Intelligent Information System for Simulation and Management Decision

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Abstract. Currently, intelligent decision support systems (IDSS) are widely used. Their main component is a knowledge base. Its adequacy determines the ability of the system to justify the recommended decisions, especially in conditions of diversity and incompleteness of input data.
Research Methods: the methods of classification and systematization, fuzzy logic was used to solve the problems. The paper presents: a model of knowledge base structure, a model of intelligent information system for assessing the adequacy of the knowledge base, a set of rules for making managerial decisions. The results were tested in the Higher School of Intelligent Systems and Cybertechnologies.

Keywords: intelligent information system, knowledge bases, neuro-fuzzy models.

1. Introduction

Studies in the field of fuzzy logic and the development of SPPR are devoted to the works of the following scientists: Zadeh L.A. [1], Mamdani E.A. [2], Sugeno M. [3].

However, their research is mainly focused on the application of knowledge engineering methods and "manual" approach to the formation of knowledge bases, which requires the involvement of experts and a lot of analytical work. Nowadays, to automate the formation of knowledge bases, data mining tools are increasingly used, in particular, fuzzy neural networks, which allow to form a system of rules of fuzzy-productive type in the process of training. Studies in this area are devoted to the works of the following scientists: Hoffman F. [4], Dzik C.S [5].

To obtain accurate and reasonable decisions in these conditions it is advisable to use methods of fuzzy logic and fuzzy logical inference mechanisms, and as a tool for forming knowledge bases - fuzzy neural networks (FNN). The use of such an approach allows to obtain solutions in a form suitable for human interpretation, taking into account the linguistic uncertainty of the decision-making problem and fuzzy neural networks. linguistic uncertainty of the decision-making task and fuzzy nature of the evaluated objects.

1.1 The Problem of Research and Hypothesis

The research problem is that there is not enough practice of applying the apparatus for selecting a specific type of fuzzy rules, taking into account the characteristics of the analyzed data for making management decisions.

The hypothesis of the research consists in the assumption that the presence of intelligent information system and knowledge base will contribute to improving the consistency of disparate quantitative and qualitative input data for the development of a logical inference algorithm justifying the possibility of making a management decision.

1.2 Research Goals and Objectives

Modeling of management decision trajectory justification on the basis of intellectual information system

The main purpose - modeling of the choice of the management decision trajectory in conditions of diversity and incompleteness of input data on the basis of the intellectual information system

Objectives:

1. To justify the choice of input data to substantiate the management decision trajectory.

2. To present the algorithm of logical inference on the rules, applied for reasonable linguistic evaluation of the management decision trajectory in conditions of diversity and incompleteness of input data;

3. To present the neuro-fuzzy model and the algorithm of knowledge base formation on the basis of the constructed model

2. Theoretical Review

The development of smart technologies and intellectualization of knowledge on the basis of new technological solutions and digitalization is shown in the works of Uskov, V.L., Bakken, J.P., Howlett, R.J., Jain, L.C [6], they reveal different approaches for making managerial decisions including.

The practice of applying new technologies for training personnel capable of making managerial decisions is shown in the works of Mirjana Ivanović, Lakhmi C. Jain [7].

The theory and practice of application of modern methods of mathematical modeling is revealed in the works of N. Serdyukov and V. Serdyukov [8].

In particular, systematization, classification and identification of smart systems built on the basis of knowledge bases is disclosed in the work [8] was reflected in the applied studies of the authors [9, 10].

3. Research Methods

In the study, the following type of fuzzy-productive rules is proposed for the evaluation of the objects' condition [11].

$$If\ x_1 = \overleftrightarrow{A}_1 \&\ x_2 = \overleftrightarrow{A}_2 \& \dots x_i = \overleftrightarrow{A}_i \& \dots x_n = \overleftrightarrow{A}_n \text{ Then } \mathrm{y} = \mathrm{B}[\mathrm{CF}], \quad (1)$$

where x_i $(i = 1 \dots n)$ - input variables;

$\tilde{A}_i$ - crisp ($\overleftrightarrow{A}_i = A_i$) and fuzzy ($\overleftrightarrow{A}_i = \tilde{A}_i$) constraints on the values of input variables, allowing qualitative and quantitative input data to be processed;

A_i - are the fuzzy values of the input variables;

$\tilde{A}_i = \{x_i, \mu_{\tilde{A}_i}(x_i)\}$ - are fuzzy sets;

$\mu_{\tilde{A}_i}(x_i)$- the membership function;

y- output variable;

B – the state of the object;

$\mathrm{CF} \in [0; 1]$- weight of the rule.

