The object of the study is the system of information and analytical support of the state level (IAS). The problem that is solved in the study is increasing the efficiency of processing various types of data while ensuring the given reliability of their processing. The hypothesis of the study is the possibility of increasing the level of efficiency of processing various types of data in the IAS system due to the development of methods of their processing.

The originality of the proposed methodology is:

– carrying out a comprehensive calculation of the uncertainty of various types of data in IAS systems according to 5 indicators, which allows to increase the accuracy of the initial setting of the IAS system;

– increasing the efficiency and reliability of the synchronization process of various types of data due to the use of an improved synchronization procedure;

– increasing the level of efficiency and reliability of the calculation process and aggregation of data circulating in the IAS system due to the use of the appropriate procedure;

– increasing the efficiency and reliability of the process of separation of various types of data circulating in the IAS system due to the use of the appropriate procedure;

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

– carry out unambiguous classification of data, their attributes circulating in IAS systems due to the use of artificial immune detectors, which increases the accuracy of setting up the IAS system and the reliability of processing various types of data.

The proposed technique ensures an increase in the efficiency of processing various types of data due to the use of additional procedures at the level of 24–28%, which is confirmed by the results of a computational experiment

Keywords: intelligent decision support systems, data uncertainty, data processing efficiency

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DEVELOPMENT OF METHODOLOGY FOR PROCESSING DIFFERENT TYPES OF DATA IN INFORMATION AND ANALYTICAL SUPPORT SYSTEMS AT THE STATE LEVEL

Dmytro Honcharuk
Head of Research Laboratory
Laboratory of Informatization Project Management Problems
Center for Military and Strategic Studies*
ORCID: https://orcid.org/0000-0002-3664-3636

Aleksandra Kuzior
PhD, Doctor of Science, Doctor Honoris Causa, Professor, Head of Department
Department of Applied Social Sciences
Silesian University of Technology
Akademicka str., 2A, Gliwice, Poland, 44-100
ORCID: https://orcid.org/0000-0001-9764-5320

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

Oleksandr Rudenko
Candidate of Technical Sciences, Associate Professor
Department of Computer and Information Technologies and Systems
National University "Yuri Kondratyuk Poltava Polytechnic"
Vitaliia Hrytsaienka ave., 24, Poltava, Ukraine, 36011
ORCID: https://orcid.org/0000-0002-7110-0653

Andrii Veretnov
Candidate of Technical Sciences, Leading Researcher
Research Department
Central Scientifically-Research Institute of Armaments and Military Equipment
of the Armed Forces of Ukraine
Povitrianykh Syl ave., 28, Kyiv, Ukraine, 03049
ORCID: https://orcid.org/0000-0003-0160-7325

Ihor Pimonov
Candidate of Technical Sciences, Associate Professor
Department of Operation, Testing, and Service of Construction and Road Machinery**
ORCID: https://orcid.org/0000-0001-6100-3529

Oleksandr Yarovyi
Candidate of Technical Sciences, Researcher
Research Institute of Military Intelligence
Yuriy Illenka str., 81, Kyiv, Ukraine, 04050
ORCID: https://orcid.org/0000-0002-3889-5730

Yevhen Sudnikov
Doctor of Philosophy (PhD), Senior Researcher
Scientific Distance Learning Centre*
ORCID: https://orcid.org/0000-0003-2484-4972

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

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
*National Defence University of Ukraine
Povitrianykh Syl ave., 28, Kyiv, Ukraine, 03063
**Kharkiv National Automobile and Highway University
Yaroslava Mudroho str., 25, Kharkiv, Ukraine, 61002

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1. Introduction

Information and analytical support (IAS) is an integral component at all levels of management, regardless of the field of use and the specifics of the tasks to be solved [1, 2]. A significant factor in the growth of the role of IAS in the modern world is the rapid growth of the volume of various types of data, the processing of which must be carried out [3, 4].

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Also, in addition to the volume of various types of data, there are constantly increasing requirements regarding the promptness, reliability, and timeliness of their processing [5].

Under these conditions, classical approaches to the processing of various types of data are either not possible and/or not expedient for several reasons [1, 6–8]:

– the subjectivity of carrying out the processing of different types of data;

– insufficient efficiency of processing various types of data;

– incompleteness of analysis of the volume of various types of data to be processed;

– lack of ability to conduct parallel processing of several streams of different types of data at the same time;

– weak adaptation of existing approaches to processing various types of data to dynamic changes in volume, type, as well as filling various types of data, etc.

That is why intelligent decision support systems (IDSS) with appropriate hardware and software are used to eliminate the above problematic issues. At the same time, there are separate problematic issues in modern IDSS [9, 10]:

– insufficient efficiency (according to defined evaluation criteria) of performing information and calculation tasks in conditions of uncertainty and incompleteness of initial data;

– weak adaptation to non-standard and atypical situations that arise during the functioning of IDSS;

– difficulty of unambiguous interpretation of various types of data circulating in IDSS, etc.

