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LOGICAL-SEMANTIC MODELS AND METHODS OF KNOWLEDGE REPRESENTATION: CASES FOR ENERGY MANAGEMENT SYSTEMS AND SMR DIGITAL INFRASTRUCTURES

The subject of this article is the development of information technologies at the end of the 20th and the beginning of the 21st century for the Fourth Industrial Revolution in the form of Industry 4.0, i.e., Internet of Things (IoT) technologies. Successes in the implementation of this technology have led to the development of new applications in the energy sector, such as energy management systems, small modular reactor (SMR) management systems, and alternative power supply systems based on renewable energy sources. The digital infrastructure of these management systems is characterized by a high "density of knowledge", which requires clarification of fundamental concepts in information theory, namely the content of the concepts "data", "information", "knowledge" and "meaning of knowledge". Special attention was given to defining the role of knowledge. The aim of this study is to further develop methods and models of semiotic theory by determining the role and place of logical as well as eight- and four-factor logical-semantic models of knowledge bases in semiotic space. The tasks: comparing existing knowledge representation methods and models. Research results: We found that the logical models used in the development of knowledge bases are based on the principles of artificial intelligence theory, which relies on sign system hypotheses and formal logic theory. The main drawback is the complexity of practical implementation in the form of expert systems. For logical-semantic models in the form of eight-vector graphic models, it was found that there is currently no theoretical justification for defining the vectors that form the coordinate axes, making these models unique to specific subject areas. It was determined that the advantage of using these methods is that an expert can independently form such a knowledge model. For logical-semantic models in the form of four-factor graphic models, there is a theoretical justification for defining the factors of the model that form the coordinate axes, making these models universal for specific subject areas. It was established that the advantage of these models is that they can be developed by experts without the involvement of a knowledge engineer. Therefore, it is proposed to use four-factor logical-semantic knowledge representation models for further application. It is also proposed to split the element "logical-semantic models" into two elements in the semiotic spatial model in vector K8 "Knowledge Representation Models", namely: "logical-semantic eight-vector models" and "logical-semantic four-factor models". Additionally, it is proposed to add the element "post-Cartesian representation of meta-knowledge" to the element "geometric" in vector K5 "Ideal Models". Conclusions: The theoretical basis for developing eight-factor logical-semantic knowledge representation models is the form of connections between adjacent vectors in the form of Cartesian products on elements of the corresponding inter-coordinate matrices. The theoretical basis for the methodology of developing four-factor logical-semantic knowledge representation models is the form of connections between adjacent vectors in the form of Cartesian products for elements of the corresponding inter-coordinate matrices, as well as for diametrically opposite pairs of factors in the form of dialectical unity of the concepts "general" and "particular." The application of logical-semantic knowledge representation models for alternative energy-source management systems will ensure increased energy efficiency. Other cases related to the development of databases for SMR digital infrastructure are discussed.

Keywords: knowledge bases; logical models; logical and semantic models; four-factor graphical models, eight-factor graphical models, small modular reactor.

1. Introduction

1.1. Motivation

According to the Law of Ukraine on Energy Efficiency, priority is being given to distributed power supply systems based on alternative energy sources. These sources include wind farms, solar power plants, and small hydropower plants. In modern times, the task of developing and implementing small modular nuclear reactors (SMR) is particularly relevant. According to the International Atomic Energy Agency, approximately 80 SMR concepts are currently being developed, representing 40% more than in 2018. SMR is a new and

potentially more sustainable paradigm for developing nuclear energy. SMR will play an important role in society's transition to low-carbon energy. The main drivers of SMR development are the need to switch to low-carbon sources of electricity; reducing greenhouse gas emissions, combating negative climate change; finding new opportunities for remote deployment, cogeneration, hydrogen production, and other applications, creating new jobs in nuclear power, among others.

Further development of these technologies requires the creation of new approaches to the informational support of these systems' activities. This is due to the large volumes of data and corresponding knowledge that require the development of knowledge representation methods and models that are accessible to ordinary users. Note that alongside the concept of Industry 4.0, the next technological revolution, Industry 5.0, is actively developing, which is defined as the Internet of Knowledge. Based on the above, it is necessary to perform a comparative analysis of existing knowledge representation models and methods. As a result of this analysis, alternative methods and models for representing knowledge from traditional expert systems can be identified and proposed for further application. Special attention is expected to be given to the logical-semantic models of knowledge representation used in educational practice, and the models proposed in economic theory.

1.2. State of the Art

The parallel development of SMRs' projects [1] and the digital technologies (IoT, big data, cloud, etc.) technologies (IT) has necessitated a reevaluation of the initial concepts underlying the concept of SMR digitalization. Mindfulness has been reinterpreted in energy facilities to enhance operational efficiency and safety by cultivating heightened awareness and attentiveness among employees, reducing human error, and improving decision-making processes [2]. The most significant changes required clarification of the content of fundamental concepts in information theory, namely, the definitions of "data", "information", "knowledge" and "meaning of knowledge". Defining the role of knowledge has required the most attention. In the 2020s, research results in the fields of knowledge theory and knowledge management theory have established knowledge as an independent primary resource for enterprises and organizations. This led to the formation of the Internet of Knowledge concept. Therefore, there arises a problem in analyzing existing methods [3] and models to form knowledge bases with the aim of further development.

The general theoretical foundation of all theories related to methods and models of knowledge representation is semiotics. The object of semiotic theory research is sign systems [4]. The fundamental concept in this theory is the concept of a "sign" [5]. Practically, methods and models for knowledge representation based on sign systems have been implemented in intelligent information technologies for knowledge manipulation [6]. The result of applying intelligent information technologies is the creation of artificial intelligence systems (expert systems, knowledge bases) [7] for specific subject areas based on logical models. However, the development of knowledge bases using these technologies requires the inclusion of a global database to which production rules can be applied. These rules are formed in a corresponding knowledge base and management system that controls the application of these rules [8, p. 23]. The formation of such a knowledge base involves experts in the subject area, a knowledge engineer capable of "extracting" knowledge from experts, and a programmer to write the corresponding code. Typically, such artificial intelligence systems (expert systems) are unique to the subject area. In addition, the extracted knowledge must be rigorously interpreted and formalized to ensure its accurate representation and applicability in the system [9].

The theoretical foundation of knowledge base formation in the form of expert systems based on artificial intelligence theory was established by A. Newell and H. Simon [10]. They identified two main concepts: symbolic systems and search. They defined a symbolic system as a set of symbols that form symbolic structures and a set of processes. These processes can produce, destroy, and modify symbolic structures.

A symbol is a primary concept. Symbolic structures can be viewed as data types in certain languages. They have two main properties:

They denote objects, processes, and other symbolic structures.

If they denote processes, they can be interpreted.

In this context, a symbolic structure denotes a certain entity (object, process, or another symbolic structure) if the symbolic system can exhibit behaviour defined by that entity or influence that entity. The system can interpret a symbolic structure if the structure denotes a specific process, and the system can execute that process.

