METHODOLOGY OF MEASUREMENT INTELLECTUALIZATION BASED ON REGULARIZED BAYESIAN APPROACH IN UNCERTAIN CONDITIONS

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ABSTRACT

Modern measurement tasks are confronted with inherent uncertainty. This significant uncertainty arises due to incomplete and imprecise knowledge about the models of measurement objects, influencing factors, measurement conditions, and the diverse nature of experimental data. This article provides a concise overview of the historical development of methodologies aimed at intellectualizing measurement processes in the context of uncertainty. It also discusses the classification of measurements and measurement systems. Furthermore, the fundamental requirements for intelligent measurement systems and technologies are outlined.

The article delves into the conceptual aspects of intelligent measurements, which are rooted in the integration of metrologically certified data and knowledge. It defines intelligent measurements and establishes their key properties. Additionally, the article explores the main characteristics of soft measurements and highlights their distinctions from traditional deterministic measurements of physical quantities. The emergence of cognitive, systemic, and global measurements as new measurement types is discussed.

In this paper, we offer a comprehensive examination of the methodology and technologies underpinning Bayesian intelligent measurements, with a foundation in the regularizing Bayesian approach. This approach introduces a novel concept of measurement, where the measurement problem is framed as an inverse problem of pattern recognition, aligning with Bayesian principles. Within this framework, innovative models and coupled scales with dynamic constraints are proposed. These dynamic scales facilitate the development of measurement technologies for enhancing the cognition and interpretation of measurement results by measurement systems.

This novel type of scale enables the integration of numerical data (for quantifiable information) and linguistic information (for knowledge-based information) to enhance the quality of measurement solutions. A new set of metrological characteristics for intelligent measurements is introduced, encompassing accuracy, reliability (including error levels of the 1st and 2nd kind), dependability, risk assessment, and entropy characteristics. The paper provides explicit formulas for implementing the measurement process, complete with a metrological justification of the solutions.

The article concludes by outlining the advantages and prospects of employing intelligent measurements. These benefits extend to solving practical problems, as well as advancing and integrating artificial intelligence and measurement theory technologies.

KEYWORDS

Measurement Theory, Bayesian approach, Uncertainty

David C. Wyld et al. (Eds): CSTY, AIMLNET, AI, BINLP -2023
pp. 37-63, 2023. CS & IT - CSCP 2023 DOI: 10.5121/csit.2023.131805

1. INTRODUCTION

The field of measurement theory has evolved significantly due to the growing complexity of practical measurement problems. This evolution has been shaped by the need to intellectualize measurement processes and systems to address the challenges posed by contemporary applications.

This paper examines the evolutionary aspects of intellectualizing measurements. Modern measurement tasks often involve complex hierarchical systems that interact dynamically with their external environment, leading to substantial uncertainty in the information available. These measurement challenges require systems that can effectively study the properties of complex objects (CO) and their environmental interactions (E). The goal is to synthesize various forms of a priori and incoming information to generate new knowledge and derive optimal solutions for specific measurement situations.

Several factors have driven the development of smart measurement methodologies:

1. Complex Measurement Objects: Modern measurement tasks frequently involve intricate hierarchical systems that exhibit property changes influenced by environmental factors.
2. Indirect Measurements: Direct measurements of these complex objects are often impossible, leading to incomplete and inaccurate information about the objects and their surroundings.
3. Information Uncertainty: Information uncertainty arises from diverse sources and types of data, ranging from big data to small samples and expert assessments.
4. Expert Knowledge: Expert assessments and information contribute significantly to the overall information landscape.
5. Subjective Interpretation: In the absence of robust interpretation technologies, subjective interpretation can introduce additional uncertainty.
6. Metrological Challenges: The lack of quality assessment and metrological support for measurement solutions is a notable concern.

The development of measurement intellectualization methods began in the 1980s and 1990s. Pioneering works in this field include the research of Dietmar Hofmann, Leonid Finkelstein [1], Dietmar Hofmann, Karaya Karaya [2], V. Ya. Rosenberg [3], V. G. Knorring [4], O. D. Duncan [5], Joel Michel [6], S. V. Prokopchina [7, 8], among others. These scholars introduced concepts such as adaptivity in measurements, cognitive ability, and the intellectualization of measurement methods and systems.

The foundational work of earlier scientists [9], [10], [11], [12], [13], and others laid the groundwork for the development of measurement science in this direction.

Measurement methods and systems of the past were characterized by certain limitations:

- Rigid Structures: They had inflexible algorithmic structures and object models.
- Lack of Metrological Support: Monitoring results lacked adequate metrological support.
- Technogenic Basis: Methods were primarily designed for situations with limited a priori uncertainty, leading to an oversimplified model of CO.
- Separation of Numeric and Non-Numeric Information: They couldn't efficiently process both numeric and non-numeric information.
- Limited Self-Learning: These systems lacked self-learning and self-development capabilities.

Many of these characteristics persist in modern measurement methods and systems. Methodologically, the principles of measurement intellectualization were influenced by representative measurement theory [4], the theory of adaptive measurements [3], statistical measurement theory, and the measurement of non-quantitative quantities [13, 14].

In the 90s, an important role in the development of the direction of measurement intellectualization was played by the II IMECO Symposium, held in 1986 in Jena, dedicated to this direction. In the work of D. Hofmann and L. Finkelstein [1], the name of this type of measurement was proposed – "intelligent measurements".

A special role in shaping the trends of intellectualization of measurement systems played the introduction to the structure of measurement systems the processor means providing broad technical capabilities for measuring computational complexity of algorithms. Works [2, 9, 13, 25] scientists have created a theoretical basis for the emergence of a new generation of tools that implement new types of algorithms. During this period, methods of adaptive [3] and statistical measurements were developed [25].

Processor measurement systems, having significant computing capabilities, allowed to provide technical support (in the environment of the measuring tool) of new information technologies for generalizing and obtaining knowledge used in the organization and conduct of measurements, to implement a fundamentally new type of measurement process, at each stage of which the optimal measurement strategy is developed automatically or automatically and the appropriate interpretation of the results is made on the basis of functional and metrological processing of various forms of incoming and a priori information, which is the essence of measurement intellectualization. This led to the need to create a single measuring chain of transformations of the results of primary indicators (according to L. Mari [16] measurements into the final solution. In [7, 8], it was proposed to consider this chain as a whole measuring process, the algorithmic basis of which is covered by the scheme of metrological verification with the implementation of the principles of uniformity of measurements [7, 8].

At that time, the conceptual basis for the intellectualization of measurement was the following principles, given in the first works on this issue [1, 2, 17]. Among the main characteristics inherent in intelligent measurement technologies and systems were the following [1, 2]:

1. Technologies of measurement intellectualization are characterized by adaptability to the conditions of measurement, correction of measurement results in case of errors of the measuring subject (meter), elimination of undesirable environmental influences.
2. Involvement of computing modules in the measurement environment. Modularity of measurement information technologies.
3. Measurement intellectualization is based on computerization and automation of preparation, planning, and performance of technical measurements.
4. To implement the principles of measurement intellectualization, you need: a developed user interface, the ability to reconfigure software and hardware, their open nature and standardization, the availability of subsystems for metrological support of the results obtained and self-calibration.
5. Intelligent systems should have explanation and learning subsystems.
6. Intelligent measurements can be used in modeling and decision support systems.

