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Identification of Multisensor Conversion Characteristic Using Neural Networks

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Abstract: A method of individual conversion characteristic identification of multisensor using reduced number of its calibration/testing results is described in this paper. The proposed method is based on the neural-based reconstruction (approximation or prediction) of surface points of multisensor conversion characteristic. Each neural network module reconstructs separate point of the surface. Our results show that the use of a Support Vector Machine (SVM) model allows improving the reconstruction accuracy of multisensor conversion characteristic. The reconstruction results obtained by SVM are compared with the results obtained by a multi-layer perceptron (MLP). *Copyright © 2013 IFSA.*

Keywords: Multisensor, Conversion characteristic, Neural networks.

1. Introduction

An interest to sensors with an output signal specially depended on several physical quantities (multisensors – MS [1]) is significantly increased in the last decade. Such sensors are successfully used for simultaneous data acquisition of several physical quantities in chemical engineering, safety systems, ecological monitoring and other appropriate fields. The main advantages of such MSs are (i) measurement of a big number of physical quantities that cannot be measured by traditional sensors, (ii) easy use and (iii) relatively small price.

One of the disadvantages of a MS is a substantial deviation of its conversion characteristic from a nominal [2]. In most cases a nominal conversion characteristic is specified with a low accuracy. Therefore MS–based measurement devices are not-accurate. An improvement is possible by usage of an individual conversion characteristic, which is defined by calibration/testing results obtained in real exploitation conditions of MS [3]. This approach leads to huge laboriousness during fulfilling the calibration/testing procedures, thus their number should be reduced as much as possible.

In our previous work [4] we have developed the neural-based identification method of MS conversion characteristic using reduced number (only nine) of real calibration results to reconstruct all 49 points of the surface of its conversion characteristic. In that paper we have (i) specified the MS conversion characteristic surface in a three-dimensional coordinate system on the example of a gas multisensor TGS-813 [2], (ii) overviewed existing approaches and proved that neural network (NN)-based methods have provided better reconstruction accuracy of the surfaces of MS conversion characteristics, (iii) presented the development of NN-based method consisting of

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three phases and (iv) showed the high reconstruction accuracy (relative reconstruction error does not exceed 0.36 %) of the first phase of the method, i.e. the reconstruction of the surface points between real calibration points by approximating neural network.

In our previous paper [5] we have presented the reconstruction results for the second phase of the proposed method [4], i.e. the reconstruction accuracy of the surface points outside real calibration points by predicting neural network. This paper is an extended version of the paper [5] and along with the experimental results for the second phase we present the experimental results of the third final phase of the proposed method.

Considering good generalization abilities of standard MLP [6], its good approximating abilities [7] and its good predicting properties on a small number of an input training data set [8], we have chosen this widely used model for the fulfillment both the approximation and prediction tasks. Meanwhile, a SVM model has successfully applied for a lot of real-world applications and showed good predicting abilities on the number of prediction tasks [9]. Therefore we also have applied this model to our task and compared the results of both approaches. The rest of the paper is organized as follows. Since we will be referring to the assigned codes of the predicting calibration points during our experiments, we have presented the developed neural-based identification method [4] of MS conversion characteristic in Section 2. Section 3, subsection 3.1 presents the comparison of the reconstruction results of MS conversion characteristic by MLP and SVM for the second phase of the method, Section 3, subsection 3.2 presents these results for the third phase of the method. Section 4 concludes the paper.

2. Development of NN-based Method of Identification of Individual Conversion Characteristic of Multisensor

A basic idea of the proposed method of identification an individual MS conversion characteristic based on a reduced number of real calibration/testing results could be explained with the help of Fig. 1. Thus the idea is: to calculate the value of the white points on the basis of the values of the black points [4]. As an example in Fig. 1, the 49 calibration points for identification of an individual conversion characteristic of MS measuring two physical quantities are encoded by two digits: the first digit describes a point by vertical axes of the physical quantity B, the second digit describes a point by horizontal axes of the physical quantity A. The nine black points 22, 24, 26, 42, 44, 46, 62, 64, 66 are the real MS calibration/testing points, others 40 points should be reconstructed by the proposed NN-based method.