They also substantiated two hypotheses that form the basis of artificial intelligence theory [10]:

- the first hypothesis asserts that symbolic systems have the necessary and sufficient conditions to perform intelligent actions;

- the second hypothesis proposes that symbolic systems solve tasks through search; that is, they generate potential solutions and progressively modify them until they satisfy the specified conditions of the solution.

These hypotheses are supported by many experts in the field of artificial intelligence.

There are also logical-semantic models based on graphical four-coordinate models, which are founded on Cartesian systems. In the work [11], 50 models of strategic thinking were considered. Eleven of these models are based on [11, p. 168]:

«Four-field matrices ... <which> help their users peer into the world, point the way to understanding and organization».

Unfortunately, the authors refer to these models as «stone-age methods». Should they be abandoned? They provided the following answer [11]:

«Does this mean you can forget all the models you have been introduced to in this book? No. The applicability of stone-age models cannot be underestimated. They help us in a world that is difficult to survey, reduce risks, systematize, and prioritize. For those who realize that models are merely a simplified slice of reality, they can be very useful».

The 10 models considered in [11] have a four-matrix structure based on the Cartesian coordinate system. The same structure is used in the generalized model [11, title page].as you can see in Fig. 1. Illustrative example of a rectangle-method algorithm with multiple execution steps
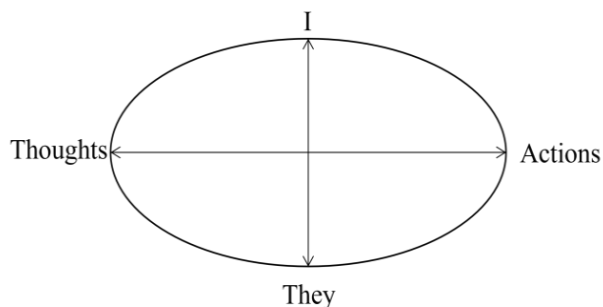

Fig. 1. Four-Factor Model

These models are classified as logical-semantic models of knowledge representation and are also studied in semiotics. In these models, the coordinate axes are denoted as factors, and the form of each factor is unique.

Unfortunately, in all these models, the nature of the relationships between diametrically opposite and adjacent factors that form these models is not clarified. In addition, the dynamics of the relationship between dead factors remain unexplored [12].

Four-factor logical-semantic models are also used in economics. An example of such a model is the BSC

(Balanced Scorecard) methodology [13], as illustrated in Fig. 2.
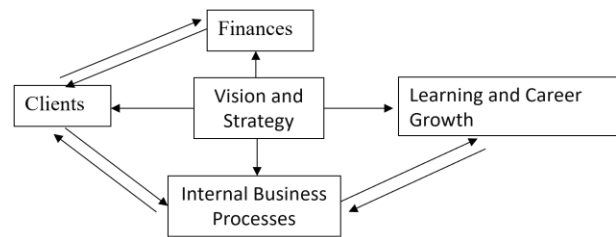

Fig. 2. Adjusted Model of the Relationship Forms Between Factors in the BSC Methodology

Their formation principle is analogous to the principle of forming logical-semantic strategic thinking models.

A common characteristic of all four logical-semantic models is that the definitions determining the axes are not presented in the form of sets with corresponding elements. There is no clear division of each matrix into individual cells.

Four-factor logic-semantic models of knowledge bases have been developed based on the factor process-resource representation of organizational activities. This development is based on the central regularity of integrative brain activity, as described in the theory of functional systems [14]. The theory of functional systems serves as a foundation for developing intelligent computer decision support systems for process management [15]. The formulation of multifactor logical models of knowledge representation is directed towards the development of the Industry 5.0 concept [16]. The theory of functional systems is a specific form of the theory of physiological cybernetics [17].

Based on the analysis of research results on methods and logical and logical-semantic models of knowledge representation [18], sign systems that are objects of semiotics, there is a need for further investigation of four-factor logical-semantic models of knowledge representation. This investigation aims to determine their place and role in semiotics and to find ways to theoretically justify the principles of their formation.

The aim of this research is to further develop the theory of semiotics by determining the role and place of four-factor logical-semantic models of knowledge bases within the semiotic space.

1.3. Objective and structure

This study aims to develop logical-semantic models and methods for forming knowledge bases, particularly in the context of energy management and

the digital infrastructure of Small Modular Reactors (SMRs). The main objectives of this study are to compare logical and logical-semantic multifactor models of knowledge representation in semiotics, identify their strengths and weaknesses, and propose ways to develop them for practical application in expert systems and other intelligent information technologies.

The main objectives and stages of this research are as follows:

− stage 1: Analyze the problem of knowledge representation in SMR digital infrastructure and other subject areas. (Section 1);

− stage 2: Define the research methodology. (Section 2);

− stage 3: Analyze methods and models for forming logical and logical-semantic models of knowledge representation, considering theoretical and practical limitations. (Section 3);

− stage 4: Case study: Practical implementation of a four-factor logical-semantic model of knowledge representation for SMR digital infrastructure. (Section 4);

− stage 5: Summarize the research results and outline future directions for development in the field of knowledge representation and semiotics (Section 5).

2. Methodology

The research approach involves identifying general patterns and hypotheses that form the basis of logical models and knowledge bases. It is proposed to use a logical-semantic semiotics model as the theoretical foundation for comparison. The basis for this decision is all known logical models of semiotic knowledge representational objects.

3. Materials and research methods

Historically, logical models were the first to be developed as a foundation for developing knowledge bases in the form of expert systems [19]. In these knowledge bases, all information necessary to solve applied problems is considered a set of facts and statements represented as formulas in a certain logic [20]. Knowledge is reflected as a collection of such formulas, and the acquisition of new knowledge is reduced to the implementation of logical inference procedures. At the core of logical models of knowledge representation is the concept of formal theory, which is defined as the tuple

$$S = \langle B, F, A, R \rangle,$$

where B is a countable set of basic symbols (alphabet);

F is a set whose elements are called formulas;

A is a distinguished subset of a priori true formulas (axioms);

R is a countable set of relationships between formulas, which is referred to as an inference rule.

As a "foundation," the classical apparatus of mathematical logic is used here, whose methods are well-studied and formally justified. The formation of knowledge bases (expert systems) based on artificial intelligence is grounded on the following principles [19]:

1. Power of an expert system: The strength of an expert system is determined primarily by the robustness of its knowledge base and capacity for expansion, and only secondarily by the methods (procedures) it employs. Power of an expert system: The strength of an expert system is determined primarily by the robustness of its knowledge base and capacity for expansion. However, experience has shown that it is more important to have a variety of specialized knowledge rather than general inference procedures.

2. Nature of Expert Knowledge: The knowledge that allows an expert (or expert system) to derive high-quality and effective solutions to problems is mainly heuristic, experimental, uncertain, and plausible. This is because the problems being solved are either non-formal or weakly formalized.