For decision making in case of incompleteness of input data, it is more appropriate to use not the eights of conditions, but an additional criterion of applicability of the logical inference algorithm.
To make decisions in case of incomplete initial data, it is more appropriate to use not the weights of conditions, but an additional criterion of applicability of the logical inference algorithm [11].
The paper [12] shows the advantages of using neural networks.
The peculiarities and advantages of fuzzy-productive rules of the form (1) are the following:

1) allow processing of dissimilar input data;
2) unambiguous linguistic interpretation;
3) are characterized by CF weight (for estimating the object state).

A special method (the method of routes) is developed for the formation of the knowledge base (KB) on the basis of the constructed neuro-fuzzy model, which allows for each input image from the initial data to construct an optimal route of its passage through the layers of the trained fuzzy neural network, to generate a fuzzy production rule corresponding to the constructed route, and to form the desired knowledge base containing unique rules.
Figure 1 shows the generalized scheme of the developed method of knowledge base formation based on the constructed neuro-fuzzy model.

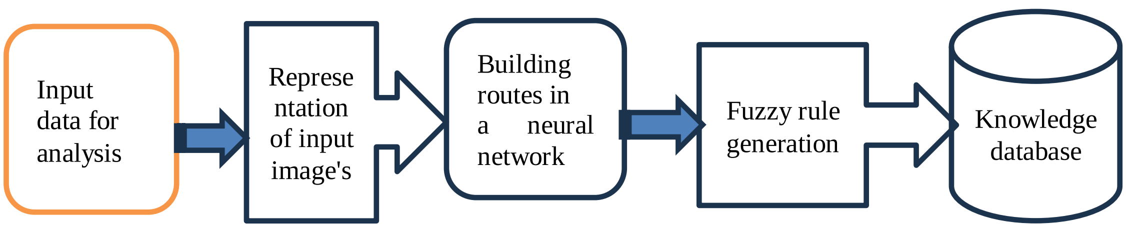

Figure 1. Generalized scheme of the method of knowledge base formation (the author vision)

The choice of the route is determined by the network architecture. In our case, a multilayer neural network with feedback is considered.

A triangular function was used as an activation function.

In the future it is planned to realize the training of the network, which is possible on the basis of updating the weights in the process of error back propagation.

The input data are coefficients (Table 1), the values are obtained by expert judgement.

As can be seen from the figure, the practical use of the developed route method will require the availability of all source data for analysis, from which the training, test and validation samples were formed. The use of all initial data in the route method guarantees that the knowledge base formed on its basis will include the full composition of fuzzy-productive rules necessary for the assessment of the state of objects.

Below we consider the obtained results on the example of an intelligent information system. described in more detail in [9,10].

4. Our Results

4.1 A Model of Justifying the Selection of Disparate Input Data Parameters for Managerial Decision Making

Table 1 shows the disparate parameters of input data for making a management decision, in our case these are indicators of the quality of the knowledge base, which are indicators of system development**.**

Table 1 - Model or Justifying the Selection of Disparate Input Data Parameters for Managerial Decision Making

Indicator name	Restrictions	Assignment
Relationship convergence indicator, K1	$K_1 \geq 0{,}9$	Responsible for adapting to the situation arising in the external environment.
Indicator of the risk of loss of convergence of relations, K2	$K_2 \rightarrow \min$	Occurrence of knowledge fragmentation due to noise influences
Indicator of intellectual activity of an employee, K3	$K_3 \geq 0{,}85$	Indicates willingness to innovate
Indicator of employee's readiness for innovation, K4	$K_4 \geq 0{,}8$	Reflects willingness to work in a team on a project
Indicator of readiness for knowledge transformation, K5	$K_5 \geq 0{,}85$	Reflects willingness to transfer and accept knowledge through team interaction.
Knowledge transfer indicator, K6	$K_6 \rightarrow 1$	Reflects maximizing team interaction through effective knowledge transfer
Indicator of compliance of available knowledge with the requirements of the external environment, K7	$K_7 \rightarrow 1$	Reflects the readiness and ability of the CO to fulfill the requests of the external environment

Indicator of efficiency of knowledge core formation, K8	$K_8 \to 1$	Economic indicator characterizing the minimization of financial flows for organizing the work of the team of performers
Knowledge volume indicator, K9	$K_9 \to \max$	Aggregate accumulator of availability of required competencies in full volume
Knowledge increment indicator, K10	$K_{10} \to \max$	Reflects the dynamics of growth of intellectual potential of employees
Knowledge core formation time indicator, K11	$K_{11} \to \min$	Time resource for updating the knowledge core, characterizes the level of ability to perceive new knowledge

Table 1 shows that only some components (highlighted by bold frame) have a significant "weight", i.e. significantly reflect the adoption of different trajectories of managerial decisions.

