Sensors & Transducers
Published by IFSA Publishing, S. L., 2021
http://www.sensorsportal.com

The Integration of Artificial Intelligence and Measurement Science Methods by the Regularizing Bayesian Approach

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Received: 29 January 2021 /Accepted: 5 March 2021 /Published: 30 April 2021

Abstract: This article substantiates the need for deep integration in the form of convolution of artificial intelligence methods and measurement theory at all levels of information acquisition and processing to improve the efficiency, stability, consistency, transparency, traceability and quality control of measurement and neural network solutions, intellectualization of data transmission and storage systems (IIoT), and the construction of highly efficient cyberphysical systems.

The paper considers the approach and methodological principles of creating a new type of neural networks, called Bayesian measurement networks. The concept and formalization of a new type of Bayesian neurons implementing Bayesian convolution based on the regularizing Bayesian approach is given. Three types of Bayesian neurons that implement the convolution of the values of quantitative and qualitative features are considered. An architectural scheme and metrological justification of BIN solutions, a platform for rapid development of applied BIN solutions, are proposed. Examples of solutions to applied problems based on BIN are given.

The concept is given and a practical example of an intelligent industrial IoT is given. The expediency and experience of using BITS and cognitive measurements for the construction of CPSS are noted.

Keywords: Artificial intelligence, Measurement theory, Neural network, Regularizing Bayesian approach, Industrial internet of things.

1. Introduction

The development of technologies in the modern information sphere clearly shows the special relevance of the development of principles for the integration of artificial Intelligence (AI) and Measurement Science (MS) methods. On the one hand, artificial intelligence methods, based on experimental information, have a need for sufficient amounts of good-quality data. The quality of the resulting solutions directly depends on the quality of the data. On the other hand, in order to successfully and fully solve applied problems, the measurement results must be interpreted, integrated and processed based on artificial intelligence methods.

The main requirements for both types of systems from international standards (for example, the ISO series) and users are: accuracy and reliability of the resulting solutions, traceability of the processes of obtaining solutions (traceability), (accountability, uniformity of measurements, tracking); transparency of technologies and algorithms for obtaining solutions (transparentability); interpretability of solutions (explainability), which are practically not performed in modern AI systems, in particular, in developments based on neural network technologies. In this aspect, measurement technologies are a good example, in which, as a rule, the first two or three requirements are met.

Until now, so-called integrated systems have combined measurement subsystems with processing subsystems purely "mechanically" in their architecture. This led to the almost autonomous existence of the measurement and computing subsystems in the information media environment. There are both theoretical and practical reasons for this. But to solve applied problems with the implementation of these requirements, it is necessary to coordinate the functioning of AI and MS technologies at each stage of information processing. It is important to "teach" measurement technologies to use information in the form of knowledge, and AI technologies to metrologically certify the resulting solutions, especially in the form of knowledge.

2. Principles of "Convolutional" Connection of AI and MS Technologies

The most significant new principle of integration is the principle of convolutional connection of AI and MS technologies, when the properties and functionality of these systems, interacting in the process of solving an applied problem, provide each other with additional information processing capabilities that are not inherent to them separately. For example, measurement technologies-the possibility of using information in the form of knowledge, extensive opportunities for cognitive methods of interpreting measurement results. Methods of artificial intelligence - the possibility of metrological justification of solutions, management of the synthesis of technologies and ensuring the required quality of the resulting solutions. The transition to a convolutional connection of AI and MS systems provides powerful incentives to implement the principles of Industry 5.0.

The distinctive characteristics of Industry 5.0 from Industry 4.0 in terms of information processing methodology are: personalization of information processing; customization of information processing services; availability of explanatory capabilities; flexibility of software models and structures; self-learning and self-development of application and system software; ensuring high reliability and quality of the resulting solutions; strengthening the cognitive capabilities of software.

Thus, overall, the new principles of Industry 5.0 is directed to methods and systems of information processing on the full intellectualization application and system software (paragraphs 1 to 5, 7) and metrological support decisions (paragraph 6).

How relevant is the issue of quality assessment of the applications of artificial intelligence, its measurement rationale is evidenced by the fact that the international Institute of standards currently offered version of the standard series ISO to control the efficiency and quality of solutions to the artificial intelligence methods.

The intellectualization of data acquisition processes by measuring systems that is, measuring processes, has been relevant since the early 90s of the last century. The first work in the formation of this direction was the work of D. Hofmann and M. Karaya [1]. This was followed in 1986 by the IMEKO Congress, in which a number of applied works devoted to this area of measurement theory appeared. However, all of them were of a very private applied nature and had no theoretical justification. In the 90s, the direction continued to develop in the works of D. Hofmann and L. Finkelstein [1, 2].

In their work, the main focus was the applied problem of self-calibration of measuring systems. For this purpose, some a priori and obtained in the course of measurement assessments and expert knowledge were used. But such additional modules were built in separately, as additional subsystems, and did not participate in the measurement process.

Thus, these were works aimed at the joint but autonomous application of artificial intelligence methods.

To implement the real integration of artificial intelligence methods and measurement theory, it is necessary to use them together in the measurement and information processing processes themselves.

This approach was proposed in the early 90s of the last century in the works [3, 4]. It is called the regularizing Bayesian approach.

The basis for obtaining solutions optimal by the average risk criterion in such technologies is the Bayesian convolution according to the modified Bayesian formula [3]. Convolution is implemented on special scales called conjugate scales with dynamic constraints [9, 22].

This name is due to the structure of the scale, which consists of numerical and linguistic scales, interfaced by their carriers. Such scales allow you to process both numerical and measurement information, as well as information in the form of knowledge. An example of such a scale is shown in Fig. 1.

Information from the instruments is sent to the numerical scale, and from experts or other sources of knowledge to the linguistic scale. For the joint processing of all types of information on the scale, both methods of measurement theory and methods of artificial intelligence, in particular methods of the theory of fuzzy sets and linguistic variables, are used. On the linguistic part of the scale, algorithms for rationing and checking by criteria can be implemented.

In accordance with this, we can call this method of integrating artificial intelligence methods and measurement theory "convolutional", which provides a deep integration of these methods.

