Розроблено штучну нейронну мережу для визначення складових похибок вимірювання кутів автоматизованими гоніометричними системами, зміна яких у часі являє собою нестаціонарний випадковий процес. Процедури обробки результатів вимірювань та нормування систематичних і випадкових складових похибок вимірювання відомі, мають багаторічну практику застосування, добре обґрунтовані, максимально формалізовані, є принципово різними та регламентуються відповідними нормативними документами. Проте досить складною та трудомісткою залишається аналітично-розрахункова процедура із застосуванням дисперсійного критерію Фішера для визначення яка саме складова похибки вимірювання наявна. З метою автоматизації процедури визначення складових похибок вимірювання та підвищення продуктивності виконуваних робіт розроблено штучну нейронну мережу (ШНМ) та досліджено її роботу. Визначено, що пропонована ШНМ може бути успішно використана замість відомої аналітично-розрахункової процедури із застосуванням дисперсійного критерію Фішера. Застосування ШНМ дозволяє суттєво зменшити трудомісткість та підвищити продуктивність визначення систематичних та випадкових складових похибок вимірювання. Це обумовлюється можливістю ШНМ здійснювати паралельну обробку вимірювальної інформації в режимі реального часу. Практична реалізація ШНМ здійснена з використанням нейроімітатору Neural Analyzer, аналітичного пакета Deductor Professional компанії BaseGroupLabs. Навчання ШНМ та перевірка її працездатності проводилась на множині результатів імітаційного моделювання та реальних багаторазових спостереженнях при вимірюванні плоского кута 24-гранної призми. Можливість ШНМ швидкого та правильного визначення складових похибок вимірювання на етапі аналізу вимірювальної інформації, дозволяє в наступному визначати методи її подальшої обробки у відповідності до нормативних вимог. Це в перспективі забезпечить підвищення точності та достовірності результатів вимірювання тому, що дозволить уникнути некоректних та неточних обчислень при нормуванні похибок вимірювання

Ключові слова: штучна нейронна мережа, випадкова складова похибки, систематична складова похибки, гоніометр

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DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK FOR DETERMINING THE COMPONENTS OF ERRORS WHEN MEASURING ANGLES USING A GONIOMETRIC SOFTWARE-HARDWARE COMPLEX

I. Cherepanska
PhD, Associate Professor*
E-mail: cherepanskairina@gmail.com
E. Bezvesilna
Doctor of Technical Sciences, Professor**
A. Sazonov
PhD*
S. Nechai
PhD, Associate Professor**
O. Pidtychenko
PhD*
*Department of Automation and Computer-Integrated Technologies named after Prof. B. B. Samotokin
Zhytomyr State Technological University
Chudnivska str., 103, Zhytomyr, Ukraine, 10005
**Department of Instrumentation
National Technical University of Ukraine «Igor Sikorsky Kyiv Polytechnic Institute»
Peremohy ave., 37, Kyiv, Ukraine, 03057

1. Introduction

Modern goniometric systems that represent complex program-technical complexes [1] are considered the most accurate optical measuring systems. Goniometric systems are used for contactless measurement of angles in different industrial fields, navigation, scientific research, at testing and calibration laboratories, as well as metrological centers.

As an example, the goniometric systems could be applied for setting navigation sensitive elements (accelerometers or gravimeters) in the electronic stability systems for cars, stabilizers for weaponry, etc.

Contemporary goniometric systems represent complex software-technical complexes, organized as a set of various technical tools with diverse properties. Specifically, they include sensors, measuring transducers, analog and digital input and output modules [1], etc. At the same time, the main trend in the development of modern measuring equipment implies the search for improving the effectiveness of its functioning. The indicators of operational effectiveness of measuring systems are, among others, the accuracy, reliability and performance efficiency of measurements. In this case, accuracy can be enhanced by improving the methods of measurement, computational algorithms and other procedures, which ensure achieving the specified accuracy via less expensive but not less effective techniques. Ensuring high reliability of measurements, in addition to the use of technical means with high instrumental precision, is achieved by additional application of the entire complex of specialized activities. Particularly, by increasing requirements for qualification of personnel, strict compliance with schedules for equipment verification, thorough performance of standard and certification tests, compliance with measurement procedures, calculation and normalization of measurement error components. As is known, the sources of measurement errors that emerge in all measuring equipment and systems, including goniometric, are methodological, instrument and subjective errors. Goniometric systems manifest in the results of measurements in the form of *systematic* and *random* components [2] whose change over time is a non-stationary random process [3]. Procedures for processing measurement results, as well as normalization of systematic and random components of measurement errors, are known, they have been practically applied for many years, they are well substantiated, maximally formalized, they are fundamentally different and are regulated by relevant normative documents [4, 5]. Thus, a random component of the measurement error changes randomly in its sign and value at repeated measurement of the same physical magnitude, performed with the same diligence under the same conditions. Random errors cannot be eliminated and are impossible to avoid. Normalization of random errors is conducted applying the theory of probability and mathematical statistics based on the results of multiple measurements. Random errors, in contrast to systematic, cannot be excluded from measurement results. However, the magnitude of random errors is significantly reduced by increasing the number of observations that can be determined, for example, from a known procedure [6]. The *systematic* component of a measurement error, as opposed to random, remains constant or naturally changes during repeated measurements of the same physical quantity. A systematic error can be predicted, identified, and almost completely eliminated by the introduction of the relevant corrections. However, the systematic component of an error, according to data from the scientific literature [3], is considered to be a specific, «degenerate» random quantity, which has some of the properties of a random magnitude, which are the subject of the theory of probability and mathematical statistics. In this case, procedures for the normalization and summation of systematic and random components of errors are fundamentally different. Specifically, according to standard [4], errors are summed up in one of the three techniques – algebraic, geometric, taking a correlation into consideration. Particularly, in the presence of a *random* component of measurement error, they use geometric summation. When there is a *systematic* component of measurement error, selecting a technique for summation is ambiguous. This is predetermined by the lack of complete information about the law of its distribution. In this case, the choice of a summing technique is made based on considerations on the likelihood of danger to the life of people, significant economic losses, anthropogenic disasters, etc. Typically, this case implies the application of algebraic technique, although it often leads to overestimated assessment of the magnitude of the error.