Therefore, in the future we will consider four input variables (K1, K6, K7, K10) on the basis of which a set of fuzzy rules is built, presented as a model for managerial decision making.

The ratio convergence coefficient (K1) is responsible for adaptation to the situation. Its value should be close to one, with an acceptable level of error γ =10%.

The coefficient of knowledge transfer (K6) allows to measure the closeness of ties arising in the transfer of knowledge between employees when performing teamwork. It should be close to one. This indicator depends on the time of project implementation and can vary from project to project, so it should be constantly evaluated and adjusted to the needs of the external environment. Note that it has the highest level of acceptable risk, as it has the property of variability and instability.

The coefficient of compliance of available knowledge with the requirements of the external environment (K7) reflects the readiness of professional communities of a self-learning organization to solve innovative problems and the ability to solve them in a given time interval with a given acceptable level of risk. The minimum level of risk should not exceed the permissible level of error γ =10%.

Knowledge increment coefficient (K10) reflects the dynamics of growth of intellectual activity of employees over time. Its value should ideally be constantly accumulating and increasing, i.e. ΔK10 should have positive dynamics, since the goal of a self-learning organization is to accumulate knowledge and constantly update it.

We will introduce conventional notations and denote them x1, x2, x3, x4.

In order to manage the process of managerial decision-making and to be able to design an optimal trajectory providing a low level of risk for making an erroneous decision, it is necessary to add a diagnostic toolkit justified by mathematical apparatus. As a diagnostic toolkit the fuzzy logic apparatus can be used [13].

The activation function is triangular, so the area of its definition is (0;1)

4.2 Fuzzy Rule Set Model for Managerial Decision Making

Parameters of the fuzzy logic inference system for assessing the quality of knowledge base filling, providing a decision-making trajectory are shown in Table 2.

Table 2 - Description of the parameters of the fuzzy logic inference system

System variables		**Linguistic variables**	**Linguistic implications**	**Fuzzy intervals**
Input Variables	x_1	Relationship convergence index, [0.5; 0.9]	Low	[0,5; 0,7]
			Medium	[0,6; 0,8]
			High	[0,7; 0,9]
	x_2	Knowledge transfer indicator, [0.5; 0.7]	Low	[0,5; 0,6]
			Medium	[0,55; 0,65]
			High	[0,60; 0,7]
	x_3	Indicator of compliance of available knowledge with the requirements of the external environment, [0.5; 0.9]	Low	[0,5; 0,7]
			Medium	[0,6; 0,8]
			High	[0,7; 0,9]
	x_4	Knowledge increment indicator, [0.5; 0.9]	Low	[0,5; 0,7]
			Medium	[0,6; 0,8]
			High	[0,7; 0,9]
Output variables	y	Integral indicator of the quality of knowledge base filling, allowing to form a decision-making trajectory, [0.5; 0.9]	Low	[0,5; 0,6]
			Below average	[0,55; 0,65]
			Average	[0,6; 0,7]
			Above Average	[0,65; 0,75]
			High	[0,70; 0,9]

Table 3 shows the formulated rule base for intelligent information system [9].

The author's vision of the construction of the system of logical input and output is shown here. Inference rules and diagnostic tools are defined. It is obtained by expert way, taking into account that the triangular activation function has the area of definition (0,1).

In order to manage the process of managerial decision-making and to be able to build an optimal trajectory that provides a low level of risk of making an erroneous decision, it is necessary to add a diagnostic toolkit substantiated by mathematical apparatus.

Table 3 - Structure of knowledge base consisting of fuzzy logic rules for managerial decision making

№ of Rules	**If "relationship convergence indicator"**	**And the "knowledge transfer indicator"**	**And "an indicator of the relevance of the available knowledge to the requirements of the external environment"**	**And "knowledge increment indicator"**	**Then "Integral indicator of the quality of knowledge base filling, allowing to form a decision-making trajectory"**

1	Low	Low	Low	Low	Low
2	Low	Low	Medium	Low	Low
3	Low	Medium	High	Low	Medium
4	Medium	Medium	Low	Medium	Average
5	Medium	High	Medium	Medium	Above Average
6	Medium	High	High	Medium	Above Average
7	High	Low	Low	High	Low
8	High	Low	Medium	High	Below average
9	High	Medium	High	High	Average
10	Low	Medium	Low	Low	Average
11	Low	High	Medium	Low	High

For each identified condition, a different management decision-making trajectory is built, as reflected in methods M1-M6.

