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DEVELOPMENT OF A METHODOLOGY FOR SOLVING PROBLEMS OF SELECTING INFORMATIVE ATTRIBUTES THAT CHARACTERIZE THE STATE OF THE LIFE CYCLE OF RADIO ELECTRONIC MEANS

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The methods of identification of states of radio electronic means, which distinctive feature is providing formulation of the rule of division of sets in space of states and the rules establishing correspondences between sets of parameters and values of indicators of efficiency of life cycle of radio electronic means (LC REM), application of the mentioned rules gives the possibility to construct and control algorithms of optimization of LC REM indicators. The methods for solving the problems of selecting informative REM attributes and displaying monitoring as a process LC REM, which are distinguished by the use of geometric interpretation, consideration of selection problems in the attribute space, and consequently visualization of the analysis and optimization of monitoring are considered.

Introduction

A distinctive feature of radio electronic means (REM) is the presence of a large number of monitored parameters. Monitoring, providing an opportunity to measure and record values and rates of change of REM parameters, can have additional capabilities, giving an insight into the state of REM under a set of parameters as a statistical ensemble. It is known in science when description of behavior of micro ensemble of particle parameters gives possibility to determine macro parameters of systems consisting of them, create phenomenological theory and use for estimation and management of state of such systems. An example is a physical medium consisting of atoms and molecules, micro-parameters here are coordinates and impulses of these particles, phenomenological theory is thermodynamics, macro parameters are volume, pressure, temperature, etc. Observation, in the field of vision, which gets a phase plane, on which it is possible to observe decay and mixing of statistical ensemble of REM parameters, gives additional possibilities for monitoring of life cycle of radio-electronic means (LC REM).

The functional problem of selecting informative features for monitoring LC REM, as well as reducing their list, reducing uncertainty can be solved within the methodology of developing a dictionary of features in systems of classification and recognition of the state of objects [1, 2, 3]. Here the purpose of the selection is to provide the optimal recognition.

Statement of the research problem

The working dictionary should use only the attributes, which, on the one hand, are the most informative and, on the other hand, can be accessible (for example, in terms of costs) for measurement. The definition of the dictionary of attributes in conditions of restrictions on the cost of creation of technical means of observation has peculiarities.

If we denote the features of objects by δ_j, $j = 1, 2, ..., N$, then each object in the N-dimensional feature space can be represented as a vector $x = (x_1, x_2, ..., x_N)$, with coordinates characterizing the properties of objects.

To determine the measure of proximity or similarity between objects in the N-dimensional feature vector space, a metric is introduced. One can use the Euclidean metric

$$d^2(w_{pk}, w_{ql}) = \sum_{j=1}^{N} \left(x_{pk}^j - x_{ql}^{\ j}\right)^2, \tag{1}$$

$$p, q = 1, 2, ..., m; \quad k = 1, 2, ..., k_p; \quad l = 1, 2, ..., k_q,$$

where x_{pk}^j – are the values of the *j*-th feature of the k -th object of the p-th class, i.e. the object of the q-th class, i.e. the object w_{ql} .

As a measure of proximity between objects of a given class Ω_p, $p = 1, 2, ..., m,$ we will use the value

$$S(\Omega_p) = \sqrt{\frac{2}{k_p} \frac{1}{k_{p-1}} \sum_{k=1}^{k_p} \sum_{l=1}^{k_p} d^2(w_{pk}, w_{pl})}, \tag{2}$$

which has the meaning of the root-mean-square scatter of the class or the root-mean-square scatter of the objects within the class Ω_p , as a measure of proximity between objects of a given pair of classes Ω_p and Ω_q, $p, q = 1, ..., m,$ – value

$$R(\Omega_p, \Omega_q) = \sqrt{\frac{1}{k_p k_q} \sum_{k=1}^{k_p} \sum_{l=1}^{k_q} d^2(w_{pk}, w_{ql})}, \tag{3}$$

which has the meaning of the root-mean-square scatter of objects of classes Ω_p and Ω_q.

The set of features used in the working dictionary can be described by an N-dimensional vector $\mathrm{A} = (\alpha_1, \alpha_2, ..., \alpha_N)$, with components take values 1 or 0, depending on whether it is possible or impossible to determine the corresponding feature of the object.

