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[1]Svitlana Kashkevych,
[2]Oleksandr Lastivka

MODEL FOR INTEGRATING DIFFERENT TYPES OF DATA IN MULTILEVEL INFORMATION STRUCTURES

Department of Intelligent Cybernetic Systems, State University "Kyiv Aviation Institute", Kyiv, Ukraine
E-mails: [1]svitlana.kashkevych@npp.kai.edu.ua ORCID 0000-0001-5615-2474,
[2]2450626@stud.kai.edu.ua ORCID 0009-0005-4754-259X

Abstract—*This article examines the problem of integrating heterogeneous data within multi-level information structures operating under conditions of heterogeneous data sources and variable dynamics of information flows. The relevance of this research stems from the growing volume of data, the diversity of formats, and the need to establish a harmonised information representation for further analysis. The aim of the work is to develop a mathematical model for the integration of heterogeneous data, which formalises the processes of harmonising information flows of different nature. The paper analyses the characteristics of information flow formation and identifies factors influencing the effectiveness of data integration, in particular varying arrival rates, noise levels and source reliability. A multi-level integration model is proposed, which includes stages of pre-processing, normalisation, harmonisation and the formation of an integrated representation. The results obtained showed that the use of a multi-level approach allows for improved consistency of information flows and a reduction in the impact of noise and uncertainty. The proposed model can be used in data processing and decision support systems within complex information environments.*

Keywords—Information system, mathematical model, data fusion, multisource data integration, information processing model, heterogeneous information streams.

I. INTRODUCTION

Modern information systems are characterised by a significant growth in the volume of data received from various sources that differ in structure, representation format, and temporal dynamics. Under such conditions, the problem of heterogeneous data integration becomes particularly important. This task involves forming a consistent information representation based on a set of heterogeneous information flows.

A particular complexity of this task lies in the need to consider the different nature of the data, their temporal dependencies, as well as possible uncertainty and noise.

The integration of heterogeneous data is one of the key stages in the functioning of modern information systems, since it is at this stage that a generalised representation of the state of the studied object or process is formed. In many cases, data obtained from different sources have different dimensionality, different update frequencies, and different levels of reliability.

This leads to difficulties in coordinating information flows and requires the application of specialised methods for their processing.

II. LITERATURE ANALYSIS

Modern research in the field of information systems is largely focused on the development of mathematical models, data analysis methods, and optimization algorithms that ensure efficient functioning of complex information structures. Particular attention is paid to the problems of heterogeneous data integration, large-scale data processing, and improvement of decision-making processes.

In paper [1], the mathematical foundations of decision support systems are considered, where special attention is given to the formalization of information processing processes and the development of mathematical support for information systems. The proposed approaches enable a comprehensive analysis of system parameters and support coordinated data processing.

Studies [2] and [6] investigate solution search methods in complex systems using bio-inspired and population-based optimization algorithms. In particular, the study [2] proposes a combined bio-inspired optimization algorithm that improves the efficiency of solving complex multidimensional problems.

In paper [6], a global search method based on population optimization algorithms is presented, demonstrating high performance in analyzing complex systems with numerous parameters.

An important direction of research involves approaches to assessing the state of complex systems. Studies [3] and [5] propose methodological approaches for evaluating the condition of complex organizational and technical systems using integrated criteria that take into account interactions between multiple factors.

In paper [4], a scientific and methodological framework for improving the efficiency of information processing using artificial intelligence techniques is proposed.

This approach enables more efficient analysis of information flows and improves data processing in complex information systems.

Another group of studies focuses on the use of modern information technologies for data integration in distributed information environments. In [8], the integration of Internet of Things technologies with cloud, fog, and edge computing is analyzed, demonstrating improved efficiency of data processing in distributed systems.

The synchronization of wireless sensor networks for monitoring short-term events is investigated in [7], where a method is proposed for improving real-time monitoring capabilities in sensor-based systems.

A significant number of studies are devoted to the application of machine learning techniques for data analysis. Works [9] – [13] investigate anomaly detection, financial fraud detection, and the use of deep learning methods for analyzing large datasets. In particular, [9] provides a review of anomaly detection techniques for financial fraud analysis, while [10] analyzes machine learning and deep learning approaches for e-commerce research. Studies [11] and [12] propose machine learning models for fraud detection and explainable artificial intelligence approaches for improving interpretability.

Issues related to cybersecurity and protection of critical information infrastructure are addressed in [14] – [16]. These studies propose methods for cybersecurity incident management, assessment of the importance of critical infrastructure objects, and management of IT threats.

In addition, fuzzy logic approaches are applied in intelligent control systems. Study [17] proposes an intelligent control system based on fuzzy logic, demonstrating its effectiveness in information processing and decision-making tasks.