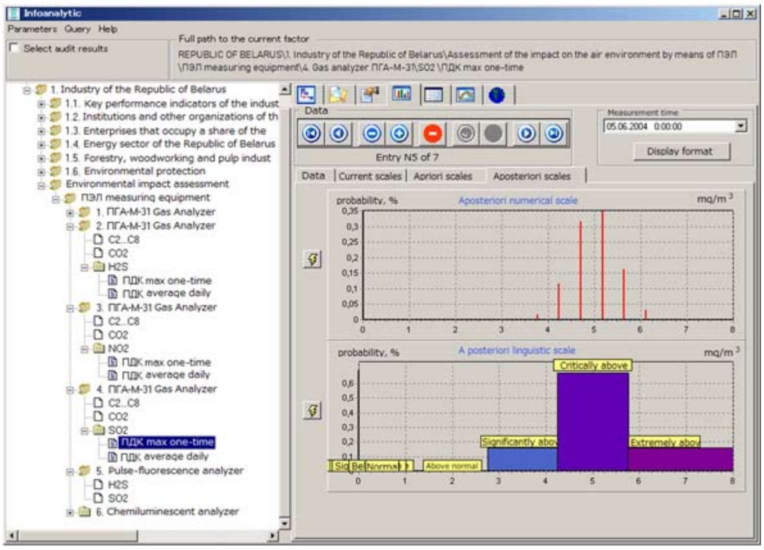

Fig. 1. The conjugate scale of the SDC type used to implement Bayesian convolution.

2.1. Measuring Scales of Quantitative Measurements

Deep integration of artificial intelligence methods and measurement theory is implemented at the lowest levels of obtaining and primary processing of non-qualitative information.

Typification and classification of measurement scales can be carried out on the basis of several main features: objective and subjective measurements and scales; quantitative and non-quantitative measurements and scales.

Quantitative scales are divided into five main types: nominal scales; ordinal scales; interval scales; ratio scales; and absolute scales.

The following classification system for non-quantitative (non-numeric) scales is proposed.

Non-quantitative scales can be divided into sensitive and cognitive scales. The first type of scales is associated with the measurement of emotional properties, sensations, and sensory perceptions; the second-with the representation of knowledge, experience, and skills of subjects and society as a whole, declarative attitudes, norms, and rules in measuring processes.

Sensitive scales are divided into: scales of maxims (sensations); intuitive.

Sensation scales are divided into: sound scales; visual scales; organoleptic (aromatic) scales; tactile scales; emotion scales.

Cognitive scales are divided into: descriptive; predictive; prescriptive scales, reflecting the available knowledge and experience of the subjects, the predictive process, as well as the predictive process with explanations.

All these scales are based on the gradation of the manifestation of properties. For their construction, the concept of an ordinal universal scale is used, for which the reference points are linguistic variables that reflect this gradation of properties.

To measure complex integral properties, we use emergent scales, which allow us to measure the emergent properties of complex objects based on measurements of simple properties.

Criterion conjugate scales. On linguistic scales, you can build criteria scales of a multi-tiered structure. The concept and technologies for creating such scales are proposed and implemented in applied problems within the framework of the regularizing Bayesian approach methodology.

Criteria scales can be objective when they are created on the basis of standards, regulations, and technical guidelines.

They can also be fiducial (subjective), when they are based on norms and principles of a subjective type.

The criteria scales in the BIT methodology are interfaced with the main linguistic SDC for multi-criteria scaling. In this case, together with the measurement process, a multi-criteria audit of the measured characteristics is carried out.

The measurement results on such scales are fuzzy alternative estimates with a full metrological justification of the BIT scales.

Integral (emergent) scales for measuring the emergent properties of complex objects and systems. This type of scale is designed to measure the integral properties of complex objects. The measurement method contains the functional possibility of implementing convolution (convolution) of intermediate measurements of simple properties included in the integral property.

Such scales are used to measure indexes, hierarchical indicators, integral characteristics, and indicators.

Such scales provide interpretability and explanation of the resulting solutions.

Examples of implementing the principles of convolutional integration of AI and MS methods can be Bayesian measurement networks and systems of the intelligent industrial Internet of Things (IIoT) based on RBA and BIT, given in the article below.

3. The Concept of a Bayesian Measurement Neural Network

In [12], the concept, structure, theoretical justification, and applied examples of using a Bayesian measurement neural network are proposed.

The traditionally noted disadvantages of neural networks include the impossibility of semantic interpretation of the received solutions, managing the network operation, and obtaining intermediate solutions. In addition, the quality of input information and its metrological specifics are not taken into account, and therefore the quality of output solutions is not determined.

These shortcomings can be successfully overcome when creating a neural network structure based on the methodology and technologies of the regularizing Bayesian approach (RBA).

It is worth noting that the RBA methodology is developed on the basis of the principles of the theory of pattern recognition and therefore can be reasonably used to build neural networks.

3.1. Methodological Foundations and Principles of Creating Bayesian Measurement Neural Networks

The regularizing Bayesian approach [3, 4] has become one of the successful examples of platform solutions to the problems of modeling and creating developing information technologies, as well as monitoring, auditing and management in conditions of uncertainty.

The modern concept of a complex object in the framework of RBA based on models with dynamic constraints (MDC) involves the construction of a specific model in the process of controlling the system of a complex object or the behavior of an object in a difficult predictive situation and allows for the possibility of changing both the composition of the object properties that form the MDC and their relationships, and the systems themselves for representing properties and relationships.

The results of the solutions are presented as benchmarks of scales $\{h_{kt}\}$ with changing properties according to the incoming information ($\{h_{kt}\} \in H_{KT}; k = 1, K; t = 1, T$). Together, these interconnected scales are a hyperscale (hypercube), which implements a model of the object and its functioning environment in the form of an MDC.

When creating neural networks based on RBA, by analogy with the considered architecture of the analytical neural network, it can be noted that, in fact, the hypercube implements the structure of a convolutional deep learning neural network of a hierarchical type. The convolution is based on a modified Bayesian formula.

All five types of hybrid system layers are present in the Bayesian convolutional network architecture. However, the number of convolutional layers in Bayesian networks is much higher, which provides deep network learning.

The first layer implements configuration (network training), which determines the types of probability density for numerical data and the types of membership functions for linguistic variables, as well as the MDC, the hierarchy of which determines the structure and number of convolutional layers of the network.