As can be seen from the listed characteristics of measurement intellectualization technologies, they are mainly related to information technology. The development of the methodology of intelligent measurements was first made in [7, 8].

The modern development of the theory of measurement intellectualization goes in several directions. These include non-quantitative measurements [5, 6, 10, 11], systematization and expansion of measurement terminology [20, 21, 22, 23, 24] non-physical measurements [6, 7, 10, 12, 28, 31, 32, 33], the use of knowledge, ideas of artificial intelligence and soft computing in measurement processes [26, 27, 28], the metrology of intelligent measurements [29], the use of the Bayesian approach to create a methodology for intelligent measurements, the creation of new types of intelligent measurements, including soft measurements.

2. THE EVOLUTION OF INTELLIGENT MEASUREMENTS

The direction of measurement intellectualization, founded in the early 1990s [7, 8], enabled the formulation of fundamental principles for this evolving field. Building upon the earlier concepts, the following additions were introduced [7, 8]:

Integration of Knowledge: Measurement intellectualization hinges on the incorporation and integration of comprehensive knowledge about the measurement object and the external environmental factors. Central to this process is the cognitive function of measurements, employing object models that draw from a wide spectrum of a priori information and data accumulated during the measurement procedure.

Metrological Justification: The realm of intelligent measurement demands meticulous metrological justification at every stage and decision, including those formulated as knowledge-based outcomes.

Development in Uncertainty: The methodology of intelligent measurement must facilitate the development of evolving models and measurement technologies that can operate effectively in the presence of uncertainty.

The methodology of measurement intellectualization, underpinned by a variation of the classical Bayesian approach termed the "regularizing Bayesian approach" (RBA), amalgamates the strengths of three fundamental approaches: the systemic approach, the measurement approach, and the Bayesian approach. Measurements grounded in RBA are recognized as Bayesian intelligent measurements (BIM). This direction emerged as an evolution of measurement theory methods to address measurements conducted under conditions of uncertainty.

In this framework, intelligent measurements are defined as the measurement of complex object properties in the face of significant information uncertainty, relying on both metrologically sound data and knowledge concerning the object, external environmental influences, and the conditions of the measurement experiment.

In 1997, the author of this article introduced the concept of "Soft" measurements, founded on RBA and L. Zadeh's fuzzy set theory [31, 32, 33].

During the early 21st century, new categories of intelligent measurements surfaced, including cognitive measurements [28], systemic and polysystem measurements [30], and global intelligent measurements [39].

Svetlana V. Prokopchina's work further developed the principles of intelligent measurements in the direction of leveraging additional metrologically certified knowledge, significantly enhancing the reliability of solutions obtained under uncertain circumstances.

Below, we present the core principles of the measurement intellectualization concept based on knowledge, initially as a generalized problem statement for broad applicability, followed by a more detailed specification of these principles within the regularizing Bayesian approach [7, 8, 26, 27, 28, 29, 30].

In a broad sense, the term "measurement" encompasses the evaluation of properties of real or virtual systems, spanning diverse domains, including social, economic, technical, psychometric, and global measurements.

In a narrower sense, "measurement" can be understood in two ways. Firstly, it refers to the measurement process, encompassing models, methods, and the means to execute measurements. Secondly, it can denote the measurement result, as understood in its secondary interpretation.
To substantiate the methodological aspects of measurement intellectualization, it's essential to define the measurement situation in which it operates. A measurement situation involves the purpose and conditions of the measurements and is characterized by the object under examination.

In the realm of intelligent measurements, objects of measurement often encompass properties and states of complex multidimensional systems, which correspond to model representations, including sets of functions, property distribution laws, vectors and fields, virtual images, and descriptions that delineate the properties of measurement objects and their interactions with the surrounding environment.

The purpose of measurement in intelligent measurements can include:
Property Evaluation and Prediction: Assessing and forecasting properties and characteristics of the measurement object.
Measurement Control: Determining the state of the measurement object via measuring instruments.

Generating Conclusions and Management Recommendations: Producing inferences, managerial decisions, and recommendations to enhance the quality of measurement outcomes.

The measurement conditions are dictated by a set of factors:

A Priori Knowledge: The extent and precision of a priori knowledge about the measurement object and the external factors impacting its operation.

Metrological and Technical-Economic Requirements: The requirements associated with metrological validity and compliance, as well as the technical and economic aspects of the measurement task.

Assumptions and Restrictions: The system of assumptions and limitations, both conceptual and technical, govern the feasibility and accuracy of imposed constraints within specific measurement tasks.

The variety of measurement conditions can be categorized based on the degree of certainty, completeness of a priori information, metrological validity, feasibility of imposed restrictions, and the level of precision in specific measurement tasks.

In [7], a classification of information situations in which measurements are conducted is provided.

1. Information Situation Type 1: A priori information about the measurement object and environmental factors is sufficient for achieving the measurement goal.
2. Information Situation Type 2: Limited a priori uncertainty exists about the models, which can be progressively resolved in an iterative process using available a priori information and collected experimental data.
3. Information Situation Type 3: Substantial a priori uncertainty prevails regarding the properties of the measurement object, the impact of environmental factors, or their mutual influence. Such conditions necessitate constant involvement, aggregation, acquisition, and utilization of additional knowledge about the measurement object and environmental factors throughout the measurement process. In such contexts, the entire measurement problem can only be addressed by intellectualizing the measurement process.

Principles of intelligent measurement implementation:

The implementation of intelligent measurements is guided by several fundamental principles:

1. **Uncertainty Embrace:** Intelligent measurements operate in contexts marked by significant uncertainty. Therefore, the methodology and principles for constructing measurement processes are designed to address this inherent information situation. Comprehensive classifications of measurement situations and types are presented in [7, 8, 30], offering detailed descriptions and equations for various measurement types.
2. **New Measurement Paradigm:** Intelligent measurements introduce a fresh measurement paradigm. In scenarios of considerable uncertainty, the objective of measuring diverse types of information is framed as the task of deriving a measurement solution through the recognition of hypotheses from various forms of imprecise and incomplete information. The principles for constructing measurement processes resemble those used in image recognition methods.
3. **Regularization of Measurement Space:** Solving problems under uncertainty, as per Tikhonov, is inherently flawed, yielding unstable solutions due to the non-satisfaction of the three Hadamard conditions. To counteract this instability, the measurement task under uncertainty necessitates the regularization of the measurement result space.
4. **Introduction of Measurement Scale:** As demonstrated in [37, 7, 8], introducing a measurement scale regularizes the solution space, allowing for stable measurement outcomes in uncertain scenarios. Such solutions are conditionally stable, quasi-stable, stable within a specific compact range of measurement solutions comprising the measurement scale range, and specific models and measurement conditions. For intelligent measurements, hypotheses concerning the "true" value of the measured attribute can be envisioned as reference points on the measurement scale.
5. **Diverse Measurement Solutions:** Alongside numerical values, reference points on the measurement scale can encompass various forms of property representations, including linguistic expressions, graphics, video, audio data, analytical expressions, transforming the measurement result into a comprehensive measurement solution. This approach distinguishes intelligent measurements from classical instrument measurements, often termed indicator measurements [16]. Comprehensive measurement solutions result from the convolution of indicator measurements with additional data and knowledge, enhancing solution reliability.
6. **Probabilistic Nature:** In scenarios of uncertainty, the probability of a measurement solution typically deviates from unity due to the reduced reliability of source information. Additionally, alternative measurement solutions may exist, each with corresponding probabilities (possibilities) of correctness. It's impractical to deem one decision as the sole correct choice; thus, considering a range of alternatives with associated probabilities (possibilities) of their validity is advisable.

