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Use of artificial neural networks to correct non-standard errors of measuring instruments when creating integral joints

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Abstract. The article presents an approach to solve the problem of non-standard errors correction in the process of creating permanent joints using high-temperature methods such as induction soldering, electron beam welding, diffusion welding. The use of such high-tech methods for creating integral joints causes the use of intelligent methods for correcting non-normative errors. Within the framework of this work, it is proposed to use artificial neural networks for correction of non-normative errors in the technological process of creating integral connections. The work includes the process of development, training and experimental verification of the non-normative errors correction method based on artificial neural networks.

1. Introduction

At present, in various fields of engineering there are methods to create permanent joints based on the heating of the elements to be connected. The most typical examples of such technological processes are induction soldering, electron beam welding, and also diffusion welding. For example, when connecting elements of waveguide paths of space vehicles, induction heating is used. When connecting the devices components of space vehicles, approaches based on the diffusion of materials (metals) under pressure and high temperature, as well as electron beam welding, are used. To monitor such technological processes in the construction of automated control systems, it is possible to use various means of measuring temperature, both contact and non-contact type. Contact means for measuring temperature have the following disadvantages:

- The need for cogging the measuring sensors on the connected elements, which leads to the need for additional technological operations to clean and level the surfaces.
- The presence of additional conductive materials in the soldering or welding zone can significantly change the course of the technological process of creating permanent joints.

The use of contactless temperature measuring devices avoids the above-described drawbacks, but the data obtained from such devices can have significant errors due to the physical features of both the temperature measuring process of proximity sensors and the process of forming permanent joints. The errors of such measuring devices can be caused by:

- Input of an incorrect value of the material emissivity of the elements being connected.
• Re-reflection by the measured object of the radiation of a closely located foreign object heated.
• The dependence of the measurement results on the distance to the measured object.
• Quality of consumables (flux, solder).
• Presence of impurities in the connected parts, causing smoke in the vacuum chamber.
• The human factor.

In [1 - 2], methods and approaches to the identification of non-normative errors for non-contact pyrometric sensors have been developed, which have shown their effectiveness in solving practical problems, but the problems of error correction are not considered at the moment. The problem of errors in the non-contact temperature measurement is a serious enough and widespread problem. The value of the connected parts emissivity has a significant influence on the quality of measurements.

In work [3], it is proposed to use multiwave pyrometry to solve the problem of the unknown or constantly changing emissivity of the joined products material. The work [4] presents an overview of temperature measurement errors in non-contact sensors in the control of the thermodynamic cycle of an aerodynamic engine. The authors of [5] presented a new method of non-contact temperature measurement, applied mainly to objects with low emissivity. The measurement results for these methods were determined with a deviation of less than 1% of the measurements using contact sensors (thermocouples). A method using a single-wave pyrometer for measuring the spectral-effective emission properties of alloys is described in [6]. The results of the study showed improvement in the quality of measurements for alloys MARM-247, MARM-509, CMSX-4, Inconel-718, N-155 and Rene-N6, coated with YSZ barrier coating. In [7], the use of artificial neural networks was proposed to calculate the exact value of the connected parts materials emissivity, which can improve the quality of temperature measurement by contactless pyrometric sensors. Oxidation of the connected parts surface can have a significant influence on the measurement of the joined parts emissivity. For example, in work [8] authors suggested the use of a neuro-fuzzy approach to temperature control.

Within the framework of our study, it is proposed to use artificial neural networks to correct the non-normative errors of non-contact pyrometric sensors in the process of creating permanent connections.

2. Materials and methods
Figure 1 shows the block diagram of the data analysis subsystem for managing the process of creating one-piece connections.

In the unit for identifying non-normative errors from the control object, the measured temperature values arrive. This unit is responsible for the identification and classification of non-normative errors arising in the process of managing the technological process of creating integral joints.

