neural networks for MAG and underwater FCAW (*a*), for FBW (*b*)

The data obtained were used as neural network inputs. For the arc welding methods the task was to analyze each section of the oscillogram equivalent to 0.1 s by the values of 5 parameters (the blocks with their dimension 1×5 were presented one by one to the input). As a result of analysis these blocks were classified as those with or without disturbances (see Fig. 5, *a*). For FBW the whole data array was presented to the network input. The data were classified as those without disturbances, those with reduced voltage (this class included extension of the adjustment length) and those with reduces speed (see Fig. 5, *b*).

Neural network training. The number of neurons in the output (linear) layer of the LVQ network is equal to number of data classes. For arc welding methods this number was 2, for FBW – 3. The number of neurons in the input (competitive) layer should exceed their number in the output layer at least twice. In the empiric way it was defined to be 10 for all the methods.

The value of error limit for the training was set at 1 %. To prevent the reverse error propagation the algorithm with inertance of weight coefficients' adjustment and shifting was applied as well as that of training speed coefficient adapting. The number of training cycles was set at 1000.

The data were presented to the network input. The data vector for training included ten data matrices of informative signals per every experiment. The target vector for arc welding methods was developed to identify the disturbance presence, for the FBW it included data about the welding parameters: without disturbances or with variation of the defined parameter.

The quality of network training was performed by the effectiveness factor [9]. After the network training the elements used for it were presented to the network input and the number of right responds was calculated.

For arc welding methods the number of right answers was equal to number of oscillogram sections for which the presence of disturbance was identified in a right way, for FBW – to the number of informative signals classified in a right way. The precision of training sequence analysis was calculated as:

$$T_{\mathrm{T}} = \frac{B}{R}, \quad (2)$$

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

For all the networks developed T_{T} was equal to 1 for every welding method.

Application of the developed networks for monitoring of welding processes

The effectiveness of the neural networks developed was performed by presenting to their inputs data matrices which were not used for training (the control sequence). For the welds obtained during the experiments included to the control sequence some additional tests were done to evaluate their quality characteristics. For arc welding methods the visual tests were applied while for FBW joints their tensile strength was determined with tensile test and the microstructure analysis was performed. The signals (for FBW) and the signal sections (for arc welding) were divided into classes by the process variations (see Fig. 6).

Effectiveness of the neural network application was calculated as [9]:

$$E = \frac{T_C}{T_T}, \qquad (3)$$

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

The neural networks developed successfully identified the defects which were formed as a result of disturbances (see Table). Effectiveness of networks' application was higher then 0.85. In FBW the variation if speed is determined error-free.

The previously defined relationships between disturbances and quality characteristics of the welded joints [1, 4, 6] as well as the results of quality control of the joints from the control sequence make it possible to apply the networks developed both for process monitoring and for prediction of presence of typical defects in the welded joints. Informative signals described in Item 3.1 of this paper appear to be qualitative characteristics of the corresponding welding processes.

Table. Results of application of neural networks

Group of specimens	Effectiveness of network application		
	MAG welding	Underwater wet FCAW	FBW
No deviations	0,92	0,92	0,96
Welding with parameter deviations	0,95	0,85	–
Reduced open circuit voltage	–	–	0,92
Reduced speed	–	–	1,0

The method described can be applied for all the welding methods involving heating of the filler material and/ or the base metal with the electric current. The general algorithm of the development of automated monitoring system based on the artificial intelligence appears to be as followed:

1. Analysis of the electrical parameters, of their dynamics and of relationship between them and processes of heating, input of filler materials to the welding zone and joint formation. The parameters to be measured and requirements to the data recording system are to be defined;
2. Development of preliminary data processing based on the process features (heating, input of filler materials to the welding zone and joint formation);
3. Development of the classification neural network, including generation of training sequence and network structure definition;
4. Generation of the control sequence based on the results of quality control of welded joints with up-to-date methods stated by the Standards;
5. Evaluation of the effectiveness of network application using the control sequence, conclusions about the possibility of application of the network developed in the conditions of welding production.

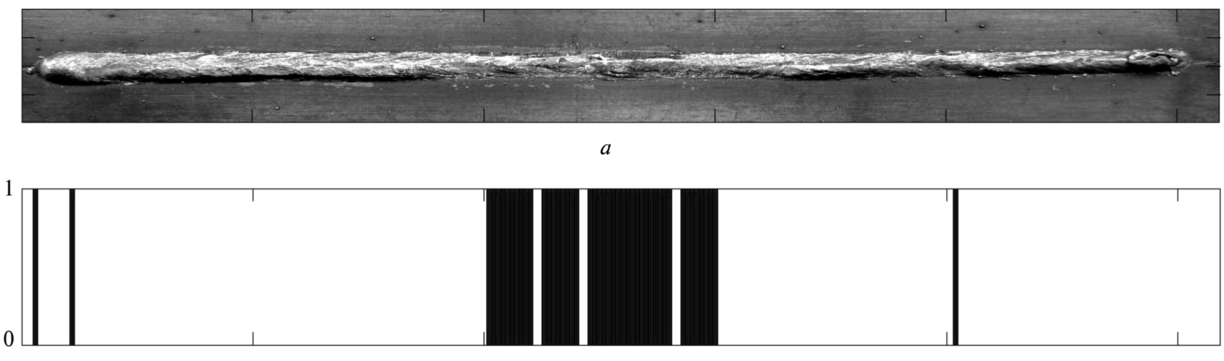

Fig. 6. Example of neural network application for MAG process monitoring (the specimen with variable gap): *a* — the welded joint; *b* — neural network respond

Conclusions

Monitoring of welding processes as well as prediction of formation of typical defects in the welded joints can be performed automatically by means of artificial intelligence systems, in particular the classification neural networks. The respond of the network is classification of the weld section or the whole joint as the one with its quality affected by the disturbances or not. The number of classes is to be defined for each process separately. The effectiveness of LVQ neural networks application appears to be sufficient for monitoring of MAG welding, underwater FCA welding and flash-butt welding.

The general algorithm of the development of automated monitoring system was developed for the welding processes involving heating of filler materials and base metal with the electric current. The development includes process parameters' analysis, development of the data collecting system, development of the neural network and check of the effectiveness of its application. Application of such method for MAG welding, underwater FCA welding and flash-butt welding has shown sufficient results.

It is reasonable to apply the welding monitoring systems developed in the way as described above in full-scale and mass production to perform 100 % quality control of the welded joints. If the deviations of the process are identified, the joints should be tested using standard methods of non-destructive testing.

Further research should be carried out to develop integrated guidance for formation of informative signals for different groups of welding methods.

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Рекомендована Радою
зварювального факультету
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Надійшла до редакції
9 січня 2014 року