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DEVELOPMENT OF METHODS FOR INTELLIGENT ASSESSMENT OF PARAMETERS IN DECISION SUPPORT SYSTEMS

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The object of the study is decision support systems.

The subject of the study is the process of evaluating the parameters of decision support systems.

The problem addressed in the study is improving the reliability of parameter evaluation in decision support systems while ensuring the required operational efficiency, regardless of the volume of incoming data.

The originality of the proposed method lies in the application of additional advanced procedures, which enable the following:

– verification of the topology and parameters of decision support systems, taking into account the degree of uncertainty in the initial data, achieved through the use of an improved penguin colony algorithm;

– preliminary selection of individuals for configuring an evolving artificial neural network using an improved genetic algorithm, which reduces solution search time and increases the reliability of the obtained results;

– adjustment of the weights of the evolving artificial neural network, leading to improved accuracy in parameter evaluation of decision support systems;

– implementation of additional mechanisms for tuning the parameters of the evolving artificial neural network through modification of the membership function;

– enhancement of the reliability of parameter evaluation in decision support systems via parallel assessment using multiple evaluation methods;

– utilization of a hybrid evaluation of decision support system parameters, enabling correct operation in the absence of conditions such as stationarity, homogeneity, normality, and independence.

An example of applying the proposed methodology to the evaluation of decision support system parameters has been conducted. The experiment demonstrated an increase in the reliability of parameter evaluation by 17–21% through the use of additional procedures, while maintaining the specified level of operational efficiency

Keywords: artificial neural networks, improved genetic algorithm, destabilizing factors, metaheuristic algorithm

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1. Introduction

The problem of improving the reliability of parameter evaluation in decision support systems is highly relevant in modern information systems of various functional purposes [1]. Experience from recent conflicts involving the use of advanced information systems has shown that existing approaches to parameter evaluation in decision support systems do not ensure sufficiently reliable assessments with the required level of timeliness [2].

This situation is associated with several reasons:

– the significant role of the human factor in the evaluation process of decision support system parameters [3];

– the large number of heterogeneous components within decision support systems [3];

– parameter evaluation of decision support systems is carried out under conditions of uncertainty, which causes delays in data processing [4];

– the presence of numerous destabilizing factors that affect the reliability of parameter evaluation in decision support systems;

– the coexistence of structured and unstructured data in decision support systems, both of which must be processed, among other challenges.

Given the heterogeneity, the significant number of destabilizing factors, and the varying dimensionality of indicators that describe them, the need for parameter evaluation in decision support systems necessitates the search for new approaches. One such approach is the use of metaheuristic algorithms [5, 6].

The application of metaheuristic algorithms in their canonical form enables an increase in the timeliness of parameter evaluation in decision support systems [7]. However, further acceleration of this process typically results in a deterioration of reliability in parameter evaluation [8].

This motivates the implementation of various strategies aimed at improving the convergence speed and accuracy of basic metaheuristic algorithms when applied to the evaluation of decision support system parameters. One promising direction for enhancing the reliability of such evaluations is the refinement of these algorithms through integration, comparison, and the development of new procedures for their combined application. This underscores the relevance of research focused on designing new approaches (or improving existing ones) for the intelligent evaluation of parameters in decision support systems.

2. Literature review and problem statement

In [9], an algorithm of cognitive modeling is presented, highlighting the main advantages of cognitive tools. However, a drawback of this approach is the failure to account for the type of uncertainty regarding the state of the analyzed object, which results from the absence of appropriate correction coefficients.

In [10], the essence of cognitive modeling and scenario planning is revealed. The authors propose a system of complementary principles for the construction and implementation of scenarios, distinguish between different approaches to scenario development, and describe a scenario modeling procedure based on fuzzy cognitive maps. Nevertheless, the proposed approach does not account for the type of uncertainty regarding the state of the analyzed object, nor does it consider noise in the input data. This limitation is due to the lack of corrective coefficients addressing uncertainty types and data noise.

In [11], the main approaches to cognitive modeling are analyzed. Cognitive analysis allows for the study of problems with fuzzy factors and interrelationships, the consideration of environmental changes, and the use of objectively formed trends in the development of a situation to one's advantage. However, the issue of describing complex and dynamic processes remains unaddressed, as the research focuses exclusively on modeling static processes.

In [12], a method for analyzing large datasets is presented, oriented toward uncovering hidden information within them. The method includes operations such as generating analytical baselines, reducing variables, detecting sparse features, and formulating rules. Its shortcomings include the inability to incorporate different decision evaluation strategies and to account for the type of uncertainty in input data, again due to the lack of corrective coefficients.

In [13], a mechanism for transforming informational models of construction objects into their equivalent structural models is described. This mechanism is designed to automate the necessary operations of transformation, modification, and supplementation during such information exchange. However, the approach does not provide for assessing the adequacy and reliability of the transformation process, nor does it allow correction of the resulting models. This limitation arises from the static structure of the models.

In [14], an analytical web platform for studying the geographic and temporal distribution of incidents is developed. The platform contains several dashboards with statistically significant territorial results. The disadvantages of this platform include the inability to assess the adequacy and reliability of information transformation, as well as high computational complexity. Another drawback is the lack of unidirectionality in solution search, caused by the mathematical apparatus employed.

In [15], a fuzzy hierarchical method for evaluating the quality of library services is proposed, enabling assessment across multiple input parameters. However, the method cannot guarantee adequacy and reliability of evaluations, nor can it estimate the associated errors.

