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Error Compensation in an Intelligent Sensing Instrumentation System

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Abstract* - Methods of improving the measurement accuracy by estimation and correction of the maximum error components, are analyzed in this paper. The functional structure of the measurement channel in an Intelligent Sensing Instrumentation System (ISIS) is described along with the procedures of component error correction. An experimental setup, implementing such methods in a multi-processing neural network configuration is presented.

***Keywords* – Intelligent instrumentation, error correction, measurement evaluation, distributed and hierarchical measurement systems**

I. INTRODUCTION

The problem of improving the accuracy of measurement of physical quantities remains open in many cases, despite the vast variety of modern sensors. The problem becomes important when either the sensor or the measurement method cannot offer inherently, the desired resolution and accuracy. Yet, this is the most usual case in many applications. The problem of inaccuracy is then associated with the dominating error of the measurement channel [1], which may be described as sensing error. While a number of research efforts [2, 3] is devoted to sensor error correction, and the availability of low cost micro-controllers (as implementation tools), such features are still a research subject and have not been incorporated in most high-quality measurement units. Only certain automated systems [4] provide the facility of calibration of the measurement channel for a particular type of sensor. The main principles of developing a hierarchical, distributed, Intelligent Sensing Instrumentation System (ISIS) were considered in other previous publications of the same team [5-9]. Automated sensor error correction based on calibrations or self-testing is provided in ISIS. The proposed system includes a structure for the prediction of sensor drift using neural networks, in order to implement an effective, generalized, and realistic (in terms of cost and complexity) error compensation procedure. The desired goal is to develop a system self-adaptable to the sensor operating conditions by self-training. Different parts of this complex system have been previously examined: the structure of the Intelligent Node (IN) as a basic ISIS element, the capabilities of a self-modified procedure implemented by remote reprogramming, and the capabilities of parallel operations at different hierarchical levels of data processing. The IN allows ease of changing algorithms for sensor signal processing (including error correction algorithms), by using the "remote reprogramming mode". At the same time there are sufficient computing resources at each IN, which permit the use of previously trained neural networks for sensor drift correction. This procedure is shown to increase its efficiency [8]. This paper is presenting a detailed analysis of all error components (i.e. sensors and other elements of the measurement channel), and a description of the method of operation of the system developed. This system is thought as a generalized implementation of an intelligent sensing structure in the sense of incorporating advanced error correction and measurements evaluation procedures.

II. FUNCTIONAL STRUCTURE OF ISIS MEASUREMENT CHANNEL

It is obvious, that the intelligent functions require significant computing resources. Therefore it is more expedient to build an intelligent sensing system as a multilevel hierarchical structure, where each level implements particular functions and the overall system has intelligence as a whole [9]. In this type of structure, the data received from each sensor are processed at an intermediate level and only the “useful” information is forwarded to the users of measurement information. These "users" are located in the higher hierarchical level, implementing thus a data reduction scheme. The important problem in such systems is the optimal separation of the functions to be performed at each level. This procedure is based on the requirement for measurement quality (minimal error) with maximal effectiveness and rational usage of measuring and computing equipment.

The ISIS structure is considered to be implemented at three different levels of measurement information processing:

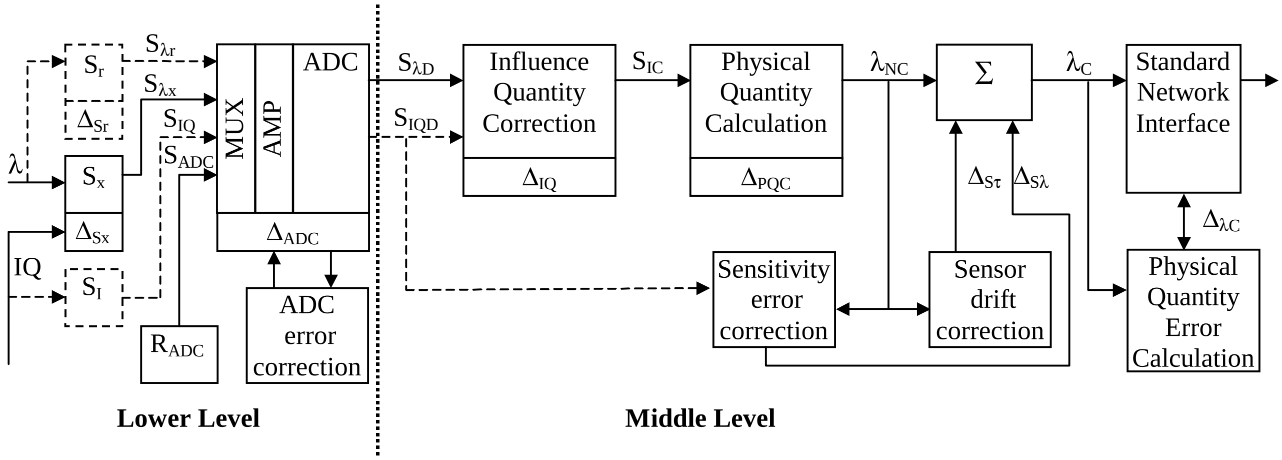
- The lower level (with multiple-inputs measurement modules) provides sensor signal conversion into a digital code, and, in most cases, simple calculations. The processing algorithms typically are implemented by a microcontroller.
- The middle level (Intelligent Nodes - IN) provides the majority of intelligent functions in relation to

