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ALGORITHMS FOR SELECTING THE OPERATING MODE OF THE TECHNOLOGICAL PROCESS OF WAVEGUIDE PATHS INDUCTION BRAZING

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Key words: *neural networks, fuzzy controller, neuro-fuzzy controller, automated control system, induction brazing, waveguide paths, intellectual system*

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ALGORITHMS FOR SELECTING THE OPERATING MODE OF THE TECHNOLOGICAL PROCESS OF WAVEGUIDE PATHS INDUCTION BRAZING

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The article presents the development of a method for selecting the operating mode of the induction brazing process based on intelligent methods. The use of intelligent methods is due to the presence of uncertain conditions caused by the complexity of the initial setting of the technological parameters of the induction brazing process, the error of measuring instruments, and the human factor. The use of smart methods will make it possible to reduce the impact of negative factors, remove uncertainty, and adequately perform the initial set of technological parameters for the induction brazing process. Artificial neural networks, the fuzzy controller and the neural fuzzy controller have been chosen as the smart methods in this work. The article gives a brief overview of the above methods, provides a rationale for the choice of intelligent methods, and also compares their effectiveness. Based on the results of the experimental efficiency check, the most suitable method for determining the choice of induction brazing process operation is proposed.

Key words: neural networks, fuzzy controller, neuro-fuzzy controller, automated control system, induction brazing, waveguide paths, intellectual system

INTRODUCTION

One of the most important technological operations in the production of almost any product is the creation of permanent connections. There are many technologies to form permanent connections. The main reason for choosing induction brazing as a permanent connection method is the possibility of creating high heating intensity in a certain area of the product at high speed. The induction brazing method makes it possible to create high-quality connections for parts and is quite easy to automate. An important advantage is the ease of maintenance of equipment to automate this technological process. [1]

Thanks to the above advantages, induction brazing has found wide application in various areas of mechanical industry [2-5]. The induction heating technology is actively used in the manufacture of MEMS devices [6]. Induction brazing has been successfully introduced in the production of superconducting tapes [7] aluminum pipes and high-pressure pipes [8]. In the production of electronic devices and solar cell components, methods based on induction brazing have also been used quite successfully [9-11]. In the aerospace industry induction brazing technology is used to produce waveguide paths [12].

A significant problem in the automation of the induction heating technology is the inaccuracy of measuring instruments, which is caused by the features of pyrometers [13]. Intelligent methods make it possible to remove uncertainties [14]. You can also improve the quality of induction soldering process control by using intelligent methods [15]. Intelligent methods have also been used for decision-making in various fields [16-20], where they have also shown quite good results.

Another significant problem in the automation of the induction brazing process is the very high complexity of correctly setting process parameters at the initial stage.

The presence of errors in the measuring instruments and the difficulty of correctly initializing the induction brazing process create conditions for uncertainty when automating the control of this technological process. Intelligent

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methods are perfectly suited to solving problems under conditions of uncertainty. As part of this work, it is assumed that intelligent methods will be used to solve the problem.

OBJECT OF STUDY

The object of study is the process of induction brazing of spacecraft's waveguide paths. To implement such a technological process an automated hardware-software complex is used, the development of which is presented in [12]. The key elements of brazing installation are:

- induction heating source;
- matching device;
- a set of inductors of various sections and sizes;
- non-contact temperature measurement sensors - pyrometers;
- manipulator-positioner.

As a control device, a compact solution is used - an industrial noise-immune computer IPPC-9171G-07BTO. The PCI-1710 interface board is used to exchange data between induction brazing devices. In addition, the industrial computer has a number of RS-232 connectors for additional devices.

The visual view and structure of the automated induction brazing installation is shown in Figure 1.

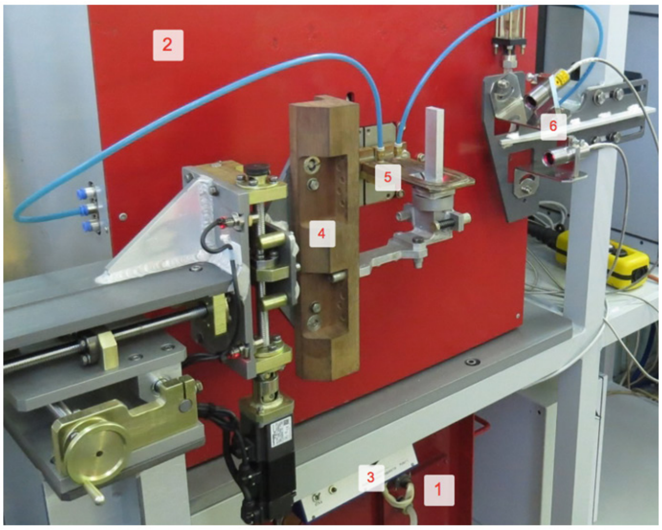

Figure 1: Brazing installation: 1 – induction heating source; 2 – matching device; 3 – the block of post brazing of waveguides management; 4 – servo; 5 – inductor; 6 – pyrometers

