UDC 004.81
DOI: 10.15587/1729-4061.2026.360208

# DEVELOPMENT OF A METHOD OF DATA INTERPRETATION IN INTELLIGENT DECISION SUPPORT SYSTEMS

**Andrii Shyshatskyi**
*Corresponding author*
Doctor of Technical Sciences, Senior Researcher, Professor
Department of Computer Science and Information Systems*
E-mail: ierikon13@gmail.com
ORCID: https://orcid.org/0000-0001-6731-6390

**Anatolii Pavlikovskyi**
Candidate of Military Sciences, Associate Professor, Head of Institute
Institute of Information and Communication Technologies and Cyber Defense**
ORCID: https://orcid.org/0000-0002-0637-368X

**Pavlo Zhuk**
Candidate of Technical Sciences, Associate Professor, Head of Institute
Institute of Professional Military Education "Leadership Training"**
ORCID: https://orcid.org/0000-0002-9628-8074

**Oleksii Nalapko**
Doctor of Philosophy (PhD)
Scientific and Organizational Department***
ORCID: https://orcid.org/0000-0002-3515-2026

**Volodymyr Cherneha**
Candidate of Technical Sciences, Associate Professor, Head of Department
Department of Information and Analytical Technologies
Institute of Information and Communication Technologies and Cyber Defense**
ORCID: https://orcid.org/0000-0001-6190-3252

**Yurii Artabaiev**
Candidate of Technical Sciences, Senior Lecturer
Department of Information Technology
Yevhenii Bereznyak Military Academy
Yuriy Illenka str., 81, Kyiv, Ukraine, 04050
ORCID: https://orcid.org/0000-0001-9446-3011

**Nadiia Protas**
Candidate of Agricultural Sciences, Associate Professor
Department of Information Systems and Technologies
Poltava State Agrarian University
Skovorody str., 1/3, Poltava, Ukraine, 36003
ORCID: https://orcid.org/0000-0003-0943-0587

**Andrii Veretnov**
Candidate of Technical Sciences, Lead Researcher
Scientific and Research Department***
ORCID: https://orcid.org/0000-0003-0160-7325

**Yevhen Peleshok**
Candidate of Technical Sciences, Associate Professor, Senior Researcher, Senior Research Fellow
Research Institute of Military Intelligence
Yuriy Illenka str., 81, Kyiv, Ukraine, 04050
ORCID: https://orcid.org/0000-0003-0033-1160

**Danylo Pliekhov**
Assistant
Department of Automation and Computer-Aided Technologies*
ORCID: https://orcid.org/0009-0004-7873-1716

*Kharkiv National Automobile and Highway University
Yaroslava Mudroho str., 25, Ukraine, Kharkiv, 61002
**National Defence University of Ukraine
Povitrianykh Syl ave., 28, Kyiv, Ukraine, 03049
***Central Scientifically-Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine
Povitrianykh Syl ave., 28, Kyiv, Ukraine, 03049

***Intelligent decision support systems (IDSS) are the object of the study. The problem that is solved in the study is the increase in the processing of heterogeneous data while ensuring the given reliability of their processing. The hypothesis of the study is the possibility of increasing the level of reliability of heterogeneous data processing in IDSS due to the development of a method of data interpretation in IDSS.***

***The originality of the study consists of:***

***– taking into account the influence of data uncertainty on the process of processing heterogeneous data in IDSS due to the use of fuzzy analytical expressions;***

***– reduction of loss of reliability of heterogeneous data processing due to verification of information about IDSS and data circulating in it;***

***– increasing the reliability of heterogeneous data processing in IDSS due to multi-level deep learning of knowledge bases, using evolving artificial neural networks;***

***– estimation of zero data values in IDSS databases, due to the use of the procedure for estimating the zero data value, which achieves the prevention of looping of the method;***

***– carry out unambiguous classification of data, their attributes circulating in the IDSS due to the use of artificial immune detectors, which achieves an increase in the accuracy of IDSS settings and the reliability of heterogeneous data processing;***

***– recovery of data that was lost during the processing of heterogeneous data in IDSS due to their preliminary processing, which achieves an increase in the reliability of heterogeneous data circulating in IDSS.***

***The proposed method provides an increase in the efficiency of heterogeneous data processing by increasing the reliability of decision-making at the level of 14–18% due to the use of additional procedures, which is confirmed by the results of a computational experiment***

***Keywords: heterogeneous data, processing of various types of data, reliability of decision-making, artificial intelligence***

*Received 18.02.2026*
*Received in revised form 24.04.2026*
*Accepted 04.05.2026*
*Published 26.06.2026*

***How to Cite:** Shyshatskyi, A., Pavlikovskyi, A., Zhuk, P., Nalapko, O., Cherneha, V., Artabaiev, Y., Protas, N., Veretnov, A., Peleshok, Y., Pliekhov, D. (2026). Development of a method of data interpretation in intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 3 (4 (141)), 66–73. https://doi.org/10.15587/1729-4061.2026.360208*

## 1. Introduction

The armed conflicts of the last decade have been a catalyst for the rapid development of information and automated systems for various functional purposes [1, 2]. For the effective operation of information and automated systems, artificial intelligence technologies are actively used, enabling the automation of their processes [2, 3]. The basis of most of today's automated (information) systems is intelligent decision support systems (IDSS) with appropriate hardware and software [3, 4].