The reconstruction process of all 40 points consists of the three phases. The first phase is to reconstruct the calibration points by approximation (interpolation) between the real calibration points using Approximating Neural Network (ANN). The codes of the reconstructed points are showed in the third column in Table 1. The codes of the real calibration points which serve as an input of approximation are showed in the second column in Table 1. The codes of the NNs for such approximation are showed in the first column in Table 1. In order to provide a transparent coding of all NNs modules used in the proposed method, the code of NN consists of the three digits: the first digit is the code of phase, the second digit is the code of variant within this phase and the third digit is the own code of the NN module. In the result of the first phase execution we reconstruct the 16 new points, obtained directly using the real calibration results. Thus, at the end of this phase we have the 25 points in total, which belong to a surface of individual MS conversion characteristic.

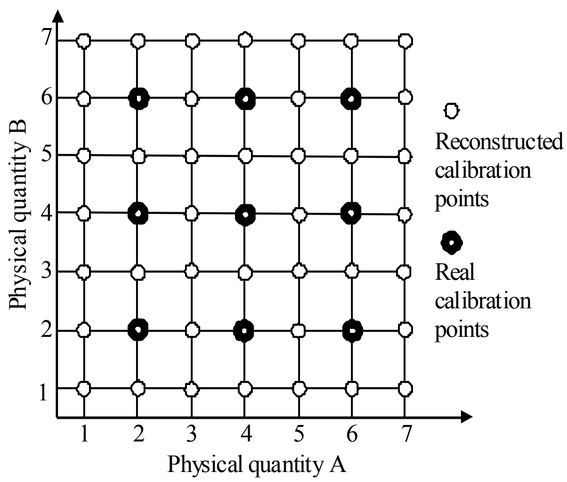

Fig. 1. A placement of real and reconstructed calibration points in the coordinates of the physical quantities.

The second phase is to reconstruct the calibration points by prediction (extrapolation) on the basis of the real calibration points using Predicting Neural Network (PNN). There are possible two variants: (i) without accounting the points, reconstructed in the first phase, in the training set and (ii) with accounting these points. The assigning of NNs for the second phase, first variant is showed in Table 2. The assigning of NNs for the second phase, second variant is showed in Table 3. In the result of the second phase execution we reconstruct the 16 new points according to the third column on Table 2 or the fourth column in Table 3. Thus, at the end of this phase, we have the 41 points in total, which belong to a surface of individual MS conversion characteristic.

Table 1. First phase.

Code of NN	Input of ANN	Output of ANN
	Code of real calibration points	*Code of reconstructed calibration points*
111	22, 24, 26	23, 25
112	42, 44, 46	43, 45
113	62, 64, 66	63, 65
114	22, 42, 62	32, 52
115	24, 44, 64	34, 54
116	26, 46, 66	36, 56
117	22, 44, 66	33, 55
118	62, 44, 26	53, 35

Table 2. Second phase, first variant.

Code of NN	Input of PNN	Output of PNN
	Code of real calibration points	*Code of reconstructed calibration points*
211	22, 24, 26	21, 27
212	42, 44, 46	41, 47
213	62, 64, 66	61, 67
214	22, 42, 62	12, 72
215	24, 44, 64	14, 74
216	26, 46, 66	16, 76
217	22, 44, 66	11, 77
218	62, 44, 26	71, 17

Table 3. Second phase, second variant.

Code of NN	Input of PNN		Output of PNN
	Code of real calibration points	*Code of points, recons-tructed on the first phase*	*Code of points, reconstructed on the second phase*
221	22, 24, 26	23, 25	21, 27
221	22, 24, 26	23, 25	21, 27
222	42, 44, 46	43, 45	41, 47
223	62, 64, 66	63, 65	61, 67
224	22, 42, 62	32, 52	12, 72
225	24, 44, 64	34, 54	14, 74
226	26, 46, 66	36, 56	16, 76
227	22, 44, 66	33, 55	11, 77
228	62, 44, 26	53, 35	71, 17

The third phase is to reconstruct the calibration points by prediction (extrapolation) based on the points, reconstructed in the first phase using PNN. The assigning of the NNs for the third phase is showed in Table 4. In the result of the third phase execution we reconstruct the 8 new points according to the third column in Table 4. Thus, at the end of this last phase we have the 49 points in total, which belong to a surface of individual MS conversion characteristic. Therefore, the proposed NN-based method allows reconstructing the 40 points on the surface based on the 9 real calibration/testing points.

