Models and Methods of Forecasting and Tasks Distribution by Performers in Electronic Document Management Systems

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Abstract This paper describes the problem of task distribution received through the electronic document management system. The fuzzy-production model underlying the solution to this problem is described. Based on the proposed model, a software package was developed for decision-making support of task performers selection, its structure is presented. A model of task distribution is considered taking into account its forecast values. The basic steps in forecasting model construction are described. The effectiveness of this approach for task distribution, based on workload indicators of specialists with different levels of working capacity and qualifications, is shown.

Keywords Electronic document management system · Task distribution · Fuzzy production model · Forecasting · Data mining

1 Introduction

Currently, electronic document management systems (EDMS) are widely used in many fields of human activity [1–3]. The use of such systems can improve the efficiency of working with documents by reducing the time for making managerial decisions and ensuring quality control of performance discipline. However, due to a large number of incoming tasks of various difficulty levels, the problem of their rational distribution among performers arises [4]. Often for solving this problem, an expert approach is used, which is effective in terms of the quality of managerial decision-making. However, in the absence of an expert, tasks distribution difficulties

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arise. To eliminate this drawback, the development of effective models, methods, and technologies for assigning tasks to performers is relevant [5]. Such technology should not only allow distributing the tasks received for execution but solve this problem taking into account the forecasting of the possible number of tasks with various categories of complexity.

As an example of the EDMS, consider the existing electronic document management system of the territorial office of The Federal Service for Supervision of Communications, Information Technology, And Mass Media (Roskomnadzor). In the field of protecting the rights of personal data subjects, the most time-consuming and urgent task, for automated decision support, is maintaining a register of personal data operators (PDO), that is, timely updating information about PDO previously included in the register, and monitoring the provision of the corresponding notification by unregistered PDO, which is the implementation of the legislation of the Russian Federation in the field of personal data in general.

2 Statement of the Tasks Distribution Objective for Maintaining the Register of Personal Data Operators

Consider the formal statement of the tasks distribution objective between performers when maintaining the register of PDO [6]. Let $Z = \{z_1, z_2, \ldots, z_N\}$ be a set of tasks of volume N. Each incoming assignment can be classified according to a specific level of difficulty. Let's highlight the following levels of complexity of incoming tasks corresponding to different categories of PDO:

(1) S_1—"Low" (this level of complexity includes tasks coming from such PDOs, such as "physical person" and "private entrepreneur");
(2) S_2—"Medium" (this level of complexity includes tasks coming from such PDOs, such as "juridical entity");
(3) S_3—"High" (this level of complexity includes assignments from such PDOs such as "government agencies and municipalities").

Let $A = \{a_1, a_2, \ldots, a_n\}$ is a set of performers who are processed incoming tasks. It should be noted that the number and composition of performers who are included in a given set may be subject to changes over time. For each potential executor of the received task, the following characteristics can be determined: the level of workload (*C1*), efficiency (*C2*), and the level of qualification (*C3*). It is necessary to carry out a rational distribution of all N tasks included in the set of received tasks Z between potential performers from set A. In this case, the individual characteristics of each performer should be taken into account in terms of the entered characteristics.

In the course of the analysis, it was found that the most rational method for solving the problem is the method of fuzzy inference [7–9], which is based on fuzzy rules [10, 11]. To implement it, it was necessary to solve the following tasks:

(1) selection of the type of fuzzy production rules for making decisions on the distribution of tasks by the performer;
(2) development of a methodology for constructing a system of fuzzy rules;
(3) development of an inference algorithm on a system of fuzzy rules;
(4) development of a method for constructing membership functions in fuzzy rules;
(5) development of a method for determining the reliability of fuzzy rules;
(6) development of a model for accounting for predicted values of the number of incoming tasks when they are distributed among performers;
(7) development of a software package for decision-making support for the distribution of tasks.

Let's consider the solution of these tasks in more detail.