The second layer performs the function of fuzzification of variables and metrological justification of decisions based on the following dependence:

$$\{h_{kt}|\{Mx\}_{kt}\} = \{\mathrm{argmin}\, C[\varphi_{it}(x_{it}|y_{it})]\}, \qquad (1)$$

where $\{h_{kt}|\{Mx\}_{kt}\}$ is the fuzzified value of the input variable with the complexes of metrological characteristics of accuracy, reliability, and reliability for each component of the fuzzy set;

C is the optimization criterion in the form of the average Bayesian risk of the solution;

φ_{it} is the Bayesian fuzzification function;

$x_{it}|y_{it}$ is the set of data obtained under y_{it} conditions, including a set of a priori information, restrictions, and metrological requirements.

The chain of constant metrological support for each stage of the implementation of the network algorithm allows us to reasonably define this type of neural network as a *measuring neural network*. And since a modified Bayesian rule (3) is used to implement convolution, such a network can be called a Bayesian *measurement neural network* (BIN) of a hierarchical type with deep learning.

With this architecture, convolutional layers can be represented as feature convolution layers, which allows you to interpret the decisions of each layer in relation to their semantic content.

When two and many features are convoluted, each neuron of such a network is activated on its convolutional layer by an optimizing Bayesian function of the minimum average risk of a C solution of the form:

$$\{h_{kt}|\{Mx\}_{kt}\} = \\ = \{\mathrm{argmin}\, C[\varphi_{jt}(x_{it}|y_{it}; x_{i+1t}|y_{i+1t})]\}, \qquad (1)$$

where $h_{kt} \in H_{KT}, k = 1, K; t = 1, T;$

$\boldsymbol{\varphi_{jt}}$ is the Bayesian convolutional function; $\boldsymbol{\varphi_{jt} \in \Phi_{JT}; j = 1, j;}$

$x_{it} \in X_{IjT}; (i = 1, I)$ are the sets of values of numerical and linguistic variables that reflect the properties of features;

$y_{it} \in Y_{IjT}; (i = 1, I)$ are the conditions for obtaining data and implementing convolution algorithms;

$Y_{IjT} = \{A_{IJT}\}$ is the set of a priori information;

O_{IJT} is the multiple constraints;

M_{IJT} is the set of metrological requirements.

The Bayesian convolution formula has the following form:

$$P(h_k|\ x_i|\ Y_i) = \frac{P(h_k|Y_{i-1})l(x_i|h_k|Y_i)}{\sum_{j=1}^{K} P(h_j|Y_{i-1})l(x_i|h_j|Y_i)}. \quad (3)$$

In the process of such convolution, the probabilities of rappers of the feature scales are transformed, information about which enters the system in the form of input data streams and knowledge about the features.

Let's call this type of neuron a *Bayesian neuron*.

Let us consider in more detail the implementation of the Bayesian convolution to explain the previously given definitions and the above reasoning.

The scale of the SDC type can change its properties and structure (carrier, reference points, composition of permissible ratios, etc.) according to the change in the structure of the MDC. That is why it is called a scale with dynamic constraints (SDC). Its appearance is shown in Fig. 1.

The SDC scale for measuring the properties of a one – dimensional indicator is a two-dimensional scale, along one of the axes of which the values of the indicator are plotted in numerical or linguistic forms, and on the other-the degree of confidence (confidence, possibility) of the result. Therefore, it is called conjugate SDC.

The synthesis of RBA information technologies is based on the principle of unity of measurements, which allows to coordinate the inputs and outputs of individual scales and transform them in accordance with the functional content of the information technology and compliance with the metrological requirements for information system solutions. At the same time, a single information space is formed with a topology determined by metrological requirements and characteristics of information flows according to the R methodology [20]. For this purpose, in parallel with the computational process, the process of metrological support of each solution is implemented in the form of indicators of accuracy, reliability, reliability, entropy and risk. These indicators are combined into complexes of metrological characteristics. Metrological complexes determine the quality of solutions by many indicators, both for solutions in numerical form and for solutions in linguistic form in the form of knowledge. The theoretical justification of the metrology of data and knowledge is given in [11].

The solution obtained on the basis of Bayesian convolutions is a series of alternative feature estimates with corresponding complexes of metrological characteristics and is a regularized Bayesian estimate, the properties of which are considered in [3].

Explanations of the functionality of the elements of this scheme are given below.

In the BIN, according to the neuron formula, three types of convolutions are implemented.

1. Convolution of a priori and a posteriori values of numerical or linguistic variables (Bayesian neuron type 1).

2. Convolution of values of numerical and linguistic variables (Bayesian neuron of the 2nd type).

3. Convolution of the integrated values of various features (Bayesian neuron of the 3rd type).

As already noted, the parallel branch of each stage on each convolutional layer implements full metrological support for solutions.

The scheme of convolution of the 3rd type is shown in Fig. 2, i.e., the structure of the implementation of a neural network on a convolutional layer with the 3rd type of Bayesian neurons is reflected when the values of two different variables are convoluted.

This allows you to create a single technology with the ability to manage the quality of the resulting solutions.

The scheme for implementing Bayesian convolution in the BIN system is shown in Fig. 4.

With repeated implementation of convolution, there is a sharp decrease in the dimension of the feature space, which allows processing a significant number of data streams at high speed.

3.2. Software Implementation of BIN

The 'Infoanalytic' platform [18], which is essentially a BIN, is built on these principles. Unlike neural networks in application systems built on its basis, all convolutional layers are easily viewed in the user interface and interpreted using cognitive graphics.

For each feature, as solutions, you can get comprehensive information, dynamic characteristics, trends, assessments of situations and recommendations for their adjustment in accordance with the specified norms and rules. Examples of applied solutions with explanations for heat power engineering are illustrated in Fig. 3, 5.

So, in the example shown in Fig. 1 on the left, a conceptual model of the measurement object (the state of the air environment) is presented in the form of a tree of factors, in fact, representing a scale of the nominal type. This model is conditionally adequate to the real object within the framework of the available and used information, requirements and restrictions.

