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USING ARTIFICIAL NEURAL NETWORKS TO REDUCE NONLINEARITY OF MEASURING DEVICES

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Abstract

The article discusses methods for reducing the impact of nonlinearity in the transformation function of measurement devices on the accuracy of measurement results by applying an additional correction device that implements a dependency that is inverse to the transformation function. The aim of the research is to explore the possibilities of using artificial neural networks, specifically multilayer perceptrons and radial basis function networks, as such correctors. The effectiveness of the proposed correction methods for the transformation function has been investigated through simulation computer modeling, examining the impact of the type of nonlinearity on the quality of such correction. A comparative analysis was carried out with traditional approaches, specifically a corrector based on polynomial approximation. The simulation results indicate that the accuracy of neural network correctors is comparable to that of polynomial correctors, and in some cases, even superior. This opens up prospects for a broader application of such modern measurement data processing methods as artificial neural networks in measurement technology.

Keywords: nonlinearity, correction, transformation function, artificial neural network, multilayer perceptron, radial basis neural network, training.

1. Introduction

The last few decades have been marked by the rapid development of information technologies, which have radically and fundamentally changed not only the usual way of human life but also entire sectors of the economy in most developed countries of the world. An undeniable achievement of scientific thought has been the successes in the development of artificial intelligence. Research in the field of artificial neural networks, deep learning, and fuzzy systems has enabled the implementation of quite complex methods of mathematical processing and analysis of large data sets, as well as solving a number of classification, optimization, management, pattern recognition, identification, approximation of complex nonlinear dependencies, diagnostics, and other tasks.

The field of measurements and measurement technology is also not left behind and is actively trying to utilize more effective methods of information processing that will enhance the accuracy and reliability of measurement results. The role of such methods becomes increasingly important with the complexity of measurements and the rising demands for their accuracy.

New directions in applied mathematics, such as the theory of artificial neural networks, interval analysis, robust and nonparametric statistics, fuzzy logic, wavelet analysis, and several others, provide a mathematical framework for solving those problems for which classical data processing methods are ineffective. The development of new methods for processing measurement information is driven by the needs of modern measurement practice, which is characterized by the increasing complexity of measurement tasks and measurement devices.

The expansion of data processing capabilities and measurement results is closely related to the development of measurement methodology, the improvement of mathematical methods, as well as the widespread implementation of computing technology in the measurement chain, including microcontrollers.

2. Problem Statement

For a measuring instrument, one of the most important are the metrological characteristics that affect the measurement result and the accuracy of this result. One such characteristic is the nominal static transformation function of the measuring device (other names include transformation equation, calibration characteristic). It establishes the dependence $y = F(x)$ of the informative parameter of the output signal y from the value of the informative parameter of the input signal x.

Usually, the transformation function is required to be linear within the working measurement range. However, quite often when solving practical measurement problems, one has to deal with measuring devices that have a nonlinear transformation function. For example, analog electronic megohmmeters in the mode of measuring high resistances (units and tens of megohms) have a reverse non-uniform scale. The sensitivity of the device in different sections of such a scale will vary, which is not entirely convenient both when taking readings and when assessing the measurement result's error. Individual elements of the measuring circuit, such as semiconductor thermistors or diodes, also have significantly nonlinear operating characteristics, which affects the transformation function of the device. Sometimes, it is possible to approximate the transformation function to a linear one using circuit design solutions, but this is not always the case.

Typically, in practice, the transformation function is approximated by a linear dependence $\hat{y} = a + bx$, the unknown coefficients a and b are found using the least squares method. However, in cases where the nonlinearity of the transformation function is significant, such an approach does not yield the desired results, as a large systematic error arises due to the deviation of the nominal transformation function from the actual one (Fig. 1).