Taking into account the α square of the distance between two objects w_{pk} and w_{ql}

$$d^2\left(w_{pk}, w_{ql}\right) = \sum_{j=1}^{N} \alpha_j \left(x^{(j)}{}_{pk} - x^{(j)}{}_{ql}\right)^2. \tag{4}$$

Consequently, the root-mean-square scatters of the class Ω_p and objects of the classes Ω_p and Ω_q can be written accordingly as follows

$$S\left(\Omega_p\right) = \sqrt{\frac{2}{k_p} \frac{1}{k_p - 1} \sum_{k=1}^{k_p} \sum_{l=1}^{k_p} \sum_{j=1}^{N} \alpha_j \left(x^{(j)}{}_{pk} - x^{(j)}{}_{pl}\right)^2}, \tag{5}$$

$$R\left(\Omega_p, \Omega_q\right) = \sqrt{\frac{1}{k_p} \frac{1}{k_q} \sum_{k=1}^{k_p} \sum_{l=1}^{k_q} \sum_{j=1}^{N} \alpha_j \left(x^{(j)}{}_{pk} - x^{(j)}{}_{pl}\right)^2}. \tag{6}$$

It can be assumed that the costs of using a feature are proportional to their informativeness, i.e., to the number of features of objects that can be determined with their help. This assumption (leaving aside the question about the accuracy characteristics of observation tools) is quite general.

Thus, the costs of using the features

$$C = C\left(\alpha_1, ..., \alpha_N\right) = \sum_{j=1}^{N} C_j \alpha_j, \tag{7}$$

where C_j – the cost of determining the *j*-th feature.

As an indicator of quality or efficiency of the designed recognition system we consider a functional, which in general depends on the function $S\left(\Omega_p\right)$, $R\left(\Omega_p, \Omega_p\right)$ of the decisive rule $L\left(w, \left\{w_g\right\}\right)$

$$I = F\left[S\left(\Omega_p\right);\ R\left(\Omega_p, \Omega_q\right);\ L\left(w, \left\{w_g\right\}\right)\right]. \tag{8}$$

Let the value $L\left(w, \left\{w_g\right\}\right)$ be a measure of proximity between a recognizable object w and a class Ω_g, $g = 1, 2, ..., m$, given by its objects $\left\{w_g\right\}$. As this proximity measure, consider the value

$$L\left(w, \left\{w_g\right\}\right) = \sqrt{\frac{1}{k_g} \sum_{g=1}^{k_g} d^2\left(w, w_g\right)}, \tag{9}$$

which is the root-mean-square distance between the object w and the objects of the class Ω_p.

The decisive rule is $w \in \Omega_g$, if

$$L\left(w,\left\{w_g\right\}\right)=extr\, L\left(w,\left\{w_i\right\}\right). \qquad (10)$$

It is important to note that the reduction of the value $S\left(\Omega_p\right)$, «compression» of objects belonging to each given class, with a simultaneous increase of $R\left(\Omega_p,\Omega_q\right)$, i.e. «dilution» of objects belonging to different classes provides, ultimately, an improvement in the quality of the recognition system. Therefore we will connect the improvement of the efficiency of the system with the achievement of the extremum of the functional *I*.

The statement of the research problem can be formulated as follows.

Let the set of objects be subdivided into classes Ω_i, $i=1, ..., m$, all classes are described a priori in the language of features x_j, $j=1, ..., N$, and funds equal to C_0 are allocated for the creation of technical means of observation. It is required, without exceeding the allocated amount of funds, to construct a working dictionary of attributes, which provides the maximum possible efficiency of the system.

Thus, the problem is reduced to finding a conditional extremum of a functional of the form (8), i.e. to determining *A* implementing $\underset{\alpha}{extr}\ I=\underset{\alpha}{extr}\, F\left[S\left(\Omega_p\right);\ R\left(\Omega_p,\Omega_q\right);\ L\left(w,\left\{w_g\right\}\right)\right]$

$$C=\sum_{j=1}^{N} C_j\alpha_j \le C_0. \qquad (11)$$

Possible kinds of the functional. Let us consider some particular kinds of the functional (11). If the required efficiency of the recognition system can be achieved by a more compact arrangement of objects of each class under some conditions concerning the value of $R\left(\Omega_p,\Omega_q\right)$, then the problem is reduced to finding

$$\min_{\alpha}\max_{i=1,...,m}\left[S\left(\Omega_i\right)\right] \qquad (12)$$

at

$$\sum_{j=1}^{N} C_j\,\alpha_j \le C_0 \text{ and } R\left(\Omega_p,\Omega_q\right)\ge R_0^{(pq)}. \qquad (13)$$