In [16], 30 algorithms for big data processing are analyzed, with their advantages and disadvantages identified. It was established that big data analysis should be conducted layer by layer, in real time, and include self-learning capabilities. Yet, these methods suffer from high computational complexity and lack mechanisms for verifying the adequacy of the obtained results.

In [17], an approach for evaluating input data in decision support systems is introduced. The approach relies on clustering a base set of input data, analyzing them, and subsequently training the system based on the analysis. However, drawbacks include the gradual accumulation of errors in evaluation and training due to the absence of mechanisms for assessing the adequacy of decisions made.

In [18], a method for processing data from multiple sources of information is described. While it enables multi-source data processing, the method produces low-accuracy results and lacks procedures for verifying their reliability.

In [19], a comparative analysis of existing decision support technologies is conducted, including the analytic hierarchy process, neural networks, fuzzy set theory, genetic algorithms, and neuro-fuzzy modeling. Their strengths, weaknesses, and areas of application are identified. It is shown that the analytic hierarchy process performs well under conditions of complete initial information, but its reliance on expert comparisons and selection of evaluation criteria introduces a high degree of subjectivity. For forecasting tasks under risk and uncertainty, fuzzy set theory and neural networks are considered more appropriate.

In [20], the use of combined strategies involving metaheuristic algorithms together with other artificial intelligence techniques is discussed. The main drawback of this approach is insufficient efficiency in processing heterogeneous data when multiple metaheuristic algorithms are applied simultaneously, due to the diversity of input data types.

The analysis of works [9–20] shows that common shortcomings of the above studies are as follows:

– lack of mechanisms for forming a hierarchical system of indicators for comprehensive evaluation of decision support system states;

– absence of consideration for the computational resources of the system performing the evaluation process;

– absence of mechanisms for adjusting the indicator system governing the evaluation process;

– absence of mechanisms for selective use of artificial neural network training methods;

– high computational complexity;

– failure to account for the available computational (hardware) resources of the system;

– lack of prioritization in the search direction.

To partially address these shortcomings, it is proposed to develop a methodology for intelligent parameter evaluation in decision support systems.

3. The aim and objectives of the study

The aim of the study is the development of a methodology for intelligent parameter evaluation in decision support systems. This will enhance the reliability of parameter evaluation in such systems while maintaining the required level of timeliness, thereby enabling subsequent managerial decisions to be based on intelligent assessment. Furthermore, this will facilitate the development (or improvement) of software for the effective functioning of decision support systems.

To achieve this aim, the following objectives were accomplished:

– to determine the algorithm of the proposed methodology;

– to provide an example of applying the methodology in the intelligent evaluation of decision support system parameters;

– to propose recommendations for integrating the methodology into decision support systems.

4. Materials and methods

The object of the study is decision support systems.

The subject of the study is the process of evaluating parameters of decision support systems.

Parameters in the evaluation system of decision support systems generally differ in origin, measurement units, and degree of influence on the overall evaluation outcome. For this reason, it is appropriate to employ artificial intelligence theory, specifically:

– improved genetic algorithm – used to automate the evaluation process, enabling random and ordered information changes as well as permutations of individuals within the evaluation space of decision support system parameters. In this study, the improved genetic algorithm is applied at the stage of preliminary selection of individuals to increase the reliability of parameter evaluation. Additionally, it is used for configuring the parameters of a convolutional artificial neural network;

– improved penguin colony algorithm – applied for the verification of the topology and parameters of decision support systems, as well as the topology and parameters of destabilizing influence factors. This enhances the reliability of the resulting parameter evaluations;

– evolving artificial neural networks – applied to obtain a generalized assessment of decision support system parameters that differ in origin and measurement units, while accounting for the number of input parameters subject to evaluation.

The hypothesis of the study is that it is possible to improve the reliability of parameter evaluation in decision support systems, while maintaining the required timeliness, through the use of the proposed intelligent evaluation methodology.

Simulation of the proposed methodology was conducted in the Microsoft Visual Studio 2022 software environment (USA). The task used for the simulation of the intelligent parameter evaluation process was the determination of the composition of a military force grouping. The hardware used for the research was an AMD Ryzen 5 processor.

The operating parameters of the improved algorithm were as follows:

– number of iterations – 25;

– number of individuals in the algorithm population – 25;

– feature space range – [–100, 100].

The structure of the evolving artificial neural network is presented in [20].

5. Development of a methodology for intelligent evaluation of parameters in decision support systems

5. 1. Algorithm of the methodology for intelligent evaluation of parameters in decision support systems

The methodology for intelligent evaluation of parameters in decision support systems consists of the following sequence of steps:

Step 1. Input of initial data.

At this stage, the available input data on decision support systems and destabilizing influence factors are introduced, namely:

– the number and type of technical tools included in the decision support system;

– the number and type of destabilizing factors affecting the objectivity of system parameter evaluation;

– technical characteristics of the components of the decision support system;

– technical characteristics of the destabilizing factors influencing the objectivity of parameter evaluation;

– topology of connections within the decision support system;

– topology of connections of destabilizing factors;

– types of data circulating within the decision support system;

– available computational resources of the decision support system;

– information about the operating environment of the decision support system, etc.

At this stage, data processing arrays are extracted within the initial observation window, exponential normalization is applied, and tasks are defined for training, testing, and forecasting processes.