The analysis of the reviewed literature shows that modern research mainly focuses on optimization algorithms, machine learning techniques, and methods for improving the efficiency of information systems. However, insufficient attention has been paid to the development of models for integrating heterogeneous data within multi-level information structures capable of harmonizing multiple information streams.

Therefore, the development of a model for integrating heterogeneous data in multi-level information structures is an important scientific task aimed at improving the efficiency of information processing and supporting decision-making in complex information systems.

III. PROBLEM STATEMENT

In the general case, the process of heterogeneous data integration can be represented as a multi-stage procedure that includes the stages of data collection, preprocessing, normalisation, alignment, and the formation of an integrated information representation. At the data collection stage, a set of information flows originating from different sources is formed.

Such flows may contain numerical values of system parameters, textual information, sensor signals, or other types of data. An important characteristic of this stage is that data may arrive asynchronously and with different update frequencies, which complicates their subsequent analysis.

The next stage involves data preprocessing, the purpose of which is to eliminate measurement errors, filter noise, and convert the data into a unified representation format.

At this stage, statistical processing methods, filtering algorithms, and normalisation procedures can be applied to improve the quality of the information entering the integration system.

An important stage of heterogeneous data integration is the alignment of data within a unified information space. Since the data may have different origins and measurement scales, it is necessary to perform a transformation procedure that converts them into a generalised representation.

This may involve the formation of feature vectors describing the state of the system at a specific moment in time. As a result, a consistent set of parameters is obtained that reflects the main characteristics of the information flows.

Considering the temporal dynamics of data changes is of particular importance in the task of heterogeneous data integration. In many information systems, parameters vary over time; therefore, data integration should account not only for their current values but also for the trends of their variation.

This makes it possible to identify patterns in system functioning and to obtain more accurate estimates of the system state.

The structure of the information system also plays an important role in the process of heterogeneous data integration. In complex systems, data processing is usually performed within multi-level information structures, where each level performs specific functions. At the lower levels, primary data processing and the formation of basic parameters are carried out, whereas at the higher levels their aggregation and analysis are performed. Such an approach makes it possible to distribute computational resources and ensure more efficient processing of large volumes of information.

IV. Elements of the Methodological Framework

The multi-level structure of an information system makes it possible to organise the data integration process in such a way that information obtained at the previous stage is generalized at each subsequent level.

This ensures a gradual reduction in data dimensionality and the formation of a more compact information representation. In addition, such a structure enables the implementation of mechanisms for adapting the system to changing operating conditions.

One of the key tasks in heterogeneous data integration is the evaluation of the reliability of information received from different sources. Since various sources may have different levels of accuracy and reliability, it is important to take these factors into account when forming the integrated result. For this purpose, information flow weighting methods may be applied, allowing the quality of data to be considered during the integration process.

Another important characteristic of the data integration process is the system's robustness to external disturbances. Under real operating conditions, information systems may process data containing significant levels of noise or measurement errors.

Therefore, the integration model must ensure the stability of results even in the presence of substantial deviations in the input data.

Thus, the integration of heterogeneous data within multi-level information structures represents a complex multi-component process that requires the use of mathematical models and specialised information processing algorithms. The proposed approach to constructing a data integration model enables the formalisation of interactions between information flows, takes into account their temporal dynamics, and ensures the formation of a consistent information representation of the system state.

Consider the problem of integrating heterogeneous data streams originating from multiple sources that may have different sampling frequencies, noise levels, and reliability levels, and may also contain missing values.

To ensure the alignment and integration of such data, a multi-level fuzzy model is applied, combining the formation of a consistent feature vector within a sliding time window, fuzzy evaluation of source reliability, fuzzy inference for aggregation, and the construction of an integrated representation.

Analytical problem statement. Consider a set of heterogeneous data streams obtained from multiple sources:

$$\mathcal{D} = \{ \mathcal{D}_1, \mathcal{D}_2, ..., \mathcal{D}_S \},$$

where each data stream $\mathcal{D}_S$ is characterized by its own dimensionality, sampling frequency, noise level, and reliability.

Each source generates a time-dependent sequence:

$$\mathcal{D}_s(t) = \{x_{s1}(t), x_{s2}(t), ..., x_{sds}\}(t)\},$$

where d_s is the dimension of the data from source s.

The main objective of the integration process is to construct a unified representation:

$$Y(t) = F(\mathcal{D}_1(t), \mathcal{D}_2(t), ..., \mathcal{D}_S(t)),,$$

which satisfies the following requirements: consistency of heterogeneous data; robustness to noise and missing values; preservation of temporal dependencies; adaptability to varying data quality.

