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TÍTULO: Sistema de apoyo a la toma de decisiones para la distribución de tareas en el registro de operadores de datos personales basado en un modelo de producción difusa.

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RESUMEN: Este artículo describe el sistema desarrollado de apoyo a la toma de decisiones para la distribución de tareas en un sistema automatizado de gestión de documentos electrónicos. La tarea principal del sistema es una distribución efectiva de tareas por parte de los artistas para mantener el registro de operadores de datos personales. Para resolver este problema, se propone un modelo de producción difusa basado en la construcción de sistemas de reglas difusas del tipo dado y un algoritmo de inferencia basado en reglas. De acuerdo con los resultados de las pruebas, se concluyó que es posible reducir significativamente la carga intelectual de una persona en la distribución de tareas.

PALABRAS CLAVES: gestión electrónica de documentos, asignación de tareas, modelo de producción difusa, complejo de software, sistema de soporte de decisiones.

TITLE: Decision-Making Support System for tasks distribution in Personal Data Operators Register Maintaining based on a Fuzzy-Production Model.

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ABSTRACT: This article describes the developed decision-making support system for tasks distribution in an automated electronic document management system. The main task of the system is an effective tasks distribution by performers for keeping the personal data operators register. To solve this problem, a fuzzy-production model is proposed, based on the given type fuzzy rules systems construction and an inference algorithm based on rules. According to the testing results, it was concluded that it is possible to significantly reduce the intellectual burden on a person in the tasks distribution.

KEY WORDS: electronic document management, assignment of tasks, fuzzy production model, software complex, decision support system.

INTRODUCTION.

At present, systems of electronic document circulation have spread in many spheres of human activity (Paramonova, 2016). Their use makes it possible to increase the efficiency of work with documents. At the same time, due to the large number of tasks being solved in document management systems, their multicriteria and fuzzy nature, it becomes necessary to find an effective approach in the distribution of these tasks by operators (Talipov and Katasev, 2016).

In most of these systems, an expert approach is used to solve this problem (Calleja and Troost, 2005), the essence of which is that the leader (expert) acting as the decision-maker, based on his experience, distributes assignments for operators, taking into account the existing criteria and limitations. With an experienced expert, this approach has a high quality of decision-making. At the same time, there are problems of inability to make adequate decisions without an expert, a high complexity of analysing the criteria and options for assigning tasks. In addition, the expert is required to assess the complexity of tasks and the laboriousness of their execution, as well as take into account the qualifications, efficiency and workload of the operators. The presence of these factors reduces the effectiveness of the expert approach to the distribution of tasks. This actualizes the need to develop effective methods and algorithms, as well as decision support systems for the rational selection of task operators.

This problem belongs to the class of problems in decision theory (Neumann, et al. 1970; Simon, 1995; Harrison and March, 1984; Cyert and March, 1963; Katasev and Kataseva, 2016). However, the traditional methods of decision theory do not always allow for consideration of factors of fuzziness and uncertainty (Ismagilov and Khasanova, 2015; Anikin, 2017). These factors are inherent in the task of distribution of tasks in electronic document management systems. Therefore, recently, in solving such problems, methods and models based on fuzzy logic are used (Salakhutdinov, Ismagilov, 2005) - fuzzy methods of rational choice of alternatives.

The theory of fuzzy sets allows to build models of approximate reasoning of a person on the basis of rules and algorithms of logical inference (Mahajan & Raghuwanshi, 2017; Mamdani, 1977; Zinoviev and Anikin, 2009; Batyrshin, e al. 1994; Yarushkina, e al. 2015). These rules should adequately describe the logic of decision-making by the expert in the distribution of tasks (Talipov, Katasev, 2016). This actualizes the need to construct a fuzzy-product model for solving the problem under consideration.

DEVELOPMENT.

Methods.

Consider the task of task distribution using the example of the electronic document management system for maintaining the register of personal data operators. Let the set of tasks $Z=\{z_1, z_2, \ldots, z_N\}$ be given and their difficulty levels are known:

- "low" (S_1) - operators "physical person";

- "medium" (S_2) - operators "legal entity";

- "high" (S_3) - operators "state and municipal bodies".

