Convolutional Development of Artificial Intelligence Methodologies and Measurement Science on the Basis of Regularizing Bayesian Approach

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Abstract

The article is devoted to the current direction of the development of methodology and artificial intelligence systems and modern measurement theory. namely, the possible path of their integration development. The regularizing Bayesian approach is an important methodological basis for the implementation of such a development.

The article presents a historical sketch of the development of the territory of intellectual dimensions. It is concluded that the regularizing Bayesian approach created in the 90s of the last century, focused on data processing in conditions of significant uncertainty, is effective for creating intelligent measurement systems and the interrelated development of artificial intelligence methods and measurement theory.

Properties of Bayesian intelligent technologies based on RBA, on the one hand, allow implementing metrologically based intelligent data processing, on the other hand, using various types of knowledge as source information in measuring technologies.

The methodological aspects of Bayous intellectual measurements are briefly considered. A new classification of types of measuring scales focused on application in intelligent measurement systems is proposed. New properties of modern technologies of intellectual processing are noted information (DATA Science, DATA Mining, NN, BI, Decision Making, etc.) when using Bayesian intelligent measurements, significantly increasing their efficiency and developing their functionality.

Keywords

Uncertainty, measurements, regularizing Bayesian approach, scales, artificial intelligence

1. Introduction

The most important task of creating artificial intelligence systems is to collect a sufficient amount of reliable data. Thus, the known difficulties of developing neural networks are often associated with the lack of the necessary set of experimental data for forming a data set and training the network. In addition, to solve applied problems by means of artificial intelligence systems, as a rule, data of a certain type is required (in particular, presented in the form of quantitative information).

However, the numerical data received at the input of AI systems can vary significantly in accuracy, relevance, completeness and clarity of the presentation of the information available in them. The absence of metrological assessment of data quality in AI systems and metrological support of the algorithms used makes it impossible not only to manage the effectiveness of such systems, but also to obtain reliable and reliable solutions based on them. Information and measurement systems have these capabilities.

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At the same time, in modern measuring systems (IS), there is no possibility of attracting and using information in the form of knowledge in the measurement process, which is one of the main advantages of AI systems and is necessary for the functioning of systems in conditions of uncertainty.

To combine these two types of information representation, it is necessary to apply special methodologies and technologies for the intellectualization of measurements in measurement systems and to use a measurement approach when creating artificial intelligence systems.

Technologies and systems built on the basis of the regularizing approach (RBA) have such functional capabilities. Such technologies are called Bayesian intelligent Measurements (BII) and technologies (BIT).

We will further consider the methodological aspects of measurement intellectualization (AI), their creation and application in AI measurements and technologies.

2. Evolutionary aspects of the development of measurement intellectualization

The increasing complexity of applied problems of measurement theory has determined its development in the direction of intellectualization of measurement processes and systems.

The complexity of formalization and complexity of solving such tasks as monitoring and managing complex systems in conditions of their active interaction with the external environment with significant information uncertainty, managing the sustainable development of socio-economic systems, digitalization of activities and at the same time the requirements of completeness, objectivity, reliability and high speed of obtaining results on the one hand, and significant capacities of technical means for obtaining, converting and displaying various types of information implemented on a process basis, on the other hand, Measurement systems of this type should be focused on the effective study of the properties of complex objects (CO) and the environment of their functioning (SF), as well as the relationships between them by generalizing all types of a priori and incoming information in order to generate new knowledge, on the basis of which optimal solutions are obtained in specific measurement situations.

Work on the development of methods for the intellectualization of measurement processes began in the 80-90s of the last century. Among the pioneering works in this direction, first of all, it is necessary to include the research of D. Hofmann [29, 33], L. Finkelstein [29], V. Ya. Rosenberg [24], V. G. Knorring [2], D. Andrich [26], O. D. Duncan [27], J. Michel [38], S. V. Prokopchina and other domestic and foreign scientists, in which the concepts of adaptability in measurements, cognitive ability and intellectualization of measurement methods were first proposed and systems.

For the information and measurement systems existing at that time, there were the following characteristics:

- Excessive “rigidity” of the structures of algorithms and models of objects; lack of security of monitoring results with metrological support
- Technogenic basis of methods focused on working in measurement systems with limited a priori uncertainty, leading to unjustified simplification and typification of CO
- Impossibility of joint formalized processing of numeric and non-numeric information; lack of algorithmic and model self-learning and self-development

Many of these characteristics have remained at the present time in measurement methods and systems.

In methodological terms, the creation of the principles of measurement intellectualization was influenced by the development of the representative measurement theory, the theory of adaptive measurements and methodological works on measurements of non-quantitative quantities.

In the 90s, IMECO congresses played an important role. So, at the II Congress in 1986 in Jena, D. Hofmann proposed the very name “intellectual dimensions”. At this congress, a number of reports were made on intelligent measurements and their applications, the main ideas of which were summarized in the article by D. Hofmann and L. Finkelstein.

A special role in the formation of the trend towards the intellectualization of measuring systems was played by the introduction of processor tools into the IC structure, which provided wide technical capabilities for the computational complexity of measuring algorithms. The works of domestic and foreign scientists have created a theoretical basis for the emergence of a new generation of AIS tools that implement a new type of algorithms. During this period, methods of adaptive and statistical measurements were developed.

Processor ICS, having significant computing capabilities, made it possible to provide technical support (in the environment of a measuring tool) for new information technologies for generalizing and obtaining knowledge used in organizing and conducting measurements, to implement a fundamentally new type of measuring process, at each stage of which the optimal measurement strategy is developed automatically or automatically and the appropriate interpretation of their results is made on the basis of functional and metrological processing of various incoming and a priori information, which is the essence of measurement intellectualization. This made it necessary to create a single measuring chain of transformations of the results of primary measurements into the final solution and to consider this chain as an integral measuring process, the algorithmic basis of which is covered by the metrological verification scheme with the implementation of the principles of uniformity of measurements.

