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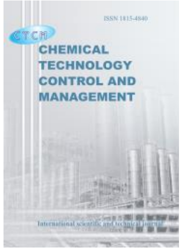

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USE OF NEURAL NETWORKS IN INTELLIGENT MEASUREMENT TOOLS

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Abstract: *The paper presents algorithms for processing the measurement signal with the possibilities of adaptation, learning and decision making. A comparative analysis of the methods of intellectual processing of measurement data is carried out. A model of a measuring instrument for determining the structure of a neural network has been developed. The problem of error reduction due to measurement noise filtering with the use of neural networks is considered. The structure of the neural network has been developed for intelligent processing of the measurement signal and ensuring the implementation of the functions of reconfiguration, calibration, self-diagnosis and self-control. A neural network training algorithm based on error back propagation was used. The results of the implementation of the neural network algorithm in measuring instruments with different training patterns are presented. The paper also describes the calibration of linear and non-linear smart sensors. The results of the study show that the proposed algorithm improves the quality of measurement of technological parameters.*
Keywords: *intelligent measuring instruments, measurement data processing, neural network, measurement errors, neural network training algorithms, calibration, adaptation of measuring instruments.*

Annotasiya. *O‘lchash signalini qayta ishlashning moslashish, o‘qitish va qaror qabul qilish imkoniyatlariga ega bo‘lgan algoritmlari keltirilgan. O‘lchash ma’lumotlarini intellektual qayta ishlash usullarini qiyosiy tahlil qilish amalga oshirilgan. O‘lchash vositasining neyron tarmog'i strukturasini aniqlash usullari ko‘rib chiqilgan. Neyron tarmoqlaridan foydalangan holda o‘lchash shovqinlarini filtrlash orqali xatoliklarni kamaytirish masalasi ko‘rib chiqilgan. O‘lchash signaliga intellektual ishlov berish hamda qayta konfiguratsiyalash, kalibrlash, o‘z-o‘zini diagnostika qilish va o‘zini o‘zi nazorat qilish funksiyalarini amalga oshirishni ta’minlaydigan neyron tarmog'ining strukturasi ishlab chiqilgan. Xatolikni teskari tarqalishi asosida neyron tarmog‘ini o‘qitish algoritmidan foydalanilgan. Turli xil o'qitish shablonlari bilan o‘lchash asboblarida neyron tarmoq algoritmini amalga oshirish natijalari keltirilgan. Shuningdek, maqolada chiziqli va nochiziqli intellektual datchiklarni kalibrlash ham bayon qilingan. Tadqiqot natijalari, taklif etilayotgan algoritm texnologik parametrlarni o‘lchash sifatini yaxshilashini ko‘rsatadi.*
Tayanch so‘zlar: *intellektual o‘lchash vositalari, o‘lchash ma’lumotlariga ishlov berish, neyron tarmog‘i, o‘lchash xatoliklari, neyron tarmog‘ini o‘qitish algoritmlari, kalibrlash, o‘lchash vositalarini moslashtirish.*

Аннотация: *Приведены алгоритмы обработки сигналов измерения в задачах адаптации, обучения и принятия решений. Выполнен сопоставительный анализ методов интеллектуальной обработки измерительных сигналов. Рассмотрены методы определения структуры нейронной сети средств измерения средств. Рассмотрена задача уменьшения погрешностей за счёт фильтрации шумов измерения с использованием нейронных сетей. Разработана структура нейронной сети, для интеллектуальной обработки измерительных сигналов и обеспечения реализации функций реконфигурации, калибровки, самодиагностики и самоконтроля. Использован алгоритм обучения нейронной сети на основе обратного распространения ошибки. Приведены результаты внедрения алгоритма нейронной сети в средствах измерения с различными шаблонами обучения. В работе также описана калибровка линейных и нелинейных интеллектуальных датчиков. Результаты исследования показывают, что предложенный алгоритм позволяет улучшить качество измерения технологических параметров.*
Ключевые слова: *интеллектуальные средства измерения, обработки данных измерения, нейронные сети, погрешности измерения, алгоритмы обучения нейронной сети, калибровка, адаптация средств измерения.*

Introduction

Intelligent measuring instruments and measuring systems, through the use of a microprocessor structure, can carry out self-calibration and adapt to operating conditions. The intellectualization of control and measuring devices cannot be carried out only using microprocessor technology, algorithms for intelligent data processing are required. Intelligent algorithms mean software with adaptive, learning, and decision-making capabilities. To date, there are many methods for developing intelligent data processing algorithms, such as measurement signal processing algorithms based on data (expert systems, past situations, etc.), fuzzy logic, neural networks and genetic algorithms.