2.1 The Type of Fuzzy Production Rules for Making Decisions on the Distribution of Tasks

Fuzzy-production rules underlie the model of the knowledge representation of an expert on the distribution of tasks between performers, taking into account their special aspects and characteristics. Within the framework of solving the problem under consideration, the following type of fuzzy rules was chosen [12]:

$$IF \wedge (x_1\ is\ \tilde{A}_1, \ldots,\ x_n\ is\ \tilde{A}_n,\ x_{n+1}\ is\ A_{n+1}) \Rightarrow y = a_i\ [CF_i], \qquad (1)$$

where $x_i,\ i = \overline{1, n}$—workload of the i- th performer; x_{n+1}—task difficulty; $\tilde{A}_i = \{x_i, \mu_{\tilde{A}_i}(x_i)\},\ i = \overline{1, n}$—fuzzy gradations of the workload of performers; $\mu_{\tilde{A}_i}(x_i) \in [0;\ 1]$—the degree of x_i belonging to $\tilde{A}_i$; A_{n+1}—the value of the complexity of the task from the set $\{S_1,\ S_2,\ S_3\}$; y—output variable that defines the executor of the task; $a_i,\ i = \overline{1, n}$—a specific performer from $\{a_1, a_2, \ldots, a_n\}$; CF_i—the utility of choosing the i-th performer.

The workload of the performers and the complexity of the task are the input parameters of the fuzzy rule. In this case, specific task executors act as output parameters. A feature of this type of rule is the use of the utility parameter CF_i of the choice of the i-th performer. Thus, the rules of the form (1) reflect the logic of an expert when making a managerial decision on the distribution of tasks between performers [13–15].

2.2 Development of a Method for Constructing a System of Fuzzy Production Rules

When deciding on the selection of a performer for a specific task, the total number, and composition of potential performers are taken into account. Let consider the developed technique for constructing a system of fuzzy production rules for a specific number and composition of task performers. This technique includes the following steps [6]:

(1) assignment of many task performers $A = \{a_1, a_2, \ldots, a_n\}$;
(2) setting the number m and names of gradations that determine the workload indicator of potential task performers (for example, for $m = 3$, the gradations can be designated as $\tilde{A}_1$ = "low workload", $\tilde{A}_2$ = "medium workload", $\tilde{A}_3$ = "high workload");
(3) construction of all possible combinations of the values of the input parameters (x_i, x_{i+1}), which are responsible for the workload of potential performers and the complexity of the assigned task, and the output parameter (y), which determines who of the potential performers is selected to perform it. Given that the number of task difficulty values is three, the number of possible combinations is calculated using the following formula:

$$N = 3\ \mathrm{mn}^2 \tag{2}$$

where m—the number of grades of the complexity of incoming tasks, n—number of tasks.

Thus, each fuzzy-production rule corresponds to a combination of input conditions that determine the rate of the workload of potential performers and the complexity of a specific task, and an output value that determines which of the potential performers is selected to complete it.

Using the developed technique, it is possible to draw up a system of fuzzy production rules for a specific number and composition of performers. This system of rules has the following form (3):

$$\begin{cases} If \wedge (x_1\, is\, \tilde{A}_1^j, \ldots,\ x_n\, is\, \tilde{A}_n^j,\ x_{n+1}\, is\, A_{n+1}^k) \Rightarrow y = a_1\ \ [CF_1] \\ If \wedge (x_1\, is\, \tilde{A}_1^j, \ldots,\ x_n\, is\, \tilde{A}_n^j,\ x_{n+1}\, is\, A_{n+1}^k) \Rightarrow y = a_2\ \ [CF_2] \\ \ldots \\ If \wedge (x_1\, is\, \tilde{A}_1^j, \ldots,\ x_n\, is\, \tilde{A}_n^j,\ x_{n+1}\, is\, A_{n+1}^k) \Rightarrow y = a_n\ \ [CF_n] \end{cases} \tag{3}$$

where $j = \overline{1, m}$ determines the value of the performer's workload, $k = \overline{1, 3}$—the difficulty of the task.

It should be noted that for a different number and composition of performers, it is necessary to form an individual system of rules. To solve the task of choosing a task performer, an inference algorithm has been developed on a system of fuzzy production rules.