Table 4. Third phase.

Code of NN	Input of PNN	Output of PNN
	Code of points, reconstructed on the first phase by interpolation	*Code of reconstructed points*
311	32, 33, 34, 35, 36	31, 37
312	52, 53, 54, 55, 56	51, 57
313	23, 33, 43, 53, 63	13, 73
314	25, 35, 45, 55, 65	15, 75

A graphical interpretation of NN-based method of individual MS conversion characteristic identification is presented in Fig. 2. As we have mentioned above, the NNs with the codes 111-118 fulfill the approximation tasks, thus we have called them the Approximating Neural Networks (ANNs). The NNs with the codes 221-228 and 311-314 fulfill the prediction tasks and we have called them the Predicting Neural Networks (PNNs). The well-known method of back propagation error [5] with adaptive learning rate [10] is used for the training of both types of NNs (in a case of MLP).

3. Simulation Modeling Results

Our previous researches showed the high reconstruction accuracy of the first phase of the considered method [4], i.e. reconstruction of the 16 surface points between real calibration points by the ANN. The maximum relative error of approximation did not exceed 0.36 % (only for two points 33 and 55), the average relative error of approximation was 0.13 %.

3.1. Results for the Second Phase of the Method

In this section we present the reconstruction results for the second phase of the proposed method, i.e. the reconstruction accuracy of the surface points outside the real calibration points by the PNN. We provide the experimental results for the second phase, second variant to predict the points from fourth column of Table 3 because this variant corresponds better to the real exploitation conditions of MS. The preliminary fulfilled experiments have showed:

- One PNN, for example with the code 221 (see Table 3), cannot predict two points 21 and 27 simultaneously because they are located in the different ends in relation to the real available data (Fig. 1). Therefore we have to apply 2 different modules of PNN for prediction, for example, point 27 on the basis of points 22,23,24,25,26 and point 21 on the basis of points 26,25,24,23,22;
- Only 5 available training data for each predicting point are not enough for appropriate PNN training in order to provide high-accurate prediction. Therefore we have artificially increased the quantity of input data for each predicting point by applying additional ANN.

