Methods for Improving the Efficiency of Diagnostic Systems in the Neural Network-based Sound Analysis

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Abstract—The study of the possibilities of modelling the use of neural networks while increasing the efficiency of diagnostic systems consists of creating a standard that would satisfy the conditions for maintaining the sound quality. At the same time, the effectiveness of diagnostic systems can be considered when applied both in a technological environment and in a virtual space. The relevance of the study is determined by the possibilities of using the reference sound, which forms and uses the basis of the neural networks. The scientific novelty of the study is determined by the fact that an adaptive method for creating standards of units of measurable quantities with specified accuracy characteristics is proposed, subject to limited resources. The first version of the mathematical model of the measurement procedure is formed during reproduction, storage and transmission of a unit of measurement developed on the basis of a physical model, which, in turn, is built in accordance with a priori information on the principle of reproduction (storage and transmission) of a unit of measurement, a list of informative parameters and influential quantities when measuring. The authors have developed the necessary accuracy characteristics, specified by the technical specifications and determined the resources allocated for the creation of the standard. The practical significance of the study lies in the establishment of distributed networks for sound quality measurement, mainly within the structures of the study of sound transmission between high-tech devices.

Keywords—measuring problem, neural network models, sensitivity coefficient, two-layer perceptron.

I. Introduction

Today, measurements are spreading to new "non-traditional" areas and, consequently, state metrological supervision extends to almost all branches of science and technology, including chemistry, biology, medicine. Due to the increased measurement accuracy, the quality of diagnostics has significantly improved, which ensures the chances of successful treatment; errors lead to negative consequences. Over the past decade, significant progress has been made abroad in metrological support in medicine. In 2003, the IVD Directive came into force, which requires traceability of measurement results to higher-order standards, ensuring comparability of results not only within the same hospital and between hospitals, but also internationally. The International Committee for Measures and Weights, and the World Health Organisation signed a Memorandum of Understanding in 2002 to develop cooperation on metrological aspects in the field of clinical chemistry and laboratory medicine.

In the United States, the National Institute of Standards, in close collaboration with the medical community (as well as in Japan and in European countries), develops a large number of standard samples, apparatus and instruments, providing more accurate and traceable measurement results in laboratory medicine.

International organisations, in accordance with the IVD Directive, initiated a new direction in ensuring traceability, the codename of which is JCTLM (Joint Committee for Traceability in Laboratory Medicine), in order to maintain

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worldwide comparability, reliability and equivalence of measurement data in laboratory medicine. The use of a neural networks makes it possible to compare the results obtained with the reference results of the research and to form features that provide accurate results on the basis of ultrasound studies or on another basis of non-contact exposure.

In modern conditions, neural network models are one of the most proven information processing tools that have been used in solving a wide variety of problems [1]. At the same time, practical experience and analysis of sources indicate that one of the most significant drawbacks of the methodology for creating neural network models is the lack of effectiveness of their training [1]. Due to this drawback, the time for constructing a neural network system increases and the recognition accuracy decreases [2]. It is noted that the modern neural networks based on a multidimensional perceptron, learn by the "supervised" method through multivalued integration representations of the training samples [3]. These neural network models include a two-layer perceptron, convolutional and deep neural networks [4].

The important parameters that determine the efficiency of neural network training are the duration and error [5]. For a given training sample, in order to reduce the error and the training duration of the neural network, most of the known studies suggest using various procedures for pre-processing the training example parameters [6]. The implementation of the procedures is reduced to centring, normalisation, scaling of the input and output parameters [7]. Thus, the listed procedures only adapt the output parameters of training examples to a form suitable for use in neural network models, but do not significantly affect the training time and error [8]. In addition, it can be concluded that most studies on the neural network training efficiency are aimed at solving the problem of forming a representative training sample [9]. Proper training sample design is critical for most machine learning tasks [10].