Step 2. Verification of parameters required for computations.

This step refines the initial data about the decision support system and destabilizing factors, considering the type of uncertainty about the system's state. The refinement is performed using the improved penguin colony algorithm proposed by the authors in [20].

Step 3. Formation of the topology of the evolving artificial neural network.

At this stage, the improved penguin colony algorithm is used to construct the topology of the evolving artificial neural network, as proposed in [20], based on the verified data.

Step 4. Preliminary selection of individuals for the genetic algorithm.

To improve the reliability of the obtained results, a preliminary selection of individuals is performed using the improved genetic algorithm described in [19]. The improved genetic algorithm is subsequently used in Step 5.3.

Step 5. Parallel evaluation of the state of the decision support system using multiple approaches.

Step 5. 1. Evaluation of the system state based on the multiple regression algorithm.

The traditional technology of sequential evaluation and forecasting of decision support system states under observations containing a stochastic component relies on the mathematical apparatus of multivariate regression [13]. In the general case, multivariate regression is an extension of the univariate linear regression algorithm to the situation of multiple interdependent variables X, which determine the structure of the baseline model.

The multiple regression algorithm describes the dependence of predicted parameters on the values of input parameters (regressors), which serve as control parameters of decision support systems. For constructing a linear forecast, regression analysis enables the sequential evaluation of state parameters, control parameters, and output parameters of decision support systems.

Let's assume that the mean values of the predicted output characteristics of decision support systems $Z_{k+\tau}=(z_1,\ldots,z_{M_y})_{k+\tau}$, $k=1, \ldots, N$, related to the state parameters, which also include control parameters $X_k=(x_1,\ldots,x_{M_x})_k$, $k=1, \ldots, N$, in the form of the functional dependence

$$Z_{k+\tau}=f\left(X_k\right)+V_k,\ k=1,\ldots,N. \tag{1}$$

It is assumed that the additive noise terms (in this case, intentional destructive influence) are centered, such that $EV_k=0$, $k=1, \ldots, N$.

The task of regression evaluation consists in establishing the form of the relationship between dependent and independent variables over time. For the task of corrective control, the functional dependence (1) allows for linearization, which makes it possible to restrict the model to a linear regression form

$$Z_{k+\tau}=C_k X_k+V_k,\ k=1,\ldots,N. \tag{2}$$

The rapid obsolescence of data, caused by the transient nature of military force group operations formed by a non-stationary process, leads to the use of a multivariate sample within a sliding observation window of size L as input data. In this case, the input data arrays at each forecasting step are represented as matrices:

$$X_{L:M_x}=\begin{bmatrix} x_{11}, & x_{12} & \cdots & x_{1M_x} \\ x_{21}, & x_{22} & \cdots & x_{2M_x} \\ \cdots & \cdots & \cdots & \cdots \\ x_{L1}, & x_{L2} & \cdots & x_{LM_x} \end{bmatrix};$$

$$Z_{L:M_Y}=\begin{bmatrix} z_{11}, & z_{12} & \cdots & z_{1M_y} \\ z_{21}, & z_{22} & \cdots & z_{2M_y} \\ \cdots & \cdots & \cdots & \cdots \\ z_{L-\tau,1}, & z_{L-\tau,2} & \cdots & z_{L-\tau,M_y} \end{bmatrix}.$$

Thus, based on the minimization of the quadratic functional

$$V^T V=\left(Z-XC\right)^T\left(Z-XC\right)= \\ =Z^T Z-2C^T X^T Z+C^T X^T XC.$$

That is, using the method of least squares, it is possible to obtain the well-known matrix expression for the predictive transfer coefficient of linear regression

$$C=\left(X^T X\right)^{-1} X^T. \tag{3}$$

In this case, the algorithm of linear regression forecasting is described by the simplest matrix relation of the form

$$Z_{k+\tau}=C_k X_k, \tag{4}$$

where $Z_{k+\tau}=(z_1,\ldots,z_{M_z})^T_{k+\tau}$, denotes the predicted values, and the regressors incorporate only those state parameters of the decision support system (or its subsystems) that allow manipulation of their values during the control process, i.e., the control parameters $U_k=(u_1,\ldots,u_{M_U})^T_k$.

The traditional scheme of linear regression includes important assumptions, known as the Gauss–Markov conditions [13, 14]. This algorithm meets the requirements of adaptation associated with changes in the pairwise correlation coefficient.

It is important to note that parameters with a correlation coefficient greater than 0.9 cannot be used, since in the matrix of normal equations derived from the least squares method, degeneracy or poor conditioning may occur.

A second distinctive feature of the developed algorithm is the application of a sliding observation window. Particular attention should be paid to the fact that within this window, the output array of predicted values of decision support system parameters $Z_{L:M_Y}$ must be shifted backward by τ samples relative to the regressor array $X_{L:M_X}$.

Within the sliding observation interval, the main forecasting cycle is carried out. At each step, the current mean values and covariance structures are corrected.

The forecast of decision support system parameters is performed as described earlier, through vector multiplication of the current centered monitoring data values and the matrix transfer coefficient of the least-squares filter. The justification for the optimality of this approach directly follows from the well-known Gauss-Markov theorem [9].

The output values of decision support system parameters from the predictor form a vector representing the development of output parameters. As quality indicators, the root means square error (RMSE) of the forecast or the average values of the obtained errors are typically used. This allows the forecast trajectory to remain sufficiently close to the trajectory of the real process (with the mean relative error not exceeding 9%).