7. **Logical Inference Mechanisms:** Technologies for acquiring measurement solutions should rely on logical inference mechanisms, necessitating the application of optimization principles grounded in chosen optimization criteria.
8. **Expanded Metrological Indicators:** Shifting the measurement paradigm calls for augmenting existing measurement quality indicators. As detailed in [26, 27], such indicators should encompass measures of solution reliability, representing their probabilities or possibilities; error levels of the 1st and 2nd kind collectively reflecting measurement reliability; conditional accuracy within the ranges of scales used in the measurement process; risk associated with each alternative solution; indicators of entropy levels involved in the measurement; and the volume of information received. Utilizing these complex metrological characteristics is essential for justifying intelligent measurements. Comprehensive explanations for selecting these indicators and functional transformations of metrological characteristics are provided in [7, 8, 29]. These works also propose principles and technologies for metrological research and support of intelligent measurements and methodologies and technologies for Metrology and synthesis processes of intelligent measurement, optimizing technology and means of implementation.
9. **Cognition Facilitation:** A key attribute of intelligent measurements is their capacity to facilitate the cognitive process. This is achieved through the development of models with dynamic constraints that represent measurement objects and the external environment within intelligent measurements. [7, 8] propose models with dynamic constraints that adapt and modify their structure as new information arrives, allowing continuous immersion in the information realms of the measured object and its surroundings. Such models align with scales featuring dynamic constraints capable of reconfiguring their structure in response to evolving object and environment models. The methodology and principles for creating such scales are expounded in [7, 8, 34].

In accordance with the classification introduced in [35], considering the stages of their evolutionary development, we categorize measurement types as follows:

1. **"Hard" Deterministic Measurements**: This category includes traditional measurements characterized by deterministic principles and direct measurement of physical parameters. These measurements assume the availability of an object of measurement where the physical parameter is directly measurable. Key attributes of "hard" deterministic measurements include:
    - Object of measurement: Directly measurable physical parameter.
    - Object model: Physical parameter.
    - Measurement principle: Algebraic comparison (e.g., simple arithmetic operations) of two numerical values.
    - Type of measuring scale: Relationship scale.
    - Type of scale reference points: Digital values.
    - Distance metric: Euclidean metric.
    - Equation of direct ("hard") classical measurements.

2. **"Flexible" Measurements**: This category encompasses adaptive and probabilistic measurements that involve processing of measurement results. "Flexible" measurements exhibit adaptability and probabilistic characteristics in their approach to measurement. This category can be further subdivided into:
    - **Adaptive Measurements**: Measurements that adapt to evolving measurement conditions and information.

- **Probabilistic Measurements with Processing of Measurement Results**: Measurements that incorporate probabilistic principles and engage in data processing.

3. **"Soft" Measurements (Intelligent Measurements)**: In this classification, "soft" measurements are understood in a broad sense, referring to measurements that are approximate, fuzzy, and conducted under conditions of uncertainty. These measurements are often based on L. Zadeh's soft logic, incorporating the theories of fuzzy sets and linguistic variables. This broader interpretation of "soft" measurements is used, aligning with the first aspect of the term. "Soft" measurements can be considered as a subset of intelligent measurements.

Considering measurement systems, we propose the following classification:

1. **"Rigid" Measuring Systems**: These systems consist of classical measuring devices and devices that adhere to traditional measurement principles.
2. **"Smart" or "Flexible" Information and Measurement Systems**: This category includes measurement systems that exhibit adaptability, data processing, self-monitoring, self-calibration, automated reorganization, and automated development of structure and functions.
3. **"Soft" Measuring Systems (Intelligent Measuring Systems)**: This category encompasses intelligent measuring systems that integrate data and knowledge, generate knowledge, and possess the capability for self-development of structure and functions. These systems can autonomously expand their applied orientation based on generated knowledge and forecast scenarios of measuring and applied situations. This aligns with the broad interpretation of "soft" measurements as approximate and uncertain measurements.

Now, let's delve into the key distinctions between the conceptual foundations of classical and intelligent measurements.

Conceptual Foundations of Classical Measurements:

- Object of measurement: Directly measurable physical parameter.
- Object model: Represents the physical parameter.
- Measurement principle: Comparison scheme involving algebraic comparison of numerical values.
- Type of measuring scale: Relationship scale.
- Type of scale reference points: Digital values.
- Distance metric: Euclidean metric.
- Equation of direct ("hard") classical measurements: [Insert equation here].

This classification and distinction provide a framework for understanding the evolution of measurement methodologies and systems, from traditional deterministic measurements to more adaptive and intelligent measurement approaches.

$$h_k = \psi(\{x_i\}), \qquad (1)$$

where represents h_k reference point of the scale with the carrier H_K; ψ stands for the measurement transformation; $\{x_i\}$ denotes the set of data arrays.

Measurement Object: These measurements pertain to properties of complex objects that aren't directly measurable.

Model Object: A model object, whether complex or virtual, serves as an analogous representation of the property being measured.

Measurement Principle: Intellectual measurements rely on information technology to execute the measurement process. This technology is grounded in solving the inverse problem of pattern recognition, utilizing scale reference points.

Reference Point Types: Intellectual measurements utilize various reference point types, including digital values, linguistic variables, expert assessments, as well as graphic and video data.

Measuring Scale Type: Intellectual measurements employ a coupled scale with dynamic constraints. Detailed methodological aspects of this scale can be found in [7, 28, 29, 36].

The equation governing smart measurements is as follows:

$$\begin{aligned}&\left\{h_{k,t}^{(Q)} | \{MX\}_{k,t}^{(Q)}\right\} | \left(Y_t^{(Q)}; \{X_{i,t}\}; G_t^{(E)}\right)\\ &\qquad = \left\{\text{argexstr C } \left[\varphi_{j,t}\left(f_{i,t}\{X_{i,t}\}\right) | \left(Y_t^{(Q)} * Y_t^{(E)} * G_t^{(E)}\right)\right]\right\}, \quad (2)\end{aligned}$$

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 category of measurement encompasses Bayesian intelligent measurements (BIM) based on a regularizing approach.

Let's briefly examine the concepts implemented in the RBA and BIM and revisit the principles articulated above.

The problem of determining the conditions and properties of complex objects based on the RBP involves continuous exploration of the characteristics and attributes of these objects through the amalgamation of past experiences and newly acquired information. This is seen from the perspective of the measurement approach, which is fundamentally rooted in metrological reasoning and decision-making. The new knowledge acquired during this measurement process is integrated with historical archives and serves as a priori information for future experiments. Furthermore, the more extensive and diverse the incoming information is, which is subsequently generalized based on measurement theory and metrology principles, the more comprehensive and reliable the results obtained.