If the required efficiency of the system can be achieved by «removing» from each other objects belonging to different classes under certain conditions concerning the value of $S\left(\Omega_i\right)$, $i=1,\dots,m$, then the problem is reduced to finding

$$\max_{\alpha}\min_{p,q=1,...,m}\left[R\left(\Omega_p,\Omega_q\right)\right] \qquad (14)$$

at

$$\sum_{j=1}^{N} C_j \alpha_j \le C_0 \text{ and } S\left(\Omega_i\right) \le S_0^i. \tag{15}$$

If the proper efficiency of the system can only be achieved by increasing the ratio of distances between classes to the root-means-square scatter of objects within classes, then the problem is reduced to finding

$$\max_{\alpha} \min_{p,q=1,\dots,m} \left[\frac{R^2\left(\Omega_p\ \Omega_q\right)}{S\left(\Omega_p\right) S\left(\Omega_q\right)} \right] \tag{16}$$

at

$$\sum_{j=1}^{N} C_j \alpha_j \le C_0. \tag{17}$$

Solving the problem of selecting informative signs that characterize the state of lc rem processes

The problem considered above is a generalization of the nonlinear programming problem. The optimality C^0 conditions for it can be formulated as follows: for the vector to be an optimal strategy, it is necessary that there exist a scalar $\beta \ge 0$ and a vector $\mu = \{\mu_1, \dots, \mu_n\}$ such that

$$\left.\begin{aligned} &\left[\sum_{r=1}^{n} \mu_r \rho_r^j \right] \frac{dP_j\left(C_j^0\right)}{dC_j} = \beta, \quad j = 1, \dots, N_p; \\ &\sum_{j=1}^{N_p} C_j^0 = C_0\ ; \\ &\sum_{r=1}^{n} \mu_r = 1, \mu_r = 0, если \sum_{j=1}^{N_p} \rho_r^j P_j\left(C_j^0\right) > W\left(C^0\right). \end{aligned}\right\} \tag{18}$$

The introduction of a scalar β and a vector μ increases the number of unknowns C_j^0, μ_r and β to the value $N_p + n + 1$. However, the number of equations equals the number of unknowns, since for any r either $\mu_r = 0$, or

$$\sum_{j=1}^{N_p} \rho_r^j P_j\left(C^0{}_j\right) = W\left(C^0\right). \tag{19}$$

Thus, the solution of the system of equations (18) makes it possible to determine the composition of the features of the working dictionary and the optimal allocation of costs for the creation of observational means of the recognition system under the assumption of dependence $P_j = P_j\left(C_j\right)$ and limitations on the total cost of these means.

With the limitations associated with the possibility of using the entire dictionary of features, the task of selecting a limited list (up to 2–3 features) arises. Here it is possible to be guided by the location of the individual components of the feature vector relative to the boundaries of the serviceability area of the monitoring objects.

Since at the boundary value of the parameter $y^j_{гр}$, the end of vector X must be at the boundary of the serviceability area, it is necessary that the equality

$$x^i{}_{гр} = a^i_j y^j{}_{гр}. \tag{20}$$

In statistical estimation, the correlation coefficient r_{ij} between the parameters can serve as an additional criterion for selection. Since the maximum correlation coefficient provides the maximum amount of information

$$J\left(y^j\right) = H\left(y^i\right) - H\left(y^j / y^i\right), \tag{21}$$

of the parameter y^i. Here $H\left(y^i\right)$ – initial entropy; $H\left(y^j / y^i\right)$ – conditional entropy of the object after measuring the parameter y^j.

The use of binary correlation algorithms makes it possible to formalize and automate the processes of input, processing and recognition of the resulting image with the participation of the decision maker (DM).

Identification of LC REM process state

Identification of LC REM implies the existence of rules defining the states of REM. The attributes allowing to distinguish the states of the monitored object are performance indicators, which for the allocated state will have a given or extreme value. In order to identify REM states in the process of monitoring, it is necessary to check whether the observed parameters are those that provide performance criteria, whether they belong to the set on which the value of performance indicators will have set or extreme values. To solve the problems of state estimation, it is possible to use methods of functional analysis [4, 5].