In the literature, various methods of its development are considered, their advantages and disadvantages are analysed, a list of characteristic errors is given, and a method for introducing new data into the training sample is proposed [11]. The development of a method for forming a representative training sample of images for automated recognition of aerial reconnaissance objects is considered [12]. The use of a distributed neural network is provided [13]. It is argued that the use of the developed method ensures the representativeness of sample by taking into account the most informative parameters [14]. Often, comparisons are made of the recognition efficiency of medical research results, the parameters of training examples of which were set by experts or calculated using the generated procedures [15]. It is argued that when performing a comparison, it is necessary to abandon the expert definition of signs. Thus, in most of the literature, the issue of coding the expected output signal remains open [16]. At the same time, the results indicate that for a given training sample, it is possible to reduce the training duration and error by displaying training examples in the expected output signal that are close to the standard in the case studies that should be recognised [17]. It was also shown that it is possible to implement the mapping using the expert assessment of the generated standards proximity [18]. However, the use of such products is associated with the need to attract qualified experts in the applied field of neural networks [19]. In many cases this is not possible. At the same time, the analysis performed makes it possible to assert that it is possible to consider the problem of assessing the proximity of a limited set of standards from the perspective of using low-resource neural networks for exploratory data analysis, which indicates the prospects of developing a method for coding the standard of the expected audio output.

II. Materials and Methods

It is necessary to develop a method for constructing measurement standards for units of measurement, which assumes an adaptive method for developing the structural, functional and schematic diagrams of the standard, the design of individual components and the standard as a whole, and an algorithm for controlling the measurement process and processing measurement information in conditions of limited resources.

Uncertainty minimisation method – PUMA (Procedure for Uncertainty MAnagement) method is designed to estimate the uncertainty when measuring the geometric parameters of products [20]. The PUMA Method is a practical, iterative method for assessing and reporting measurement uncertainty. The iterative method is based on the upper limit strategy, that is, on the reassessment of uncertainty at all levels, but with iterative control over the revaluation result. A prerequisite for budgeting and managing uncertainty is a well-defined measurement target. A method for minimising uncertainty for a specified and developed measurement process is often considered.

At the first iteration, the model equation is usually built on the basis of the black-box method, which provides for writing the model equation in the following form:

$$Y = X + \sum_{i=1}^{m+q} C_i \quad (1)$$

where Y – measured value; X – readings of the measuring device; C_i–i – additive correction for a known (non-excluded) systematic error (calibration error, temperature error, error due to deformation, etc.); m, q – respectively the number of uncorrelated and correlated sources of uncertainty.

With a gradual refinement of the model equation, the transparent-box method is used to write the model equation (accustomed to writing through the communication function). Over time, the model equation becomes more complicated, it can become substantially nonlinear, the analytical method for assessing uncertainty becomes fundamentally unsuitable, in particular, the calculation of the sensitivity coefficients as partial derivatives becomes a difficult and sometimes unsolvable problem. Therefore, the PUMA method was improved: instead of the transparent-box method (analytical method), digital methods were introduced – the numerical differentiation method and/or the simulation method (Monte Carlo method (MCM)).

For the improved PUMA method, the uncertainty budget is compiled according to the algorithm:

Step 1. Determine the nominal values and accuracy characteristics of the input quantities.

Step 2. The distribution law of the input quantities is determined and the standard uncertainties of the input quantities u(xk) are calculated:

$$u(x_k)=a_k b \tag{2}$$

where a_k – known NSP boundaries (accuracy characteristics) of the *k*-th input quantity; *b* – distribution coefficient involving the distribution law of the error in the middle of these boundaries: *b*=0.5 for a normal distribution (Gaussian distribution); *b*=0.6 for even distribution; *b*=0.7 for U-distribution (arcsine distribution).

If the distribution law of the NSP is unknown, then it is necessary to choose the U-distribution (with the largest *b*).

Step 3. At the first iterations, when the model equation is found from a combination of the black box and transparent box methods, the sensitivity coefficients ck are calculated.

When calculating the sensitivity coefficients, use:

- for the input quantities that are explicitly included in the model function, the partial derivatives are found;

- for input quantities that are not included in the model function, but their contribution significantly affects the final result, the so-called black-box method is used. Corrections for the known systematic error of these input quantities are added to the model function. In this case, the sensitivity coefficients are taken as equal to one.

On subsequent iterations, when the model equation becomes more complicated, the sensitivity coefficients ck for the input quantities that are nonlinearly included in the model equation are not calculated.