Step 1. Generalised description of different types of data in a time window:

$$\mathcal{D}(t) = \{y_s(\tau) | \; s = 1, \ldots, S, \; \tau \in [t - \Delta, t]\},$$

where S is the number of sources; y_s is the source data dimension; Δ is the sliding window width; $(\tau) \in \{0,1\}$ is the data availability indicator.

Step 2. Construction of a coordinated feature vector (reduction of heterogeneity):

$$x(t) = [g_1(y_1([t - \Delta, t])), \ldots, g_S(y_S([t - \Delta, t]))]^{\mathrm{T}},$$

where g_S is the feature extraction operator.

Step 3. Fuzzy evaluation of source quality using a quality aggregate:

$$q_s(t) = \mathcal{A}\big(\xi_s(t), \upsilon_s(t), \kappa_s(t), \eta_s(t)\big),$$

$$\mathcal{A}(\cdot) = \sum_{r=1}^{R_q} \omega_r^{(q)} \cdot \prod_{j=1}^{4} z_j(t)^{\pi_{rj}},$$

where $q_s(t)$ is the source trust metric *s*; $\xi, \upsilon, \kappa, \eta \in [0,1]$ is the standardised quality indicators; A is the generalised aggregator (additive and multiplicative effects); Rq is the number of aggregator components.

Step 4. Fuzzy faction: fuzzy sets for quality and attributes:

$$\mu_{s,a}^{(Q)}(t) = \mu_a^{(Q)}(q_s(t)), \quad a \in \mathcal{L}_Q,$$

$$\mu_{i,b}^{(X)}(t) = \mu_b^{(X)}(x_i(t)), \quad b \in \mathcal{L}_X,$$

$$\mu_c^{(\cdot)}(u) = \exp\left(-\frac{(u-c_1)^2}{2c_2^2}\right)\cdot 1_{[c_3,c_4]}(u) + \max\left(0, \min\left(\frac{u-c_3}{c_1-c_3}, \frac{c_4-u}{c_4-c_1}\right)\right),$$

where $\mathcal{L}_Q, \mathcal{L}_x$ are indexed sets of terms for source characteristics and quality in the rule k; Z is the output variable; c_k is the exit term; K is the number of rules.

Step 5. Activating the rules:

$$\alpha_k(t) = \lambda_k \left(\prod_{(i,b)\in\mathcal{I}_k} \mu_{i,b}^{(X)}(t)\right)^{\theta_k} \times \left(\prod_{(s,a)\in\mathcal{J}_k} \mu_{s,a}^{(Q)}(t)\right)^{(1-\theta_k)}, \quad 0 \le \theta_k \le 1,$$

where $\alpha_k(t) \in [0,1]$ is the rule activation strength *k*; $\lambda_k \in [0,1]$ is the trust in the rule; θ_k is the balance between the contribution of characteristics and the quality of sources.

Step 6. Aggregate the conclusions of the rules into the initial fuzzy set:

$$\mu_Z(z;t) = \mathcal{S}_{k=1}^{K}\left(\alpha_k(t) \otimes \mu_{c_k}^{(Z)}(z)\right),$$

$$\mu_Z(z;t) = 1 - \prod_{k=1}^{K}\left(1 - \left[\alpha_k(t)\cdot\mu_{c_k}^{(Z)}(z)\right]\right),$$

where $\mu_{c_k}^{(Z)}$ is the function of belonging to the initial term c_k.

Step 7. Defasification:

$$z^*(t) = \frac{\int z\mu_Z(z,t)\,dz}{\int \mu_Z(z,t)\,dz},$$

where $z^*(t)$ is the integrated value.

Step 8. Multi-level (hierarchical) structure of fuzzy inference:

$$h^{(1)}(t) = \mathcal{F}^{(1)}(x(t), q(t)),$$

$$h^{(\ell+1)}(t) = \mathcal{F}^{(\ell+1)}(h^{(\ell)}(t), q(t)), \quad \ell = 1, \ldots, L-1,$$

$$z(t) = \mathcal{G}\left(h^{(L)}(t), W_o\right), \quad q(t) = [q_1(t), \ldots, q_S(t)]^{\mathrm{T}},$$

where $F^{(\ell)}$ is the fuzzy level block (own rules, terms, membership functions); $h^{(\ell)}$ is the interim integrated presentation; $\mathcal{G}$ is the final composition (e.g., weighted projection/compression); L is the number of levels.