3. User Interaction: Given the non-formalized nature of the problems being solved and the heuristic, personal nature of the knowledge used, the user (expert) must have the capability to directly interact with the expert system in the form of a dialogue.

These principles are implemented as follows.

The formation of an artificial intelligence system involves organizing declarative (global database), procedural (productions), and control components of the entire production system based on knowledge about the tasks the system aims to solve [19]. This approach indicates that the primary knowledge about the subject area is transformed into data in the declarative component (global database, working memory).

Figure 3 illustrates a generalized schema of an expert system [19, p. 12].

The architecture of an expert system corresponds to the structure of the knowledge used in its operation (Figure 4) [19, p. 12].

Analyzing this structure reveals that the actual knowledge about the subject area comprises only a *small* portion of the used knowledge (domain knowledge). Most knowledge pertains to the processes of *manipulating* knowledge within the expert system, which are handled by the knowledge engineer and the programmer.

In an expert system, only *domain-specific knowledge* elements that can be formalized using methods of mathematical logic are used.
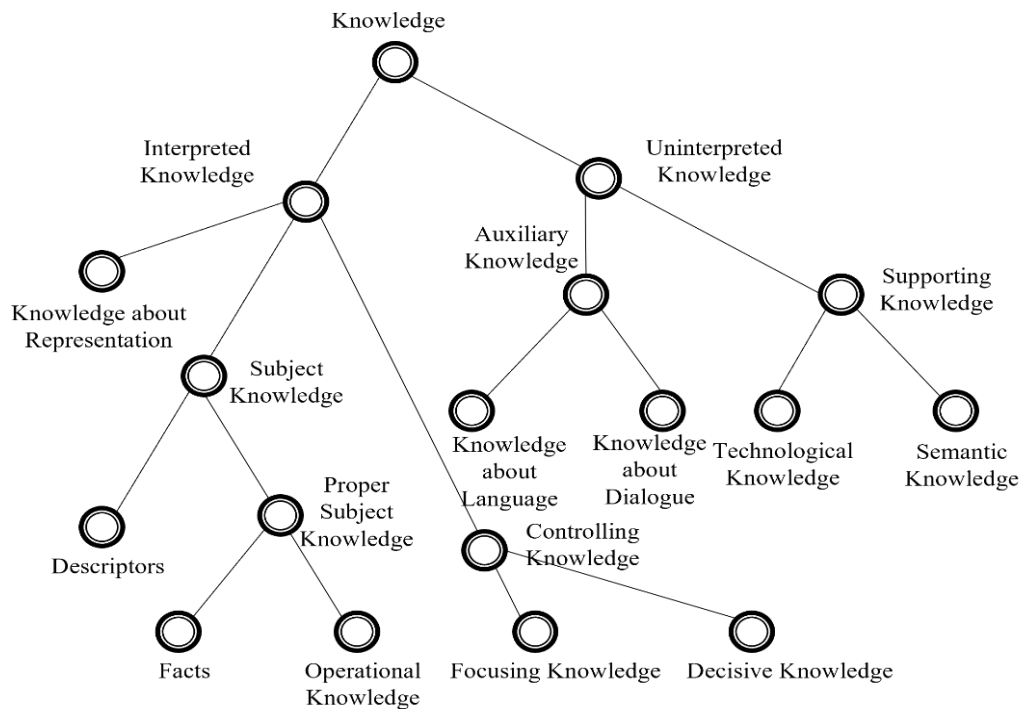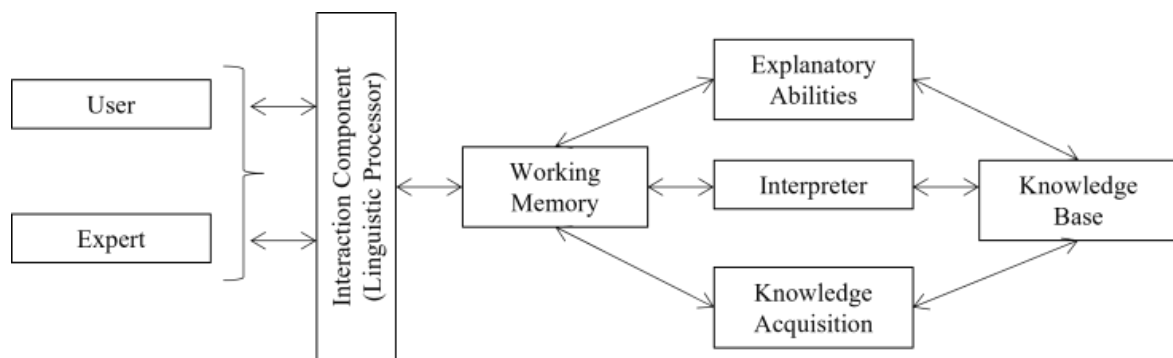
Fig. 3. Knowledge structure in the knowledge base

Fig. 4. Generalized Schema of an Expert System

From this, we conclude that the focus in developing artificial intelligence systems is on the processes of manipulating data and knowledge. The data related to the subject area are viewed as a tool for solving problems in the subject area.

As noted by N. Nilsson [8, p. 128]:

«The general strategy is to represent specialized knowledge about the target area as predicate calculus expressions, and the problem or query is a theorem to be proved. Then, the system attempts to prove the theorem based on the given expressions.»

With this approach, each developed expert system is unique because the subject area under which it is developed and the problems it addresses are unique. Therefore, primary attention is given to developing knowledge representation models for the working memory, interpreter, and knowledge base (Fig. 4).

At the same time, it is precisely the "unreliable or uncertain knowledge in various respects, common reasoning about cause and effect, knowledge about plans and processes, predictions, goals of oneself and others, and knowledge about knowledge" that describe the activity of objects in the subject area. With this approach, each developed expert system is unique because the subject area under which it is developed and the problems it addresses are unique. Therefore, primary attention is given to developing knowledge representation models for the working memory, interpreter, and knowledge base [10]:

– the first hypothesis asserts that symbolic systems have the necessary and sufficient conditions to perform intelligent actions;

– the second hypothesis posits that symbolic systems solve tasks through search, i.e., they generate potential solutions and gradually modify them until they satisfy the specified conditions.

Thus, knowledge bases are symbolic systems, which are semiotic objects [4].

To explore the place and role of knowledge base models in the form of logical models among other models (sign systems) in semiotics, we consider the representation of the semiotic space presented in the literature [6] (Figure 5).

The primary carrier of information, the semantic component, is key words in natural language (the language of instruction). These are fragments of text and can be classified as conventional sign systems and information models [6].

An auxiliary carrier of information (logical component) is the graphical representation of a coordinate-matrix system of the reference-node type, which can be classified as a group of iconic sign systems and ideal models.

The systematic combination of semantic and logical components was carried out as shown in Fig. 6 [6]:

– linguistic or textual information is transformed into a condensed system of key words that represent the main elements of the educational topic or object of study;

– the solar graphic image is expanded into a coordinate-matrix system of the reference-node type, with enough coordinates and nodes to provide unambiguous addressing of each key word or phrase, as shown in Fig. 6 [6].