This ideological foundation of RBA, derived from the classical Bayesian approach and its inductive (generalizing) logic, forms the basis for the integration and convolution of information. In the conclusions drawn from the inductive logic of the Bayesian approach, solutions with a certain degree of uncertainty can be obtained, expressed through a quantitative measure of the a posteriori Bayesian probability (reliability) of the solution P(N). This value is calculated using the modified Bayes formula in 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 regarded as non-random events, giving rise to multiple hypotheses about their underlying causes.
- A priori information is combined with incoming information through integral convolution of information flows to yield the post-priori distribution of hypotheses.
- Decisions are made based on an optimization rule aimed at minimizing decision-related risks or maximizing utility and safety.

These principles, further developed by Bayesian scientists, led to the concept of subjective (fiducial) probability. This concept, in turn, allowed for the inclusion of linguistic variables (from L. Zadeh's theory of fuzzy sets and linguistic variables) in the measurement process. It also facilitated the incorporation of knowledge presented in linguistic form and the use of both numerical probability measures and membership functions for linguistic measurement decisions as confidence indicators.

The methodology of RBA relies on the notion of a dynamic compact solution space – a compact space with changing boundaries. This allows for the creation of models with dynamic constraints (MDC) for objects. For measurement processes, this means that the model of the measurement object and its external environment adapts to new situations autonomously as new information is received. This adaptation applies to both knowledge production and its utilization. Detailed theoretical foundations for constructing such compacts are discussed in [7, 8, 26, 27], among others.

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

To obtain stable solutions (satisfying Hadamard conditions), the solution compact is discretized and represented as a two-dimensional metric space encompassing object property gradations and their associated probabilities, as illustrated in the upper part of the scale in Figure 1. In the realm of linguistic solutions, a metric space of possibilities or subjective probabilities accompanies the measurement result, represented in the lower part of the scale in Figure 1.

When measurement results are presented linguistically, computationally lightweight, semantically rich scales (nominal and ordinal) are employed.

Models with dynamic constraints are employed as models for the measurement object and its environment. BIM results are typically multi-alternative and can be interpreted as "fuzzy" measurements.

Bayesian intelligent measurement (BIM) is characterized by measurements grounded in probabilistic logic and the regularizing Bayesian approach as the primary rule for deriving measurement results.

Soft measurements (SM) refer to expanded measurements where measurement outcomes are based on parametric logic [31, 32, 33].

System measurements entail the measurement of emergent properties of complex objects, inherent in such objects as a comprehensive system of interconnected attributes [7].

Cognitive measurements (CM) are used when the subject of measurement is involved in any measuring system, including an intelligent measuring system, as a source or recipient of information. Such measurements are conducted to enhance the cognitive aspect of the measurement process [28].

In conditions of significant uncertainty, the model of a complex object and its environment must adapt to the received information and changing requirements, constraints, target functions, and task criteria.

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, which 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.

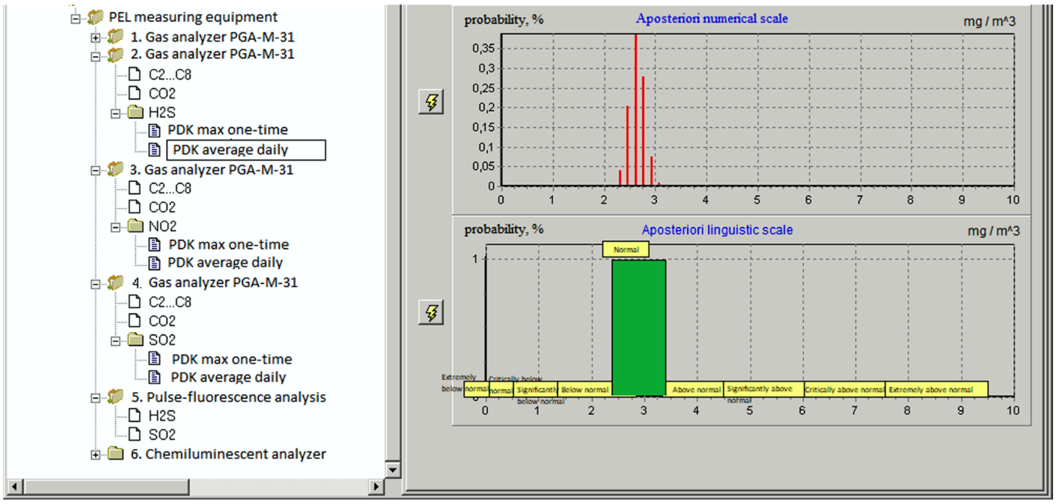

Figure 1. A model of a measuring system in the form of an MDC for air control based on BIM technologies (left part). A scale with dynamic constraints for the convolution of numerical and linguistic information according to the formula (4) for estimating the concentration of pollutants in the air. (right part).

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 (3), 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].

$$P^{(ap)}\left(h_{k,t}|Y_t\right) = \frac{P^{(a)}\left(h_{k,t-1}|Y_{t-1}\right)\left(P\left(h^*_{k,t}|Y_t\right)\right)}{\sum_{j=1}^{K} P^{(a)}\left(h_{j,t-1}|Y_{t-1}\right)\left(P\left(h^*_{j,t}|Y_t\right)\right)}, \qquad (3)$$

where $P^{(a)}\left(h_{k,t}|Y_{t-1}\right)$ is the prior p$Y_t$robability 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 (3), a probabilistic convolution of the values of the indicators is performed, the scheme of which is shown in Figure 2.

