DOI: https://doi.org/10.15276/hait.09.2026.13
UDC 004.021:004.415

Model and method for evolutionary control of the decision-making structure in intelligent systems

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ABSTRACT

The relevance of the study is обусловлена the fact that modern intelligent software systems operate under conditions of incomplete, conflicting, and dynamically changing data, as well as limited computational resources, which necessitates improving the adaptability, robustness, and correctness of decision-making processes compared to traditional approaches focused on tuning individual algorithms. Furthermore, the increasing complexity of information environments and the need to process heterogeneous data sources intensify the requirements for consistency and reliability of analysis results. Under such conditions, the transition to controlling the structure of the decision-making process as a higher-level object becomes particularly important. **The aim of the study** is to improve the adaptability, robustness, and correctness of decisions by shifting from the tuning of individual algorithms to the controlled modification of the structure of the analysis process, including the composition of active software components, the order of their interaction, and the rules governing transitions between processing modes. **The methods** of the study are based on the approach of evolutionary control of the decision-making structure, which involves controlled transformations of admissible configurations, integration of fuzzy interpretation and evidence aggregation, assessment of the reliability and consistency of information sources, as well as formal proof of correctness, finite convergence, and local optimality properties. The proposed approach enables adaptive selection of the analysis process configuration depending on the level of uncertainty and available resources. In addition, the method ensures a balance between decision-making accuracy and computational resource costs under dynamic operating conditions. **The results** of the study consist in the development of a model and a method for evolutionary control of the decision-making structure, as well as their practical implementation in the form of an intelligent medical diagnostic system, where experimental studies have shown that as the level of uncertainty increases, the system automatically activates additional mechanisms for source consistency control and predictive analysis, thereby providing enhanced robustness of results compared to a baseline fixed configuration.

Keywords: Adaptive systems; intelligent software systems; evolutionary control; decision-making structure; uncertainty; fuzzy interpretation; evidence aggregation; source reliability; adaptive architecture; life cycle

***For citation*: Komleva N. O. "Model and method for evolutionary control of the decision-making structure in intelligent systems". *Herald of Advanced of Information Technology*. 2026; Vol.9 No.2: 181–198. DOI: https://doi.org/10.15276/hait.09.2026.13**

INTRODUCTION

Modern intelligent software systems operate in environments characterized by a high level of information uncertainty, conflicting input data, dynamic changes in operating conditions, and limited computational resources. Under such conditions, system effectiveness is determined not only by the accuracy of individual analysis algorithms, but also by the system's ability to adapt the decision-making process as an integral structure, including the set of involved components, their interaction modes, and the rules governing transitions between processing regimes. Most existing approaches focus on parametric adaptation or on selecting among predefined operating modes, which significantly limits the system's ability to respond correctly to changes in data quality and uncertainty levels.

Within the scope of this work, the model and method are developed for an adaptive intelligent system in which the control object is the structure of the decision-making process, including the set of active algorithms, the order of their interaction, and the conditions for their activation. In what follows, optimization is understood as a process of controlled structural and algorithmic adaptation aimed at aligning decision quality with the level of uncertainty and resource constraints, rather than as a classical search for a global optimum.

The absence of formalized mechanisms for controlling the structure of the decision-making process leads to two typical problems: making insufficiently justified decisions under a lack of information, or, conversely, employing excessively complex analysis mechanisms in situations where this is not justified. In view of the above, the transition from evaluating individual decisions to assessing system behavior at the meta-level becomes a relevant task – that is, evaluating the system's ability to modify its own decision-making logic depending on the level of uncertainty, data conflict, and available resources. Such a transition requires not only new control models, but also appropriate criteria and metrics that make it possible to assess the adaptability, robustness, and correctness of structural transformations during system operation.

LITERATURE REVIEW AND PROBLEM STATEMENT

In contemporary research, the problem of decision-making under uncertainty has been primarily examined in the context of complex information and networked systems. In [1], a systematic review of decision-making methods for hyperconnected networks was conducted, where uncertainty arose due to incomplete information and dynamic changes in the environment. Similar issues related to inference stabilization and belief updating under stochastic conditions were analyzed in [2]. At the same time, in these works the decision-making process was considered mainly at the level of individual inference algorithms, without explicit formalization of the structure of the analysis and decision-selection process itself.

Subsequent studies focused on the formalization of knowledge and belief updating processes. In [3], it was shown that conditional belief updating makes it possible to reduce the effect of implicit uncertainty during evidence accumulation. The study presented in [4] examined learning and decision-making under different types of uncertainty, including expected and unexpected uncertainty, which confirmed the limitations of classical learning models. However, the proposed approaches did not specify how changes in the level of uncertainty should influence the selection or restructuring of the decision-making logic as an integrated process.

To overcome these limitations, the use of extended formal frameworks was proposed. In [5], a model for joint assessment of stochasticity and volatility was developed, enabling adaptation of the learning process to environmental changes. In turn, [6] generalized approaches to uncertainty representation using fuzzy relations, which laid the foundation for hybrid decision-making models. Nevertheless, these models focused on improving evaluation and inference mechanisms and did not address the problem of controlling the structure of the decision-making process depending on system operating conditions.

A separate line of research addressed methods for control and optimization of decision-making processes. In the monograph [7], model predictive control methods were formalized and later used as a basis for controlling complex adaptive systems. The application of fuzzy multicriteria methods to decision-making problems was demonstrated in [8]. However, within these approaches, the structure of the decision-making process was generally assumed to be fixed, and adaptation was reduced to adjusting parameters or criterion weights.

Architectural aspects of adaptive and self-adaptive software systems were investigated in [9], where the evolution of approaches to engineering such systems was outlined. In [10], a systematic review of existing architectural solutions, feedback mechanisms, and scalability issues was carried out. Despite the attention given to architectural adaptation, formal decision-making models in these works were considered in isolation from mechanisms for controlling the structure of analysis and decision selection processes.

Further studies focused on the formalization of adaptation processes.

In [11], the integration of fuzzy logic was proposed to optimize decision support systems operating under highly uncertain data. In [12], approaches to the engineering of self-adaptive systems were generalized in the form of a structured survey, which made it possible to systematize existing solutions. At the same time, adaptation was interpreted mainly as the system’s reaction to external changes, without formalized control over the evolution of the internal structure of the decision-making process.

In [13], the life cycle and requirements of software systems using smart contracts were analyzed, demonstrating the necessity of formalized control over process structures throughout their operation. Architectural mechanisms for supporting high adaptability were proposed in [14], where the concept of multilevel feedback loops was introduced. In [15], self-organizing demand–supply management systems were examined, confirming the feasibility of decentralized solutions in dynamic environments. However, these approaches did not establish an explicit relationship between the level of uncertainty, data conflict, and the choice of the decision-making process structure.

Formal models of adaptive systems based on fuzzy rules and Petri nets were proposed in [16], enabling the description of system behavior at the structural level. The problem of evaluating such systems was systematized in [17], where the absence of a unified formal approach to assessing adaptation effectiveness was shown. This significantly complicates the comparative evaluation of different decision-making structures and the justification of their selection under specific operating conditions.

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

Issues related to information loss, the impact of missing and redundant data on decision quality during result aggregation were analyzed in [18], which is consistent with multicriteria analysis approaches and confirms the need to control source reliability in decision-making processes [19]. The application of fuzzy sets to safety and reliability problems was investigated in [20], demonstrating the effectiveness of fuzzy models in critical systems. However, mechanisms for assessing trust in information sources typically did not influence changes in the overall structure of the decision-making process.