From the unit for identifying the non-normative errors of the measuring instruments, an error class and a running measured value enter the error correction block. This block is responsible for compensation and correction of non-normative errors arising in the process of managing the creating integral connections. In the control system of the creating integral connections process, the true temperature values arrive, on the basis of which a control action is applied to the control object.

To detect non-normative errors in the process of creating permanent joints on the basis of induction heating, a method of identification and classification has been developed. The mathematical formulation of the problem of identifying non-normative errors is closest to the classification problem. The mathematical formulation of the problem of classifying non-normative errors looks as follows.

Let X be the set of a description of the technological process of creating integral connections in the form of a time series and tuning parameters of pyrometric temperature sensors, and Y is a finite set of class labels. There is an unknown target dependence - a mapping whose values are known only at the objects of the final training sample. It is required to construct a mapping algorithm capable of classifying an arbitrary object from X.
One of the most powerful and effective methods for classification is artificial neural networks. To solve the problem of identifying non-normative errors, an artificial neural network was developed that showed the best accuracy of 95.02% during the experimental verification.

Figure 2 shows a typical temperature profile with an error caused by the influence of flux on the quality of pyrometric temperature sensors measurement.

Various methods can be used to correct non-normative errors: analytical methods, methods of control theory, statistical methods, intellectual methods.

The use of intelligent methods in this work is due to the presence of a large number of uncertainties in the control process caused by the non-standard errors in the measuring instruments. Correction of errors using intelligent methods will allow one to eliminate the arising uncertainties with the use of heuristics. The most suitable intellectual methods for correction of non-normative errors are fuzzy logic and artificial neural networks.
Fuzzy logic is based on the theory of fuzzy sets. With the help of the theory of fuzzy sets, one can formally define such inaccurate concepts as "high temperature", "young man", "average growth", etc. The intuitive simplicity and power of the fuzzy logic apparatus [9] make it possible to use it in various information management and analysis systems. In this case, fuzzy logic allows one to connect the power of human intuition and the operator's experience to the management process.

Neural networks can be considered as modern computer systems that transform information according to the image of processes occurring in the human brain. The information being processed is of a numerical nature, which makes it possible to use a neural network, for example, as an object model with completely unknown characteristics. [9]

The task of correcting the non-normative errors in measuring instruments is closest to the classification problem, for which artificial neural networks are ideally suited. To determine the optimal structure of the artificial neural network to correct the non-normative errors, and to approbate this correction method, it is necessary to conduct a series of experiments.

The typical structure of an artificial neural network for solving the problem of non-normative errors correction is:

1. The input layer of the neural network is given by:
   - Temperature of uncontrolled pyrometer.
   - Temperature of the controlled pyrometer.
   - Time of temperature values measurement.

2. Hidden layers of neurons, the optimal structure of which will be determined during the experiments.

3. The value of the correction is returned at the output of the neural network.

The arrangement of the pyrometers during the experiments is shown in Figure 3.

![Figure 3. Arrangement of pyrometric temperature sensors: 1 - waveguide pipe; 2 - flange of the waveguide path; 3 - inductor; 4 - pyrometer directed to the surface without flux; 5 - ray of the pyrometer directed to the surface without flux; 6 - pyrometer directed to the surface covered with flux; 7 - ray of a pyrometer directed to the surface covered with flux.](image)

Separately it is worth noting that at the inputs of the neural network, it is not advisable to supply directly the values of the measured temperatures themselves. To solve the problem of the measuring instruments non-normative errors correction, immersion in the lag space is performed, i.e. calculations are performed based on previous values of the measured parameters. [10 - 12]

In the framework of this task, immersion in the lag space is carried out for 60 measurements.
3. Experimental study
The training sample for obtaining the optimal structure of an artificial neural network and approbation of the optimal structure was obtained using contact temperature sensors. The training sample contains 1383 examples, of which 549 are test samples. A comparative analysis of the structures of an artificial neural network is presented in Table 1.