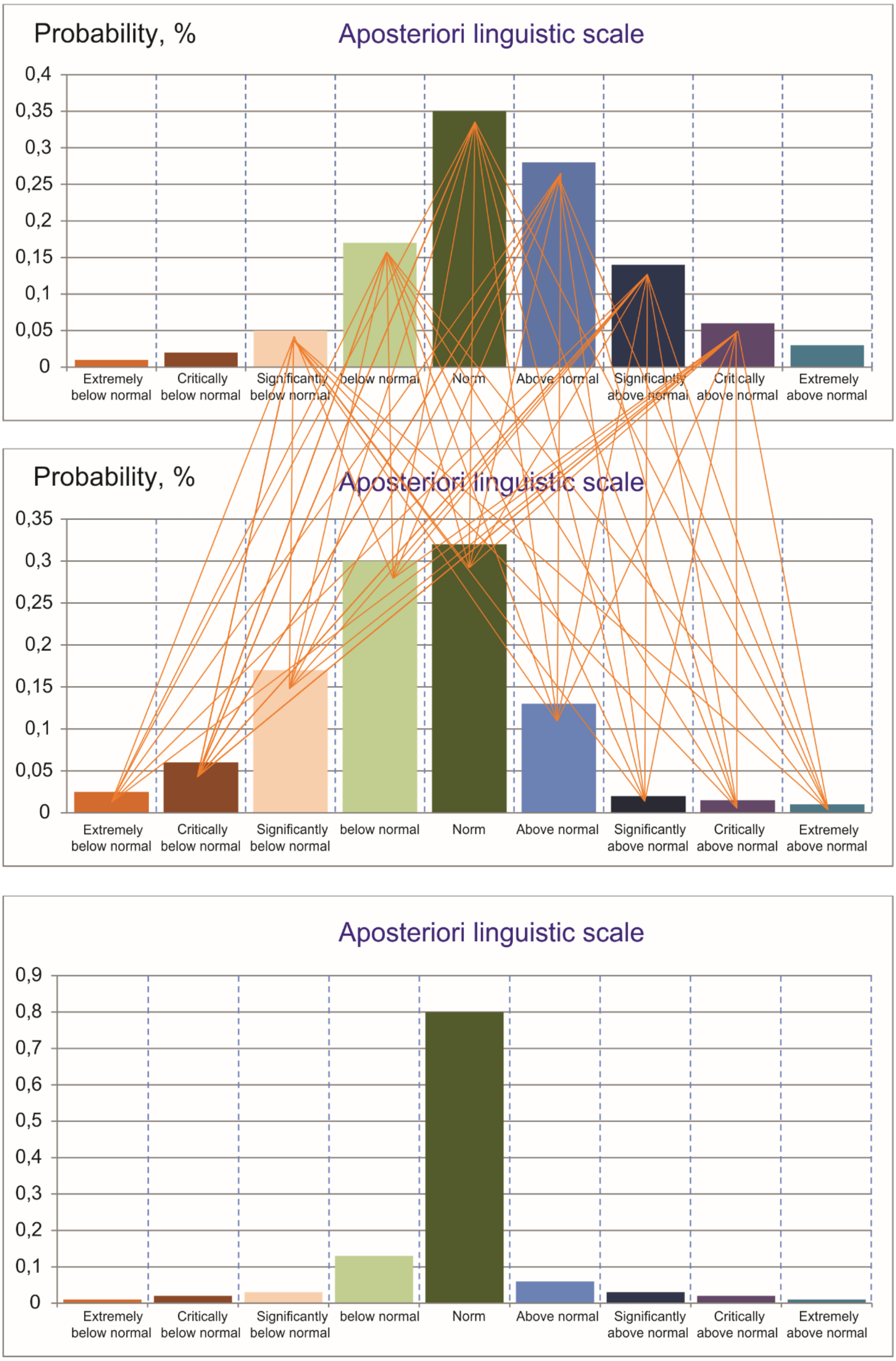

Figure. 2. An illustration of the principles of Bayesian convolution for two indicators.

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.

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.

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:

$$P\left(h_k^{(apN)}|\{MX\}_k^{(aN)}\right) = \frac{P\left(h_k^{(aN)} \cdot P\left(h_k^{(N)}|\{X_i\}\right)\right)}{\sum_{j=1}^{K} P\left(h_j^{(aN)} \cdot P\left(h_j^{(N)}|\left\{X_i^{(N)}\right\}\right)\right)}, \tag{4}$$

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:

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

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

$$P\left(h_k^{(ap)} | \{MX\}_k^{(ap)}\right) = \frac{P\left(h_k^{(apN)} \cdot P\left(h_k^{(apL)} \middle| \{X_i\}\right)\right)}{\sum_{j=1}^{K1} P\left(h_j^{(apN)} \cdot P\left(h_j^{(apL)} \middle| \{X_i\}\right)\right)}, \tag{6}$$

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:

$$P\left(h_{k3}^{(apL)} | \{MX\}_{k3}^{(apL)}\right) = \\ = \frac{P\left(h_{(k1)}^{(apL)}\right) \cdot P\left(h_{k2}^{(apL)}\right)}{\sum_{j=1}^{K1} P\left(h_{j1}^{(apL)}\right) P\left(h_{k2}^{(apL)}\right) \cdot \sum_{z=1}^{K2} P\left(h_{k1}^{(apL)}\right) P\left(h_{z2}^{(apL)}\right)}, \tag{7}$$

Convolution of two factors according to the formula (7) 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.

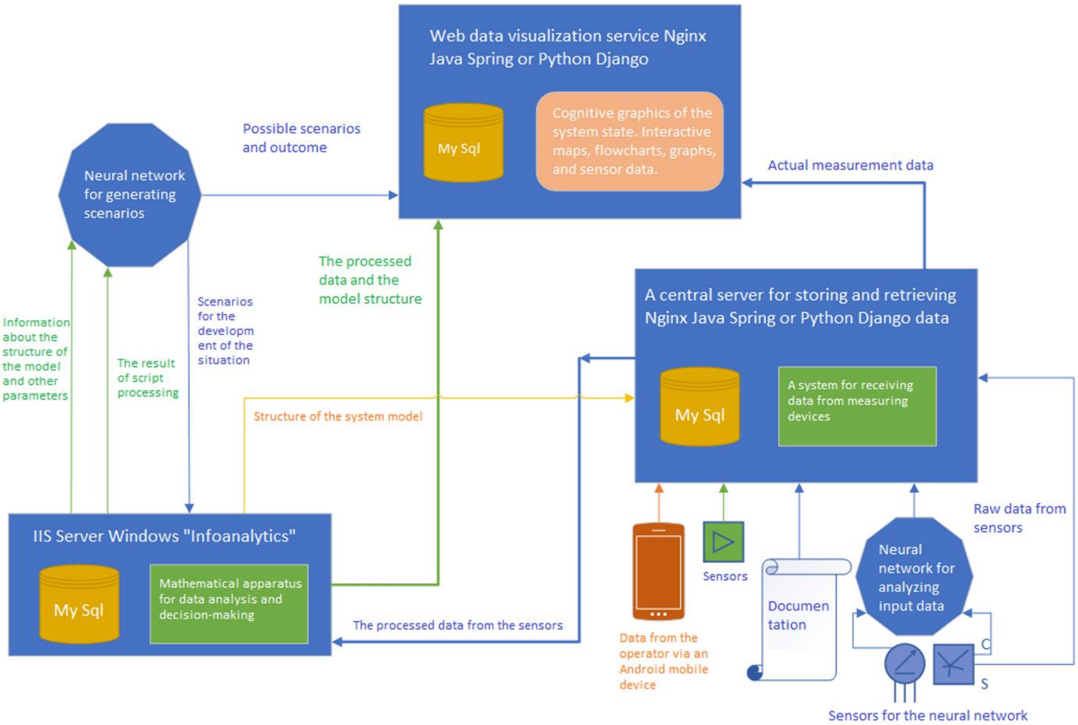

Figure 3. Architecture of an intelligent complex for monitoring the water supply network based on Bayesian intelligent measurement technologies.

Based on these calculations and considerations, it can be concluded that when dealing with high initial information uncertainty, regularizing Bayesian estimates exhibit high reliability. This reinforces the effectiveness of the regularizing Bayesian approach in such situations.
Furthermore, the development of the structure of the SDC (Solution Decision Center) is closely aligned with the structure of the MDC (Model Decision Center). This alignment leads to the emergence of new branches of information technologies focused on measuring new indicators, monitoring and auditing them, interpreting complex situations, generating recommendations, and more. This continuous development of models and information technologies based on the regularizing Bayesian approach (RBA) highlights the adaptability and versatility of this approach.