Taking into account the above, one of the options for increasing the efficiency of the functioning of the IDSS, which function under the conditions of the complex influence of destabilizing factors, is the development of a methodology for processing various types of data in information and analytical support systems at the state level.

Therefore, study aimed at improving the efficiency of processing various types of data in state-level information and analytical systems is relevant and warrants further scientific study.

2. Literature review and problem statement

Work [11] identifies the main advantages and disadvantages of cognitive algorithms. The disadvantages of this approach include the lack of consideration of the type of uncertainty and the inability to search in different directions by several agents. In the study, insufficient 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, insufficient 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 an appropriate correction of the obtained models. In the study, insufficient 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, insufficient 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 minimizing the uncertainty of various types of data in IAS under conditions of uncertainty;

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

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

All this allows to state that it is expedient to conduct a study dedicated to increasing the efficiency of processing various types of data in information and analytical systems under conditions of uncertainty.

3. The aim and objectives of the study

The aim of the study is to increase the efficiency of processing various types of data in state-level IAS systems due to the development of a methodology for processing various types of data in state-level IAS systems. This will allow comprehensive, objective, and complete decision-making regarding the management of processing parameters of various types of data in IAS systems at different levels of their functioning (individual elements of the IAS system). Also, this will make it possible to develop (improve) the software of modern and promising IAS systems by integrating the proposed methodology into the corresponding software.

To achieve the aim, the following objectives were set:

– to develop a set of procedures for processing various types of data in state-level information and analytical support systems;

– to evaluate the effectiveness of the proposed methodology according to the defined indicators and evaluation criteria.

4. Materials and methods

The object of the study is the IAS system. The hypothesis of the study is the possibility of increasing the level of efficiency of processing various types of data in the IAS system due to the development of methods for processing various types of data.

The assumptions of this study are the possibility of increasing the efficiency of the functioning of the information and analytical support system due to the development of new approaches to the processing of various types of data.

Simplifications of this study are:

– data on the input of the IAS system are received evenly during the observation period;

– the type of data received at the input of the IAS system during the observation period does not change;

– the effect of the destructive effect system on the IAS system is unchanged during the observation period.

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

– general scientific method of analysis – for decomposing problematic issues of the functioning of the IAS system, processing various types of 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 processing of various types of data in IAS systems when they perform tasks as intended;

– general scientific method of synthesis – to substantiate the most expedient approaches to the processing of various types of data in IAS systems when they perform tasks as intended;

– artificial neural networks, with an evolving structure – for active database learning, when processing various types of data. The specified mathematical apparatus provides the possibility of adaptation to the required number of data flows and types circulating in the state-level IAS system;

– artificial immune detectors – for verification of the structure of the IAS system and classification of data circulating in it. The specified mathematical apparatus allows for unambiguously classifying the data and structure of the IAS system and level the role of the human factor in the processing of various types of data and data interpretation;

– improved combined bio-inspired algorithm [19] – for performing basic procedures for processing various types of data in the IAS system. This approach was chosen for the possibility of parallel use of several bio-inspired algorithms, which increases the efficiency and reliability of processing various types of data.

As an object for carrying out a computational experiment, the present study adopted a system for communication and informatization of the strategic grouping of troops (forces). The strategic grouping of troops (forces) is formed according to the state of martial law (typical state). Mode of operation of the communication system and information systems – stabilization operation.

The hardware of the research process is server equipment with the following configuration:

– Intel Xeon Platinum 8592+ Qs Cpu Lga4677 1.9 Ghz 64 Cores 128 Threads – 4 pcs;

– RAM – 8 TB;

– Video card 4 × NVIDIA H100 PCIe/SXM5.

The number of information sources for processing is 600 units.

Research Software – Microsoft Visual Studio 2022 (USA).

The final processing of the research results was carried out on the Acer Aspire 515 laptop, based on the AMD Ryzen 5 processor.

An important issue in the field of artificial intelligence is how to obtain hidden (valuable) disparate data and measure its uncertainty. This work examines the measurement of uncertainty for various types of data circulating in the IAS system and provides its application in attribute reduction.

Randomness and vagueness are the two main types of uncertainty. Randomness means that there is no clear causal link between conditions and outcomes, as the conditions for events are insufficient. Fuzzy refers to whether an array of data about an object corresponds to this concept, which is difficult to define, and has no clear meaning in nature because there is no definite limit in quantity. Unlike randomness and vagueness, roughness is another kind of uncertainty that researchers have been paying more and more attention to in recent years. This refers to distinguishing arrays of data about objects due to incompleteness or inaccuracies of knowledge. The uncertainty measurement for the IAS system reflects the classification capacity of this system, which significantly affects the accuracy of data classification [17, 19].

