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Article

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Reference: Gaman, Oleksandr/Shyshatskyi, Andrii et. al. (2023). An analysis of knowledge representation methods in intelligent decision-making support systems. In: Technology audit and production reserves 5 (2/73), S. 15 - 19.
https://journals.uran.ua/tarp/article/download/289747/283531/669290.
doi:10.15587/2706-5448.2023.289747.

ISSN 2664-9969

UDC 355/359
DOI: 10.15587/2706-5448.2023.289747

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AN ANALYSIS OF KNOWLEDGE REPRESENTATION METHODS IN INTELLIGENT DECISION-MAKING SUPPORT SYSTEMS

The scientific task, which is solved in the research, is the analysis of knowledge representation methods in intelligent decision-making support systems. The problem is explained by the fact that the form of knowledge representation significantly affects the characteristics and properties of the system. In order to operate all kinds of knowledge from the real world with the help of a computer, it is necessary to carry out their simulation. In such cases, it is necessary to distinguish knowledge intended for processing by computational devices from knowledge used by humans. In addition, with a large amount of knowledge, it is desirable to simplify the sequential management of individual elements of knowledge. A homogeneous representation leads to a simplification of the logic management mechanism and a simplification of knowledge management. The research is aimed at the analysis of knowledge representation methods in intelligent decision-making support systems. Currently, many models of knowledge representation have been developed. The main models include: logical models; frame model; network models (or semantic networks); production models. Therefore, the object of research is the intelligent decision-making support system. The subject of research is an intelligent decision-making support system.

The following is set:

– the methods (models, approaches) presented in the research for presenting knowledge in intelligent decision-making support systems in a canonical form are not advisable to use for a number of objective reasons given in subsection 3.1 of the research;

– it is necessary to develop new (improvement of existing) representations of knowledge in intelligent decision-making support systems, which will have the advantages of these approaches without their disadvantages.

Further improvement of these approaches to reduce the number of shortcomings and limitations of their application should be considered as the direction of further research.

Keywords: *decision making support systems, efficiency, cognitive models, global and local optimization.*

Received date: 28.08.2023
Accepted date: 18.10.2023
Published date: 26.10.2023

How to cite

Gaman, O., Shyshatskyi, A., Babenko, V., Pluhina, T., Degtyareva, L., Shaposhnikova, O., Pronin, S., Protas, N., Stasiuk, T., Kutsenko, I. (2023). An analysis of knowledge representation methods in intelligent decision-making support systems. Technology Audit and Production Reserves, 5 (2 (73)), 22–26. doi: https://doi.org/10.15587/2706-5448.2023.289747

1. Introduction

One of the most important problems inherent in knowledge-based systems is the problem of knowledge representation [1, 2]. This is explained by the fact that the form of knowledge representation significantly affects the characteristics and properties of the system. In order to operate all kinds of knowledge from the real world with the help of a computer, it is necessary to carry out their simulation. In such cases, it is necessary to distinguish knowledge intended for processing by computational devices from knowledge used by humans. In addition, with a large amount of knowledge, it is desirable to simplify the sequential management of individual elements of knowledge.

While designing a knowledge representation model, factors such as uniformity of representation and ease of understanding should be taken into account. A homogeneous representation leads to a simplification of the logic management mechanism and a simplification of knowledge management. Presentation of knowledge should be understandable to experts and users of the system. Otherwise, it becomes more difficult to acquire knowledge and evaluate it.

Currently, many models of knowledge representation have been developed [3–5]. The main models include:

– logical models are theoretically based models that guarantee the correctness of decisions;

– frame model consists in such a concept as a frame. A frame is a data structure of a representation of a con-

ceptual object. Information related to a frame is contained in its slots. Slots can be terminals or be frames themselves, including forming a whole hierarchical network;
– network models (or semantic networks) – in knowledge engineering, it means a graph that reflects the content of a complete image. Graph nodes correspond to concepts, objects and arcs correspond to relations between objects;
– production model is the model, which is based on rules, allows to imagine knowledge as propositions of the type: «IF condition, THEN action». The production model has the disadvantage that with the accumulation of a sufficiently large number (the order of several hundreds) of products, the probability of conflicts between products, in which they begin to contradict each other, increases.

