The New Method of Historical Sensor Data Integration Using Neural Networks

V.Turchenko[1], V.Kochan[1], A.Sachenko[1], Th.Laopoulos[2]

[1] Laboratory of Automated Systems and Networks, Ternopil Academy of National Economy, 3 Peremoga Square, Ternopil, 46004, Ukraine, E-mail: vtu@tanet.edu.te.ua

[2] Electronics Laboratory, Physics Department, Aristotle University of Thessaloniki, 54006, Thessaloniki, Greece, E-mail: laopoulos@physics.auth.gr

***Abstract**: The main feature of neural network using for accuracy improvement of physical quantities (for example, temperature, humidity, pressure etc.) measurement by data acquisition systems is insufficient volume of input data for predicting neural network training at an initial exploitation period of sensors. The authors have proposed the technique of data volume increasing for predicting neural network training using (i) additional approximating neural network; (ii) method of "historical" data integration (fusion). In this paper we have proposed the advanced method of "historical" data integration and presented simulation results on mathematical models of sensor drift using single-layer perceptron.*

Keywords: – historical sensor data integration (fusion), sensor drift prediction, accuracy improvement, intelligent systems

1. INTRODUCTION

The authors have shown in [1, 2], that the error of modern data acquisition systems is much less than sensor's error in many cases. The accuracy improvement of physical quantity measurement is provided by (i) sensor calibration using special calibrator or (ii) sensor's periodic testing by reference sensor on the exploitation place [3]. The frequency of calibration/testing procedure is called as inter-testing interval. However operations, which implement these methods are rather laborious. Sensor drift prediction provides low laboriousness. Prediction based on average drift of similar sensors has low reliability and does not take into account an individual native of sensor in specific exploitation conditions. Sensor drift prediction during inter-testing interval can be used in order to reduce laboriousness of calibration or testing procedures. Using artificial intelligence methods, in particularly neural networks is most effective in this case [4, 5].

The same team of authors considers an approach to sensor drift prediction in number of publications [1, 2, 6, 7]. In [7] it is proposed and experimentally analysed the two methods: (i) additional approximating neural network and (ii) integration of "historical" data, which allow sharply reducing number of sensor calibrations or testing by artificial increasing of training set of predicting neural network. The advanced method of "historical" sensor data integration and its simulation modelling on mathematical models of sensor drift in comparison with the basis method of data integration are considered below.

2. BASIS METHOD OF HISTORICAL DATA INTEGRATION

It is proposed to use three groups of data about sensor drift in [1]: real data, "historical" data and hypothetical data. The real data are not available at the beginning of sensor exploitation. Using "historical" data (obtained as result of calibration or testing of the same type sensors in the similar exploitation conditions) can compensate this disadvantage. It is obviously, that predicting neural network can provide the best quality of sensor drift prediction in case of its training using real data about sensor drift. Therefore the "historical" data should be replaced by real data for each particular sensor during its exploitation.

The "historical" data should be integrated in order to account individual properties of each sensor drift. It is proposed to use a set of Integrating "Historical" Data Neural Networks (IHDNN) for such integration. Let us consider the "historical" data of sensor drift as curves $x1...xn$ (Fig. 1), which are equal to xai, xbi, xci, $i=\overline{1,n}$ into calibration points a, b, c. The first calibration of the new sensor allows correcting initial sensor error at the moment 0. The second calibration of the new sensor allows receiving the first real value xak of sensor drift in calibration point a. The main goal of the IHDNN using is provide prediction of point xbk on the basis of xak and xai, $i=\overline{1,n}$, the next point xck on the basis of xbk and xbi, $i=\overline{1,n}$ and etc. The number of available "historical" curves of sensor drift determines structure of IHDNN's input layer.