MATERIALS AND METHODS

As part of this study, the objective is to intelligently determine the operating mode of the induction brazing process. From a formal point of view, such a task corresponds most closely to the classification task, in which it is necessary to select values for one or several classes (single or multi-criteria task) according to a set of specific descriptive characteristics (criteria).

Strict mathematical formulation of the problem in this case will look as follows.

Let the following sets be available: A_{heat}-a set of algorithms for controlling the heating of a workpiece (PID regulator variations), A_{move}-multiple workpiece motion control methods, and K_p, K_d, K_i-control parameters; T_{st}-many values of process stabilization temperature, Vheat-many values of assembly heating rate, E_{pyr1}, E_{pyr2}-many values of emissivity coefficients for pyrometers, P_{heat}-many values of induction heating source power. There is a dependency : $f\ T_{st}, V_{heat}, E_{pyr1}, E_{pyr2}, P_{heat} \rightarrow A_{heat}, A_{move}, K_p, K_d, K_i$, the value of which is known only in the training sample. A mapping algorithm capable of classifying an arbitrary object from the sets T_{st}, V_{heat}, E_{pyr1}, E_{pyr2}, P_{heat} should be developed.

There are many intelligent methods for solving a problem such as the classification task. The most common of these methods are considered in this work. In this case, we consider artificial neural networks, fuzzy regulator, and neural fuzzy regulator.

The article [21] solves a rather similar problem. The difference in this paper is that another set of sets has been chosen as the descriptive characteristics of the classification object. With this formulation, the process control method made it possible to significantly reduce the errors of measuring instruments in the process control of induction brazing. This, in turn, improved the quality of the brazing products. This work is a development of the ideas presented in the above work. The studies presented in [12] show that the most significant factor influencing the quality of induction brazing process control is the initial setting of process parameters for the induction brazing process. The method of making technological decisions presented in this paper focuses primarily on the initial setting of the induction brazing process, which is due to the choice of new input parameters different from those used in the work [21]. The combined use of the methods proposed in this paper and in paper [21] will make it possible to cover most variations in the induction brazing process, which will significantly improve the quality of induction brazing process management.

Fuzzy logic

One intelligent method for solving the classification task is a fuzzy controller. The fuzzy controller is based on the mathematical apparatus of fuzzy sets. Within this task, an example of a fuzzy set and a fuzzy variable can be a fuzzy set of values for the assembly heating rate. In terms of fuzzy logic, this speed can be significantly low, low, slightly low, medium, slightly high, and very high.

Operating with fuzzy sets is intuitive. The fuzzy conclusion itself is based on fuzzy rules. Fuzzy rules are very easily drafted by a subject matter expert. In such a situation, the empirical experience of experts is connected to the solution of the task, which significantly improves the quality of the process, reducing the impact of incomplete process data and involving expert experience to determine the optimal operating mode of the induction soldering process. [22]

In this article, a logical conclusion is drawn using the Mamdani algorithm. The visualization of the general solution method based on the fuzzy regulator is shown in Figure 2.

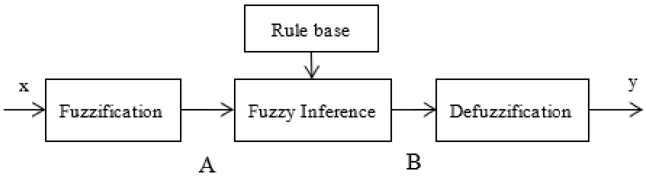

Figure 2: Solution method based on a fuzzy controller, where: x - input values, A - input fuzzy sets, y - output values, B - output fuzzy sets

Artificial neural networks

The mathematical apparatus of artificial neural networks offer a completely different approach to the classification problem. An artificial neural network is a set of interrelated elements-artificial neurons. Each neuron is essentially an adder with a given weighting factor [22]. Artificial neural networks have a key advantage; their quality can simply be constantly improved. Training of neural network model is essentially a task of the above weighting weights on artificial neuron bonds. The most common method of training artificial neural networks is reverse gradient descent, which will be used in this study. The method of teaching with the teacher is used in this study. In this case, this means that the input-output data pairs are submitted to teach artificial neural network. Once trained, the artificial neural network will be able to classify an object that was not part of the training data. This is the power of the artificial neural network. The disadvantage in this case is that the model is essentially a black box. The typical neural network model can be seen in Figure 3.