Taking into account the advantages and disadvantages of each of the methods of presenting information, an urgent scientific task is to carry out the decomposition of the specified methods of presenting information.

The aim of the research is an analysis of knowledge representation methods in intelligent decision-making support systems.

2. Materials and Methods

The object of the research is intelligent decision-making support systems.

The subject of the research is the method of presenting knowledge in intelligent decision-making support systems.

The research problem is to determine the advantages and disadvantages of knowledge representation methods in intelligent decision-making support systems. Modeling was carried out using MathCad 14 (USA). Aser Aspire based on the AMD Ryzen 5 processor was used as hardware. Artificial intelligence methods used to represent knowledge in intelligent decision-making support systems were chosen as the basic mathematical apparatus in the proposed research.

3. Results and Discussion

3.1. An analysis of advantages and disadvantages of knowledge presentation methods. Let's analyze the advantages and disadvantages of knowledge representation methods in intelligent decision-making support systems.

A logical model is used to represent knowledge in the system of first-order predicate logic and draw conclusions using syllogism.

The main advantage of using predicate logic for knowledge representation is that a powerful inference mechanism with well-understood mathematical properties can be directly programmed. With the help of these programs, new knowledge can be obtained from previously known knowledge.

Distinctive features of logical models are the unambiguity of the theoretical justification and the possibility of implementing a system of formally precise definitions and conclusions.

The main idea while building logical models of knowledge is the following – all information necessary for solving applied problems is considered as a set of facts and statements, which are presented as formulas in some logic. Knowledge is displayed by a set of such formulas and obtaining new knowledge is reduced to the implementation of logical inference procedures.

The main advantages of logical knowledge models are:
– the classic apparatus of mathematical logic is used as a basis in logical models, the methods of which are quite well studied and formally substantiated;
– there are quite effective derivation procedures, including those implemented using a logical programming language;
– only sets of axioms can be stored in knowledge bases, but other knowledge can be obtained from them according to the rules of inference.

3.1.1. Frame model. The frame model or model of knowledge representation is a systematized model of human memory and consciousness.

Frames take the form of structured components of situations called slots. A slot can point to another frame, thus establishing a link between the two frames. General communication type connections can be established. Various information (including procedures) are associated with each frame, for example, expected situation procedures, ways to obtain information about slots, default values, output rules.

The advantage of the frame is that representations are largely based on the inclusion of assumptions and expectations. This is achieved by assigning standard situation frame slots by default. In the process of finding solutions, these values can be replaced by more reliable ones. Some variables are highlighted in such a way that the system must ask the user about their value.

Frame models provide the requirements of structuredness and connectedness. This is achieved by using the inheritance and nesting properties of frames, so slots can act as lower-level slot naming systems and slots can be used as calls to any routines for execution. The values of the frame slots may be refined during the processing of the knowledge represented in this model. Part of the variables can be defined in the form of built-in procedures. As variables are given certain values, other procedures are called. This type of representation combines declarative and procedural knowledge.

For many subject areas, personnel models are the main way of formalizing knowledge.

3.1.2. Semantic networks. A semantic network is an oriented graph structure, each vertex of which represents a certain concept (object, process, situation) and the edges of the graph correspond to relations of the type «it is», «belong», «be the cause», «enter into», «consist of», «be like» and analogous between pairs of concepts. Semantic networks use special inference procedures: replenishment of the network, inheritance of properties, search by pattern, etc. A characteristic feature of semantic networks is the presence of three types of relationships:

1) class – class element (part – whole, class – subclass, element – set, etc.);
2) property – value (have a property, have a value, etc.);
3) an example of a class element (element for, element under, earlier, later, etc.).

The advantages of semantic networks are the clarity of knowledge representation, which makes it convenient to represent causal relationships between elements (subsystems) and even the structure of complex systems. The disadvantage of such networks is the difficulty of deriving and finding a subgraph that corresponds to the request.