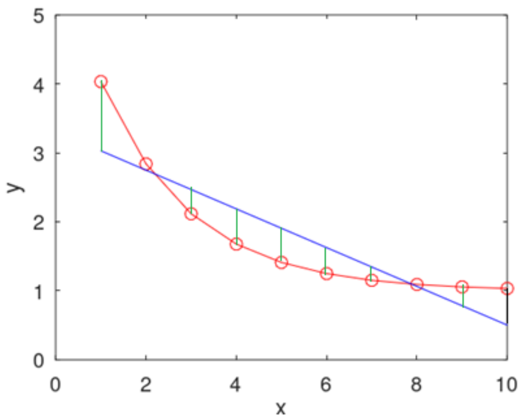

Fig. 1. Linearization errors of the transformation function

To reduce this error, one can attempt to convert the nonlinear function $y = F(x)$ into a linear form $\tilde{y} = a + b\tilde{x}$ by changing the variables

$$\tilde{y} = \varphi(y), \quad \tilde{x} = \psi(x)$$

with subsequent determination of the coefficients a and b of the linear function using the least squares method [1]. However, in this case, it is necessary to know in advance what the nonlinear transformation function looks like, that is, to have prior information about the structure of the mathematical model of the measurement device. The justified choice of the type of this nonlinear dependence is quite a complex task, which is poorly amenable to formalization and is carried out based on known physical laws or the personal experience of the specialist solving the problem.

One of the well-known approaches to reducing the impact of the nonlinearity of the transformation function on the measurement result error, which can be considered universal, is the algorithmic correction of the transformation function. A special correction device is connected in series with the measuring instrument, which performs the inverse transformation with respect to its characteristic $\hat{x} = F^{-1}(y)$. As a result of such correction, we obtain an estimate $\hat{x}$ of the input signal (measured quantity) x, and the resulting transformation function becomes linear. An important additional condition is the invariance of such a converter to the form of the nonlinear function being corrected, that is, the ability to adapt to any transformation function.

The aim of this article is to investigate an adaptive system for correcting the transformation function of a measurement device, which will utilize an artificial neural network as a correction device and ensure the linearity of the transformation function across the entire range of possible values of the measured input quantity.

3. Correction of the transformation function using an artificial neural network

Artificial neural networks (ANN) are computational structures built on the principles of biological neural networks formed by the cells of the brains of living organisms. A distinctive feature of ANNs is their ability to learn, which has made them a priority area of research in the field of artificial intelligence. The theory of ANNs has been rapidly developing in recent years, contributing to an increased interest in their application across various fields of science, technology, economics, medicine, military affairs, and more. Due to properties such as high reliability of operation, noise immunity, ability to generalize, and the possibility of implementing complex multidimensional mappings, neural networks are widely used for pattern recognition and classification, decision-making and control, optimization, function approximation, forecasting, filtering, and memory organization [2-5].

Considering the aforementioned features of ANNs, particularly its ability to serve as a universal approximator of complex nonlinear dependencies, it is most appropriate to use a neural network as a correction device, as demonstrated in a number of studies [6-10]. Figure 2 shows the structure of such an adaptive correction system for the transformation function of the measurement device. The effect of internal and external random factors on the measurement process is represented by additive noise $\xi(t)$ at the output of the measuring device, where t – current time. The output signal $y(t)$ is fed into the correction neural network, which performs the inverse transformation and generates an estimate of the input signal (measured quantity) $\hat{x}(t)$.

The training algorithm adjusts the synaptic weight coefficients of the neural network in such a way as to ensure the best approximation of its output signal $\hat{x}(t)$ to the known value of the input signal $x(t)$. In this process, the mean squared error of the correction $e(t) = x(t) - \hat{x}(t)$ is minimized using one of the known gradient optimization procedures.

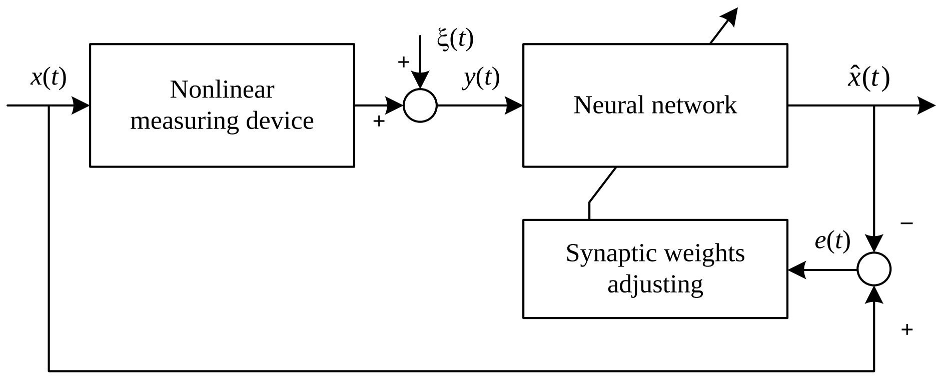

Fig. 2. Structure of the adaptive system for correcting the nonlinearity of the transformation function of the measuring device