A new direction of measurement intellectualization, described in the early 90s in other works of the author [3-9] based on the use of a modification of the classical Bayesian approach, called the "Regularizing Bayesian Approach", combined the advantages of three fundamental approaches: system, measurement and Bayesian. Measurements based on RBA are called Bayesian intellectual measurements. On their basis, methodologies, technologies and systems of Bayesian mathematical statistics, Bayesian econometrics, Bayesian measurement neural networks, as well as various classes of applied systems in the field of industry, energy, economics, social sphere, ecology, geopolitics were created. The direction of Bayesian intelligent measurements was proposed as a development of measurement theory methods for measurements in uncertainty conditions [3-9].

In 1997, the author of this article proposed the direction of "Soft" measurements, based on the RBA and the theory of fuzzy sets by L. Zadeh.

At the beginning of the current millennium (the first decade), new types of intellectual measurements were created, such as cognitive measurements, systemic and poly-systemic measurements, global intellectual measurements.

The modern development of the theory of measurement intellectualization goes in several directions. These include, first of all, the involvement of the ideas of artificial intelligence and soft computing in measurement processes (S. V. Prokopchina, V. B. Tarasov), non-quantitative measurements (L. Finkelstein, M. Wilson), metrology of non-physical measurements, systematization and expansion of the measurement.

3. Conceptual foundations of the methodology of intelligent measurements

In order to determine the main provisions of the concept of intellectualization of measurements, we use the definition of the term "measurement" in its three interpretations.

In a broad sense, the term "measurement" is used to determine the directions of evaluating the properties of a real or virtual system (for example, social, economic, technical, psychometric, global and other dimensions).

In a narrow sense, the term "measurement" can be used in two ways. On the one hand (the second interpretation), it can be used to define the measurement process, including models, methods and means of implementing measurements; on the other hand (the third interpretation), it can denote the measurement result. In this concept, the term "measurement" is used in its second interpretation.

The conceptual basis for the intellectualization of measurements is the following principles given in the first works devoted to this issue [3-9]:

1. The intellectualization of measurements is based on taking into account the fullness of knowledge about the object of measurement, and an important place in this process is given to the cognitive function of measurements, the use of object models based on a variety of a priori information and information received in the measurement process
2. Measurement intellectualization technologies are characterized by adaptability to the conditions of measurement, correction of measurement results in case of errors of the measurement subject (meter), elimination of undesirable environmental influences
3. It is possible to plan a measurement experiment in real-time measurements
4. The rules of logical inference and decision-making are included in the measurement process
5. There is a modularity of measurement information technologies

6. Measurement intellectualization is based on computerization and automation of preparation, planning, and technical measurements
7. To implement the principles of measurement intellectualization, it is necessary: a developed user interface, the possibility of reconfiguration of software and hardware, their open nature and standardization, the presence of subsystems for metrological support of the results obtained and self-calibration, the presence of a subsystem of explanations and training

As can be seen from the listed characteristics of measurement intellectualization technologies, the first four of them are methodological, and the last ones are informational and technical. In reviews and publications on the intellectualization of dimensions as their main distinctive property, the inclusion of object models and measurement conditions in the measuring circuit is noted. Based on the above principles, in this work, measurement intelligence is understood as an optimized process of automatic or automated obtaining, generalization and use of metrologically based knowledge about the measurement object and the influencing factors of the environment by means of AIS in order to improve the efficiency and quality of measurements.

Therefore, one of the main tasks of the development of the theory and practice of intelligent measurements is the development of their full metrological justification, the specifics of which is to implement the measurement approach at the level of object models, measurement conditions and obtaining measurement solutions. The first works on AI metrology are mainly theoretical and conceptual in nature. The complexity of the mathematical problem of metrological support of AI explained the lack of an acceptable solution at the practical level. This significantly affected the effectiveness of AI development. Therefore, the study of the problems of AI metrology, its methodological and information technology aspects was an urgent task of the measurement theory and measurement technology.

To substantiate the methodological aspects of measurement intellectualization, it is appropriate to determine the measurement situation in which it is necessary. The measurement situation in which the measurements are implemented is characterized by the purpose, object and measurement conditions. The measurement conditions are determined by a set of a priori knowledge about the object of measurement (OI), the factors affecting it (VF) of the environment, metrological and technical and economic requirements of the measuring task, as well as a system of accepted assumptions and restrictions at the conceptual and technical levels.

In the intellectualization of measurements, the purpose of measurement can be:

- Valuation, forecasting (retrospective or prospective) of the properties and characteristics of OI
- Measurement control, which means the determination of the state of the OI by measuring instruments
- Issuing recommendations on the management of the OI or the measurement process itself in order to improve the quality of the measurement results obtained, as well as solving the management problem based on them

Consideration of a variety of measuring tasks in the application areas allows to distinguish three major groups of objects measurements on the complexity of their model-based representations:

- Multidimensional objects of measurement, which is a system of inter-related components, which correspond to the model-view basis of kupeste functions, systems of vectors and fields that describe the properties of the measurements and their relationship with the external environment, including measuring instruments
- Measurement objects represented by a function of one or more instruments

The set of measurement conditions can be typed according to the degree of certainty and completeness of a priori information about the OI and the VF of the environment of its functioning, its metrological validity and the degree of compliance with the requirements, the actual feasibility or practical feasibility of the accepted restrictions and assumptions, the degree of their correctness and rigor for a specific measuring task.