Step 5. 2. Evaluation of the state of the decision support system based on the improved canonical correlation method.

The improved canonical correlation method generalizes multiple correlation to the case where two or more sets of interrelated variables X and Y are considered [9, 18]. From the perspective of constructing a linear forecast, the application of canonical correlation analysis enables simultaneous evaluation of groups of interrelated output parameters, which are treated as generalized linear combinations of interdependent parameters.

Let's consider the mathematical apparatus of canonical correlations. Let's define possible linear combinations for q variables Y and p variables X in the general population

$$X^* = \sum_{i=1}^{p} \alpha_i X_i;\ Y^* = \sum_{j=1}^{q} \beta_j Y_j.$$

The tasks of canonical correlation analysis include determining the coefficients α_i and β_i [10].

The algorithm of multivariate analysis is based on the improved canonical correlation method, in which the initial dataset is divided into an observed part and an unobserved part: $X \in N_p\left\{\mu_1, P_1\right\}$ and $Y \in N_q\left\{\mu_2, P_2\right\}$. In this case, the covariance matrix takes the form:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}; \tag{5}$$

$$\rho_c = \frac{\operatorname{cov}\left(X\alpha, Y\beta\right)}{\sqrt{\operatorname{var}\left(X\alpha\right)\cdot \operatorname{var}\left(Y\beta\right)}} = \frac{\alpha^{\mathrm{T}} P_{12} \beta}{\sqrt{\left(\alpha^{\mathrm{T}} P_{11} \alpha\right)\cdot\left(\beta^{\mathrm{T}} P_{22} \beta\right)}}.$$

It is supposed now that the state of the decision support system at time k is described (with sufficient accuracy) by m parameters combined into the vector $X = (x_1, \ldots, x_m)$. Geometrically, this means that the state of the decision support system corresponds to a point in an m-dimensional phase space R^m. Let the measurement results of these parameters be available at discrete time moments $k = 1, \ldots, N$.

It is possible to combine the obtained measurement results of the decision support system parameters into a matrix X of dimension $n \times m$. The i-th row of this matrix corresponds to the result of the i-th vector measurement, $i = 1, \ldots, n$, and the j-th column corresponds to the set of n measurement values of the j-th parameter of the decision support system across all observations, $j = 1, \ldots, m$.

The task is to refine or construct, based on the available data, a mathematical model suitable for both forecasting parameter values and control. In the case of non-stationary processes, such a model is not universal and requires continuous reconfiguration.

If the data are normalized, estimates of the covariance and correlation matrices are constructed. The correlation matrix estimate involves normalization by the standard deviation; if this operation has already been performed, then the two estimates coincide. These calculations are carried out for known a and P, which are replaced by their estimates. The quality of the estimation depends on the size and reliability of the available input data regarding the decision support system parameters.

The defined problem is as follows: there are m parameters, of which p are observed and the remaining q are unobserved. It is required to estimate the predicted parameters based on the available input data.

As an assumption, it is considered that the input data are already normalized and centered. The covariance matrix has the form (5), where P_{11} – the covariance matrix of the observed parameters obtained during monitoring, P_{22} – the covariance matrix of the predicted parameters, and P_{12} – the mutual covariance matrix of observed and unobserved parameters.

The task reduces to finding the weight coefficient matrix C by minimizing the mean value of the sum of squared residuals

$$trE\left[\left(x_2 - C\cdot x_1\right)^T \left(x_2 - C\cdot x_1\right)\right] \to \min.$$

As a result of transformations, this expression takes the form

$$\begin{aligned} &trE\left[\left(x_2 - C\cdot x_1\right)^T \left(x_2 - C\cdot x_1\right)\right] = \\ &= tr\begin{bmatrix} E\left(x_2 x_2^T\right) - C\cdot E\left(x_1 x_2^T\right) - \\ - E\left(x_2 x_1^T\right)\cdot C^T + C\cdot E\left(x_1 x_1^T\right)\cdot C^T \end{bmatrix} = \\ &= tr\left[P_{22} - C\cdot P_{12} - P_{21}^T\cdot C^T + C\cdot P_{11}\cdot C^T\right] \to \min, \end{aligned}$$

where the optimal linear estimate of the vector X_2 based on the known vector X_1 is given by

$$\hat{X}_2 = E\left(X_2\right) + P_{12}^T \cdot P_{11}^{-1} \cdot \left(X_1 - E\left(X_1\right)\right). \tag{6}$$

Here, sample estimates are used

$$\hat{X}_2 = \bar{X}_2 + \hat{P}_{12}^T \cdot \hat{P}_{11}^{-1} \cdot \left(X_1 - \bar{X}_1\right).$$

In terms of the task of forecasting the output characteristics of decision support systems, expression (7) takes the form

$$\tilde{Z}_{t+\tau} = \bar{Z}_{t-L,t} + \hat{P}_{UZ}^T \cdot \hat{P}_u^{-1} \cdot \left(U_t - \bar{U}_{t-L,t}\right). \tag{7}$$

By substituting the obtained value of the matrix $\hat{C}$ into the expression for the mean value of the sum of squared residuals, the covariance matrix of estimation errors is obtained in the form

$$\begin{aligned} &P_v = P_{22} - 2C\cdot P_{12} + C\cdot P_{11}\cdot C^T = \\ &= P_{22} - 2P_{12}^T\cdot P_{11}^{-1}\cdot P_{12} + P_{12}^T\cdot P_{11}^{-1}\cdot P_{11}\cdot P_{11}^{-1}\cdot P_{12} = \\ &= P_{22} - P_{12}^T\cdot P_{11}^{-1}\cdot P_{12}. \end{aligned} \tag{8}$$

The diagonal elements of this matrix represent the variances of the estimates of the corresponding components (in dimensionless form). Typically, confidence intervals calculated using this formula turn out to be overly pessimistic. Variances can alternatively be estimated by computing the sum of squared forecast errors using the available dataset; however, this estimate only pertains to the given data. Its correspondence with theoretical characteristics depends on the sample size of the decision support system parameters.