4. Correction device based on a multilayer perceptron

A multilayer feedforward neural network, or multilayer perceptron (MLP), consists of several layers of formal neurons connected in sequence: an input layer, hidden layers, and an output layer (see Fig. 3). Neurons within the same layer are not connected to each other; the outputs of the neurons in the *n*-th layer are fed into the inputs of the neurons in the next $n+1$- th layer. The input vector signal is fed into the inputs of the neurons in the first layer, and the output signals of the last layer form the output vector signal of the network. The configuration of MLP is determined by the number of layers, the number of neurons in each layer, and the activation functions of the neurons. Training involves adjusting the connection weights between neurons in such a way as to ensure the required values of the output signals of the network. During the training process, a multilayer neural network is capable of identifying complex dependencies between input and output signals and performing generalization. When using the supervised learning, the dataset on which the neural network is trained must be labeled or marked, meaning it should contain the correct answers (outputs of the neural network) for each input sample of the training sequence.

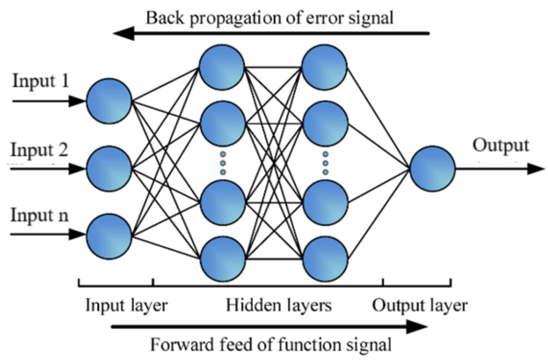

Fig. 3. Multilayer perceptron

It is proposed to implement a device for correcting the nonlinearity of the transformation function of the measurement device based on a three-layer perceptron, the structure of which is shown in Fig. 4.

The output layer of the perceptron consists of one neuron that generates the signal $\hat{x}$ as a weighted sum of the output signals of the neurons in the hidden layer

$$\hat{x} = \sum_{j=1}^{n} V_j O_j, \tag{1}$$

where O_j is the output signal of the *j*-th neuron in the hidden layer; V_j is the synaptic weight of the *j*-th input of the output layer neuron; *n* is the number of neurons in the hidden layer.

The hidden layer of the MLP is formed by neurons with sigmoid activation functions. Each neuron of this layer is described by the following equations

$$O_j = \frac{1}{1+e^{-S_j}},$$

$$S_j = \sum_{i=1}^{m} W_{ij} O_i,$$

where O_i is the output signal of the *i*-th neuron in the input layer; W_{ij} is the synaptic weight of the *i*-th input of the *j*-th neuron in the hidden layer; *m* is the number of neurons in the input layer.

The input layer of neurons is formed by the input signals of the neural network, which in the context of the problem under consideration are the output signal of the measuring device *y* and a constant signal equal to one, introduced to account for the constant offset.

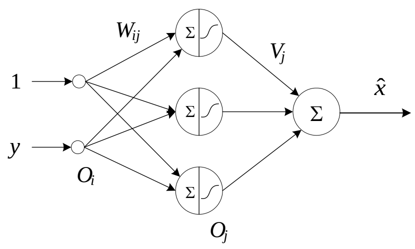

Fig. 4. MLP-corrector

MLP training is based on minimizing the mean squared error

$$E = \frac{1}{2}\sum_{k=1}^{N} e^2(k) = \frac{1}{2}\sum_{k=1}^{N}\left(x(k) - \hat{x}(k)\right)^2 \tag{2}$$

by adjusting the synaptic weight coefficients of neurons using gradient methods. The two most popular learning algorithms are:

– back propagation;

– Levenberg-Marquardt algorithm, which is a combination of the Gauss-Newton method and the gradient descent method.

In our case, it is more appropriate to use the Levenberg-Marquardt algorithm for training the MLP, as it has a higher convergence speed compared to other gradient optimization methods.