There is propose to form the IHDNN's training set by the following algorithm:

1. One curve of sensor drift xi is considered as real data and all other curves xj, $j=\overline{1,i-1}$, $j=\overline{i+1,n}$ are considered as "historical" data. Thus, the real sensor drift is describes as xai value in point a and dbi value in point b;

2. To calculate absolute deviations $\Delta ij = |xai - xaj|$ of point xai from all other points xaj, where $i = \overline{1,n}$, $j = \overline{1,i-1}$, $j = \overline{i+1,n}$;

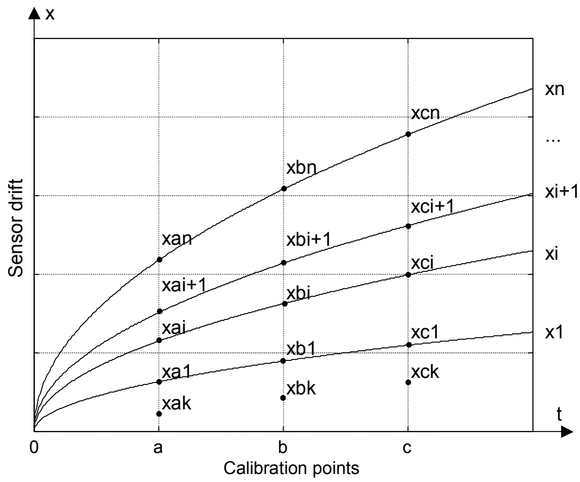

Fig.1 - Historical Data about Sensor Drift of Similar Sensors

3. To sort all absolute deviations, calculated in the previous step, in decreasing order; to calculate maximum $\Delta ij^{max} = \max \Delta ij$ and minimum $\Delta ij^{min} = \min \Delta ij$ values of absolute deviations;
4. To generate each training vector as set of values xbi, xai, xaj, where xaj, $j = \overline{1,i-1}$, $j = \overline{i+1,n}$ values is necessary to put into training vector according to sorted (in decreasing order) values of absolute deviations $E(t)=\sum E(t)$ from value xak(see Table 1);
5. To repeat steps 1-4 above for $i = \overline{1,n}$.

Table 1. Internal structure of training vector for IHDNN according to basis method of "historical" data integration

Max value	In-med. values	Min value	Drift in a	Drift in b
xaj, at $\Delta_{ij} = \Delta_{ij}^{max}$	. . .	xak, at $\Delta_{ij} = \Delta_{ij}^{min}$	xai	xbi

Thus the training set of IHDNN, which predicts sensor drift in the moment b should be formed on the basis of xai and xbi values, where $i = \overline{1,n}$ (see Fig. 1). These values can be considered as "window" of the "historical" data for training set forming. Therefore it is necessary to shift this "window" to right on one calibration point after prediction sensor drift value xbk in the moment b. Then the training set of IHDNN, which predicts sensor drift in the moment c should be formed on the basis of xbi and xci values, where $i = \overline{1,n}$ for next calibration point.

As have simulation results shown, the basis method gives good results for no noise data at using single-layer perceptron as IHDNN. For example [6], the given method is researched on the mathematical model of sensor drift "with saturation" (drift's speed decreases during exploitation) and "with acceleration" (drift's speed increases during exploitation). The maximum and average percentage errors of data integration did not exceed 7% and 3% for drift "with saturation" and 25% and 8% for drift "with acceleration" respectively. The researches of mathematical model of the combined sensor drift have shown, that the maximum and average percentage errors of data integration is more than 52% and 30% [6] and these results are received using multi-layer perceptron (single-layer perceptron has not given desirable result). Also the acceptable results are received using multi-layer perceptron [8] at experimental research of mathematical models of noise sensor drifts (see Fig. 2 and Fig. 3). Using multi-layer perceptron requires significant computing power in multi-channel data acquisition systems. That is inadmissible at using microcomputer AT89C51 on the middle level of such systems [9]. The advanced method of «historical» data integration is considered below, which allows using simple single-layer perceptron model as IHDNN.

