Improving the Adaptive Neuro-Fuzzy Method to Intellectualize Multisensor Signals Processing

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Abstract— **This research paper presents an improved method and software implementation of intellectualization processing for multisensor signals by integrating the modified method of identifying individual conversion functions of multisensor and adaptive neuro-fuzzy inference system. The results of the training and data approximation of adaptive neuro-fuzzy inference system with noise amplitude of 2.5% in training vector for an advanced set of rebuilt points on the surface of the individual conversion function are obtained. The proposed algorithm provides high accuracy of training and approximation data and a low error of artificial neural network training.**

Keywords—multisensor; sensor; adaptive neuro-fuzzy inference system; individual conversion functions

I. INTRODUCTION

Multisensors (MS) have become widely used in such fields as chemistry, safety systems, environmental monitoring, etc. [1]. However, a MS has some significant drawbacks: the complexity of the output signal processing [2] and significant deviations of the conversion function (CF) from the nominal function [3].

To improve the accuracy, it is recommended to use the individual conversion function (ICF) of the MS that can be determined by verifying (testing) [4]. However, the use of the MS ICF requires additional costs.

One-parameter sensor requires 3 … 4 verification points at low tolerances of the ICF from the nominal static characteristics of the sensor (NSCS) (for example, resistance thermometer) and 5 … 7 verification points at high tolerances of the ICF of the NSCS (e. g. semiconductor and film sensors). Accordingly, a two-parameter film sensor should have $N^2 \approx 25 \ldots 49$ verification points for reliable ICF identification of both measured quantities. A three-parameter sensor, in this case, requires 125 ... 343 verification points. Thus, the use of ICF to improve the accuracy of MS requires a significant increase in the cost of their identification.

In such a situation the solution can consist in using the methods of artificial intelligence for the results processing of MS verification [5, 6] to split the measured values and to reduce the number of necessary verification points. To solve the mentioned task of the MS CF recognition (see Fig. 1) it is reasonable to use methods of artificial intelligence, in particular, the methods that are capable of generalizing.

As it was shown by the analysis, the neural network methods [7] demonstrate better results in comparison with other methods, due to their general properties and possibility of self-learning. However, they are quite complicated to be implemented on architectures with limited resources such as microcontrollers. Also, due to the use of random coefficients at the initial stage of the neural networks (NN) training, there is no required repeatability of the result. This requires more stable methods of NN training with improved resistance to random variables of measurement result and during the training of NN.

Therefore, the purpose of this research article is to develop and study the intellectualization method of MS data processing using adaptive neuro-fuzzy inference system.

II. AN IMPROVED METHOD FOR IDENTIFYING THE INDIVIDUAL CONVERSION FUNCTIONS OF MULTISENSORS

The proposed method [8] enables to significantly reduce the number of verification points for MS. However; it is suggested to improve this method by using a tool of adaptive neuro-fuzzy logic inference (Adaptive Neuro-Fuzzy Inference System – (ANFIS) [10]. ANFIS offered by R. Jang [11] implements the Takagi-Sugeno [12] fuzzy inference system as a five-layer neural network of direct signal propagation. This system combines the advantages of NN and instruments of fuzzy logic, it has a high approximating ability and allows formalizing and

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incorporating fuzzy information obtained from experts and presented in a linguistic form to the model.

The essence of the proposed method is that additional data about the nature of the MS ICF are used for approximation, and these data are retrieved from the verification results of the group of similar MS for a relatively large number of verification points, for example, 49 (see Fig. 1). According to their results, as well, as the results of verification procedure of the target MS for the reduced (minimal) number of verification points, a prediction of verification value for those points of target MS is performed, for which the verification has not carried out. For each verification point (target MS) that has not been verified a particular NN is used, which has been trained to predict the verification value at exactly this point based on the verification results of a group of the same type MS for a large number of points [9, 10]. To train this particular NN there are used only the verification points (from the group of similar MSs) belonging to a strictly defined set, concerning the verification point, the value of which is predicted.

The decrease in the number of verification points is about 80%, see Fig. 1, and instead of 49 points of ICF the real verification can be done only for 9 points.