Step 4. Sources of uncertainty are weakly correlated with each other are considered as non-corrodible (correlation coefficient *r*=0); for strongly correlated ones, the correlation coefficient is taken equal to +1 or -1, depending on the nature of the relationship.

Step 5. The contribution of each input quantity $u_k(y)$ to the combined standard uncertainty is calculated:

– at the first iterations

$$u_k(y)=c_k u(x_k) \tag{3}$$

where $u(x_k)$ – standard uncertainty of the *k*-th input quantity; ck – sensitivity coefficient of the *k*-th input quantity.

– at the next iterations, by the method of numerical differentiation, the contribution $u_k(y)$ is calculated as partial increments of the model function Δf_k at deviated values of x_k from the nominal one.

$$u_k(y)=\Delta f_k=f(x_k)+-f(x_0) \tag{4}$$

where $f(x_0)$ – the function value at the nominal values of all input quantities at the selected point in the parameter space;

$f(x_k)^+$ – the function value at the nominal values of the input quantities, with the exception of one, the *k*-th input quantity, which is substituted with a deviation from the nominal value by the value of the standard uncertainty.

Step 6. The combined standard uncertainty u_c is calculated by the formula:

$$u_c^2=u_A^2+u_B^2 \tag{5}$$

where u_A – the standard uncertainty, calculated by type A; u_B – standard uncertainty, which is calculated according to type B: uncorrelated (r=0) components are added geometrically, and strongly correlated (r=+1 or r=-1) components are added arithmetically:

$$u_B^2 = u_q^2 + \sum_{k=1}^{m} u_k^2(y) \tag{6}$$

where $u_k(y)$ – the contribution of the *k*-th input quantity to the combined standard uncertainty; m – the number of uncorrelated sources of uncertainty; u_q – the sum of highly correlated uncertainty components:

$$u_q = \sum_{k=1}^{q} u_k(y) \tag{7}$$

where *q* – the number of strongly correlated components.

$$u_A=S_X \tag{8}$$

where S_X – form of measurement result when transmitting a power unit.

Step 7. The expanded uncertainty U is calculated (with the expansion coefficient *k*=2).

$$U=ku_c \tag{9}$$

where u_c – combined standard uncertainty.

Step 8. Contribution fractions for the analysis of the contributions of the standard uncertainty of the input quantities to the expanded uncertainty are calculated, which allow identifying those sources of uncertainty that make the greatest contribution to the combined uncertainty of the output quantity and whose reduction brings the greatest effect:

$$\varsigma = \frac{u_k^2(y)}{u_c^2} \tag{10}$$

where $u_k(y)$ – contribution of the k-th input quantity to the combined standard uncertainty; u_c – combined standard uncertainty.

Step 9. The calculation data is summarised in a general table – uncertainty budget.

III. Results and discussion

The Monte Carlo method can be used to calculate the combined standard uncertainty and expanded uncertainty if the model equation is substantially nonlinear or takes a long time to make a measurement. For the secondary standard of the unit of ultrasound power in the aquatic environment, PUMA method was first applied at the initial stage of its creation to substantiate the structure and composition of the measuring channels under conditions of a priori uncertainty, when the construction of the secondary standard is only being developed and there are no sufficient data and experimental results to assess the expected accuracy characteristics. In this case, the model equation is significantly simplified and therefore it was possible to use an analytical method for assessing the uncertainty, including the black-box method.

Since, in the process of creating a standard, more and more factors and their functional relationships affecting the final result were taken into account, the model equation was refined and complicated, it became nonlinear, therefore, for further calculations, the improved PUMA method was applied. The adaptive method is based on the principles of information technology – simulation, numerical differentiation in combination with theoretical and experimental research and is used at all stages of building a standard. It is based on iterative refinement of an adequate model equation as the measurement information is accumulated and the applied improved PUMA uncertainty estimation method. The adaptive method aims to achieve the highest accuracy at the lowest cost. The maximum allowable cost to create a reference and the minimum allowable accuracy are limiting factors.

The proposed adaptive method is implemented in several iterations. In the first iteration, the following steps are performed:

– analyse a priori information obtained from the results of previous research and development work, the experience of the national metrological institutes of developed countries, domestic and international regulatory documents, catalogues of companies producing measuring instruments, literature sources, etc.