There are also many operators $A=\{a_1, a_2, \ldots, a_n\}$ and their characteristics are known:

- C_1 - current level of congestion;

- C_2 - working capacity;

- C_3 - level of qualification.

It is required to distribute all assignments for operators, taking into account their number, composition, qualification, efficiency and current workload. It is necessary to build a model for assigning tasks based on fuzzy-production rules and an algorithm of logical inference on rules.

Consider the requirements for the form of fuzzy rules for the distribution of tasks:

1) The possibility of using different types of input parameters;

2) The ability to process clear and fuzzy input data;

3) The consideration of the significance (reliability) of each rule.

Fuzzy rules of the form (Katasev and Gazimova, 2011) satisfy these requirements:

$$If \wedge (x_1 \; is \; \widetilde{A}_1, x_2 \; is \; \widetilde{A}_2, \ldots, x_n \; is \; \widetilde{A}_n, x_{n+1} \; is \; A_{n+1}) \; Then \; y = a_i \;\; [CF_i] \qquad (1)$$

where x_i, $i=\overline{1,n}$ - the workload of the i-th operator;

x_{n+1} - the complexity of the task;

$\widetilde{A}_i = \left(x_i, \mu_{\widetilde{A}_i}(x_i)\right)$, $i=\overline{1,n}$ - the fuzzy gradations of workload of operator;

$\mu_{\widetilde{A}_i}(x_i) \in [0;1]$ - the degree of belonging of the values of x_i к $\widetilde{A}_i$;

A_{n+1} - the value of the complexity of the task from the set {S_1, S_2, S_3};

y - the variable that defines the task's operator;

a_i, $i = \overline{1,n}$ - the concrete operator of the task from {a_1, a_2, …, a_n};

CFi - reliability of the rule ("usefulness" of the choice of the operator).

Let's consider a technique of system construction of rules (1) for a concrete number and structure of operators of tasks:

1) Assignment of the set for operators A={a_1, a_2, …, a_n};

2) Setting the number m and the names of fuzzy grades of workload for operators (for example, $\widetilde{A}_1$ = "low", $\widetilde{A}_2$ = "medium", $\widetilde{A}_3$ = "high");

3) Construction of combinations of the values of the input (x_i and x_{i+1}) and the output (y) parameters of the rules, provided that the number of task complexity values (x_{i+1}) = 3.

4) For each combination, the specification of a rule of the form (1).

Thus, the system of rules S_{ij}^k, $i = \overline{1,n}$, $j = \overline{1,m}$, $k = \overline{1,3}$ is a combination of input conditions with task operators.

Using this technique allows to create a system of rules

$$S_{ij}^k : \begin{cases} If \wedge (x_1\ is\ \widetilde{A}_1^1, ..., x_n\ is\ \widetilde{A}_n^1, x_{n+1}\ is\ A_{n+1}^1)\ Then\ y = a_1\ \ [CF_1] \\ ... \\ If \wedge (x_1\ is\ \widetilde{A}_1^j, ..., x_n\ is\ \widetilde{A}_n^j, x_{n+1}\ is\ A_{n+1}^k)\ Then\ y = a_i\ \ [CF_i] \\ ... \\ If \wedge (x_1\ is\ \widetilde{A}_1^m, ..., x_n\ is\ \widetilde{A}_n^m, x_{n+1}\ is\ A_{n+1}^3)\ Then\ y = a_n\ \ [CF_n] \end{cases} \quad (2)$$

where $i = \overline{1,n}$ - defines the task operator,

$j = \overline{1,m}$ - determines the fuzzy gradation of workload, and

$k = \overline{1,3}$ - determines the complexity of the task.

Consider the proposed algorithm of inference. In this algorithm, for each rule R_r the following $r = \overline{1,N}$ are calculated:

- $V_{R_r} \in (0;1)$ - the degree of reliability of antecedent rule:

$$V_{R_r} = \min\left(\mu_{\tilde{A}_1^j}(x_1^*),...,\mu_{\tilde{A}_i^j}(x_i^*),...,\mu_{\tilde{A}_n^j}(x_n^*),\mu_{A_{n+1}^k}(x_{n+1}^*)\right) \qquad (3)$$

where $x_i^*, i = \overline{1,n}$ - the number of tasks of the i-th operator,

x_{n+1}^* - the complexity of the task.