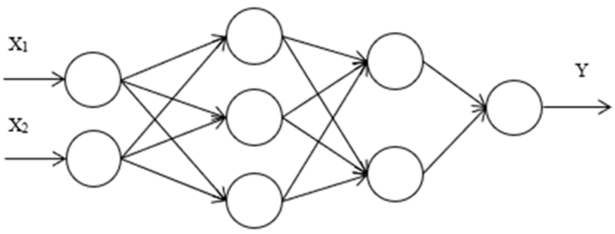

Figure 3: Typical structure of an artificial neural network, where: X_1, X_2 are the inputs of the neural network model Y is the output of the artificial neural network

Fuzzy neural network controller

The fuzzy neural network controller makes it possible to add the power of fuzzy logic to the computational power of artificial neural networks. If, as mentioned above, the artificial neural network is a black box, because knowledge of the patterns of operation of the system being simulated is distributed throughout the network in an opaque manner. According to the structure of the fuzzy neural network controller, data about the control object are distributed in a more transparent way. Figure 4 shows a typical structure of the ANFIS neuro-fuzzy controller.

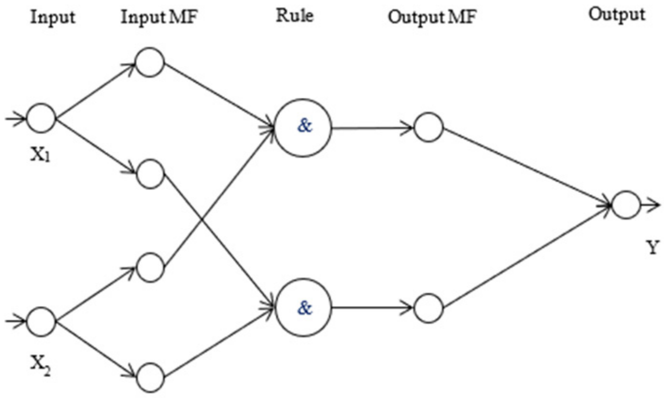

Figure 4: Typical structure of the neuro-fuzzy controller ANFIS, where X1, X2 are the inputs of the neuro-fuzzy controller, Y is the output of the neuro-fuzzy controller

EXPERIMENTAL RESEARCH

Fuzzy controller

To experimentally check the proposed method of solving the problem of determining the operating mode of the induction soldering process, the classification task has been adapted for each of the three intelligent classification methods. The input of the fuzzy regulator is fed with descriptive characteristics of the technological process in accordance with the definition of the classification task. In the course of the logical output, the fuzzy controller returns specific values that allow classification of the object according to the classification task definition.

The terms for the required fuzzy variables should be mentioned separately. In particular, the following terms correspond to the variable «stabilization temperature»:

- NULL - the value of the stabilization temperature of the process is small;
- LT, HT - moderately low/high stabilization temperature value;
- SLT, SHT - a significantly low/high stabilization temperature value.

The «product heating rate» variable corresponds to the following terms:

- NULL - the heating rate of the product is low;
- LR, HR - moderately low/high product heating rate;
- SLR, SHR - significantly low/high value of the product heating rate.

The «control algorithm» variable corresponds:

- PI-controller.
- PD-controller.
- PID-controller.

The structure of the fuzzy controller is shown in Figure 5.

Training data obtained using a mathematical model was used to test the effectiveness of the experiment [23]. Based on the results of numerical modeling, the conjugation tables (Table 1) on heating and movement of the workpiece were obtained.