In physics, entropy is often used to measure the degree of disorder in a system. The greater the value of entropy, the higher the level of disorder in the system. The study applied the concept of entropy in physics to information theory to measure the uncertainty of the IAS system [17, 19].

5. Research on the development of methods of processing various types of data in state-level information and analytical support systems

5. 1. Development of a set of procedures for processing various types of data in state-level information and analytical support systems

The set of procedures proposed for processing various types of data in state-level IAS systems consists of the following sequence of actions:

Action 1. Entering initial data about the state-level IAS system.

Initial data on the IAS system and the conditions of its functioning are entered.

The following output data are entered:

– the total number of radio-electronic countermeasures (RECs) that affect the mining elements of the IAS system;

– total number of means of cyber influence, intensity of cyber influence on the IAS system;

– type of cyberattacks that act on the IAS system in each element of the IAS system;

– spectral-energy parameters of obstacles of the REC means affecting the mining elements of the IAS system;

– the number of means of fire damage that act in the field of operation of the mining elements of the IAS system;

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

– type of data by categories to be processed in the IAS system;

– volumes of data for each category that must be processed by the IAS system;

– intensity of fire impact on mining elements of the IAS system, etc.

Action 2. Verification of information about the IAS system and data circulating in it.

A classification binary tree is used to verify information about the IAS system and the data circulating in it. Formally, such a structure of a hierarchical verification system 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 $\mu=\{0,\ldots,m\}$ – the output set of data class labels of the IAS system, $L_{\mu}\subsetneq\mu$ – an arbitrarily generated or defined subset of IAS system data classes; $\mu\left(\#L_{\mu}<\#\mu\right)$, $R_{\mu}=\mu\backslash L_{\mu}$ – 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

$$\left\{\left(x_l,0\right)\middle|\,\overline{c}_l\in L_{\mu}\right\}_{l=1}^{M}\cup\left\{x_l,1\middle|\,\overline{c}_l\in R_{\mu}\right\}_{l=1}^{M}.$$

The output of the detector is adjusted to be 0 if the input data x_l, those circulating in the IAS system belong to the class with the label $\overline{c}_l\in L_{\mu}$ and 1, if input data x_l IAS systems belong to the class with the label $\overline{c}_l\in L_{\mu}$.

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 $\varphi^{(i)}_j$, which sets the sequential dichotomy of the set μ:

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

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

Application function $\phi^{(i)}_j$ the output set of data class labels in the IAS system allows to unambiguously search for the data class label in the IAS system circulating in it.

Action 3. Determination of the degree of uncertainty of various types of data on IAS according to certain indicators.

Action 3. 1. Calculation of the uncertainty of the IAS system.

This study used the following uncertainty estimation indicators about the IAS system (data detail indicators, data information entropy, coarse entropy, data volume, fuzzy entropy for fuzzy relation for a separately defined data category) to measure uncertainty.

Action 3. 1. 1. Calculation of the degree of data detail for the IAS system.

Let the IAS system be described as (U, A), where A – the final set of attributes of the IAS system, B – finite set of one-dimensional noise variables, $B\subseteq A$. Then the degree of detail of the data in the information and analytical subsystem (U, B) IAS systems are defined as follows

$$G\left(B\right)=-\frac{1}{n^2}\sum_{i=1}^{m}\left|X_i\right|^2, \quad (3)$$

where G – fuzzy data granule, U – nonempty finite set, $U=\{x_1, x_2, \ldots, x_n\}$; R_B – equivalence relation on U; $U\setminus R^*_B=\{X_1,X_2,\ldots,X_m\}$.

Expression (3) illustrates that the degree of detail of the data in the IAS system is based entirely on the information structure of this fuzzy relation.

The limitation of data granulation values in the IAS system under conditions of uncertainty is determined as follows

$$\frac{1}{n}\leq G\left(B\right)\leq 1. \quad (4)$$

Moreover, if $R^*_B=\Delta$, then $G(B)$ reaches the minimum value $1/n$; if $R^*_B=\omega$, then $G(B)$ reaches the maximum value 1.

The detailing of data in the IAS system corresponds to the characteristics of granulation calculations and clarifies data from different levels of the IAS system. This indicator decreases monotonically as the equivalent class of data circulating in the IAS system is refined.

Action 3. 1. 2. Calculation of information entropy for the IAS system.

Information entropy of the information and analytical subsystem (U, B) IAS systems have been defined

$$H\left(R\right)=-\sum_{i=1}^{m}\frac{\left|X_i\right|}{n}\log_2\frac{\left|X_i\right|}{n}, \quad (5)$$

where

$$U\setminus R^*_B=\left\{X_1,X_2,\ldots,X_m\right\}.$$

Action 3. 1. 3. Calculation of coarse entropy for the IAS system.