- $C_{R_r} \in (0;1)$ - complex estimation of reliability of the rule decision:

$$C_{R_r} = V_{R_r} * CF_{R_r}, \qquad (4)$$

where CF_{R_r} - the "utility" of choosing the operator in the rule R_r, $r = \overline{1,N}$.

The proposed algorithm includes the following steps:

1) Definition of the complexity of the task x_{n+1}^*;

2) Determination of the number of assignments for each operator x_i^*;

3) Calculation of the degrees of operation $\mu_{\tilde{A}_i^j}(x_i^*)$ and $\mu_{A_{n+1}^k}(x_{n+1}^*)$ for each rule;

4) Calculation of the reliability of the antecedents of the rules V_{R_r} according to the formula (3);

5) Obtaining a conflicting set of rules $S_{conf} = \{R_r \mid V_{R_r} \neq 0\}$, $r = \overline{1,N}$;

6) Calculation for all rules $R_r \in S_{conf}$ of the estimate C_{R_r} by the formula (4);

7) Choice of the rule $R_r^* : \max\limits_{r: R_r \in S_{conf}} C_{R_r}$;

8) Obtaining the value a_i^* of the rule R_r^* as the operator of the task.

Thus, the task distribution model is a system of rules of the form (2) and an algorithm for deriving rules. The parameters of the model are the membership functions in the rules and the validity of the rules. To use it, you need to determine the values of these parameters.

Consider the method of constructing membership functions. Let there be n operators {a1, a2, ..., an}, each of which needs to estimate the levels of its workload by the number of tasks performed based on the scale from Table 1.

Table 1 - Estimates of the confidence of operators

Numeric value of confidence, α	**1**	**0.8**	**0.6**	**0.4**	**0.2**
Linguistic meaning of confidence	Absolutely confident	Substantially confident	Strongly confident	More or less confident	Weakly confident

This method is based on four stages:

1. Assignment by the expert the S support of a fuzzy set $\widetilde{A}$ corresponding to the membership function for the workload of the operators.

2. Survey of operators and formation of estimations of conformity of the left $L_i(\alpha^*)$ and the right $R_i(\alpha^*)$ bounds of the level of the workload to the value $\alpha^* \in \{1, 0.8, 0.6, 0.4, 0.2\}$ in accordance with the data from Table 1, where $[L_i(\alpha^*);\ R_i(\alpha^*)] = A_{\alpha^*} \subset S$, and $A_{\alpha^*} - \alpha^*$ is cut of $\widetilde{A}$.

3. For each $\alpha^* \in \{1, 0.8, 0.6, 0.4, 0.2\}$, the calculation of the mean of the left $L_i(\alpha^*)$ and the right $R_i(\alpha^*)$ bounds of the α^* cut by the formulas:

$$L_{cp}(\alpha^*) = \sum_{i=1}^{n} \frac{L_i(\alpha^*)}{n}; \qquad R_{cp}(\alpha^*) = \sum_{i=1}^{n} \frac{R_i(\alpha^*)}{n}$$

4. Construction of the membership function of a set $\widetilde{A}$ by combining of α^* cuts $\widetilde{A} = \bigcup_{\alpha^*} \alpha^* A_{\alpha^*}^{cp}$ and linear approximation of their vertices by the method of least squares.

Let's consider a method for determining the reliability of *CF* in the rules. We introduce the notation:

- $\mu_{\widetilde{C}_1}(a_i) \in (0;1)$ - the "utility" of the i-th operator on the workload;

- $\mu_{\tilde{C}_2}(a_i) \in (0;1)$ - the "utility" of the i-th operator in terms of operability;

- $\mu_{\tilde{C}_{3k}}(a_i) \in (0;1)$ - the "utility" of the i-th operator for qualification of the tasks of the k-th level of complexity, $k = \overline{1,3}$.

The developed method is based on three stages.

1. Calculation of the "utility" of the i-th operator on the workload:

$$\mu_{\tilde{C}_1}(a_i) = \begin{cases} 1 - \dfrac{n_i}{N_I}, if\ N_I \neq 0; \\ 1, if\ N_I = 0 \end{cases}$$

where n_i is the number of tasks for the i-th operator, $N_I = \sum_{i=1}^{n} n_i$ - the total number of tasks.