measurement process formulated as calculations and logical (usually non-linear) operations.

- The higher level (central computer) supervises proper functioning of all ISIS elements, controls the self-modification procedure of the processing algorithms, and handles the data storage.

The main feature of proposed ISIS structure is this distribution of intelligent “treatment” of data to different levels (permanent prediction of correction factor, of the error elements of the measurement channel, and correction of current measurement results using individual mathematical models). Neural networks are used mainly in the representation of the individual mathematical models of each sensor's error. The ISIS central computer trains neural network models using calibration or testing results, and modifies the IN software if needed. All real-time processing of sensors' signals is completed at the lower and middle ISIS levels. Thus, the IN transmits the physical quantity measurement results with allowable error as reply to the request from the users of information on the higher ISIS level.

The functional structure of ISIS measurement channel is presented in Fig. 1, where the lower and middle ISIS levels are considered. The lower level is presented as minimum set of hardware blocks providing sensor signal conversion to code. If correction of systematic ADC error could be executed under rigid algorithms, then it is rational to implement these algorithms into lower ISIS level using proper microcontroller or embedded microprocessor. Otherwise ADC error correction is expedient to transfer to the middle ISIS level.



λ	– Physical Quantity
IQ	– Influence Quantity
S_r	– Reference Sensor of Physical Quantity
Δ_{Sr}	– Reference Sensor Error
S_x	– Sensor of Physical Quantity
Δ_{Sx}	– Sensor Error
S_I	– Sensor of Influence Quantity
$S_{\lambda r}$	– Reference Sensor Signal
$S_{\lambda x}$	– Sensor Signal of Physical Quantity
S_{IQ}	– Sensor Signal of Influence Quantity
S_{ADC}	– Signal of Reference Source
R_{ADC}	– Reference Source
Δ_{ADC}	– Residual ADC Error

MUX	– Multiplexer
AMP	– Amplifier
ADC	– Analog-to-Digital Converter
$S_{\lambda D}$	– Digital Code of S_λ
S_{IQD}	– Digital Code of S_{IQ}
Δ_{IQ}	– Residual Error of Influence Quantity Correction
S_{IC}	– Corrected S_λ
Δ_{PQC}	– Residual Error of Physical Quantity Calculation
λ_{NC}	– No Corrected Physical Quantity
λ_C	– Corrected Physical Quantity
$\Delta_{S\lambda}$	– Sensitivity and Offset Error
$\Delta_{S\tau}$	– Sensor Drift
$\Delta_{\lambda C}$	– Current Value of λ_C Residual Error

Fig. 1. General structure of ISIS measurement channel (lower and middle levels)

III. SENSOR ERROR CORRECTION PROCEDURES

The middle ISIS level is presented as software blocks (procedures) providing calculation of measured physical quantity, and error correction of practically all predictable elements of the measurement channel. Such implementation of sensor signal processing procedures is possible using IN remote reprogramming [7], and provides maximum adaptability and universality of ISIS operation [9].

Usually, the first correction procedure is correction of the influence quantity error (see Fig. 1). These errors have a direct influence on a sensor signal (the cold junction temperature of a thermocouple, the working current of an RTD, etc) and could be evaluated using the additional channels. It is possible to use simple neural networks for correction of the influence quantity error if correction function is nonlinear. Fig. 2 represents the dependence between approximation error of cold junction and number of single layer perceptron inputs for widely used thermocouples.