– choose the principle of the measurement unit reproduction and develop a physical measurement model based on the analysis;

– based on the physical model of the first approximation, a mathematical measurement model (model equation) is developed. A combination of black-box and transparent-box methods is used to construct the model equation;

– assess the degree of uncertainty in the measurement using the advanced PUMA method. Make up the uncertainty budget. For clarity, the uncertainty budget is presented in the form of a histogram of the contributions of sources of uncertainty to the total uncertainty. Simultaneously, a simplified structural-functional diagram of the reference is developed and resource costs are estimated on its basis;

– compare the obtained results of the expanded uncertainty assessment with the one specified in the technical specifications (TS) and check the resources necessary for the implementation of a standard version for compliance with the limit. A decision is made on the direction of further work on the development of the standard and improving the accuracy characteristics of the future standard.

The first iteration is close and provides a first insight into the main sources of uncertainty. At the second iteration and, if necessary, at the third and subsequent iterations:

– analyse the results of calculations performed at the first iteration, identify the sources that make the greatest contribution to the total uncertainty of the initial (measured) value, look for technical solutions to reduce them (if necessary);

– improve the physical model of measurement during reproduction, storage and transmission of the unit of measurement. An improved version of the structural and functional diagram of the standard is developed and the necessary resources are estimated;

– clarify the mathematical model, taking into account, if possible, both informative parameters and influencing quantities that could not be taken into account explicitly at the first iteration;

– assess the degree of uncertainty in the measurement using the improved PUMA method.

According to a refined mathematical model and a pre-selected structural diagram, all possible additional sources of uncertainty are analysed, all available a priori information is collected and analysed regarding the accuracy characteristics of informative parameters and indirect quantities, and a list of input quantities is compiled. They use various sources of information: technical documentation for devices, reference books, international standards and regulatory documents, reports on international reconciliation, technical literature, etc. The accuracy characteristics of the input quantities lead to a uniform form – to the standard uncertainty.

Based on the calculations, an uncertainty budget is compiled in the form of a table, the end result of which is an expanded uncertainty in measurement (according to a preselected structural scheme of the reference) and the share of contributions of each of its sources to the total uncertainty of the initial value. For clarity, the uncertainty budget is presented, in addition, in the form of a histogram of the contributions of sources of uncertainty to the total uncertainty. Further, the obtained results of the assessment of the expanded uncertainty are compared with that specified in the specification. The resources required for the implementation of this version of the standard are checked against the limit. Therefore, the most effective will be measures aimed at reducing the influence of dominant sources, which were identified in the previous iteration. The proposed adaptive method makes it possible to find optimal solutions in such situations.

If at the second, third and subsequent iterations it is not possible to achieve the specified accuracy characteristics, that is, the current level of development of science and technology does not allow fulfilling the requirements set in the TS, or requires very large expenses, then other ways of reproducing the unit of measurement are considered, the question is raised on increasing resources for creating a standard or reducing the requirements in relation to its accuracy.

The development of a secondary standard for the unit of ultrasound power in an aqueous medium was carried out according to the proposed adaptive method.

1. First iteration.

a) analysis of a priori information and the choice of reproduction principle of the unit of measurement. On the basis of the collected information, the method of radiation pressure balance using a precision electronic weight, recommended by the international standard IEC 61161, was chosen to implement the unit of ultrasound power in water medium in the standard.

b) physical model.

The authors have considered a simplified physical model for measuring ultrasonic power in an aqueous medium by the force balance method.

At the first iteration, a simplified version of the standard structure was considered, which included only a generator, a power amplifier, an ultrasonic emitter, a container with a target, a class 3rd weight, and a water treatment system. The cost of creating such a standard is minimal.

c) mathematical model.

The formulas (1) and (4) were taken as a mathematical model of the measurement process.

d) estimation of uncertainty by the improved PUMA method.

According to the mathematical model and the pre-selected structural scheme, all possible sources of uncertainty are analysed, all available information on the accuracy characteristics of the input quantities (informative parameters and influential quantities) is collected and analysed, and a table (list) of the input quantities is drawn up. As an example, a table of input quantities for the secondary standard of the unit of ultrasound power is given (Table 1). Accuracy characteristics lead to a unified form – standard uncertainty.