2. On the basis of the Saati hierarchy analysis method, the definition of $\mu_{\tilde{C}_2}(a_i)$ and $\mu_{\tilde{C}_{3k}}(a_i)$, $k = \overline{1,3}$.

3. Calculation of the reliability of the rules by the formula:

$$CF_k^i = \mu_{\tilde{C}_1}(a_i) * \mu_{\tilde{C}_2}(a_i) * \mu_{\tilde{C}_{3k}}(a_i), k = \overline{1,3}.$$

As a result of the application of the described methods, the values of the membership function parameters and the reliability of each rule are determined.

Results and discussion.

On the basis of the software, a software package was developed to support the decision-making on the distribution of tasks (see Figure 1) (Talipov, Katasev, 2016).

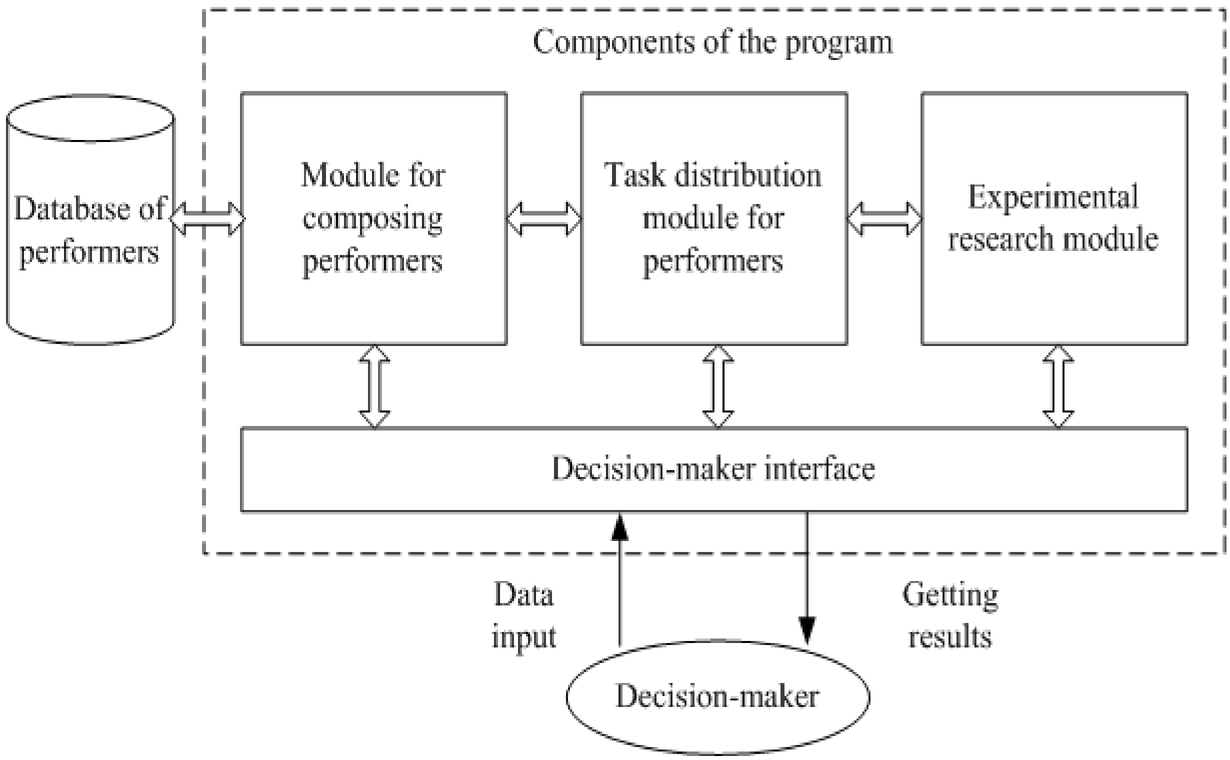

Figure 1 - Block diagram of the software package.

The first module allows you to add operators and specify their characteristics. The second module includes a block for constructing the task allocation model and a block of fuzzy logic inference. The third module is used for generating tasks, estimating the accuracy of the constructed model and visualizing the results.