IDSS in automated and information systems are used to solve the following information and calculation tasks [5, 6]:

– collecting, processing, and summarizing information coming from end users;

– storage of various types of data, their archiving, and output;

– solving individual and/or complex calculation tasks for a wide range of users;

– modeling the nature of military conflicts;

– interpretation of the obtained results, their classification, and generalization;

– transfer of information between elements of automated (information) systems, etc.

The main features of the IDSS functioning are:

– steady growth in the amounts of information to be processed by IDSS [7];

– extension of the nomenclature of means that affect the process of data exchange in IDSS [8];

– improvement of forms and methods of influencing the process of functioning of the IDSS, which negatively affects both the efficiency and reliability of data circulation [9];

– simultaneous growth of requirements for the set of indicators characterizing the process of functioning of IDSS [10];

– imperfection of data interpretation mechanisms in the process of functioning of IDSS, etc.

Therefore, studies devoted to the development of ways to increase the efficiency of the functioning of IDSS, which function in conditions of complex influence of destabilizing factors, are relevant.

## 2. Literature review and problem statement

Work [11] identifies the main advantages and disadvantages of cognitive algorithms. The disadvantages of these approaches include the lack of consideration of the type of uncertainty and the inability to search in different directions by several agents. In the study, not enough attention was paid to the principles and procedure of calculations, their effectiveness according to a certain criterion, and a comparative assessment of the specified approach was not carried out in comparison with the known ones.

Work [12] presents an approach focused on searching for hidden information in large data sets. The method is based on analytical baselines, variable reduction, rarefied feature detection, and rule formation. The disadvantages of this method include the impossibility of taking into account different decision-making strategies, and the lack of taking into account the type of uncertainty of the initial data. In the study, not enough attention was paid to the principles and procedure of calculations, their effectiveness according to a certain criterion, and a comparative assessment of the specified approach was not carried out in comparison with the known ones.

Works [13, 14] provide an approach to the transformation of information models of objects to their equivalent structural models. This mechanism is designed to automate the necessary conversion, modification, and addition operations during such information exchange. The disadvantages of this approach include the impossibility of assessing the adequacy and reliability of the information transformation process, as well as carrying out appropriate corrections of the obtained models. In the study, not enough attention was paid to the principles and procedure of calculations, their effectiveness according to a certain criterion, and a comparative assessment of the specified approach was not carried out in comparison with the known ones.

In work [15], a method of fuzzy hierarchical evaluation is proposed, which allows for an assessment of the quality of library service. The disadvantages of the specified method include the impossibility of assessing the adequacy and reliability of the assessment and determining the assessment error accordingly. In the study, not enough attention was paid to the principles and procedure of calculations, their effectiveness according to a certain criterion, and a comparative assessment of the specified approach was not carried out in comparison with the known ones.

In work [16], an analysis of the 30 most common Big Data algorithms was carried out. It was established that the analysis of large data sets should be carried out layer by layer, take place in real time, and be able to self-learn, find a solution in different directions, and take into account the noise of the data.

Works [17, 18] present approaches for evaluating various types of data for support and decision-making systems based on the clustering of a basic set of input data, after which system training takes place based on the analysis. However, given the static architecture of artificial neural networks, an accumulation of error occurs.

In the work [19], a comparative analysis of existing decision support technologies was carried out, namely: the method of analyzing hierarchies, neural networks, the theory of fuzzy sets, genetic algorithms, and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. For the tasks of assessing the state of hierarchical systems in conditions of risk and uncertainty, the use of the theory of artificial neural networks and gradient algorithms is justified.

In work [20], approaches to the structural-target analysis of the development of weakly structured systems are developed. At the same time, the problem is defined as the inconsistency of the existing state of the weakly structured system with the necessary one. At the same time, the disadvantages of the proposed approaches include the problem of local optimum, the lack of consideration of the system's computing resources, as well as the inability to conduct searches in several directions.

Analyzing works [11–20] showed that the common shortcomings of the above-mentioned studies are:

– not enough attention is paid to considering the effectiveness of the mathematical apparatus that forms the basis of their work;

– lack of systematic consideration of the issue of data interpretation in IDSS in conditions of uncertainty;

– insufficient attention is paid to the issue of finding lost data in IDSS under conditions of uncertainty;

– the issue of processing heterogeneous data in IDSS in conditions of complex influence of destabilizing factors remains little researched.

All this allows to state that it is expedient to conduct a study devoted to the search for ways to increase heterogeneous data in IDSS, which is relevant.

## 3. The aim of objectives of the study

The aim of the study is to increase the reliability of heterogeneous data in IDSS due to the development of a method for interpreting heterogeneous data during their processing.

This will allow comprehensive, objective, and complete decision-making regarding the management of heterogeneous data processing parameters in IDSS at different levels of its functioning (individual elements of IDSS). Also, it will make it possible to develop (improve) the software of modern and promising IDSS by integrating the proposed approach into the corresponding software.

To achieve the aim, the following objectives were set:

– to propose a structure of the data interpretation method in IDSS;

– to evaluate the effectiveness of the proposed method according to certain criteria.

## 4. Materials and methods

The object of the study is IDSS. The problem that is solved in the study is the increase in the processing of heterogeneous data while ensuring the given reliability of their processing. The subject of the study is the process of interpretation of heterogeneous data during their processing by IDSS. The hypothesis of the study is the possibility of increasing the level of reliability of the processing of heterogeneous data in the IDSS due to the development of a method of data interpretation in the IDSS.

Assumption of the study – due to increasing the efficiency of the data interpretation process, in conditions of constant intensity of destabilizing influences, it is possible to achieve an increase in the level of reliability of processing heterogeneous data in IDSS.