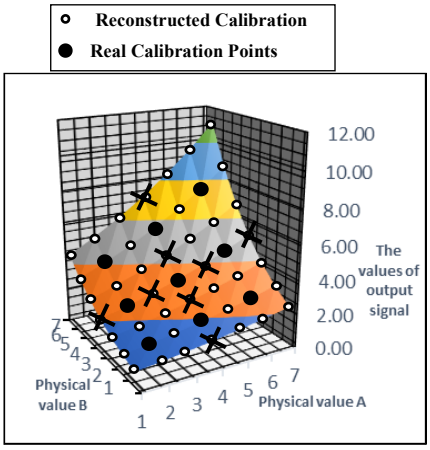

Fig. 1. ICF of the MS and placement of actual verification points and predicted points.

In the process of studying the method, the nominal CF of MS was described by the product of polynomials [13].

$$Y_{NOM} = (A \times (X_1 + B)^k + C \times (X_1 + B)) \times \\ \times (D \times (X_2 + E)^l + F \times (X_2 + E)) \times G, \quad (1)$$

where X_1, X_2 – measured physical quantities (PQ) A i B respectively; A…G, k, l – coefficients and degrees of power respectively; Y_{NOM} – MS nominal output signal.

Apparently, the additive and multiplicative errors of the MS can be corrected without using NN. So, it is necessary to conduct the influential study of the nonlinear component of the MS error on the result of correction using the proposed method. For this purpose, this nonlinear component can be described by polynomials of different degrees. Since the MS errors for different physical quantities can differ not only quantitatively but also qualitatively, the research should conduct various combinations of the model of errors described by the function of the form (2)

$$Y = Y_{NOM} \pm n\Delta\left(\pm K_1 (i-4)^a \pm K_2 (j-4)^b\right), \quad (2)$$

where n – number of study options, n = 100 (that is, 50 experiments for each polarity) is accepted; Δ – quantization step of MS error, 0,1% (that is, the maximum error of the MS for each physical quantity can be 5%) is accepted; K_1, K_2 – coefficients characterizing the nonlinearity of the MS error function, and equal to 1% (0.01); the exponents of a and b can take values of 2, 3, 4 and higher orders.

Also, the MS output signal is distorted by a random error, which is described by the function of the form

$$Y_{NOM} = Y + \xi, \quad (3)$$

where ξ – uniformly distributed on [0, K_3] random value.

The coefficient K_3 is chosen so that the random error does not exceed 2.5% of the MS nominal output signal.

III. Adaptive Neuro-Fuzzy System of the Intelligent Data Processing using Multisensors

To implement the method proposed in Section 2, three new procedures were introduced into the structure of the algorithm [9]: the procedure for forming the training and predictive vectors for ANFIS; ANFIS training procedure; the procedure of data predicting using ANFIS.

For ANFIS, the formation of training and predictive vectors consists of the following steps [14]: the main module UAITF (Fig. 2) of the program reads the data of the MS ICF, the percentage of random error is introduced to the training vector and writes the model of additive and multiplicative errors and their values (powers of polynomials and their signs) according to formula (2).

Then, the procedure of the training vector formation uses the following order: a) the points values of actual verification belonging to the direct line; b) the values of an entire direct line; c) the next value in the layer which is located next; d) the least similar value (the most unsimilar) and the last, the value that is being searched (the result, purpose of verification).

After reading the sorted data, the number of training epochs is read and the UTest module is invoked (see Fig. 2), which provides the interaction of the program graphical interface with Matlab programs. The above-mentioned read data are passed to the UTest module in the appropriate format.

The module also records the period of time from the beginning to the end of the training and passes these values to the UAITF module to display. Then the control is transferred to the CreateAndTrainANFIS module (Fig. 3), which generates FIS-structure and the rule bases and reads the training parameters and the initial values (Fig. 3).

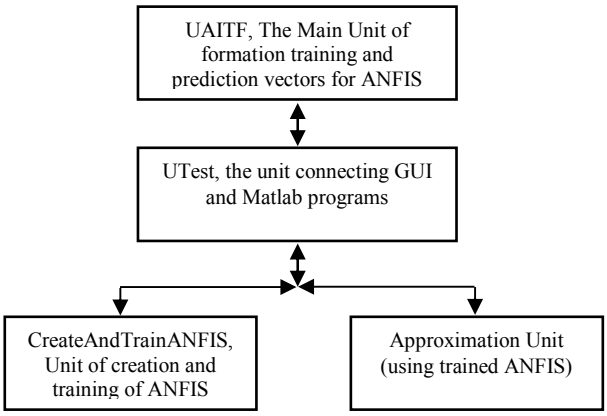

Fig. 2. Generalized structure of the modules.