For the integral indicator, a new two-dimensional scale of this type is formed:

$$\mathbf{h_t^{integral}|\{MX\}_t^{integral} = h_{It}|\{MX\}_{It} * h_{2t}|\{MX\}_{2t} * \ldots * h_{kt}|\{MX\}_{kt}}, \quad (2)$$

where $h_t^{integral}|\{MX\}_t^{integral}$ is the set of alternative solutions of an integral indicator with complexes of metrological characteristics containing indicators of accuracy, reliability and reliability of solutions $h^{integral}$ belonging to a dynamic compact of solutions H, *is a symbol of generalization of elements, systems $\{h_{kt}|\{MX\}_{kt}\}$ is a set of alternative solutions of one-dimensional indicators with complexes of metrological characteristics containing indicators of accuracy, reliability and reliability of solutions h_t belonging to a dynamic compact of solutions H.

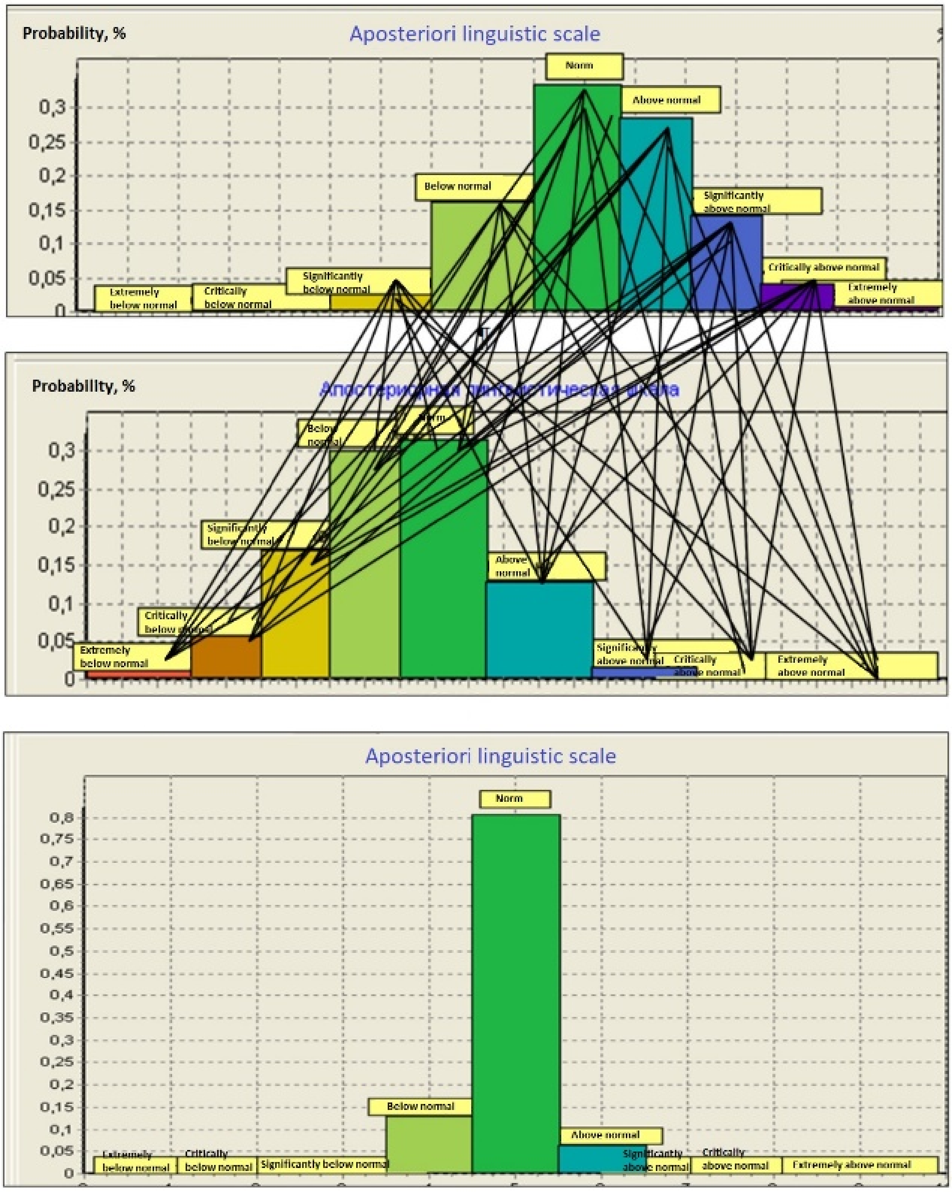

Fig. 2. Illustration of Bayesian convolution principles for the BIN scheme.

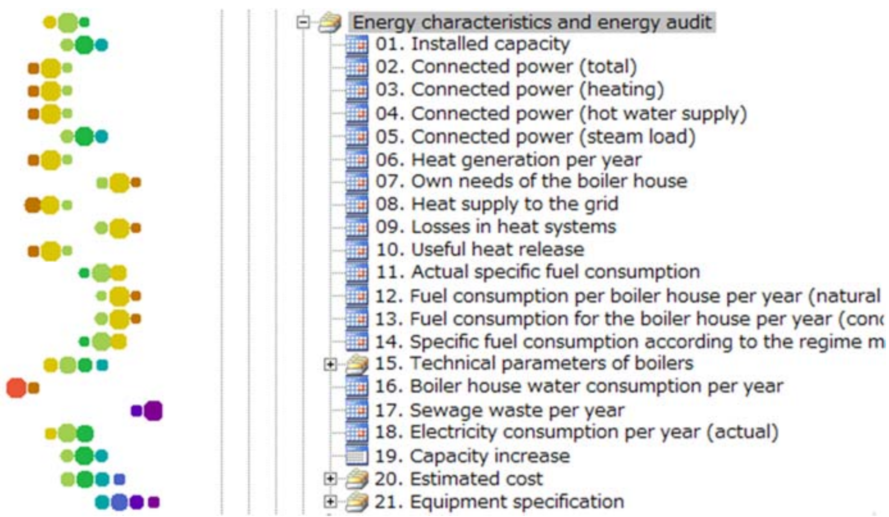

Fig. 3. Convolution of indicators of heat-generating systems with cognitive interpretation of solutions.