The dataset for the training procedure of the correction neural network will consist of pairs of values

$\{<y(1), x(1)>, <y(2), x(2)> \dots <y(N), x(N)>\}$,

obtained during the calibration of the measurement device by applying a reference signal $x(k)$ and receiving the corresponding output signal value $y(k)$.

5. Correction device based on radial basis function neural network

Another universal approximator of complex functional dependencies is the radial basis function neural network (RBFN). The architecture of such a network consists of three layers: an input layer, which receives the vector of input signals; a hidden layer, composed of radial-type neurons; and an output layer, which forms a weighted linear combination of the outputs of the hidden layer neurons (Fig. 5).

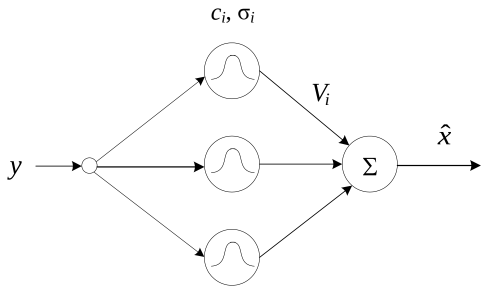

Fig. 5. RBFN- corrector

If the Gaussian function is used as the activation function of the hidden layer neurons, then the equation of such a transformer will have the form

$$\hat{x} = \sum_{i=1}^{n} V_i \exp\left(-\frac{(y-c_i)^2}{2\sigma_i^2}\right), \qquad (3)$$

where c_i is the center of the i-th basis function, and σ_i is its radius (width). The training of RBFN involves determining the linear weight coefficients V_i of the output neuron, centers c_i and widths σ_i hidden layer neurons. In this case, the following options are possible:

1) fixed values for the centers and widths of the hidden layer neurons are set, and the weight coefficients of the output neuron are determined through training;

2) the centers and widths are determined through self-learning (most often using clustering methods), and then the weights of the output neuron are adjusted to minimize the objective function (2);

3) all network parameters are determined using supervised learning.

6. Results of experimental studies

To study the properties of the proposed neural network systems for correcting the transformation functions of measurement devices, computer modeling was performed in the MATLAB environment using the Neural Network Toolbox. During the modeling process, the influence of the type of nonlinearity on the quality of the correction of the transformation function was investigated, while the following types of functions were used for modeling the nonlinear measurement device [1]:

1) sinusoidal $y = \sin(ax + b)$;

2) power $y = ax^b$;

3) hyperbolic $y = a + b/x$;

4) fractional-linear I $y = \frac{1}{a + bx}$;

5) fractional-linear II $y = \frac{cx}{a + bx}$;

6) exponential I $y = ae^{bx}$;

7) exponential II $y = ae^{b/x}$;

8) logarithmic I $y = a + b\ln x$;

9) logarithmic II $y = a + b/\ln x$.

Additive noise at the output of the measurement device was modeled as a Gaussian random process with a zero mean and a standard deviation of 0.005. The quality of the correction was assessed by the root mean square deviation of the corrected signal estimate from its true value

$$s = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}\left(x(k) - \hat{x}(k)\right)^2}. \qquad (4)$$

For comparison, modeling of a similar correction system for the transformation function based on a 5th degree polynomial approximator was carried out. The modeling results are presented in Figures 6-11 and in Table 1.