Further research aimed at combining architectural and stochastic models. In [21], stochastic modeling of adaptation processes based on software system architecture was proposed. The integration of requirements, control models, and a model predictive approach was implemented in [22]. Nevertheless, structural transformations of the decision-making process in these works were not formalized as a controllable meta-level object.

Hybrid decision-making methods based on information fusion were proposed in [23], while fuzzy control systems with a limited number of parameters were presented in [24].

Decision-making problems in conflict and cooperative scenarios with incomplete information were formalized in [25], [26]. The theoretical foundations of network-based decision analysis methods were summarized in [27], and modern approaches to measuring uncertainty within evidence theory were reviewed in [28].

Further development of evidence theory and belief structures was carried out in [29], where mechanisms for weight generation and decision support were formalized. The application of intelligent methods in complex engineering and industrial systems was generalized in [30]. Finally, works [31], [32] demonstrated the use of probabilistic and Bayesian models for decision support in critical systems, particularly in emergency control tasks. Subsequent studies [33], [34] extended these approaches through dynamic and hybrid models focused on risk analysis and the control of complex technical objects. Papers [35], [36] addressed general problems of decision adaptation and data consistency in complex information environments. At the same time, studies [37], [38] showed that, despite the effectiveness of such models, the formalized representation and controlled evolution of decision-making structures in intelligent software systems remain an open scientific problem.

Thus, the literature analysis indicates the existence of a scientific and applied problem related to the lack of formalized models and methods for controlling the structure of the decision-making process itself in intelligent software systems under uncertainty. Most existing approaches focus either on improving individual inference algorithms or on architectural adaptation of software components, without considering the structure of the analysis and decision selection process as an explicit control object. As a result, changes in the level of informational uncertainty, data conflict, or resource constraints do not have a formalized reflection in the choice of analysis logic, the set of active components, or their interaction modes.

There is also a lack of a unified formal framework that would allow describing, comparing, and controllably evolving different decision-making structures throughout the life cycle of an intelligent system. Existing models generally do not ensure coordination between mechanisms for uncertainty assessment, trust correction for information sources, and structural transformations of the decision-making process, which prevents a systematic evaluation of the adaptability and robustness of such systems.

In this context, the development of a formalized model and method for evolutionary control of the decision-making process structure is a relevant task, in which the analysis structure is treated as a controllable meta-level object capable of changing according to the current operating conditions of the system. Solving this task enables a transition from fragmented parametric adaptation to the controlled evolution of decision-making logic, aligned with the level of uncertainty, information quality, and resource constraints.

RESEARCH AIM AND OBJECTIVES

The aim of this study is to improve the adaptability, robustness, and correctness of the decision-making process in intelligent software systems under conditions of informational and structural uncertainty by means of evolutionary control of the decision-making structure, which enables the system to modify the logic of analysis, information processing modes, and component activation rules in accordance with current operating conditions.

To achieve the stated aim, the following objectives are addressed in this study.

1. To analyze existing approaches to adaptive control and decision-making in intelligent software systems and to identify their limitations with respect

to managing the structure of the decision-making process.

2. To formalize the decision-making structure as a control object defined by a set of components, their interaction modes, and admissible configurations under conditions of uncertainty.

3. To develop an algebraic representation of the space of control structures that enables the description of composition, extension, reduction, and adaptation operations while accounting for multi-level uncertainty and resource constraints.

4. To propose a method for synthesizing control strategies that realizes the selection and evolution of decision-making structures as a controlled sequence of algebraic transformations.

5. To define an evolutionary life-cycle model of an intelligent software system in which iterations correspond not only to the refinement of implementation parameters but also to the controlled restructuring of the decision-making process.

6. To demonstrate the feasibility of the proposed approach through modeling the selection of control structures under different levels of uncertainty and resource constraints.

MATERIALS AND METHODS OF EVOLUTIONARY CONTROL OF THE DECISION-MAKING STRUCTURE

Formalization of the decision-making process structure

The model of evolutionary control of the decision-making structure in intelligent software systems constitutes the main scientific result of this study and defines a formalized representation of the decision-making process as a controllable structure. Within this work, a model is understood as a formal representation of the decision-making process in which the structure of analysis and decision selection is treated as an explicit control object that can be modified depending on the system's operating conditions. The decision-making process in an intelligent software system is considered as a formalized sequence of data-processing stages, within which the interpretation of input information, evaluation of alternative decisions, reconciliation of results from different knowledge sources, and control of the uncertainty level of the obtained conclusion are performed. Such a process structure determines the order of interaction between software components of the system and the rules for transitions between the stages of analysis and decision selection.

Input data are represented in the form of a vector of observable parameters $x = (x_1, x_2, \ldots, x_n)$, which is formed on the basis of measurement results, logs, sensor data, or expert assessments. At the first stage, these parameters undergo semantic interpretation using fuzzy rules, as a result of which a generalized fuzzy assessment $\mu_L(x) \in [0,1]$ is computed, reflecting the degree of conformity of the current state to the target state.

For further formalized processing of the interpretation results, a set of alternative decisions $\Theta=\{H_1,H_2\}$ is introduced, where H_1 corresponds to accepting the target decision, and H_2 represents its alternative.

Within the integration of fuzzy inference with evidence theory, the mass function is constructed by taking into account both the degree to which the current state belongs to the target class and the level of trust in the information source. The support of the hypotheses is defined so that a portion of the mass, proportional to the value of the fuzzy assessment, is distributed between hypotheses H_1 and H_2, while the remaining mass is interpreted as generalized uncertainty and assigned to the entire set Θ. This approach corresponds to the classical discounting mechanism in Dempster–Shafer theory and makes it possible to separate the support of the alternative hypothesis from residual uncertainty.

Taking into account the trust coefficient $\gamma \in [0,1]$, the mass function takes the following form:

$$m(H_1) = \gamma * \mu L(x),$$
$$m(H_2) = \gamma * (1 - \mu L(x)),$$
$$m(H_1 \cup H_2) = 1 - \gamma.$$

The specified representation of mass functions does not assume an explicit assignment of mass to the empty set, since conflicts between knowledge sources are not modeled at the stage of forming individual assessments but are identified and taken into account separately during inter-source consistency analysis. This makes it possible to separate the mechanisms of local interpretation from those of global consistency evaluation. As a result, this approach to constructing mass functions ensures a balanced representation of fuzzy inference outcomes and provides a foundation for subsequent analysis of assessment consistency and adaptive adjustment of the decision-making structure.

The initial values of the trust coefficients $\gamma_i^{(0)}$ are computed as a weighted sum of the normalized expert characteristics:

$$\gamma_i^{(0)} = \sum_{k=1}^{q} z_k c_{ik}, \quad \sum_{k=1}^{q} z_k = 1, \;\; z_k \geq 0,$$

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

where z_k are the weighting coefficients of the criteria that reflect their relative importance in a specific application context of the system.

Such characteristics include indicators of professional competence, stability of assessments, and expert behavior during interaction with the system. This makes it possible to define the initial parameters of the decision-making process without relying on external, non-formalized procedures. In the case of multiple information sources, the described method for constructing mass functions is applied to each source individually, followed by consideration of their individual trust coefficients.

To automatically detect discrepancies between knowledge sources within the process structure, the Kullback–Leibler divergence between the corresponding mass functions is used.