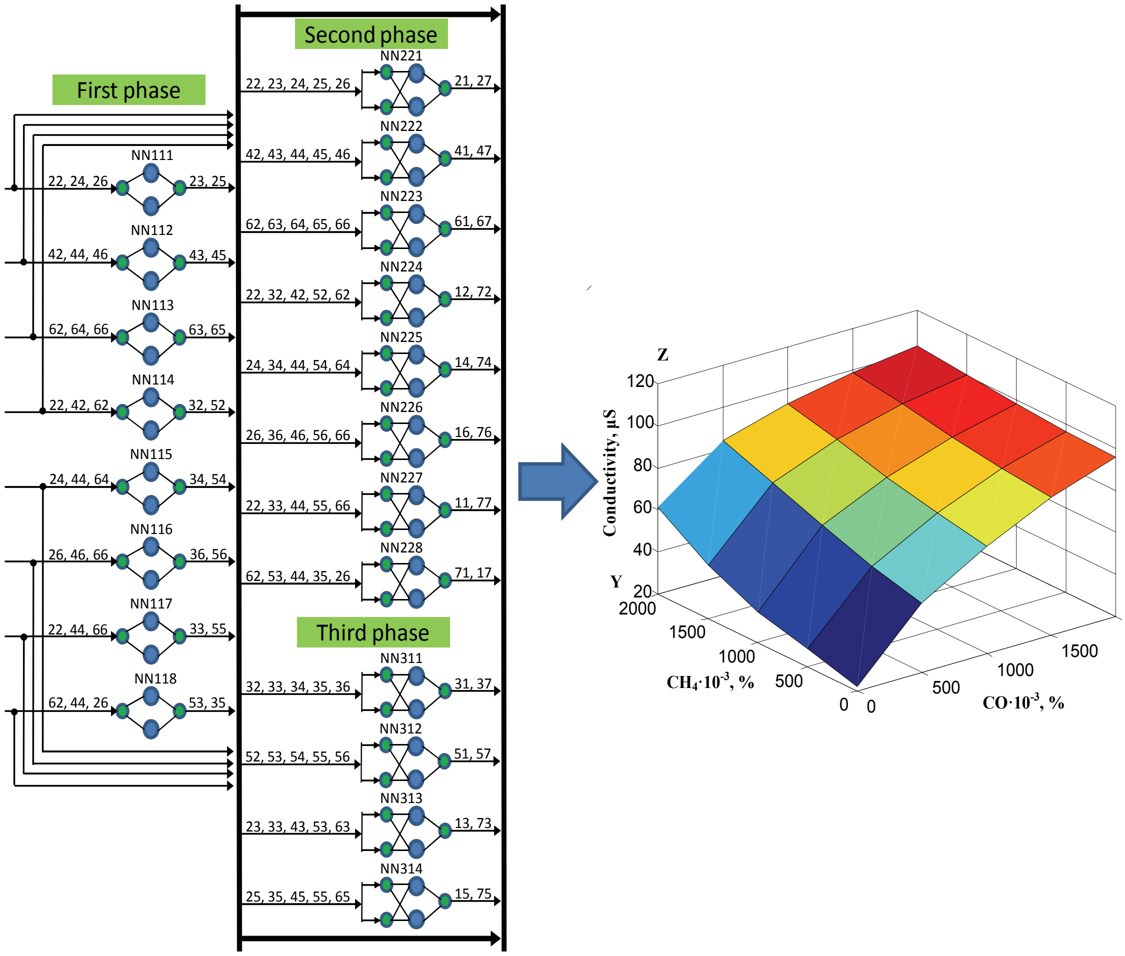

Fig. 2. Graphical interpretation of NN-based method of individual MS conversion characteristic identification.

Thus, in order to prepare an input training set for each PNN, the additional ANN – a MLP with the structure 1-3-1 and sigmoid neurons in the hidden and output layers was used. We have increased the quantity of the input data for PNN from 5 to 11. The limit number of training iteration was fixed to $2 \cdot 10^7$, the results of approximation are presented in Table 5.

Table 5. Approximation results of input data preparation for PNN.

Code of recons-tructed points	Reached SSE	Relative approximation error in real calibration points		
		#1 (22 … 42 … etc)	***#2 (24 … 44 … etc)***	***#3 (26 … 46 … etc)***
21, 27	$1.9 \cdot 10^{-8}$	0.25	0.01	0.04
41, 47	$4.5 \cdot 10^{-8}$	0.12	0.05	0.10
61, 67	$8.1 \cdot 10^{-9}$	0.02	0.00	0.02
12, 72	$9 \cdot 10^{-8}$	0.06	0.01	0.05
14, 74	$2 \cdot 10^{-8}$	0.09	0.02	0.05
16, 76	$1.6 \cdot 10^{-6}$	0.20	0.19	0.39
11, 77	$3.3 \cdot 10^{-7}$	0.26	0.20	0.11
71, 17	$6 \cdot 10^{-8}$	0.16	0.11	0.17

We have evaluated the relative approximation errors only for 3 real calibration points (see Table 3, column 2) because these data are known for each approximation case. For example, for the approximation points 21, 27 we have evaluated the approximation errors in the points 22, 24, 26, for the case 41, 47 – the approximation errors in the points 42, 44, 46 and so on (Table 5). As we can see, a MLP, as a universal approximator [7], showed very low relative approximation errors, the maximal error does not exceed 0.39 %, the average error is equal 0.11 %. Thus we have used the obtained 11 points as the training set for the appropriate PNN to predict the values of each point of fourth column of Table 3.