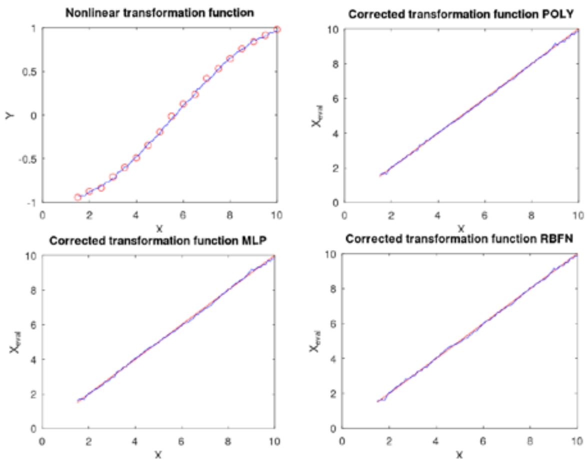

Fig. 6. Correction of the sinusoidal transformation function

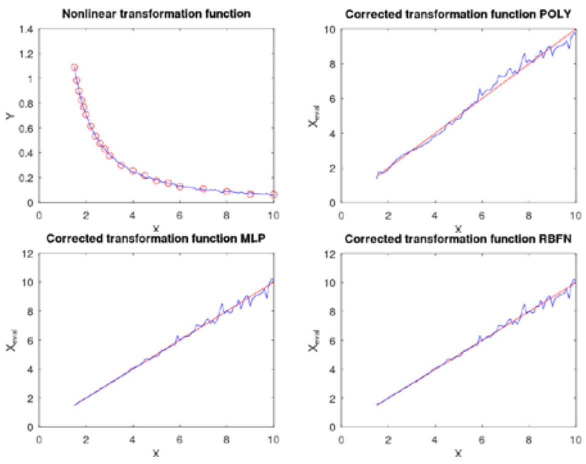

Fig. 7. Correction of the power transformation function

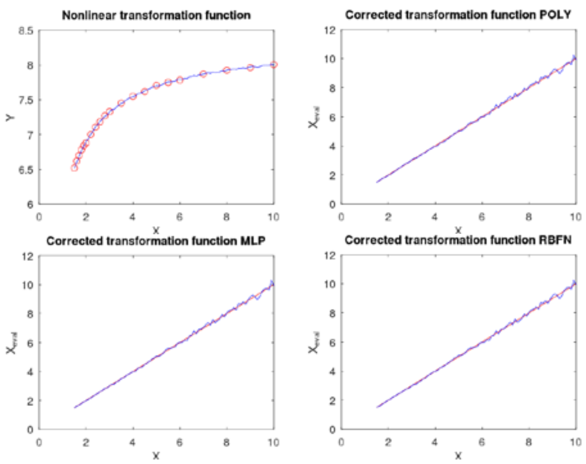

Fig. 8. Correction of the fractional-linear II transformation function

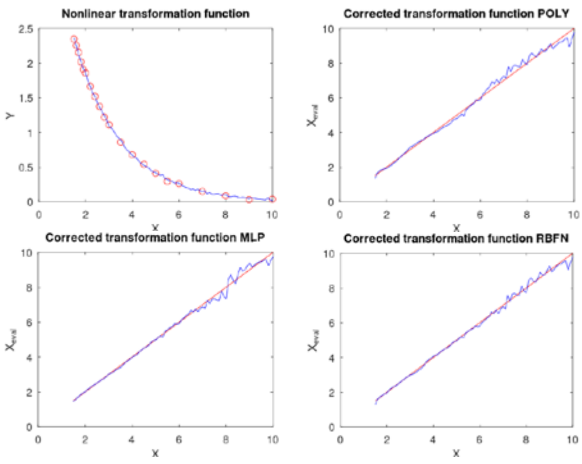

Fig. 9. Correction of the exponential I transformation function

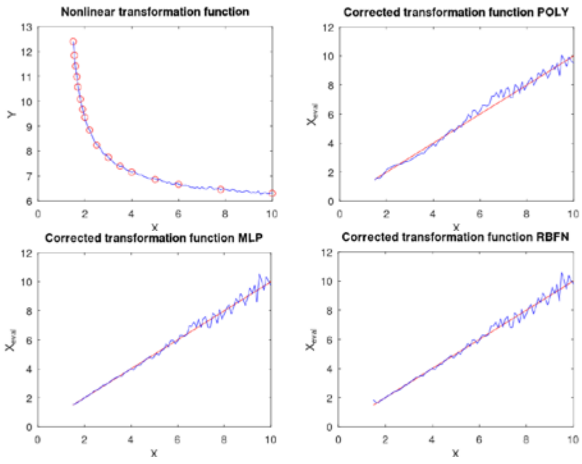

Fig. 10. Correction of the logarithmic II transformation function

Table 1 – Root mean square error of correction for various nonlinear functions and correctors