3.1.3. Production model. Currently, the most widely used type of expert systems are rule-based systems. In rule-based systems, knowledge is represented not in a declarative, static way (as a series of true statements), but in the form of numerous rules that indicate the conclusions that should or should not be made in different situations. A rule-based system consisting of «IF-THEN» rules, facts and an interpreter that controls which rule should be invoked depending on the availability of facts in working memory.

A classic expert system embodies informal knowledge that must be obtained from an expert. This process of creating an expert system is called knowledge engineering and is carried out by an engineer according to knowledge.

There are two main types of rule-based systems: forward logic systems and reverse logic systems. A direct inference system starts with known initial facts and continues by using rules to draw new conclusions or perform certain actions. A reverse logic system starts its work with some hypothesis or aim that the user is trying to prove and continues its work by looking for rules that will prove the truth of the hypothesis. New sub-aims are created to break down a large task into smaller, more easily demonstrable parts. Forward logic systems are mostly data-driven and reverse logic systems are aim-driven.

Working memory can contain facts about the current state of an object. A rule whose patterns are all satisfied is called activated or implemented. Several activated rules can be present in the working rule list. In this case, the inference engine must choose one of the rules to run.

The THEN part of the rule is followed by a list of actions to be performed after the rule is run.

The logical inference machine works in the mode of performing cycles of verification and execution of rules. During each cycle, multiple rules can be activated and placed in the working rule list.

Conflicts occur in the rule list if different activated rules have the same priority and the inference engine must decide which of these rules to use. After all the rules have been executed, control is returned to the command interpreter so that the user can issue additional instructions to the expert system's command interpreter.

Also, a feature of the expert system are the devices of explanation provided in it, which enables the user to ask questions about how the system reached a certain conclusion and why it needs certain information. A rule-based system can easily answer the question of how a certain conclusion was reached, because the history of rule activation and the contents of working memory can be stored on the stack.

The widespread use of rule-based systems is due to the following reasons:

– modular organization, thanks to such an organization, the presentation of knowledge and the expansion of the expert system by the method of incremental development are simplified;
– an availability of explanation devices.

Such expert systems make it easy to create rule-based explanations because the rule's antecedents specify what is needed to activate the rule. The explanation tool allows monitoring which rules were triggered, so it makes it possible to reconstruct the course of reasoning that led to a certain conclusion.

Having an analogy with the cognitive process of a person, rules are a natural way of solving problems by a person. While trying to discover the knowledge that experts have, it is easier to explain the structure of knowledge presentation to experts, since a simple representation of the rules is used.

3.1.4. Fuzzy expert systems. The functioning of expert systems is based on the knowledge model [6]. It contains a set of principles that describe the state and behavior of the research object. The most widely used knowledge model of expert systems is the production model, because it is quite simple to process and understand by the end user.

However, recently fuzzy expert systems have become widespread [7]. This type of expert systems is based on a set of rules that use linguistic variables and fuzzy relations to describe the state and behavior of the object under investigation [8]. The rules presented in this form are the closest to natural language, so there is no need to use a separate expert knowledge engineer to create and edit the rules. They can be edited by the expert itself with practically no special training. Also, the results of the work of such systems are issued in a limited natural language, which increases their degree of adaptation to the end user. Let's consider the organization of fuzzy expert systems in more detail.

Fuzzy expert system uses knowledge representation in the form of fuzzy products and linguistic variables [9]. Each linguistic variable is defined using its term-set consisting of fuzzy variables [10].

3.1.5. Fuzzy variable. The concept of a fuzzy variable is used while describing objects and phenomena with the help of fuzzy sets, so sets, the membership of a particular element to which is specified according to a certain membership function $\mu z(u)$, which characterizes the degree of the ratio of the value of the variable u to the set z [11–13]. Any fuzzy variable is characterized by a triple:

$$<z, U, Z>,$$

where z is the name of the variable; U is a universal set; Z is a fuzzy subset of the set U, which is a fuzzy restriction of the value of the variable $u \in U$ determined by z [14].