In this methodology, an eight-coordinate representation of knowledge is generally used.
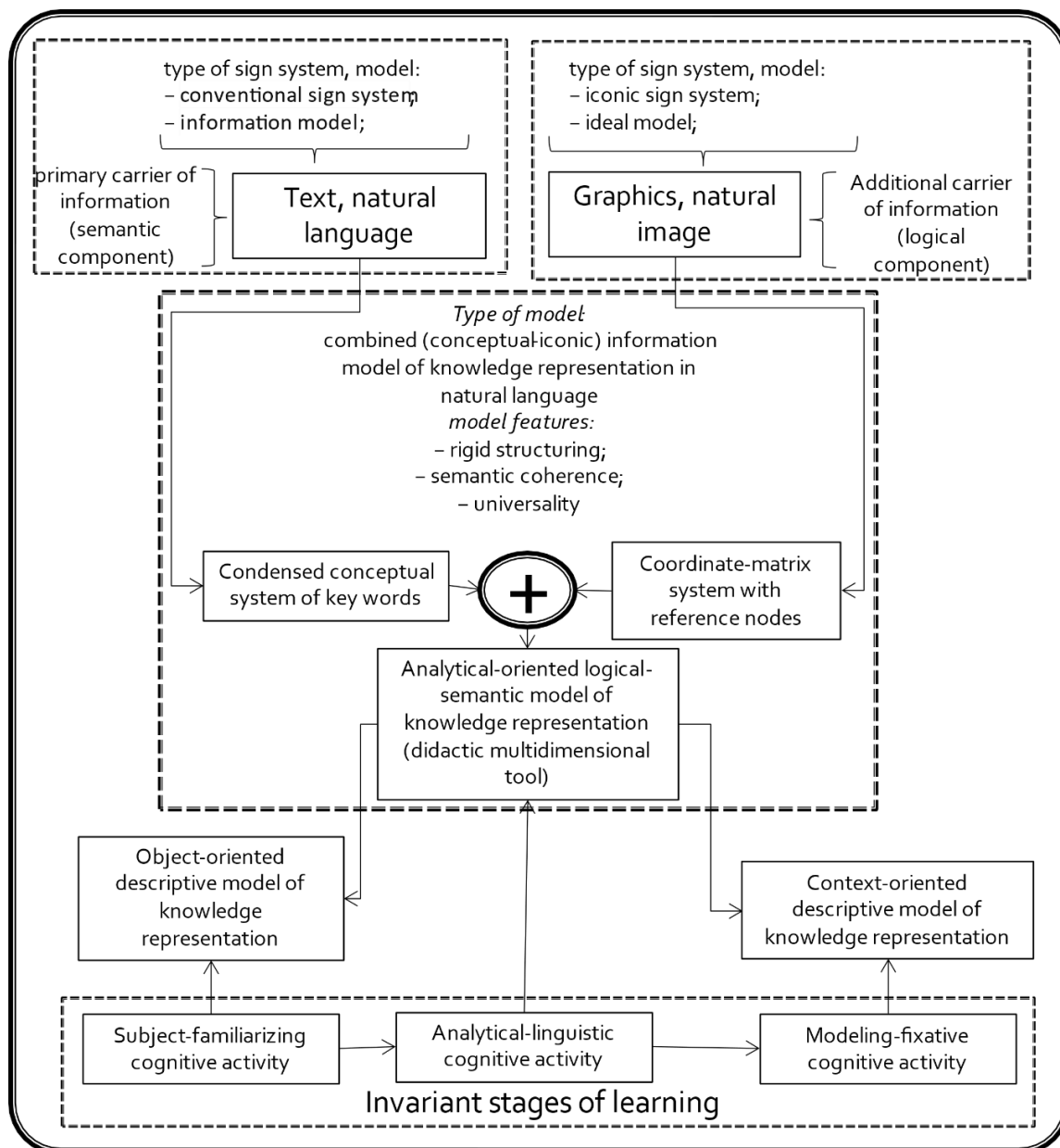
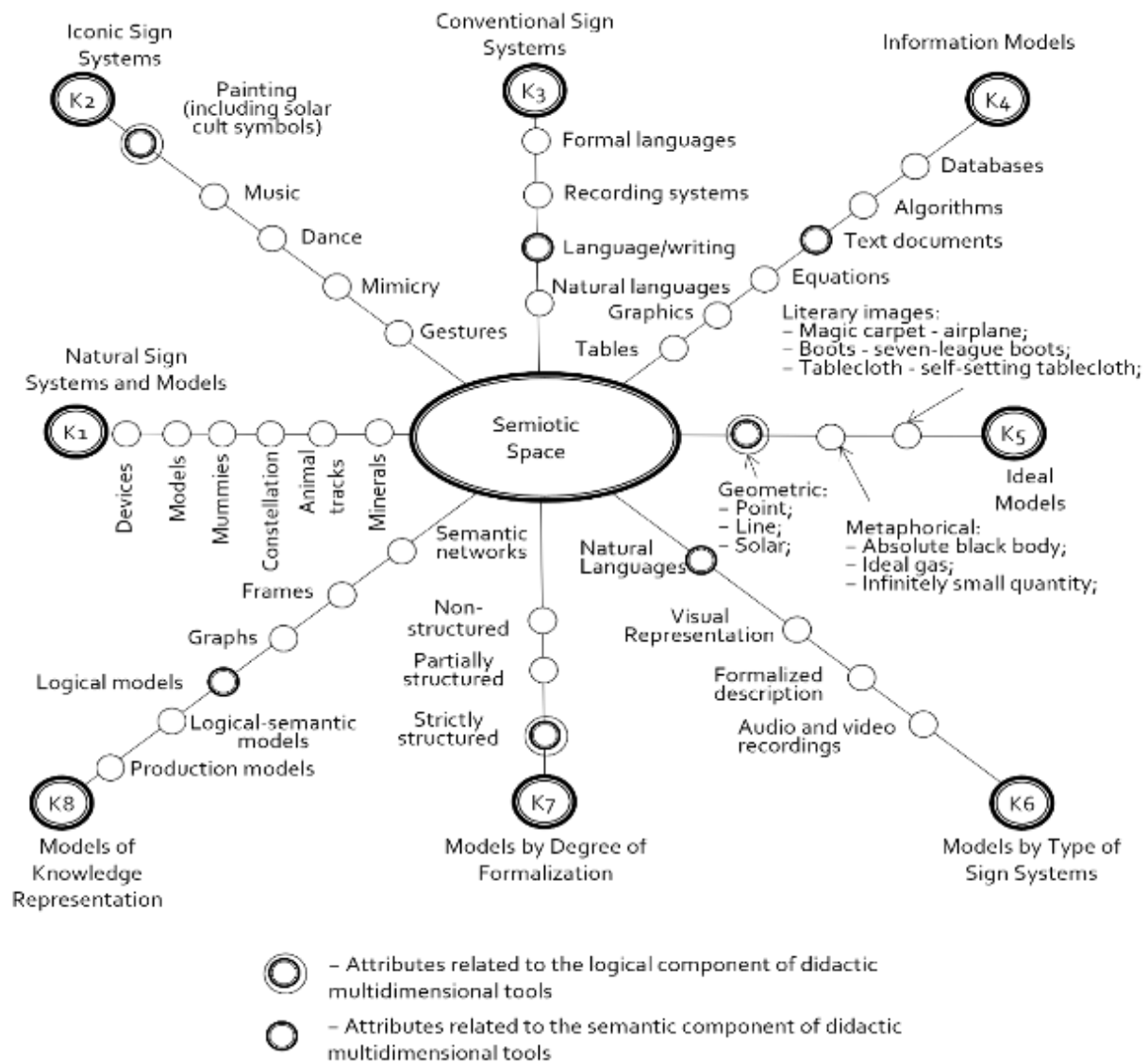