Thus, there is an obvious need to analyze in advance measurement results in order to determine which component of the error is included in the set of measurement data. After all, correct determination of error components in the measurement results would subsequently make it possible to correctly apply appropriate methods for processing measurement data, to avoid mistakes and inaccuracies, and, consequently, improve the accuracy and reliability of measurements in general. That predetermines the relevance of such a research.

2. Literature review and problem statement

To determine the components of measurement errors, the scientific literature [3, 7] describes analytical-calculation methods based on the application of a Fisher's dispersion criterion and a Wilcoxon criterion. Fisher's dispersion criterion makes it possible to establish the fact of presence of a systematic component of measurement error and to analyze sources of its origin, while the Wilcoxon criterion is used to identify a systematic component of measurement error at the unknown distribution law of measurement results. It is believed that the most effective is the use of the Fisher's dispersion criterion. At the same time, scientists [3, 7] indicate that determining the components of measurement errors when applying these analytical- calculation methods is a multistage [3] and routine [7] and, accordingly, a rather time-consuming process, which requires considerable time cost.

Automation of determining the components of measurement errors and improving the efficiency of operations performed could be achieved by employing intelligent methods and systems, such as artificial neural networks (ANN). ANNs have been successfully applied for solving various problems on the processing and analysis of data under conditions of incompleteness, controversy, and the dynamic nature of input information based on the methods of its parallel processing. There are known cases of applying ANN in the algorithm for estimating angles of bending the knees [8], in the procedure for predicting a bending angle of the finger joint [10]. ANNs have been used in the procedure for estimating the angle and rotation speed of the generator's rotor, specifically, to assess the stability and control over transient processes in real time [11]. There is also the system for automated measurement of the Cobb angle based on ANN, to assess scoliosis of the spine [12]. Papers argue that using ANN makes it possible to improve the performance efficiency, reliability, and accuracy of performed operations. Work [13] reports the algorithm of a neural network for deriving aerosol properties from the ground-based spectropolarimetric measurements and indicates that applying ANN allows for a more accurate assessment. Paper [14] reports a technique to determine angles in the Boler equation using ANN for the diagnosis and treatment of bone fractures. The results indicate high accuracy. Article [15] describes a method for automatic measurement of rotation angle of a two-dimensional object employing a single-layer neural network. Paper [16] reports a method for calibrating an angle sensor based on an artificial neural network. The authors proved that ANN has the advantage in that it demonstrates greater performance and higher accuracy. In addition, it is noted that ANN could be a new method to effectively correct errors.

There are several studies which solve the task on improving the accuracy of measurements by the automated determining of errors using ANN [17–20], genetic algorithms [21], as well as other means [22].

In paper [17], ANN is used to estimate an error in odometers of a mobile robot, in particular, to predict error behavior over time, however, the authors did not determine the systematic and random components of the error.

In study 18], ANN is applied for the automated detection of a systematic error during calibration of angle-measuring geodetic instruments. It is shown that using neural network algorithms makes it possible to reduce the time and simplify the procedure. However, the task on the preliminary determining of error components when measuring with angle-measuring geodetic devices is not solved.

Paper [19] reports a model of the neural-network measuring converter for angular measurements. An analysis and compensation of error occurs at the level of elements and subsystems of the converter. ANN is used to highlight the impact of separate elements of the system on the magnitude of a systematic error in general. The random component of the error is not determined.

Study [20] describes results of research into an error of the optical method to control vibration frequency of technological equipment during its work, based on the genetic algorithm. It is shown that the application of an intelligent method makes it possible to significantly improve performance efficiency in measurements. However, components of the measurement error are not determined.

Paper [21] gives a structure of the genetic algorithm in order to improve accuracy and reduce disruptions in the work of an automated technological system. No analysis of errors in the system's operation was performed.