The requirements for manufactured products are becoming more and more stringent, making high-precision production control an important task today. New control technologies use a large number of measuring instruments; to obtain the optimal value from sensors, many studies show the effectiveness of using neural networks that solve the problems of self-calibration and self-diagnosis of measuring instruments [1-4].

It is confirmed in [5,6] that the use of algorithms with a neural network to monitor a large number of sensors allowed the processing of measurement data in real time and increased the measurement range in which the system became more efficient. The works [7,8] are devoted to the processing of the measurement signal, the results of which showed a significant improvement in the operation of the system and the importance of processing the measurement signals. Also, the authors of [9,10] investigated the possibility of using artificial neural networks for the intellectualization of measuring instruments, which ensures high measured accuracy.

The data-based measurement signal processing algorithm consists in solving the problems of self-calibration, self-control and self-diagnosis of measuring instruments based on data from previously worked out tasks that are stored in the device’s memory. These decisions must be reviewed by experts. When solving the problem of measuring instruments that have arisen in the work, the system looks for the most suitable answer from the database. If there is no solution to a specific problem, the algorithm chooses the most appropriate or closest solution for this problem. The advantage of this method is the great flexibility of the system, the possibility of presenting and developing your own knowledge base. The disadvantage of this method is that in measuring instruments, the use of situational old data as a comparison does not always guarantee a good result. Since in situations that are not available in the database, these systems lose a lot of time, and the risk of inferring the wrong solution also increases.

Main part

Consider the creation of a neural network algorithm for measuring instruments. For intelligent processing of the measurement signal and data acquisition to provide the functions of reconfiguration, calibration, self-diagnosis and self-control, a neural network structure was chosen that covers a large number of simple elements interconnected with each other. A neural network for measurement devices can be composed of a certain number *N* of neurons that transmit information through a weight function, having different weights. Each neuron has many inputs from other neurons, but only one output. The neuron processes the received information and sends it to the output. The weight function w_{ij} connects the neurons N_i with N_j, and make up the elements of the weight matrix *W*.

$$W = \begin{bmatrix} w_{11} & \cdots & w_{i1} \\ \vdots & \ddots & \vdots \\ w_{1j} & \cdots & w_{ij} \end{bmatrix}$$

For a general definition of weighting, the weight function can be conditionally divided into the following cases:

$$w_{ij} = \begin{cases} 0, & there\ is\ no\ connection\ between\ neurons; \\ > 0, & signal\ amplification; \\ < 0 & signal\ reduction. \end{cases}$$

The purpose of neural networks is to process the measured signal and obtain a reliable result at the output. To do this, you need to train the created neural network. Training is performed with the adjustment of the weight function by repeatedly presenting the training schemes. In theory, there are many possibilities for training a neural network, they are chosen depending on the specific use case. For measuring instruments, supervised learning is most suitable. Where patterns are made from the measured data, and there is also an expert system that knows the exact result of the input signal.

According to taxonomy, artificial neural networks are divided into neural networks with direct and feedback. Based on the task, the structure of a neural network with direct connections can be single-layer or multi-layer. In multilayer neural networks, a neuron from one layer is connected to a neuron or neurons of another layer; in this structure, there is no connection between neurons of one or the previous layer. Increasing the number of layers improves the intelligent processing capability of neural networks. Figure 1 shows a diagram of a multi-level forward neural network. This neural network has a 3-3-1 scheme, since there are three inputs, three neurons in the hidden layer and one in the output. The neural network model has inputs x1, x_2, x_3 that are fed from sensors after primary processing, a weight function w_{ij}, an activation function in the range [0;1] or [-1;1]. The neural model has an additional input b to enter the offset value. The input value g serves to compensate for the offset.

This structure is sufficient for a variety of measuring instruments to implement the functions of self-calibration, self-control and self-diagnosis. But in some cases (in some analytical measuring instruments) neural networks with feedback are used. Also, to increase or decrease the neuron, you can use the direct feedback of the neural network, where the output of the neuron is fed back to itself. Feedback neural networks are required when the measurement signal processing needs additional re-processing. Feedback can also be used when connecting neurons of the same layer. Shortcuts can sometimes be used to connect multiple layers of neurons to an output.