For each source E_i, an aggregated discrepancy measure is computed:

$$S_i = \sum_{j \neq i} D_{KL}(m_i || m_j).$$

Based on this value, the trust coefficient is adjusted to reflect the actual consistency of the assessments in the current analysis session:

$$\gamma_i^{(cons)} = \frac{1}{1 + \lambda S_i},$$

where $\lambda > 0$ determines the sensitivity of the model to inter-expert discrepancies.

The integral trust coefficient is formed as a combination of the initial estimate and the result of the correction:

$$\gamma_i = \beta_1 \gamma_i^{(0)} + \beta_2 \gamma_i^{(cons)}, \ \ \beta_1 + \beta_2 = 1,$$

which ensures a balance between the initial characteristics of the expert and the actual consistency of their judgments within a particular decision-making session. To align the trust coefficients with the evidence aggregation procedure, the experts' weighting coefficients are determined through normalization.

$$w_i = \frac{\gamma_i}{\sum_{k=1}^{n} \gamma_k},$$

after which the weighted aggregation of mass functions is performed:

$$m_{agg}(H_1) = \sum_{i=1}^{n} w_i * m_i(H_1),$$
$$m_{agg}(H_2) = \sum_{i=1}^{n} w_i * m_i(H_2),$$
$$m_{agg}(H_1 \cup H_2) = 1 - m_{agg}(H_1) - m_{agg}(H_2).$$

The belief distribution obtained as a result of evidence aggregation is used not only to accept or reject a decision, but also as an indicator of the current operating mode of the intelligent system. In particular, the level of residual uncertainty is interpreted as a quantitative characteristic of the complexity and reliability of the information situation in which the analysis is performed.

At low values of generalized uncertainty, the system can operate in a simplified mode, using a minimally sufficient structural configuration of the decision-making process. In this case, only basic mechanisms of fuzzy interpretation and aggregation are applied, which makes it possible to reduce computational costs and system response time without loss of correctness of the results.

When the level of uncertainty increases or significant discrepancies between knowledge sources are detected, a transition to an extended control structure is initiated. Such a structure may include additional information sources, refined fuzzy inference rules, mechanisms for conflict assessment, and adaptive correction of trust coefficients. The selection of an extended configuration is interpreted as a structural response of the system to the increased complexity of the analysis conditions.

Thus, the aggregated measure of uncertainty acts as a control signal that determines the appropriateness of applying a particular decision-making structure, allowing system adaptation to be interpreted not only at the parametric level, but also at the level of controlling the logic and organization of the analysis process.

Algebraic representation of the space of control structures

To move from parametric adaptation to evolutionary control of decision-making logic, it is necessary to formalize the notion of a *control structure* as a meta-level object. Unlike descriptions of individual algorithms (fuzzy inference, evidence aggregation, etc.), the control structure defines the *admissible organization of the process itself*: which components are involved, in what sequence, under what conditions they are activated/deactivated, and how the analysis mode changes depending on uncertainty and resource constraints.

Let $\check{S}$ denote the universal set of possible control structures of an intelligent software system. Each structure $S \in \check{S}$ is interpreted as a formalized representation of a configuration of control components (for example, fuzzy interpretation modules, Dempster–Shafer theory mechanisms, conflict evaluation procedures, decision acceptance/rejection rules, threshold and trust update mechanisms), as well as the relations between them, transition rules, and interaction modes.

Since the selection and feasibility of a structure depend on the current operating conditions, a vector of multilevel uncertainty is introduced:

$$U = \langle U^{info}, U^{struct}, U^{context}, U^{res} \rangle, \quad (1)$$

where U^{info} reflects data incompleteness and conflict, U^{struct} denotes uncertainty related to the structure of the object or hypotheses, $U^{context}$ characterizes the variability of operating conditions, and U^{res} represents computational resource constraints.

For each vector U, a set of admissible control structures is defined as $\breve{S}(U) \subseteq \breve{S}$, which includes only those structures that can be correctly applied under the current constraints.

To quantitatively represent the correspondence of a structure to the operating conditions, an admissibility function is defined as $\breve{D}_U: \breve{S} \rightarrow [0,1]$, where $\breve{D}_U(S)=1$ indicates full compliance with the imposed constraints, and $\breve{D}_U(S)=0$ denotes an inadmissible structure. In practice, $\breve{D}_U(\cdot)$ is used as a formal control mechanism ensuring that structural transformations do not lead the system into an incorrect or unrealizable operating mode.

The algebra of control structures under conditions U is defined as a parameterized algebraic system

$$\breve{A}_{\breve{S}}(U) = \langle \breve{S}(U),\ \circ_U,\ \oplus_U,\ \ominus_U,\ I_U \rangle,$$

where $I_U \in \breve{S}(U)$ is the neutral element corresponding to the minimally admissible structure, that is, the baseline analysis mode under conditions U.

The proposed algebraic representation of the space of control structures differs from existing approaches in that the object of formalization is not individual algorithms or architectural patterns, but the very logic of organizing the decision-making process as a controllable configuration. This makes it possible to treat structural changes not as a side effect of parameter adaptation, but as a purposeful operation within a clearly defined algebraic space constrained by the current operating conditions of the system.

The operations have the following meaning.

1. Composition $\circ_U$. The operation $S_1 \circ_U S_2$ forms a structure in which the mechanisms of S_1 and S_2 are combined (for example, adding a conflict assessment module and source trust adjustment within the fuzzy inference and evidence aggregation process). The composition is partially defined: it is admissible only if the resulting structure remains within $\breve{S}(U)$ and does not violate resource or structural constraints.

2. Structural extension $\oplus_U$. The operation $S \oplus_U \Delta$ corresponds to a controlled increase in structural complexity (adding new knowledge sources, introducing more detailed rules, or activating additional validation and consistency-checking procedures), provided that it is consistent with U^{res} and does not reduce admissibility below an acceptable level.

3. Reduction $\ominus_U$. The operation $S \ominus_U \Delta$ implements structural simplification (removal of certain components or transition to a more conservative or resource-efficient mode) under increasing uncertainty or resource scarcity. Reduction is also partial: the resulting structure must remain admissible within $\breve{S}(U)$.

In addition to algebraic operations, a partial dominance relation $S_1 \preceq_U S_2$ is introduced for the comparative analysis of alternative structures. This relation is interpreted as S_2 being no worse than S_1 under conditions U, taking into account structural complexity, resource cost, and robustness to uncertainty. Such an ordering makes it possible to treat $\breve{S}(U)$ as a partially ordered set and to formally pose structure selection problems without binding them to specific algorithmic implementations.

The dynamic aspect of evolutionary control is represented by the evolution operator $\breve{F}: \breve{S}(U_t) \rightarrow \breve{S}(U_{t+1})$, which defines the transition from a structure that is valid under conditions U_t to a structure that is admissible under the updated conditions U_{t+1}. Within this formulation, the dynamics of the intelligent system are described not only as changes in numerical estimates or parameters, but as an evolution in the space of control structures – a sequence of algebraic transformations that modify the configuration of the decision-making process in accordance with the level of uncertainty, data conflict, and available computational resources.

Method for synthesizing evolutionary control strategies

This method is intended for the formalized construction and adaptation of the control structure of the decision-making process in intelligent software systems under changing levels of multi-level uncertainty. The method is based on the algebra of control structures and implements control as a sequential evolution of structures that are admissible under the current operating conditions.

A key feature of the proposed method is that the synthesis of the control strategy is performed

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

without fixing a predefined architecture or adaptation scenario. Instead, the strategy is formed dynamically as a trajectory in the space of admissible structures, determined by the current level of multi-level uncertainty and available resource constraints.