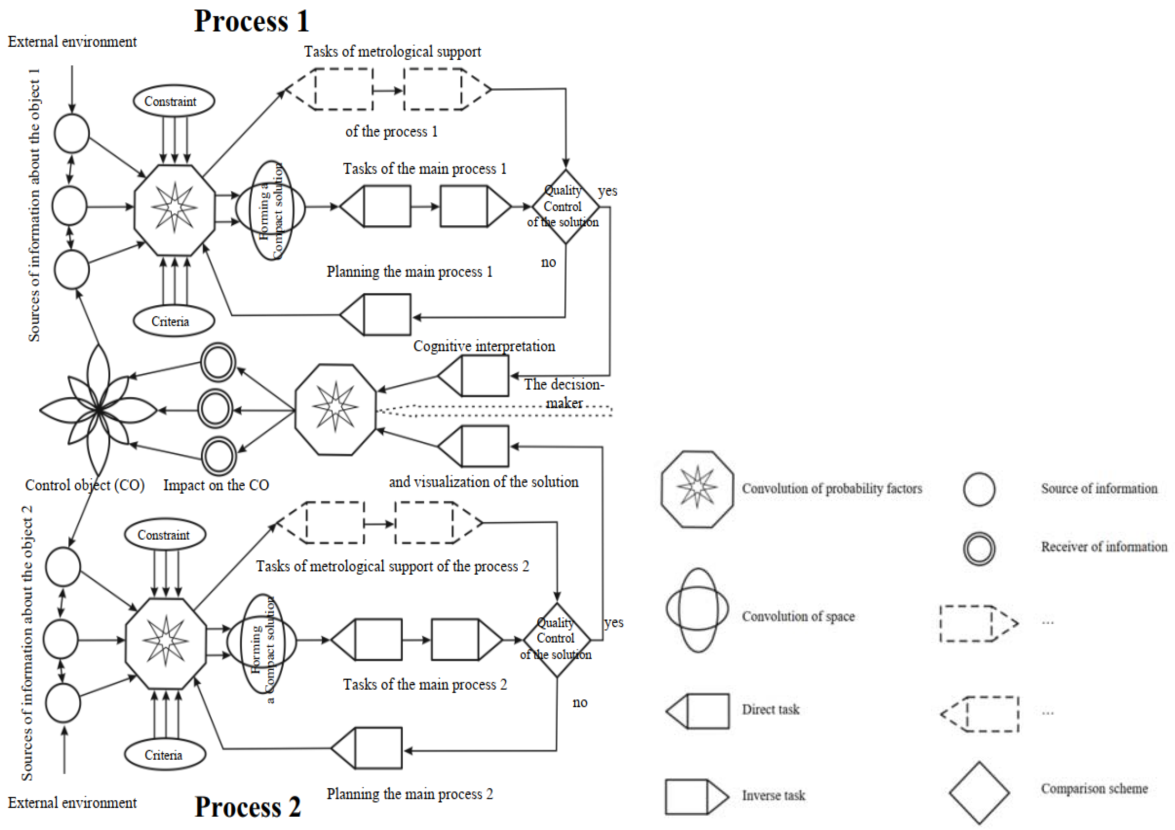

Fig. 4. A scheme for implementing convolution with Bayesian neurons of type 3.

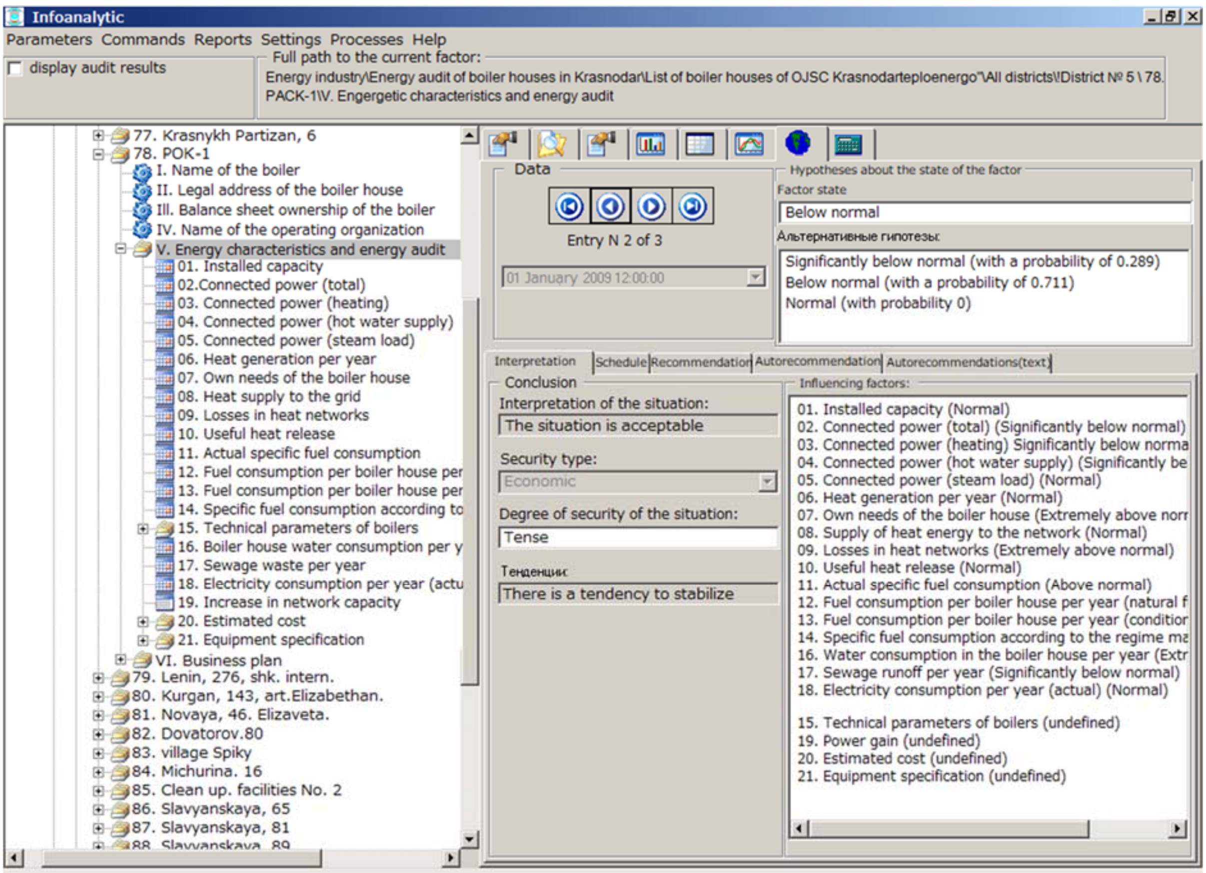

Fig. 5. Convolution of signs of the state of the energy-generating system with explanations.