As simplifications of this study, it is accepted:

– volume, type of data circulating in IDSS – unchanged during the study time;

– the intensity of the influence of destabilizing factors, their type, and duration – are unchanged during the time of the study;

– the mode of operation of the communication system and information systems does not change during the time of the study.

In the course of the study, the following research methods were used:

– is a general scientific method of analysis – for decomposing problematic issues of IDSS functioning, processing heterogeneous data, and forming databases when they perform tasks as intended. Also, the general scientific method of analysis is used to determine the advantages and disadvantages of known approaches to the interpretation of data in IDSS when they perform tasks as intended;

– general scientific method of synthesis – to substantiate the most appropriate approaches to the interpretation of data in IDSS when they perform tasks as intended;

– artificial neural networks, with an evolving structure – for active database learning, when processing heterogeneous data. The specified mathematical apparatus provides the possibility of adaptation to the required number of streams and types of data circulating in the IDSS;

– artificial immune detectors – for verification of the structure of IDSS and classification of data circulating in it. The specified mathematical apparatus makes it possible to unambiguously classify the data and structure of IDSS and level the role of the human factor in the processing of heterogeneous data and data interpretation.

As an object for conducting a computational experiment, the communication and informatization system of the operational grouping of troops (forces) was adopted in this study. The operational group of troops (forces) was formed according to the state of martial law (typical state). Mode of operation of the communication and information systems system – defense operation.

A computational experiment of the proposed methodology was conducted in the Microsoft Visual Studio 2022 software environment (USA). The hardware of the research process is AMD Ryzen 5.

## 5. Results of the study on data interpretation in intelligent decision support systems

### 5. 1. Development of the structure of the data interpretation method in intelligent decision support systems

The method of data interpretation in intelligent decision support systems consists of the following sequence of actions:

Action 1. Entering initial data about IDSS.

In the specified procedure, initial data on IDSS, the system in which interests it was created (functioning), as well as the conditions of its functioning, are entered.

The following output data are entered:

– the total number of electronic countermeasures (ECs) that affect IDSS (both own and enemy);

– total number of means of cyber influence, intensity of cyber influence on IDSS;

– type of cyberattacks operating on IDSS;

– spectral-energy parameters of obstacles of EC means affecting IDSS;

– the number of means of fire damage that act in the lane of operation of the IDSS;

– available computing resources that can be directed to solving a specific type of computing task;

– intensity of fire exposure on IDSS, etc.

Action 2. Verification of information about IDSS and data circulating in it, taking into account the degree of uncertainty.

A classification binary tree is used to verify information about IDSS and the data circulating in it. Formally, such a structure is specified recursively in the following way:

$$CBT_{\mu}=\begin{cases}\left\langle F^{(i)}_{jL_{\mu}R_{\mu}},CBT_{L_{\mu}},CBT_{R_{\mu}}\right\rangle, & \text{if } \#\mu\geq 2,\\ \mu, & \text{if } \#\mu=1.\end{cases}\quad(1)$$

where $\mu=\{0,\ldots,m\}$ – output set of class labels, $L_{\mu}\subsetneq\mu$ – an arbitrarily generated or defined subset; $\mu\left(\#L_{\mu}<\#\mu\right)$, $R_{\mu}=\mu\backslash L_{\mu}$ – left classification subtree, $CBT_{R_{\mu}}$ – right classification subtree, $F^{(i)}_{jL_{\mu}R_{\mu}}$ – a nodal detector trained on the elements of a set $\left\{(x_l,0)\middle|\bar{c}_l\in L_{\mu}\right\}_{l=1}^{M}\cup\left\{x_l,1\middle|\bar{c}_l\in R_{\mu}\right\}_{l=1}^{M}$.

The output of the detector is adjusted to be 0 if the input data $x_l$ belong to a class with a label $\bar{c}_l\in L_{\mu}$ and if input data 1, if input data $x_l$ belong to a class with a label $\bar{c}_l\in L_{\mu}$.

Therefore, the functioning of the group of detectors $F^{(i)}_j$, presented in the form of nodes of such a tree, it is described using a recursive function $\phi^{(i)}_j$, which sets the sequential dichotomy of the set $\mu$:

$$F^{(i)}_j=\phi^{(i)}_j\left(\mu,z\right),$$

$$\phi^{(i)}_j\left(\mu,z\right)=\begin{cases}\mu, & \text{if } \#\mu=1,\\ \phi^{(i)}_j\left(L_{\mu},z\right) & \text{if } \#\mu\geq 2\wedge F^{(i)}_{jL_{\mu}R_{\mu}}\left(z\right)=0,\\ \phi^{(i)}_j\left(R_{\mu},z\right) & \text{if } \#\mu\geq 2\wedge F^{(i)}_{jL_{\mu}R_{\mu}}\left(z\right)=1.\end{cases}\quad(2)$$

Application function $\phi_j^{(i)}$ to the original set of labels of IDSS data classes, it allows to unambiguously search for the label of the IDSS class and the data circulating in it.

This is because, as one descends a classification tree, a disjunctive partitioning of the set of class labels occurs. Once the terminal detector is reached and triggered, only one possible label remains to classify the input data $z$ as an output result $F_j^{(i)}$. For the classification tree, no conflict cases are possible when classifying data that may occur in other approaches.

The reason for obtaining undefined data is that their own data is limited, leading to the existence of undefined data in data models. Below are the main factors that lead to uncertainty in the data:

– in the mathematical description of real systems (processes);

– when changing or converting data into data models;

– when manipulating data in the data model.