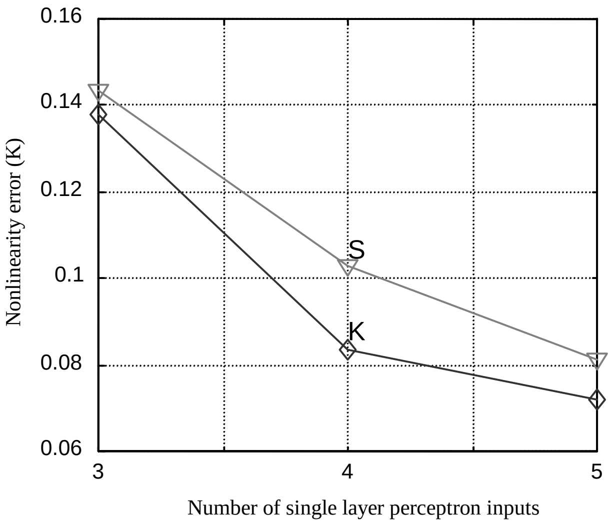


Fig. 2. The cold junction approximation error

A significant number of sensors have nonlinear conversion characteristic, therefore the calculation of the output value is based on a nonlinear transformation. The linearization process of the sensor input/output (I/O) characteristic is performed by a single-layer perceptron scheme, with large number of inputs (Fig. 3) or by a multi-layer neural network. However, it is estimated that a 5- to 7-inputs single-layer perceptron (Fig. 4) is enough for an accurate transformation to a linear I/O characteristic.

The error of each type of sensors may be divided in two error components: the initial component (sensitivity and offset error) and drift. The initial component usually has a nonlinear character and can be corrected (by initial testing or calibration results) using neural networks as in the case of influence quantity error. Correction of drift error is more complicated, because it has individual random components. The use of neural networks offers a better prediction, which could be adapted to the individual features of each sensor drift [7].

The periodic sensor testing/calibration provides the correction of the mathematical model of prediction process. Note that neural network training is performed at the higher level of ISIS, while correction factor calculation is performed at the middle level. It is necessary to use multi-layer perceptron or recurrent neural network because of the complicated prediction process. Thus, the neural network calculations requirements determine the computing power needed at the middle level of ISIS. For example, the AT89C51 microcontroller used at the middle level is capable of processing signals, in real-time mode, for a small number only, of slow response sensors. The computing power of this microcontroller becomes inadequate when employing a certain number of measurement channels or high-speed sensors.

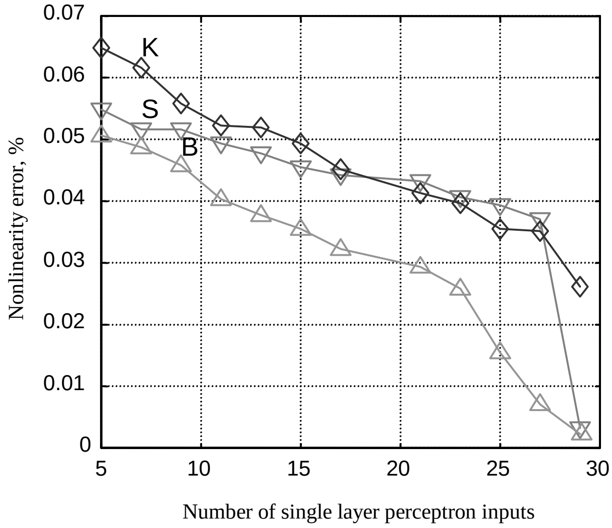


Fig. 3. The nonlinearity error by approximation of thermocouple I/O characteristic

The use of a specialized controller for neural network calculations (of the same type microcontroller [10]) is more effective and economical solution in that case.

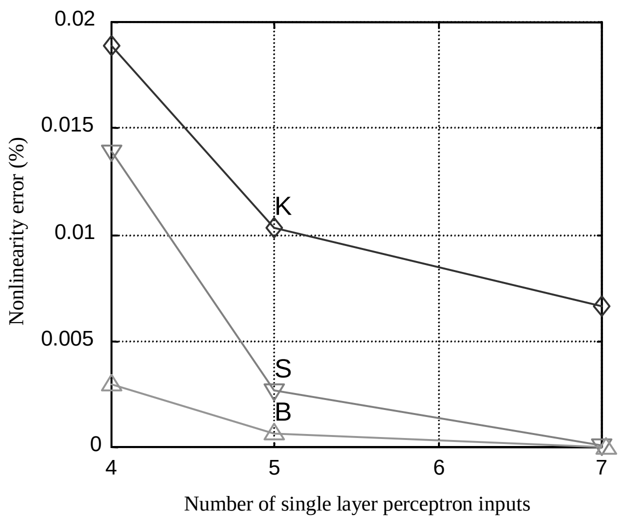


Fig. 4. The nonlinearity error by approximation of the nonlinearity component only of thermocouple I/O characteristic