At this stage, training is performed using data within the sliding observation window.

Step 5. 3. At this stage, training is performed using data within the sliding observation window.

As noted earlier, the proposed statistical algorithms for evaluating decision support system parameters provide optimal solutions under a set of constraints (stationarity, homogeneity, normality, independence, etc.), which in practice are often not satisfied.

However, a complete abandonment of statistical algorithms for forecasting decision support system parameters is also not rational. The universality of the quadratic criterion allows good initial approximations to the averaged dynamics of the forecasted process to be obtained.

Therefore, this study proposes the development of a hybrid algorithm that combines multivariate statistical analysis algorithms with a self-developing computational scheme based on evolutionary modeling. The key idea is to replace optimization of the dynamic system with the process of its evolution. In fact, this refers to the stochastic self-organization of the applied mathematical model.

Based on the traditional statistical algorithm, $A\{S(A), x\}$ is characterized by a given structure $S(A)$ and a set of parameters x, the required output parameter of the decision support system $\hat{y}$.

At the same time, the efficiency of the algorithm $Eff(A)$ is evaluated based on its application to input data within the sliding observation window. As efficiency indicators, general qualitative rules described earlier are used, or local accuracy measures of prediction quality, such as the total squared prediction error.

At this stage, the second part of the improved genetic algorithm proposed in [19] is applied. Two operators are introduced:

– variation operator $Var(A)$

$$A \Rightarrow \left\{A_1,\ldots,A_{N_a} : A_i \neq A_j \neq A, \forall i,j\right\};$$

– selection operator $Sel(A_1,\ldots,A_{N_g})$

$$\left\{A_1,\ldots,A_{N_g}\right\} \Rightarrow \left\{\begin{matrix} A_{<1>},\ldots,A_{<N_a>} : Eff\left(A_{<1>}\right) \geq \ldots \geq \\ \geq Eff\left(A_{<N_a>}\right) \geq Eff\left(A_j\right), \forall j > N_a \end{matrix}\right\},$$

where N_a – the number of "selected" algorithms used for further reproduction; $N_g = N_a(1 + N_d)$ – the number of strategies per generation subject to selection; N_d – the number of offspring strategies generated according to predefined rules at each iteration.

Let $A_0 = A\{S_0(x), x_0\}$ – be a certain variant of a forecasting algorithm with specified parameters and structure, accepted as the baseline "parent" algorithm. Then the evolutionary modeling technology reduces to repeated application of the sequence of operators

$$\begin{matrix} A_o \Rightarrow Var\left(A_0\right) = \left\{A_a\right\} = \left\{A_1,\ldots,A_{N_g}\right\} \Rightarrow Var\left(A_d\right) = \left\{A_d\right\} = \left\{A_1,\ldots,A_{N_d}\right\} \\ \Uparrow \qquad\qquad\qquad\qquad\qquad\qquad \Downarrow \\ \psi\left(A_1,\ldots,A_{N_g}\right) = A_0 = \left\{A_{<1>},\ldots,A_{<N_a>}\right\} \Leftarrow \left\{A_g\right\} = \left\{A_a \cup A_d\right\}. \end{matrix} \quad (9)$$

The presented approach to evolutionary optimization, combined with the algorithm based on the canonical correlation method described earlier, forms a single hybrid algorithm. This algorithm retains all the advantages of statistical analysis while complementing them. It allows for the avoidance of shortcomings associated with the lack of Gaussianity and stationarity in real observation series of parameters of complex, non-stationary technical systems.

Step 6. Formation of a generalized evaluation of decision support system parameters.

Based on an evolving artificial neural network, a generalized evaluation of the state of the decision support system is formed. This is achieved through the convolution of each group of state parameters of the decision support system. The architecture of the evolving artificial neural network used for parameter evaluation is presented in [20].

Step 7. Verification of the stopping criterion of the combined algorithm. The algorithm terminates if the maximum number of iterations is reached. Otherwise, new generations are produced, and the verification conditions are repeated.

Step 8. Determination of the required computational resources for evaluation.

To avoid infinite computational loops in Steps 1–8 of the proposed method and to increase computational efficiency, the system load is additionally assessed. If the computational complexity exceeds a predefined threshold, the number of software and hardware resources that must be additionally engaged is determined using the method proposed in [20].

Step 9. Training of agent knowledge bases.

At this stage, the knowledge bases of agents from the set of bio-inspired algorithms employed in this study are trained. As the training method, deep learning, as proposed in [20], is used.

The end.

5. 2. Example of applying the proposed methodology to the evaluation of decision support system parameters

Like any mathematical or informational tool, the effectiveness of the proposed methodology for evaluation and forecasting can only be assessed through the quality indicators of the metasystem for which it is designed and improved.