Article [22] reports a method for the automated evaluation of a geometric measurement error using digital processing of images acquired from a video camera. The method allows the automated calculation of errors based on the regression estimations, as well as a geometric measurement error based on image processing, but does not make it possible to identify its components.

Thus, the task on the automated determining of components of measurement errors, including in real time, remains unresolved. Therefore, our work is necessitated by the lack of developments, which would make it possible to conduct highly efficient automated determining of components of measuring errors for their subsequent correct processing by personnel. The result could improve the accuracy and reliability of measurements in general.

3. The aim and objectives of the study

The aim of present study is to develop an artificial neural network to determine the components of angle measurement errors by automated goniometric systems in order to automate the determining of measurement error components in real time and to improve performance efficiency of executed operations.

To accomplish the aim, the following tasks have been set:

– to algorithmize the analytically-computational procedure for determining the components of measurement errors using the Fisher's dispersion criterion;

– to synthesize an ANN model for the automated determining of measurement error components based on the analytical-computational procedure using the Fisher's dispersion criterion;

– to explore the influence of ANN parameters on the quality of determining the components of a measurement error.

4. Algorithm for the procedure of determining the components of measurement errors using the Fisher's dispersion criterion

The analytical-computational procedure for determining the components of measurement errors using the Fisher's dispersion criterion, which is performed at the stage of analysis of measurement results, implies the execution of a number of steps and can be stated in the form of an explicit algorithm. A generalized block diagram of the algorithm, illustrating the work of this analytical-computational procedure, is shown in Fig. 1.

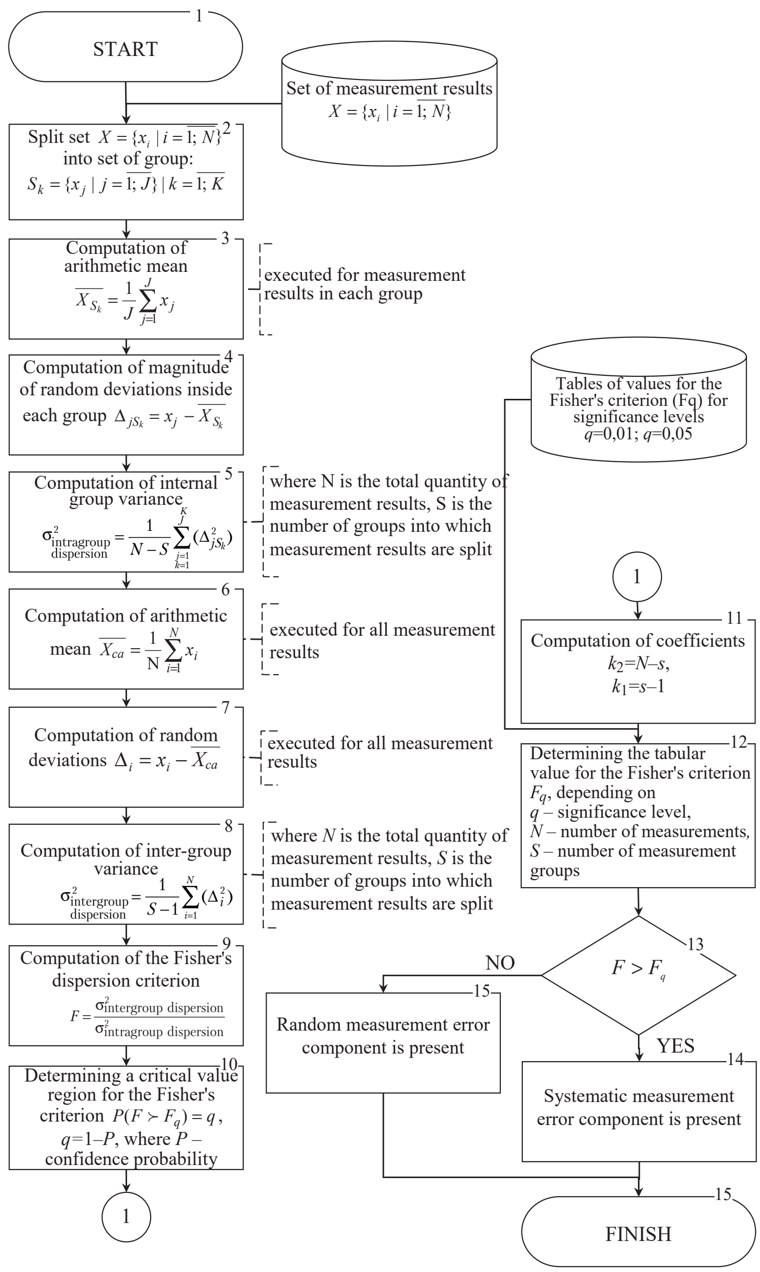

Fig. 1. Generalized block-diagram of the algorithm for an analytical-computational procedure of determining the components of a measurement error using the Fisher's dispersion criterion

Its implementation implies the execution of 13 steps and emphasizes considerable complexity of the process of determining the components of a measurement error. As an example, Table 1 gives the results of determining the components of a measurement error analytically based on the proposed algorithm when deriving the flat angle of a 24-facet prism. We determined components of the measurement error based on the set of observation results, which was preliminary defined in line with known procedure [6]; in this case, the required set of observations is N=37).