3. ADVANCED METHOD OF HISTORICAL DATA INTEGRATION

The disadvantage of basis method of «historical» data integration can be considered as follows. This method takes into account sensor drift values, which have placed in "window" only. For example, it is values xai and xbi, $i = \overline{1,n}$ for the calibration point b. The main idea of advanced method of "historical" data integration is necessity to take into account specific data for all past calibration points. For example, the training set for IHDNN in calibration point b should be formed on the basis of xai, xbi and xci, $i = \overline{1,n}$ values for prediction sensor drifts values at the following calibration point c (see Fig. 1). Therefore the IHDNN's training sample in calibration point b is formed as follows:

1. One curve of sensor drift xi is considered as real data and all other curves xj, $j = \overline{1,i-1}$, $j = \overline{i+1,n}$ are considered as "historical" data. Thus, the real sensor drift is describes as xai value in point a, dbi value in point b and xci value in point c;
2. To calculate absolute deviations $\Delta ij = |xbi - xbj|$ of point xbi from all other points xbj, where $i = \overline{1,n}$, $j = \overline{1,i-1}$, $j = \overline{i+1,n}$;
3. To sort all absolute deviations, calculated in the previous step, in decreasing order; to calculate maximum $\Delta ij^{max} = \max \Delta ij$ and minimum $\Delta ij^{min} = \min \Delta ij$ values of absolute deviations;
4. To generate each training vector as set of values xaj and xbi, where $j = \overline{1,i-1}$, $j = \overline{i+1,n}$ values is necessary to put into training vector according to sorted (in decreasing order) values of absolute deviations xbj from value xbi (see Table 2);
5. To repeat steps 1-4 above for $i = \overline{1,n}$.

Table 2. Internal structure of training vector for IHDNN according to advanced method of "historical" data integration

Drift value in calibration point a on drift curve j	Value with max. deviation in calibration point b	Intermediate pare values	Drift value in calibration point a on drift curve j	Value with max. deviation in calibration point b	Drift value in calibration point b on drift curve i	Drift value in calibration point c on drift curve i
xaj	xbj, at $\Delta_{ij} = \Delta_{ij}^{max}$	xaj, … xbj	xaj	xbj, at $\Delta_{ij} = \Delta_{ij}^{min}$	xbi	xci

4. SINGLE-LAYER PERCEPTRON MODEL

The model of single-layer perceptron with linear neuron activation function should be used as IHDNN. The output value of perceptron

$$Y = \sum_{i=1}^{n} w_{i1} x_i - T, \tag{1}$$

where w_{i1} are the weight factors of inputs of linear neuron, x_i is the input data, T is the neuron's threshold. The Widrow-Hoff rule [10] is used for perceptron training. The total sum-square error of training is

$$E = \sum_{p=1}^{P} E(p) = \frac{1}{2}\sum_{p=1}^{P} (Y^p(t) - D^p)^2, \tag{2}$$

where P is the size of training set, a,b,c is the sum-square error for p input vector (pattern), $Y^p(t), D^p$ are the output and desirable values for p input vector respectively.

The final expressions for modification of weight factors and thresholds are

$$w_{i1}(t+1) = w_{i1}(t) - \alpha(t)(Y^p(t) - D^p)x_i^p, \tag{3}$$

$$T(t+1) = T(t) + \alpha(t)(Y^p(t) - D^p), \tag{4}$$

where $i = \overline{1,n}$, x_i^p – there is i-component of input p vector,

$$\alpha(t) = \left(1 + \sum_{i=1}^{n} x_i(t)^2\right)^{-1} \tag{5}$$

is the adaptive learning rate [2].

The following algorithm is used for training [7]:

1. To set the adaptive learning rate as value $0 < \alpha < 1$ and minimum sum-square error $E_{\min}$;
2. To initialise the weight factors and threshold of perceptron by randomise values;
3. To give an input data to perceptron input, to calculate the output according to expression (1);
4. To update the values of weight factors and threshold according to expressions (3-5);
5. To execute steps 3-4 while total sum-squared error (2) will not become less minimal $E \le E_{\min}$.