The traditional formulation of the measurement problem corresponds to the situation when the measurement conditions allow a priori to determine the OI and VF models with an accuracy up to the measured property represented by a parameter characterized by the value of a physical quantity.

The second common type of statement of the measurement problem corresponds to the measurement conditions under which the OI and VF models, although completely unknown a priori, can be determined in the process of iterations of the measurement experiment from a limited range of them, determined at the stage of measurement preparation. Such types of measurement situations correspond, as a rule, to fairly strict model restrictions and broad assumptions, which is usually true for objects of a fairly simple structure, well studied or allowing a comprehensive and complete study before the experiment.

As noted above, the emergence of a new type of tasks is due to the need to measure the properties of more complex objects in more complex measurement situations, when a priori and received measurement information is not enough to unambiguously determine the measurement result, and the measurement goal cannot be achieved without involving additional knowledge and technologies for obtaining them in the measurement process. At the same time, the models of OI, VF and their interaction should be modified in the process of obtaining new knowledge in a measurement experiment, reaching a level at which it is possible to solve the measurement problem as a whole.

Thus, three types of measurement situations can be distinguished:

- Type A – a priori information about OI and VF under measurement conditions, including knowledge about the operating environment (SF), the measurement environment (SI) and their interrelations with the object, is sufficient to achieve the measurement goal
- Type B – there is a limited a priori uncertainty about the models of OI, VF or SI, which can be completely removed when implementing measurements in an iterative process based on the available a priori information and the experimental data obtained about OI
- Type C – the existing significant a priori uncertainty about the properties of OI, VF, SI or their mutual influence is essential for achieving the measurement goal and cannot be completely removed with known technologies and measuring instruments, which determines the need for constant attraction, generalization, obtaining and using additional knowledge about OI, VF and SI in the measurement process

The measurement situation of the third type can take place for all the above types of measurement goals and objects and at all stages of the measurement process implementation. The solution of the measurement problem as a whole under such conditions can be carried out only on the basis of the intellectualization of the measurement process.

Based on the above conceptual provisions and definitions, a classification of measurement types is proposed, taking into account the type of measurement situations. Based on this classification, it is possible to represent the types of measurements in accordance with the stages of their evolutionary development in the following form:

1. “hard” – deterministic measurements
2. “flexible” – adaptive and probabilistic measurements with the processing of measurement results
3. “soft” – intelligent measurements

In accordance with this, it is proposed to classify measuring systems as follows:

1. “Rigid” – measuring devices and devices of the classical type
2. “Smart” or “flexible”:

- Measurement systems with data adaptation and processing
- Measuring systems with self-monitoring
- Measuring systems with self-calibration
- Measurement systems with automated reorganization
- Measuring systems with automated development of structure and functions

3. “Soft” – intelligent measurement systems:

- Intelligent measurement systems with the integration of data and knowledge
- Intelligent measurement systems with knowledge generation
- Intelligent measuring systems with self-development of the structure, functions and with an independent expansion of the applied orientation on the basis of the knowledge generated by them and forecast scenarios for the development of measuring and applied situations

The main attributes of the implementation of measurements in the intellectual measurement.

Measurement object – properties of a complex object that are not available for direct measurement

A model object is a complex or virtual object that is analogous to a measured property.

The measurement principle – information technology for the implementation of the measurement process, based on the solution of the inverse problem of pattern recognition-scale reference points.

The type of reference points – digital values, linguistic variables, expert assessments, graphic, video information.

The type of measuring scale is a coupled scale with dynamic constraints, the methodological aspects of which are given in [7, 28, 29, 36].

The smart measurement equation is written as follows:

$$\left\{h_{k,t}^{(Q)}|\{MX\}_{k,t}^{(Q)}\right\}|\left(Y_t^{(Q)};\{X_{i,t}\};G_t^{(E)}\right)=\left\{\text{argexstr C}\left[\varphi_{j,t}\left(f_{i,t}\{X_{i,t}\}\right)|\left(Y_t^{(Q)}*Y_t^{(E)}*G_t^{(E)}\right)\right]\right\}, \quad (1)$$

where * is the convolution symbol; Q – the measured property; $h_{k,t}^{(Q)}$ – measurement solution in the form of rapper conjugate scale $H_{k,t}$ with dynamic constraints (smart scale); $\{MX\}_{k,t}^{(Q)}$– a set of metrological characteristics, including indicators of accuracy, reliability, accuracy of the solution; C is the criterion for the selection of measurement solutions (for example, the criterion of minimum average risk solutions); $\varphi_{j,t}$ – forming technology solutions; $f_{i,t}$ – functional transformations of the primary data; $\{X_{i,t}\}$ – a set of information flows ; $G_t^{(E)}$ – information about the factors affecting the external environment; $Y_t^{(Q)}$– conditions for the implementation of the measurement experiment; $Y_t^{(E)}$ – conditions for obtaining information about the influencing factors of the external environment.

This type of measurement includes Bayesian intelligent measurements (BIM) based on a regularizing approach.

Let us briefly consider the ideas implemented in the RBA and BIM and reflect the principles formulated above.

The problem of determining the conditions and properties of complex objects on the basis of RBA are continuous study of the properties and characteristics of these objects by generalization from past experience with him and the newly incoming information from the positions of the measurement approach, the fundamental metrological which is based on the rationale of the decisions. The new knowledge gained during this measurement process is combined with the archives of past periods and serves as a priori information for future experiments. Moreover, the more voluminous and diverse the incoming information, which is further generalized on the basis of the principles of measurement theory and metrology, the more complete and reliable the results obtained.

It is this ideological basis of RBA, laid down in the classical Bayesian approach, its inductive (generalizing) logic that served as the basis for the implementation of the principle of integration and convolution of information.