TABLE I. NAME, DESIGNATION AND UNITS OF MEASUREMENT OF INPUT QUANTITIES

Input quantity	Designation	Measurement units
Frequency	f	MHz
Sound speed in wate	c	m/s
The angle between the direction of propagation of the acoustic wave and the normal of reflecting (conical convex) surface	ϑ	degree
Ultrasonic emitter radius	a	mm
Density of liquid (distilled water)	ρ	kg/m^3
Temperature	t	^{o}C
Target radius	b	mm
Non-centeredness of ultrasonic beam and target, obliqueness	Sp	%
Weight force (mass, which is equivalent to radiation force)	F_b	g
Voltage at the ultrasonic emitter	V	V

Based on the calculations in Table 1, the uncertainty budget of the first iteration was compiled in the form of a table, the end result of which is the expanded uncertainty in the measurement according to the pre-selected structural scheme of the standard and the share of the contribution of each of the sources of uncertainty to the total uncertainty of the initial value.

The distribution law of the input quantities was assumed to be uniform for all quantities, with the exception of a random error. The space has a normal distribution.

When analysing the relationships between the input quantities, no significant correlation was found, therefore, all sources of uncertainty were assumed to be uncorrelated.

Table 2 provides an example of an uncertainty budget for 0.005 W power at 5 MHz. When constructing the table, various sources of information about the accuracy characteristics of the input quantities were used (technical documentation for devices, reference books, international standards, in particular IEC 61161, reports on international reconciliation, technical literature).

The first iteration is rather rough, performed on the basis of a simplified mathematical model in order to preliminary estimate the expanded uncertainty and compare it with the technical specification requirements for creating a standard, as well as in order to identify the dominant components of uncertainty. In our case, the expanded uncertainty at the first iteration was approximately 39% and turned out to be significantly higher than that listed in the technical specification. With this physical model, the resources required to create the reference did not exceed the allocated limit

e) making a decision on the direction of further work on the creation of a standard.

The authors looked for ways to reduce the expanded uncertainty and performed a second iteration.

2. Second iteration.

a) analysis of the uncertainty budget and search for ways to reduce the uncertainty of the input quantities

Analysis of the results of the first iteration showed that the dominant components were the inaccuracy of the weights of the 3rd class, the expanded uncertainty in the measurement of which was 17% and the random component, which reached 8%. Therefore, to reduce the expanded uncertainty in the composition of the standard, a weight of increased accuracy was used. To reduce the random component of uncertainty, its possible sources were shown when choosing a structural scheme, developing the design of the standard, software and arranging the room where the standard was located, which made it possible to reduce the random component of the measurement error by half.

b) improvement of the physical model.

According to the refined physical model, a new structural and functional diagram was developed. Class 1 weight, a system of protection against acoustic interference and vibrations, a voltmeter to control the voltage stability at the input of the ultrasonic emitter, and a thermometer to control the change in water temperature were introduced into the structural and functional diagram of the standard. Formulas (1) and (3) are approximate, they are used only for working measurements, therefore, (2) – (6) was taken as a refined mathematical model of the measurement process (2)-(6).

c) the procedure for assessing uncertainty using the improved PUMA method.

To calculate the contribution of the radius of the ultrasonic emitter $u_4(y)$ to the total standard uncertainty, the method of numerical differentiation was used by the formula (4).

TABLE II. FIRST ITERATION UNCERTAINTY BUDGET (FREQUENCY 5 MHZ, POWER 0.005 W)

Input quantities					Output quantities	
Quantity designations	**Nominal sensitivity coefficients**	**Accuracy characteristics (deviations), %**	**Sensitivity coefficients**	**Standard uncertainty, $u(x_k)$, %**	**Contribution, $u_k(y)$, %**	**Contribution share, %**
f^1	5.00	$0.20 \cdot 10^{-5}$	1.00	0.00	0.00	0.00
c^1	1491.5	0.000070	1.00	0.00	0.00	0.00
ϑ^1	45.00	3.50	1.49	2.02	3.01	2.36
a^2	13.50	3.70	0.00	2.14	0.00	0.00
ρ^2	$997.54 \cdot 10^{-1}$	$0.\ 10 \cdot 10^{-4}$	1.00	0.00	0.00	0.00
t^2	23.00	0.20	1.00	0.12	0.12	0.00
b^2	41.00	2.00	1.00	1.15	1.15	0.34
S_p2	3.00	3.00	1.00	1.73	1.73	0.78
F_b1	$34.13 \cdot 10^{-5}$	29.30	1.00	16.92	16.92	74.32
V^2	var	4.00	2.00	2.31	4.62	5.54
Average		8.00	1.00	8.00	8.00	16.61
Combined standard uncertainty u_c, %					19.62	
Extended uncertainty U, % (k=2)					39.25	