Table 1

Results of analytical determination of the measurement error components at repeated measurements of values for the flat angle of a 24-facet prism using the Fisher's dispersion criterion

No. of entry	Angle measured values, φ_k		
	degrees	minutes	seconds
1	164	59	59.66
2	164	59	59.75
3	164	59	59.84
4	164	59	59.74
5	164	59	59.84
6	164	59	59.67
7	164	59	59.73
8	164	59	59.61
9	164	59	59.86
10	164	59	59.81
11	164	59	59.28
12	164	59	59.08
13	164	59	59.11
14	164	59	59.16
15	164	59	59.18
16	164	59	59.11
17	164	59	59.37
18	164	59	59.33
19	164	59	59.37
20	164	59	59.37
21	164	59	59.42
22	164	59	59.43
23	164	59	59.36
24	164	59	59.35
25	164	59	59.34
26	164	59	59.27
27	164	59	59.36
28	164	59	59.05
29	164	59	59.18
30	164	59	59.18
31	164	59	59.43
32	164	59	59.23
33	164	59	59.28
34	164	59	59.36
35	164	59	59.32
36	164	59	59.18
37	164	59	59.35
Fisher's criterion value			
estimated F			2.39
tabular F_q		$F_{0.01}\|P=0.99$	4.41
		$F_{0.05}\|P=0.95$	2.88
Conclusion: the results of measuring contain a random component of the measurement error			

It was established that the results of measurement contain a random component of the error. Therefore, when processing the results of measurements and normalizing the random error, we must employ methods of mathematical statistics and probability theory; summing should be performed by a geometric technique, which is regulated by normative documents [4, 5]:

$$\sigma_\Sigma = \sqrt{\sum_{i=1}^{N} \sigma_i^2},$$

where σ_Σ is the total magnitude of the random error based on all results of the observation; σ_i is the mean-square value of the i-th error; N is the number of measurement results.

When applying the analytical-computational procedure for determining the components of measurement errors, the operator must perform 223 mathematical operations, including 114 operations of addition, 46 – subtraction, 46 – multiplication, and 17 – division. That points to significant complexity of a given procedure. In addition, given that measurements typically imply multiple observations, the number N of whose results could be quite big (Table 1), then there is a significant increase in time required to perform measurements and process the results obtained. Therefore, automating the determination of components of measurement errors based on ANN would make it possible to reduce the labor intensity of performed operations, reduce the time, and improve performance efficiency of performed operations.

5. Model of artificial neural network for the automated determining of a measurement error components

ANN for the automated determining of measurement errors components is a set of mathematical and algorithmic methods for solving a wide range of problems on processing and analysis of data. In the context of problems being solved, ANN makes it possible to automate the analysis of a set of measured data in real time. In this case, high efficiency, probability of correct processing of information under conditions of its incompleteness and controversy, as well as ease of training and retraining, allow the timely transition to new types of problems to be solved when external factors change.

In order to determine the components of measurement errors automatically, the ANN with direct propagation were synthesized [24] that are called the multilayer perceptrons. ANN has significant computing power, as well as the capability to generalize the learning experience, which favorably distinguishes it from other ANN, for example, ANN by Hopfield, ANN by Hamming, ANN with radial basis elements (RBF) and others. Schematic model of ANN for the automated determining of measurement errors components is shown in Fig. 2.

The structure of the ANN model, specifically the number of layers and input and output neurons in layers, is predetermined by the conditions of the problem. We have chosen, as a function for activating the ANN, a sigmoid function (or Fermi function).

The first so-called «input» layer of ANN is formed by input neurons and is designed to accept input information in the form of input vector $X=\{x_k|k=\overline{1;N}\}$, where N is the amount of measured data. Dimensionality of the input layer is defined by the dimensionality of input information and, accordingly, of the input vector. This is predetermined by the fact that the generally accepted means for submitting input signals is such at which all the neurons of the first (input) layer receive a single input signal. The dimensionality of input vector X in this case will be predetermined by the set of measurement results. For example, when measuring the angle of a 24-facet prism, the required number of N measurements, according to known procedure [6], is 37. In this case, the input vector will take the form $X=\{x_k|k=\overline{1;37}\}$. The structure and components of the input vector for this example are given in Table 2.