The process of implementing Bayesian convolution of two indicators, as defined by the formula (7), is depicted in Figure 2. Through multiple convolutions, there is a significant reduction in the dimensionality of the feature space, enabling the processing of a large number of data streams at high speeds.

Central to the synthesis of information technologies based on RBA is the principle of unity of measurements. This principle allows for the coordination of inputs and outputs of individual scales, transforming them as needed to meet the functional requirements of the information technology and to comply with metrological standards for information system solutions. Alongside the computational process, the metrological support of each solution is integrated, encompassing indicators such as accuracy, reliability, consistency, entropy, and risk. These indicators are organized into comprehensive metrological characteristics.

The solution obtained through Bayesian intelligent measurements (BIM-solution) consists of a series of alternative estimates for the property of interest, each accompanied by corresponding metrological characteristics. This BIM-solution is essentially a regularized Bayesian estimate (RBE), and it is demonstrated in [7] that these estimates possess desirable properties of being unbiased, consistent, and efficient.

It's worth noting that in scenarios with significant uncertainty, individual elementary solutions within the RBE composition may not exhibit high reliability or reliability. However, collectively, the RBE provides adequate coverage of the true value with satisfactory quality indicators and minimal risk.

The metrological justification of information technologies for addressing problems in uncertain conditions enables the evaluation of the quality of information from each data source and each resulting solution. This evaluation is facilitated through the use of metrological indicators such as accuracy, reliability, consistency, risk, entropy, and information volume. Accuracy, for example, is determined by the following formula:

$$\xi_s = \frac{\max\limits_{h_s \in H_k} \rho(h_s, h_{s+1})}{\rho(h_K, h_1)}, \tag{8}$$

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:

$$V_s = (1 - \alpha_s)(1 - \beta_s), \tag{9}$$

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 is a crucial aspect of the measurement process. The reliability of each hypothesis on the scale is determined by the a posteriori probability of its occurrence, which is calculated using the Bayes formula. It's important to note that the confidence of the entire scale is considered to be the sum of the confidence of the individual hypotheses, and therefore, it equals one.

However, in practical situations, it may be necessary to simplify the scale by retaining only a subset of hypotheses that meet specific significance criteria. In such cases, the reliability of the decision on the scale is determined as follows:

$$P = P^a \cdot \sum_{h_j \in H_r} P(h_j), \tag{10}$$

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 distinctive characteristics of BIM and SM can be summarized as follows:

1. Measurement is treated as a decision-making process concerning the size of the object being measured.
2. Information sources include both data in the form of information flows and expert assessments and other forms of knowledge.
3. The dynamic compactness of measurement solutions constitutes a two-dimensional metric space encompassing gradations (including values) of measured object properties along with their associated probabilities, possibilities, or subjective probabilities.
4. Measurement results can be presented either in numerical or linguistic form, typically as a list of alternative estimates accompanied by their corresponding sets of metrological characteristics, particularly reliability.
5. BIM and SM employ computationally efficient but semantically rich scales, such as nominal and ordinal scales for linguistic information. For numerical information, ratio scales are employed, which differ in computational power. The conjugate scale, as depicted in Figure 1, combines the properties of these scales, offering both computational capabilities and semantic interpretation for processing both numerical and linguistic information.
6. BIM and SM produce results in the form of a set of alternatives with metrological justification and can be viewed as "fuzzy" measurements.
7. Results obtained through BIM and SM are accompanied by comprehensive sets of metrological characteristics encompassing accuracy, reliability, robustness, risk, entropy, Fischer's information volume, and more.
8. The outcomes of BIM and SM include explanations for the results, including reasons for their derivation, identification of influencing factors, determination of trends in indicators, and, when necessary, suggestions for improvement.
9. Recalculations are conducted using special scales, such as scales with dynamic constraints, where reference points represent hypotheses regarding possible values or gradations of the measured property.
10. Logic criteria and inference rules are tailored to the specific measurement task and conditions.
11. Scales and models within the BIM and SM frameworks are dynamic entities and can undergo transformation during the measurement process.
12. BIM and SM are particularly valuable when conditions for conducting measurement experiments lack repeatability, and only individual facts, small data samples, and significant uncertainties are available.

4. CONCLUSION: KEY FINDINGS AND FUTURE PROSPECTS FOR BIM AND SM

The emergence of new technological trends in the contemporary IT industry, such as the Internet of Things (IoT), Big Data, Data Science, and Business Intelligence (BI), is intricately linked to the acquisition and processing of diverse data streams. These data exhibit unique characteristics, including diversity, spatial and temporal distribution, varying physical attributes, complexity of interpretation, and uniqueness, making their processing challenging within the aforementioned technologies. Measurement information is frequently a prominent source of such data. These data usually originate from complex anthropogenic or natural objects and systems.

The specificity of complex objects and systems lies in their fundamental unknowability, unpredictability, and inaccessibility for direct observation to the extent necessary for a reliable assessment of their properties. This scenario leads to a state of information uncertainty wherein precise values or conclusions cannot be obtained through parameter measurements, property evaluations, or system audits. In such situations, measurement accuracy is achieved by incorporating additional information in the form of knowledge about the object under measurement and the factors influencing it. In this context, approaches that yield multiple alternative solutions, encapsulated within a specific interval (space) of solutions, are employed. This methodology aids in reducing result uncertainty by leveraging additional information derived from alternative solutions. The acquisition of these alternatives necessitates the utilization of specially designed methods.

Given the requirements described above and focusing on the attributes of integration, metrology, and the self-development of methodological foundations of the Regularized Bayesian Approach (RBA) underpinned by intelligent technologies, specifically Bayesian Intelligent Technology (BIT) and Bayesian Intelligent Measurement (BIM), it becomes evident that these approaches hold promise for developing intelligent measurement and monitoring systems for complex objects and implementing a "soft control" scheme.

An essential facet of the future prospects of BIM methodology and systems involves their integration with emerging realms of artificial intelligence.

BIM and Soft Measurement (SM) methodologies and systems exhibit potential in various domains:

1. **Data Science Systems:** They are employed for metrological certification of data and knowledge flows and their subsequent integration.
2. **IoT Systems:** These systems are instrumental in collecting, integrating, and interpreting instrument data.
3. **BI Systems:** They play a vital role in the analytical processing and interpretation of information.
4. **Neural Networks:** They facilitate the collection, metrological certification, and convolution of data and knowledge to enhance data set compilation and neural network training.
5. **Big Data Processing Systems:** BIM and SM aid in significantly reducing the dimensionality of information flows.
6. **Mathematical and Analytical Information Processing Systems:** They are beneficial, especially for handling uncertainty and small sample sizes.
7. **Complex System Monitoring and Management:** These methodologies find application in monitoring and managing intricate industrial and socio-economic complexes, as well as facilitating their sustainable development.

The integration of measurement approaches and methodologies grounded in intelligent measurements defines a necessary and promising stage in the evolutionary development of measurement theory and artificial intelligence.

Figure 5: Dynamic Model of Pressure Fluctuations in a Pipeline, Constructed by Integrating Various Data Types.

Figure 4: Cognitive Graphic Model of a Section of a Water Supply Network.