Objects of observation – parameters and characteristics of REM can be considered as points of vector and functional spaces. For all possible pairs of points on the set Q, there exists a binary relation of comparative efficiency: a point x is more efficient than y if and only if $(x, y \in \Phi)$ or in another notation $x \, \Phi \, y$. Providing LC REM solves the problem of selecting the kernel – the set of maximal elements from by the X binary relation $\Phi : X^{*} = Max\,(Q, \Phi)$. It is assumed that the solution to the problem exists, i.e. the set X^{*} is not empty. In many problems we can assume that the solution – set X^{*} – consists of one element, and the relations between the elements are established with the help of functionals $\Lambda(x)$. For example, point x is more efficient than y when $\Lambda(x) < \Lambda(y)$ or $\Lambda(x) > \Lambda(y)$. It can be shown that in the problems of determining effective points $x_0 \in X^{*}$ in the presence of constraints $x \in Q_1$, the functional $f = \lambda \Lambda'(x_0)$, where $\Lambda'(x_0)$ is the Frechette derivative at the point x_0, is a reference functional to Q_1, at the point x_0 (i.e. $(f, x_0) < (f, x)$ for all $x \in Q_1$.

Thus, the task of analyzing the results of observations in the monitoring process is reduced to determining the reference functionals in the observation points, which makes it possible to assess the deviation of the observed points from the effective ones.

In terms of functional analysis: let Q be a set in a linear topological space E, E' – a conjugate space, $x_0 \in Q$ – an outermost point Q, K_b – a cone of possible directions in Q at the point x_0, K_k – a cone of tangent directions for Q in x_0. If we denote the set of linear functionals, referenced to Q at the point x_0, by Q^{*}, then $Q^{*} = f \in E', f(x) \geq f(x_0)$ for all $x \in Q$, i.e., the reference functionals and the endpoint $x_0 \in Q$ allow us to distinguish the set Q. It can be shown that if Q is a closed convex set, then $Q^{*} = K_k^{*}$, i.e., it makes cones formed by the set of linear functionals, reference to Q at x_0. The cone of tangent directions can be defined by the Frechette derivatives of the operators (convex functions) which link the sets of parameters and performance measures.

Let's consider the methods of finding K^{*} for the ways of setting K with the help of different functionals.

Variant 1: For a cone of decreasing directions K_0. A functional $\Lambda(x)$ in linear space E has a derivative $\Lambda'(x_0, g)$ at a point x_0 in the direction g, i.e., there exists

$$\frac{\lim}{\varepsilon \to +0} \frac{\Lambda(x_0 + \varepsilon g) - \Lambda(x_0)}{\varepsilon} = f(x_{0,} g). \tag{22}$$

$\Lambda(x)$ satisfies the Lipschitz condition in the neighborhood x_0 (for some $\varepsilon_0 > 0$ will be $\varepsilon_0 > 0$ at all $\|x_1 - x_0\| \le \varepsilon_0$, $\|x_2 - x_0\| \le \varepsilon_0$)) and $\Lambda'(x_0, g) < 0$, then $\Lambda(x)$ – correctly decreasing at x_0, and $K = \{g : \Lambda'(x_0, g) < 0\}$.

Variant 2. For a cone of possible directions. In the case of a set which is not defined by a functional. If Q is a convex set, then the set of decreasing directions K_b at a point x_0 has the form

$$K_b = \{\lambda(Q - x_0), \lambda > 0\},$$

$$\text{(i.e. } K_b = \{g : g = \lambda(x - x_0), x \in Q, \lambda > 0\}).$$

Variant 3. For a cone of possible directions. In the case of definition Q by means of affine sets: $E = E_1 \times E_2$, E_1, E_2 are linear topological spaces, the set of efficiency features is defined in E_2, D is a linear operator from E_1 to E_2, $K = \{x \in E,\ x = (x_1, x_2) : Dx_1 = x_2\}$, $K^* = \{f \in E',\ f = (f_1, f_2) : f_1 = -D^* f_2\}$, and as a reference separating function we can use

$$f(x) = \left(-D^* f_2, x_1\right) + (f_2, x_2) = -\left(f_2, D^* x_1 - x_2\right).$$

The application of this function to divide the sets in the parameter space and to formulate rules that establish a correspondence between the parameter sets and the values of performance indicators can provide identification of states in the LC REM monitoring process.