2.3 Development of an Inference Algorithm Based on a System of Fuzzy Production Rules

To determine the specific executor of the received task, an inference algorithm was developed based on the rules of a fuzzy production model. The following indicators are calculated for each rule [6]:

(1) a confidence level of the antecedent of rule $V \in [0;1]$ *(veracity):*

$$V = \min\Big(\mu_{\tilde{A}_1^j}(x_1^*), \ldots, \mu_{\tilde{A}_i^j}(x_i^*), \ldots, \mu_{\tilde{A}_n^j}(x_n^*), \mu_{A_{n+1}^k}(x_{n+1}^*)\Big) \tag{4}$$

where $x_i^*, \quad i = \overline{1, n}$—number of tasks of the i-th performer, x_{n+1}^*—the difficulty of the task, moreover $\mu_{\tilde{A}_i^j}(x_i^*) \in [0; 1]$, $\mu_{A_{n+1}^k}(x_{n+1}^*) = \begin{cases} 1, \ if \ x_{n+1}^* = A_{n+1}^k \\ 0, \ if \ x_{n+1}^* \neq A_{n+1}^k \end{cases}$;

(2) complex assessment of the reliability of the rule solution $C \in [0;1]$ (*complex*):

$$C = V * CF, \tag{5}$$

where *CF*—the usefulness of choosing a performer in a rule.

Consider the stages of the developed algorithm for assigning tasks to performers, taking into account the introduced indicators [6]:

(1) determination of the level of complexity x_{n+1}^* of the requirements of the task entering the EDMS;
(2) determination of the number of tasks x_i^*, that are simultaneously performed by the *i*-th performer;
(3) calculation of the degrees of operation $\mu_{\tilde{A}_i^j}(x_i^*)$ and $\mu_{A_{n+1}^k}(x_{n+1}^*)$ conditions for each *r*-th rule of the system $Rule_r, \ r = \overline{1, N}$ of the S_R system;
(4) for each rule, the calculation of values V_r by the formula (4);
(5) formation of a set of rules with a non-zero degree of confidence: $S_{conf} = \{Rule_r | V_r \neq 0\}, r = \overline{1, N}$;
(6) calculation of the estimate C_r by formula (5) for all rules from the set $Rule_r \in S_{conf}$;
(7) selection of the rule with the maximum complex assessment $Rule_r^* : \max\limits_{r:\ Rule_r \in S_{conf}} C_r$;
(8) getting the value a_i^* of a rule $Rule_r^*$ as a solution to a problem.

Thus, the fuzzy-production model of task distribution is a system of fuzzy-production rules of the form (3), which are determined by a combination of input conditions with task executors, as well as an inference algorithm based on rules. The membership functions (MF) and the reliability of the rules are used as model parameters. For the practical use of the model, it is necessary to identify the values of these parameters [16–18].

2.4 Development of a Method for Constructing Membership Functions in Model Rules

For the formation of MF in the rules of the model, a method for approximating the subjective assessments of performers (SAP) has been developed [6]. Let there be n potential executors of tasks $\{a_1, a_2, \ldots, a_n\}$. Each of them sets the value of its workload level based on the number of tasks that it performs simultaneously. The method is based on the processing of the subjective assessment of the level of the performer's workload using the scale, which is presented in Table 1.

The SAP method includes the following main stages:

(1) assignment by the expert of the carrier S of a fuzzy set $\tilde{A}$, which corresponds to the MF for the level of the workload of performers;
(2) survey of performers and the formation of their subjective assessments of the correspondence of the left $L_i(\alpha^*)$ and right $R_i(\alpha^*)$ boundaries of the selected workload level to a specific value of α^* from the set $\{1, 0.8, 0.6, 0.4, 0.2\}$ in accordance with Table 1 (moreover $[L_i(\alpha^*);\quad R_i(\alpha^*)] = A_{\alpha*} \subset S$, where $A_{\alpha*}$ is an α*- a slice of a fuzzy set $\tilde{A}$);
(3) calculation of the average values of the left $L_{cp}(\alpha^*)$ and right $R_{cp}(\alpha^*)$ boundaries of the α*- slice $A^{cp}_{\alpha*} = [L_{cp}(\alpha^*);\quad R_{cp}(\alpha^*)]$ for all α^* from the set of values of the performer's confidence $\{1, 0.8, 0.6, 0.4, 0.2\}$ according to the following formulas:

$$L_{cp}(\alpha^*) = \sum_{i=1}^{n} \frac{L_i(\alpha^*)}{n};\quad R_{cp}(\alpha^*) = \sum_{i=1}^{n} \frac{R_i(\alpha^*)}{n} \tag{6}$$