3.1.6. Linguistic variable. The rules of operation of fuzzy expert systems are based on the concept of a linguistic variable [11]. Each linguistic variable has a set of values – these are fuzzy variables that form its term set [4, 10].

The linguistic variable L is characterized by the following set of properties:

$$L=(X, T(X), U, G, M), \tag{1}$$

where X is the name of the variable; $T(X)$ is the term-set of the variable X, thus the set of names of linguistic values of the variable X and each of these values is a fuzzy variable (x') with values from the universal set U with the base variable u; G is a syntactic rule that generates the names of the values of the variable X; M is a semantic rule that matches each fuzzy variable x' with its meaning $M(x')$, thus a fuzzy subset $M(x')$ of the universal set U.

3.1.7. Unclear rule base of the expert system. The behavior of the researched system is described in a limited natural language in terms of linguistic variables [12, 13]. Input and output parameters of the system are considered as linguistic variables and the description of the process is given by a set of rules [6, 15]. The formal model of the rule base of the developed expert system has the form [7, 8]:

$$R_1: A_{1,1} \text{ and/or } A_{1,2} \text{ and/or ... and/or } A_{1,m1} \to$$
$$\to B_{1,1} \text{ and/or ... and/or } B_{1,k1},$$
$$R_2: A_{2,1} \text{ and/or } A_{2,2} \text{ and/or... and/or } A_{2,m2} \to$$
$$\to B_{2,1} \text{ and/or... and/or } B_{2,k2},$$
$$R_n: A_{n,1} \text{ and/or } A_{n,2} \text{ and/or... and/or } A_{n,mn} \to$$
$$\to B_{n,1} \text{ and/or... and/or } B_{n,kn}, \quad (2)$$

where $A_{i,j}$, $i=1,2,\ldots,n$, $j=1,2,\ldots,m_i$ are the fuzzy statements defined on the values of the input linguistic variables, where $B_{i,q}$, $i=1,2,\ldots,n$, $q=1,2,\ldots,$ k_i are the vague statements defined on the values of the initial linguistic variables.

In the general case, fuzzy solution derivation takes place in four stages [9–11]:

1) the phase of fuzzification (transformation using membership functions χ of precise input data into fuzzy values of linguistic variables);

2) the stage of direct fuzzy inference (on the basis of a set of rules of the fuzzy knowledge base, the truth value for the conditions of each rule is calculated according to the rules for calculating T-norms, T-conorms and objections);

3) the stage of composition (the values of the initial linguistic variables are formed for each rule that worked);

4) defuzzification stage (transformation of vague values of initial linguistic variables into precise values).

3.1.8. A vague logical conclusion. Let's consider the stages of the fuzzy decision conclusion in more detail [14]:

The fuzzification phase. With the help of the membership functions of all the terms of the input linguistic variables and on the basis of clear values that are set, the degree of confidence that the output linguistic variable acquires a specific value is determined from the universes of the input linguistic variables [7, 8].

The stage of direct fuzzy conclusion. From the set of rules (fuzzy knowledge base), the truth value for each rule is calculated, based on specific fuzzy operations, the corresponding conjunction or disjunction of the terms in the left part of the rules. Most often, it is the maximum or minimum of the degrees of confidence of the terms calculated at the phase of fuzzification, which is applied to the compilation of each rule. Using one of the methods of constructing a fuzzy implication, a fuzzy variable is formed that corresponds to the calculated value of the degree of confidence on the left side of the rule and the fuzzy set on the right side of the rule [9, 10].

The composition stage (aggregation, accumulation). All fuzzy sets assigned to each term of each output linguistic variable are combined together to form a single fuzzy set of values for each output linguistic variable. Usually, maximum or summation functions are used [11, 16].