Fig. 5. Semiotic Space [6]

Fig. 6. Logical-Semantic Model "Semiotic Space" [6]

Each coordinate is represented as a set of elements (Figure 6). This figure is formed according to the rules for creating didactic multidimensional tools (DMT) and is a logical-semantic model of semiotic space [6].

Didactic multidimensional tools are Mult coordinate models of knowledge representation in natural language that can be used in various teaching technologies, such as orientational frameworks for actions, didactic tools to support collaborative activities between teachers and students, knowledge base navigators, and cognitive "meaning maps" that supplement textual or verbal information. DMTs are created using a combination of verbal and graphical elements that serve as semantic and logical components, respectively [6].

This methodology allows for the formation of inter-coordinate matrices between adjacent vectors, where operations with knowledge elements using transformation operators can be performed at nodes (Fig. 7). Unfortunately, the form of the relationships (transformation operators) between pairs of coordinate elements that form the matrix elements is not defined. There is no indication that these coordinates establish relationships in the form of a Cartesian product of sets. This results in multiple principles underlying the formation of didactic multidimensional tools, preventing users from directly forming knowledge models.

The main problem with this methodology is that it applies a systemic approach in the form of the "principle of system-multidimensionality." The problem of defining the meaning of each coordinate in the corresponding subject area K1... K8 is overlooked. Without determining the composition and content of these vectors, which describe the subject area, modeling knowledge about the subject area remains an art, not a rigorously theoretically justified methodology.
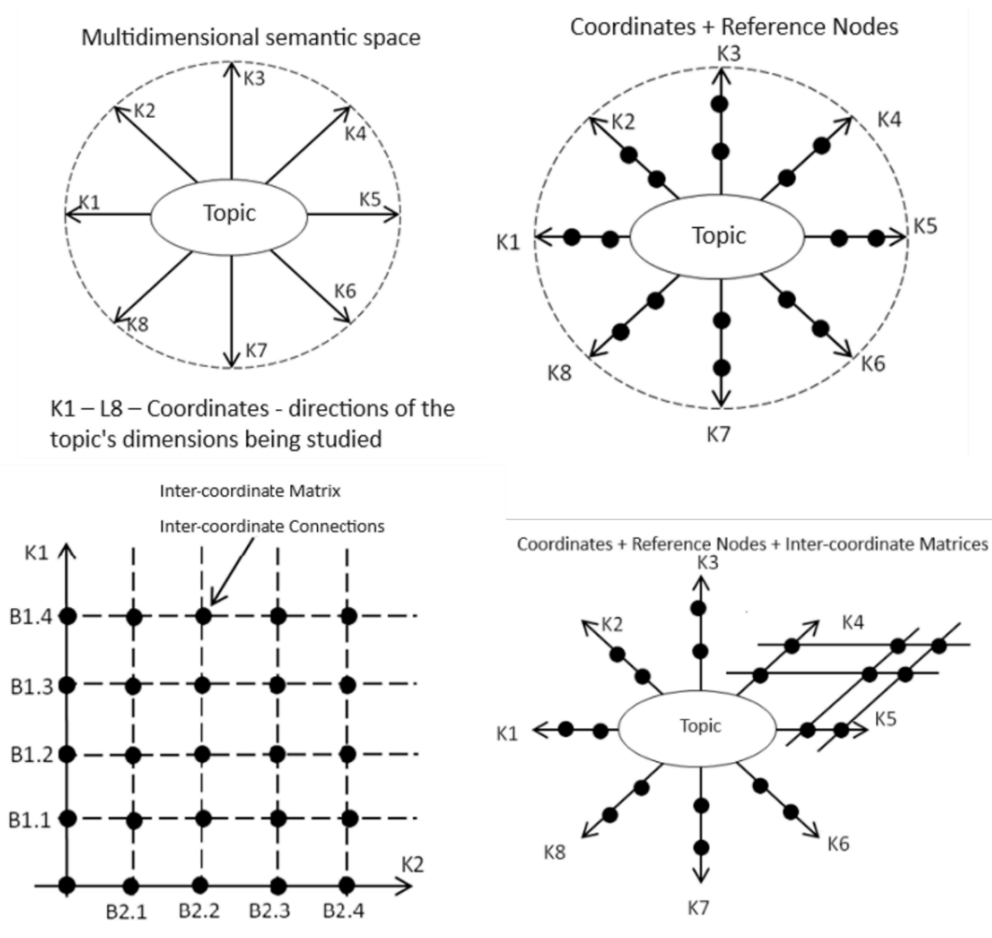
Fig. 7. Coordinate-Matrix Reference-Node System [6]

In [6], more than forty developments of didactic multidimensional (typically eight-vector) technologies were presented by various authors. In each of these models, the meanings of the coordinate axes K1 ... K8 are unique (Fig. 7).

The advantage of these logical semantic models of knowledge representation is their openness to developers and users. This ensures their widespread use by users without the need for special training.

The actual models of knowledge representation in the form of knowledge bases, both logical models and logical-semantic models in the form of eight-vector and four-factor representations within the semiotic space, constitute the elements of the set of vector K8. The elements of this vector include semantic networks, frames, graphs, logical models, logical-semantic models, and production models.

Logical models form the basis of traditional knowledge bases based on artificial intelligence. Logical-semantic models form the foundation of didactic multidimensional tools.

While the theoretical basis in logical models of knowledge representation is the classical apparatus of mathematical logic, according to [6], there is no theoretical (mathematical) justification for either the

textual (semantic) [11] or graphical (logical) components [13].

Unfortunately, none of these models do not clarify the relationships between diametrically opposite and adjacent factors that form these models.

A characteristic feature of all four-factor models is that the factors defining the axes are not presented as sets of corresponding elements. There is no clear division of each matrix into individual cells.

Four-factor logical models of knowledge representation about human activity have also been developed, which use a factor-based process resource representation of activities (Fig. 8 [15]).