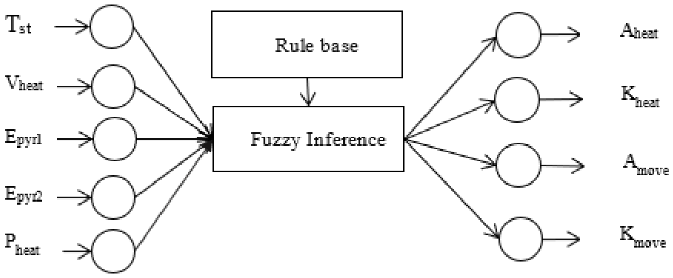

Figure 5: Fuzzy regulator to solve the problem, where: Tst - value of stabilization temperature, V_{heat} - value of heating speed of the node, E_{pyr1}, E_{pyr2} - value of emission coefficients of pyrometers, P_{heat} - value of power of induction heating source, A_{heat} - selected approach of heating control, K_{heat} - value of heating control algorithm, A_{move} - algorithm of product movement control, K_{move} - parameters of methods

Table 1: Modeling results

Predicted value	A_{heat}				A_{move}			
	Actual value				Actual value			
	PD	PI	PID	Total	PD	PI	PID	Total
P	156	14	12	182	168	4	5	177
PI	7	193	16	215	11	183	12	206
PID	15	37	150	203	11	13	193	217
Total	178	244	178	600	190	200	210	600

The results of model training are shown in Table 1. The recognition accuracy of the output variable «product heating control algorithm» is 83%.

For the output variables «assembly movement control algorithm» and the algorithm factors are 91% and 89% respectively. Based on the above, the overall method recognition accuracy based on the fuzzy controller was 88%.

Neuro-fuzzy controller

The input layer of the neuro-fuzzy regulator is fed with the descriptive characteristics of the technological process in accordance with the classification task. Target values are formed on the output layer of the neuro-fuzzy controller, allowing the classification of an object in accordance with the classification task.

The distribution of artificial neurons on the hidden layer of the fuzzy controller should be described separately.

The hidden layer of input fuzzy variables includes five artificial neurons corresponding to the fuzzy variables "heating temperature mismatch" and "heating rate mismatch". The thermal layer is implemented as two artificial neurons for the fuzzy variable "previous heating control algorithm" and three artificial neurons for the fuzzy variable "algorithm coefficients".

The logical rules layer contains five artificial neurons corresponding to the logical "I" ligaments. The fuzzy output layer contains five artificial neurons corresponding to all output variables according to the classification task.

The structure of the neural fuzzy model is shown in Figure 6.

The numerical modeling gave the results presented in Table 2. Table 2 includes connection tables for heating and moving the workpiece.

Table 2 clearly shows the results of the method training based on the neuro-fuzzy controller.

The recognition accuracy of the output variable «product heating control algorithm» is 96%.

For the output variables «assembly movement control algorithm» and the algorithm coefficients are 85% and 93% respectively.

Based on the above, the overall method recognition accuracy based on the fuzzy controller was 91%.

Table 2: Modeling results

Predicted value	A_{heat}				A_{move}			
	Actual value				Actual value			
	PD	PI	PID	Total	PD	PI	PID	Total
P	161	11	11	183	173	3	4	180
PI	5	198	14	217	9	186	10	205
PID	12	35	153	200	8	11	196	215
Total	178	244	178	600	190	200	210	600

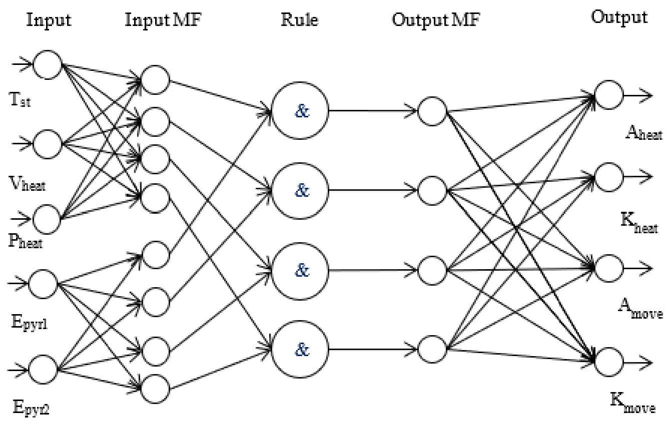

Figure 6: Neural fuzzy model to solve the problem, where: T_{st} is the value of stabilization temperature, V_{heat} is the value of heating rate of the assembly, E_{pyr1}, E_{pyr2} are the value of emission coefficients of the pyrometers, P_{heat} is the value of power of the induction heating source, A_{heat} is the product heating control algorithm, K_{heat} is heat control algorithm coefficients, A_{move} - product motion control algorithm, K_{move} - motion control algorithm coefficients

Artificial neural network

The input layer of the artificial neural network is fed with descriptive characteristics of the technological process in accordance with the classification task. Target values are formed on the output layer of the artificial neural network, which allows classifying the object according to the classification task definition.