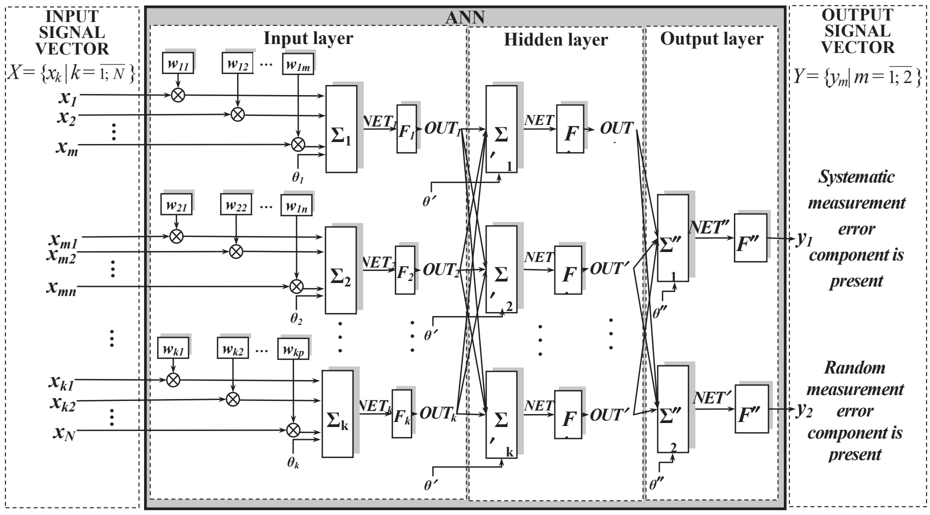

Fig. 2. Schematic model of ANN for the automated determining of measurement errors components [24]

Table 2

Vector representation of results of measuring the flat angle of a 24-facet prism according to the requirements of ANN technology

No. of entry	Measured angle values, φ_k			Vector alphabet
	degrees	minutes	seconds	
1	164	59	59.66	x_1
2	164	59	59.75	x_2
3	164	59	59.84	x_3
4	164	59	59.74	x_4
5	164	59	59.84	x_5
6	164	59	59.67	x_6
7	164	59	59.73	x_7
8	164	59	59.61	x_8
9	164	59	59.86	x_9
10	164	59	59.81	x_{10}
11	164	59	59.28	x_{11}
12	164	59	59.08	x_{12}
13	164	59	59.11	x_{13}
14	164	59	59.16	x_{14}
15	164	59	59.18	x_{15}
16	164	59	59.11	x_{16}
17	164	59	59.37	x_{17}
18	164	59	59.33	x_{18}
19	164	59	59.37	x_{19}
20	164	59	59.37	x_{20}
21	164	59	59.42	x_{21}
22	164	59	59.43	x_{22}
23	164	59	59.36	x_{23}
24	164	59	59.35	x_{24}
25	164	59	59.34	x_{25}
26	164	59	59.27	x_{26}
27	164	59	59.36	x_{27}
28	164	59	59.05	x_{28}
29	164	59	59.18	x_{29}
30	164	59	59.18	x_{30}
31	164	59	59.43	x_{31}
32	164	59	59.23	x_{32}
33	164	59	59.28	x_{33}
34	164	59	59.36	x_{34}
35	164	59	59.32	x_{35}
36	164	59	59.18	x_{36}
37	164	59	59.35	x_{37}
General structure of input vector $X=\{x_k|k=\overline{1;37}\}$: $X=\{x_1; x_2; x_3; x_4; x_5; x_6; x_7; x_8; x_9; x_{10}; x_{11}; x_{12}; x_{13}; x_{14}; x_{15}; x_{16}; x_{17}; x_{18}; x_{19}; x_{20}; x_{21}; x_{22}; x_{23}; x_{24}; x_{25}; x_{26}; x_{27}; x_{28}; x_{29}; x_{30}; x_{31}; x_{32}; x_{33}; x_{34}; x_{35}; x_{36}; x_{37}\}$				

There are no computational procedures in the input layer and information is transmitted from the input to the output of neurons by changing the activation of neurons.

At the output of ANN there forms the input vector Y of the values for the presence of a systematic and random components of measurement errors. A decision on the presence of the type of a component of measurement error is taken by the so-called interpreter of the network response. In a given case, we use the interpreter «the winner takes it all», in which the number of output signals matches the number of variants of response, and the number of the response corresponds to the number of the neuron that issued the maximum signal at the output. That is, when determining the components of a measurement error, there may be two variants of response: «measurement results contain a systematic component of the measurement error» and «measurement results contain a random component of the measurement error». Accordingly, the structure of the output vector can be represented as follows: $Y=\{y_m|m=\overline{1;2}\}$ (Table 3).

Table 3

Characteristic of ANN output vector

Component of measurement error	Information about the presence of an error component in measurement results	Vector alphabet	
		maximal value of signal	components of output vector
Systematic	present	1	y_1
	absent	0	
Random	present	1	y_2
	absent	0	
General structure of output vector $Y=\{y_m|m=\overline{1;2}\}$: $Y=\{y_1; y_2\}$			

The structure of the output vector defines dimensionality of the output layer of ANN for the automated determining of measurement errors components.

The «hidden» layer executes information intermediate processing in such a way that the output layer of neurons receives the linearly-separated sets. The dimensionality of the hidden layer was determined empirically in two stages and varied during the experimental study into ANN. Specifically, at the first stage of the ANN synthesis, the number of a hidden layer's neurons was accepted to be equal to the number of neurons at the input. At the second stage, when training the ANN, the number of a hidden layer's neurons was adjusted depending on the success of its learning. In this case, the boundary numbers of a hidden layer's neurons were calculated from known heuristic formulae (1) and (2).