The control strategy is formalized as a sequence of control structures

$$\breve{T} = \{S_t\}_{t=0}^{T}, \quad S_t \in \breve{S}(U_t),$$

where U_t is the vector of multi-level uncertainty at step t in accordance with (1).

The transition between structures is defined by the evolution operator:

$$S_{t+1} = \breve{F}(S_t, U_t, \Delta U_t),$$

which is implemented through algebraic operations of composition, structural expansion, or reduction of control structures.

The correctness of using a given structure is controlled by the admissibility function:

$$\breve{D}_{U_t}(S) : \breve{S} \to [0,1],$$

which reflects the degree of consistency of structure S with the current informational, structural, and resource constraints. A structure is considered admissible if

$$\breve{D}_{U_t}(S) \geq \delta,$$

where $\delta \in (0,1]$ is a predefined admissibility threshold.

The appropriateness of using a control structure is evaluated using a local efficiency function:

$$E(S, U_t) = \sum_{k=1}^{K} \alpha_k e_k(S, U_t), \qquad (2)$$

where e_k represent partial criteria – namely, the reliability and soundness of diagnostic decisions, robustness to uncertainty, resource cost, and explainability – and α_k are the corresponding weighting coefficients.

The strategy synthesis method is implemented through the sequential execution of the following steps.

Step 1. Fixing the operating conditions. Based on the current state of the system, the value of the multilevel uncertainty vector U_t is determined, which defines the admissible space of control structures $\breve{S}(U_t)$.

Step 2. Formation of the candidate set. For the current structure S_t, the set of structures reachable through a single algebraic transformation is determined:

$$\breve{N}(S_t, U_t) \subseteq \breve{S}(U_t).$$

Step 3. Verification of structural admissibility. From the set $\breve{N}(S_t, U_t)$, a subset of admissible structures is selected:

$$\breve{N}_\delta(S_t, U_t) = S \in \breve{N}(S_t, U_t) | \breve{D}_{U_t}(S) \geq \delta\}.$$

Step 4. Efficiency evaluation. For each structure $S \in \breve{N}_\delta(S_t, U_t)$, the value of the local efficiency function $E(S, U_t)$ is computed.

Step 5. Selection of the next structure. The next control structure is determined according to the rule of local optimization:

$$S_{t+1} = \text{select} \max_{S \in \breve{N}_\delta(S_t, U_t)} E(S, U_t).$$

If $E(S_{t+1}, U_t) \leq E(S_t, U_t)$, stabilization of the structure is allowed, that is, $S_{t+1} = S_t$.

Step 6. Feasibility control of synthesis. If the set $\breve{N}_\delta(S_t, U_t)$ is empty, the synthesis process is terminated, and the system formally records the impossibility of constructing a justified control strategy under the current conditions.

Step 7. Transition to the next cycle. When the operating conditions change, a new value U_{t+1} is formed, after which the synthesis procedure is repeated.

Thus, the proposed method for synthesizing evolutionary control strategies implements a controlled construction of a trajectory in the space of control structures, ensuring consistency between the decision-making logic and the current levels of uncertainty and resource constraints.

The method enables formal switching of analysis modes, stabilization of the structure under stationary conditions, or a correct termination of the synthesis process in the case of excessive uncertainty, which makes it suitable for use in adaptive intelligent systems.

For the proposed evolutionary strategy synthesis method, formal properties of correctness, finite convergence, and optimality can be established; these properties are summarized in the following theorem.

Theorem on the correctness, finite convergence, and local optimality of the evolutionary control method for decision-making structures.

Let U denote fixed operating conditions (levels of uncertainty, data conflict, and resource availability). Assume that: $\breve{S}(U)$ is a finite set of admissible control structures; $\breve{D}_U$:$\breve{S}(U)\to[0,1]$ is an admissibility function; $\delta \in (0,1]$ is a predefined admissibility threshold; $\breve{N}_\delta(S, U) \subseteq \breve{S}(U)$ is the set of structures reachable from S in one step that satisfy the admissibility condition, i.e. $\breve{N}_\delta(S, U) \subseteq \{S' \in$

$\breve{S}(U)|\breve{D}_U(S') \geq \delta\}$; $E(S,U)$ is a local efficiency function used to evaluate the suitability of a structure under the given operating conditions.

Consider a local synthesis algorithm that, for an initial structure $S_0 \in \breve{S}(U)$ with $\breve{D}_U(S_0) \geq \delta$, constructs a sequence $\{S_t\}_{t\geq 0}$ according to the rule

$$S_{t+1} = \text{select} \max_{S\in\breve{N}_\delta(S_t,U)} E(S,U).$$

and terminates when $S_{t+1}=S_t$.

Assume that the following conditions hold:

1. $\breve{S}(U)$ is finite.
2. For every $S \in \breve{S}(U)$, the set $\breve{N}_\delta(S,U)$ is non-empty.
3. (Non-degeneracy of the step) If there exists $S' \in \breve{N}_\delta(S,U)$ such that $E(S',U)>E(S,U)$, then the algorithm selects some $S^+ \in \text{select} \max_{S\in\breve{N}_\delta(S,U)} E(S,U)$ such that $E(S^+,U)>E(S,U)$. If, for all $S' \in \breve{N}_\delta(S,U)$ holds, then selecting $E(S',U) \leq E(S,U)$ – $S \in \text{select} \max_{S\in\breve{N}_\delta(S,U)} E(S,U)$ is allowed.

Then:

(a) Correctness: $\forall t \geq 0$: $S_t \in \breve{S}(U)$ and $\breve{D}_U(S_t) \geq \delta$.;

(b) Finite convergence: the algorithm terminates after a finite number of steps at some structure S^*;

(c) Local optimality: the obtained structure S^* is locally optimal with respect to $\breve{N}_\delta(\cdot,U)$, i.e.,

$E(S^*,U) \geq E(S,U)$ $\forall S \in \breve{N}_\delta(S^*,U)$.

Proof of the theorem.

Proof of (a): correctness.

We prove the statement by induction on t.

Base case $t=0$. By assumption, $S_0 \in \breve{S}(U)$ and $\breve{D}_U(S_0) \geq \delta$. Hence, the statement holds for $t=0$.

Inductive step. Assume that for some $t \geq 0$ we have $S_t \in \breve{S}(U)$ i $\breve{D}_U(S_t) \geq \delta$. By the algorithm rule,

$$S_{t+1} \in \text{select} \max_{S\in\breve{N}_\delta(S_t,U)} E(S,U).$$

By definition of the candidate set, $\breve{N}_\delta(S_t,U) \subseteq \breve{S}(U)$ and every element of this set satisfies $\breve{D}_U(S) \geq \delta$. Therefore, $S_{t+1} \in \breve{S}(U)$ and $\breve{D}_U(S_{t+1}) \geq \delta$. The inductive step is proved.

Hence, $\forall t \geq 0$ we have $S_t \in \breve{S}(U)$ and $\breve{D}_U(S_t) \geq \delta$. Item (a) is proved.

Proof (b): finite convergence.

Consider any step t. There are two cases:

1. Stop: $S_{t+1}=S_t$. Then the algorithm terminates.
2. Transition: $S_{t+1} \neq S_t$. Then, by condition 3 (non-degeneracy of the step), it follows that $E(S_{t+1},U)>E(S_t,U)$.

Thus, at every non-terminating step the value $E(S_t,U)$ increases strictly.