Table 1 Performer confidence rating scale

The numerical value of confidence, α	1	0.8	0.6	0.4	0.2
Interpretation	Absolutely sure	Substantially sure	Very sure	More or less sure	Poorly sure

(4) construction of the MF of a fuzzy set $\tilde{A}$ by combining the obtained α^*-slices $\tilde{A} = \bigcup_{\alpha*} \alpha^* A_{\alpha*}^{cp}$ and approximating their vertices by the method of least squares [19].

The proposed method allows you to build membership functions that determine the workload of performers in a fuzzy production model of assignment distribution.

2.5 Development of a Method for Determining the Reliability Values of Fuzzy Production Rules

To determine the values of the reliability of fuzzy rules, the *CF*-expert method was developed. Let *CF*—the reliability of the fuzzy rule *Rule*, which expresses the degree of the expert's confidence in the correctness and optimality of his decision on the distribution of the received task to a specific performer (the usefulness of the performer's choice). This parameter depends on the workload, performance, and qualifications of potential performers.

Within the framework of the method under consideration, the following concepts of the utility of choosing an executor are used, which take into account various factors for calculating the values of the *CF* parameter:

(1) $\mu_{\tilde{C}_1}(a_i) \in [0;1]$—the usefulness of choosing the *i*-th performer according to his current workload;
(2) $\mu_{\tilde{C}_2}(a_i) \in [0;1]$—the usefulness of choosing the *i*-th performer according to his performance;
(3) $\mu_{\tilde{C}_{3k}}(a_i) \in [0;1]$—the usefulness of choosing the *i*-th performer according to his qualifications for performing tasks of the *k*-th level of complexity.

The method for determining the reliability of fuzzy rules includes the following main stages:

(1) calculating the utility of choosing the *i*-th performer based on his current workload $\mu_{\tilde{C}_1}(a_i)$ based on the following formula:

$$\mu_{\tilde{C}_1}(a_i) = \begin{cases} 1 - \frac{n_i}{N},\ if\ N \neq 0; \\ 1,\ if\ N = 0 \end{cases} \tag{7}$$

where n_i—the number of simultaneously performed tasks by the *i*-th performer, $N = \sum_{i=1}^{n} n_i$—the total number of tasks for all performers;
(2) determination of utility $\mu_{\tilde{C}_2}(a_i)$ and $\mu_{\tilde{C}_{3k}}(a_i)$ based on the method of paired comparisons [20];
(3) calculation of the reliability of fuzzy production rules by the formula:

$$CF_k^i = \mu_{\tilde{C}_1}(a_i) * \mu_{\tilde{C}_2}(a_i) * \mu_{\tilde{C}_{3k}}(a_i) \tag{8}$$

Thus, the *CF*-expert method is based on numerical utility estimates calculated by the formula (7), and an assessment of the utility of choosing a particular contractor based on his performance and qualifications.

The use of the SAP and *CF*-expert methods allows determining the values of the parameters of the membership functions $\mu_{\tilde{A}_i}(x_i)$ and the reliability *CF* of each fuzzy production rule. As a result of the application of these methods, parametric identification of the fuzzy production model of the distribution of tasks occurs [6]. Thus, we can conclude that the construction of a set of rule systems for a different number and composition of task executors, identification of model parameter values, as well as the use of an inference algorithm on a rule system allows us to form a fuzzy production model of task distribution in the EDMS.

2.6 Decision Support Software Package

Based on the developed mathematical support, a software package has been implemented that allows decision-making support [21] on the choice of an executor for a specific task. The structure of the software package is shown in Fig. 1.