As the PNN we have used a MLP model with the structure 3-2-1 and sigmoid neurons in the hidden and output layers. The ANN and PNN routines are developed on C. All experiments were fulfilled on the computer with Intel Core 2 Duo processor 2.4 GHz with 3 GB of RAM. The MLP training parameters and the prediction results are collected in Table 6. As another model of PNN we have used a nu-SVR model, a SVM working in a regression mode available within the LIBSVM library [11]. All the input parameters and the prediction results of SVM model are collected in Table 7. Using input parameters s=4 and t=1 we have chosen the nu-SVR type and polynomial kernel of the SVM respectively. All other input parameters c, d, g, r were chosen empirically. The training time of the SVM model does not exceed several milliseconds for each predicting calibration point on the same computer. Thus the maximum and average relative errors of prediction are 0.69 % and 0.28 % by the SVM model and 5.2 % and 1.29 % by the MLP model respectively. The comparative analysis of the relative errors of prediction is depicted in Fig. 3 and Fig. 4. As it is seen, the SVM model showed much better prediction results in comparison with the MLP model for the 14 cases. Only for two cases, for the points 77 and 71, the MLP model outperformed the SVM model.

Table 6. MLP training parameters and prediction results for the second phase.

Point	Reached SSE	Training iterations	Training time, s	Rel. error of prediction, %
72	$3.2\cdot10^{-7}$	$3\cdot10^{6}$	25.00	0.1
12	$3.3\cdot10^{-8}$	$3\cdot10^{7}$	247.00	5.2
74	$8.9\cdot10^{-8}$	$3\cdot10^{7}$	248.00	1.5
14	$6.6\cdot10^{-8}$	$3\cdot10^{7}$	248.00	3.4
76	$1.7\cdot10^{-7}$	$6\cdot10^{7}$	49.00	1.5
16	$7.8\cdot10^{-9}$	$3\cdot10^{7}$	243.00	1.4
27	$7.8\cdot10^{-9}$	$3\cdot10^{7}$	247.00	0.6
21	$2.8\cdot10^{-9}$	$3\cdot10^{7}$	247.00	1.5
47	$1.3\cdot10^{-8}$	$1.5\cdot10^{7}$	120.00	0.4
41	$1.0\cdot10^{-9}$	$3.8\cdot10^{7}$	34.00	1.3
67	$6.0\cdot10^{-9}$	$3\cdot10^{7}$	25.00	0.5
61	$3.5\cdot10^{-9}$	$2\cdot10^{7}$	164.00	0.8
77	$6.8\cdot10^{-9}$	$3\cdot10^{7}$	263.00	0.1
11	$5.5\cdot10^{-9}$	$3\cdot10^{7}$	243.00	1.7
71	$1.3\cdot10^{-8}$	$3\cdot10^{7}$	248.00	0.2
17	$3.6\cdot10^{-9}$	$3\cdot10^{7}$	246.00	0.5

Table 7. SVM training parameters and prediction results for the second phase.

Po-int	c	g	d	r	Training iterations	MSE	Rel. error of predict-tion, %
72	40	4.5	1.5	-1100	3722	$5.4\cdot10^{-6}$	0.08
12	40	4.5	1.5	-1100	86	$7.2\cdot10^{-7}$	0.19
74	40	4.5	1.5	-	1	$3.6\cdot10^{-6}$	0.34
14	40	4.5	1.5	-	2	$4.4\cdot10^{-7}$	0.62
76	40	20.5	1.5	1000	72686	$1.5\cdot10^{-8}$	0.02
16	45	5	1.5	-	3970	$9.2\cdot10^{-7}$	0.67
27	40	20.5	1.5	22000	1	$1.8\cdot10^{-7}$	0.25
21	40	20.5	1.5	22000	1	$1.7\cdot10^{-9}$	0.04
47	40	20.5	1.5	-	1	$3.2\cdot10^{-7}$	0.15
41	40	20.5	1.5	1100	2	$1.3\cdot10^{-8}$	0.08
67	4	20.5	1.5	22000	1	$3.4\cdot10^{-7}$	0.09
61	40	20.5	1.5	22000	2	$2.2\cdot10^{-8}$	0.06
77	40	20.5	1.5	220	1	$2.5\cdot10^{-7}$	0.64
11	40	20.5	2.5	100	28297	$1.8\cdot10^{-7}$	0.69
71	1	5.5	2.5	10	1139	$2.3\cdot10^{-6}$	0.44
17	1	5.5	2.5	10	1	$1.1\cdot10^{-7}$	0.18