The required number of synaptic weights L_w was derived from expression (1).

$$\frac{m \cdot N}{1+\log_2 N} \leq L_w \leq m \cdot \left(\frac{N}{m}+1\right) \cdot (n+m+1)+m, \tag{1}$$

where L_w is the number of synaptic weights; n is the dimensionality of the input layer; m is the dimensionality of the output layer; N is the number of elements in the training set in the learning database [23, 25, 26].

The numbers of a hidden layer's neurons in ANN were computed depending on the number of synaptic weights from expression (2).

$$L = \frac{L_w}{n+m}, \tag{2}$$

where L is the number of a hidden layer's neurons.

In order to practically implement ANN, one can use specialized software tools – neuro-simulators, specifically, for a given case, we employed the neuro-simulator Neural Analyzer, which is part of the analytical software Professional Deductor made by BaseGroupLabs.

We trained the ANN using the method of «learning with a trainer» based on the algorithm of error back propagation. We compiled a training database (DB) as a set of pairs of vectors $\langle X_i; Y_i \rangle$, where i is the number of elements in the training database, $\{X_i\}=\{x^1, ..., x^s\}$ is the condition of the problem in a vector form; $\{Y_i\}=\{y^1, ..., y^k\}$ is the desired value of ANN outputs for a given condition. For example, for the case of determining the error components in measuring the flat angle of a 24-facet prism, the size of the training database was 60 examples. The training database was compiled based on the results of actual multiple observations when measuring the plane angle of a 24-facet prism and the results of simulation on a personal computer. A condition for establishing the size of the training database was a known argument on that the number of pairs of vectors $\langle X_i; Y_i \rangle$ in the training database should be such that running the algorithm could generate such a set of ANN parameters, which would produce the desired representation of transforming the signals of input vector X into output vector Y. A fragment of the screen copy of software with the training set for ANN learning aimed at determining the error components of measuring the plane angle of a 24-facet prism, chosen as an example, is shown in Fig. 3.

Training ANN implies a reduction of the mean square error E between the actual values of output signals $Y'=\{y'_1, ..., y'_m\}$ and the desired values $Y=\{y_1, ..., y_m\}$ for ANN outputs.

6. Examining the influence of parameters of the artificial neural network on the quality of determining the components of a measurement error

Experimental study into influence of the ANN parameters, specifically the dimensionality of its hidden layer, in terms of correct determination of measurement errors components was conducted using the neuro-simulator Neural Analyzer, analytical software Deductor Professional developed by BaseGroupLabs. To this end, we generated a training set (Fig. 3) in advance. The criterion for optimizing the learning algorithm was the magnitude of the mean square error E at 5 %, that is, $E=0.05$. The step magnitude is 0.1; momentum is 0.9; steepness of activation function is 1.

The number of a hidden layer's neurons changed in the range that was preliminary calculated from expression (2).

The results of experimental study into a change in the error during ANN operation depending on the number of a hidden layer's neurons are given in tabular (Table 4) and graphical (Fig. 4) form.

To solve the set problem, we examined the work of ANN for the automated determining of measurement errors components with a different dimensionality of the hidden layer (Table 3). ANNs with a different dimensionality of the hidden layer was conditionally named ANN 1 – ANN 7. The results of experimental study in accordance with Table 4 and Fig. 4 revealed the following:

– at an insufficient quantity of neurons in the hidden layer ANN is poor at learning with the error during operation remaining quite large (ANN 6, ANN 7);

– an excessive increase in the number of a hidden layer's neurons leads to that the well-trained ANN does not demonstrate generalizing properties with the error in operation becoming too great (ANN 3, ANN 4, ANN 5). In addition, the excessive increase in the number of a hidden layer's neurons worsens the work of ANN, which manifests itself in a decrease in its high-speed performance (ANN 4, ANN 5).

No. of example of the training set	Measurement result/ No. of measurement																	Component of measurement error	
																		Systematic	Random
	Input vector																	Output vector	
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10		X35	X36	X37	X38	X39	X40	Y1	Y2
1	60	60	60,5	60	60	60,5	60	60	60,5	60		0	0	0	0	0	0	1	0
2	60	60	60,5	60	60	60,5	60	60	60,5	60		60,5	60	60	60,5	60	60	0	1
3	60	60	60,5	60	60	60,5	60	60	60,5	60		0	0	0	0	0	0	1	0
4	60	60	60,5	60	60	60,5	60	60	60,5	60		60,5	60	60	60,5	60	60	0	1
5	60	60	60,5	60	60	60,5	60	60	60,5	60		60,5	60	60	60,5	60	60	1	0
6	1,04	1,16	2,98	1,26	0,06	2,59	2,71	2,34	59,9	0,83		0,62	2,68	1,9	2,86	1,34	2,79	0	1
7	1,04	1,16	2,98	1,26	0,06	2,59	2,71	2,34	59,9	0,83		0,06	2,59	2,71	2,34	59,9	0,83	0	1
8	1,04	1,16	2,98	1,26	0,06	2,59	2,71	2,34	59,9	0,83		0,06	2,54	2,7	2,31	0,83	2,42	0	1
9	1,03	1,03	1,04	1,04	1,03	1,03	1,03	1,04	1,04	1,04		0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	0,01	0,01	0,01	0,01		1,03	1,03	1,03	1,04	1,04	1,04	1	0
11	0	0	0	0	0	0	0,01	0,01	0,01	0,01		1,03	1,03	1,03	1,04	1,04	1,04	1	0