Table 3 provides an example of an uncertainty budget for 0.005 W power at 5 MHz. In addition, for clarity, they are presented in the form of a histogram of the sources of uncertainty contribution.

According to the results of the second iteration, the obtained expanded uncertainty only in some measurement subranges slightly exceeded that specified in the specification.

The resources required to create the benchmark have not exceeded the allocated limit.

d) making a decision on the direction of further work on the creation of the standard.

The authors made a decision to improve the accuracy so as to meet the requirements of the technical specification in the entire frequency and power range and performed the next iteration.

3. Third iteration.

a) analysis of the uncertainty budget and finding ways to reduce the uncertainty of input quantities.

The dominant components were spaces of random error and uncertainty in measuring input voltage. To further reduce the random component of the error, the measuring part of the standard was equipped with a protective casing; the rooms where the standard was located were additionally protected from the influence of such influential factors as noise and vibration, air movement, changes in environmental parameters; the measuring channels of the standard were protected from electromagnetic interference and interference, etc. The algorithm for controlling the measurement process and processing the measurement information was built in a way to minimise the random component of the error, for example, by using an adaptive method for collecting the number of observations during measurement, and more. To reduce the contribution of the voltage measurement error, a voltmeter with higher accuracy characteristics was chosen.

b) improvement of the physical model.

At the third iteration, the structural diagram of the standard provided for the improvement of the software and a more effective system of protection against external influences, which reduced the random component of the error to 2%. In addition, a voltmeter with a maximum permissible error of no more than 2% was used, as well as an oscilloscope and frequency meter to determine and control the signal parameters at the input of the ultrasonic emitter and a barometer, thermometer, and hygrometer to measure environmental parameters. The target was chosen as an absorbent type.

TABLE III. SECOND ITERATION UNCERTAINTY BUDGET (FREQUENCY 5 MHZ, POWER 0.005 W)

Input quantities					Output quantities	
Quantity designations	Nominal sensitivity coefficients	Accuracy characteristics (deviations), %	Sensitivity coefficients	Standard uncertainty, $u(x_k)$, %	Contribution, $u_k(y)$, %	Contribution share, %
f^1	5.00	$0.20\cdot10^{-5}$	1.00	0.00	0.00	0.00
c^1	1491.5	0.000070	1.00	0.00	0.00	0.00
ϑ^1	45.00	3.50	0.79	2.02	1.59	5.35
a^2	13.50	3.70	0.01	2.14	0.00	0.00
ρ^2	$997.54\cdot10^{-3}$	$0.\ 10\cdot10^{-4}$	1.00	0.00	0.00	0.00
t^2	23.00	0.20	1.00	0.12	0.12	0.03
b^2	41.00	2.00	1.00	1.15	1.15	2.81
S_p2	3.00	3.00	1.00	1.73	1.73	6.36
F_b1	$34.13\cdot10^{-5}$	29.30	1.00	16.92	1.69	6.07
V^2	var	4.00	2.00	2.31	4.62	45.37
Average		8.00	1.00	8.00	4.00	34.01
Combined standard uncertainty u_c, %					7.33	
Extended uncertainty U, % (k=2)					13.72	

c) refinement of the mathematical model.

Formulas (1) – (6) were taken as a mathematical model.

In addition, key comparisons of national standards of the unit of ultrasonic power, which were carried out under the control of the International Committee of Measures and Weights, showed that for the standards of the highest rank it is more important to reproduce not the unit of power, but the electroacoustic conductivity:

$$G = \frac{W_{out}}{C_{in}^2} \tag{11}$$

where W_{out} – ultrasonic output power; V_{in} – effective value of the input voltage.

d) the procedure for estimating uncertainty by the improved PUMA& method.