To represent activity as a **process**, the category of "**factor**" has been additionally introduced. In the proposed approach to modeling the process, specific *resource factors* in dialectical unity are suggested:

- Resource Factors of Organizational Activity (RFOA) – (general);

- Resource Factors of Technological Activity (RFTA) – (specific).

In addition, *process* factors in their dialectical unity are proposed as follows:

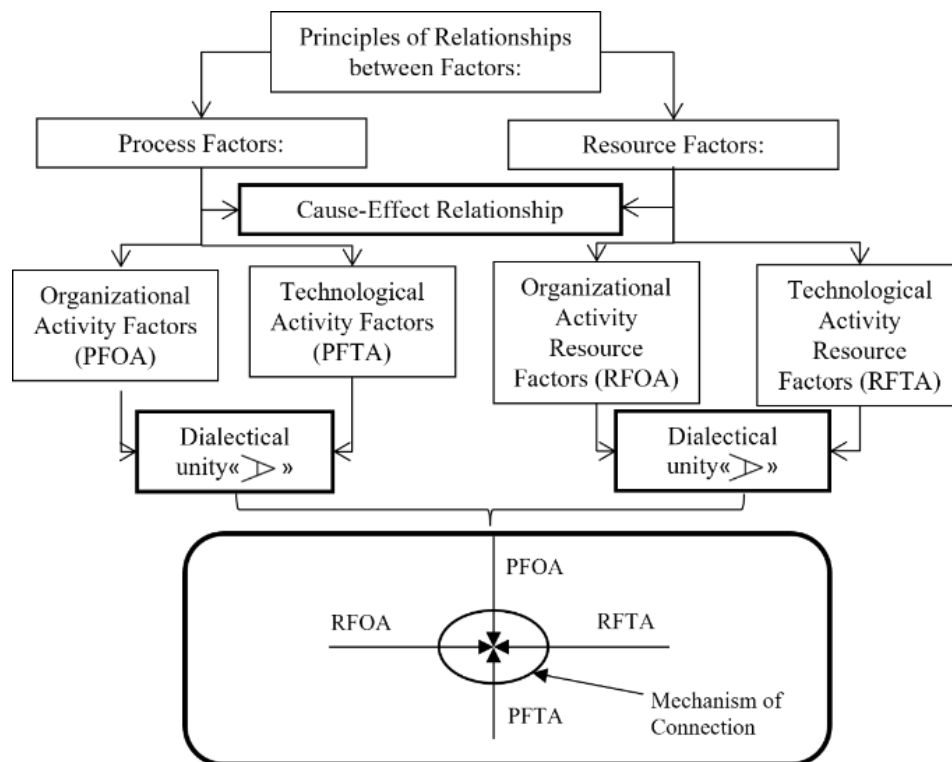- Process Factors of Organizational Activity (PFOA) – (general);

Fig. 8. Architecture of the Logical-Semantic Model of Knowledge Representation
for Factor-Based Process Representation

- Process Factors of Technological Activity (PFTA) – (specific).

The dialectical unity of the concepts "general" $\rhd$ "specific" is represented by the relational operator $\rhd$.

This method for defining factors' content is universal and independent of specific form of activity. This universality is due to the isomorphism established between process and resource factors on the one hand and factors of the central regularity of integrative brain activity on the other. The simultaneous convergence of these factors ensures the formation of the activity's goal [15].

Further research on this model in [15] demonstrated that the dialectical relationships between the factors in the model are shown in Fig. 8 is a practical manifestation of the central regularity of integrative brain activity.

Hegel noted [21, p. 19]: "Rational activity <understanding> defines and firmly holds to definitions; reason, however, is negative and dialectical, since it turns the definitions of understanding into nothing; it is positive because it generates the universal and recognizes the particular in it."

Ancient Greek philosophers understood that thinking is connected to the measurement of things [22, p. 283]:

"Protagoras: 'Man is the measure of all things.' Socrates: 'Man, as a thinking being, is the measure of all things'.

According to Hegel [21, p. 19]:

"Measure is primarily the immediate unity of quantitative and qualitative, so that, on the one hand, it is a defined quantity that has qualitative significance and exists as a measure. Its further definition lies in the fact that within it, in its self-defined state, the difference in its moments, qualitative and quantitative determinateness, emerges".

Thus, according to Socrates, thinking is the process of representing things in measure. Based on the rule of dialectics, the following definitions of the concepts "thinking," "measure," and "intellect" are possible [15]:

Definition 1. Thinking is the ability to represent a thing in its own measure.

Definition 2. Measure is the representation of a thing in the form of the dialectical unity of the concepts "general (qualitative determination) specific (quantitative determination)", i.e., a general concept regarding a thing being a specific concept.

For example, Hegel's well-known "fruit" "cherry" is an example of measuring a specific thing through the dialectical unity of the quantitative (cherry) and qualitative (fruit).

Definition 3. Intellect is the ability to realize the process of measuring a thing.

Therefore, both natural and artificial intellectual systems must be able to "measure" things and their properties.

This also implies that concepts in which knowledge about the subject area of intellectual systems is defined in the knowledge base must be represented in measure.

Thus, intellectual activity involves solving the task of forming "measures" of knowledge concepts in the subject area rather than merely forming systems of concepts as implemented in logical, production, frame, and semantic models of knowledge.

Another advantage of this logical-semantic model is that it establishes relationships between diametrically opposite factors in the form of the dialectical unity of the concepts "general" "specific" [15] (see Fig. 8).

Further development of this model involves creating logical-semantic models of the measure of metaknowledge and the measure of knowledge, leading to the introduction of the concepts "unit of metaknowledge" (Fig. 9) and "unit of knowledge" Fig. 10 [14].
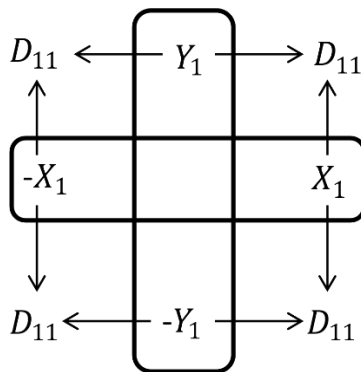

Fig. 9. Architecture of the Logical-Semantic Model
" Unit of Metaknowledge's Measure "
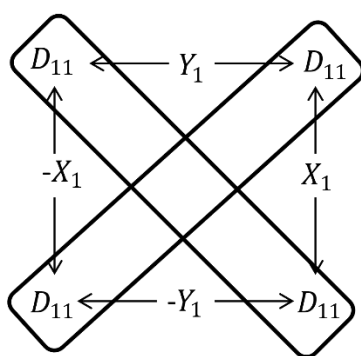for Post-Cartesian Representation of Metaknowledge

Fig. 10. Architecture of the Logical-Semantic Model
" Unit of Knowledge's Measure " for the Unitary
Post-Cartesian Representation of Metaknowledge
about Activity

The coordinate axes +X, -X, +Y, -Y represent sets of elements corresponding to the factors of the central regularity of integrative brain activity or its isomorphic

process and resource factors of the activity of an intellectual system [23]. These axes are defined unambiguously to form the content of the unit of metaknowledge.