In the conclusions of the inductive logic of the Bayesian approach, it is possible to obtain solutions with a certain degree of doubt, expressed by a quantitative measure of the a posteriori Bayesian probability (reliability) of the solution P (N). This value is calculated using the modified Bayes formula for the RBA.

The principles of the classical Bayesian approach serve as the postulates of the RBA:

- The properties of the task objects, their characteristics and parameters are considered undefined
- The results of observations and experiments are considered non-random events that give rise to a number of hypotheses about the causes that caused them: events, processes, situations
- A priori information is combined with the incoming information based on the integral convolution of information flows to obtain the post-priori distribution of hypotheses
- The conclusion or decision is made on the basis of an optimization rule that minimizes the risk of making the resulting decision or maximizes the usefulness and safety

These principles, developed later in the works of Bayesian scientists, allowed us to come to the concept of subjective (fiducial) probability, which, in turn, allowed the author to involve linguistic variables (from the theory of fuzzy sets and linguistic variables by L. Zadeh) in the measurement process, and then the knowledge presented in linguistic form, as well as to use as a confidence measure both the probability for numerical measurement results and the membership function for linguistic measurement decisions.

The RBA methodology is based on the concept of a dynamic compact solution space - a compact that changes its boundaries, which allows you to create models of objects with dynamic constraints (MDC). For measurement processes, this means that when new information is received, the model of the measurement object and the external environment will change, adapting to the new situation independently. This applies both to the areas of knowledge production and its use. The theoretical foundations for constructing such compacts are discussed in detail in [7, 8, 26, 27] and others.

Measurement is implemented as a decision-making process on coupled numerical and linguistic scales, such as scales with dynamic constraints. A view of this type of scale is shown in Figure 1.

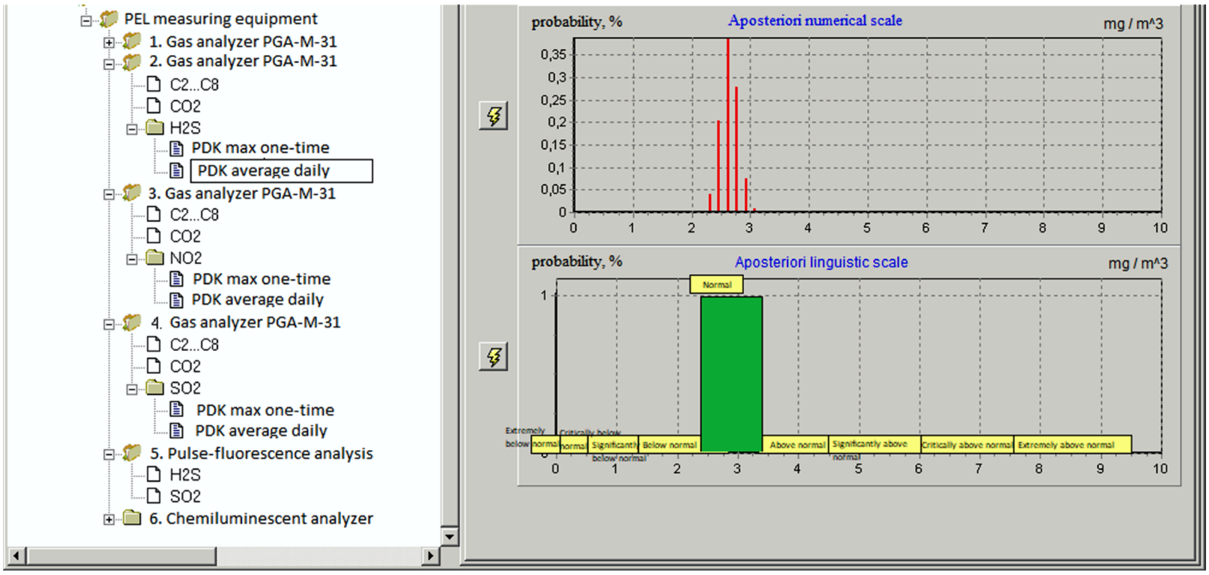

Figure 1: A model of a measuring system in the form of an MDC for air control based on BIM technologies (left part). A scale with dynamic constraints for the convolution of numerical and linguistic information according to the formula (3) for estimating the concentration of pollutants in the air (right part)

To obtain stable (under Hadamard conditions) solutions, the solution compact is discretized and represented by a two-dimensional metric space of gradations of object properties and their probabilities. The upper part of the scale represents this space. In the field of linguistic solutions, a metric space of possibilities or subjective probabilities is entered, the values of which accompany the measurement result. This space represents the lower part of the scale in Figure 1.

When the measurement result is presented in linguistic form, computationally weak, semantically rich scales (nominal and ordinal) are used.

Models of the measurement object and its environment are used as models with dynamic constraints. The BIM results are multi-alternative and can be interpreted as “fuzzy” measurements.

Bayesian intelligent measurement (BIM) is a measurement based on probabilistic logic and a regularizing Bayesian approach as the main rule for the output of measurement results.

Soft measurements (SM) are called extended measurements, where the measurement results are obtained based on parametric logic [31, 32, 33].

System measurements are measurements of the emergent properties of complex objects, which are inherent in a complex object as a complete system of interrelated properties [7].

If the subject of measurement is included in the contour of any measuring system, including an intelligent measuring system, as a source or receiver of information, then such measurements are called cognitive measurements (CM) [28].