4.1. Solutions to Applied Problems in Conditions of Significant Information Uncertainty Based on BIM

The BIM and SM methodologies, technologies, and systems have given rise to a multitude of applications spanning Bayesian mathematical statistics, Bayesian econometrics, Bayesian measurement neural networks, and various applied systems in domains such as industry, energy, economics, the social sphere, ecology, and geopolitics. These applications are constructed on the foundation of BIM and SM.

The BIM methodology enables the organization of problem-solving processes in uncertain scenarios, encompassing the following stages:

- **Problem Definition:** Identifying goals, constraints, and requirements.
- **Measurement Situation Identification:** Determining the measurement type and conditions.
- **Compact Solution Formation:** Building a compact solution based on measurement conditions.
- **Input Information Space Creation:** Establishing a space for input data.
- **Metrological Justification of Information Sources:** Ensuring information source reliability.
- **Hierarchical Modeling:** Constructing hierarchical models of the measurement object and environmental models using dynamic constraints.
- **Indicator Selection:** Choosing balanced indicators based on developed models and integrating them into a unified measurement space using regularizing Bayesian methods.
- **Inference Rule Selection and Decision Logic:** Determining the inference rule and decision logic.
- **Measurement Scale Creation:** Developing specific measurement scales for selected indicators.
- **Information Mapping to Scales:** Transferring information to the scales.
- **Information Convolution:** Employing modified Bayesian convolution to derive solutions in the form of multiple alternatives, along with their associated likelihood, reliability, risk, informativeness, and more.
- **Quality Control:** Ensuring solution quality.
- **Decision Process Correction:** Adjusting all components of the decision-making process.
- **Iterative Self-Development:** Repeating the process, starting from the initial stage, to obtain refined solutions.

These technologies have proven effective in the auditing and management of distributed man-made systems that interact dynamically with the external environment. Such systems include fuel and energy complexes, transportation networks, and territories. These systems represent typical subjects for multisystem auditing and management in the context of complex dynamic systems with changing spatial and temporal characteristics. In situations of active interaction between these systems and the external environment, along with significant information uncertainty, measurement system limitations may change as the systems operate according to varying measurement conditions. This dynamic feature ensures the continued adequacy of the models used in these systems, even as properties and characteristics of the managed systems, business landscapes, or natural and economic environments evolve.

To implement the BIM methodology, a range of platforms has been developed for the rapid creation of application systems dedicated to intelligent data processing under conditions of uncertainty. These platforms support monitoring, auditing, decision support, management, risk assessment, and control of complex systems. An example of such a system is the intelligent monitoring system for water supply networks developed on the "Infoanalytic" platform.

The relevance of establishing a methodology and system for monitoring water supply networks within the context of big data and information uncertainty can be attributed to several factors:

1. **Diverse Information Sources:** Various metering and monitoring devices provide real-time data.
2. **Extensive Network Length:** Water supply networks often span great distances.
3. **Information Source Uncertainty:** Information sources regarding water supply networks are often uncertain.
4. **Expert Knowledge:** A substantial portion of information relies on expert opinions, assessments, and specialist knowledge.
5. **Subjectivity:** Assessments of water supply network conditions and integral indicators can be subjective.
6. **Decision-Making Subjectivism:** Management decisions may also be subjective.
7. **Lack of Automated Coordination:** Coordination in monitoring and managing water supply networks is often not automated.

The intelligent system's objectives include:

1. **Cost Reduction:** Optimize resource allocation to minimize repair expenses.
2. **Enhanced Energy Efficiency:** Identify and address losses promptly to improve energy efficiency.
3. **Decision Support:** Assist municipal heating network and water utility leaders in making decisions regarding planned and unscheduled pipeline repairs.
4. **Technological Scheme Creation:** Prepare materials for pipeline technological schematics and certification.

The system's tasks encompass:

1. Building a hierarchical model of interrelated enterprise processes and factors influencing the water management complex and water supply enterprise.
2. Assessing indicators determining the state of heat and water supply networks and water supply processes under conditions of uncertainty and limited information.
3. Evaluating and analyzing the production situation within the chosen enterprise.
4. Identifying key production processes.
5. Formulating principles and creating an effective water supply management scheme.
6. Developing and employing forecasts of the company's operational development to facilitate effective management decisions.

The complex's structure comprises a primary unit for mathematical data processing based on BIM, neural network processing of thermal images, neural network decision-making for comprehensive water distribution network assessment based on RBA, data extraction, transformation, and loading (ETL) block with advanced processing capabilities, IoT integration, cognitive user interfaces, web services, and other components.

Data sources include measurement data from pressure sensors in pipes, water flow velocity meters, flow meters, leak meters, thermometers, vibrometers, thermal imagers, and other sensors. This measurement information undergoes analytical processing after collection.

Production information encompasses:

- Water Supply Network Structure
- Network Equipment Configuration
- Water Supply Network Operation Rules
- Water Quality Control
- Production Process Automation
- Analysis of Water Supply Incidents
- New Construction
- Capital Construction and Network Reconstruction

Information is received at varying frequencies, including monthly and quarterly reports, daily operation logs, daily device diagrams, and continuous annual reports.

Linguistic information sources for assessing the water supply network's condition include:

- Logs of preventative maintenance work
- Logs of well and chamber processing
- Logs of pressure gauge health
- Logs of valve inspections (Diameter: 600-1200 mm)
- Logs of network inspections in reservoirs during winter
- Logs of well and chamber inspections during winter
- Logs of intersections with metro and railway inspections
- Intelligent measurement technologies and sensors for water supply systems
- Journals of intelligent measurement technology and sensor usage for water supply systems
- Journals of winter work preparations
- Journals of valve insulation in chambers
- Logs of insulation removal from fittings in chambers
- Journals of water supply source examinations

Figures 4 and 5: These figures display the results of modeling, calculations of characteristics, and cognitive assessments of the water supply network's condition in various Russian cities, all based on the BIM methodology.

The functioning of this intelligent system yields the following conclusions:

1. Integration of IoT, Bayesian intelligent measurement, and neural networks, guided by a regularizing Bayesian approach, is effective in addressing water management network monitoring challenges.
2. Bayesian intelligent technologies facilitate the efficient utilization of diverse information types, both numerical and linguistic, encompassing measurement data and specialist knowledge.
3. Leveraging regularizing Bayesian approach technologies ensures the system's operational stability, even in scenarios involving significant information uncertainty and vast data processing.
4. Metrological support, in the form of comprehensive metrological characteristics covering accuracy, reliability, solution robustness, risk assessments, and information quantity assessments, is provided for all measurement solutions, ensuring control over solution quality.

5. Solutions obtained exhibit stability under uncertain conditions, enabling their application in the measurement of technical and socio-economic system properties, as well as in their monitoring and management within complex information environments.
6. All decisions are accompanied by explanatory descriptions and cognitive interpretations, enhancing specialists' control over the measurement process and enabling online management.
7. Integration of IoT and neural network technologies with Bayesian intelligent technologies extends their capabilities, allowing them to address an expanded range of tasks.
8. The proposed BIM methodology and technologies find relevance in various industries.