To assess the adequacy of the fuzzy production model of task distribution, the data accumulated in the real system of electronic document management are used. Comparison of the results of the model work with standard (expert) schemes of task distribution is made. In total, 10 schemes with an average number of tasks in each scheme equal to 166 have been formed for research.

Table 2 shows a fragment of one of these schemes.

Table 2. Fragment of the expert scheme of tasks distribution.

No.	Task complexity level	Current number of tasks for operator				Operator
		a1	a2	a3	a4	
1	High	14	16	14	6	a1
2	High	15	16	14	6	a3
3	Low	15	16	15	6	a4
4	Medium	15	16	15	7	a4
5	Medium	15	16	15	8	a4
6	Medium	15	16	15	9	a4
7	High	15	16	15	10	a3
8	High	15	16	16	10	a3
9	High	15	16	17	10	a3
10	High	15	16	18	10	a3

Let us consider a method for assessing the adequacy of the assignment distribution model (Talipov, et al. 2017). Suppose that there are schemes $S_j = \{a_1, a_2, \ldots, a_{n_j}\}$, and the number of tasks in the scheme is N_j, $j = \overline{1, 10}$. For each scheme, we introduce the notation:

- $n(M^j_{ki})$ - number of tasks of the k-th level of complexity, distributed by the model to the i-th operator ($i = \overline{1, n_j}$);

- $n(\Omega^j_{ki})$ - number of tasks of the k-th level of complexity, distributed by the expert to the i-th operator ($i = \overline{1, n_j}$).

Where $\sum_{k=1}^{3}\sum_{i=1}^{n_j} n(M^j_{ki}) = \sum_{k=1}^{3}\sum_{i=1}^{n_j} n(\Omega^j_{ki}) = N_j$ (all assignments are distributed).

Let's consider the work stages of this method:

1) For each reference scheme S_j, $j = \overline{1, 10}$:

1.1) Receiving tasks in the volume N_j for distribution;

1.2) Determination of the structure $n(\Omega_{ki}^{j})$ of expert assignment of tasks;

1.3) Determination of the structure of their distribution $n(M_{ki}^{j})$;

1.4) Calculation of the accuracy of tasks distribution

$$P_j = \left(1 - \frac{\sum_{k=1}^{3}\sum_{i=1}^{n_j}\left| n(M_{ki}^{j}) - n(\Omega_{ki}^{j}) \right|}{N_j} \right) * 100\%;$$

2) Calculation of the overall accuracy of the model $P = \frac{\sum_{j=1}^{10} P_j}{10}$.

Thus, the adequacy of the model is determined by its averaged accuracy with respect to all expert schemes. Table 3 shows the results of the experiments.

Table 3 - Results of experimental accuracy evaluation of fuzzy production model of tasks distribution

Scheme No. S_j / Accuracy	1	2	3	4	5	6	7	8	9	10
P_j, %	93,24	94,23	94,44	96,55	95,79	95,71	96,06	95,56	94,69	95,53
P, %	95,18									

The average error of the model is no more than 5%, therefore, the model is adequate (it forms the schemes of distribution of tasks close to the expert ones).

The developed software package is implemented and used as part of the electronic document management system in the form of the subsystem "Distribution of tasks for keeping the register of personal data operators" (see Figure 2).