In conditions of significant uncertainty, the model of a complex object and its environment must change depending on the information received and the changing requirements, constraints, target functions and criteria of the task being performed. In a conceptual form, this can be defined as a change in the degree of “immersion” of the model system $G_{(t)}^{(M)}$ in the object system $G_{(t)}^{(O)}$ and formally represented as a homomorphic map: $G_{(t)}^{(O)} \rightarrow G_{(t)}^{(M)}$, where $G_{(t)}^{(O)}$ is the dynamic object $G_{(t)}^{(O)} = Q_{(t)}^{(O)} * R_{(t)}^{(O)}$ with the properties of $Q_{(t)}^{(O)}$, the relations $* R_{(t)}^{(O)}$, varying depending on time t and $G_{(t)}^{(M)}$ is the system of dynamic object model $G_{(t)}^{(M)} = Q_{(t)}^{(M)} * R_{(t)}^{(M)} * L_{(t)}^{(M)}$ with the properties of $Q_{(t)}^{(M)}$ and the relations $R_{(t)}^{(M)}$, and constraints, assumptions, requirements, $L_{(t)}^{(M)}$ of the problem statement, also changing in time. For natural and man-made objects that actively interact with the natural environment, this immersion is endless due to the fundamental impossibility of obtaining comprehensive information about them.

The quality of knowledge can be expert assessments and conclusions, theoretical knowledge and analytical dependencies, applied or system information technologies, models and methods. For each type of such information, its own scales with dynamic constraints are built. In fact, the MDC, when translated into the metric space of hierarchical scales, is a hypercube of interrelated factors, wh ich makes it possible to flexibly adapt it to changing flows of incoming information and situations. An example of a model of the MDC type is illustrated in Figure 1.

Figure 1 also shows a view of the conjugate scale with dynamic constraints for the implementation of the BIM. With this approach, each solution is obtained on the corresponding scale of measurements with a certain degree of probability (reliability, possibility) of the solution. For numerical data the accuracy is determined as the frequency probability, and high-quality information frequentism is replaced by subjective decisions, “fiducial” probability, which, in contrast to the frequency, does not require long samples, stable experimental conditions and other requirements and limitations of the postulates of the theory of probability and mathematical statistics. The measurement results are formed based on the principles of pattern recognition, where the images are the reference points of the scale. In the RBA, the Bayesian decision rule is chosen as the decision rule.

For convolution, we use a modified Bayesian convolution formula (2), obtained for the first time in [7], which allows us to use the Bayesian formula and the Bayesian approach in general under conditions of uncertainty. Proofs of non-bias, consistency, sufficiency and efficiency are given in the author's works [7, 8].

$$P^{(ap)}\left(h_{k,t}\middle|Y_t\right) = \frac{P^{(a)}\left(h_{k,t-1}\middle|Y_{t-1}\right)\left(P\left(h_{k,t}^{*}|Y_t\right)\right)}{\sum_{j=1}^{K} P^{(a)}\left(h_{j,t-1}\middle|Y_{t-1}\right)\left(P\left(h_{j,t}^{*}|Y_t\right)\right)}, \tag{2}$$

where $P^{(a)}\left(h_{k,t}\middle|Y_{t-1}\right)$ is the prior Y_t probability of the measurement result (hypothesis) $h_{k,t-1}$ under the conditions of measurement Y_{t-1} at time $t-1$;

$P\left(h_{k,t}^{*}|Y_t\right)$ – the probability of the measurement result from the newly received information at time t under the measurement conditions Y_t;

K is the number of scale reference points.

According to this modified formula (2), a probabilistic convolution of the values of the indicators is performed, the scheme of which is shown in Figure 2.

Linguistic variables can be used to measure qualitative indicators. Weak scales are used as scales: nominal scales and order scales, which do not have computational capabilities, but have a strong semantic content that allows you to interpret the solutions in accordance with the goals of the measurement problem. In soft measurement, parametric logics can be implemented (the logic of Zadeh, Lukasevich, etc.).

The BIM scale can change its properties and structure (carrier, reference points, the composition of acceptable ratios, etc.) according to the change in the structure of the MDC. Therefore, it is called a scale with dynamic constraints (SDC).

Scale type SDC to measure the properties of one-dimensional figure is a two-dimensional scale one of the axes which are deposited indicator value in a numeric or linguistic forms, on the other the degree of certainty (certainty, possibility) of the result.

When adding the number of controlled indicators in the multidimensional parameter space, a multidimensional scale is constructed, which, when moving to a new, higher level of the hierarchy, collapses into an integral indicator, for which a new two-dimensional scale is formed.

In the BIM process, three types of convolution are implemented: convolution of a priori numerical or linguistic and current information, convolution of a posteriori numerical and linguistic information, and convolution of a posteriori information about two or more factors.