By the present time, significant experience has been accumulated in the application of Bayesian measurement technologies in information-related tasks across various domains of human activity. Such applications include tasks related to assessing the state of complex objects, managing them, monitoring situations, and developing scenarios in industrial, energy, socio-economic, and other fields.

The methodology of Bayesian intelligent measurements (BIM) is particularly relevant for enhancing the resilience and efficiency of small businesses. The application of the RBA methodology not only allows for assessing the business situation but also enables the creation of digital twins of small enterprises to increase profitability, create a comfortable environment for employees, and enhance competitiveness within the market.

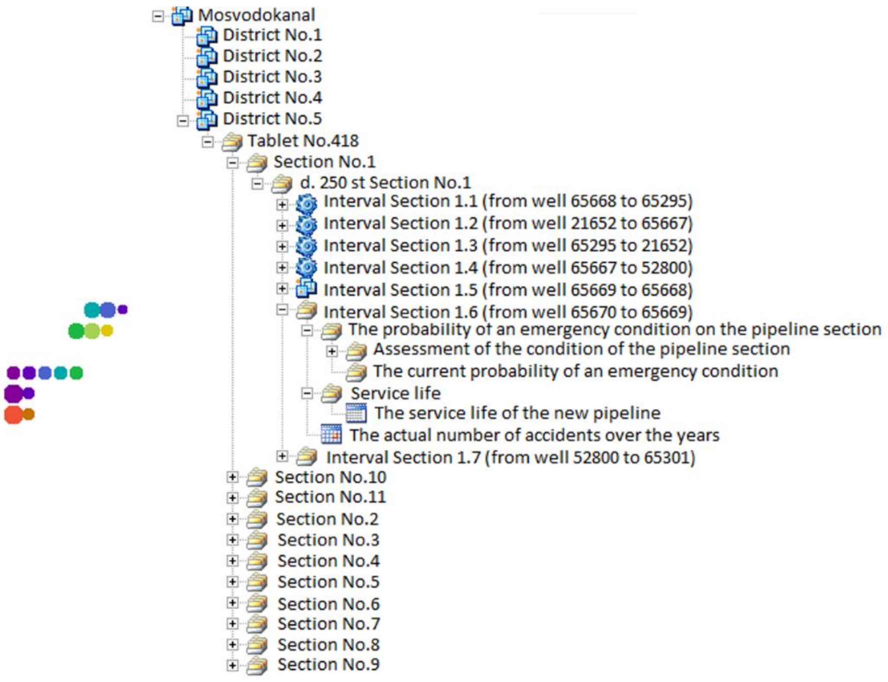

Figure 4: Cognitive Graphic Model of a Water Supply Network Section

This illustration depicts a cognitive graphic model representing a section of a water supply network. The model provides a visual representation of the network's components and their interactions, allowing for a better understanding of the system's behavior and performance.

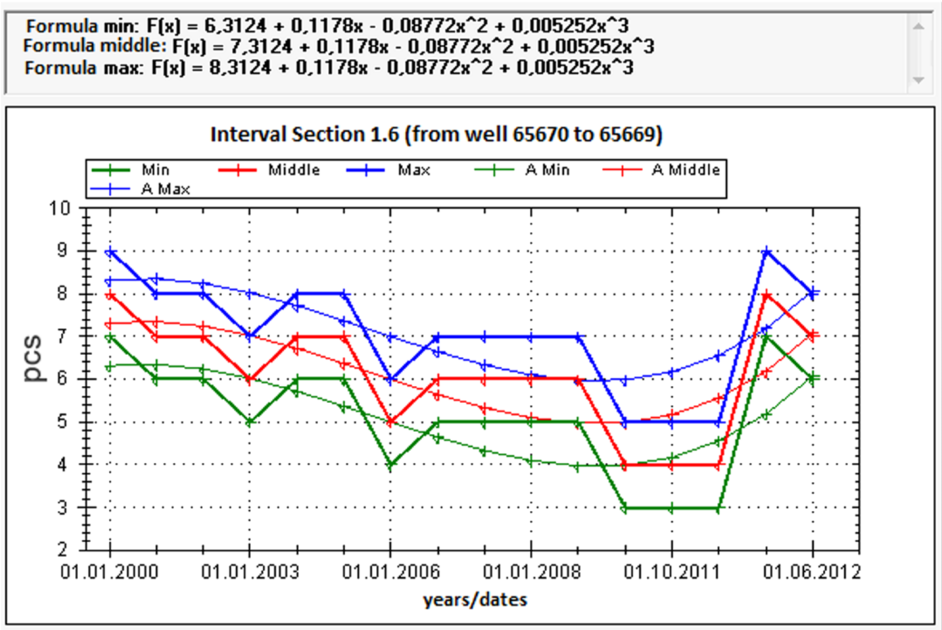

Figure 5: Dynamic Model of Pipe Pressure Change

This figure illustrates a dynamic model of pressure changes within the pipe. The model is constructed through the integration of various types of data, allowing for a comprehensive understanding of pressure fluctuations and variations over time.

5. Conclusion: Key Insights and Future Prospects for BIM and SM

The evolving landscape of the modern IT industry, marked by trends like IoT, BIG DATA, DATA SCIENCE, and BI, involves the acquisition and processing of diverse and complex information streams. This information, characterized by its diversity, spatial and temporal distribution, varying physical attributes, and interpretational complexities, presents challenges for these technologies. A significant source of such intricate data is measurement information, often originating from complex anthropogenic or natural systems.

Complex objects and systems inherently possess fundamental characteristics of unknowability, unpredictability, and limited accessibility for direct observation, making it challenging to reliably assess their properties and states. Consequently, this results in situations of information uncertainty, where precise values or conclusions cannot be obtained solely from parameter measurements or property evaluations. In these scenarios, accuracy in measurements is achieved by incorporating additional knowledge about the object and influencing factors. Approaches that yield multiple alternative solutions within a defined interval are employed to mitigate result uncertainty by harnessing this supplementary information. Specialized methods are developed to obtain these alternatives.

Given these requirements and with a focus on integration, Metrology, and self-development, the methodological foundations of the Regularizing Bayesian Approach (RBA) combined with intelligent technologies (Bayesian Intelligent Technology - BIT) offer promising avenues for specific Soft Bayesian Measurements (CM). These approaches are well-suited for the development of intelligent measurement and monitoring systems for complex objects, auditing, and soft control schemes.

An important prospect lies in the integration of BIM methodologies and systems with emerging areas of artificial intelligence.
The methodologies and systems of BIM and Soft measurements show promise in various domains, including:

1. In DATA SCIENCE systems, for the metrological certification of data and knowledge flows and their seamless integration.
2. In IoT systems, for the collection, integration, and interpretation of instrument data.
3. In BI systems, for the analytical processing and interpretation of information.
4. In neural networks, for data collection, metrological certification, and convolution, aiding in additional information integration during dataset compilation and network training.
5. In big data processing systems, for significantly reducing the dimensionality of information flows.
6. In systems for mathematical and analytical information processing, particularly for handling uncertainty and small datasets.
7. For creating systems to monitor and manage complex industrial and socio-economic complexes, fostering sustainable development.

The integration of measurement approaches and methodologies rooted in intelligent measurements represents a necessary and promising stage in the evolutionary development of measurement theory and artificial intelligence.

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