The distribution of artificial neurons in the hidden layers of the artificial neural network should be described separately.

The number and composition of hidden layers in the artificial neural network is determined empirically each time, as there is currently no universal algorithm for determining the optimal structure of the artificial neural network. For this reason, experimental research is carried out in each case to determine the optimal structure of the artificial neural network to solve a specific problem, in our case to determine the operating mode of the induction soldering process. Experimental studies have shown that the optimal structure is an artificial neural network with five hidden layers of five neurons on each hidden layer. This configuration provides an optimal solution to the problem with the available set of training data. At the same time, there is no over-training or insufficient training.

Figure 7 shows the structure of an artificial neural network to solve the task.

Table 3 clearly shows the results of the method training based on the neuro-fuzzy controller.

The recognition accuracy of the output variable «product heating control algorithm» is 95%.

For the output variables «assembly movement control algorithm» and the algorithm factors are 91% and 95% respectively.

Based on the above, the overall method recognition accuracy based on the fuzzy controller was 94%.

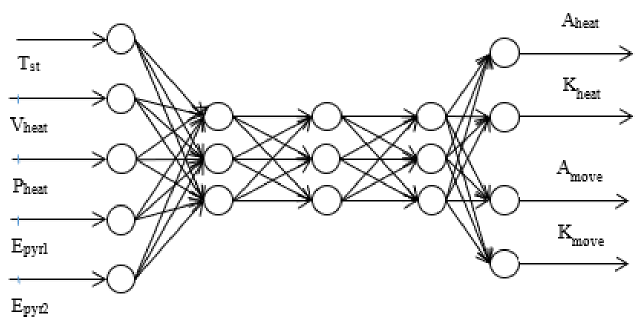

Figure 7: Neural network model to solve the problem, where: T_{st} is the stabilization temperature, V_{heat} is the heating rate of the assembly, E_{pyr1}, E_{pyr2} are the emission coefficients of the pyrometers, P_{heat} is the power of the induction heating source, A_{heat} is the product heating control algorithm, K_{heat} are the coefficients heat control algorithm,A_{move} - product motion control algorithm, K_{move} - motion control algorithm coefficients

Table 3: Modeling results

Predicted value	A_{heat}				A_{move}			
	Actual value				Actual value			
	PD	PI	PID	Total	PD	PI	PID	Total
P	167	8	8	183	177	1	3	181
PI	3	221	10	234	7	191	5	203
PID	8	15	160	183	6	8	202	216
Total	178	244	178	600	190	200	210	600

Comparison of the algorithms' efficiency

All 3 variants of implementation of the method for determining the operating mode of the induction soldering process on the basis of intelligent methods showed quite high results in terms of recognition quality.

A comparison of the efficiency of the proposed methods was carried out using numerical simulation. The results of the direct comparison of the efficiency of the proposed methods are summarized in Table 4.

A direct comparison of the results showed that the optimal solution is to use a neural network model. Also, this method provides the highest computational power for solving the problem. It should also be noted that the method based on an artificial neural network has higher flexibility. The method provides the possibility of continuous additional training to improve the accuracy of recognition. The composition of internal layers can be adjusted to the volume of training data. This is necessary to avoid situations in which the artificial neural network may be either overtrained or insufficiently trained, which harms the quality of recognition.

Table 4: Algorithm efficiency comparison table

Control algorithms	Input variable			
	A_{heat}	A_{move}	K	Total
Fuzzy controller	83	91	89	88
Neuro-fuzzy controller	85	96	93	91
Artificial neural network	91	95	95	94

APPROBATION OF THE PROPOSED APPROACH

The developed approach was experimentally tested in the framework of field experiments. For correct and complete verification of adequacy of the proposed methods, processes for different types of waveguide pipes were launched. Types of pipe sizes used were 22 x 11 mm, 19 x 9.5 mm, and 35 x 15 mm. Figures 8 to 10 show temperature graphs of the waveguide assembly elements for sizes 22 x 11 mm, 19 x 9.5 mm, and 35 x 15 mm, respectively.

The essence of the experimental test is to run a series of processes for each pipe size in the technological regimes defined by the developed methods. Based on the results of each series of experiments, qualitative soldered joints were obtained, which confirms the adequacy of the developed method.

Figure 8 shows a graph where the temperature difference between the assembly elements of the waveguide path is minimal. It can be clearly seen that there is no overregulation at the moment before flux melting and solder. When the assembly elements of the waveguide path reach the melting point, the technological process stabilizes at the stabilization temperature with the formation of a strong brazed joint.