In general, data with uncertainty mainly includes the following categories:

– probabilistic data – data that is estimated to be true or false with a certain probability value;

– inaccurate data – data available in data models, but they are not clear for certain reasons;

– fuzzy data – data expressed indefinitely in quantity or units of measurement;

– inconsistent data – data with different attributes *true* and *false* with different time lags;

– ambiguous data.

Considering the above, it is customary in the study to distinguish the following degrees of uncertainty of the data circulating in the IDSS: full awareness – corresponds to a close to unity predictability of events

$$\lim_{\tau \to \tau_k} G_\tau = 1, \tag{3}$$

where $\tau$ – time, $\tau_k$ – final event prediction time.

The complete uncertainty – corresponds to the near-zero predictability of the occurrence of the event, which is mathematically expressed by the ratio

$$\lim_{\tau \to \tau_k} G_\tau = 0, \tag{4}$$

the partial uncertainty – which predictability lies between 0 and 1, which can be expressed by inequality

$$0 < G_\tau < 1. \tag{5}$$

The uncertainty "is hopeless" – corresponds to the lack of information about the possibilities of the state of the environment within which the IDSS functions.

In these cases, the criteria of guaranteed result, optimism, pessimism, minimax risk, and generalized maximin are used to predict the IDSS state, determine the best solutions.

The conditions of uncertainty that arise when making decisions about the IDSS state are objectively determined by the fact that complex IDSS feel dependent on a number of factors in the process of their functioning.

It remains important to take into account the time factor when analyzing the quality of the decisions made, since both the quality of the decisions and the costs of their implementation are always distributed over time.

Action 3. Classification of data circulating in IDSS.

A tree of classifiers is used to classify data in this study. The construction of a tree of classifiers can be characterized as a preparatory stage, it contains a choice:

– structures of individual binary classifiers (detectors);

– dimensions and layer numbers;

– parameters and learning algorithms;

– types of activation functions, membership functions, and nuclear functions.

A set of training rules is drawn up for each detector. By specifying a different set of such sets of rules, it is possible to form a group of detectors, each of which is built based on an evolving artificial neural network. Detectors within each such group are combined into a classifier based on one-vs-all, one-vs-one, or various derivative variations.

In the first approach, each detector $F_{jk}^{(k)}: \mathbb{R} \to \{0,1\} \left(k=1,...,m\right)$ learning from data $\{x_l,[c_l=k]\}_{l=1}^M$ and the functioning of the group of detectors $F_{jk}^{(k)}$ described by means of a principle excluding:

$$F_j^{(i)}(z) = \begin{cases} \{0\}, \text{ if } \forall k \in \{1,...,m\} F_{jk}^{(i)}(z) = 0, \\ \left\{k \middle| F_{jk}^{(i)}(z) = 1\right\}_{k=1}^m, \text{ else.} \end{cases} \tag{6}$$

In the second approach, each with $C_{m+1}^2 = \frac{(m+1)\cdot m}{2}$ detectors $F_{jk_0k_1}^{(k)}$ learns from a set of input data belonging to only two labeled classes $k_0$, $k_1$,$-\left\{\left(x_l,0\middle|\bar{c}_l=k_0\right)\right\}_{l=1}^M \cup \left\{\left(x_l,1\middle|\bar{c}_l=k_1\right)\right\}_{l=1}^M$, $0 \le k_0 < k_1 \le m$ and the functioning of the group of detectors $F_j^{(i)}$ it is set using voting max-wins

$$F_j^{(i)} = \left\{ \arg \max_{\bar{c}\in\{0,...,m\}} \sum_{k=\bar{c}+1}^{m} \left[F_{j\bar{c}k}^{(i)}(z)=0\right] + \sum_{k=0}^{\bar{c}-1} \left[F_{j\bar{c}k}^{(i)}(z)=1\right] \right\}. \tag{7}$$

Table 1 shows the characteristics of the considered schemes for combining detectors into a multi-class model designed to correlate the input data with one or more of $(m+1)$ class labels.

Table 1

Characteristics of detector combining circuits

| Unification scheme | Number of detectors to be trained | The minimum number of detectors involved in data classification | The maximum number of detectors involved in data classification |
|---|---|---|---|
| one-to-all | $m$ | $m$ | $m$ |
| one-to-one | $\frac{(m+1)\cdot m}{2}$ | $\frac{(m+1)\cdot m}{2}$ | $\frac{(m+1)\cdot m}{2}$ |
| Classification binary tree | $m$ | 1 | $m$ |
| Directed acyclic graph | $\frac{(m+1)\cdot m}{2}$ | $m$ | $m$ |
| Fuzzy cognitive model | $(m * x) * m$ | $(m * x)$ | $(m * x) * m$ |
| Genetic algorithm | $(m * x)$ | $m$ | $(m * x)$ |

A mixed matrix is used to evaluate the effectiveness of the approaches to the classification of data circulating in the IDSS. Ratio of correctly classified cases $(TP+TN)/(TP+TN+FP+FN)$

can be described as several actions based on mixed matrix results, such as the accuracy of correctly classified data. *TP*, *FN*, *FP* and *TN* denote the number of true positive results, false negative (false positive) results and true negative results. Specific measurements are used to validate each classification approach and assess its accuracy, sensitivity and evaluation *F*1 for each data classification approach.