The module for forming the composition of performers is designed to add or exclude, if necessary (vacation, business trip, sick leave, etc.) performers of tasks and indicate their characteristics. The module for distributing tasks among performers includes a block for constructing a fuzzy-production model of assigning tasks, as well as a block for fuzzy inference. The experimental research module is designed to generate tasks, assess the accuracy of the task distribution model, and visualize the results obtained.

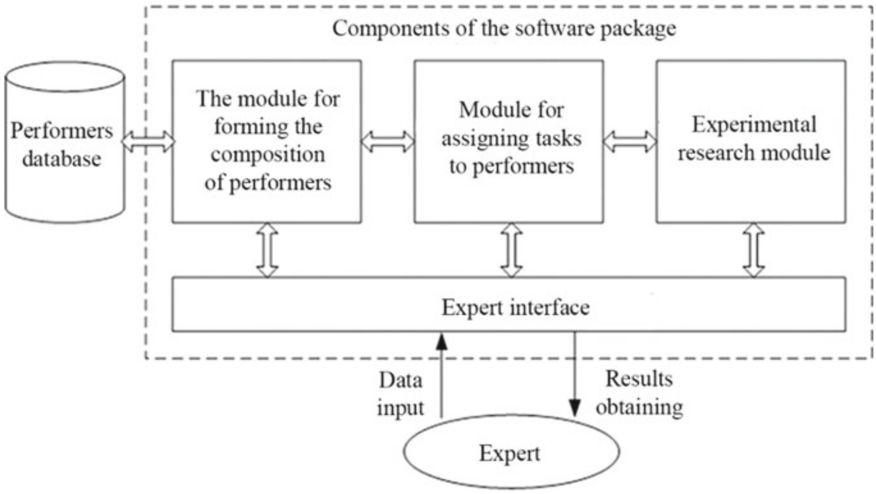

Fig. 1 Block diagram of the software package

Table 2 Fragment of the expert task distribution scheme

№ п/п	Difficulty level of the task	The current number of tasks for the performers				Executor of the task
		a_1	a_2	a_3	a_4	
1	High	14	16	14	6	a_1
2	High	15	16	14	6	a_3
3	Low	15	16	15	6	a_4
4	Middle	15	16	15	7	a_4

3 Formation of Reference Schemes for the Distribution of Tasks

To check the adequacy of the developed fuzzy-production model for the distribution of tasks, the data accumulated in the EDMS of the Roskomnadzor Office for the Republic of Tatarstan were used. A comparison of the results of the model with the reference (expert) schemes of task distribution was done. Table 2 shows a fragment of one of the schemes used.

In total, 10 reference schemes for the distribution of tasks were formed. The average number of tasks included in each scheme is 166. Table 3 shows the characteristics of the generated reference circuits.

The table for each scheme indicates the total number of tasks, their distribution by difficulty levels, the total number, and composition of task performers, as well as the structure of the expert distribution of tasks by performers.

4 Models of Assignment Distribution by Performers

The module for assigning tasks to performers has two modes of operation: direct assignments distribution (see Fig. 2) and assignments distribution, taking into account their predicted value (see Fig. 3).

It can be seen from the figure that the tasks to be distributed go to the tasks distribution module. This takes into account the composition of their potential performers. At the output, tasks are formed, distributed by performers.

In this case, the tasks to be distributed are a set of actually received and predicted values of the number of tasks from the PDOs. All tasks are submitted to the input of the task distribution module and are distributed among performers, taking into account the complexity of each task, as well as the qualifications, workload, and performance of the performers. After the distribution of the entire set of the current and predicted number of tasks, those tasks that have not been received yet, but were only predicted are excluded from the resulting distribution. Thus, the final set of tasks is formed, rationally distributed among the performers.