The defuzzification stage. It is used when it is useful to convert a fuzzy set of derived linguistic variable values to a precise one. There are quite a few methods of transition to accurate. The method of full interpretation and the method of maximum interpretation are most often used. In the full interpretation method, the exact value of the output variable is calculated as the «center of gravity» value of the membership function for the fuzzy value. In the maximum method, the maximum value of the membership function is taken as the exact value of the derived variable [12–14].

The greatest computational costs appear at the stage of fuzzy logical inference. In this regard, the paper considers the proposed method of accelerating the search for a solution (the stage of fuzzy logical conclusion) [7, 15].

3.1.9. The task of accelerating the search for a solution in fuzzy expert systems. To formulate the formulation of the task of accelerating the search for a solution, the definition of one iteration of a logical conclusion is introduced [8, 9]. It is proposed to present it in the form of a function F, which transforms many conditions into many consequences and has the form:

$$F:\begin{Bmatrix} A_{1,1}, A_{1,2},\ldots, A_{1,m1}, A_{i,1}, A_{i,2},\ldots, \\ A_{i,mi}, A_{n,1}, A_{n,2},\ldots, A_{n,mn} \end{Bmatrix} \to$$
$$\to \begin{Bmatrix} B_{1,1}, B_{1,2},\ldots, B_{1,k1}, B_{i,1}, B_{i,2},\ldots, \\ B_{i,ki}, B_{n,1}, B_{n,2},\ldots, B_{n,kn} \end{Bmatrix}. \quad (3)$$

The task of accelerating the search for a solution consists in minimizing the calculations performed while processing the matrix of conditions A of fuzzy rules, thus in constructing a set of fuzzy conditions A^* that $|A^*|<|A|$, provided the result is preserved, namely: if $F(A)\to B$, then $F(A^*)\to B$.

An acceleration of finding a solution can be achieved in two ways [10, 11, 16]:

1. An exception to some processing rules.

Let's assume that rules $i1, i2,\ldots, is$ are excluded. In this case:

$$|A^*| = |A| - \sum_{t=1}^{S}(m_{it}). \quad (4)$$

2. The search for the same conditions and exclude their repeated calculation. Let's say that p matches between the terms of the species are found in the knowledge base:

$$A_{i,j} = A_{v,w},$$

where $i=1,2,\ldots,n$, $j=1,2,\ldots,m_n$, $v=1,2,\ldots,n$, $w=1,2,\ldots,m_n$.

Then:

$$|A^*| = |A| - p. \quad (5)$$

The input data for the method being developed are the rules from the fuzzy rule base.

3.2. The results of the analysis and discussion of the results. The following is set:

– the methods (models, approaches) presented in the research for presenting knowledge in intelligent decision-making support systems in a canonical form are not advisable to use for a number of objective reasons given in subsection 3.1 of the research;

– it is necessary to develop new (improvement of existing) representations of knowledge in intelligent decision-making support systems, which will have the advantages of these approaches without their disadvantages.

Further improvement of these approaches to reduce the number of shortcomings and limitations of their application should be considered as the direction of further research.

4. Conclusions

The analysis of knowledge representation models was performed, the advantages of using production representation of knowledge in expert systems were substantiated. The advantages of production representation of knowledge in expert systems are:

– the possibility to process raw data that are different in size and origin;

– the possibility of further accelerating the results of processing heterogeneous data due to the further integration of data models into decision making support systems.

The main concepts of fuzzy expert systems are presented, based on which a formal statement of the problem of accelerating the search for a solution in the rule base of a fuzzy expert system is proposed. An analysis of the stages of fuzzy logical conclusion was performed.

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.

Financing

The research was performed without financial support.

Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Shevchenko, A. I., Baranovskyi, S. V., Bilokobylskyi, O. V., Bodianskyi, Ye. V., Bomba, A. Ya. et al.; Shevchenko, A. I. (Ed.) (2023). *Stratehiia rozvytku shtuchnoho intelektu v Ukraini.* Kyiv: IPShI, 305.
2. Shyshatskyi, A. V., Bashkyrov, O. M., Kostyna, O. M. (2015). Rozvytok intehrovanykh system zv'iazku ta peredachi danykh dlia potreb Zbroinykh Syl. *Ozbroiennia ta viiskova tekhnika, 1 (5),* 35–40.
3. Sova, O., Shyshatskyi, A., Salnikova, O., Zhuk, O., Trotsko, O., Hrokholskyi, Y. (2021). Development of a method for assessment and forecasting of the radio electronic environment. *EUREKA: Physics and Engineering, 4,* 30–40. doi: https://doi.org/10.21303/2461-4262.2021.001940
4. Zuiev, P., Zhyvotovskyi, R., Zvieriev, O., Hatsenko, S., Kuprii, V., Nakonechnyi, O. et al. (2020). Development of complex methodology of processing heterogeneous data in intelligent decision support systems. *Eastern-European Journal of Enterprise Technologies, 4 (9 (106)),* 14–23. doi: https://doi.org/10.15587/1729-4061.2020.208554
5. Yeromina, N., Kurban, V., Mykus, S., Peredrii, O., Voloshchenko, O., Kosenko, V. et al. (2021). The Creation of the Database for Mobile Robots Navigation under the Conditions of Flexible Change of Flight Assignment. *International Journal of Emerging Technology and Advanced Engineering, 11 (5),* 37–44. doi: https://doi.org/10.46338/ijetae0521_05
6. Rotshtein, A. P. (1999). *Intellektualnye tekhnologii identifikatcii: nechetkie mnozhestva, geneticheskie algoritmy, neironnye seti.* Vinnitca: UNIVERSUM, 320.
7. Pérez-González, C. J., Colebrook, M., Roda-García, J. L., Rosa-Remedios, C. B. (2019). Developing a data analytics platform to support decision making in emergency and security management. *Expert Systems with Applications, 120,* 167–184. doi: https://doi.org/10.1016/j.eswa.2018.11.023
8. Chen, H. (2018). Evaluation of Personalized Service Level for Library Information Management Based on Fuzzy Analytic Hierarchy Process. *Procedia Computer Science, 131,* 952–958. doi: https://doi.org/10.1016/j.procs.2018.04.233
9. Chan, H. K., Sun, X., Chung, S.-H. (2019). When should fuzzy analytic hierarchy process be used instead of analytic hierarchy process? *Decision Support Systems, 125,* 113114. doi: https://doi.org/10.1016/j.dss.2019.113114
10. Osman, A. M. S. (2019). A novel big data analytics framework for smart cities. *Future Generation Computer Systems, 91,* 620–633. doi: https://doi.org/10.1016/j.future.2018.06.046
11. Gödri, I., Kardos, C., Pfeiffer, A., Váncza, J. (2019). Data analytics-based decision support workflow for high-mix low-volume production systems. *CIRP Annals, 68 (1),* 471–474. doi: https://doi.org/10.1016/j.cirp.2019.04.001
12. Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies, 24 (1),* 65–75. doi: https://doi.org/10.1016/s0020-7373(86)80040-2
13. Gorelova, G. V. (2013). Kognitivnyi podkhod k imitatcionnomu modelirovaniiu slozhnykh sistem. *Izvestiia IuFU. Tekhnicheskie nauki, 3,* 239–250.
14. Orouskhani, M., Orouskhani, Y., Mansouri, M., Teshnehlab, M. (2013). A Novel Cat Swarm Optimization Algorithm for Unconstrained Optimization Problems. *International Journal of Information Technology and Computer Science, 5 (11),* 32–41. doi: https://doi.org/10.5815/ijitcs.2013.11.04
15. Ramaji, I. J., Memari, A. M. (2018). Interpretation of structural analytical models from the coordination view in building information models. *Automation in Construction, 90,* 117–133. doi: https://doi.org/10.1016/j.autcon.2018.02.025
16. Harding, J. L. (2013). Data quality in the integration and analysis of data from multiple sources: some research challenges. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-2/W1,* 59–63. doi: https://doi.org/10.5194/isprsarchives-xl-2-w1-59-2013

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