Rough entropy is used to measure the degree of detail. Coarse subsystem entropy (U, B) IAS systems are defined as follows

$$E_r\left(B\right)=-\sum_{i=1}^{m}\frac{\left|X_i\right|}{n}\log_2\frac{1}{\left|X_i\right|}, \quad (6)$$

where

$$U\setminus R^*_B=\left\{X_1,X_2,\ldots,X_m\right\}.$$

Action 3. 1. 4. Calculation of the amount of data for the IAS system. Subsystem data scope (U, B) in the IAS system, it is proposed in the following definition

$$E\left(B\right)=\sum_{i=1}^{m}\frac{\left|X_i\right|}{n}\frac{\left|U-X_i\right|}{n}, \quad (7)$$

where

$$U\setminus R^*_B=\left\{X_1,X_2,\ldots,X_n\right\}.$$

Action 3. 1. 5. Definition of fuzzy entropy for a fuzzy relation for a separately defined IAS system data category.

Let $R \in I^{U \times U}$, where U – not an empty finite set, R – fuzzy set, I – the set of all fuzzy relations on U.

For any $x \in U$, defined $G_R(x)(y) = R(x, y)$, $\forall y \in U$. $G_R(x)$ – granule of fuzzy point information x regarding R. Fuzzy entropy then R defined as

$$H(R) = -\sum_{i=1}^{m} \frac{|X_i|}{n} \log_2 \frac{|G_R(x)|}{n}, \quad x \in X_i. \tag{8}$$

Fuzzy entropy can be seen as an extension of Shannon entropy.

Action 4. Classification of data circulating in IAS.

A tree of classifiers is used to classify data in this study. 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 on the basis of 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 $F_{jk}^{(k)}$: $\mathbb{R} \to \{0,1\}$, $k = 1,...,m$ learns from various types of 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:

$$F_j^{(i)}(z) = \begin{cases} \{0\}, \text{ if } \forall k \in \{1,...,m\} F_{jk}^{(i)}(z) = 0, \\ \left\{k \middle| F_{jk}^{(i)}(z) = 1\right\}_{k=1}^{m}, \text{ otherwise.} \end{cases} \tag{9}$$

In the second approach, each of $C_{m+1}^2 = \frac{(m+1) \cdot m}{2}$ detectors $F_{jk_0k_1}^{(k)}$ learns from a set of different types of input data belonging only to two classes with labels k_0 and 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

$$F_j^{(i)} = \left\{ \arg \max_{\bar{c} \in \{0,...,m\}} \sum_{k=\bar{c}+1}^{m} \left[F_{j\bar{c}k}^{(i)}(z) = 0 \right] + \sum_{k=0}^{\bar{c}-1} \left[F_{j\bar{c}k}^{(i)}(z) = 1 \right] \right\}. \tag{10}$$

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

The ratio of correctly classified cases $(TP + TN)/(TP + TN + FP + FN)$ is described as several actions based on the results of a mixed matrix, such as the accuracy of correctly classified various types of data circulating in the IAS system.

TP, *FN*, *FP*, and *TN* – number of true positive results, false negative (false positive) results, and true negative results. Specific measurements are used to verify each classification approach and assess its accuracy, sensitivity, and *F*1 estimate for each classification approach of various types of data circulating in the IAS system. Estimates used in this study are: accuracy (11), error (12), reactivity (13), and *F*1 score (14):

$$Accuracy = (TP + TN)/(TP + FP + FN + TN), \tag{11}$$

$$Precision = TP / (TP + FP), \tag{12}$$

$$Recall = TP / (TP + FN), \tag{13}$$

$$F1 = 2 \times Precision \times Recall/(Precision + Recall). \tag{14}$$

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

Table 1

Characteristics of detector combining circuits

Unification scheme	Number of detectors to be trained	The minimum number of detectors involved in the classification of various types of data	The maximum number of detectors involved in the classification of various types of data
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	$(m \cdot x) \cdot m$	$(m \cdot x)$	$(m \cdot x) \cdot m$
Genetic algorithm	$(m \cdot x)$	m	$(m \cdot x)$

Action 5. Dispersion analysis for each type of data circulating in the IAS system.

In this work, the standard deviation coefficient is applied to analyze the effectiveness of the proposed measures.

Let's suppose that $X_i = \{x_1, ..., x_n\}$ this is a set of various types of data circulating in the IAS system. Then the arithmetic mean, the standard deviation, and the standard deviation coefficient X, what are marked $\bar{x}$, $\sigma(X)$ and $CV(X)$, accordingly, they are defined as follows:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i,$$

$$\sigma(X) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2},$$

$$CV(X) = \frac{\sigma(X)}{\bar{x}}. \tag{15}$$

Action 6. Carrying out a correlation analysis of each type of different types of data circulating in the IAS system.

In statistics, the Pearson correlation coefficient is a measure of the strength of a linear correlation between two sets of different types of data.