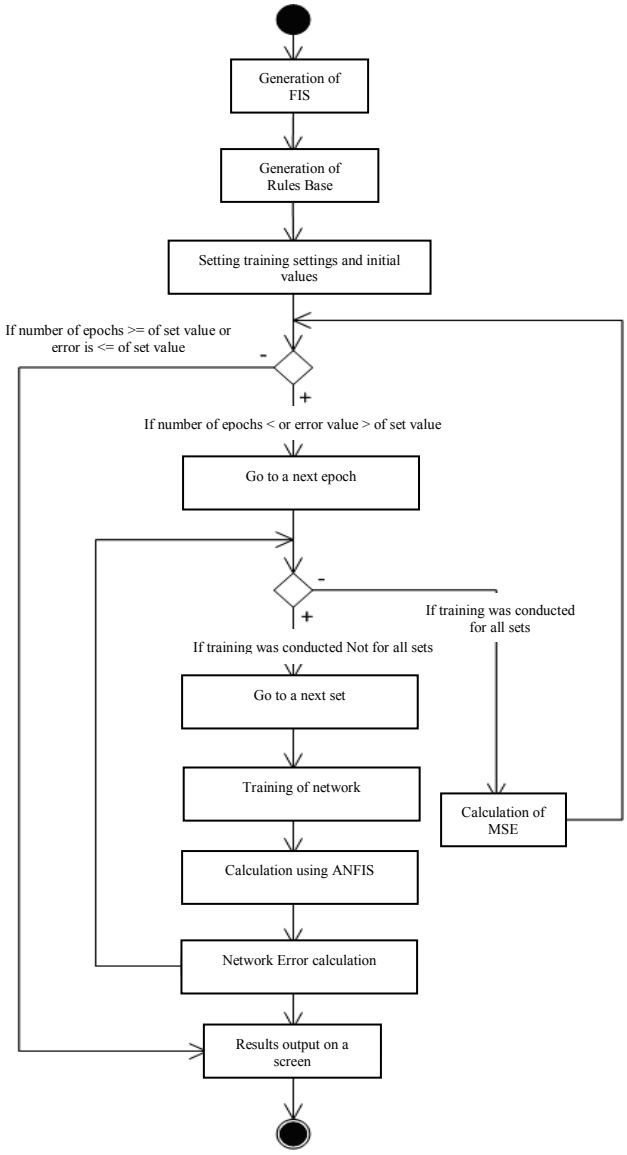

Fig. 3. Module states diagram CreateAndTrainANFIS.

At the next stage, the residual error is calculated. Then performed the following verification: if there are unconsidered rules that affect the result, then the nodes of the first layer are detected, which are the preconditions of the current rule; the derivative of the membership functions of the nodes of the first layer is calculated; the increment of the membership function parameters is calculated, and changing the membership function parameters of the first layer are performed. And if all the rules are considered, the exit from the procedure is executed.

The ANFIS training procedure is implemented by a set of the following steps. Firstly, the rules that affect the result (those that do not equal zero) are defined and the verification is performed, if there are unconsidered rules that affect the result then the increment of the membership function parameters is calculated. Secondly, the values of the membership function parameters are changed to the calculated value. At these two steps training of the nodes of the output layer actually occurs. And thirdly, if all the rules affecting the result are considered, the transition to the calculation of the output value of the network is performed.

After ANFIS training, data are predicted using the Approximation module (Fig. 2) with the following sequence of operations: a) the input vector for approximation, i.e., the aim of prediction (the last column) from UTest module is received. Next, from the saved file with the trained network the Fis-structure is downloaded using the “readfis function”, the Fuzzy Logic Toolbox toolkit and the Matlab package. Next, the approximation of the prediction goal is performed by processing the input vector by the trained network and the function of performing fuzzy output using the “evalfis command.”

Through the UTest module, the approximation result is transmitted to the UAITF main module for displaying and plotting the prediction goal graphs and the received result of the prediction.

IV. CASE STUDY

Because of simulation modelling with a constant value of random noise 2.5%, using the method proposed in Section 2 for point #34 (Fig.1), training errors (Table 1) and prediction errors (Table 2) of the ICF are received for points, for which actual verification has not been carried out (point #34).