The procedure for estimating uncertainty is similar to that given in the second iteration.

At the third iteration, the expanded uncertainty did not exceed 10%, which satisfied the TS requirements. The total cost of creating a benchmark was within the foreseen limit.

It should be noted that with a decrease in the dominant sources of uncertainty, more weight, a larger share of the contribution acquired and became dominant, and other sources of uncertainty, for example, the non-centeredness of the ultrasonic field and the target, obliqueness. These new dominant sources also controlled. Therefore, the design of the standard power meter provided the required positioning accuracy of the ultrasonic emitter and the target dimensions.

e) decision making.

In accordance with the above, a secondary standard for the unit of ultrasound power in an aqueous medium was created.

When developing the design of the standard, software and equipment of the room where the standard was located, the measures listed above were implemented.

The structural and functional diagram of the secondary standard of the unit of ultrasound power in the aquatic environment, developed by the adaptive method, was presented in the form of a linear model. From the generator through the power amplifier, an electrical harmonic signal of a given level is fed to the ultrasonic emitter at its resonance frequency. An ultrasonic emitter immersed in distilled and degassed water in a measuring vessel creates an ultrasonic beam that interacts with the target. The value of the radiation force that arises in this case is determined by an electronic balance, the measurement result is transmitted to a personal computer, where the power is determined according to the mathematical model described above. The parameters of the electrical signal coming from the generator through the power amplifier are monitored using an oscilloscope, the voltage across the ultrasonic emitter is measured with a voltmeter.

A set of ultrasonic emitters is used to ensure the specified operating frequency range and reproducible power range.

Control of the process of measurement and processing of measurement information in real time and the procedure for assessing the accuracy characteristics are performed on a computer with appropriate software. The temperature of the water and the content of dissolved oxygen in it during the measurement are monitored with a water thermometer and an oximeter, respectively. A barometer, thermometer and hygrometer are provided to monitor environmental conditions. A system of protection against vibrations, noise and air flows has been developed.

IV. Conclusion

As a result of a study on the standard formation and its modelling in a sound environment based on a neural network, the authors have improved the method for minimising uncertainty (PUMA method) by using methods of numerical differentiation and simulation modelling instead of an analytical method for assessing uncertainty. In the system, which made it possible to obtain the standard, an improved method for minimising uncertainty (PUMA method) was applied for the standard of the ultrasound power unit at the initial stage of its development. A new adaptive method and information technology for creating standards of units of measured quantities with specified high accuracy characteristics, subject to limited resources, has been developed in the structural equipment and application in the industrial sphere. As a method of measurement uniquelisation, the developed adaptive method was applied to create a standard for the unit of ultrasound power in an aqueous medium and a structural and functional diagram of a standard for a unit of ultrasound power in an aqueous medium is presented. The necessary accuracy characteristics, specified by the technical specifications and determined the resources allocated for the creation of the standard were developed.

The results of the article can be used for establishment of distributed networks for sound quality measurement, mainly within the structures of the study of sound transmission between high-tech devices. The future research will be focused on other methods for improving the efficiency of diagnostic systems in the neural network-based sound analysis.

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References

[1] M. R. Kandroodi and B. Moshiri, “Identification and model predictive control of continuous stirred tank reactor based on artificial neural networks,” Proceed. 2011 2nd Int. Conf. Control, Instrum. Autom., pp. 338–343, 2011. https://doi.org/10.1109/ICCIAutom.2011.6356680

[2] R. H. Abiyev and K. Altunkaya, “Iris recognition for biometrie personal identification using neural networks,” in Lecture Notes in Computer Science, pp. 554–563, 2007. [Online] https://link.springer.com/chapter/10.1007%2F978-3-540-74695-9_57

[3] J. D. Tan and H. N. Ting, “Malay speaker identification using Neural Networks,” Int. Conf. Inf. Sci. Tech., pp. 476–479, 2011. https://doi.org/10.1109/ICIST.2011.5765294

[4] J. W. Brooks, M. W. Maier and S. R. Vechinski, “Applying system identification and neural networks to the efficient discrimination of unexploded ordnance,” IEEE Aerosp. App. Conf. Proc., vol. 2, pp. 449–467, 1997.