Fig. 3. Screen copy of software with a fragment of the training set for ANN learning in order to automatically determine components of measurement errors

Table 4

Parameters of the examined ANN for the automated determining of measurement errors components with a different dimensionality of the hidden layer and the time of their training

Conditional name for ANN	Parameters of examined ANN	Number of training iterations	Operation duration, s	Dimensionality of training set
ANN 1	Input layer – 37 neurons, output layer – 2 neurons, hidden layer – 37 neurons	52	1 s	60 examples
ANN 2	Input layer – 37 neurons, output layer – 2 neurons, hidden layer – 40 neurons	72	2 s	
ANN 3	Input layer – 37 neurons, output layer – 2 neurons, hidden layer – 57 neurons	284	4 s	
ANN 4	Input layer – 37 neurons, output layer – 2 neurons, hidden layer – 67 neurons	310	17 s	
ANN 5	Input layer – 37 neurons, output layer – 2 neurons, hidden layer – 100 neurons	350	21 s	
ANN 6	Input layer – 37 neurons, output layer – 2 neurons, hidden layer – 20 neurons	43	1 s	
ANN 7	Input layer – 37 neurons, output layer – 2 neurons, hidden layer – 1 neuron	40	1 s	
Range of change in the magnitude of a hidden layer based on expression (1)	from 1 to 67 neurons			

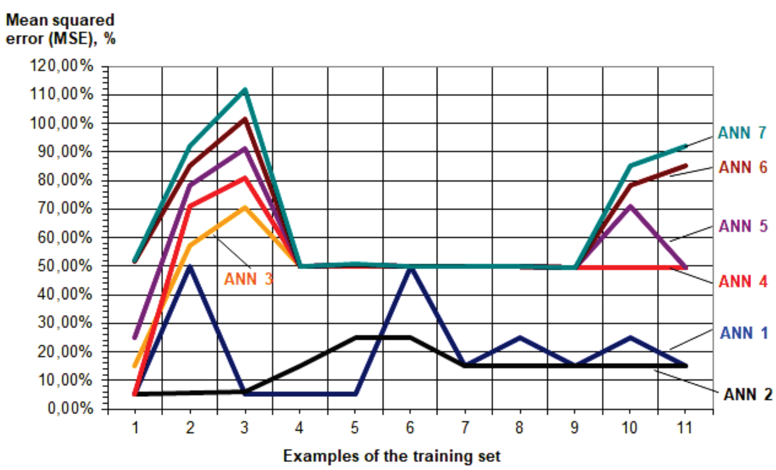

Fig. 4. A chart of change in the magnitude of the mean square error of ANN for the automated determining of measurement errors components with a different dimensionality of the hidden layer based on Table 3

The above-specified indicates the possibility of using ANN 2 with the following parameters: the number of inputs is 37 neurons, the number of outputs is 2 neurons, the number of a hidden layer's neurons is 40 neurons, the number of hidden layers is 1 (Table 3). The indicated ANN made it possible to determine the random component of the measurement error when deriving the flat angle of a 24-facet prism based on the results of multiple measurements (N=37) over 2 s (Table 3).

7. Discussion of results of applying the artificial neural network for the automated determining of measurement errors components

The proposed neural-network method for determining the measurement errors components makes it possible to automate the analytical-computational procedure using the Fisher's dispersion criterion, and as a consequence, reduce labor intensity and improve performance efficiency of executed operations. This statement is justified by the fact that for the examined example, the case concerning the determining of an error's components when measuring the plane angle of a 24-facet prism, the application of ANN made it possible to determine the measurement error components over 2 seconds. In this case, employing the analytical-computational procedure requires that an operator should perform 223 mathematical operations (including 114 operations to add, 46 to subtract, 46 to multiply, 17 to divide). It is obvious that the time that would be taken is significantly larger than the time required by ANN.

High performance efficiency of the proposed method is ensured by the possibility of ANN to perform parallel processing of measuring information in real time. In this case, high efficiency, probability of correct processing of information under conditions of its incompleteness and controversy, as well as ease of training and retraining of ANN, allow the timely transition to new types of problems that are being solved.

The possibility to quickly and correctly determine measurement errors components at the stage of analysis of measuring information would make it possible to subsequently define methods for its further processing in accordance with regulatory requirements. In the long term, that would improve the accuracy and reliability of measurement results as it could help avoid incorrect and inaccurate calculations when normalizing measurement errors.