For each identified condition, a different management decision-making trajectory is built, as reflected by the M1-M6 methodologies.

The validity of actions in each methodology is coordinated with the developed and implemented author's Regulations (R_i), which are not considered in detail here. Each of the provisions can be considered a documented procedure, which is a guide to action for the decision maker.

4.3 The Model of Knowledge Base Structure

The model of the knowledge base structure as part of an intelligent information system, which allows to diagnose the level of compliance of the available knowledge with the requests of the external environment is shown in Fig. 2.

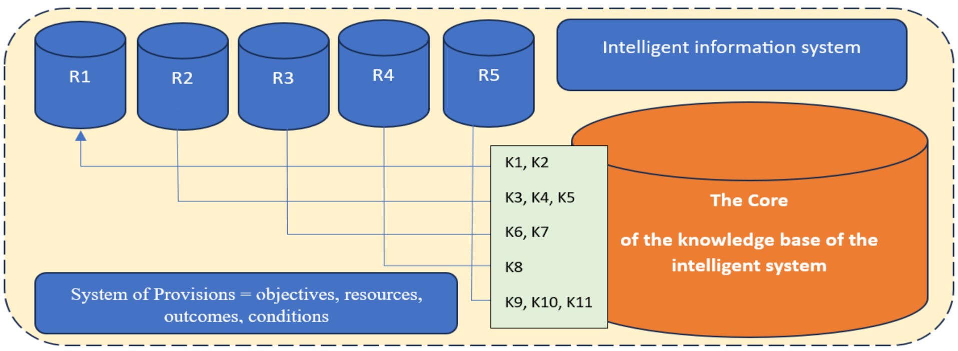

Figure 2. The Model of Knowledge Base Structure

Figure 2 shows the process of knowledge bases expanding. Each coefficient is justified by a specific conceptual statement, which is not considered here. The main idea is to evaluate the level of knowledge content in the KB. It is necessary that the KB should always be up-to-date and relevant.

Figure 3 shows the results obtained after training the staff of the higher school of intellectual systems and cybertechnologies by method M5, and the performed attestation of controlled parameters by methods M4-M6.

The M5 methodology is described here.

Its advantage is that it allows us to assess the quality of the existing level of knowledge of the employees' team in the aggregate knowledge base.

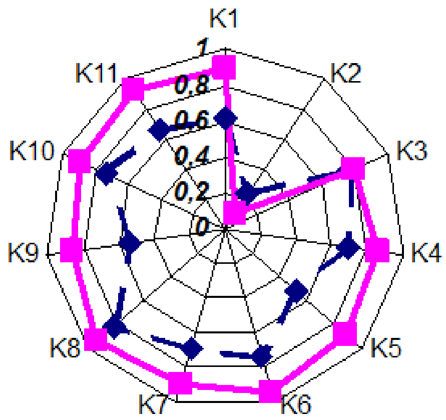

Figure.3. Evaluation of the results of the formation of the core knowledge of the teaching staff according to the method M5

The figure shows that the solid line marks those indicator values that should be formed in the knowledge base of the scientific and professional community.

The M5 methodology consists of the following steps:

#1. Definition of diagnostic goals and objectives

#2. Development of criteria for assessing the level and completeness of knowledge

#3. Selection of methods and tools of diagnostics

#4. Carrying out diagnostics of completeness and consistency of knowledge

#5. Analyzing the obtained results of diagnostics

#6. Feedback and correction

The results of the experiment show that the increase of knowledge occurred, scientific and professional pedagogical organization can claim to a higher level of development.

4. Conclusions

1. On the basis of scientific approaches. in particular, fuzzy logic methods, the structure of information-intellectual system is substantiated, which can be used to adapt the activities of scientific and professional pedagogical community to the demands of unstable external environment.
2. Based on the described structure of the information-intelligent system, a neural network allowing to select the routes of managerial decisions depending on the activation function has been designed.
3. The possibility of knowledge extraction and management of knowledge actualization process in the knowledge base of the scientific and professional community is shown.

Next Steps

1. It is planned to implement training of the neural network, which is possible on the basis of updating the weights in the process of error back propagation. The input data are the coefficients justified by the authors, the values of which were obtained by expert judgement
2. Development of machine learning algorithms, based on new route maps for extracting big data.
3. Development of a methodology for applying the neural network model.
4. Introduction of machine learning algorithms into scientific and pedagogical area.

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