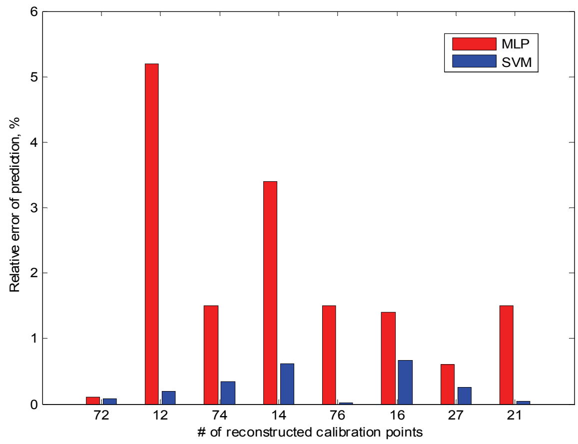

Fig. 3. Comparison of prediction results by MLP and SVM for the first part of calibration points: second phase.

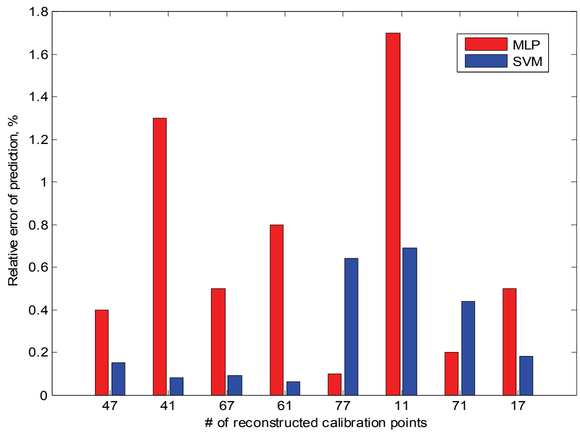

Fig. 4. Comparison of prediction results by MLP and SVM for the second part of calibration points: second phase.

3.2. Results for the Third Phase of the Method

In this section we present the reconstruction results for the third phase of the proposed method, i.e. the reconstruction accuracy of the surface points from third column of Table 4. We have used the same methodology, hardware and software as in the previous subsection 3.1. We have used the same approach with approximation, described in Table 5, for the improvement of the further prediction accuracy of the PNN and we have increased the quantity of the input data for PNN from 5 to 11. Similarly to the results of the second phase, the reconstruction (prediction) results for the third phase are collected in Tables 8 and 9 using MLP and SVM respectively. Thus the maximum and average relative errors of prediction are 0.54 % and 0.28 % by the SVM model and 2.3 % and 1.18 % by the MLP model respectively. The comparative analysis of the relative errors of prediction is depicted in Fig. 5. As it is seen, the SVM model showed much better prediction results in comparison with the MLP model for all the points of the third phase. Thus these high-accurate prediction results provided by the SVM model allow applying the proposed method in real measurement conditions to reconstruct an individual conversion characteristic of a multisensor.

Table 8. MLP training parameters and prediction results for third phase.

#	Architecture MLP, SIG-SIG	SSE (required 0.0000000010)	Training iterations	Training time, s	Relative error of prediction, %
13	3-2-1	0.0000000267	$3\cdot10^7$	243.00	2.3
73	3-2-1	0.0000001306	$3\cdot10^7$	244.00	2.0
15	3-2-1	0.0000000249	$3\cdot10^7$	241.00	2.3
75	3-2-1	0.0000000056	$3\cdot10^7$	239.00	0.5
31	3-2-1	0.0000000019	$3\cdot10^7$	242.00	0.7
37	3-2-1	0.0000000024	$3\cdot10^7$	242.00	0.5
51	3-2-1	0.0000000043	$3\cdot10^7$	471.00	0.6
57	3-2-1	0.0000000176	$3\cdot10^7$	473.00	0.6

Table 9. SVM training parameters and prediction results for third phase.