At present, there are several studies into automated determining of measurement errors using ANN. However, there is no research into automated determining of measurement errors components applying ANN that could take place at the stage of analysis of measuring information.

It should be noted that the basic requirement when using ANN for the automated determining of measurement errors components is the high qualification of personnel, which, accordingly, could require additional training or even partially restrict the application of ANN.

8. Conclusions

1. We have algorithmized the analytical-computational procedure for determining the measurement errors components using the Fisher's dispersion criterion. That made it possible to establish that when processing the results of measuring, for example, a 24-facet prism, the operator is required to perform 223 mathematical operations (including 114 operations to add, 46 to subtract, 46 to multiply, and 17 to divide).

2. The ANN model has been synthesized intended for the automated determining of measurement errors components, which enables the high-speed (2 seconds for the example

considered in this paper) determination of measurement errors components under automated mode. The time that could be taken by ANN to process information is obviously much smaller in comparison with the time required during application of the analytical-computational procedure using the Fisher's dispersion criterion. That significantly reduces labor-intensity of performed operations while processing measuring information.

3. We have studied influence of ANN parameters on the quality of determining the components of a measurement error. It was established that at the insufficient number of a hidden layer's neurons (Table 3), ANN is poor at learning with error during operation remaining quite large (Fig. 4). An excessive increase in the number of a hidden layer's neurons leads to that the well-trained ANN does not demonstrate generalizing properties with an error of its operation being too great, while its performance would be compromised. We have experimentally determined the structure of ANN for the automated determining of measurement errors components. ANN is a three-layer perceptron with a dimensionality of the input layer of 37 neurons, the hidden layer – 40 neurons, the output layer – 2 neurons. The ANN neurons activation function is a sigmoid function. The ANN learning algorithm is an error back propagation algorithm [23, 25, 26].

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DEVELOPMENT OF THE SYSTEM FOR VIBRATION DIAGNOSIS OF BEARING ASSEMBLIES USING AN ANALOG INTERFACE

V. Dovhan
Deputy Head
Scientific and Research Department of Measurements of Electrical and Magnetic quantities measurements
SE «UKRMETRTESTANDART»
Metrologichna str., 4, Kyiv, Ukraine, 03143
E-mail: dovgan_csm@ukr.net

V. Kvasnikov
Doctor of Technical Sciences, Professor, Head of Department
Department of Computerized Electrical Systems and Technologies*

D. Ornatskiy
Doctor of Technical Sciences, Associate Professor, Head of Department
Department of Information and Measuring Systems*
*National Aviation University
Kosmonavta Komarova ave., 1, Kyiv, Ukraine, 03058

Запропоновано систему ранньої вібраційної діагностики газоперекачувальних агрегатів, а саме підшипникових вузлів з покращеними метрологічними характеристиками. Спосіб дозволяє вирішувати задачу раннього діагностування підшипників кочення при несприятливих умовах застосування. Дослідження показали, що це досягнуто завдяки використанню слідкуючих режекторних фільтрів на базі N-канальних структур з використанням ітераційних-інтегруючих перетворювачів. Результати моделювання 4-ох канального фільтра, при реальних вхідних сигналах підшипникових пошкоджень, показали його дієздатність. На цій основі була створена підсумкова модель вихідного сигналу фільтра. Представлена функціональна схема детектора середньоквадратичних значень з моделлю вихідного сигналу слідкуючого режекторного фільтра при реальних вхідних сигналах. Для створення моделі сигналу на вході детектора середньоквадратичних значень були визначені реакції фільтра на кожну частоту яка відповідає за певне пошкодження. Час аналізу вибрано так, щоб він був рівний періоду мінімальної частоти биття, тобто T_a=164 мс (для підшипника типу 222).

Досліджено ефективність пристрою шляхом моделювання пошкоджень реального підшипника газотурбінного двигуна. Запропонована методика аналізу та узагальнений вібродіагностичний критерій, який дає можливість врахувати степінь навантаження двигуна. Це підвищує точність та достовірність попереднього аналізу при діагностуванні підшипника кочення на стадії зародження пошкодження.

Наведено характеристики електрометричного вимірювального підсилювача для роботи з п'єзоелектричними датчиками та запропонованого зарядового вимірювального підсилювача для роботи з п'єзоелектричними датчиками. При умові розбалансу вхідної ланки, що зумовлено не ідентичністю паразитних ємностей вхідного кабелю. Показано, що проникнення мережевої завади на вихід зарядового вимірювального підсилювача, забезпечує на два порядки краще співвідношення сигнал/шум ніж у електрометричного вимірювального підсилювача

Ключові слова: вібраційна діагностика, газотурбінний двигун, диференціальний зарядовий підсилювач, підшипниковий вузол, слідкуючий режекторний фільтр

1. Introduction

At present, there is a pressing issue related to the improvement of reliability of the gas transportation system of Ukraine (GTU), which is one of the major national achievements. Gas-turbine engines (GTE) are the most responsible functional nodes in GTU. Requirements aimed at improving the reliability and durability of structural elements and units