Let's suppose that $X_i = \{x_1, ..., x_n\}$ and $Y = \{y_1, ..., y_n\}$ there are two sets of different types of data. Pearson correlation coefficient between X and Y, which is denoted as $r(X, Y)$ and defined accordingly

$$r(X,Y) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}, \tag{16}$$

where $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$, $\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$.

Correlation between X and Y can be obtained according to the Table 2.

Table 2

Corresponding correlation between X and Y

$r(X, Y)$	Correlation between X and Y	Abbreviation
$r(X, Y) = 1$	Fully positive correlation	CPC
$0.7 \le r(X, Y) < 1$	Positive correlation	HPC
$0.4 \le r(X, Y) < 0.7$	Moderate positive correlation	MPC
$0 < r(X, Y) < 0.4$	Weak positive correlation	LPC
$r(X, Y) = 0$	Lack of correlation	NC
$-0.4 < r(X, Y) < 0$	Weak negative correlation	LNC
$-0.7 \le r(X, Y) < -0.4$	Moderate negative correlation	MNC
$-1 \le r(X, Y) < -0.7$	Negative correlation	HNC
$r(X, Y) = -1$	A completely negative correlation	CNC

Thus, an IAS system architecture is proposed, differing in the use of an equivalence relation on a plurality of objects to measure the uncertainty of the IAS system, and providing a reduction of multivariate analyzed attributes based on data granulation and information entropy.

Action 6. Separation of various types of data circulating in the IAS system.

The procedure for separating the various types of data circulating in the IAS system is described by the following sequence of actions [21]:

6. 1. List received L (the result of the procedure for synchronizing various types of data circulating in the IAS system).

6. 2. Create an empty list $R\langle JSONObject\rangle$, what contains different types of data according to the template "*Parameter Template*".

6. 3. For each element of the list L, execute:

6. 3. 1. Split the elements according to the 'Data Source Template" template and get the list L_s.

6. 3. 2. For each element of the list L_s execute: split items according to "Parameter Template" template and add to list L_p.

For each list item L_p execute: create a new object, which information needs to be processed *JSONObject.* Save the received data to a crafted object *JSONObject*, information about which needs processing, according to the parameter template. Add object to list $R\langle JSONObject\rangle$.

6. 4. Return the list $R\langle JSONObject\rangle$.

Action 7. Calculation and aggregation of data circulating in the IAS system.

Information and settlement operations are carried out in accordance with the proposed combined algorithm given in the study [19].

As a result of the system analysis of the collection process and data structure of the IAS system, a procedure for aggregation of various types of data is proposed in accordance with the concept of a data lake [21]

$$S = \left\langle \{DT\}_{i=1}^{n_{ST}}, \{SS\}_{j=1}^{m_{ST}}, \{E\}_{k=1}^{p_E}, IS, DS \right\rangle, \quad (17)$$

where $\{DT\}_{i=1}^{n_{ST}}$ – a set of templates of various types of data circulating in the IAS system; n_{ST} – the number of templates of various types of data circulating in the IAS system; $\{SS\}_{j=1}^{m_{ST}}$ – methods of dividing various types of data circulating in the IAS system; m_{ST} – the number of types of various types of data circulating in the IAS system; $\{E\}_{k=1}^{p_E}$ – a set of executors of tasks of collecting various types of data circulating in the IAS system; IS – the method of indexing data in the storage of the lake of data circulating in the IAS system; DS – the structure of the lake of various types of data circulating in the IAS system.

Action 8. Indexing of various types of data circulating in the IAS system.

To improve the efficiency of the collection and storage of various types of data, a procedure for indexing them is proposed [21]. Each file stored in a store of different types of data is a pair $\langle t,v\rangle$, where t – time of generation of various types of data, v – the value of various types of data.

Clarification on the application of the proposed procedure for indexing miscellaneous data:

1. *The_root_to_store_heterogeneous_data* – root directory for storing data.

2. *ot_IDn* – object template identifier *n*.

3. *od_IDm* – unique object identifier *m*.

4. *ds_IDk* – unique source identifier of a given object to *k*.

5. *p_IDl* – the unique parameter identifier of this source *l*.

6. *f_IDp* – unique parameter file identifier *p*.

For simplicity and reduction of processing time of various types of file data, a name is assigned that contains time *t* data block generation.

Action 9. Synchronization of various types of data circulating in the IAS system.

The procedure for synchronizing data circulating in the IAS system consists of the following sequence of actions [21]:

1. A set of different types of data was obtained *P*. At the specified stage, the value of uncertainty about information sources is taken into account, according to expressions (3)–(8).

2. Create empty lists $L_i\langle t,d\rangle$ for storing objects $L_i\langle t,d\rangle = \phi$, $I = 1$, n where n – number of templates of objects for which information is to be processed, t – data generation time d(d in the form *JSONObject* (JavaScript Object Notation).

3. For each element of the received data package, follow the following steps:

3. 1. Determine the object for which information is to be processed according to the key parameters included in the received data.