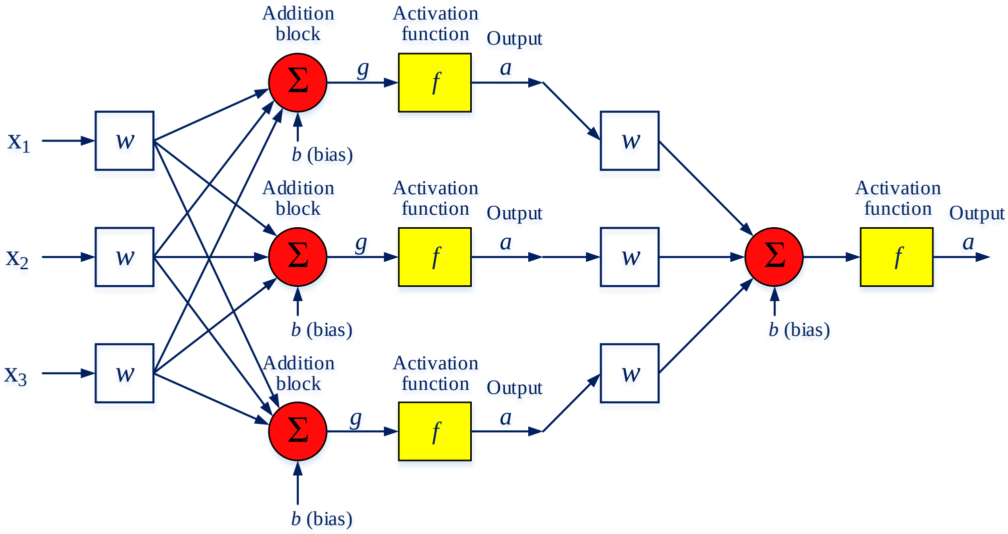


Fig. 1. ***Scheme of a multilevel direct neural network.***

Let us describe the neural network equation from fig. 1 as follows:

$$a = f(t_k + b),$$
$$t_k = \sum_{i=1}^{n} x_i w_{ik},$$
$$g_k = t_k + b,$$

where x_i - is the input data, w_{ij}- is the weight function, t_k - is the adder block, f - is the activation function, b- is the offset value, a - is the output value. g_k - is the output of the adder block.

The activation function is determined from the membership of the calculation function of the algorithm. The Gaussian activation function is used in many works on the intellectualization of neural networks, since it considers the function of a random normally distributed variable [11].

For the operation of the neural network, it is necessary to consider the model of the measuring instrument. Typically, for measuring instruments, the following equation applies, which describes the output value of the sensor x to the variable external influences w.

$$x = f(w).$$

As already mentioned, the range must be in the interval [0,1], for this we apply a number of mathematical equations.

$$w = \frac{w - w_{min}}{w_{max} - w_{min}};$$

$$\mathrm{x} = \frac{\mathrm{x} - \mathrm{x}_{\mathrm{min}}}{\mathrm{x}_{\mathrm{max}} - \mathrm{x}_{\mathrm{min}}}.$$

It is known that the purpose of calibration is to reduce the difference in the size of the measurement signal from the true value of the measured process variable. The model of the response of the measurement signal (electrical signal) to the value of the measured parameter can be linear, quasi-linear and non-linear. The most common are linear functions.

$$y_n = ax_n + b.$$

For a linear equation, it is very easy to find a calibration model, but not all measurement values obtained will be on the line of this model. To determine the validity and reliability of the calibration data, it is required to determine the validity interval for the measured measurement signals. The standard deviation from the linear model is calculated as follows. Let us determine the standard deviation of x and y. Next, we determine the sum of the standard deviation for both parameters.

$$\delta_x = \sum_{n=1}^{N} (x_n - x_r)^2,$$

$$\delta_y = \sum_{n=1}^{N} (y_n - y_r)^2,$$

$$\delta_{yx} = \sum_{n=1}^{N} (y_n - y_r)^2 (x_n - x_r)^2.$$

From the above equations, you can calculate the coefficient a, where:

$$\mathrm{a} = \frac{\delta_{yx}}{\delta_x}, \quad \mathrm{b} = \frac{\delta_{yx}}{\delta_y}.$$