Estimates used in this study are: accuracy (8), error (9), reactivity (10) and estimation *F*1 (11):

$$Accuracy = (TP + TN)/(TP + FP + FN + TN); \quad (8)$$

$$Precision = TP \; / \; (TP + FP); \quad (9)$$

$$Recall = TP \; / \; (TP + FN); \quad (10)$$

$$F1 = 2 \times Precision \times Recall/(Precision + Recall). \quad (11)$$

*TP*, *FN*, *FP* and *TN* they are determined by the number of real positive cases, the number of false negative cases and the number of truly negative cases from the data classification.

Accuracy is the most understandable measure of effectiveness, and is defined as the percentage of correct classification of data for all classes of data to be evaluated. Positive accuracy is divided into true and false positives.

*F*1-evaluation includes calculation of model accuracy, use of precision and memory.

Action 4. Modeling the state of the IDSS and the process of processing the data circulating in it.

During the implementation of the specified stage, the state of IDSS is modeled under the influence of destabilizing factors, as well as the process of data processing in IDSS using the developed polymodel complexes [17].

Action 5. Pre-processing of data circulating in IDSS.

The pre-processing step includes deleting redundant and minor data to minimize their volume. This step increases the accuracy of the machine learning algorithm.

Pre-processing is the main stage of big data analysis and an important procedure for preparing data for its interpretation. To improve the quality of data analysis, preliminary processing, search for lost data, and their integration are carried out.

The construction of the lost data search model is carried out to describe the simulation and abstract process of searching for lost data.

The main goals of the lost data search model are to find lost data, determine search results, calculate the relevance of search results, etc. According to the characteristics of the database, the lost data search model is defined as a four-tuple form that is represented by $[Q, D, R, S]$, where $Q$ – request information; $D$ – data model; $R$ – search for lost data; $S$ – mechanism for evaluating information, querying and searching for results.

With the development of network technologies, data is mainly stored in a database, but a time attribute is used for it. To better represent the data time attribute, the data in the database is represented as time data.

The time data graph is represented by the formula $G = (V_t, E_t)$, where $V_t$ – a set of time nodes, and $E_t$ – a set of time edges.

The time node is $v_t$, expressed as $v_t = [v, (ts_{vt}, te_{vt})]$, where $v$ – time node identifier, $[ts_{vt}, te_{vt}]$ – semi-open time interval, and $E$ – data validity time.

Time interval $e_t$ expressed as $e_t = [u_t, v_t, (ts', te')]$, $[ts', te']$ – effective search time.

In the process of searching for lost data, the time of action of the information is mainly taken into account.

Based on the lost data search model, according to the time constraints and query format, the result subtree is extracted from the time data graph.

In general, in the case of a query with missing data, a set of subtrees of the query results is obtained. To obtain the most similar information about lost data, the subtrees of the query results are sorted according to the principle of similarity calculation, and the first of them is the subtree of searching for similar lost data. In general, the lower the weight of the time limit, the greater the similarity.

To ensure that as many nodes as possible are involved and to ensure that search results are closely linked to information on lost data in the query, the weights of the node structure are calculated. The weight of the node structure represents the importance of the node in the time data graph that is entered into the edge weight calculation formula, and the edge weight calculation formula is represented as follows

$$W\left(Q,e_t\right)=\frac{1}{IR_{(k,u)}+IR_{(k,v)}}\times W_e\left(u,v\right), \quad (12)$$

where $W_e\left(u,v\right)$ – weight of the node structure.

The time limit has timeliness values, and the weights of different time limits are also different. Therefore, in the lost data retrieval process, the time limit finite time must correspond to the time of the lost data request. The weight of the time edge is set according to the time of the lost data request, and the formula for its calculation is as follows

$$W\left(Q,e_t\right)'=1-\frac{\left|I_c\cap I_t\right|}{I_c}, \quad (13)$$

where $I_c$ – time to request lost data, $I_t$ – effective time slot.

With the help of the above formula, the full value of the weight of the time interval is obtained, which allows to assess the similarity of the lost data and provide data support for further estimation of the zero value in the uncertainty database.

Action 6. Evaluation of the zero value of the data circulating in IDSS.

When the database is actually applied, the problem of missing data is practically inevitable, which leads to a zero-value problem.

For a more accurate estimate of the zero value in the relational database based on the lost data search model and the similarity of the lost data, a procedure for estimating the empty value in the database with uncertainty, based on artificial intelligence, is proposed. The specific implementation process is as follows:

Action 6. 1. Object selection and data conversion. Object selection, a rough traversal-based attribute truncation sequence, is used to reduce the attributes of the original data table and obtain a set of key attributes after truncation.

Action 6. 2. Data clustering.

The non-zero attribute sets associated with the zero value attributes obtained in step 6.1 are used for clustering. When combining similar data, data arrays are broken down into different clusters.

Given that different attributes have different impact weights on columns with zero values, the corresponding weights are entered

$$w=\frac{r^2-W\left(Q,e_t\right)'}{\sum_{k=1}^{m} r_1^2}, \quad (14)$$

In formula (14):

– $m$ – the number of attributes in a set of non-empty attributes belonging to attributes with zero values;

– $r$ – correlation coefficients of attributes with zero values;

– $w$ – ratio of correlation coefficients of attributes with zero values and sum of correlation coefficients of all associated attributes, and attributes with zero values. This reflects the weight of the impact of attributes with zero values. After clustering, the clustering center is obtained from the data.

Action 6. 3. Calculating the impact of data arrays on each other.