Table 3 Characteristics of reference job distribution schemes

Table 3 Characteristics of reference job distribution schemes

№ of schemes	Total tasks	Number of tasks by difficulty levels			Total performers	The structure of the expert distribution of tasks					
		Low (L)	Middle (M)	High (H)		a_1 (L, M, H)	a_2 (L, M, H)	a_3 (L, M, H)	a_4 (L, M, H)	a_5 (L, M, H)	a_6 (L, M, H)
1	148	2	36	110	4		0,0,40	0,0,36		0,6,34	2,30,0
2	156	21	109	26	4	0,37,11	0,36,12		13,15,3		8,21,0
3	180	15	82	83	4	0,18,38		0,17,35	6,22,10	9,25,0	
4	174	18	78	78	4		0,21,27	0,19,29	6,18,22	12,20,0	
5	190	14	116	60	5	0,16,21	0,20,19	0,23,15		4,28,5	10,29,0
6	163	12	89	62	5	0,18,22		0,20,19	1,23,13	2,12,8	9,16,0
7	127	14	65	48	5	0,5,18	0,8,14	0,11,12	1,18,4	13,23,0	
8	135	17	65	53	6	0,4,22	0,7,16	0,11,9	0,14,6	4,15,0	13,14,0
9	207	20	119	68	6	0,10,23	0,19,17	0,22,16	0,24,11	8,23,1	12,21,0
10	179	21	111	47	6	0,8,18	0,12,16	0,24,9	0,26,4	7,25,0	14,16,0

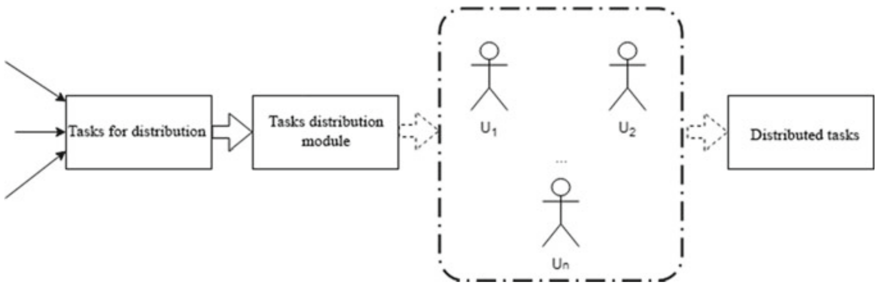

Fig. 2 Scheme of the model of the direct distribution of tasks without taking into account their predicted values

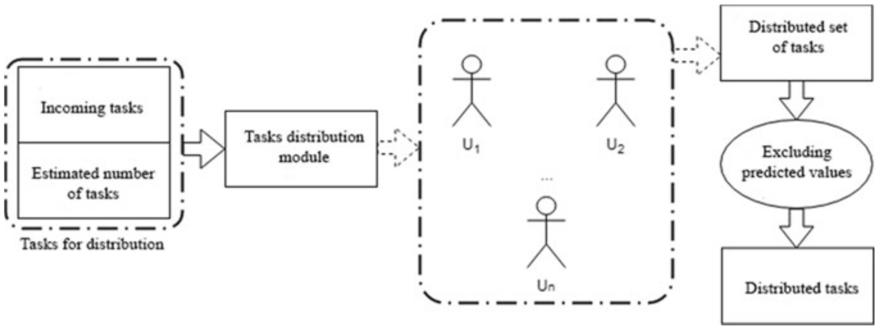

Fig. 3 Scheme of the task distribution model taking into account their predicted values

5 Solving the Problem of Predicting the Number of Tasks Received Through the EDMS

To solve the problem of predicting the number of tasks received through the EDMS, we used real data in the form of time series [22–24], describing the actual number of received jobs of varying complexity with a step of one month, starting from April 2015 to the present. The tasks are classified according to three levels of difficulty, respectively, three-time series were used for the analysis. Each such series was a sample containing the following data: date (month, year) and the number of tasks.

A multilayer feedforward neural network was used as a model for predicting the number of tasks [25–29]. For its construction, the analytical platform Deductor was used [30], on the basis of which the following stages of modeling were performed:

(1) loading and preparing initial data for analysis;
(2) building neural network models of various structures with a change in the number of hidden layers and neurons in each layer;
(3) testing the constructed models and choosing the best one in terms of the accuracy of the predicted values obtained;

(4) application of the selected neural network model to predict the number of tasks arriving for distribution with different levels of complexity.