After defining the composition and content of the elements of these sets, it becomes possible to determine the unambiguous content of the elements of each D11 matrix based on the Cartesian product of the corresponding elements of the coordinate axis sets +X, -X, +Y, -Y.

After forming a unitary post-Cartesian representation of metaknowledge, it becomes possible to construct the corresponding architecture of a logical-semantic model for the unit of the measure of knowledge. Figure 10 shows the architecture of the "unit of the measure of knowledge" for the unitary post-Cartesian representation of metaknowledge about activity.

For the physical implementation of the proposed architecture of the logical-semantic model for measuring metaknowledge, a spreadsheet processor is sufficient.

The architecture of the logical-semantic model of the measure of metaknowledge is defined as the post-Cartesian representation of metaknowledge [15].

In addition to the established properties of the post-Cartesian representation of metaknowledge, it is necessary to highlight the following property of each pair of sets that form the architecture of the logical-semantic model of the measure of metaknowledge (+X, -X, and +Y, -Y): they are dialectical metameters for the factorized space of the subject area «activity» [14].

Elements D11 for each of the quadrants G1 ... G4 are elementary pieces of knowledge generated by the corresponding unitary post-Cartesian representation of metaknowledge and define the composition and content of the unit of knowledge.

Thus, the architectures of the logical-semantic units' models are interconnected. The primary model is the unitary post-Cartesian representation of metaknowledge.

4. Case study: the practical implementation of a four-factor logical-semantic model of knowledge representation for SMR digital infrastructures

The digital infrastructure (DI) constitutes the SMR core. A set of information and communication systems that ensures safe operation, monitoring, and protection from environmental factors and supports interaction with other energy facilities. In a purely technical sense, DI SMR is a set of software and hardware items combined into a single system to ensure the safe and

reliable operation of SMR in automatic or automated mode.

DI SMR also includes support and decision-making systems for operational personnel. Such systems are based on modern technologies (artificial intelligence, machine learning, etc.) and are used in cases where rapid adoption is necessary in emergencies.

4.1. Knowledge Representation for Teacher Activity

Fig. 11 shows an example of the practical implementation of a four-factor logical-semantic model of knowledge representation for the subject area «teacher activity» of Knowledge Representation in Microsoft Excel

The application of the developed logical-semantic knowledge representation model in Microsoft Excel ensured the formation of a knowledge base containing all the necessary knowledge for the teacher to implement the educational process. Relevant materials are placed in folders that are linked via hyperlinks to the corresponding cells on the factor axes and respective matrices.

This knowledge base is open to teachers who act as developers, administrators, and users. The user only needs basic Microsoft Excel skills to work.

4.2. Knowledge Representation for Decision Makers in DI Control Centers

As an example of the practical application of the four-factor logical-semantic model of knowledge representation, we consider its use in forming a knowledge base for decision makers (DMs) of DI control centers to assure the safe and profitable deployment and operation of SMR technologies.

This knowledge base should provide the DM with the necessary knowledge from both a technological and organizational perspective. Particularly important is the formation of a list of regulatory documents (a set of resource factors of organizational activities, axis "A"), the compliance with which ensures the formation of specific knowledge for the elements of the "A-B" matrix.

The regulatory framework is based on the hierarchy of various documents and standards, such as the following:

- National Laws;
- IAEA NPP Safety Standards applicable to SMR;
- IAEA NPP Safety Standards applicable to the SMR I&C systems and digital components;
- International Industry Standards;
- National safety standards identical to

international;
- National safety standards (specific) to local regulations;
- IEC standards applicable to I&C;
- IAEA-TECDOC;
- IAEA Nuclear Energy Series.

This ensures the formation of specific knowledge for the resource factors of organizational activities (axis "B"), namely, policies, strategies, goals, tasks, and key performance indicators of the project, the requirements for which are defined in regulatory documents. The knowledge thus formed is then used to form the elements of the "B-C" matrix. This step identifies the specific knowledge that forms the policy, strategy, goals, tasks, and key performance indicators of the project for each technological process (elements of axis "C") as illustrated in Fig. 12.

On the other hand, for the elements of the "A-D" matrix, based on the requirements of regulatory documents (axis "A"), requirements are formed for the knowledge that ensures the use of each type of resource in the project for the defined resource factors of technological activity (axis "D"). Based on this knowledge, it is possible to develop the necessary knowledge for the use of the defined resource factors of technological activity (axis "D") for the implementation of each technological process (elements of axis "C"). Thus, the elements of the "C-D" matrix are formed.

The knowledge formed for each of these matrices supports the project manager's decisions throughout the implementation period, as well as the entire life cycle of the project.

5. Discussion

The study highlights several key differences between various knowledge representation methods and models:

− Logical models: These models are based on the principles of artificial intelligence theory, which relies on sign system hypotheses and formal logic theory.

− Logical-semantic models in the form of eight-vector graphical models: There is no theoretical justification for the definitions of the vectors forming the coordinate axes, making these models unique to specific subject areas.

− Logical-semantic models in the form of four-factor graphical models: There is a theoretical justification for the definitions of the model factors forming the coordinate axes, making these models more universal for specific subject areas.

These models have been practically applied in various fields:

− Pedagogical practice: Over the past decade, eight logical-semantic models have been used to present educational material [6].

D Resource Factors of Technological Activity									
A-D	6	5	4	3	3	1	0 OTHER		
3	3	3	3	3	3	3	7 Lab Work	utenko V	
2	2	2	2	2	2	2	2 Lists, Phones, Calendar, Plans, Attendance	5-4 CKC + 3-2 CKCc	
1	1	1	1	1	1	1	1 Discipline		

A — Process Factors of Organizational Activity

- 0 Other Ukrzaliznytsia Zhebko
- 6 Schedules
- 5 Orders NMW Anti-plagiarism
- 4 Orders CZAO
- 3 Orders NDC
- 2 Rector's Orders UDUZT
- 1 Law of Ukraine on Higher Education, Ministry of Education and Science of Ukraine

	Resource Factors of Technological Activity
1. Postgraduate studies	Postgraduate studies
2. Human-Machine Interfaces	Human-Machine Interfaces
3. Fundamentals of Scientific Research and TPE	Fundamentals of Scientific Research and TPE
4. Organization and Systems of Database Management	Organization and Systems of Database Management
5. Startup Development Technologies	Startup Development Technologies
6. Computer Networks, IT and IS	Computer Networks, IT and IS
0 Other	C-D

C — Process factors of technological activity

B — Resource Factors of Organizational Activity

	5 Calendar Plan	4 Syllabus	3 Working Program	2 Curriculum	1 Educational Program Standard	0 Other
A-B	5	4	3	2	1	
6	5	4	3	2	1	
5	5	4	3	2	1	
4	5	4	3	2	1	
3	5	4	3	2	1	
2	5	4	3	2	1	
1	5	4	3	2	1	
1	5 +++	4 +++++	3 +++	2	1	2
2	5	4 КУС маг	3 +++	2	1	3
3	5	4 +++++	3 +++	2	1	4
4	5	4	3	2	1	5
5	5	4	3	2	1	6
C-B	5	4	3	2	1	0 Other

Fig. 11. Example of Practical Implementation of a Four-Factor Logical-Semantic Model of Knowledge Representation in Microsoft Excel

Fig. 12. Four-Factor Logical-Semantic Model for Project Management of Small Modular Reactors

– Automated teacher workstation: A four-factor logical-semantic model was applied at the Ukrainian State University of Railway Transport in the Department of Specialized Computer Systems for the past five years to form a knowledge base.