The estimation algorithm determines the optimal coefficients using the least squares method, in which the deviations tend to a minimum.

$$\delta_{yx} = \sum_{n=1}^{N} (y_n - y_r)^2 (x_n - x_r)^2 \quad \Rightarrow \; min.$$

The measurement of technological parameters shows that the measurement signal from the sensors will not always be in the considered function. Each measurement has its own deviation, which differs from previous measurements. To determine the true value of the measured parameter, a confidence interval is introduced. Where the value of x is considered valid if it is in the given range.

$$\frac{\mathrm{a}_i}{\delta_{a_i}} > \mathrm{a}_{krit.}$$

$$\mathrm{a}_i - \delta_{a_i} > \mathrm{a}_{\mathrm{cons.}} > \mathrm{a}_i + \delta_{a_i}$$

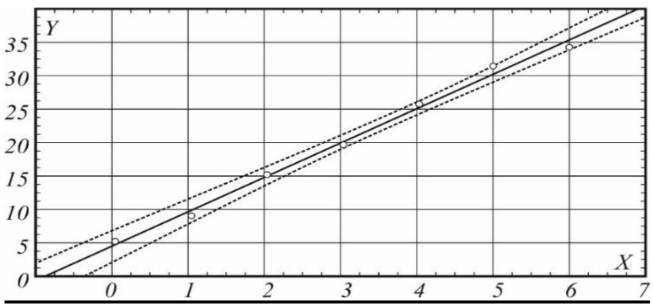


*Fig. 2. **Calibration function and valid range of the measuring instrument.***

Figure 2 shows the calibration function and the valid measurement range.

For non-linear functions, well-known functions are used. In these cases, methods of fitting the available calibration model to the activation function are used. The activation functions in this case perform the function of sorting information, which are the noise or interference of the measurement. This function is achieved due to the fact that the constructed neurons fire only when they reach certain values.

After the structure of the neural network is developed, it is required to train these neurons. The learning process of neural networks determines the quality of the intelligence systems using this algorithm. When training neural networks, training examples are used, which are compiled from data covering the entire task. Neuron training can be compared to parameter tuning, where weights are tuned. When training neural networks in measurement tools, the following training methods are commonly used: supervised learning, reinforcement learning, and unsupervised learning.

Supervised training of a neural network involves the use of known examples with ready-made answers for training under the supervision of an expert (teacher). Each example used to train a neural network includes an input template, a target, and a correct answer. The learning process compares the output signal (reaction of the neural network to the input example) and the correct answer. Based on the comparison, we get an error. This error is used to correct the weight functions. After training the neural network and correcting the weight functions, the errors for all training examples should be minimized or should be in a reliable interval. Based on these examples, an algorithm is built that determines the dependence of the function $y=f(x)$ between the input variables and the output of the neural network. Supervised learning is sometimes also referred to as associative learning.

Supervised training of a neural network involves the use of known examples of training under the supervision of an expert (teacher), but does not give the correct answer. The learning process is based on the fact that the teacher indicates the correctness or incorrectness of the output of the neural network to the incoming example. Due to this training, the weight functions that generate the correct answer increase and the weight functions that generate the wrong answer decrease.

In unsupervised learning, the neural network does not receive feedback about the correct output. The system must learn itself by discovering the structured properties of the input parameters. This training can be done using training templates.

From the analysis carried out, it can be said that supervised neural network training is the most appropriate method. Since the technological parameters are very sensitive and do not always have a certain pattern, where the intervention of an expert will be required. To train a neural network using the supervised learning method, it is necessary to determine the error (the difference between the output values from the neural network and the correct values). Backpropagation uses a function that calculates the sum of squared error deviations.

$$E(w) = \frac{1}{2}\sum_{i=1}^{n} |y(x_n, w) - t_n|^2,$$

here x_n - input parameters, w - weight function. t_n - sought values.

The input parameters remain constant during the learning process, and the error E(w) depends only on the weight function w. The calculated error values are used as feedback inputs, on the basis of which weight functions are found.