In the context of this study, the metasystem is represented by a proactive decision support system. In this case, the effectiveness of such a system is measured by external, or exogenous, numerical characteristics, which are hierarchically defined by a higher-level decision support system.

The suitability criterion of the forecasting algorithm (9) consists in verifying the condition that the predicted values of the decision support system state vector parameters belong to the constraint set $\{|x_i^* \pm \Delta_i| \wedge \Omega_{per}^i\}, \forall i = 1,\ldots,M$.

Here $x_i^* \pm \Delta_i, \forall i = 1,\ldots,M$ – the set of constraints ensuring stabilization of decision support system parameter values within the neighborhood of a reference value $x_i^*, \forall i = 1,\ldots,M$, represents constraints defined by the regulations of the controlled parameter of the decision support system, Ω_{per} – the set of technical constraints imposed on decision support system parameters.

As an example, a proactive evaluation system of decision support system parameters was constructed based on an algorithm of exhaustive search over possible values of control parameters.

The formation of an ε-neighborhood $\Delta = \Delta(U_0, (t))$ can be carried out using several approaches:

1. $\Delta = [U_0 - R/2; U_0 + R/2]$, where $R = \text{abs}(U_{\max} - U_{\min})$; $U_{\max}$, $U_{\min}$ – the admissible bounds of the control parameter.

2. $\Delta = [U_0 - s(U); U_0 + s(U)]$, where $s(U)$ – the root mean square deviation of the control parameter.

3. $\Delta = [U_0 - t_0 \cdot s / \text{sqrt}(N); U_0 + t_0 \cdot s / \text{sqrt}(N)]$, where t_0 – the critical value of the Student's t-statistic for a given confidence level α, N – the number of samples in the observation window.

4. $\Delta = [U_0 - \%R \cdot U_0; U_0 + \%R \cdot U_0]$, where $\%R$ – the proportion of the mean value used as the half-interval of the search for the optimal solution (e.g., $\%R = 0.05$ for 5% – for a 5% deviation).

Next, the number of search steps in the parameter variation range is set as N_{step}. The total number of possible values for the parameter estimates of the decision support system, formed as the number of arrangements with repetitions, is equal to $(N_{step})^{M_{man}}$, where M_{man} – the number of decision support system parameters used for manipulation.

It is important to note that the number of possible control strategies grows rapidly with increasing N_{step} and M_{man}. Examples of the number of possible parameter evaluation variants for several N_{step} and M_{man} values are presented in Table 1.

Given that each step is associated with a considerable number of operations, including the computation of inverse matrices, the increase of the above-mentioned parameters should be carried out considering the performance capabilities of the hardware.

Table 1

Number of variants generated through exhaustive search

M_{man}	N_{step}				
	5	10	15	20	25
2	25	100	225	400	625
3	125	1000	3375	8000	15625
4	625	10000	50625	160000	390625
5	3125	100000	759375	3200000	9765625

According to the adopted algorithm, for each variant of parameter evaluation, a forecast is generated using regression, neural network, or other technologies. A comparison of the forecasted output parameter values is then performed, considering the set of technological constraints imposed on the parameters of the decision support system. This makes it possible to directly identify the optimal value of the system state parameter at a given moment in time.

A comparison of the obtained results with the traditional scheme of situational assessment, which is implemented in the decision support system management process, allows the terminal effectiveness of the hybrid evaluation and forecasting approach to be assessed through the quality indicators of the higher-level system for which it was developed.

5. 3. Recommendations for integrating the proposed methodology into decision support systems

As an example of implementing hybrid evaluation and forecasting of decision support system parameters for non-stationary processes, it is possible to consider its construction based on a back estimation (BE) procedure of the decision support system state parameters. Improved evaluation of the system state is achieved through:

– sequential (step-by-step) modification of a preselected output parameter;

– backward recalculation of the output parameters (with improved values) into manipulation parameters (i.e., the control parameters applied in the current situation).

A formalized formulation of intelligent evaluation and forecasting of decision support system parameters is presented on the basis of constructing a back estimation algorithm for possible parameter values.

Let there be an initial parameter value U_0, obtained from the data of the considered decision support system. Then, using a predetermined incremental step δY for improving the system state indicator, it is possible to form $Y = Y_0 + \delta Y$, where the efficiency of evaluation according to the chosen criterion is found to be higher, i.e., $Eff(Y) > Eff(Y_0)$.

The size of the step is selected with consideration of the physical and technical characteristics of the specific decision support system; in the example under consideration, it was chosen as 2–3% of the forecast estimated from the current state of the system. For a non-degenerate operator F, it is possible to construct a back mapping $\widehat{U}_k^* = F^{-1}(\tilde{Y}_{k+1} + \delta Y_{k+1})$, which provides control parameter values $\widehat{U}_k^*$, with higher efficiency compared to the reference control. At the same time, it is necessary to additionally verify the admissibility of the obtained control values $\widehat{U}_k^*$ and other state parameters X, i.e., whether the corresponding numerical values belong to the set of admissible values $\widehat{X}_k^*$.

Variations in the decision support system state parameters are considered using a sliding observation window. The window size is chosen based on the dynamics of variation in the mean values of the monitored parameters.

Neural network forecasting technologies are based on iterative refinement of the weight coefficients of multiplicative inputs of nonlinear nodes, combined within a unified network structure [19, 20].