The lack of data about sensor drift at initial sensor exploitation period is one of the main problems for sensor drift prediction using neural networks. It is necessary to have 30 to 50 values of real drifting effect, for accurate neural network training. Periodic testing or calibration allows gathering the appropriate amount of data, but requires a certain cost and long time (which is commensurable with sensor lifetime). A different prediction method has been proposed [6] for solution of this problem, based on "historical" data, which are the results of testing or calibration for the same type sensors in the similar operating conditions. The cooperation of different types of neural networks has been proposed for this implementation (Fig. 5). This cooperation increases artificially the size of Predicting Neural Network (PNN) training set. This technique provides interaction of the set of Integrating Historical Data Neural Networks (IHDNN) with Approximating Neural Network (ANN) and PNN.

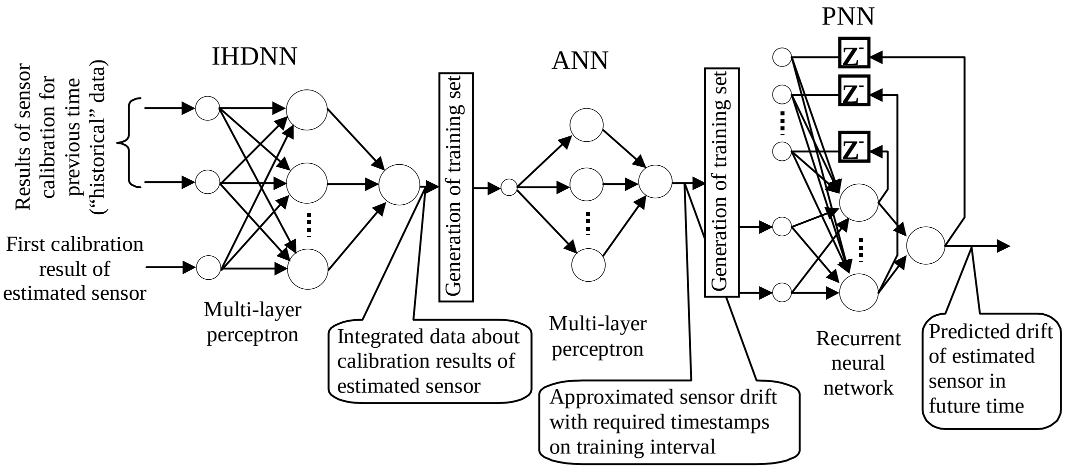


Fig. 5. Combination of Integrating Historical Data Neural Network (IHDNN), Approximating Neural Network (ANN) and Predicting Neural Network (PNN) for Error Compensation in ISIS

The number of IHDNNs must correspond to the number of sensor testing (or calibration) during the acquisition of the "historical" data. The set of IHDNNs is trained on "historical data" of sensor drift. During every cycle of IHDNN training one of the "historical"-data-curves is simulating the sensor real data curve. The IHDNN, which was previously trained on the first calibration results from "historical" data, is now used for drift prediction of estimated sensor at the time of the second calibration. The next IHDNN is then using this value for drift prediction of the same sensor at the time of the third calibration, etc. The output of integration on the "historical" data is then driven to the ANN input. The ANN generates an extended training set for PNN. The ANN and the PNN structures are used for the individual prediction of sensor drift during the normal operation at the middle ISIS level. ANN is used within the initial time of sensor operation (during the validation time of "historical" data). PNN is used after that. The remote reprogramming mode of the "Intelligent Node" is then used for the transfer of the new (working) model of neural network to the middle ISIS level.

It is certainly difficult to obtain actual drift information for the particular type of sensors under specific operating conditions, which could be used in the evaluation of the proposed methods. Therefore the experimental verification was performed by simulation of the sensor drift. It is necessary to note that the valid parameters of sensor drift process are unknown during simulation. It is possible to define the drift parameters only with limited accuracy (during calibration or testing), which then gives an additional error of drift correction. Therefore, one should consider the general mathematical model of sensor drift in order to evaluate the proposed method.