Consider the compiled neural network (fig. 1) for smart sensors with three inputs x_1, x_2 and x_3, h hidden layer neurons, w_{ij} weight functions u between the hidden and output layers, and v_{ij} between the input and hidden layers

$$y = f\left(\sum_{j=1}^{h} w_{ij}\, f\left(\sum_{i=n}^{3} v_{ij} x_i\right)\right).$$

When learning, we have a certain number of templates, the number of which we denote m. Each template must have its own objective function M_k^l, where l=1…m, k determines the outputs. For our neural structure, k=1. If we calculate the error by the least squares method, we get:

$$\xi(w_{ij}) = \sum_{l=1}^{m} \frac{M^l - y(x_1^l, x_2^l, x_3^l)}{2}.$$

After determining the error, the weight functions w_{ij} are corrected as follows:

$$w_{ij} = -ή \frac{\partial \xi}{\partial w},$$

where ή is a weighting factor in the range[0;1].

Let's make a measurement in these equations with the following value:

$$A_j = \sum_j w_{ij} x_{ij}$$

we get

$$\frac{\partial \xi}{\partial w} = \frac{\partial \xi}{\partial A_j} * \frac{\partial A_j}{\partial w} = x_{ij} \frac{\partial \xi}{\partial A_j}.$$

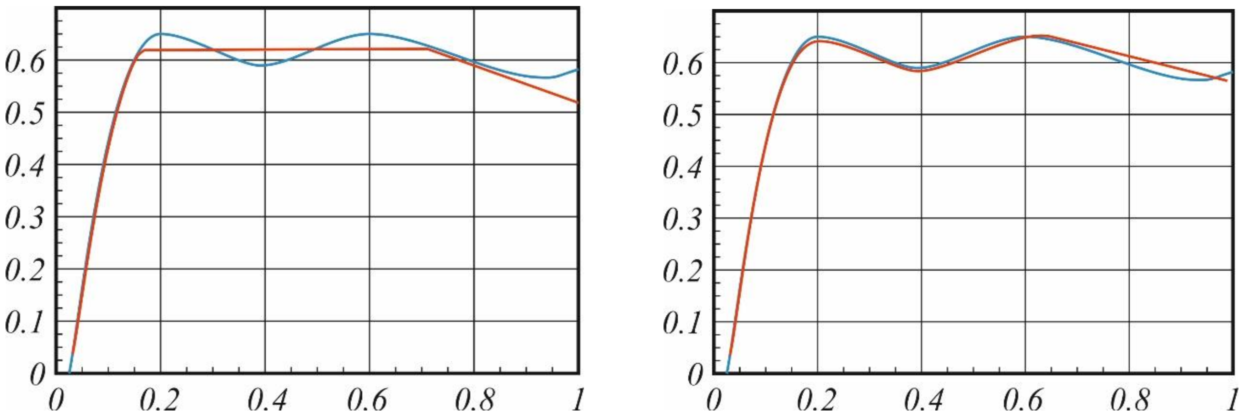
Since s_j only affects the error in the output of the neural network, the equation can be transformed into the following form:

$$\frac{\partial \xi}{\partial A_j} = \left(\frac{\partial \frac{(M^l - y)^2}{2}}{\partial y} \right) * \frac{\partial \delta(A_j)}{\partial A_j} = \left(\frac{1}{2} \frac{\partial (M^l - y)^2}{\partial y} \right) (y(1-y)).$$

Based on the above equations, we will correct the weight functions, where $\frac{\partial \xi}{\partial A_j}$ is the correction for the internal node of the neuron, and to correct the last weight function, we apply the following equation

$$A_j = y(1-y)(M^l - y).$$

To filter and get a reliable value, we use a neural network. Trained with a teacher using templates. On fig. 3 (a, b) shows the results of neural network training. At the same time, in Fig. 3a, training was carried out from 100 templates. And in Figure 3b, 1000 templates were used. For these models, training time took from 5 to 120 minutes, respectively. With an increase in examples of training a neural network, the duration of training and the quality of the output signal from the neural network increase.



a) *b)*

Fig. 3. ***Results of neural network training.***

Conclusion

Checking the measurement signal of the measurement sensor showed that the processing of the measured signals based on neural networks ensures the implementation of the functions of reconfiguration, calibration, self-diagnosis and self-control of measuring instruments. However, in the case of insufficient training, the error of the measuring instruments cannot be detected either by the neural network or by linear approximation. The results of the study show that it is much more efficient to transform sensor data using a simple neural network that is trained under supervision.

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