Variant 4. For a cone of tangent directions. $P(x)$ is an operator from E_1 to E_2, differentiable in the neighborhood of the point x_0, $P'(x)$ is continuous in the neighborhood of x_0, and $P'(x_0)$ maps E_1 to all E_2 (i.e. the linear equation $P'(x_0)g = b$ has a solution g for every $b \in E_2$), the set of tangent directions K to the set $Q = \{x : P(x) = 0\}$ at a point x_0 is a subspace $K = \{g : P'(x_0)g = 0\}$.

Variant 5. A typical case for a cone of tangent directions. Let $x \in R^m$, $Q = \{x : G_i(x) = 0,\ i = 1,...,n\}$, where $G_i(x)$ are functions continuously differentiable in the neighborhood of point x_0, $G_i(x_0) = 0$, $i = 1,...,n$, and vectors $G_i'(x_0)$ are linearly independent. Then $K=\left\{g\in R^n:\left(G_i'\left(x_0\right),g\right)=0,i=1,...,n\right\}$. Here $E_1=R^m$, $E_2=R^n$, $P\left(x\right)=\left(C_1\left(x\right),\ldots,G_n\left(x\right)\right)$, $P'\left(x_0\right)$ is a matrix $m\times n$ with i-th column equals $G_i'\left(x_0\right)$.

Variant 6. In the process of monitoring, it is necessary to determine whether the effective value of the function REM characteristic $w\left(z\right)$, in the simplest case the extreme value of the differentiable target function of one variable is provided, for this purpose it is necessary to check whether the derivative is equal to zero at the observed value of the parameter. For multidimensional target functions and their arguments this problem can be considered within the framework of set theory and functional analysis.

The formalization in the problem of observing the optimal tuning, as one of the LC REM processes, is that it is necessary to evaluate the optimality of the tuning process function $v\left(z\right)\in M$ where z is a parameter that determines the numerical value of the required characteristic $w\left(z\right)$ of the tuning object to provide a phase trajectory that provides equality $w\left(0\right)=c$, $w\left(Z\right)=d$, and the extremal value of the integral functional $\int\limits_0^Z \Phi\left(w\left(z\right),v\left(z\right),z\right)dz$, in the presence of the relation given by the differential equation $\dfrac{dw\left(z\right)}{dz}=\varphi\left(w\left(z\right),v\left(z\right),z\right)$.

In problems requiring the maximum correspondence of the optimized characteristic and some desired one, the criterion of minimum of the root-mean-square deviation finds application

$$W_2\left(X\right)=\overline{\left(Y\left(X\right)-Y^*\right)^2}, \tag{23}$$

where Y^* – the desired or required by the technical specification value of the characteristic.

For a characteristic given by a discrete set of points, the target function

$$W_2\left(X\right)=\frac{1}{N}\sum_{i=1}^{N}\gamma_i\left(Y\left(X,p_i\right)-Y_i^*\right)^2, \tag{24}$$

where N – the number of discretization points of the independent variable p;

$Y\left(X,p_i\right)$ – the number of discretization points of the independent variable;

γ_i – weight coefficient of the i-th value of the optimized characteristic, reflecting the importance of the i -th point in comparison with the others (as a rule, $0 < \gamma_i < 1$).

In some optimization problems it is necessary to ensure that the optimized characteristic exceeds or does not exceed some given level. These optimality criteria are realized by the following functions:

– to ensure that a given level is exceeded

$$W_3(X) = \begin{cases} 0 & \text{at} \quad Y(X) \geq Y_L^*, \\ \left(Y - Y(X)\right)^2 & \text{at} \quad Y(X) < Y_L^*; \end{cases} \tag{25}$$

– to ensure that the set level is not exceeded

$$W_4(X) = \begin{cases} 0 & \text{at} \quad Y(X) \leq Y_U^*, \\ \left(Y - Y(X)\right)^2 & \text{at} \quad Y(X) > Y_U^*, \end{cases} \tag{26}$$

where $Y_L{}^*$, $Y_U{}^*$ – lower and upper limits of the allowable area for the characteristic $Y(X)$.