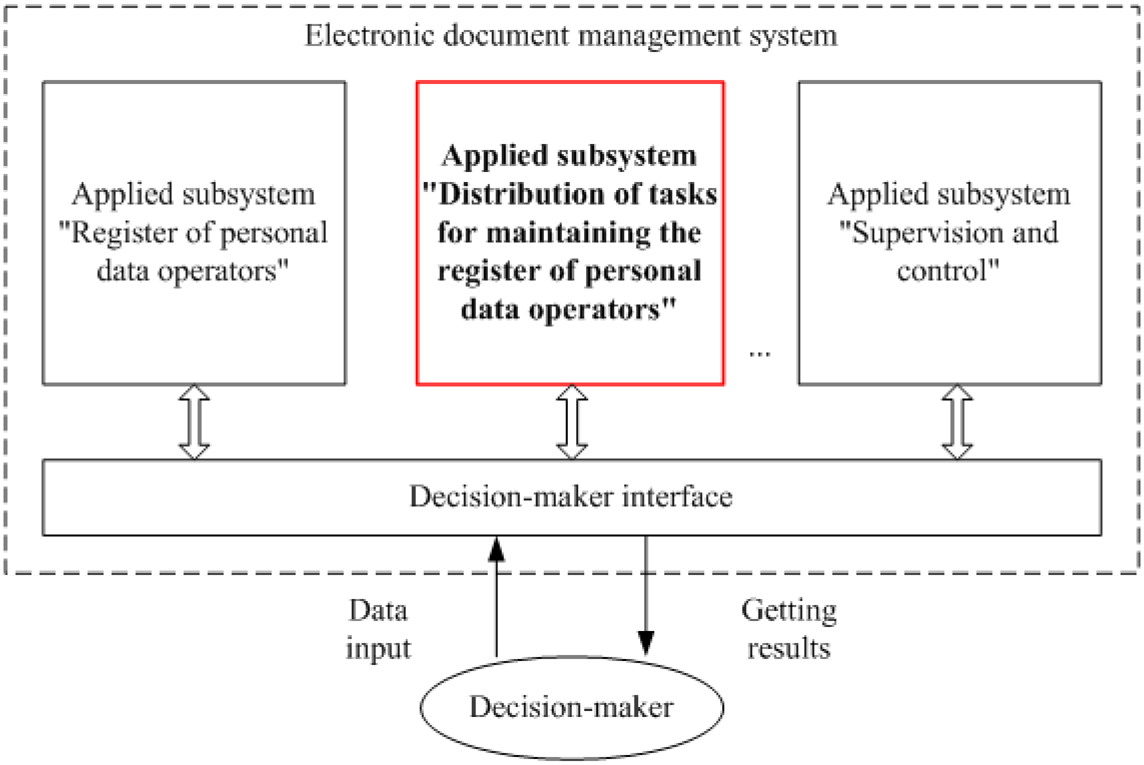

Figure 2 - Subsystem of task distribution as part of the electronic document management system.

In order to determine the effectiveness of the model, the intellectual load on the expert was evaluated before and after the implementation of the program. The main objectives of the expert in the distribution of tasks are to assess the level of complexity of the task, determine the workload of the operators and build a scheme for assigning tasks. These tasks were carried out by the expert manually before the implementation of the program. The implementation of the program allowed to automate their solution and reduce the intellectual burden on the expert.

Studies to estimate the time spent by the expert on the distribution of 35 randomly generated tasks were conducted. Table 4 presents the averaged time characteristics of the solution of this problem.

Table 4 - Estimated time of tasks distribution before and after program implementation.

No.	Main expert tasks	Average time of task solving, minutes	
		Before implementation	After implementation
1	Assessing the difficulty level of one task	5	1
	Assessing of the difficulty level of 35 tasks	5×35 = 175	1×35 = 35
2	Determining the workload of operator	5	0,5
3	Building a task distribution scheme	10	2
Total:		190	37,5

The results of the studies indicate the efficiency of task distribution based on the fuzzy-product model. Its use makes it possible to increase the expert's work speed by 80% and reduce the time for making decisions five times.

Summary.

The developed model is an effective tool for assigning assignments to operators in electronic document management systems. The advantage of the model in comparison with the expert approach is the possibility of reducing the requirements for experience and qualification of the person making decisions on the distribution of tasks. Automation of task allocation processes on the basis of the software package allows to reduce the intellectual load on the expert and reduce the time for decision-making.

CONCLUSIONS.

The results of the research showed that the proposed model of assignment distribution is adequate. The developed software package allows to automate the process of assigning assignments to operators in electronic document management systems. Practical use of the program allowed to reduce the intellectual burden on the expert in the distribution of tasks, increase the speed of its work by 80% and reduce the time for making decisions by them 5 times.

In the future, in order to increase the effectiveness of forming fuzzy rules, it is advisable to use methods of machine learning: neural networks (Talipov, et al. 2017) and fuzzy neural networks (Katasev and Kataseva, 2016, Azimov, e al. 2015; Emaletdinova and Kabirova, 2016; Zhang and Tao, 2018; Elgueta, 2018). This can shorten the time to build a fuzzy model, improve its accuracy and adequacy.

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