Function	Formula	Root mean square correction error		
		POLY	MLP	RBFN
1. Sinusoidal	$y=\sin(0{,}3x-1{,}7)$	0,0615	0,0752	0,0700
2. Power	$y=2\cdot x^{-1{,}5}$	0,2621	0,1992	0,1983
3. Hyperbolic	$y=5+3/x$	0,1360	0,1374	0,1414
4. Fractional-linear I	$y=\frac{1}{0{,}05+0{,}1x}$	0,0974	0,0985	0,1016
5. Fractional-linear II	$y=\frac{10x}{0{,}5+1{,}2x}$	0,1076	0,1061	0,1053
6. Exponential I	$y=5\cdot e^{-0{,}5\cdot x}$	0,2160	0,1870	0,1611
7. Exponential II	$y=5\cdot e^{0{,}5/x}$	0,1780	0,1727	0,1590
8. Logarithmic I	$y=5+3\cdot\ln x$	0,0704	0,0715	0,0911
9. Logarithmic II	$y=5+3/\ln x$	0,3099	0,2814	0,2849

The points of the training sample are marked with circles on the graph of the function.

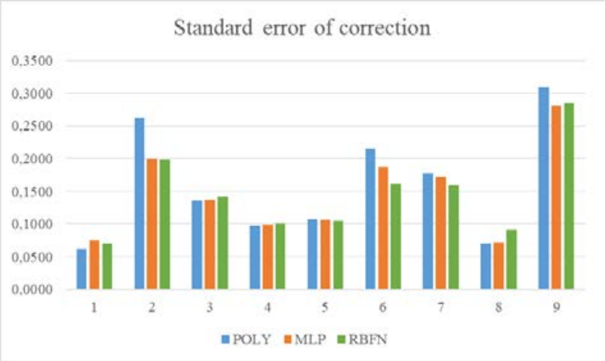

Fig. 11. Correction errors

7. Conclusions

The analysis of the simulation results presented in Figs. 6-11 and in Table 1 indicates that the proposed neural network system for correcting the nonlinearity of the transformation function of the measurement device based on MLP and RBFN is suitable for correcting a fairly wide class of nonlinear transformation functions encountered in measurement tasks. Comparison of the characteristics of neural network correctors and a similar system based on a polynomial approximator shows that the root mean square error of correction for some types of nonlinear transformation functions differs insignificantly between traditional and neural network correctors, while for others, the neural network approach demonstrates better results.

From this, it can be concluded that the simulation results fully confirm the operability of the proposed adaptive system for correcting the nonlinearity of transformation functions based on ANN and are consistent with theoretical assumptions. The advantage of the proposed approach is the invariance of neural network correctors to the type of nonlinear characteristic of the measurement device and the ability to synthesize such systems through training, without involving complex design methods. This significantly expands the application possibilities of such systems in metrological practice, particularly in the channels of information-measurement systems, where it is quite straightforward to implement methods of digital processing of measurement information.

The use of the proposed correction based on a neural network approach will significantly reduce the systematic measurement error caused by the discrepancy between the nominal and actual transformation functions of the measurement device.

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Використання штучних нейронних мереж для зменшення нелінійності вимірювальних пристроїв

С.М. Авакін, С.О. Довгополий, І.О. Мощенко, О.В. Запорожець

Анотація

У статті розглянуто методи зменшення впливу нелінійності функції перетворення вимірювальних приладів на точність результатів вимірювань шляхом застосування додаткового пристрою корекції, що реалізує залежність, обернену до функції перетворення. Метою дослідження є вивчення можливостей використання в якості таких коректорів штучних нейронних мереж, зокрема багатошарових персептронів і мереж радіальних базисних функцій. Ефективність запропонованих методів корекції функції перетворення досліджено шляхом імітаційного комп'ютерного моделювання з вивченням впливу типу нелінійності на якість такої корекції. Здійснено порівняльний аналіз з традиційними підходами, зокрема коректором на основі поліноміальної апроксимації. Результати моделювання показують, що точність нейромережевих коректорів порівнянна з точністю поліноміальних коректорів, а в деяких випадках навіть перевершує їх. Це відкриває перспективи ширшого застосування у вимірювальній техніці таких сучасних методів обробки вимірювальної інформації, як штучні нейронні мережі.

Ключові слова: нелінійність, корекція, функція перетворення, штучна нейронна мережа, багатошаровий перцептрон, радіальна базисна нейронна мережа, навчання.