Figure 9 shows the difference in graphs due to excessive heating of the pipe. Before reaching the stabilization stage, which means the formation of a reliable soldered connection.

Figure 10 presents a graph of an attenuating oscillating process that moves to a stable state where stabilization

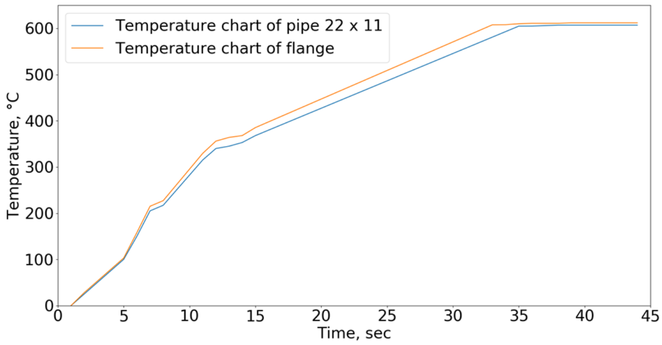

Figure 8: Diagram of the process of brazing pipe-flange 22 x 11 mm

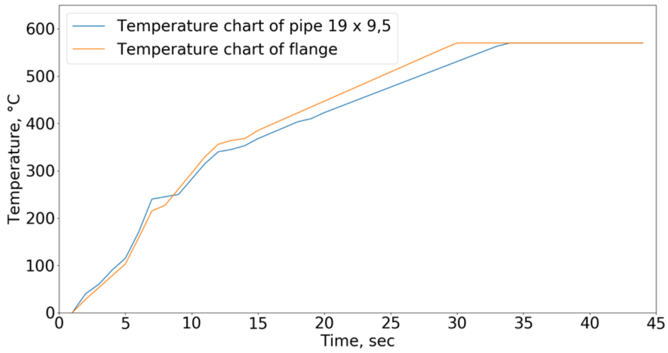

Figure 9: Diagram of the process of brazing pipe-flange 19 x 9.5 mm

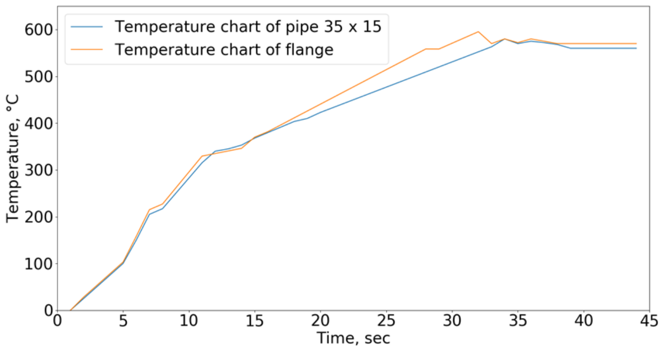

Figure 10: Diagram of the process of brazing pipe-flange 35 x 15 mm

is achieved after flux melting and solder, after which the process is completed.

The statistical significance of the results was checked using the Student's test. For a series of experiments with a standard size of 22 mm x 11 mm, the Student's t-criterion is 0.98. For a series of experiments with a standard size of 19 mm x 9.5 mm, the value of the Student's t-criterion is 0.96, and for a series of experiments with a standard size of 35 mm x 15 mm, the value of the Student's t-criterion is 0.97. The results show a fairly high statistical significance of the obtained results.

The results of experimental studies prove the applicability and effectiveness of the proposed approach to determining the operating mode of the induction soldering process, which ensures the creation of a quality solder joint in the production of waveguide paths of spacecraft.

CONCLUSION

This article demonstrates the development of a method for determining the operating mode of the induction soldering process for the waveguide paths of spacecraft. As part of the study, a review of the subject area was carried out, and a formal and mathematical formulation of the task in the form of a classification task was given. A review was made of the intellectual methods most suitable for solving the classification problem. An experimental comparison of the effectiveness of the proposed methods was made. Based on the results of experimental studies, it has been concluded that the most suitable method for determining the operating mode of the induction soldering process is the method based on artificial neural networks. The proposed method has been tested on real technological processes of soldering of waveguide paths of different sizes. The testing showed rather high efficiency of the developed method. The use of the proposed method will allow improving the quality of management of the technological process of induction soldering of waveguide paths, which in turn will improve the quality of the most produced products for the aerospace industry. Further research is expected to focus on studying the applicability of similar methods to other technological processes.

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