The sensor drift is considered as a set of separate, second-order, non-stationary, random figures. The general trend of these figures can be characterized by curves "with saturation" (drift velocity decreases during exploitation time). Such curves can be simulated by expression $y = \sqrt{x}$. It is necessary to receive a set of curves, which describe non-stationary and irregular sensor drift at development phase of the generalized mathematical model. The mathematical model C_d will result as a set of j-curves, which are passing through the point of origin (since the offset factor C_1 is defined by the outcome of the first testing procedure). The separate realizations of curves C_d should deviate from the expected (average of distribution) curve in order to present the non-stationary behavior of the sensor drift. They may be simulated by the expression

$$y = (a + bn_j)x^n + cn_j x \qquad (1)$$

where $n_j = n_{j-1} + d \cdot j + e \cdot j \cdot randn$. The symbols a - l, which are used in (1) and in the following expressions (2, 3), are coefficients of mathematical model of sensor drift. The expression $randn$ is the random generator with the normal law of distribution. The drift velocity can change in relation to average value in real exploitation conditions. Hence it is possible to use a sinusoid expression with random change of phase from case to case

$$y = f\sin(gx + n_j)\,, \tag{2}$$

where f and g is the coefficients of mathematical model.

The model of sensor drift should also show the errors of obtain of drift values ΔC_d. At the same time the error of reference sensor includes systematic and random components. Systematic components have a constant value for each realization of drift curve. It can be also simulated by a sinusoidal curve with random changing of phase from case to case

$$y = h\sin(x + n_j)\,, \tag{3}$$

where h is the coefficient of mathematical model.

The random component of reference sensor error and truncation error Δ_{met} has a different value for each testing procedure. They may be simulated by random function with uniform law of distribution $k \cdot rand$. The measurement errors of signals of reference and tested sensors are the same in case of their connection to the same measuring channel. The effective methods of all components of measurement error reduction are usually applied in precision systems of physical quantity measurement. Therefore, the residual error has a random nature and a normal law of distribution. In this case the measurement error may be obtained by the expression $l \cdot randn$.

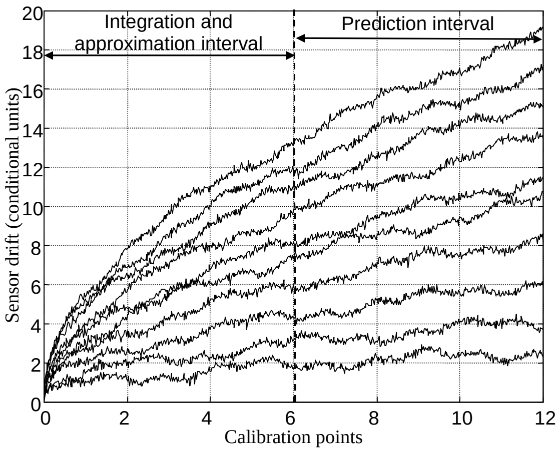


Fig. 6. Mathematical model of sensor drift "with saturation"

The general sensor drift is expressed as the sum of separate components, including (1-3). The following expression

$$\begin{aligned} y &= 0.2 + (0.1 + 0.2n_j)\sqrt{x/n_j} + 0.25\sin(0.3x + n_j) \\ &+ 0.2rand + 0.15\sin(x - n_j) + 0.1randn \end{aligned} \tag{4}$$

is used to generate 10 such curves of sensor drift (Fig. 6).
The coefficients of mathematical model of sensor drift (equation 4) are specially chosen so that the drift curves from Fig. 6 correspond (by form) to previously obtained results of experimental data from K-type thermocouples drift at operation temperatures 1000-1100˚C into air electric furnaces. The main goal of this paper is to investigate the capabilities of the proposed methods, therefore interesting interval defines abscissa axis into the following figures. Similarly conditional units are shown at the axis of ordinates instead of certain values of sensor drift.

The mathematical model of sensor drift "with acceleration" (drift velocity increases during exploitation time) developed for evaluation purposes of the proposed methods. This model is used for generate 10 curves of sensor drift "with acceleration" (Fig. 7).