And similarly, there are received:

- for point #45 (Fig.1) - training error (Table 3) and prediction errors (Table 4) of the ICF for the points, for which actual verification has not been carried out (point #45);
- for point #54 (Fig.1) - training error (Table 5) and prediction errors (Table 6) of the ICF for the points, for which actual verification has not been carried out (point #54);
- for point #43 (Fig.1) - training error (Table 7) and prediction errors (Table 8) of the ICF for the points, for which actual verification has not been carried out (point #43).

The results of the values prediction are shown in Tables 2, 4, 6 and 8 with a positive (black arrow in Fig. 4) and a negative component (black arrow in Fig. 5) relative to the ideal data. In the numerator, the values of the ideal data are shown and in the denominator – the sign and the value of the prediction result.

TABLE I. THE VALUE OF THE TRAINING ERROR (%) FOR POINT # 34 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	8.8 E-05	3.6 E-04	1.4 E-04	7.4 E-05	1.1 E-04	7.3 E-05
K_2→-, k=2	6.3 E-05	2.2 E-04	1.8 E-04	8.7 E-05	1.6 E-04	1.3 E-04
K_2→+, k=3	1.1 E-04	8.0 E-05	6.8 E-05	1.4 E-04	1.1 E-04	1.0 E-04
K_2→-, k=3	2.04 E-04	8.7 E-05	8.03 E-05	1.0 E-04	7.8 E-05	1.04 E-04
K_2→+, k=4	8.6 E-05	7.5 E-05	9.5 E-05	1.04 E-05	7.6 E-05	7.1 E-05
K_2→-, k=4	9.04 E-05	8.9 E-05	1.3 E-04	7.7 E-05	1.2 E-04	1.6 E-04

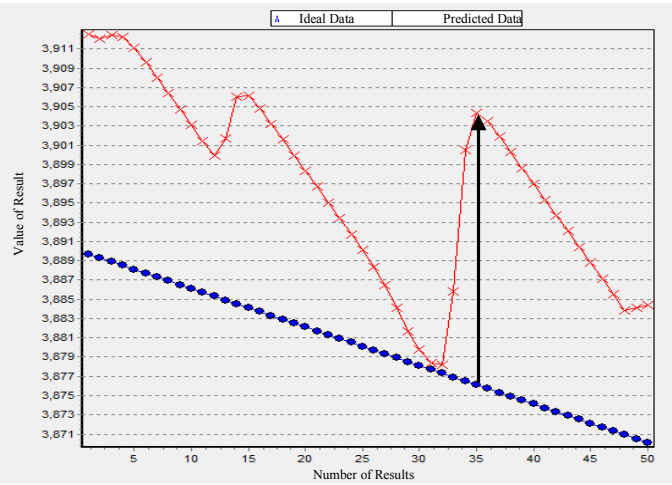

Fig. 4. The value of the prediction error for point #34 with a positive component relative to the ideal data.

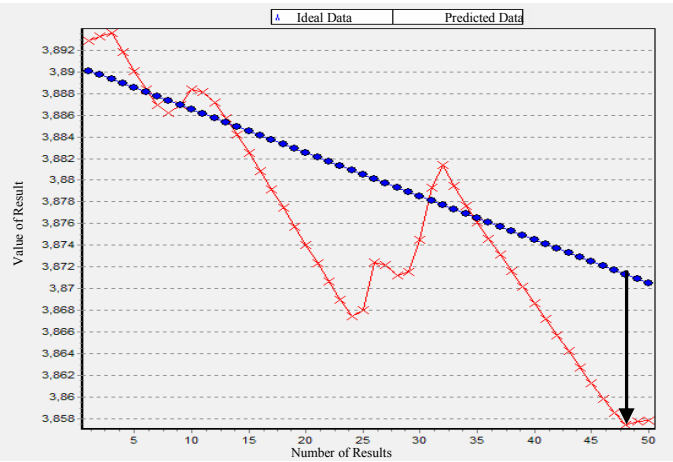

Fig. 5. The value of the prediction error for point #34 with a negative component relative to the ideal data.