Automated manager workstation: There is experience using a four-factor logical-semantic model for forming a knowledge base for an energy manager's workstation [15].

Future Research Directions: This research will focus on the development of four-factor logic-semantic models for knowledge representation, which will be part of an automated workstation for project managers in the development and implementation of Small Modular Reactors (SMRs).

6. Conclusion

The results of the research indicate that in the semiotic space model (see Fig. 5), within vector K8 "Knowledge Representation Models," the element "logical-semantic models" can be divided into two elements: "logical-semantic eight-vector models" and "logical-semantic four-factor models".

It is also proposed to add the element «post-Cartesian representation of metaknowledge» to vector K5 «Ideal Models», under the «geometric» element.

The theoretical basis for developing eight-factor logical-semantic knowledge representation models is the relationship between adjacent vectors in the form of a Cartesian product of the elements of the respective inter-coordinate matrices (see Fig. 7).

The theoretical basis for developing four-factor logical-semantic knowledge representation models includes the relationship between adjacent vectors in the form of a Cartesian product of the elements of the respective inter-coordinate matrices, and for diametrically opposite pairs of factors in the form of the dialectical unity of the concepts «general» $\rhd$ «specific» (see Fig. 8).

The following hypotheses are proposed to form four-factor logical knowledge models:

Measure is the representation of a thing in the form of the dialectical unity of the concepts «general (qualitative determination) $\rhd$ specific (quantitative determination) » i.e., a general concept regarding a thing $\rhd$ a specific concept.

Intellect is the ability to realize the process of measuring a thing.

At present, there has been a decade of experience in using eight-factor logical-semantic models for knowledge representation in pedagogical practice to present educational material [6].

A four-factor logical-semantic model of knowledge representation (see Fig. 11) has been applied at the Ukrainian State University of Railway Transport in the Department of Specialized Computer Systems to form a knowledge base as part of an automated teacher's workstation for the past five years.

The application of these models enhances the efficiency of teaching activities.

There is also experience in using a four-factor logical-semantic model to form a knowledge base for an automated energy manager's workstation [15]. Based on the experience of developing this model, a knowledge base model for project managers is proposed for the development and implementation of small modular reactors has been proposed (see Fig. 12). Currently, research is being conducted on ways to implement small modular reactors in Ukraine, the results of which are presented in this article [23].

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Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

Data availability

The manuscript contains no relevant data.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods in their work.

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ЛОГІКО-СЕМАНТИЧНІ МОДЕЛІ ТА МЕТОДИ ПРЕДСТАВЛЕННЯ ЗНАНЬ:
КЕЙСИ ДЛЯ СИСТЕМ УПРАВЛІННЯ ЕНЕРГОПОСТАЧАННЯМ
І ЦИФРОВОЇ ІНФРАСТРУКТУРИ ММР

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Предметом цієї статті є розвиток інформаційних технологій наприкінці 20-го та на початку 21-го століття для Четвертої промислової революції у вигляді Індустрії 4.0, або іншими словами, технологій Інтернету речей. Успіхи у впровадженні цієї технології призвели до розробки нових застосувань в галузі енергетики, таких як системи енергетичного менеджменту, системи управління малими модульними реакторами (ММР), альтернативними системами електропостачання на базі відновлюваних джерел енергії. Цифрова інфраструктура вказаних систем управління характеризується високою «щільністю знань», що вимагає уточнення фундаментальних понять теорії інформації, а саме змісту понять «дані», «інформація», «знання» та «значення знання». Особливу увагу було приділено визначенню ролі знань. **Метою** є подальший розвиток методів та моделей теорії семіотики шляхом визначення ролі та місця логічних, а також восьми- та чотирифакторних логіко-семантичних моделей баз знань у семіотичному просторі. **Завдання**: порівняння існуючих методів та моделей представлення знань. **Результати дослідження**: встановлено, що логічні моделі, які використовуються при розробці баз знань, засновані на положеннях теорії штучного інтелекту, яка базується на гіпотезах про знакові системи та теорії формальної логіки. Основним недоліком є складність їх практичної реалізації у вигляді експертних систем. Для логіко-семантичних моделей у вигляді восьмивекторних графічних моделей встановлено, що на даний момент немає теоретичного обґрунтування визначення векторів, які утворюють осі координат, що робить ці моделі унікальними для конкретних предметних галузей. Визначено, що перевагою їх використання є те, що експерт може самостійно сформувати таку модель знань. Для логіко-семантичних моделей у вигляді чотирифакторних графічних моделей існує теоретичне обґрунтування визначень факторів моделі, які формують осі координат, що робить ці моделі універсальними для конкретних предметних галузей. Встановлено, що перевагою цих моделей є те, що вони можуть бути розроблені експертами без залучення інженера знань. Тому пропонується для подальшого застосування використовувати саме чотири факторні логіко-семантичні моделі представлення знань. Пропонується також в семіотичній просторовій моделі у векторі К8 «Моделі представлення знань» розділити елемент «логіко-семантичні моделі» на два елементи, а саме: «логіко-семантичні восьми-векторні моделі» та «логіко-семантичні чотирифакторні моделі». Також пропонується додати елемент «постдекартове представлення метазнань» до елемента «геометричний» у векторі К5 «Ідеальні моделі». **Висновки**: Теоретичною основою методології розробки восьмифакторних логіко-семантичних моделей представлення знань є форма зв'язків між суміжними векторами у вигляді декартових добутків на елементи відповідних міжкоординатних матриць. Теоретичною основою методології розробки чотирифакторних логіко-семантичних моделей представлення знань є форма зв'язків між суміжними векторами у вигляді декартових добутків для елементів відповідних міжкоординатних матриць, а також для діаметрально протилежних пар фактори у вигляді діалектичної єдності понять «загальне» і «одиничне». Застосування логіко-семантичних моделей представлення знань для систем управління альтернативними джерелами енергії забезпечить підвищення енергоефективності цих технологій. Інший приклад стосовно використання моделей для цифрової інфраструктури ММР аналізується.

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