Thus, the SDC structure is developed according to the MDC structure, and the model and the nominal scale of factors representing it in the Infoanalytic environment are continuously developed.

4. Metrological Characteristics of the Quality of BIT Solutions

As it is noted about many scientific works, the most important issue of intellectualization is the question of the truth of the knowledge and solutions obtained. In Bayesian intelligent technologies, every decision, every model, and every management recommendation has decision confidence indicators that characterize the conditional truth of the decision in terms of available constraints, a priori information, and criteria requirements. In addition, the solution is accompanied by indicators of accuracy, reliability (in the form of estimates of error levels of the 1st and 2nd kind), indicators of the information utility of the solution, the risk of solutions, entropy characteristics, which are combined into complexes of metrological characteristics that ensure the stability and convergence of the obtained solutions under uncertainty. The rationale for the choice of indicators of metrological complexes is given in [11] Such complexes are interconnected for individual solutions and together form a system of metrological support, which allows the synthesis of bits in accordance with the required metrological characteristics. This determines the uniqueness of bits among all similar technologies. The solution obtained on the basis of Bayesian intelligent technologies is a series of alternative property estimates with corresponding sets of metrological characteristics.

However, it should be noted that all estimates of metrological indicators are conditional within the framework of the available a priori information and restrictions.

Therefore, the absolute truth of solutions is unattainable because of the fundamental unknowability of absolutely all the properties, characteristics and relationships of complex systems.

The introduction of a system of scales in BIT allows you to control and control the conditional accuracy of solutions, their reliability and reliability in solving the problem of system synthesis, which is considered in a number of works by the author [3, 9, 11].

5. IIIOT – Intelligent Industrial Internet of Things

Currently, the IIoT direction is actively developing. Understanding the need to pre-process measurement data before transmitting it through communication channels led to the formation of the direction of peripheral computing and the concept of DATALAKE.

From ETL structures, the transition is made to some ground-based local data storage (DATALAKE), focused on the specifics and mode of operation of applied information systems. At the same time, there is a clear trend towards the inclusion of data pre-processing modules for the organization of peripheral computing.

To implement this trend, it is proposed to use Bayesian intelligent technologies and neural network application systems based on them. Such systems will make it possible to significantly reduce the dimension of the stored data in the framework of solving specific application tasks, while fully preserving their information content. In addition, such systems can be used to integrate data and knowledge in the field of information collection, transmitting ready-made assessments of processes and situations, as well as local management decisions, over the network.

An example of such systems is the monitoring systems of water management, power generation, control organizations and services [16, 19].

The distinctive characteristics of intelligent IIoT from traditional IIoT structures are the presence of intelligent data processing systems in them, in particular, in the example given, the presence of a Bayesian measuring neural network for convolving data received from devices and obtaining solutions in the form of assessments of situations with explanations of the reasons and factors for their formation, as well as with recommendations for correcting the situation on the ground. In this way, the IIoT structure is arranged in all sections of the water supply network. The integrated information is then transmitted by IIIoT to the central processing unit for information received from other types of sources.

One example is a system that is a hierarchically organized, geographically distributed environment for monitoring the state of water management networks and supporting water management decision-making in conditions of significant amounts of data, diverse information and uncertain situations.

The system architecture is shown in Fig. 6.

The system consists of the following main blocks:

1. The central block of intelligent information processing based on a neural network of the BIN type with a library of mathematical modeling and development of scales of the SHDO type (G1)
2. Analytical neural network for generating scenarios and recommendations; (G2)
3. A unit of measuring instruments with converters and controllers and with pre-processing of measurements; (G3)
4. Thermal image processing neural network; (G4)
5. System interface for analytical neural network; (G5)
6. System interface for image neural network; (G6)
7. User interface; (G7)
8. Server blocks. (G8)
9. WEB servers and services
10. A block (local) IIIoT with a built-in neural network of the BIN type.

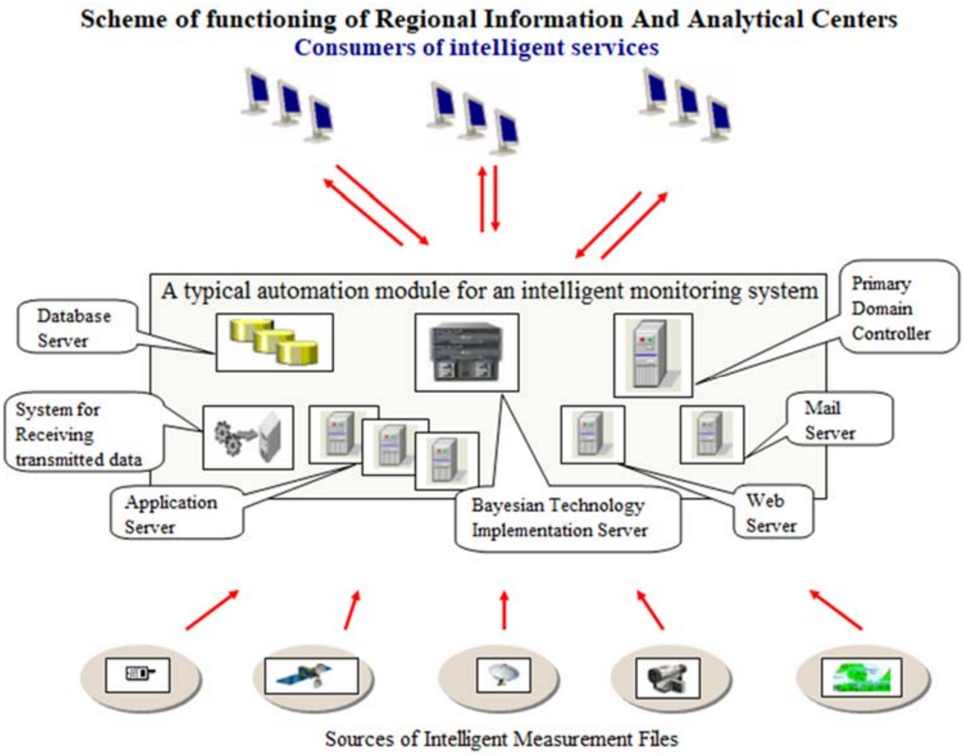

Fig. 6. Architecture of the intelligent industrial Internet of Things based on a typical module of the intelligent DATALAKE.