Assume, to the contrary, that the algorithm never terminates. Then for all t we have $S_{t+1} \neq S_t$, hence $E(S_1,U)>E(S_0,U)$, $E(S_2,U)>E(S_1,U),\ldots$, i.e., $\{E(S_t,U)\}_{t\geq 0}$ is a strictly increasing infinite sequence.

Since $\breve{S}(U)$ is finite, the set of possible values $\{E(S,U)|S \in \breve{S}(U)\}$ is also finite. A strictly increasing infinite sequence cannot take values from a finite set without repetition – this is a contradiction.

Therefore, the assumption is false, and the algorithm terminates after a finite number of steps. Item (b) is proved.

Proof (c): local optimality of the terminal structure.

Let the algorithm terminate at structure S^*. By the termination condition, there exists t such that $S_{t+1}=S_t=S$.

By the selection rule, at the terminal step we have $S^* \in \text{select} \max_{S\in\breve{N}_\delta(S^*,U)} E(S,U)$. By the definition of *select max*, this is equivalent to $E(S^*,U) \geq E(S,U)$ $\forall S \in \breve{N}_\delta(S^*,U)$. Hence, S^* is locally optimal with respect to the set of reachable admissible candidates $\breve{N}_\delta(S^*,U)$. Item (c) is proved.

The proposed method implements a *local synthesis* of the control structure, since the selection of the next configuration is performed within the set of structures that are reachable by a single algebraic transformation and admissible under the current operating conditions. The structure obtained as a result of the synthesis is locally optimal with respect to this neighborhood. Global optimality over the space of all possible structures is neither guaranteed nor pursued, since the structure space is combinatorially complex and the operating conditions vary over time. Such an approach corresponds to the objectives of evolutionary control, where the key priorities are ensuring correctness, stability, and adaptability of the system in dynamic environments.

For the proposed method of synthesizing evolutionary control strategies, formal properties of correctness and convergence under stationary operating conditions can be established.

Let the vector of multilevel uncertainty U be fixed, the set of admissible control structures $\breve{S}(U)$ be finite, and for each structure $S_t \in \breve{S}(U)$ a nonempty set of admissible candidates reachable in one step, $\breve{N}_\delta(S_t,U)$, be defined. Let the local efficiency function $E(\cdot,U)$ be used as the criterion for selecting the next structure according to the rule $S_{t+1} = select \max_{S\in\breve{N}_\delta(S_t,U)} E(S,U)$. Then, the iterative synthesis procedure has the following properties:

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1. Correctness. At each synthesis step, the control structure remains admissible, i.e., $S_t \in \breve{S}(U)$, $\breve{D}_U(S_t) \geq \delta \;\; \forall t \geq 0$.

2. Finite convergence. The synthesis procedure terminates after a finite number of steps at some structure S^* such that $S_{t+1} = S_t = S^*$.

3. Local optimality. The terminal structure S^* is locally optimal with respect to the set of reachable admissible candidates: $E(S^*, U) \geq E(S, U) \quad \forall S \in \breve{N}_\delta(S^*, U)$.

Within this study, the local efficiency function $E(S, U)$ is specified in terms of a set of indicators that can be directly measured during the experimental evaluation. These indicators include the reliability of diagnostic decisions, assessed by classification accuracy; the resource cost of the selected structure (processing time, CPU usage, and memory consumption); and the stability of system operation under different levels of information uncertainty. In addition, the correctness of the control structure is verified by checking compliance with admissibility conditions under resource and timing constraints, while decision explainability is ensured by recording the active configuration of the decision-making structure for each diagnostic conclusion.

Evolutionary life cycle and criteria for method evaluation

The proposed method for synthesizing evolutionary control strategies is implemented within an evolutionary life cycle of an intelligent software system which, in its overall logic, is close to the classical iterative (incremental) development model, but differs in the object of iterative transformations. A comparative scheme of the iterative and evolutionary life-cycle models is shown in Fig. 1.

As in traditional iterative approaches, the process of system development and operation is organized as a sequence of recurring cycles that include requirements analysis, design, implementation, testing, and evaluation of results, followed by a return to the initial stages. At the same time, as shown in Fig. 1, in the proposed evolutionary model these stages are supplemented with formalized procedures for handling uncertainty, resource constraints, and the decision-making structure, which determine the controlled nature of system evolution.

At the requirements analysis stage, in addition to defining functional and non-functional characteristics, uncertainty and resource constraints are formalized, which specify the current vector of operating conditions U_t. This vector is used at subsequent stages of the life cycle as a control parameter and directly influences the selection and synthesis of control structures.

Design within the evolutionary life cycle is interpreted not as the construction of a single fixed architecture, but as the formation of a space of admissible control structures with respect to the current operating conditions. Within this space, admissibility conditions for structures are defined, as well as permissible operations of their composition, reduction, extension, and adaptation. As illustrated in Fig. 1, on this basis a local synthesis of the control structure is performed, during which a structure that is relevant to the current level of uncertainty and available resources is selected or constructed.

The implementation and testing stages retain their roles typical of iterative models; however, in the proposed life cycle they are supplemented with a formalized assessment of conflict and the quality of knowledge sources. This makes it possible to analyze not only the correctness of the implementation, but also the consistency of input data, expert assessments, and inference results, which is critical for subsequent control of the decision-making structure.

Result evaluation in the proposed evolutionary model (Fig. 1) performs not only the function of monitoring the achievement of target indicators, but also serves as a trigger for evolutionary transformations of the control structure. Based on the evaluation results, structural reduction may be initiated in order to decrease computational costs, structural extension to improve accuracy, or adaptation to changed operating conditions. After that, the control structure is resynthesized and a new iterative cycle is launched.

To evaluate the effectiveness of the proposed method within the evolutionary life cycle, the following criteria are used: the value of the local efficiency function $E(S_t, U_t)$, the level of residual uncertainty of the aggregated results, the stability of trust coefficients assigned to knowledge sources, as well as the number and nature of evolutionary transformations of the control structure initiated during system operation. The combination of these criteria makes it possible to assess not only the quality of individual decisions, but also the adaptability and robustness of the intelligent software system as a whole.

Thus, unlike classical iterative models, in which the software implementation or architecture evolves, in the proposed approach the object of evolution is the formalized structure of the decision-making process, which is controlled and modified in accordance with the level of uncertainty and the quality of information.