The process of adjusting the weight coefficients is carried out according to a feedback signal, formed by the difference between the network's output signals and the actual measured values, combined with the corresponding input signals into the training dataset.

Let $(x_1, x_2,..., x_p)^T$ – be the input parameters, $w^1 = (w_{11}^1, w_{22}^1, \ldots, w_{p1}^1)^T$, $w^{12} = (w_{11}^2, w_{22}^2, \ldots, w_{p1}^2)^T$ – denote the boosting coefficients of the first- and second-generation models. The evolving artificial neural network has a varying number of neurons at each level: level A (input layer) – p neurons, level S (first hidden layer) – l neurons, and level R (second hidden layer) – k neurons.

Let N be the number of input–output points obtained experimentally or through simulation, $X = (X_1, X_2, \ldots, X_p)$ – be the input vector, and $D = (d_1, d_2, \ldots, d_k)$ – the set of real or calculated outputs [15, 18].

The objective function to be minimized is expressed as

$$E(\varpi) = \frac{1}{2}\left[\sum_{i=1}^{N}\sum_{j=1}^{l}\left(y_{ij}^1 - d_{ij}^1\right) + \sum_{i=1}^{N}\sum_{j=1}^{k}\left(y_{ij}^2 - d_{ij}^2\right)\right]^2 = \frac{1}{2}\sum_{i=1}^{N}\left(\sum_{j=1}^{l}\left(y_{ij}^1 - d_{ij}^1\right) + \sum_{j=1}^{k}\left(y_{ij}^2 - d_{ij}^2\right)\right)^2.$$

Minimization is achieved through gradient descent, meaning that the adjustment of weight coefficients is represented as

$$\Delta\varpi_{ij}^{(n)} = -\eta\frac{\partial E}{\partial \omega_{ij}}, n = 1, 2,$$

where $\varpi_{ij}^{(n)}$ – the weight of the connection between the i-th neuron of layer $n-1$ and the j-th neuron of layer n, and $1 < 0 < \eta$ – the learning rate. It is known that: $\frac{\partial E}{\partial \omega_{ij}} = \frac{\partial E}{\partial y_j}\cdot\frac{\partial y_j}{\partial S_j}\cdot\frac{\partial S_j}{\partial \omega_{ij}}$, where y_j – the output of the neuron, $S_j = \sum_{i=1}^{N}\omega_{ij}x_{ij}$ – the weighted sum of its input signals (the argument of the activation function). The sigmoid function is typically used as the standard activation function $A = \frac{1}{1 + e^{-\sum \omega_i x_i}}$ or the hyperbolic tangent $A = \text{th}\, x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$, $\text{th}' x = \frac{1}{\text{ch}^2(x)}$, where ch($x$) – denotes the hyperbolic cosine and x – the hyperbolic tangent $(\text{th}\, x)' = 1 - (\text{th}\, x)^2$. The third factor represents the output of the neuron from the previous layer. The first factor is expanded as $\frac{\partial E}{\partial y_i} = \sum_k \frac{\partial E}{\partial y_k}\cdot\frac{\partial y_k}{\partial S_k}\cdot\frac{\partial S_k}{\partial y_i} = \sum_k \frac{\partial E}{\partial y_k}\cdot\frac{\partial y_k}{\partial S_k}$.

The final summation is carried out over the neurons of the (n–1)-th layer. Introducing a new substitution, it is possible to obtain a recursive formula $\delta_j^{(n)} = \left[\sum_k \delta_k^{(n+1)}\cdot\omega_{jk}^{(n+1)}\right]\cdot\frac{\partial y_j}{\partial S_j}$ that, knowing $\delta_j^{(n+1)}$, makes it possible to compute $\delta_j^{(n)}$. For the output layer $\delta_e^{(n)} = (y_e^{(n)} - d_e)\cdot\frac{dy_e}{dS_e}$. Thus, the adjustment of the weight coefficients takes the following form $\Delta\varpi_{ij}^{(n)} = -\eta\cdot\delta_j^{(n)} y_i^{(n-1)}$, $n = 1, 2$ [5, 8].

To provide the weight correction process with a certain degree of inertia, thereby smoothing abrupt jumps when moving across the surface of the objective function, the final expression is supplemented with the weight changes from the previous iteration

$$\Delta\varpi_{ij}^{(n)} = -\eta \cdot \begin{pmatrix} \mu \cdot \Delta\omega_j^{(n)} \cdot (t-1) + \\ +(1-\mu) \cdot \delta_j^{(n)} y_i^{(n-1)} \end{pmatrix}, \; n = 1, 2,$$

where μ – the momentum coefficient and t – the current iteration number. For the sigmoid activation function, $\delta_e^{(n)} = (y_e^{(n)} - d_e) \cdot (1 - S_e) \cdot S_e$, and for the hyperbolic tangent $\delta_e^{(n)} = (y_e^{(n)} - d_e) \cdot (1 - S_e^2) \cdot S_e$ [5, 8].

An evaluation of the effectiveness of the proposed methodology for parameter assessment in decision support systems was carried out in comparison with well-known approaches for evaluating this type of system. The evaluation results, according to the criterion of decision reliability, are presented in Table 2.