#	s	t	C	g	d	r	Training iterations	Mean squared error	Rel. error of prediction, %
13	4	1	1	5.5	2.5	1	1052	$4.9\cdot10^{-8}$	0.17
73	4	1	1	5.5	2.5	1000	1	$2.6\cdot10^{-6}$	0.38
15	4	1	1	6.5	3.5	1000	862	$5.0\cdot10^{-7}$	0.54
75	4	1	4	20.5	1.5	22000	1099	$1.2\cdot10^{-6}$	0.06
31	4	1	1	6.5	3.5	1000	1	$3.1\cdot10^{-7}$	0.38
37	4	1	1	6.5	3.5	1000	1	$3.1\cdot10^{-7}$	0.18
51	4	1	1	6.5	3.5	1000	2	$4.2\cdot10^{-7}$	0.30
57	4	1	3.5	0.8	1.5	1000	1	$2.4\cdot10^{-6}$	0.22

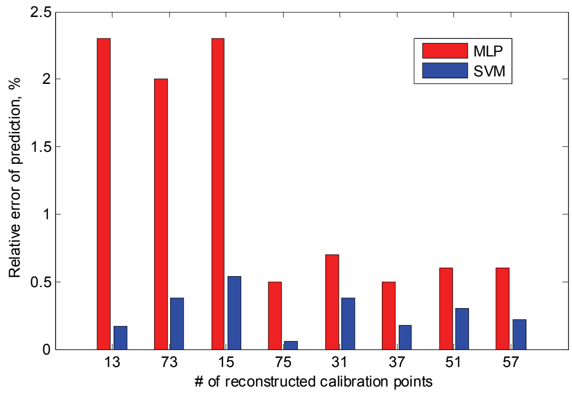

Fig. 5. Comparison of prediction results by MLP and SVM for the third phase.

4. Conclusions

The neural network based method of individual conversion characteristic identification of multisensor using reduced number of its calibration/testing results is considered in this paper. The proposed NN-based method allows reconstructing the 40 points on the surface based on only 9 real calibration/testing points. We have evaluated the reconstruction accuracy of the points on multisensor conversion characteristic surface outside the real calibration points predicted by a Multi-Layer Perceptron and a Support Vector Machine. Our results show good potential abilities of a Support Vector Machine model to provide high-accurate prediction of a multisensor conversion characteristic surface at the small quantity of input data for neural network training. The maximum relative prediction error during the reconstruction of the surface points does not exceed 0.7 %. These high-accurate prediction results provided by the SVM model allow applying the proposed method in real exploitation conditions to improve the measurement accuracy of multisensors.

References

[1]. A. H. Taner and J. E. Brignell, Virtual instrumentation and intelligent sensors, *Sensors and Actuators A: Physical*, Vol. 61, No. 1-3, 1997, pp. 427-430.

[2]. http://www.figarosensor.com/products/813pdf.pdf.

[3]. E. J. Brignell, Digital compensation of sensors, *Scientific Instruments*, Vol. 20, No. 9, 1987, pp. 1097-1102.

[4]. I. Turchenko, O. Osolinsky, V. Kochan, A. Sachenko, R. Tkachenko, V. Svyatnyy and M. Komar, Approach to neural-based identification of multisensor conversion characteristic, in *Proceedings of the 5th IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS'09)*, 2009, Rende, Italy, pp. 27-31.

[5]. I. Turchenko, V. Kochan, Improvement of identification accuracy of multisensor conversion characteristic using SVM, in *Proceedings of the 6th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS' 2011)*, Prague, Czech Republic, 2011, pp. 388-392.

[6]. S. Haykin, Neural networks: A comprehensive foundation, 2nd edition: eds. by N. N. Kussul, *Williams*, Moscow, 2006, 1104 p. (in Russian).

[7]. K. Hornik, M. Stinchcombe and H. White, Multilayer feedforward networks are universal approximators, *Neural Networks*, Vol. 2, 1989, pp. 359-366.

[8]. A. Sachenko, V. Kochan and V. Turchenko, Instrumentation for gathering data, *IEEE Instrumentation & Measurement Magazine*, Vol. 6, Issue 3, 2003, pp. 34-40.

[9]. Support Vector Machine application site, http://www.clopinet.com/isabelle/Projects/SVM/applist.html

[10]. V. Golovko, Neural networks: training, models and applications, *Radiotechnika*, Moscow, 2001, 256 p. (in Russian).

[11]. Chih-Chung Chang and Chih-Jen Lin, LIBSVM: a library for support vector machines, 2001. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm

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