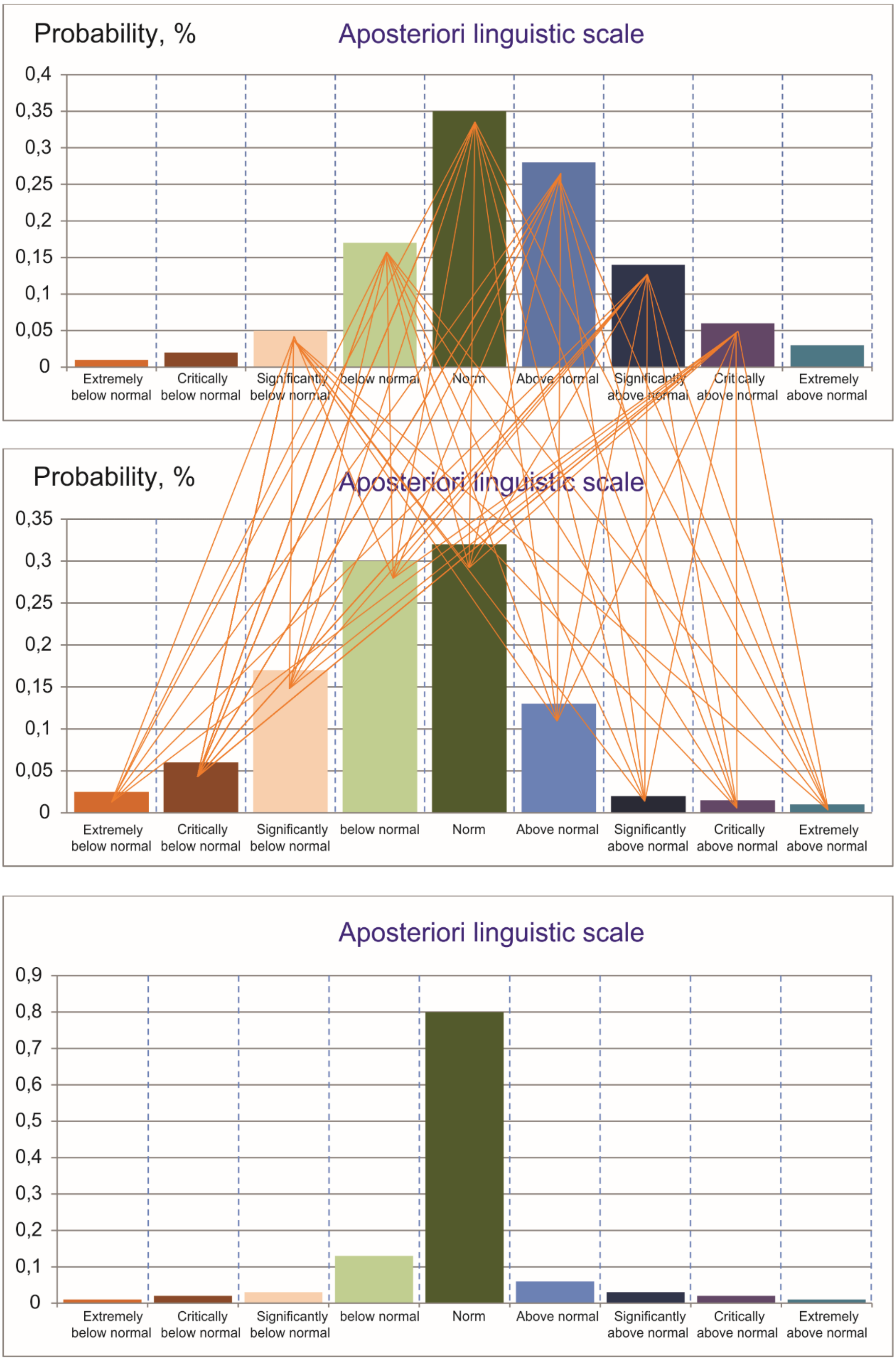

Figure 2: An illustration of the principles of Bayesian convolution for two indicators. Scale reference points – scale reference points – are considered as random variables, in accordance with the principles of the Bayesian approach. When forming a measurement solution, several reference points of the scale may be possible, which form a number of alternative measurement results

1. Probabilistic convolution of numerical a priori and incoming information in the form of benchmarks of the corresponding numerical a priori $h_k^{(aN)}$ and the current scale $h_k^{(N)}$ is realized by the formula:

$$P\left(h_k^{(apN)}|\{MX\}_k^{(aN)}\right) = \frac{P\left(h_k^{(aN)} \cdot P\left(h_k^{(N)}|\{X_i\}\right)\right)}{\sum_{j=1}^{K} P\left(h_j^{(aN)} \cdot P\left(h_j^{(N)}|\left\{X_i^{(N)}\right\}\right)\right)}, \tag{3}$$

where K is the number of scale reference points.

2. Probabilistic convolution of linguistic a priori and incoming information in the form of reference points of the corresponding linguistic a priori $h_k^{(aL)}$ and the current scale $h_k^{(L)}$ by the formula:

$$P\left(h_k^{(apL)}|\{MX\}_k^{(aL)}\right) = \frac{P\left(h_k^{(aL)} \cdot P\left(h_k^{(L)}|\left\{X_i^{(L)}\right\}\right)\right)}{\sum_{j=1}^{K1} P\left(h_j^{(aN)} \cdot P\left(h_j^{(N)}\middle|X_i^{(L)}\right)\right)}, \tag{4}$$

3. Probabilistic convolution of estimates (benchmarks) of numerical $h_k^{(apN)}$ and linguistic $h_k^{(apL)}$ a posteriori scales according to the formula:

$$P\left(h_k^{(ap)}|\{MX\}_k^{(ap)}\right) = \frac{P\left(h_k^{(apN)} \cdot P\left(h_k^{(apL)}\middle|\{X_i\}\right)\right)}{\sum_{j=1}^{K1} P\left(h_j^{(apN)} \cdot P\left(h_j^{(apL)}\middle|\{X_i\}\right)\right)}, \tag{5}$$

4. Probabilistic convolution (integration) of a posteriori estimates (benchmarks) of linguistic scales of various indicators, for example, indicators $h_{k1}^{(apL)}$ and $h_{k2}^{(apL)}$ by the formula:

$$P\left(h_{k3}^{(apL)}|\{MX\}_{k3}^{(apL)}\right) == \frac{P\left(h_{(k1)}^{(apL)}\right) \cdot P\left(h_{k2}^{(apL)}\right)}{\sum_{j=1}^{K1} P\left(h_{j1}^{(apL)}\right) P\left(h_{k2}^{(apL)}\right) \cdot \sum_{z=1}^{K2} P\left(h_{k1}^{(apL)}\right) P\left(h_{z2}^{(apL)}\right)}, \tag{6}$$

Convolution of two factors according to the formula (6) shown in figure 3.