If it is necessary that the optimized characteristic passes in some acceptable zone (corridor), use a combination of the previous two optimality criteria

$$W(X) = \begin{cases} 0 & \text{at} \quad Y_L^* \leq Y(X) \leq Y_U^*, \\ \left(Y(X) - Y_U^*\right)^2 & \text{at} \quad Y(X) > Y_U^*, \\ \left(Y_L - Y(X)\right)^2 & \text{at} \quad Y(X) < Y_L^*. \end{cases} \tag{27}$$

In cases where you want to realize only the shape of the curve, while ignoring the constant vertical displacement, the shift criterion is used

$$W_6(X) = \sum_{i=1}^{N} \gamma_i \left(Y_i^* - Y(X, p_i) - Y_{cp}\right)^2, \tag{28}$$

where $Y_{cp} = \dfrac{1}{N} \sum_{i=1}^{N} \left(Y_i^* - Y(X, p_i)\right)$.

Important characteristics of computational process and, first of all, the convergence of optimization process depend on the kind of target function. Signs of target function derivatives on controllable parameters do not remain constant in the whole admissible domain, the latter circumstance leads to their gully character (for example, circuit design problems), which leads to large computational costs and requires special attention to the choice of optimization method.

Another peculiarity of target functions is that they are usually multiextremal and along with the global minimum there are local minima.

Multicriteria optimization problems constitute a general class of problems of identification of the set of effective solutions. They are characterized by the fact that a binary relation on the set of alternatives, from which it is necessary to choose, is connected with a set of indices – criteria forming a vector efficiency criterion. This binary relation is generated in different ways. So, if

$$W(x)=\left(W^{1}(x),...,W^{m}(x)\right) \tag{29}$$

vector criterion on set X, then the binary relation can be a Pareto relation or a Slater relation. In other cases the binary relation on X is set by the system of DM preferences. It is assumed that the main source of information is a person who has sufficient information to make a (single) decision. Identification of the system of preferences of the DM is one of the main problems in solving multicriteria problems. Usually the procedures for identifying preferences of the DM are built on the language of vector evaluations of alternatives, i.e. based on the values of the vector criterion.

DM decision making is facilitated by finding the Pareto set or Slater set by criterion (29), here methodological problems lose their acuteness to a large extent, since the notion of solving a multicriteria problem has already been clearly defined. There remain difficulties of computational character typical for extreme problems.

Methods for solving the problem of finding efficient (Pareto-optimal) and inefficient (Slater-optimal) alternatives are being intensively developed [6, 7, 8], there are programs, software packages and software systems implemented on computers.

Algorithms based on scalarization – reduction to parametric family of scalar optimization problems have great «visualization».

From convex analysis it follows that if $x_{*}\in P(X,W)$ is an effective point in a linear multicriteria problem (with linear criteria in polyhedron X), then there exists vector Λ

$$\lambda\in\Lambda=\left\{\lambda\in E^{m}\,/\,\lambda_{i}>0,\ i=1,\ldots,\ m;\ \sum_{i=1}^{m}\lambda_{i}=1\right\},$$

such that x^{*} is a solution to the linear and nonlinear programming problem

$$\sum_{i=1}^{m}\lambda_{i}W^{i}(x)\to\max_{x\in X}. \tag{30}$$

Inversely, for any $\lambda\in\Lambda$ solution of problem (30) is an effective point.

Hence, it follows that well-developed methods of linear and nonlinear programming can be used for the search of $P(X,W)$ and use the result as an effective set in the process of mapping the situation related to the location of the set of real values of the attribute parameters, relative to the set of their effective values in the implementation of LC REM monitoring.

Conclusion

Methods of solving problems of selecting informative signs for monitoring LC REM, by classifying the states of REM and LC processes in the space of signs, each of which has a certain importance, which allowed to find a comprehensive criterion and formalize the selection procedure.

Methods for identifying REM states that interpret them as elements of conjugate linear spaces and setting initial sets using linear and nonlinear functionals are improved, which makes it possible to formulate rules for separating sets in the space of states and rules that establish correspondences between sets of parameters and values of LC REM performance indicators. The application of these rules makes it possible to construct algorithms for optimization of LC REM performance indicators.

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