5. EXPERIMENTAL RESEARCHES

The experimental researches have executed by simulation modelling using mathematical models of noise sensor drift (10 sensor drift curves). The mathematical model of noise sensor drift "with saturation" (Fig. 2) corresponds to results of experimental researches of 30K5A1 sensor drift at working temperatures 150°C. The drift "with acceleration" (Fig. 3) corresponds to results of experimental researches of KMT-4 sensor drift at working temperature 120°C.

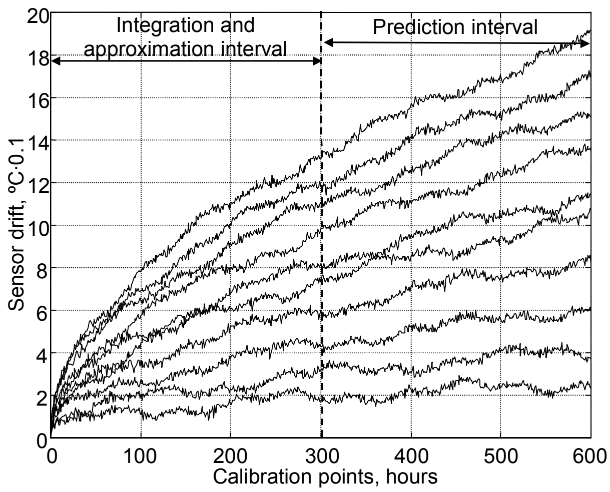

Fig. 2 - Mathematical model of sensor drift "with saturation"

There are researched the percentage errors of integration at the third calibration point (calibration point b), because the first calibration at the moment 0 allows to correct initial sensor error and the second calibration at the moment a allows to receive real value xak of sensor drift (see Fig. 1). The single-layer perceptron model (described in Section 4) is used during modelling. The training time (for 10 curves) on the computer Pentium-III-600 for basis method of «historical» data integration and for advanced method of integration has made 3 and 1.6 min for sensor drift "with saturation" and 5 and 2 min for sensor drift "with acceleration" respectively. The average percentage error of data integration in calibration point *b* (corresponds to 200 hours on Fig. 2) has made 19% at usage of basis method and 10% at usage of advanced method for sensor drift "with saturation". The average percentage error of data integration in calibration point *b* (corresponds to 20 days on Fig. 3) has made 41% at usage of basis method and 15% at usage of advanced method for sensor drift "with acceleration". Therefore, the results of simulation modelling at the use simple single-layer perceptron allow to make conclusion, that advanced method of "historical" data integration allows to improve integration accuracy in 2-3 times in comparison with the basis method.

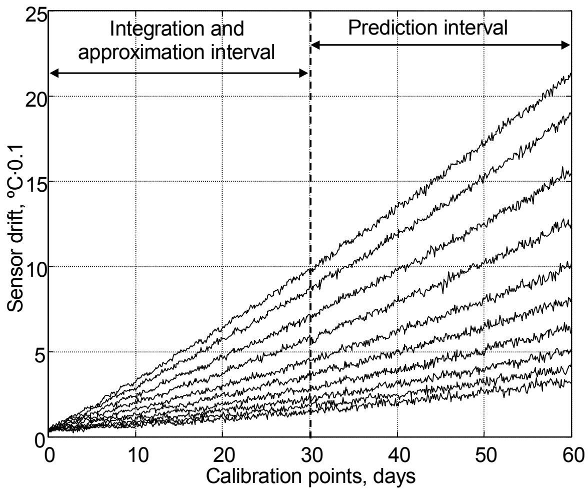

Fig. 3. Mathematical model of sensor drift "with acceleration"

6. CONCLUSION

The obtained experimental results confirm efficiency of proposed advanced method of historical data integration. This method can be used together with approximating and predicting neural networks in order to improve accuracy of sensor signal processing by permanent prediction of sensor drift at simultaneous increasing of inter-testing interval. The usage of proposed methods in intelligent data acquisition systems provides sharply reduction of error of physical quantity measurement, i.e. provides high system's adaptability to external exploitation conditions. These methods are implemented in the prototype of an Intelligent Sensing Instrumentation System (ISIS) within the project INTAS-OPEN-97-0606 [11-13], where neural networks training is fulfilled on the higher ISIS level and proper prediction is fulfilled on the middle level.

