NEURAL NETWORK BASED ESTIMATOR OF THE ELECTRODE DEVIATION IN ROBOTIC WELDING WITH ARC OSCILLATIONS

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Abstract

In automatic and robotic welding with arc oscillations, in order to adapt the trajectory of the welding torch to the real location of the joint of the parts, it is promising to estimate the position of the electrode relative to the welding line based on the current of the welding arc. The significant advantages of using estimators are the absence of additional equipment on the welding torch, as well as the combination of welding and measuring points. The paper proposes a new approach based on the use of an artificial neural network to solve the problem of estimating the position of the electrode relative to the seam line. The quality indicators of the estimation processes have been investigated using mathematical modelling.

Keywords

Neural network, estimator, electrode deviation, welding, arc oscillations, robot

1. Introduction

One of the main ways of developing automatic and robotic welding systems is the use of tools for adapting the trajectory of the welding torch [1]. The analysis of literary sources shows that today such means are most often visual sensors (VS) [2-4]. According to the signal of the VS, the trajectory of the welding torch is adapted to the real location of the joint of the parts [2, 3]. In [4], the possibility of using a VS to assess the quality of welds is considered. The prospects for using artificial intelligence methods in welding operations with visual sensors are highlighted in [5].

An alternative to VS are the so-called arc sensors of the position of the electrode relative to the connection line of the welded parts [6]. Such sensors are suitable for welding technologies with transverse oscillations of the arc. It is known that as a result of transverse oscillations of the arc, there are such positive effects as an increase in the width of the seam, a decrease in the penetration depth, and a decrease in overheating of the metal [7-8].

Arc sensors allow the $\hat{\varepsilon}$ estimate of the transverse deviation ε of the electrode tip from the weld line to be obtained not on the basis of direct measurements, but indirectly, on the basis of measurement of the welding arc current. Essential advantages of the arc sensors include the absence of any extra equipment on the welding torch and combining the welding points with the measurement ones.

Functional dependence of the welding current upon ε under steady conditions in welding fillet, T-overlap or butt joints with groove preparation is of a clearly defined extremal (unimodal) character, resulting from the V-shaped profile of surfaces of the parts joined. Minimum of this functional dependence always falls on the weld line between the parts joined. One of the most common approaches to finding extremum is based on activation of the system using probing oscillations and the method of synchronous detection [9]. Transverse oscillations of the welding torch can be used as the probing oscillations for the case of arc welding. With such oscillations the synchronous detector receives a signal proportional to amplitude of the 1st harmonic of the welding current to obtain the $\hat{\varepsilon}$ estimate [6].

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However, having such an important advantage as the high frequency selectivity under conditions of substantial interference, the method of synchronous detection is not free from certain drawbacks. The latter include the need to adjust the initial phase of the harmonic signal coming to a multiplication link of the synchronous detector, depending upon the phase delay of the 1st harmonic of the welding current in an inertia control object of the extremal system, which (delay) can vary with the unstable parameters of the object. In addition, determination of the amplitude of only the 1st harmonic of the welding current gives no way of obtaining the $\hat{\varepsilon}$ estimate, which is insensitive to variations in the welding process parameters. To do this, it is necessary to determine also the amplitude of the 2nd harmonic of signal [6].

The purpose of this article is to consider a new approach, based on using the artificial neural network (NN), to solving the problem of estimation of the position of the electrode relative to the connection line of the welded parts in welding with arc oscillations.

2. Method for estimation of the electrode deviations

Fig. 1 schematically shows the system of welding with arc oscillations. The welding current source WCS is connected to parts welded and the welding torch. Voltage is in the welding torch fed through a sliding contact to the welding wire which serves as the consumable electrode. During the welding process the torch is brought into oscillation in a direction across the weld line. That is, in the system of the X – Y coordinates with a centre on the weld line, where the Y axis is parallel to a longitudinal axis of the electrode extension and the X axis is normal to the weld line, the current position of the electrode tip is determined as follows:

$$x(t) = \varepsilon(t) + A \sin \omega t; \quad \omega = 2\pi f, \tag{1}$$

where A and f are the amplitude and frequency of the torch oscillations, respectively, and ε is the deviation of the middle position of the electrode from the joining line. The welding current signal i(t) from the current sensor CS is fed to a band filter BF which passes frequencies in a range from f to 2f. In this case the δ(t) signal of oscillations of the welding current at an outlet of BF will be determined as follows [6]:

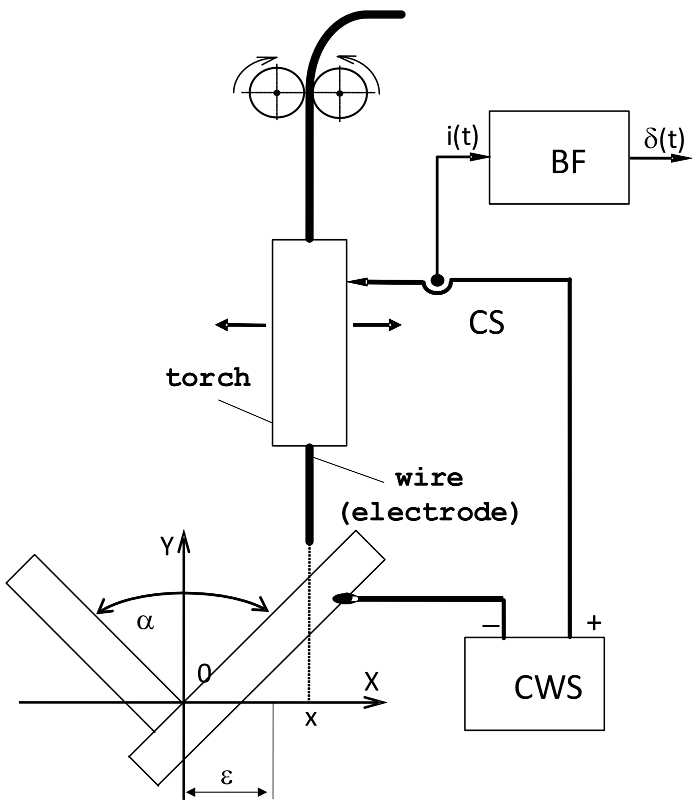


Figure 1: Schematic of the system for welding with arc oscillations

$$\delta(t) = A_1 \cos(\omega t - \beta - \phi_1) + A_2 \sin(2\omega t - \gamma - \phi_2), \tag{2}$$

where A_1 and A_2 are the amplitudes of the 1st and 2nd harmonics of the $\delta(t)$ signal, respectively; β and γ are the phase shifts of these harmonics due to dynamics of the welding circuit; ϕ_1 and ϕ_2 are the phase delays of the above harmonics in the filter. Values in (2) are found from the following formulae:

$$A_1 = \frac{AKE\ th(\mu\varepsilon)}{R_w\sqrt{1+(\omega T_w)^{-2}}}; \tag{3}$$

$$A_2 = \frac{A^2 KE\mu}{4R_w ch^2(\mu\varepsilon)\sqrt{1+(2\omega T_w)^{-2}}}; \tag{4}$$

$$\beta = arctg(\omega T_w); \quad \gamma = arctg(2\omega T_w), \tag{5}$$

where M is the slope of electrode melting rate characteristic depending upon the welding current; E is the intensity of the electric field in the arc column; R_w is the welding circuit resistance; $T_w=R_w/EM$ is the time constant of the welding circuit; $K = tg\left(\frac{\pi-\alpha}{2}\right)$; $\mu = d_e{}^{-1}\sqrt{K\pi v_w/v_e}$, where d_e is the electrode diameter, v_w is the welding speed and v_e is the electrode feed speed. It should be noted here that relationships (1) through (5) are valid on condition of confirmation of a hypothesis of the $\delta(t)$ signal being quasi-stationary, i. e. having rather small variations for a period of oscillations of the torch.

As it can be seen from expression (3), upon determining amplitude A_1 of the 1st harmonic of the $\delta(t)$ signal, we can find the $\hat{\varepsilon}$ estimate of the transverse deviation ε of the electrode tip from the weld line. This was a traditional approach to determination of $\hat{\varepsilon}$, based on the use of the method of synchronous detection to find A_1 [9]. The synchronous detector is a device for current averaging the $\delta(t) \times \sin(\omega t + \phi_D)$ signal, for a period of probing oscillations of where ϕ_D is the adjusted initial phase determined as $\phi_D = \frac{\pi}{2} - \beta - \phi_1$. However, during the welding process there is a probability of variations in some parameters of the welding circuit, such as R_w, M and E. To obtain the $\hat{\varepsilon}$ estimate, which would be insensitive to variations in these parameters, it is necessary also to determine the amplitude of the 2nd harmonic of $\delta(t)$ [6]. Upon meeting the $T<T_w$ condition, where $T=1/f$ is the period of the torch oscillations, by dividing (3) by (4) we will obtain an expression for determination of this estimate:

$$\hat{\varepsilon} = \frac{1}{2\mu} ash\left(\frac{\mu A}{2} \times \frac{A_1}{A_2}\right). \tag{6}$$