[5] Q. Zhao, X. Su and S. Zhou, “Research of power system stabilizer based on prony on-line identification and neural network control,” Proceed. 11th Int. Conf. Electr. Mach. Syst., pp. 146–150, 2008.

[6] Y. Bao, J. M. Velni and M. Shahbakhti, “Epistemic uncertainty quantification in state-space LPV model identification using Bayesian neural networks,” IEEE Control Syst. Let., vol. 5, no. 2, pp. 719–724, 2021. https://doi.org/10.1109/LCSYS.2020.3005429

[7] I. Aizenberg, T. Bregin, C. Butakoff, V. Karnaukhov, N. Merzlyakov and O. Milukova, “Type of blur and blur parameters identification using neural network and its application to image restoration”, in Lecture Notes in Computer Science, 2415 LNCS, pp. 1231–1236, 2002. [Online] https://link.springer.com/chapter/10.1007%2F3-540-46084-5_199

[8] X.-D. Yuan, J. Zhou and M. Huang, “Method of structural damage identification using neural networks based on static displacements and natural frequencies,” J. Harbin Inst. Tech., vol. 37, no. 4, pp. 488–490, 2005.

[9] R. A. Felix and E. N. Sanchez, “Chaos identification using variable structure recurrent neural networks,” Neural Networks IEEE Trans., vol. 15, no. 6, pp. 1450–1457, 2002.

[10] T.-P. Chen, “Approximation problems in system identification with neural networks,” Sci. China (Scientia Sinica) Series A, vol. 37, no. 4, pp. 414–421, 1994.

[11] F. Mohd-Yasin, A. L. Tan and M. I. Reaz, “The FPGA prototyping of Iris recognition for biometric identification employing neural network,” Proceed. Int. Conf. Microelectronics, pp. 458–461, 2004.

[12] X. Du, R. An and Z. Chen, “Model identification of coal main fans in mine based on neural network,” in Lecture Notes in Computer Science, pp. 178–185, 2011. https://doi.org/10.1007/978-3-642-23896-3_21

[13] A. I. Hanna and D. P. Mandic, “On an improved approach for nonlinear system identification using neural networks,” J. Franklin Instit., vol. 340, no. 5, pp. 363–370, 2003. https://doi.org/10.1016/j.jfranklin.2003.07.001

[14] G. Ye, W. Li and H. Wan, “Study of RBF neural network based on PSO algorithm in nonlinear system identification,” Proceed. – 8th Int. Conf. Intell. Comput. Tech. Automat., pp. 852–855, 2016. https://doi.org/10.1109/ICICTA.2015.217

[15] J. F. Pollard, M. R. Broussard, D. B. Garrison and K. Y. San, “Process identification using neural networks,”

Comput. Chem. Eng., vol. 16, no. 4, pp. 253–270, 1992. https://doi.org/10.1016/0098-1354(92)80046-C

[16] Y. Liu and J. J. Zhu, "Continuous-time nonlinear system identification using neural network," Proceed. Am. Control Conf., pp. 613–618, 2008. https://doi.org/10.1109/ACC.2008.4586560

[17] J. S. Yoon, J. H. Park and H. K. Kim, "Gammatone-domain model combination for consonant recognition in noisy environments," Proceed. Ann. Conf. Int. Speech Commun. Assoc., pp. 1773–1776, 2008.

[18] T. Yamada and T. Yabuta, "Dynamic system identification using neural networks," IEEE Trans. Syst., Man Cybernetics, vol. 23, no. 1, pp. 204–211, 1993. https://doi.org/10.1109/21.214778

[19] L. Samir, G. Said, K. Nora and S. Youcef, "Improved Pi-Sigma Neural Network for nonlinear system identification," 5th Int. Conf. Electr. Eng., pp. 1–5, 2017.

[20] N. Yadaiah, L. Sivakumar and B. L. Deekshatulu, "Parameter identification via neural networks with fast convergence," Math. Comp. Simul., vol. 51, nos. 3–4, pp. 157–167, 2000. https://doi.org/10.1016/s0378-4754(99)00114-7

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