3. 2. If the object for which the information to be processed is not found in the list L_k, which corresponds to a given object in a pattern, $k = 1$, n that's it.

3. 2. 1. Create a new object *JSONObject*.

3. 2. 2. Save the received data to a crafted object *JSONObject* in accordance with the object pattern.

3. 2. 3. Add the created object to the list L_k.

Otherwise:

3. 2. 4. Sort all data about the found object by time *timestamp T* object data block generation.

3. 2. 5. Save the received data to a crafted object *JSONObject* in accordance with the template of the object for which the information is to be processed.

3. 2. 6. Display list *L*.

Action 10. Training of IAS knowledge bases.

In the course of performing the specified procedure, IAS knowledge bases are trained using the deep learning method based on the use of evolving artificial neural networks [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 11. Determination of the amount of necessary computing resources for IAS.

In order to prevent looping of calculations on actions 1–10 of the specified technique and to increase the reliability of processing various types of data, the load of the IAS system

is additionally determined. If the specified computational complexity threshold is exceeded, the number of software and hardware resources that must be additionally attracted is determined using the method proposed in work [19].

5. 2. Evaluation of the effectiveness of the method of processing various types of data in the systems of information and analytical support at the state level

To determine the effectiveness of the method of processing various types of data in the systems of information and analytical support at the state level, its modeling was carried out. The simulations were carried out when solving the task of processing heterogeneous data of the communication system and the informatization of the strategic grouping of troops (forces) under the given initial conditions.

The general computational experiment is laid out on 281 sheets; in this section, only its separate part is presented.

A computational experiment was carried out with four sets of different types of data obtained from the machine learning database repository, which is shown in Table 3, and a comparison of four tools for measuring the uncertainty of the IAS system was carried out.

The following data sets from the machine learning database repository are selected. Table 3 provides information for these sets of various types of data circulating in the IAS system.

Table 3

4 datasets from the machine learning database repository

No.	Data set	Number of IAS elements	Scalable	Ordinal	Nominal	Classes
1	Set 1	368	5	2	15	2
2	Set 2	583	5	4	1	2
3	Set 3	155	2	4	13	2
4	Set 4	270	1	6	6	2

Set 1 describes the information and analytical subsystem of the IAS system (U, A) and its properties with the help of $|U| = 368$, $|A| = 23$. Marked $A_i = \{a_1, ..., a_i\}$ ($i = 1, ..., 23$). Then for everyone i there is an equivalence relation induced by A_i in set 1. The four sets of measures in set 1 are defined as follows:

$$X_G(\mathrm{He}) = \left\{G\left(R^*_{A_1}\right),\ldots,G\left(R^*_{A_{23}}\right)\right\},$$
$$X_E(\mathrm{He}) = \left\{E\left(R^*_{A_1}\right),\ldots,E\left(R^*_{A_{23}}\right)\right\},$$
$$X_{E_r}(\mathrm{He}) = \left\{E_r\left(R^*_{A_1}\right),\ldots,E_r\left(R^*_{A_{23}}\right)\right\},$$
$$X_H(\mathrm{He}) = \left\{H\left(R^*_{A_1}\right),\ldots,H\left(R^*_{A_{23}}\right)\right\}. \quad (18)$$

Set 2 describes the information and analytical subsystem of the IAS system (V, B) and its properties with the help of $|V| = 583$, $|B| = 1$. Marked $B_i = \{b_1, ..., b_i\}$ ($i = 1, ..., 11$). Then for everyone i there is an equivalence relation induced by B_i in set 2. The four sets of measures in set 2 are defined as follows:

$$X_G(\mathrm{ID}) = \left\{G\left(R^*_{B_1}\right),\ldots,G\left(R^*_{B_{11}}\right)\right\},$$
$$X_E(\mathrm{ID}) = \left\{E\left(R^*_{B_1}\right),\ldots,E\left(R^*_{B_{11}}\right)\right\},$$
$$X_{E_r}(\mathrm{ID}) = \left\{E_r\left(R^*_{B_1}\right),\ldots,E_r\left(R^*_{B_{11}}\right)\right\},$$
$$X_H(\mathrm{ID}) = \left\{H\left(R^*_{B_1}\right),\ldots,H\left(R^*_{B_{11}}\right)\right\}. \quad (19)$$

Set 3 describes the information and analytical subsystem of the IAS system (W, C) and its properties with the help of $|W| = 155$, $|C| = 20$. Marked $C_i = \{c_1, ..., c_i\}$ ($i = 1, ..., 20$). Then for everyone i there is an equivalence relation induced by C_i in set 3. The four sets of measures in set 3 are defined as follows:

$$X_G(\mathrm{Hs}) = \left\{G\left(R^*_{C_1}\right),\ldots,G\left(R^*_{C_{20}}\right)\right\},$$
$$X_E(\mathrm{Hs}) = \left\{E\left(R^*_{C_1}\right),\ldots,E\left(R^*_{C_{20}}\right)\right\},$$
$$X_{E_r}(\mathrm{Hs}) = \left\{E_r\left(R^*_{C_1}\right),\ldots,E_r\left(R^*_{C_{20}}\right)\right\},$$
$$X_H(\mathrm{Hs}) = \left\{H\left(R^*_{C_1}\right),\ldots,H\left(R^*_{C_{20}}\right)\right\}. \quad (20)$$