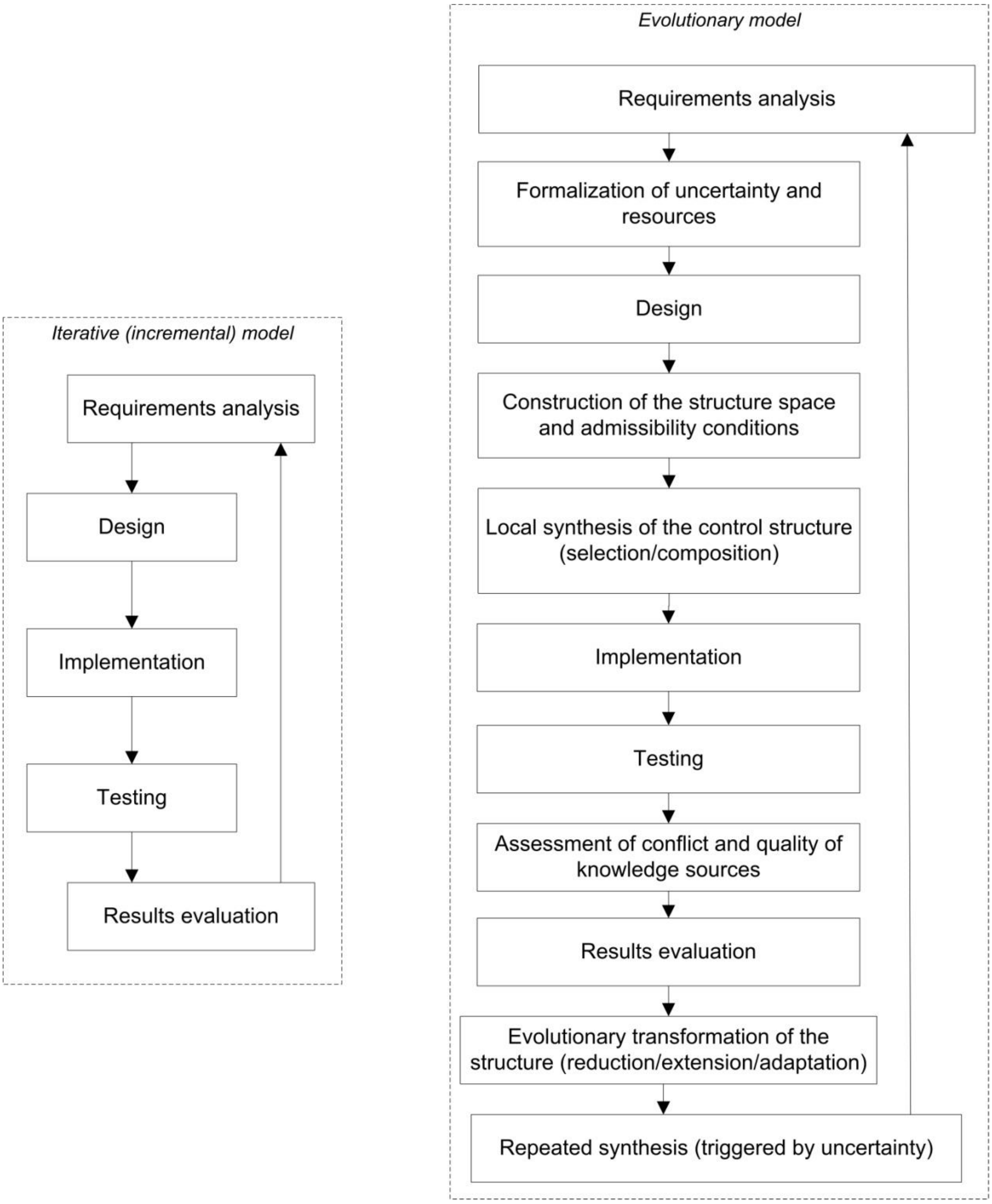

Fig. 1. **Comparison of the iterative and evolutionary life-cycle models of an intelligent system**
***Source*: compiled by the author**

Practical application of the evolutionary control method in the medical intelligent system EvoMedSys

To verify the operability of the proposed model and method for evolutionary control of the decision-making structure, an intelligent clinical decision support system, IDSS-EvoMed, was developed. The system is intended for monitoring the general physiological state of patients and for early detection of potentially dangerous deviations associated with cardiovascular parameters, thermoregulation, and blood oxygenation.

The main function of the system is the integration of data from multiple physiological sources, assessment of the level of uncertainty and consistency of these data, and generation of a well-grounded diagnostic conclusion regarding the presence or absence of a risk condition in real time. The system is designed to be used as an auxiliary tool in telemedicine and clinical environments to support physicians' decisions under conditions of incomplete, noisy, or conflicting data.

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General characteristics and layered structure.

The architecture of IDSS-EvoMed implements a modular, object-oriented approach, which ensures flexibility, extensibility, and support for evolutionary control of the diagnostic process.

The system comprises three levels:

1) data acquisition,
2) intelligent analysis,
3) evolutionary control and decision making.

The relationships between the components are illustrated in the UML diagram (Fig. 2).

Data acquisition level. At this level, the PatientMonitor component is responsible for acquiring signals (illustrated using medical diagnostic studies, as described below) from sensors, including a heart rate monitor, blood pressure sensor, temperature sensor, and oxygen saturation sensor, as well as, if necessary, questionnaire data entered by medical personnel. The module performs noise filtering using a moving average method, data normalization, and unification of data formats. The PatientProfile component stores individual patient characteristics (such as age, presence of chronic conditions, and admissible value ranges) which enables personalization of the diagnostic process.

Intelligent analysis level. The processed data are passed to the FuzzyInterpreter module, which implements fuzzy interpretation of physiological parameters using the *scikit-fuzzy* library (version 0.4.2). Fuzzy rules form a knowledge base of medical hypotheses, for example: “if the heart rate is high and oxygen saturation is low, then there is a risk of hypoxia”. The output is a set of linguistic assessments that reflect the degree to which the patient’s current state belongs to specific diagnostic scenarios.

Subsequently, the EvidenceAggregator component combines results from different knowledge sources using Dempster–Shafer theory (*pyds* version 1.0.0), forming an aggregated belief function that accounts for residual uncertainty. Source weight adjustment is performed by the TrustManager, which computes the level of consistency between sensors based on the Kullback–Leibler divergence (*SciPy* version 1.11.3). When anomalies are detected, trust in the corresponding source is reduced, which automatically decreases its influence in subsequent computations.

Evolutionary control and decision-making level. The key component of IDSS-EvoMed is the EvolutionaryController, which implements the method of evolutionary control of the decision-making process structure. The controller receives an integrated assessment of the patient’s state from the EvidenceAggregator and analyzes the UncertaintyVector, which includes informational, sensor-related, contextual, and resource components.

On this basis, the system can perform:

– reduction – disabling unreliable sensors or simplifying the analysis logic;

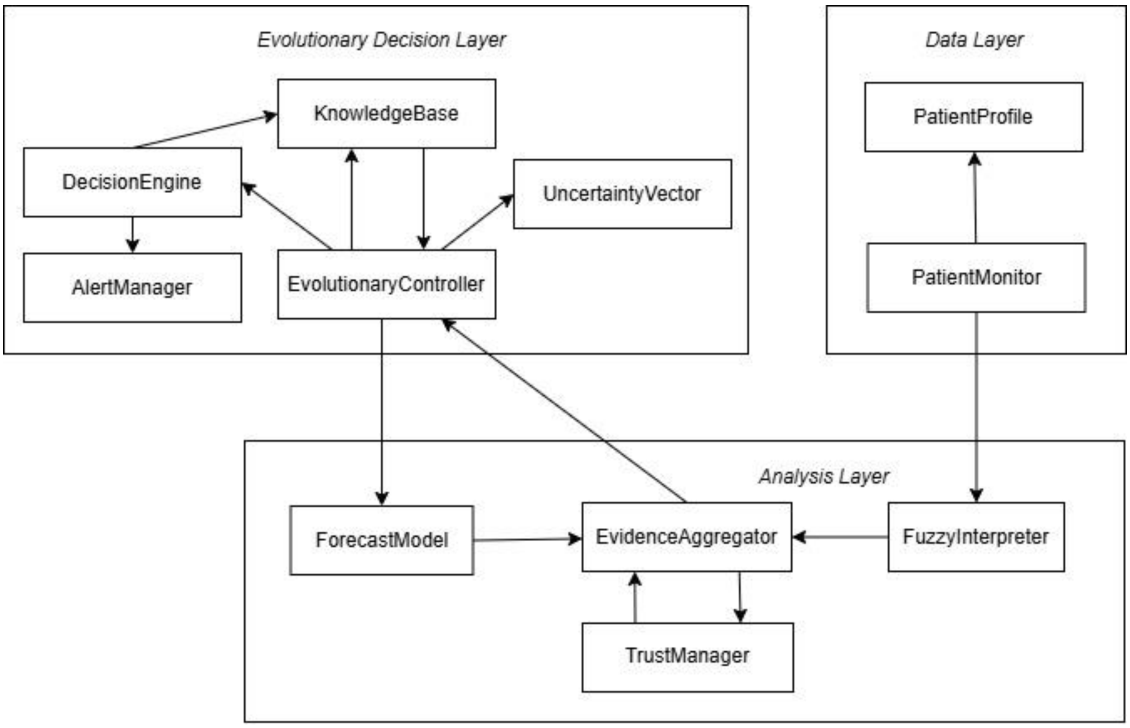

Fig. 2. **UML component diagram of the software architecture of the intelligent system IDSS-EvoMed**
***Source*: compiled by the author**

– extension – activating additional modules (e.g., a classifier or a predictive model);

– composition – combining multiple methods to improve accuracy.