Table 2

Evaluation of the effectiveness of the proposed methodology for parameter assessment in decision support systems

Approach	Completeness	Accuracy	Sensitivity	Mean value
Densenet 201	0.6163	0.4243	0.4485	0.4335
Densenet 121	0.9523	0.8489	0.8590	0.8588
MobileNetV2	0.9289	0.9295	0.9289	0.9287
DenseNet-SEGR	0.9588	0.9514	0.9511	0.9512
Gradient Boosting Classifier	0.92021	0.91128	0.9003	0.91449
KNN	0.8736	0.8839	0.88529	0.9003
LSTM	0.7981	0.8005	0.8191	0.8217
RNN	0.8014	0.8122	0.8022	0.8101
CNN	0.9232	0.9104	0.9271	0.9301
Proposed Method	0.9511	0.9611	0.9601	0.9612

As can be seen from Table 2, the improvement in the reliability of parameter evaluation in decision support systems is achieved at the level of 17–21% using additional procedures, while maintaining the specified level of timeliness.

6. Discussion of the results of the methodology for evaluating decision support system parameters

The advantages of the proposed method are determined by the following factors:

1. Verification of the topology and parameters of decision support systems is carried out with consideration of the degree of uncertainty in the input data (Step 2), using the improved penguin colony algorithm, compared with [9]. This reduces the time required for the initial setup of the evaluation methodology.

2. Preliminary selection of individuals for configuring the evolving artificial. The neural network (Step 3) is performed using the improved genetic algorithm, which decreases solution search time and increases the reliability of results, compared with [14].

3. Exploration of solution spaces for the problem of parameter evaluation in decision support systems, including those described by non-standard functions, is achieved using the improved penguin colony algorithm (Steps 2, 3), compared with [13].

4. Adjustment of weights in the evolving artificial neural network improves the running an accuracy of parameter evaluation (Step 9), compared with [17].

5. Additional correction mechanisms of the evolving artificial neural network are applied through membership function modification procedures (Step 9), compared with [15].

6. Increased reliability of decision support system parameter evaluation is achieved through parallel assessment with multiple methods (Step 5), compared with [16].

7. Hybrid evaluation of decision support system parameters ensures correct operation in the absence of stationarity, homogeneity, normality, and independence (expressions (1)–(9), Step 5. 3), compared with [12].

8. Simultaneous multi-directional solution search (Steps 1–9, Table 2).

9. Estimation of required computational resources that must be additionally engaged in cases where available resources are insufficient (Step 8), compared with [18].

The drawbacks of the proposed methodology include:

– loss of informativeness during parameter evaluation due to the construction of membership functions;

– lower accuracy in the evaluation of individual parameters of decision support systems;

– reduced reliability of obtained solutions when searching for solutions in several directions simultaneously;

– higher computational complexity compared to other methods, due to the use of advanced correction procedures for the evolving artificial neural network parameters.

The proposed methodology allows for:

– determination of the optimal indicator for evaluating decision support system parameters according to a selected optimization criterion;

– identification of effective measures to improve the efficiency of parameter evaluation in decision support systems;

– acceleration of the parameter evaluation process in decision support systems.

The limitations of the study include the requirement for information about the degree of uncertainty in the evaluation parameters of decision support systems, and the necessity of accounting for delays in collecting and transmitting information from system components.

The proposed methodology is advisable for solving the problem of evaluating parameters in decision support systems characterized by a high degree of complexity and restricted available hardware resources. It is particularly appropriate for application in automated systems such as Dzvin-AS and Oreanda-PS, as well as in information systems such as Delta.

Integration into these automated control (information) systems will improve the timeliness of decision support system state evaluations, while ensuring the required level of reliability.

7. Conclusions

1. An algorithm of the proposed methodology has been defined, which through the use of additional and improved procedures makes it possible to:

– verify the topology and parameters of decision support systems while accounting for the degree of uncertainty in the initial data, using the improved penguin colony algorithm.

This reduces the time required for the initial configuration of the evaluation methodology;

– perform a preliminary selection of individuals for the configuration of the evolving artificial neural network using an improved genetic algorithm, thereby reducing solution search time and increasing the reliability of the obtained results;

– explore the solution spaces of the parameter evaluation problem in decision support systems, including those described by non-standard functions, by applying the improved penguin colony algorithm;

– adjust the weights of the evolving artificial neural network, thereby increasing the accuracy of parameter evaluation in decision support systems;

– employ additional mechanisms for tuning the parameters of the evolving artificial neural network through the use of membership function modification procedures;

– improve the reliability of parameter evaluation in decision support systems through parallel assessment using multiple evaluation methods;

– apply a hybrid evaluation of decision support system parameters, ensuring correct operation even in the absence of stationarity, homogeneity, normality, and independence conditions;

– conduct simultaneous solution searches in different directions using a multi-agent approach;

– calculate the required amount of computational resources to be engaged in cases where the available computational resources are insufficient for evaluation.

2. An example of applying the proposed methodology to the evaluation of the decision support system parameters have been provided. The results demonstrated an increase in the reliability of parameter evaluation by 17–21% using additional procedures, while maintaining the specified level of timeliness.

3. Recommendations for integrating the proposed methodology into decision support systems have been presented. As an example of implementing hybrid evaluation and forecasting of parameters in decision support systems for non-stationary processes, a variant based on the back estimation procedure of system state parameters has been considered.

Conflict of interest

The authors declare that they have no conflict of interest regarding this study, including financial, personal, authorship, or any other form of conflict that could have influenced the research and its results presented in this article.

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Data availability

The manuscript has associated data stored in a data repository.

Use of artificial intelligence tools

The authors confirm that no artificial intelligence technologies were used in the preparation of this work.

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