A posteriori linguistic evaluation of the first factor (upper scale) is represented by a list of 6 components and has the form:

$\left\{h_{k2}^{(apL)}|P\left(h_{k2}^{(apL)}\right)\right\}$ = {“normal” with a probability of 0.35; “above normal” with a probability of 0.28; “below normal” with a probability of 0.17; “significantly above normal” with a probability of 0.15; “significantly below normal” with a probability of 0.15; “critically above normal” with a probability of 0.03.}

As can be seen from the above estimate, each of the alternative estimates has a low confidence (a high degree of uncertainty). However, in the aggregate, this estimate has a confidence close to one, namely, its probability is 0.99.

A posteriori linguistic evaluation of the second factor (the average scale) is represented by a list of 6 components and has the form:

$\left\{h_{k2}^{(apL)}|P\left(h_{k2}^{(apL)}\right)\right\}$ = {“normal” with probability 0.31; “below normal” with probability 0.29; “significantly below normal” with probability 0.17; “above normal” with probability 0.12; “critically below normal” with probability 0.07; “extremely below normal” with probability 0.01}.

The reliability of the combined assessment of the second factor is 0.97.

A posteriori linguistic assessment of the second factor (middle scale) is represented by a list of 6 components has the form: A posteriori linguistic assessment of the second factor (middle scale) is represented by a list of 6 components has the form: A posteriori linguistic assessment of the integral third factor (lower scale) is represented by a list of 3 components and has the form:

$\left\{h_{k3}^{(apL)}|P\left(h_{k3}^{(apL)}\right)\right\}$ = {“normal” with probability 0.8; “below normal” with probability 0.12; “above normal” with probability 0.07}.

The reliability of the integral factor estimation is 0.99.

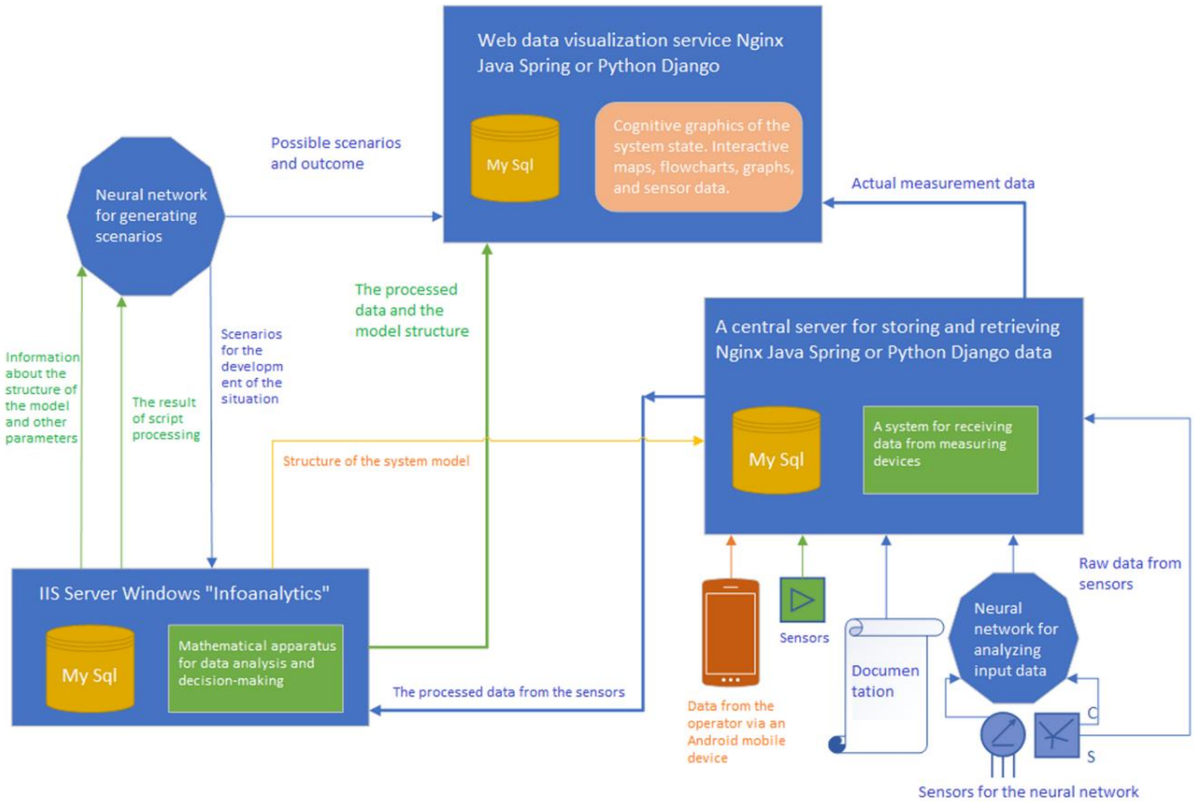

Figure 3: Architecture of an intelligent complex for monitoring the water supply network based on Bayesian intelligent measurement technologies

In accordance with these calculations, it can be concluded that with a sufficiently high initial information uncertainty, regularizing Bayesian estimates have high reliability, which confirms the effectiveness of this approach.

Similarly, the development of the structure of the SDC is carried out according to the structure of the MDC. According to this, there are new branches of information technologies for measuring new indicators, monitoring and auditing them, interpreting situations, generating recommendations, and so on. So, there is a continuous development of models and information technologies based on RBA.

The scheme for implementing the Bayesian convolution of two indicators according to the formula (7) is shown in Figure 2.

With multiple 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.

The basis for the synthesis of information technologies of RBA is 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 information technology and compliance with metrological requirements for information system solutions. 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.

The solution obtained on the basis of Bayesian intelligent measurements (BIM-solution) is a series of alternative estimates of the property with the corresponding complexes of metrological characteristics and is a regularized Bayesian estimate (RBE). In [7] the properties of the unbiased, consistency and efficiency of such estimates are proved.