Set 4 describes the information and analytical subsystem of the IAS system (X, D) and its properties with the help of $|X| = 270$, $|D| = 14$. Then for everyone $d \in D$, R_d – fuzzy ratio caused by set 4. Marked $D_i = \{d_1, ..., d_i\}$ ($i = 1, ..., 14$). Then for everyone i, $R^*_{D_i}$ will be the equivalence relation induced by D_i in set 4. The four sets of measures on set 3 are defined as follows:

$$X_G(\mathrm{Ht}) = \left\{G\left(R^*_{D_1}\right),\ldots,G\left(R^*_{D_{14}}\right)\right\},$$
$$X_E(\mathrm{Ht}) = \left\{E\left(R^*_{D_1}\right),\ldots,E\left(R^*_{D_{14}}\right)\right\},$$
$$X_{E_r}(\mathrm{Ht}) = \left\{E_r\left(R^*_{D_1}\right),\ldots,E_r\left(R^*_{D_{14}}\right)\right\},$$
$$X_H(\mathrm{Ht}) = \left\{H\left(R^*_{D_1}\right),\ldots,H\left(R^*_{D_{14}}\right)\right\}. \quad (21)$$

Data granulation G that gross entropy E_r monotonically decrease with increasing equivalence ratio. At the same time, the data quantity E and the information entropy H increase monotonically as the equivalence ratio increases. This means that the uncertainty of the fuzzy relation decreases as the equivalence relation increases.

Thus, data granulation G, rough entropy E_r, data volume E and information entropy H can be applied to measure the uncertainty of the IAS system.

To further evaluate the effectiveness of the proposed measures for the IAS system, the Friedman and Bonferroni-Dan tests are listed below. The Friedman test – is a statistical test that uses algorithm ranking. Friedman's statistic is defined as

$$\chi^2_F = \frac{12N}{k(k+1)}\left(\sum_{i=1}^{k} r_i^2 - \frac{k(k+1)^2}{4}\right), \quad (22)$$

where k – the number of algorithms, N – the number of sets of different types of data, r_i – average rating i-th algorithm. When k and N quite large, Friedman's statistics correspond to the distribution χ^2 with $k - 1$ degrees of freedom. However, such a Friedman criterion is too complex and is usually replaced by the following statistics

$$F_F = \frac{(N-1)\chi^2_F}{N(k-1) - \chi^2_F}. \quad (23)$$

The FF statistic corresponds to the Fisher distribution of $k - 1$ and $(k - 1, N - 1)$ degrees of freedom. If the statistical indicator FF exceeds the critical value $F_\alpha(k - 1, N - 1)$, this means that the null hypothesis is rejected according to Friedman's criterion. The Bonferroni-Dunn test can be used to further study which algorithm is better from a statistical point

of view. If the average distance level exceeds the critical value CD_α, then the performance of the two algorithms will differ significantly. Critical value CD_α denoted as

$$CD_\alpha = q_\alpha \sqrt{\frac{k(k+1)}{6N}}, \quad (24)$$

where q_α – critical tabular value for the test, and α – significance level of the Bonferroni-Dunn test. Below, four indicators of data uncertainty in the IAS system are considered as four algorithms, and statistical significance is demonstrated using the Friedman test and the Bonferroni-Dunn test (Table 4).

Based on the *CV* values of the four indicators, the ranking of the four indicators with four data sets, respectively, is given.

Table 4

Ranking of CV values of four indicators by four data sets

Datasets	*G*	*E*	E_r	*H*
Set 1	4	1	3	2
Set 2	3	1	2	4
Set 3	4	1	3	2
Set 4	3	1	4	2
Average	3.5	1	3.0	2.5

A Friedman test was performed to find out if the *CV* values for the four measures differ significantly, respectively. For four indicators and four data sets, *FF* corresponds to a distribution with 3 and 9 degrees of freedom. Then it is easily possible to determine the statistics $F_F = 7$. Note that the critical value of the Fisher distribution $F_{0.05}$ (3,9) equals 3.863. Obviously, that $7 > 3.863$. This means that at a significant level $\alpha = 0.05$ it is necessary to reject the null hypothesis, which means that the CV values of the four indicators differ significantly.

To further demonstrate a significant difference between the four measures, the Bonferoni-Danna test is introduced. For a significant level $\alpha = 0.05$ the corresponding critical distance was calculated $CD\alpha = 2.569$.