ACKNOWLEDGEMENT

The authors would like to thank European organisation INTAS for financial support of research, grant reference number INTAS-OPEN-97-0606.

REFERENCES

[1] Golovko V., Grandinetti L., Kochan V., Laopoulos T., Sachenko A., Turchenko V. Sensor Signal Processing Using Neural Networks. *Proceedings of IEEE Region 8 International Conference Africon'99*, Cape Town, South Africa, 1999, pp. 339-344.

[2] V.Golovko, J.Savitsky, A.Sachenko, V.Kochan, V.Turchenko, T.Laopoulos, L.Grandinetti. Intelligent System for Prediction of Sensor Drift. *Proceedings of the International Conference of Neural Networks and Artificial Intelligence ICNNAI'99,* Brest, Belarus, 1999, pp. 126-135.

[3] Brignell J. Digital compensation of sensors, *Scientific Instruments*, 20 (9), 1987, pp. 1097-1102.

[4] C.Alippi, A.Ferrero, V.Piuri. Artificial Intelligence for Instruments & Applications, *IEEE I&M Magazine*, Jun'98, pp. 9-17.

[5] P. Daponte, D. Grimaldi. Artificial Neural Networks in Measurements", *Measurement*, 23, 1998, pp. 93-115.

[6] A.Sachenko, V.Kochan, V.Turchenko. Sensor Drift Prediction Using Neural Networks. *Proceedings of the International Workshop on Virtual and Intelligent Measurement Systems VIMS'2000*, Annapolis, USA, 2000, pp. 88-92.

[7] A.Sachenko, V.Kochan, V.Turchenko, V.Golovko, J.Savitsky, A.Dunets, T. Laopoulos. Sensor Errors Prediction Using Neural Networks. *Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks IJCNN'2000*, Como, Italy, 2000, vol. IV, pp. 441-446.

[8] A.Sachenko, V.Kochan, V.Turchenko, V.Golovko, J.Savitsky, T. Laopoulos. Sensor Drift Prediction Using Neural Networks. *IEEE Transactions on Neural Networks*, submitted.

[9] A.Sachenko, V.Kochan, V.Turchenko, V.Tymchyshyn, N.Vasylkiv. Intelligent Nodes for Distributed Sensor Network. *Proceedings of 16th IEEE Instrumentation and Measurement Technology Conference IMTC/99*, Venice, Italy, 1999, pp. 1479-1484.

[10] Widrow B., Hoff M. Adaptive Switching Circuits. In 1960 IRE WESCON Conv. Record, *DUNNO*, 1960, pp.96-104.

[11] A.Sachenko, V.Kochan, V.Turchenko. Intelligent Distributed Sensor Network. *Proceedings of 15th IEEE Instrumentation and Measurement Technology Conference IMTC/98,* St. Paul, USA, 1998, pp. 60-66.

[12] A.Sachenko, V.Kochan, V.Turchenko, T.Laopoulos, V.Golovko, L.Grandinetti. Features of Intelligent Distributed Sensor Network Higher Level Development. *17th IEEE Instrumentation and Measurement Technology Conference IMTC/2000*, Baltimore, USA, 2000, pp. 335-340.

[13] V.Golovko, L.Grandinetti, V.Kochan, T.Laopoulos, A.Sachenko, V.Turchenko, V.Tymchyshyn. Approach of an Intelligent Sensing Instrumentation Structure Development. *Proceedings of IEEE International Workshop on Intelligent Signal Processing*, Budapest, Hungary, 1999, pp. 336-341.