Integration with the specified software blocks takes place according to the selected data exchange protocols in the on-line and of-line modes.

The information model is focused on the object of monitoring, in particular, the section of the water supply network. (Go).

The object is a node of a section of a heating main. The parameters of the heating main unit must be controlled by the measuring unit (Gm). A measurement unit is a measurement system that receives measurement information, logs it, and transmits it to a top-level information system. Controlled parameters: water flow-two flow meters Gd; pressure-two pressure sensors Gp; temperature-two temperature sensors Gt; humidity sensor Gg.

The information model of the measuring unit has the following form:

$$\mathrm{Gm} = \mathrm{Gd} * \mathrm{Gp} * \mathrm{Gt} * \mathrm{Gg},$$

where * is the convolution symbol of the information according to the modified Bayes formula.

In addition to the numerical measurement information specified above, a series of Gi images obtained by means of a thermal imager is used as an information stream, identifying the heating of the surface of water supply pipes at their surface locations.

With this in mind, the information model can be presented in an expanded form: $\mathbf{Gm1} = \mathbf{Gm} * \mathbf{Gi}.$

Another important information flow is the recommendations and scenarios coming from the analytical neural network (Gn).

Then the information model of the system can be represented as: $\mathbf{Gm2} = \mathbf{Gm1} * \mathbf{Gn}.$

The mathematical basis of this project and the system of monitoring and management decision-making are the regularizing Bayesian approach (RBP) and Bayesian intelligent technologies, the basic ones of which are Bayesian intelligent measurements (BII).

Since BII-type measurements are made under conditions of significant uncertainty regarding the exact knowledge about the model of the measurement object, measurement conditions, and measuring instruments, which can be either instrument-based or expert knowledge, which introduces instability in the measurement process and the resulting solutions, it is necessary to implement measurements within a single regularized solution space.

As a model object, in particular, the reference points of measurement scales, can be not only numerical values, but also functions, situations, images of objects, scenarios, which together represent a conditionally complete group of events reflected by the reference points of the measurement scale carrier. Such scales can be parametric, functional, or system scales with their corresponding benchmarks in the form of parameter values, model functions, and systems.

The problem of measurement in conditions of uncertainty is set as the problem of restoring values or metrological classification of images, which determines the need to ensure the stability of its solutions. Therefore, in complex measurement situations, the representation of the measurement problem is used as a set of inverse problems of restoring values, states, and situations from the received information.

The measurement technique can be a complex information technology.

For each measurement solution, metrological justification of models, algorithms, and solutions is provided in the form of indicators of accuracy, reliability, reliability, risk, and information content of solutions.

5.1. Generalized BII Equation

For the purpose of methodological formalization, a generalized measurement solution is obtained for all types of measurements, including BII and MI measurements. The measurement equations for all types of classical measurements, as shown in [15], are special cases of this generalized equation.

So, for Bayesian intelligent measurement, the measurement equation is written as follows:

$$\left\{h_{kt}^{(Q)}\middle|\{MX\}_{kt}^{(Q)}\right\}|\left(Y_t^{(O)} * Y_t^{(OE)} * G_t^{(OE)}\right) = \{\text{argexstr } C^{(B)}[\varphi_j\left(f_{it}\{X_{it}\}|\left(Y_t^{(Q)}\right)\right) * * Y_t^{(OE)} * G_t^{(OE)}]\}, \quad (1)$$

where $\left\{h_{kt}^{(Q)}\middle|\{MX\}_{kt}^{(Q)}\right\}|\left(Y_t^{(O)} * Y_t^{(OE)} * G_t^{(OE)}\right)$ is the fuzzy solution to the problem under the conditions of $Y_t^{(O)}$, (determined by a priori information, requirements, restrictions and assumptions) of the functioning of the object; under the conditions of influencing environmental factors $Y_t^{(OE)}$; in the compacts of the set of properties of the object $G_t^{(O)}$ and the environment $G_t^{(OE)}$.

$\{MX\}_{kt}^{(Q)}$ is the set of metrological characteristics of solutions containing indicators of accuracy, reliability, reliability, solution risk, entropy, and Fischer information;

$C^{(B)}$ is the criterion that sets the logic of solving the problem; in Bayesian intelligent technologies, it is the Bayesian criterion of the average risk of solving; in soft dimensions, it is the Zadeh logic; in classical dimensions, it is the Lukasevich logic;

φ_j is the Bayesian intelligent technologies that define and implement solution regularization;

f_{it} is the computational or algorithmic technologies used to process the available primary information;

X_{it} is the set of information flows (data and knowledge) used to obtain solutions.

The equation for fuzzy measurements differs in that, in general, it can have non-Bayesian criteria for the output of solutions to C. But its result, as in equation (1), is represented by a list of alternative solutions with different degrees of confidence, which is calculated for any indicator, for example, for evaluating the influencing factors of the external environment, according to the modified Bayes formula [3]:

$$\mathbf{P}\left(\mathbf{h}_{kt}^{F_t}|\mathbf{G}_t^{(OE)}\right) = = \frac{\mathbf{P}^a\left(\mathbf{h}_{kt-1}^{(F_t)}\middle|\mathbf{G}_{t-1}^{(OE)}\right) \overset{\mathbf{L}}{\circ}\mathbf{P}\left(\mathbf{G}_t^{(OE)}\middle|\mathbf{h}_{kt}^{(F_t)}\right)}{\sum_{j-1}^{J}\mathbf{P}^a\left(\mathbf{h}_{jt-1}^{(F_t)}\middle|\mathbf{G}_{t-1}^{(OE)}\right) \overset{\mathbf{L}}{\circ}\mathbf{P}\left(\mathbf{G}_t^{(OE)}\middle|\mathbf{h}_{jt}^{(F_t)}\right)} \quad (3)$$

The differences from the measurement equation according to the classical scheme of measuring physical quantities are: the explicit introduction into the equation of the criterion for choosing a measurement solution, information and technological transformations in accordance with the methodology and methodology of measurements, influencing external factors, as well as conditions that formalize the measurement situation.