As can be seen from Table 3, 4, increasing the efficiency of processing various types of data is achieved due to the use of a set of improved procedures at the level of 24–28% due to the use of additional procedures.

6. Discussion of the results of the development of the method of processing various types of data in information and analytical support systems

The advantages of the proposed method of processing various types of data in state-level information and analytical support systems are as follows:

– conduct a multi-level and systematic assessment of the state of processing of various types of data using the proposed set of analytical expressions. This will allow a comprehensive and objective assessment of the state of processing of various types of data in IAS systems, both its individual elements and the IAS system as a whole (expressions (1)–(24)), compared to works [4, 5];

– carry out a comprehensive calculation of the uncertainty of various types of data in IAS systems according to 5 indicators (expressions (3)–(8)), which allows for increasing the accuracy of the initial setting of the IAS system, compared to robots [3, 7];

– increase the efficiency and reliability of the synchronization process of various types of data by using an improved synchronization procedure (action 9), compared to works [11, 17];

– increase the efficiency of the indexing process of various types of data by using an improved indexing procedure (action 8), compared to works [13, 15];

– increase the efficiency and reliability of the process of calculation and aggregation of data circulating in the IAS system due to the use of the appropriate procedure (action 7), compared to works [9, 12];

– increase the efficiency and reliability of the process of separation of various types of data circulating in the IAS system due to the use of the appropriate procedure (action 6), compared to works [9, 12];

– reduce the loss of reliability of processing various types of data by verifying information about the IAS system and the data circulating in it (action 2), compared to works [4, 7];

– attract additional computing resources (if necessary) (action 11), which achieves the prevention of looping of the methodology's work, compared to study [13, 16];

– increase the reliability of processing various types of data in IAS systems due to multi-level deep learning of knowledge bases, using evolving artificial neural networks (action 10) compared to works [11, 18];

– carry out an unambiguous classification of data, their attributes circulating in IAS systems due to the use of artificial immune detectors (action 3), which achieves an increase in the accuracy of setting up the IAS system and the reliability of processing various types of data, compared to works [12, 18].

The proposed technique 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".

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

Disadvantages of the proposed method of processing various types of data in state-level information and analytical support systems include:

– significant time for the initial adjustment of the IAS system to the operating conditions;

– taking into account the delay time of information receipt from technical sources of extraction of the IAS system.

The proposed technique allows:

– conduct modeling of the state of processing of various types of data circulating in the IAS system under the conditions of complex influence of destabilizing factors;

– determine effective measures to increase the level of reliability of processing various types of data circulating in the IAS system;

– comprehensively assess the change in the level of reliability and efficiency of processing various types of data circulating in the IAS system, and the effects of control on the process of processing various types of data.

7. Conclusions

1. The study proposes a set of procedures for processing various types of data in state-level information and analytical

support systems. The originality of the proposed set of procedures is:

– conducting a multi-level and systematic assessment of the state of processing of various types of data using the proposed set of analytical expressions. This will allow a comprehensive and objective assessment of the state of processing of various types of data in IAS systems, both its individual elements and the IAS system as a whole;

– carrying out a comprehensive calculation of the uncertainty of various types of data in IAS systems according to 5 indicators, which allows to increase the accuracy of the initial setting of the IAS system;

– increasing the efficiency and reliability of the synchronization process of various types of data due to the use of an improved synchronization procedure;

– increasing the efficiency of the indexing process of various types of data due to the use of an improved indexing procedure;

– increasing the level of efficiency and reliability of the calculation process and aggregation of data circulating in the IAS system due to the use of the appropriate procedure;

– increasing the efficiency and reliability of the process of separation of various types of data circulating in the IAS system due to the use of the appropriate procedure;

– reducing the loss of reliability of processing various types of data due to the verification of information about the IAS system and the data circulating in it;

– carrying out the attraction of additional computing resources (if necessary), which achieves the prevention of looping of the methodology;

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

– carry out unambiguous classification of data, their attributes circulating in IAS systems due to the use of artificial immune detectors, which increases the accuracy of setting up the IAS system and the reliability of processing various types of data.

2. The proposed technique ensures an increase in the efficiency of processing various types of data due to the use of additional procedures at the level of 24–28%, 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 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

Dmytro Honcharuk: Conceptualization, Methodology, Project administration, Writing – original draft, Writing – review & editing; **Aleksandra Kuzior**: Methodology, Writing – review & editing; **Nadiia Protas**: Writing – original draft; **Oleksandr Rudenko**: Writing – review & editing; **Ihor Pimonov**: Resources, Data Curation; **Andrii Veretnov**: Validation, Data Curation; **Oleksandr Yarovyi**: Software, Validation, Data Curation; **Yevhen Sudnikov**: Methodology, Formal analysis, Visualization; **Danylo Pliekhov**: Software, Validation, Data Curation, **Andrii Shyshatskyi**: Software, Validation, Data Curation.

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