As is seen, here there are no parameters depending upon variations in the welding process conditions. Therefore, we will take expression (6), which allows determination of the $\hat{\varepsilon}$ estimate of the electrode deviation from the weld line, which is robust to variations in the welding circuit parameters, as the basis for the development of the NN-based estimation device.

3. The use of NN for estimation of the electrode deviations

In building the device for estimation of the lateral electrode deviation, the task was to obtain current values of the estimate every half-period of the torch oscillation, i. e. determine $\hat{\varepsilon}$ with a period of $T_0=T/2$. Fig. 2 shows a block diagram of the NN-based estimator for ε. The diagram comprises two pulse elements with a closing period of T_0 and T_1.

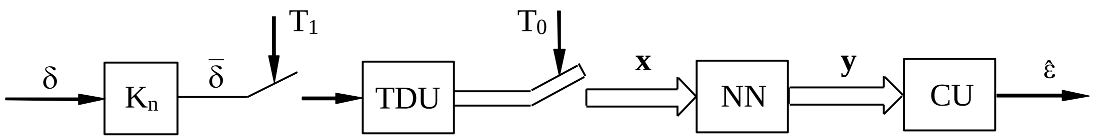


Figure 2: Block-diagram of the electrode deviation estimator

Operation of these elements is synchronized between each other and $T_1=T_0/N$, where N is an integer. The welding current oscillation signal $\delta(t)$ comes to the estimator input. Upon passing a link with the rate-fixing coefficient K_n, this signal becomes such that $|\bar{\delta}(t)| \leq 1$. The rate-fixed signal $\bar{\delta}(t)$ is sampled in time with a period of T_1 and comes to the time delay unit TDU. The N-dimensional vector $\boldsymbol{x}$, the components of which are N of the last values of the sampled signal $\bar{\delta}(nT_1)$, $n = 0,1,2,\ldots$, is formed in the TDU. Vector $\boldsymbol{x}$ sampled with a period of T_0 comes to the input of NN, where the two-dimensional vector $\boldsymbol{y}$ is determined, whose components are values of the amplitudes of the 1st and 2nd harmonics of the $\bar{\delta}$ signal. The $\hat{\varepsilon}$ estimate of the electrode deviation from the weld line is determined in the deviation computation unit CU according to (6). Therefore, according to the described principle of operation of the estimator, it can be seen that the signal at its output will be determined discretely by the T_0 sampling period and the certain time delay.

Fig. 3 shows architecture of the neural network employed, where black circles designate the inputs of NN and white circles designate the neurons proper. This NN is a feedforward network, comprising inputs of NN and two layers of neurons, i. e. hidden and output, which we designate by indices i, j, m, respectively.

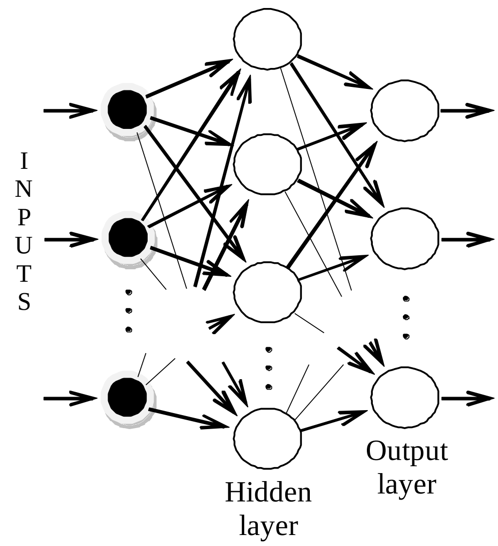


Figure 3: Architecture of the neural network

Each input of NN is connected to the input of each neuron in the hidden layer via coupling with a weight factor w_{ij}. In turn, the output of each neuron in the hidden layer is connected to the input of each neuron of the hidden layer via coupling with a weight factor w_{jm}. The h_j signal at the output of the j-th neuron in the hidden layer is determined as:

$$h_j = f\left(\sum_i x_i w_{ij} + b_j\right), \tag{7}$$

where x_i is the i-th input of NN, b_j is the bias of the j-th neuron in the hidden layer (in Fig. 3 the neuron biases are not shown) and $f(\cdot)$ is the activation function of the type of a hyperbolic tangent:

$$f(\lambda) = \frac{1 - e^{-2\lambda}}{1 + e^{-2\lambda}}. \tag{8}$$

Output of the m-th neuron in the output layer y_m is the weighted sum of the input signals h_j and the biases b_m

$$y_m = \sum_j h_j w_{jm} + b_m \tag{9}$$

The feedforward NN, having only one hidden layer with a certain number of neurons contained in it, is known to be capable of approximating a wide range of continuous non-linear functions at a preset accuracy. In this case the minimum required number of neurons in the hidden layer is determined heuristically, based on the tolerated approximation error.

The purpose of teaching (training) the multi-layer feedforward network consists in finding weight factors of couplings and neuron biases. The method of error backpropagation is employed most frequently to train this type of NN. This method belongs to the supervision type of the teaching methods. The main point of this method is that an error arising during training, which presents a difference between the actual and preset values of the network output, is re-distributed by varying the coefficient of coupling between the network layers in a direction from the output to input of NN to minimize the total network error. An improvement in the backpropagation algorithm is described [10]. This improvement made it possible to substantially increase the rate of teaching the networks. So, it is this Levenberg-Marquardt modification that we use in our work.

To train the network, we formed arrays of 500 values of its output vector $\boldsymbol{x}$ and the preset output vector $\mathbf{y}$. Dimensionality of the input vector was assumed to be equal to dim $(\boldsymbol{x})$=N=20. Arrays of the vectors $\boldsymbol{x}(k) = [x_1(k), x_2(k), \ldots, x_{20}(k)]^T$; $\boldsymbol{y}(k) = [y_1(k), y_2(k)]^T$, $k = \overline{1{,}500}$ were determined as:

$$x_i(k) = y_1(k)\cos\left(\frac{\pi(i-1)}{N} - \beta - \phi_1 + \Delta\beta(k)\right) + y_2(k)\sin\left(\frac{2\pi(i-1)}{N} - \gamma - \phi_2 + \Delta\gamma(k)\right), \quad i = \overline{1{,}20} \tag{10}$$

where y_1, y_2, $\Delta\beta$ and $\Delta\gamma$ are the random, uniformly distributed values within their variation ranges. In the hidden layer of NN were selected 13 neurons and this network was being trained for 1200 epochs.

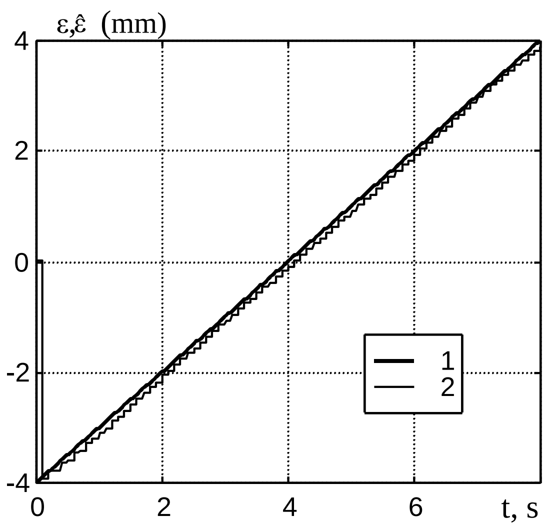
4. Results of modelling

The computation experiments involving a mathematical model of the system were conducted to determine qualitative indicators of the processes of estimation of the electrode position with respect to the weld line. The following parameters of the welding process were selected for modelling:

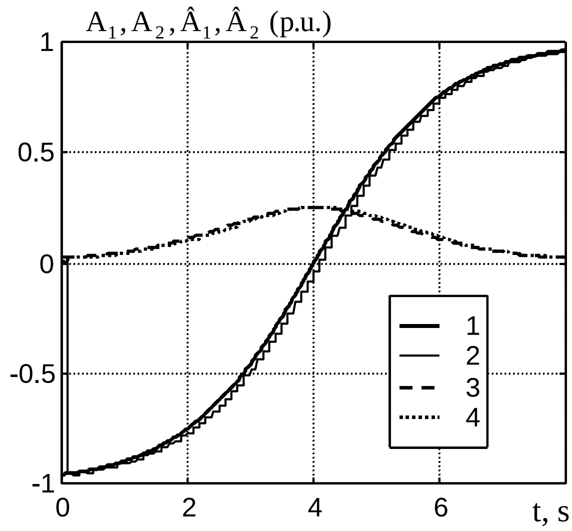
M=0.35 mm/A·s; E=2 V/mm; R_w=0.2 Ohm; d_e=1.2 mm; v_e=45 mm/s; v_w=5 mm/s; K=1; A=2 mm; f=5Hz.

Phase shifts of the welding current oscillation signal due to BF were assumed to be ϕ_1=-0.8 rad and ϕ_2=1.6 rad. During the modelling process the δ(t) signal was found using expressions (1) through (5). In the model of the estimator the time delay caused by NN computer emulation and performance of mathematical operations was ignored.

The first computation experiment simulated the next practical situation. During welding with arc oscillations, the torch moves along the weld so that the path of its middle position ε(t) is a straight line, but the angle between ε(t) and the weld line is equal to 0.2 rad. At the time t=0, where ε(t)=-4 mm, the δ(t) signal is fed to the input of the estimator. Processes occurring in this case are shown in Fig. 4,a, where are depicted the ε(t) (curve 1) and $\hat{\varepsilon}(t)$ (curve 2) signals. It can be seen from this figure that after the first period T_0, where the adequate input vector $\boldsymbol{x}$ of the network is just being formed, the $\hat{\varepsilon}(t)$



a



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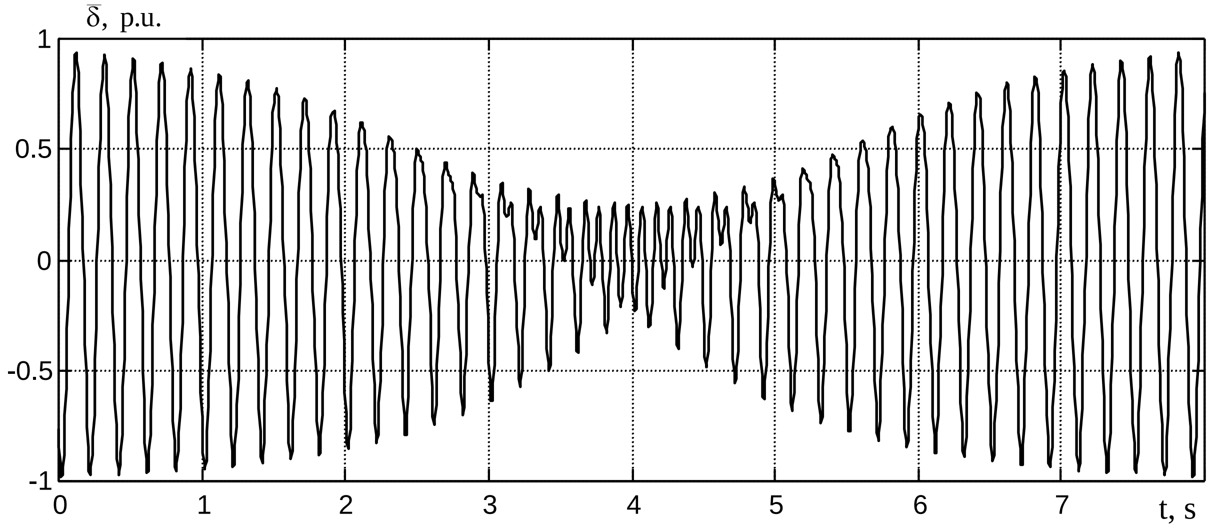

c

Figure 4: Processes occurring in the estimator at linearly varying ε: a – estimation of ε; b – amplitudes of harmonics of the current and their estimates; c – signal $\bar{\delta}(t)$

signal at the output of the estimator with a small-time delay almost copies the ε(t) signal within its variation range.