The Forecast Model component implements predictive analysis of patient state dynamics. It is activated by the evolutionary controller under high data uncertainty and performs short-term forecasting of changes in physiological parameters over time (e.g., decreasing oxygen saturation or increasing blood pressure). Predictive estimates are fed back to the Evidence Aggregator to refine belief functions and increase system robustness to delayed or incomplete data. Thus, the ForecastModel enhances the system's ability to proactively respond by forming anticipatory diagnostic decisions.

For adaptive search of an optimal configuration of the decision-making process structure, the *DEAP* library (version 1.4.1), which implements evolutionary optimization algorithms, is used. The search is conducted in the space of admissible control structures and is guided by the local efficiency function (2), which aggregates criteria of diagnostic reliability and soundness, robustness to uncertainty, resource cost, and explainability. Adaptation results and the history of structural changes are stored in the KnowledgeBase, enabling experience accumulation and evolutionary improvement of decisions.

The final decision is produced by the DecisionEngine module, which determines the diagnostic status –"normal", "risk", or "critical condition". In the event of a critical condition, the AlertManager sends a notification to medical personnel and records the event in the system log.

The architectural levels form a closed loop: data acquisition → fuzzy interpretation → evidence aggregation → trust evaluation → evolutionary adaptation of the structure → decision making → knowledge accumulation. This approach ensures system self-learning, robustness to noise and uncertainty, and the possibility of gradual improvement of decision-making logic based on accumulated experience.

The temporal characteristics of system operation were evaluated at the level of the complete decision-making cycle – from the arrival of a new portion of sensor data to the formation of a diagnostic conclusion. Measurements were performed by recording timestamps at the input and output of key processing stages without modifying component logic. The results showed that, for the baseline structural configuration, processing latency remains stable and does not exceed acceptable limits for interactive medical monitoring, whereas activation of extended mechanisms (evidence aggregation with trust correction and predictive analysis) leads to a controlled increase in processing latency. Thus, time costs directly correlate with the complexity of the current control structure, which confirms the appropriateness of using evolutionary control to balance analysis accuracy and system responsiveness.

EXPERIMENTAL EVALUATION AND DISCUSSION OF RESULTS

To evaluate the effectiveness of evolutionary control, a series of experiments was conducted in an environment emulating medical data streams. The study was performed using synthetic patient profiles that reproduced characteristic variations of physiological indicators typical of an unstable general condition of the organism, including changes in body temperature, cardiovascular parameters, oxygen saturation, and stress load levels.

From the perspective of clinical application, the system was considered as a clinical decision support tool intended to analyze patient conditions under incomplete, noisy, and conflicting data and to generate an aggregated diagnostic conclusion without replacing the clinician's decision.

The simulation platform reproduced five physiological channels: heart rate, blood pressure, oxygen saturation, body temperature, and a stress indicator. The stress indicator was used as a synthetic auxiliary parameter derived from a combination of heart rate and its variability and did not have a dominant influence on the decision-making process. The generated signals contained controlled noise and missing values, which made it possible to model different levels of information uncertainty (from 0.1 to 0.9).

The experimental study was carried out in a real-time simulation environment of medical data streams. The duration of each simulation session was 30 minutes with a sampling frequency of 1 Hz. For each level of information uncertainty, 30 independent runs were performed with fixed initial parameters of the pseudo-random number generator (seed), which ensured reproducibility of the results.

Information uncertainty was modeled by controlled addition of noise and missing values to the input signals. Noise was specified as an additive random variable with a normal distribution, while missing values were modeled as random exclusion of signal values with a given probability. The uncertainty level varied in the range from 0.1 to 0.9 with a step of 0.1. For each configuration, mean

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ISSN 2663-7731 (Online)

values of the indicators and their standard deviations were recorded.

During the experiments, the IDSS-EvoMed system operated in real time, automatically activating or deactivating individual components depending on the situation:

– at low uncertainty, only the basic mechanisms of data acquisition and fuzzy data analysis were used;

– at medium uncertainty, the TrustManager was enabled to assess sensor consistency;

– at high uncertainty, the EvolutionaryController activated the ForecastModel for predictive evaluation of trends in patient state changes.

During the trials, the following were recorded: the average processing time of a single diagnostic cycle, CPU load and memory usage, and the value of an integral indicator of analytical complexity. The latter was defined as an integrated aggregation of three groups of parameters: the number of classes in the current configuration of active components, the average computational complexity of their algorithms, and the intensity of interaction between them (number of calls and data exchanges). The obtained results are presented in Table 1.

Decision explainability was evaluated separately in the context of the proposed structural approach to evolutionary control. Explainability was interpreted as the system's ability to unambiguously reproduce the active configuration of the decision-making process for each diagnostic conclusion, including the set of involved components and the conditions of their activation. Within the experiments, for each run the structure S_t selected by the evolutionary controller and the corresponding level of information uncertainty U_t that triggered transitions between operating modes were recorded. The results showed that in 100 % of cases, the decisions made were accompanied by a formally defined structural configuration, without the use of hidden or non-interpretable mechanisms. This confirms the explainability of the system at the level of the structural organization of the decision-making process.

In addition, during the experiments, the correctness of structural transitions was monitored in accordance with the admissibility condition defined in the evolutionary control model. At each synthesis step, it was verified that the activated component configuration did not exceed the established thresholds for computational resource usage and processing latency, i.e., it satisfied the admissibility condition of the structure under the current operating conditions. Across all experimental runs, no cases of transitions to inadmissible structures were observed, which confirms the correctness of the evolutionary control mechanism at the structural level.

As can be seen from the obtained results, with increasing levels of uncertainty the system dynamically expands the active configuration while maintaining the stability of diagnostic decisions. The reported indicator values are averages over a series of repetitions; for each point, standard deviations were also calculated, which made it possible to assess the stability of the results under stochastic simulation conditions.

Fig. 3 presents the results of experimental modeling of the dependence of diagnostic decision reliability on the level of information uncertainty for the baseline system and the developed intelligent system IDSS-EvoMed. In this study, diagnostic decision reliability is understood as the classification accuracy of determining the patient's diagnostic state across three classes – "normal", "risk", and "critical condition" – computed with respect to reference scenarios defined in the data generation model. In addition, the rate of abstention from decision making was analyzed, which reflects the system's ability to correctly refrain from producing a diagnostic conclusion under excessive uncertainty.