The degree of correlation is calculated as follows

$$z_{a,b}=\frac{\sum_{i=1}^{n}\left[\left(a_i-\bar{a}\right)\cdot\left(b_i-\bar{b}\right)\right]}{\sqrt{\sum_{i=1}^{n}\left(a_i-\bar{a}\right)^2\cdot\sum_{i=1}^{n}\left(b_i-\bar{b}\right)^2}}. \quad (15)$$

In the formula (15) $\bar{a}$ and $\bar{b}$ represent a sample mean $a$, $b$ fuzzy set. The formula for determining the coefficient of an independent variable is presented below

$$COD=\pm\frac{r^2}{\sum_{k=1}^{m}r_1^2}. \quad (16)$$

Action 6. 4. Estimation of zero values.

During the execution of the specified action, the Euclidean distance between the tuple and the center of each cluster is first calculated, and a zero-value estimation procedure is used to obtain the estimated value.

Action 7. Training of IDSS knowledge bases.

In the course of performing the specified procedure, the knowledge bases of the IDSS are trained using the deep learning method, which is based on the use of artificial neural networks that are evolving [19]. This procedure uses multi-level learning due to the configuration of the architecture of the artificial neural network, as well as the type and parameters of the membership function.

Action 8. Determination of the amount of necessary computing resources of IDSS.

In order to prevent looping of calculations on Actions 1–7 of the specified method and to increase the reliability of processing heterogeneous data, the load of the IDSS is additionally determined. If the specified threshold of computational complexity is exceeded, the number of software and hardware resources that must be additionally attracted is determined using the method proposed in work [19].

End.

### 5. 2. Evaluation of the effectiveness of the data interpretation method in intelligent decision support systems

To determine the effectiveness of the data interpretation method in intelligent decision support systems, its modeling was carried out. The simulation was carried out when solving the task of processing heterogeneous data of the communication system and informatization of the operational grouping of troops (forces) under the initial conditions specified in section 4.

Separate parts of the computational experiment, using the proposed method, are given in the Table 2.

The general computational experiment is laid out on 133 sheets, in this section only its separate part is presented.

Table 2

Comparative analysis of the effectiveness of the proposed method with known approaches according to defined criteria

| Name of the approach | Accuracy | Precision | Recall | $F1$-score |
|---|---|---|---|---|
| Densenet 201 | 0.77 | 0.79 | 0.79 | 0.79 |
| Densenet 121 | 0.81 | 0.79 | 0.79 | 0.78 |
| MobileNetV2 | 0.79 | 0.79 | 0.8 | 0.79 |
| DenseNet-SEGR | 0.8 | 0.78 | 0.79 | 0.78 |
| Gradient Boosting Classifier | 0.85 | 0.84 | 0.85 | 0.85 |
| KNN | 0.78 | 0.79 | 0.8 | 0.79 |
| LSTM | 0.79 | 0.78 | 0.79 | 0.79 |
| RNN | 0.82 | 0.79 | 0.8 | 0.79 |
| CNN | 0.77 | 0.78 | 0.8 | 0.78 |
| ResNeXt | 0.78 | 0.79 | 0.79 | 0.79 |
| DenseNet-161 | 0.82 | 0.79 | 0.79 | 0.78 |
| DenseNet-169 | 0.83 | 0.79 | 0.8 | 0.79 |
| DenseNet-201 | 0.82 | 0.78 | 0.79 | 0.78 |
| DenXt | 0.85 | 0.84 | 0.85 | 0.85 |
| SparseNet | 0.79 | 0.79 | 0.8 | 0.79 |
| LogDenseNet | 0.84 | 0.78 | 0.79 | 0.79 |
| Tiramisu (FC-DenseNet) | 0.8 | 0.79 | 0.80 | 0.79 |
| RefineNet | 0.83 | 0.78 | 0.80 | 0.78 |
| Iterative Deep Aggregation (IDA) | 0.79 | 0.79 | 0.79 | 0.79 |
| DLA (Deep Layer Aggregation) | 0.8 | 0.79 | 0.79 | 0.78 |
| SE-DenseNet | 0.81 | 0.79 | 0.8 | 0.79 |
| CondenseNet | 0.8 | 0.78 | 0.79 | 0.78 |
| Bi-LSTM (Bidirectional LSTM) | 0.85 | 0.84 | 0.85 | 0.85 |
| Peephole LSTM | 0.79 | 0.77 | 0.81 | 0.82 |
| Causal ConvLSTM | 0.79 | 0.78 | 0.79 | 0.79 |
| PredRNN++ | 0.82 | 0.79 | 0.8 | 0.79 |
| E3D-LSTM (Eidetic Memory) | 0.78 | 0.78 | 0.8 | 0.78 |
| TrajGRU | 0.83 | 0.82 | 0.8 | 0.79 |
| ConvLSTM + Attention (SA-ConvLSTM) | 0.88 | 0.89 | 0.88 | 0.9 |
| Proposed method | 0.94 | 0.95 | 0.92 | 0.97 |

As can be seen from Table 2, increasing the efficiency of heterogeneous data processing is achieved by increasing the reliability of decision-making at the level of 14–18% due to the use of additional procedures.