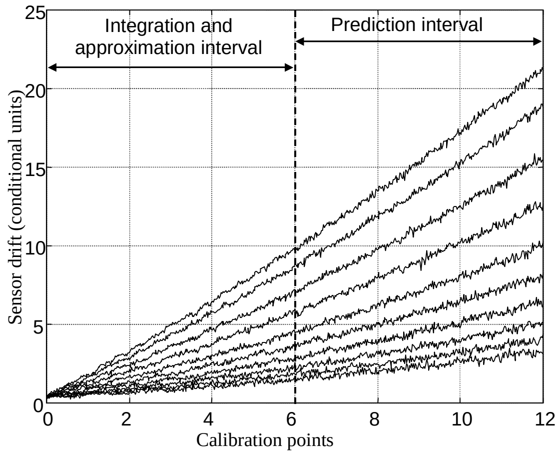


Fig. 7. Mathematical model of sensor drift "with acceleration"

Each IHDNN has 9 inputs for these 10 curves. The 6 independent IHDNNs were used for each calibration point from the integration interval (see Fig. 6, 7). The models of 9-input single-layer perceptron and multi-layer perceptron (9 input neurons, 9 neurons on a hidden layer with logistic function and one output linear neuron) are used as IHDNN. The IHDNN training is conducted up to different sum-square errors, while the average training time is from 12 sec. to 1.5 minutes for each curve. The average percentage of errors, on "historical" data integration procedure, has not exceeded 15%. It should be noted that the error of integration decreases in each following point of calibration. The results of 6-points-integration are used for ANN training and for each particular curve. The multi-layer perceptron model (1 input neurons, 5 neurons on the hidden layer with logistic function and one output linear neuron) is used as ANN [6]. The average percentage of approximation errors (total errors including integration error), has not exceeded 20% for sensor drift "with saturation", and 23% for sensor drift "with acceleration". The average percentage of approximation error has decreased to 8% and 7% accordingly at the end of training set (after 25-30 points). The 30 approximated points are used as training set for the predicting neural network. The model of recurrent neural network (10 input neurons, 10 neurons on the hidden layer with logistic function, 11 pseudo-neurons on the hidden level and one output linear neuron) is used as PNN [6]. The average and maximum percentage of prediction errors have not exceeded 9%, and 31% for sensor drift "with saturation" (Fig. 8), and 14% and 27% for sensor drift "with acceleration" (Fig. 9), respectively.

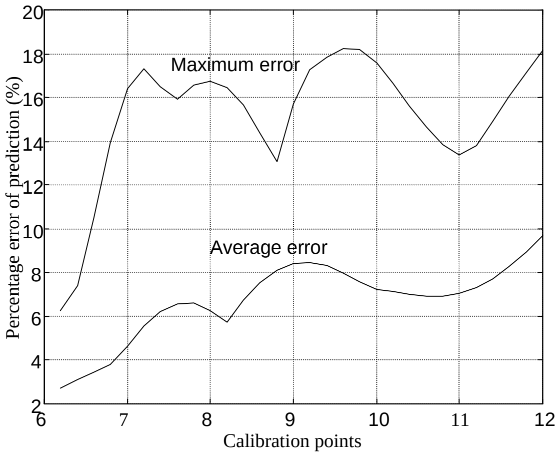


Fig. 8. The percentage error of prediction of sensor drift "with saturation"

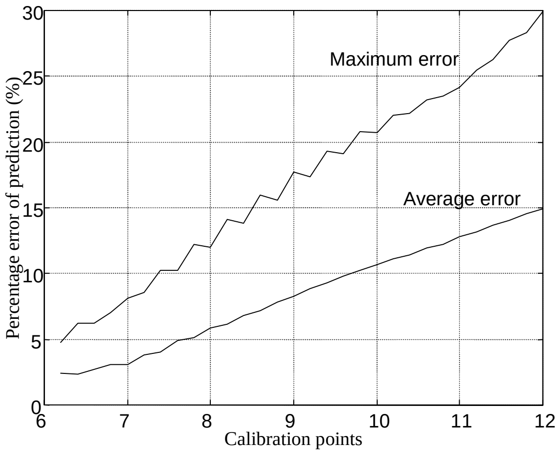


Fig. 9. The percentage error of prediction of sensor drift "with acceleration"

Thus, the results of simulation permit us to conclude, that the use of the “historical” data integration method, increases the inter-testing interval about 12 times. Under these conditions the average percentage prediction error is 9% (for sensor drift "with saturation") and 14% respectively (for sensor drift "with acceleration").

IV. CONCLUSIONS

The error analysis and automated correction procedure of a proposed Intelligent Sensing Instrumentation Structure (ISIS), is presented in this work. The ISIS measurement channel is thought to provide correction of systematic errors in precision intelligent measurement systems. Neural networks are used as a basic functional module for error correction, which allows a generalization of the software at the middle level intelligent node, while being compatible with the ISIS higher level software.

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