Table 1. **Adaptation and resource behavior of the IDSS-EvoMed system under different levels of uncertainty**

No.	Level of information uncertainty	Active components	Average processing time, s	Computational resources (CPU/memory)	Analytical complexity (relative)
1	Low (0.1-0.3)	PatientMonitor, FuzzyInterpreter, EvidenceAggregator	0.8	21 % / 185 МБ	1.0
2	Medium (0.4-0.6)	+ TrustManager	1.2	36 % / 243 МБ	1.6
3	High (0.7-0.9)	+ EvolutionaryController, ForecastModel	1.9	54 % / 311 МБ	2.4

***Source*: compiled by the author**

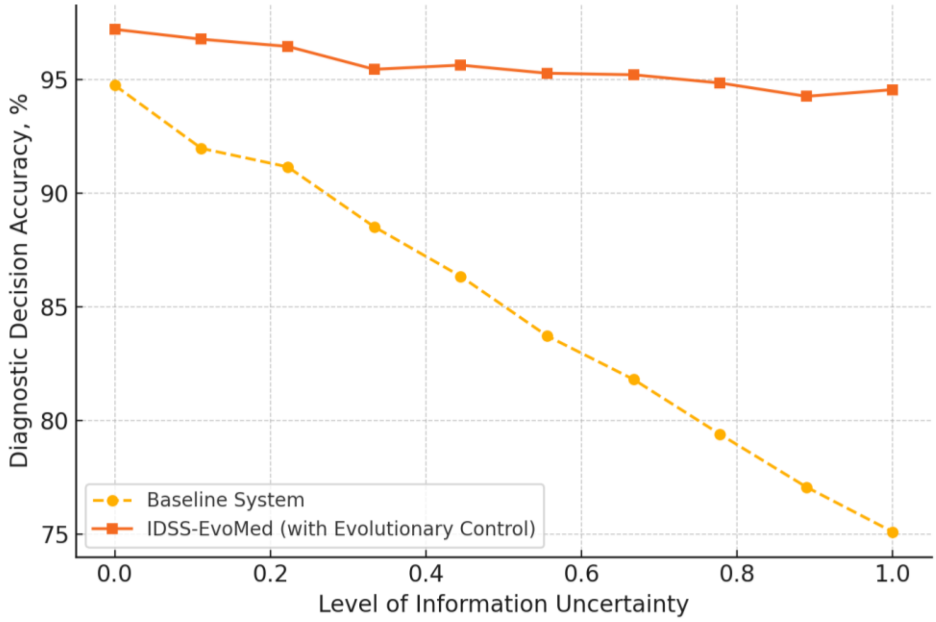

Fig. 3. **Dependence of diagnostic accuracy on information uncertainty**

***Source*: compiled by the author**

The experiments showed that at low levels of uncertainty the rate of abstention did not exceed 2%, at medium levels it increased to 4-5 %, and at high uncertainty it reached approximately 9 %. This indicates that the system does not compensate for increasing uncertainty by artificially inflating confidence in its conclusions, but instead correctly implements a decision abstention mechanism consistent with the formalized control model.

As a baseline for comparison, a configuration with a fixed decision-making structure was used, in which only the data acquisition, fuzzy interpretation, and evidence aggregation modules remained active, without accounting for source consistency. In the baseline configuration, mechanisms for dynamic trust correction (TrustManager), evolutionary structure control (EvolutionaryController), and predictive analysis (ForecastModel) were not applied.

As shown in the graph, in the baseline system the accuracy decreases sharply as uncertainty increases, which indicates its sensitivity to noise and conflicting data. In contrast, IDSS-EvoMed, due to the built-in mechanism of evolutionary control of the decision-making structure, demonstrates high robustness – the diagnostic accuracy remains at the level of 94-97 % even under high uncertainty. This confirms the effectiveness of the adaptive synthesis of control structures implemented in the system, which ensures stable operation under dynamic conditions and improves the reliability of medical conclusions.

CONCLUSIONS

This paper proposes a method for evolutionary control of the decision-making structure in intelligent software systems, which enables adaptation of the diagnostic process logic to changes in uncertainty levels, data quality, and available resources. Unlike traditional approaches that are limited to parametric adjustment of algorithms, the developed method provides for controlled structural transformations—reduction, extension, and composition of system components. This makes it possible to maintain decision correctness even under conditions of incomplete or conflicting input data.

The developed intelligent medical diagnostic system IDSS-EvoMed implements the main provisions of the proposed method at the software level. It combines fuzzy interpretation of medical indicators, evidence aggregation based on Dempster–Shafer theory, dynamic assessment of sensor trust, and evolutionary control of the diagnostic process architecture. Practical experiments demonstrated that, as the level of uncertainty increases, the system automatically activates additional components, improving analysis accuracy and result robustness while maintaining control over resource consumption.

Further research should focus on extending the model to support multi-agent medical data sources and on developing metrics for evaluating the evolutionary stability of decision-making structures over long-term operation.

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

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Conflicts of Interest: The authors declare that they have no conflict of interest regarding this study, including financial, personal, authorship, or other interests, which could influence the research and its results presented in this article

Received 23.01.2026
Received after revision 10.03-2026
Accepted 18.03.2026

DOI: https://doi.org/10.15276/hait.09.2026.13
УДК 004.021:004.415

Модель та метод еволюційного управління структурою прийняття рішень в інтелектуальних системах

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ABSTRACT

Актуальність дослідження зумовлена тим, що сучасні інтелектуальні програмні системи функціонують в умовах неповних, суперечливих і динамічно змінюваних даних, а також обмежених обчислювальних ресурсів, що потребує підвищення адаптивності, стійкості та коректності процесів прийняття рішень порівняно з традиційними підходами, орієнтованими на налаштування окремих алгоритмів. Додатково, зростання складності інформаційних середовищ та необхідність обробки гетерогенних джерел даних підсилюють вимоги до узгодженості та надійності результатів аналізу. У таких умовах особливої актуальності набуває перехід до керування структурою процесу прийняття рішень як об’єкта вищого рівня. **Мета дослідження** полягає у підвищенні адаптивності, стійкості та коректності рішень шляхом переходу від налаштування окремих алгоритмів до керованої зміни структури процесу аналізу, зокрема складу активних програмних компонентів, порядку їх взаємодії та правил переходів між режимами оброблення. **Методи** дослідження ґрунтуються на підході еволюційного управління структурою прийняття рішень, що передбачає керовані перетворення допустимих конфігурацій, інтеграцію нечіткої інтерпретації та агрегування доказів, оцінювання надійності й узгодженості джерел інформації, а також формальне доведення властивостей коректності, скінченної збіжності та локальної оптимальності. Запропонований підхід дозволяє реалізувати адаптивний вибір конфігурації процесу аналізу залежно від рівня невизначеності та доступних ресурсів. Крім того, метод забезпечує узгодження між точністю прийняття рішень і витратами обчислювальних ресурсів у динамічних умовах функціонування системи. **Результати** дослідження полягають у розробленні моделі та методу еволюційного управління структурою прийняття рішень, а також їх практичній реалізації у вигляді інтелектуальної медичної діагностичної системи, де експериментальні дослідження показали, що зі зростанням рівня невизначеності система автоматично активує додаткові механізми контролю узгодженості джерел і прогнозного аналізу, забезпечуючи підвищену стійкість результатів порівняно з базовою фіксованою конфігурацією.

Ключові слова: адаптивні системи; інтелектуальні програмні системи; еволюційне управління; структура прийняття рішень; невизначеність; нечітка інтерпретація; агрегування доказів; надійність джерел; адаптивна архітектура; життєвий цикл

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