In accordance with the forecasts obtained, in the further distribution of tasks between the performers, the following number of tasks was used: 1 task of high difficulty, 15—of medium difficulty, and 22—of low difficulty.

6 Solution of the Task Distribution Problem Taking into Account Their Predicted Values

Let us consider the distribution of tasks between the performers, taking into account the predicted values obtained as a result of applying the neural network predictive model. Tasks were distributed among four specialists of the personal data protection department of the territorial office of Roskomnadzor:

(1) chief specialist (performance level—1, qualification for performing tasks of high complexity—1, medium complexity—1, low complexity—1);
(2) leading specialist (performance level—0.8, qualification for performing tasks of high complexity—1, medium complexity—1, low complexity—1);
(3) a specialist-expert (performance level—0.6, qualification for performing tasks of high complexity—0.5, medium complexity—0.9, low complexity—1);
(4) specialist of the 1st category (performance level—0.7, qualification for performing tasks of high complexity—0.2, medium complexity—0.8, low complexity—0.9).

During the setting parameters for performers, the initial number of tasks was set to zero. In the next step, the current number of tasks was generated:

(1) high level of complexity—2;
(2) medium level of complexity—14;
(3) low level of complexity—21.

After the successful generation of tasks, they were distributed among four performers by their levels of performance and qualifications for performing tasks of a specific level of complexity.

Consider the distribution of tasks taking into account their predicted values. As described earlier, to distribute tasks taking into account the predictive model, it is necessary to form a set consisting of the current number of tasks and their predicted number. In this case, the current number of tasks is represented by 2 tasks of high complexity, 14 tasks of medium complexity, and 21 tasks of low complexity. Per the constructed predictive models, the predicted number of tasks of high complexity is 1, tasks of medium complexity—15, tasks of low complexity—22. Accordingly, the following number of tasks will participate in the current distribution:

(1) 3 tasks of high complexity;

Table 4 Workload of performers with different models of assignment distribution

№	Performers	The workload in the distribution of tasks, without taking into account the predicted values,%	The workload in the distribution of tasks, taking into account the predicted values before their exclusion,%	The workload in the distribution of tasks, taking into account the predicted values after their exclusion,%
1	Chief specialist	65	95	40
2	Leading specialist	50	95	45
3	Specialist-expert	35	90	55
4	Specialist of the 1st category	35	95	45

(2) 29 tasks of medium complexity;
(3) 43 tasks of low complexity.

As a result of the distribution for execution, the chief specialist received 19 tasks, the leading specialist received 19 tasks, the specialist-expert received 18 tasks, and the specialist of the 1st category received 19 tasks.

In accordance with the described model, after the distribution of all tasks among the performers, it is necessary to exclude the forecast tasks from the resulting distribution. In this case, this is 1 task of high complexity, 15 tasks of medium complexity, and 22 tasks of low complexity.

Distributing tasks without taking into account and taking into account their predicted values, the results of the workload of performers were obtained, shown in Table 4.

As can be seen from the presented table, the use of the proposed technology for forecasting and distribution of tasks allows reducing the burden of maintaining the register of PDOs on the chief and leading specialists. This is a positive effect since the main job responsibilities of these specialists include the implementation of inspections of the activities of the PDOs for compliance with the legislation of the Russian Federation in the field of personal data protection and responding to complaints from citizens in this area.

The main duties of a specialist-expert and a specialist of the 1st category include maintaining a register of PDOs, which explains the increased load on them to perform the type of tasks under consideration.

7 Conclusion

The proposed model for the distribution of tasks, taking into account their predicted values in comparison with the original model, allows achieving the following results:

(1) reducing the workload of the chief and leading specialists;

(2) more even distribution of workload between performers;
(3) the possibility of the optimal distribution of tasks between performers, taking into account such features of time series as trend and seasonality;
(4) the possibility of the optimal distribution of tasks between performers, taking into account the vacation schedule and other situations involving the replacement of any position by another specialist.

Thus, the results of the research have shown the effectiveness of the proposed approach and the possibility of its practical use for forecasting and assigning tasks to performers in EDMS.

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