TABLE II. THE VALUE OF THE PREDICTION ERROR (%) FOR POINT # 34 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	3.878 / + 3.904	3.872 / - 3.838	3.889 / + 3.912	3.890 / + 3.925	3.885 / + 3.912	3.888 / + 3.921
K_2→-, k=2	3.888 / + 3.913	3.882 / + 3.907	3.890 / + 3.925	3.871 / - 3.850	3.882 / + 3.901	3.888 / + 3.907
K_2→+, k=3	3.884 / - 3.867	3.875 / + 3.892	3.889 / + 3.912	3.882 / - 3.865	3.872 / - 3.858	3.873 / - 3.868
K_2→-, k=3	3.880 / - 3.862	3.873 / - 3.856	3.884 / + 3.898	3.886 / + 3.897	3.871 / - 3.857	3.883 / + 3.901
K_2→+, k=4	3.880 / + 3.998	3.882 / + 4.006	3.890 / + 4.029	3.883 / + 3.967	3.886 / + 3.978	3.883 / - 3.988
K_2→-, k=4	3.888 / + 3.973	3.878 / + 3.983	3.876 / + 3.979	3.875 / + 3.953	3.880 / + 4.038	3.887 / + 4.002

TABLE III. THE VALUE OF THE TRAINING ERROR (%) FOR POINT # 45 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	1.6 E-04	1.1 E-05	1.8 E-04	8.5 E-05	8.8 E-05	1.9 E-04
K_2→-, k=2	2.6 E-04	8.6 E-05	7.7 E-05	6.1 E-05	1.3 E-04	1.6 E-04
K_2→+, k=3	8.6 E-05	8.0 E-05	1.3 E-04	8.6 E-05	8.5 E-05	1.1 E-04
K_2→-, k=3	9.1 E-05	3.01 E-04	1.09 E-04	9.03 E-05	8.9 E-05	7.8 E-05
K_2→+, k=4	8.9 E-05	8.9 E-05	1.0 E-04	7.6 E-05	8.05 E-05	8.4 E-05
K_2→-, k=4	8.9 E-05	8.6 E-05	7.7 E-05	1.2 E-04	9.4 E-05	1.05 E-04

TABLE IV. THE VALUE OF THE PREDICTION ERROR (%) FOR POINT # 45 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	3.889 / + 3.911	3.887 / + 3.902	3.907 / + 3.884	3.886 / + 3.911	3.884 / + 3.911	3.885 / + 3.912
K_2→-, k=2	3.879 / + 3.901	3.876 / + 3.902	3.883 / + 3.902	3.885 / + 3.911	3.880 / + 3.902	3.888 / + 3.921
K_2→+, k=3	3.888 / + 3.904	3.876 / + 3.888	3.877 / + 3.888	3.882 / - 3.860	3.877 / + 3.898	3.884 / - 3.870
K_2→-, k=3	3.875 / + 3.892	3.885 / - 3.871	3.883 / - 3.868	3.886 / + 3.905	3.872 / - 3.859	3.881 / + 3.868
K_2→+, k=4	3.876 / + 3.988	3.885 / + 3.999	3.887 / + 3.999	3.888 / + 3.983	3.872 / - 3.857	3.882 / + 3.998
K_2→-, k=4	3.883 / + 3.991	3.879 / + 3.969	3.874 / + 3.953	3.875 / + 3.879	3.879 / + 3.992	3.884 / + 4.019

TABLE V. THE VALUE OF THE TRAINING ERROR (%) FOR POINT # 54 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	1.6 E-04	1.1 E-04	2.2 E-04	8.5 E-05	1.7 E-04	2.08 E-04
K_2→-, k=2	2.6 E-04	8.8 E-05	6.9 E-05	7.7 E-05	1.3 E-04	1.6 E-04
K_2→+, k=3	8.6 E-05	8.1 E-05	1.0 E-05	1.3 E-04	1.0 E-04	1.0 E-04
K_2→-, k=3	8.1 E-05	3.01 E-04	7.8 E-05	9.03 E-05	6.4 E-05	8.9 E-05
K_2→+, k=4	7.6 E-05	9.9 E-05	1.0 E-04	9.1 E-05	7.1 E-05	1.5 E-04
K_2→-, k=4	6.6 E-05	8.5 E-05	1.01 E-04	8.5 E-05	7.1 E-05	1.6 E-04

As it can be seen in received training tables (tables 1, 3, 5, 7), the value of the training error does not exceed 6.4 E -04 % (Table 7) of formula 2 for the values K_1 +, K_2+ with the degrees *a* and *b* – 3 and 4 respectively. This indicates the high accuracy of the training epoch of the ANFIS system.