Among the main differences from the classical methodology for measuring physical quantities are also the following.

Ensuring the development of measurement methods, models, and algorithms depending on changing measurement conditions.

Cognitiveness and interpretability are provided directly in the process of forming a measurement solution.

In the measurement process, it is possible to use, process and convolve both numerical and qualitative, linguistic information

Ensuring the stability of the resulting solutions during integration, identification of system models and their characteristics

Obtaining measurement solutions not only in the form of numerical parameter values as in classical measurements, but also in the form of models, audit decisions, recommendations, assessments, conclusions, and scenarios.

The conditional nature of the obtained solutions, that is, the measurement solutions will be valid only if the experimental conditions are met, namely: within the given compact of solutions, the set constraints, metrological requirements, and the available a priori information.

A mathematical model of the monitored object in the view of the portion of the water distribution network can be represented as a set of properties of a complex system in the form of Go: $\mathbf{Go} = * \mathbf{i} = \mathbf{1}, \mathbf{I}\ \mathbf{Gbi}\ (* \ \mathbf{j} = \mathbf{1}, \mathbf{J}\ \mathbf{Gbiq}),$

where Gbi – a conceptual model of the linear sections of the network I is the number of line sections of the water distribution network; Gbiq models of built-in blocks (wells) on the i-th section of the network, J is the number of wells in the i-th linear part of the network.

The mathematical model for the implementation of the project in the software environment should be supplemented with the system model of the Gs information and measurement complex blocks.

The mathematical model for the implementation of the project in the software environment should be supplemented with the system model of the Gs information and measurement complex blocks.

$$Gs = G1 * G2 * G3 * G4 * G5 * G6 * G7 * G8 * G9$$

The generalized model of information processing in the system, taking into account the above dependencies, has the form: $\mathbf{G = Go * Gs * Gm2}$.

Examples of the implementation of such a system are given in [16, 19].

6. Application of the Concepts and Tools of BIN and IIIOT in the Creation of Cyber-Physical (CPS) and Cyber-Physical-Social (CMS) Systems

In general, the concept of CPS is far from new, since its theoretical basis has not yet been developed, which allows us to consider CPS as a fundamentally new object in the field of IT. As often happens, well-known objects are given a new name. In particular, cyber-physical systems are, in fact, well-known systems for monitoring and managing man-made natural complexes, which have been worked with since the 70s.

An important aspect of the functioning of the CPS is the conditions of uncertainty of information and information situations that lead to instability of evaluation and management decisions. Therefore, methods and technologies based on the regularizing approach and BITS have proved to be very effective for creating such systems of various applications.

Many examples of the use of BIN in monitoring and management tasks in natural and man-made complexes are given in the literature [15, 16, 18, 19, 25].

So, since the 90s of the last century, systems for monitoring and supporting management decisions in the energy, industry, ecology, environmental protection and social spheres have been created on the basis of BIT. They weren't called cyberphysical systems, but they were essentially them.

In such intelligent distributed systems based on BITS and BINS, the IIIoT in the locations of the distributed system used intelligent workstations of specialists (IRM) of an applied orientation. A total of 28 types of IRMS were developed.

CPSS are social-oriented cyberphysical CPS systems in which the physical natural environment is considered in conjunction with human communities.

In such systems, it is advisable to use cognitive measurements [10] within the BIN with the inclusion of a person in the CPSS system circuit as a decision-maker, source and receiver of information.

Cognitive measurement is organized by combining experimental information $\{X_{it}\}$ and available data with assessments, knowledge, and solutions $\{X_{it}(st)\}$ of the measuring subject, which was proposed and discussed in detail in [10]. It provides a theoretical justification for the degree of uncertainty and the amount of information value introduced by the subject into the measurement and computing process, and also proves the need to convolve the subject's information with the main information flows coming from technical devices. In these works, the theoretical foundations of the metrology of subjective information are presented. At the same time, a portrait of the subject's competence is drawn up, which is taken into account when processing information.

Based on this, the equation for cognitive measurements is written as:

$$\{\mathbf{h_{kt}(Q)}|\{\mathbf{MX}\}_{\mathbf{kt}}(\mathbf{Q})\}|\big(\mathbf{Y_t(O) * Y_t(OE) * G_t(OE)}\big) = \big\{\mathbf{argexstr\, C(L)[\, \varphi_j(f_{it}\{X_{it}\} * \{X_{it}(st)\}|(Y_t(Q)\} * * Y_t(OE) * G_t(OE)]}\big\}, \qquad (4)$$

where $\{X_{it}(st)\}$ is the information received from the entities participating in the system.

Based on this equation, cognitive measurement networks are created.

7. Conclusion. Prospects of Integration of BII and BIT Technologies with Modern Information Technologies of Artificial Intelligence and IIOT Systems

DATA Science, BIG DATA, BI, IoT, DSS, DATA Mining, and other systems related to intelligent data processing can be mentioned as promising areas for using the methodology, technologies, and tools of intelligent measurement, as discussed in detail in [12, 15]. The advantages of using intelligent measurements for modern artificial intelligence and measurement technologies can be expressed as follows:

1) In DATA Science systems - for metrological certification of data and knowledge flows, as well as their integration;

2) In IoT systems-for the collection, integration and interpretation of instrumental data for the creation of data lakes with prescriptive analytics, for the development of MES technologies and platforms;

3) In BI-systems - for analytical processing and interpretation of information;

4) In neural networks - for the collection, metrological certification and convolution of data and knowledge in order to attract additional information when compiling a data set and training a neural network;

5) For BIG DATA systems – in order to significantly reduce the dimension of information flows;

6) For systems of mathematical and analytical information processing, in particular for uncertainties and small samples;

7) For digitalization systems – for the collection, intelligent processing of information, the creation of systems for monitoring and managing complex industrial and socio-economic complexes, as well as their sustainable development.

Thus, the main idea of this article is formulated as the need for deep integration in the form of a convolution of artificial intelligence methods and measurement theory at all levels of information acquisition and processing to improve the efficiency, stability, consistency, transparency, traceability and quality control of measurement and neural network solutions, the intellectualization of data transmission and storage systems (IIoT), and the construction of highly efficient cyberphysical systems.

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