It is appropriate to note that in conditions of significant uncertainty, each elementary solution from the RBE composition does not have high reliability and reliability indicators. However, in general, the RBE covers the true value with sufficiently high quality indicators and a minimum of risk.

Metrological justification of information technologies for solving problems in conditions of uncertainty allows evaluating the quality of information from each data source and each resulting solution in the form of complexes of metrological indicators: accuracy, reliability, reliability, risk, entropy, and the amount of information.

The accuracy is determined by the formula:

$$\xi_s = \frac{\max\limits_{h_s \in H_k} \rho(h_s, h_{s+1})}{\rho(h_K, h_1)}, \tag{7}$$

where $\rho(h_K, h_1)$ is the scale range, $\max\limits_{h_s \in H_k} \rho(h_s, h_{s+1})$ – maximum distance between adjacent elements of the scale carrier.

The reliability of the result characterizes the stability of the solution. The reliability indicator is based on the error levels of the first and second kind and is defined as:

$$V_s = (1 - \alpha_s)(1 - \beta_s), \tag{8}$$

where α_s is the level of errors of the first kind (reflecting the probability of rejecting the correct decision on the scale); β_s – the level of errors of the second kind (characterizing the probability of making the wrong decision on the scale).

Reliability. An indicator of the reliability of each hypothesis on the scale is the a posteriori probability of its occurrence, determined by the Bayes formula. The confidence of the scale itself is assumed to be the sum of the confidence of the hypotheses and, accordingly, is equal to one. However, in many cases, for practical reasons, in order to remove unimportant hypotheses, only a set of hypotheses that satisfy some criterion of significance is left on the scale. In this case, the reliability of the decision on the scale is defined as:

$$P = P^a \cdot \sum_{h_j \in H_r} P(h_j), \tag{9}$$

where P is the final confidence of the solution on the scale P^a is the confidence of the scale before removing non-significant hypotheses; H_r is the set of significant hypotheses on the scale.

Risk – a value that indicates the risk of making this decision. Calculated as $(1 - P)$, where P is the confidence.

The tasks of rationing, criteria selection, and audit are performed on criteria scales. When changing the criteria base or changing the properties of the controlled object, when the norm of indicators of its properties changes, the scale is adjusted to the new values of the norms automatically or by the user. In this way, the dynamics of norms and criteria can be monitored. In addition, these scales can be coupled to implement the control of the same indicator for a variety of different criteria.

The distinctive properties of BIM and SM can be summarized as follows:

1. Measurement is carried out as a process of making a decision about the size of the measured object
2. Sources of information are both information flows in the form of data, and in the form of expert assessments and other knowledge
3. The dynamic compact of measurement solutions is a two-dimensional metric space of gradations (in particular, values) of the measured properties of objects and their probabilities, possibilities, or subjective probabilities, the values of which accompany
4. The measurement result can be presented both in numerical and linguistic form in the form of a list of alternative estimates with their corresponding sets of metrological characteristics, in particular, their reliability
5. When implementing BIM and SM, computationally weak, semantically rich scales (nominal and ordinal) are used to measure linguistic information. To measure the numerical information, the ratio scales are used, which differ in computing power. In this case, the conjugate scale, which is shown in Figure 1, combines the properties of these scales, and based on their integration, provides both computational power and semantic interpretation in the processing of both numerical and linguistic information
6. The results of BIM and SM are a set of alternatives with metrological justification and can be interpreted as “fuzzy” measurements

7. The results of BIM and SM are accompanied by special complexes of metrological characteristics of accuracy, reliability, reliability, risk, entropy, volume of information on Fischer, etc
8. The results of BIM and SM are characterized by the results with explanations of the reasons for obtaining the result, indicating the influencing factors, determining the trends of indicators and, if necessary, ways to improve them
9. Recalculations are implemented on special scales (for example, scales with dynamic constraints), the reference points of which are hypotheses about the possible values (gradations) of the measured property
10. Logic criteria and inference rules are determined based on the type of measurement task and measurement conditions
11. Scales and models of BIM and SM are dynamic objects and can be transformed in the measurement process
12. BIM and SM are used when there is no repeatability of the conditions for conducting a measurement experiment, there are only individual facts, small samples of experimental data and significant uncertainty

4. Conclusion

Thus, intelligent measurement systems for the effective solution of applied problems, the objects of measurement, monitoring, management are complex man-made or socio-economic complexes operating under conditions of uncertainty, must have the following characteristics:

- Ensuring the processing of different types of information flows both in the form of data and in the form of knowledge
- Ensuring quality control of the results obtained and determining their main metrological indicators in the form of accuracy, reliability and reliability values that form the fundamental basis of metrological support
- Integration of a priori and experimental information obtained
- Accounting of measurement conditions in the measurement object model and measurement technologies; the possibility of optimizing the planning of the measurement experiment in accordance with metrological requirements and restrictions
- Ensuring the completeness and sufficiency of the solutions obtained through self-learning and self-development of models and measurement technologies
- The ability to dynamically adapt the technology to changing conditions and properties of the measured object during the experiment
- The possibility of self-learning and on the basis of this reorganization of technologies and systems
- Creation of conditions and generation of developing information technologies and systems.

DATA Science, BIG DATA, BI, IoT, DSS, DATA Mining and other systems related to intelligent data processing can be mentioned as promising areas of using the methodology, technologies and tools of intelligent measurements, as discussed in detail in [12, 15]. The advantages of using intelligent measurements for modern 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 collecting, integrating and interpreting instrumental data
3. In BI-systems – for analytical processing and interpretation of information
4. In neural networks – for collecting, 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 monitoring and management systems for complex industrial and socio-economic complexes, as well as their sustainable development.

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