TABLE VI. THE VALUE OF THE PREDICTION ERROR (%) FOR POINT # 54 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	3.877 / + 3.898	3.887 / + 3.902	3.889 / + 3.881	3.881 / + 3.913	3.884 / + 3.908	3.886 / + 3.909
K_2→-, k=2	3.880 / + 3.899	3.864 / + 3.902	3.885 / + 3.910	3.883 / + 3.902	3.887 / + 3.906	3.884 / + 3.910
K_2→+, k=3	3.889 / + 3.905	3.875 / + 3.892	3.871 / - 3.849	3.886 / + 3.905	3.885 / + 3.909	3.881 / + 3.901
K_2→-, k=3	3.875 / + 3.888	3.886 / - 3.871	3.889 / - 3.789	3.878 / + 3.888	3.873 / - 3.860	3.875 / + 3.896
K_2→+, k=4	3.880 / + 3.986	3.879 / + 3.976	3.880 / + 4.002	3.879 / + 3.982	3.878 / + 3.973	3.885 / + 4.001
K_2→-, k=4	3.876 / + 3.941	3.886 / + 4.003	3.886 / + 3.964	3.880 / + 3.968	3.887 / + 3.968	3.884 / + 4.001

TABLE VII. THE VALUE OF THE TRAINING ERROR (%) FOR POINT # 43 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	5.8 E-05	6.3 E-04	2.2 E-04	7.03 E-05	8.2 E-05	7.2 E-05
K_2→-, k=2	3.9 E-05	1.4 E-04	1.2 E-04	1.8 E-04	1.1 E-04	1.6 E-04
K_2→+, k=3	9.4 E-05	5.9 E-05	4.8 E-05	6.5 E-05	7.9 E-05	1.4 E-04
K_2→-, k=3	6.04 E-05	1.0 E-04	7.5 E-05	1.6 E-04	1.4 E-04	6.4 E-05
K_2→+, k=4	5.7 E-05	5.6 E-05	6.4 E-04	7.5 E-05	6.5 E-05	1.7 E-04
K_2→-, k=4	5.1 E-05	5.4 E-05	7.4 E-05	6.9 E-05	8.0 E-05	6.3 E-05

TABLE VIII. THE VALUE OF THE PREDICTION ERROR (%) FOR POINT # 43 AT RANDOM ERROR OF 2.5%

PQ A / PQ B	K_1→+, k=2	K_1→-, k=2	K_1→+, k=3	K_1→-, k=3	K_1→+, k=4	K_1→-, k=4
K_2→+, k=2	2.867 / + 2.889	2.869 / + 2.886	2.867 / + 2.894	2.859 / + 2.875	2.857 / + 2.880	2.862 / + 2.887
K_2→-, k=2	2.857 / + 2.873	2.855 / + 2.879	2.851 / + 2.896	2.854 / + 2.875	2.868 / + 2.889	2.864 / + 2.892
K_2→+, k=3	2.865 / + 2.882	2.856 / + 2.879	2.860 / - 2.840	2.858 / + 2.877	2.854 / + 2.879	2.863 / + 2.883
K_2→-, k=3	2.865 / + 2.889	2.860 / - 2.841	2.854 / + 2.870	2.857 / + 2.881	2.852 / + 2.872	2.866 / - 2.851
K_2→+, k=4	2.867 / + 2.957	2.864 / + 2.939	2.862 / + 2.950	2.864 / + 2.972	2.861 / + 2.934	2.863 / + 2.969
K_2→-, k=4	2.858 / + 2.932	2.866 / + 2.954	2.864 / + 3.075	2.859 / + 2.935	2.851 / + 2.902	2.856 / + 2.920

The errors of the values prediction are presented in Tables 2, 4, 6 and 8. It is seen that for a lower degree of the polynomial (formula 2) the errors are relatively small, although in some cases they increase.

In future it is advisable to carry out further research of the proposed method, namely, the variations of noise values, the expansion of the training epochs range, the time of training and the use of the full set of reconstructed points.

V. CONCLUSIONS

A proposed approach to the signal processing of multisensors based on the improved method identification of the individual conversion function of multisensors using an adaptive neuro-fuzzy system of logic deduction enables to significantly reduce the number of verification points and improves the accuracy of the identification of their individual conversion functions compared with other known approaches.

Its advantages were investigated of an extended set of predicted points of the multisensor conversion characteristics.

The simulation modeling of the multisensor has confirmed that the accuracy of the verification results prediction for multisensors is improved in comparison with other known methods.

In future, the robustness bounds of the proposed method for random errors for higher amplitudes and with another type of law of error distribution can be studied.

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