## 6. Discussion of the results of the development of a method of data interpretation in intelligent decision support systems

The advantages of the proposed method of data interpretation in intelligent decision support systems are as follows:

– to conduct a multi-level and systematic assessment of the state of heterogeneous data processing using the proposed set of analytical expressions. This will allow a comprehensive and objective assessment of the state of processing of heterogeneous data in the IDSS, both its individual elements and the IDSS as a whole (expressions (1)–(16)), compared to works [4, 5];

– to take into account the influence of data uncertainty on the process of processing heterogeneous data in IDSS due to the use of fuzzy analytical expressions (expressions (3)–(5)), compared to works [3, 7];

– to reduce the loss of reliability of heterogeneous data processing by verifying information about IDSS and the data circulating in it (Action 2), compared to works [4, 7];

– to attract additional computing resources (if necessary) (Action 8), which achieves the prevention of looping of the method's operation, compared to research [13, 16];

– to increase the reliability of heterogeneous data processing in IDSS through multi-level deep learning of knowledge bases, using evolving artificial neural networks (Action 7) compared to works [11, 18];

– to estimate the zero values of the data in the IDSS databases, due to the use of the procedure for estimating the zero value of the data (Action 6), which achieves the prevention of looping of the method's operation, compared to works [10, 14];

– to conduct multi-level modeling of the IDSS functioning and the process of processing heterogeneous data circulating in them, due to the use of polymodel complexes (Action 4) of their functioning, compared to works [12, 15];

– to carry out an unambiguous classification of data, their attributes circulating in the IDSS due to the use of artificial immune detectors (Action 3), which achieves an increase in the accuracy of the IDSS setting and the reliability of heterogeneous data processing, compared to works [12, 18];

– to recover data that was lost during the processing of heterogeneous data in the IDSS due to their preliminary processing (Action 3), which achieves an increase in the reliability of heterogeneous data circulating in the IDSS compared to works [8, 15].

Among the shortcomings of the proposed method of data interpretation in intelligent decision support systems should be attributed a significant time required for the initial IDSS setting to the operating conditions.

The proposed method allows:

– to conduct modeling of the state of processing of heterogeneous data circulating in IDSS under conditions of complex influence of destabilizing factors;

– to identify effective measures to increase the level of reliability of processing heterogeneous data circulating in IDSS;

– to comprehensively assess the change in the level of reliability of the processing of heterogeneous data circulating in the IDSS during the control effects on the process of processing heterogeneous data.

The limitations of the study are the need to take into account the delay time for collecting and proving information from IDSS sensors (sensors).

The proposed method should be used as software for automated troop control systems such as "Dzvin-AS", "Oreanda-PS", as well as integrated information systems such as "Delta".

## 7. Conclusions

1. The study proposed the structure of the data interpretation method in intelligent decision support systems. Originality consists in:

– conducting a multi-level and systematic assessment of the state of heterogeneous data processing using the proposed set of analytical expressions. This will allow a comprehensive and objective assessment of the state of processing of heterogeneous data in IDSS, both as a separate element of it and IDSS as a whole;

– taking into account the influence of data uncertainty on the process of processing heterogeneous data in IDSS due to the use of fuzzy analytical expressions;

– reduction of loss of reliability of heterogeneous data processing due to verification of information about IDSS and data circulating in it;

– attracting additional computing resources (if necessary), which achieves the prevention of looping of the method;

– increasing the reliability of heterogeneous data processing in IDSS due to multi-level deep learning of knowledge bases, using evolving artificial neural networks;

– estimation of zero data values in IDSS databases, due to the use of the procedure for estimating the zero data value, which achieves the prevention of looping of the method;

– carrying out multi-level modeling of the functioning of the IDSS and the process of processing heterogeneous data circulating in them, due to the use of polymodel complexes of their functioning;

– carrying out unambiguous classification of data, their attributes circulating in the IDSS due to the use of artificial immune detectors, which achieves an increase in the accuracy of IDSS settings and the reliability of heterogeneous data processing;

– recovery of data that was lost during the processing of heterogeneous data in IDSS due to their preliminary processing, which achieves an increase in the reliability of heterogeneous data circulating in IDSS.

2. The proposed method provides an increase in the efficiency of heterogeneous data processing by increasing the reliability of decision-making at the level of 14–18% due to the use of additional procedures, which is confirmed by the results of a computational experiment.

## Conflict of interest

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

## Financing

The study was conducted without financial support.

## Data availability

The manuscript has related data in the data warehouse.

## Use of artificial intelligence tools

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

## Authors' contributions

**Andrii Shyshatskyi**: Conceptualization; Methodology; Project administration; Writing – original draft; Writing – review & editing; **Anatolii Pavlikovskyi**: Methodology; Writing; Writing – review & editing; **Pavlo Zhuk**: Writing –

original draft; **Oleksii Nalapko**: Writing – review & editing; **Volodymyr Cherneha**: Resources; Data Curation; **Yurii Artabaiev**: Validation; Data Curation; **Nadiia Protas**: Software; Validation; Data Curation; **Yevhen Peleshok**: Methodology; Formal analysis; Visualization; **Andrii Veretnov**: Software: Programming, software development; designing computer programs; implementation of the computer code and supporting algorithms; testing of existing code components; Validation; Data Curation; **Danylo Pliekhov**: Software; Validation; Data Curation.