Table 1. Different artificial neural network structures recognition quality (%)

| Number of layers | Number of neuron on each layer | 1  | 2  | 3  | 4  | 5  | 6  |
|------------------|--------------------------------|----|----|----|----|----|----|
| 1                | 59.36                          | 61.97 | 63.85 | 72.96 | 83.22 | 67.46 |
| 2                | 61.56                          | 78.31 | 88.86 | 86.26 | 86.126 | 74.62 |
| 3                | 69.56                          | 81.56 | 81.71 | 82.65 | 85.76 | 85.76 |
| 4                | 79.90                          | 82.79 | 82.43 | 83.66 | 83.95 | 86.98 |

* The best neural network structure

Based on the experiments results, it can be concluded that the best quality of the measuring instruments of non-normative errors correction is achieved in the structure of an artificial neural network with two hidden layers of 3 neurons on each layer. The quality of correction for this structure was 88.86%.

The graph of the experimental verification of the method for correcting the non-normative errors is shown in Figure 4.

![Figure 4. Temperatures chart after correction of non-normative errors: blue graph - pipe covered with flux measured temperature, orange graph - clean pipe temperature, green graph - pipe covered with flux corrected temperature.](image)

As can be seen from the graph, the correction of the non-normative measurement errors associated with the flux meltdown was carried out with sufficient quality.
4. Conclusion
During the research, the choice of the optimal structure of the neural network, its training, as well as the experimental verification of the method of measuring instruments non-normative errors correction on the basis of artificial neural networks, were carried out. The quality of correction is 88.86%.

As a further development direction, it is proposed to implement other methods for correcting the non-normative errors of measuring instruments and comparing them with the realized method.

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References
[1] Milov A V, Tynchenko V S and Murygin A V 2018 Experimental verification of the flux effect on the process of aluminium waveguide paths induction soldering Int. Conf. on Ind. Eng., App. and Man. (ICIEAM 2108) in press
[2] Milov A V, Tynchenko V S and Petrenko V Y 2018 Algorithmic and software to identify errors in measuring equipment during the formation of permanent joints Int. Multi-Conf. on Ind. Eng. and Modern Tech. (FarEastCon 2018)
[3] Coates P B 1981 Multi-wavelength pyrometry Metrologia 17 103
[4] Kerr C and Ivey P 2002 An overview of the measurement errors associated with gas turbine aeroengine pyrometer systems Measurement science and technology 13 873
[5] Tank V and Dietl H 1990 Multispectral infrared pyrometer for temperature measurement with automatic correction of the influence of emissivity Infrared physics 30 331-342
[6] Alaruri S, Bianchini L and Brewington A 1998 Effective spectral emissivity measurements of superalloys and YSZ thermal barrier coating at high temperatures using a 1.6 μm single wavelength pyrometer Optics and lasers in engineering 30 77-91
[7] Chun-Ling Y, Jing-Min D and Yan H 2003 Optimum identifications of spectral emissivity and temperature for multi-wavelength pyrometry Chinese physics letters 20 1685
[8] Lai J H and Lin C T 1999 Application of neural fuzzy network to pyrometer correction and temperature control in rapid thermal processing IEEE Trans. on Fuzzy Sys. 7 160-175
[9] Rutkovskaya D, Pilinskiy M and Rutkovskiy L 2006 Neural networks, genetic algorithms and fuzzy systems (Moscow: Hotline-Telecom)
[10] Rafiq M Y, Bugmann G and Easterbrook D J 2001 Neural network design for engineering applications Computers & Structures 79 1541-1552
[11] Kavzoglu T 1999 Determining optimum structure for artificial neural networks 25th Ann. Tech. Conf. and Ex. of the Remote Sensing Soc. 675-682
[12] Murata N, Yoshizawa S and Amari S 1994 Network information criterion-determining the number of hidden units for an artificial neural network model IEEE Trans. on Neural Net. 5 865-872