Fig. 4,b shows actual values of amplitudes (in per unit – p. u.) of the 1st (curve 1) and 2nd (curve 3) harmonics of the $\bar{\delta}$ signal and the corresponding estimates of amplitudes of these harmonics (curves 2 and 4), while Fig. 4,c shows the $\bar{\delta}(t)$ signal. It can be seen from these Figures that NN is characterized by a rather high accuracy of functioning.

The next experiment was in modelling, similar to that in the first experiment, of the process of estimation at $\varepsilon(t)=3\sin(\pi t)$. Fig. 5 shows the ε signal (curve 1) and the $\hat{\varepsilon}$ estimate (curve 2).

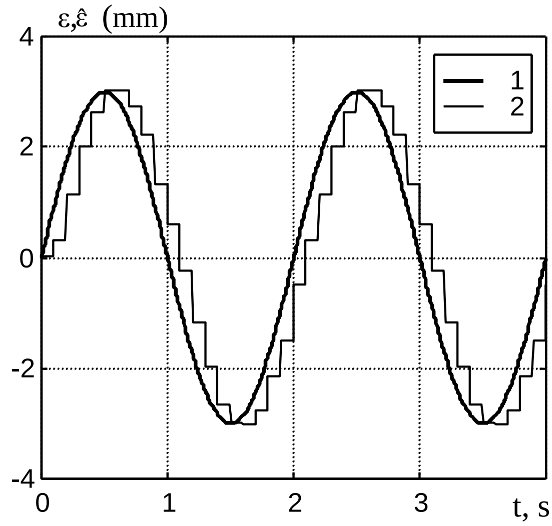

Figure 5: Estimation of harmonic varying in ε

The latter experiment consisted in investigation of the process of estimation of the electrode deviation at ε varying following the exponential law. Approximately the same character of variation in ε will persist in the weld tracking system closed by the $\hat{\varepsilon}$ signal, providing that the controller of this system is synthesized to ensure the well-damped transient processes. Fig. 6 shows the ε signal with an amplitude of 2 mm (curve 1), varying following the exponential law, and the estimate of this signal (curve 2).

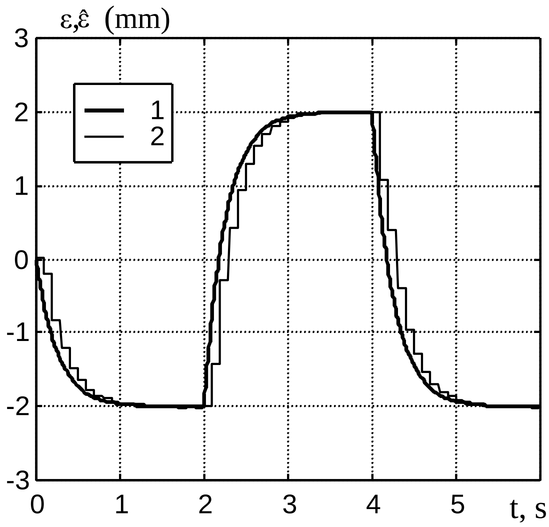

Figure 6: Estimation of exponential varying in ε

Analyzing the modelling results shown in Fig. 4-6, one can note that the estimator thus built provides a high accuracy of estimation of the electrode deviation from the weld line, with a variation in the deviation following different functional dependencies and within different ranges.
There is another important advantage of using NN for estimation of ε. Under certain conditions of the welding process, such as those involving short circuiting of the arc gap, some noise ξ(t) may be present at the output of BF. In this case, if we use the model of such a noise in preparation of the network teaching data arrays, we can train NN so that it becomes adapted to the effect of this noise.

5. Conclusions

In robotic welding with arc oscillations, in order to adapt the trajectory of the welding torch to the actual location of the connection of parts, it is promising to use arc sensors that estimate the position of the electrode relative to the welding line based on the current of the welding arc.

A new approach based on the use of an artificial neural network is proposed to solve the problem of estimating the position of the electrode relative to the seam line.

A two-layer feedforward neural network with a 20-13-2 type architecture was used to construct the electrode deviation estimator. Based on the welding current signal, the estimator evaluates the relative position of the electrode twice during the arc oscillation period.

Mathematical modelling shows that the estimation processes are characterized by a sufficiently high accuracy indicators.

6. References

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