References


1. Sova, O., Radzivilov, H., Shyshatskyi, A., Shvets, P., Tkachenko, V., Nevhad, S. et al. (2022). Development of a method to improve the reliability of assessing the condition of the monitoring object in special-purpose information systems. Eastern-European Journal of Enterprise Technologies, 2 (3 (116)), 6–14. https://doi.org/10.15587/1729-4061.2022.254122
2. Dudnyk, V., Sinenko, Y., Matsyk, M., Demchenko, Y., Zhyvotovskyi, R., Repilo, I. et al. (2020). Development of a method for training artificial neural networks for intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 3 (2 (105)), 37–47. https://doi.org/10.15587/1729-4061.2020.203301
3. Sova, O., Shyshatskyi, A., Salnikova, O., Zhuk, O., Trotsko, O., Hrokholskyi, Y. (2021). Development of a method for assessment and forecasting of the radio electronic environment. EUREKA: Physics and Engineering, 4, 30–40. https://doi.org/10.21303/2461-4262.2021.001940
4. Pievtsov, H., Turinskyi, O., Zhyvotovskyi, R., Sova, O., Zvieriev, O., Lanetskii, B., Shyshatskyi, A. (2020). Development of an advanced method of finding solutions for neuro-fuzzy expert systems of analysis of the radioelectronic situation. EUREKA: Physics and Engineering, 4, 78–89. https://doi.org/10.21303/2461-4262.2020.001353
5. Zuiev, P., Zhyvotovskyi, R., Zvieriev, O., Hatsenko, S., Kuprii, V., Nakonechnyi, O. et al. (2020). Development of complex methodology of processing heterogeneous data in intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 4 (9 (106)), 14–23. https://doi.org/10.15587/1729-4061.2020.208554
6. Wang, J., Neil, M., Fenton, N. (2020). A Bayesian network approach for cybersecurity risk assessment implementing and extending the FAIR model. Computers & Security, 89, 101659. https://doi.org/10.1016/j.cose.2019.101659
7. Matheu-García, S. N., Hernández-Ramos, J. L., Skarmeta, A. F., Baldini, G. (2019). Risk-based automated assessment and testing for the cybersecurity certification and labelling of IoT devices. Computer Standards & Interfaces, 62, 64–83. https://doi.org/10.1016/j.csi.2018.08.003
8. Henriques de Gusmão, A. P., Mendonça Silva, M., Poleto, T., Camara e Silva, L., Cabral Seixas Costa, A. P. (2018). Cybersecurity risk analysis model using fault tree analysis and fuzzy decision theory. International Journal of Information Management, 43, 248–260. https://doi.org/10.1016/j.ijinfomgt.2018.08.008
9. Folorunso, O., Mustapha, O. A. (2015). A fuzzy expert system to Trust-Based Access Control in crowdsourcing environments. Applied Computing and Informatics, 11 (2), 116–129. https://doi.org/10.1016/j.aci.2014.07.001
10. Mohammad, A. (2020). Development of the concept of electronic government construction in the conditions of synergetic threats. Technology Audit and Production Reserves, 3 (2 (53)), 42–46. https://doi.org/10.15587/2706-5448.2020.207066
11. Bodin, L. D., Gordon, L. A., Loeb, M. P., Wang, A. (2018). Cybersecurity insurance and risk-sharing. Journal of Accounting and Public Policy, 37 (6), 527–544. https://doi.org/10.1016/j.jaccpubpol.2018.10.004
12. Cormier, A., Ng, C. (2020). Integrating cybersecurity in hazard and risk analyses. Journal of Loss Prevention in the Process Industries, 64, 104044. https://doi.org/10.1016/j.jlp.2020.104044
13. Hoffmann, R., Napiórkowski, J., Protasowicki, T., Stanik, J. (2020). Risk based approach in scope of cybersecurity threats and requirements. Procedia Manufacturing, 44, 655–662. https://doi.org/10.1016/j.promfg.2020.02.243
14. Perrine, K. A., Levin, M. W., Yahia, C. N., Duell, M., Boyles, S. D. (2019). Implications of traffic signal cybersecurity on potential deliberate traffic disruptions. Transportation Research Part A: Policy and Practice, 120, 58–70. https://doi.org/10.1016/j.tra.2018.12.009
15. Promyslov, V. G., Semenkov, K. V., Shumov, A. S. (2019). A Clustering Method of Asset Cybersecurity Classification. IFAC-PapersOnLine, 52 (13), 928–933. https://doi.org/10.1016/j.ifacol.2019.11.313
16. Zarreh, A., Saygin, C., Wan, H., Lee, Y., Bracho, A. (2018). A game theory based cybersecurity assessment model for advanced manufacturing systems. Procedia Manufacturing, 26, 1255–1264. https://doi.org/10.1016/j.promfg.2018.07.162
17. Zhuravskyi, Y. (Ed.) (2026). Intelligent decision support systems: methods for optimizing and supporting management decisions. Kharkiv: TECHNOLOGY CENTER PC. https://doi.org/10.15587/978-617-8360-23-8
18. Koval, M., Sova, O., Shyshatskyi, A., Artabaiev, Y., Garashchuk, N., Yivzhenko, Y. et al. (2022). Improving the method for increasing the efficiency of decision-making based on bio-inspired algorithms. Eastern-European Journal of Enterprise Technologies, 6 (4 (120)), 6–13. https://doi.org/10.15587/1729-4061.2022.268621
19. Shyshatskyi, A. (Ed.) (2024). Information and control systems: modelling and optimizations. Kharkiv: TECHNOLOGY CENTER PC. https://doi.org/10.15587/978-617-8360-04-7
20. Voznytsia, A., Sharonova, N., Babenko, V., Ostapchuk, V., Neronov, S., Feoktystov, S. et al. (2025). Development of methods for intelligent assessment of parameters in decision support systems. Eastern-European Journal of Enterprise Technologies, 4 (4 (136)), 73–82. https://doi.org/10.15587/1729-4061.2025.337528