Step 9. Adaptation of rule weights and source weights (update):

$$\lambda_k(t+1) = \Pi_{[0,1]} \times \left(\lambda_k(t) - \epsilon_\lambda \cdot \frac{\partial}{\partial\lambda_k}\sum_{\tau=t-\Delta}^{t}\left(\ell(z(\tau), z^{\mathrm{ref}}(\tau)) + \gamma\,\| \mathrm{U}(\tau) \|_2^2\right)\right),$$

$$w_s(t+1) = \frac{\exp\left(-\epsilon_w \cdot \sum_{\tau=t-\Delta}^{t}(1-q_s(\tau))\right)}{\sum_{r=1}^{S}\exp\left(-\epsilon_w \cdot \sum_{\tau=t-\Delta}^{t}(1-q_r(\tau))\right)},$$

$$\sum_{s=1}^{S} w_s(t) = 1.$$

$\Pi_{[0,1]}$ is the projection onto a segment [0,1]; $\ell(\cdot)$ is the loss function; z^{ref} is the reference (preferred source); γ is the regularisation of management; $w_s(t)$ is the importance of the source in integration.

The resulting mathematical apparatus formalises the process of integrating different types of data in multi-level information structures and allows describing the interaction of information flows within a single analytical representation.

The proposed model ensures consistent consideration of system parameters that change over time and creates a basis for further analysis of data integration efficiency.

Based on the developed mathematical apparatus, simulation modelling of system functioning processes and research into the impact of various factors on the results of information flow integration can be carried out.

IV. Prospective Issues of the Theory and Practice of AMS Design

To verify the properties of the proposed multilevel fuzzy model, a comparative visualization of its key internal characteristics was performed: the dependence of the integrated output on data quality indicators, the distribution of fuzzy rule activations over time, and the adaptation of source weights in the process of integrating different types of flows. Unlike classical graphs of system state dynamics, the visualisations presented reflect the mechanisms of fuzzy inference and data reconciliation.

Figure 1 shows the dependence of the integrated output on two generalised parameters: the confidence index of sources and the noise level. The surface reflects the nonlinear nature of fuzzy inference and demonstrates areas of stable solutions, as well as zones where the system switches to more conservative estimates when data quality degrades.

Visualisation is formed by scanning a pair $(q,\eta)\in[0,1]\times[0,1]$, with fixed values of other model inputs and calculations $z*$ step 4 – 9. Values are displayed as a 3D surface or contour map of levels.

Figure 2 shows a heat map of values $\alpha_k(t)$ where the observation moments are plotted on the time axis, and the rule indices are plotted on the rule axis $\mathcal{R}$.

This format allows you to highlight groups of rules that are activated in identical data modes, as well as to assess how well the rule base works in different conditions. It is interpreted as follows: the dominance of a narrow set of rules corresponds to modes with clearly defined data states; an increase in the number of active rules often corresponds to an increase in noise or the emergence of contradictions between flows.

Figure 3 shows the change in source weights over $w_s(t)$ time, formed by the step adaptation mechanism (10). The visualisation reflects how the model redistributes the contribution of different flows when their quality changes, gaps appear, and noise increases.

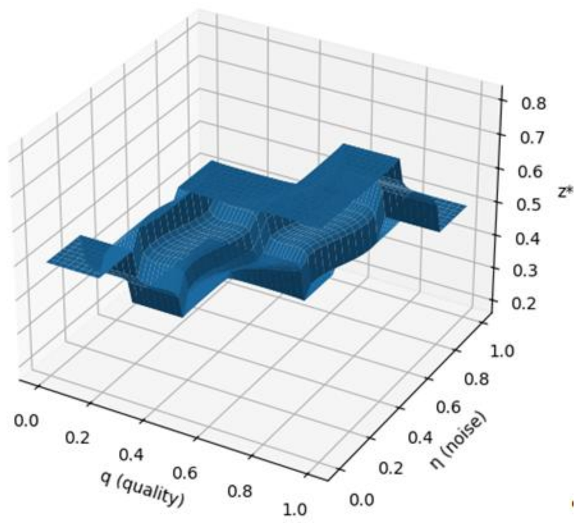

Fig. 1. Fuzzy output surface

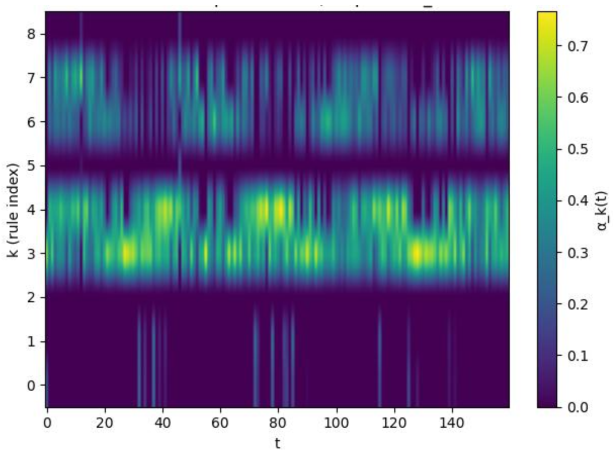

Fig. 2. Heat map of rule activations

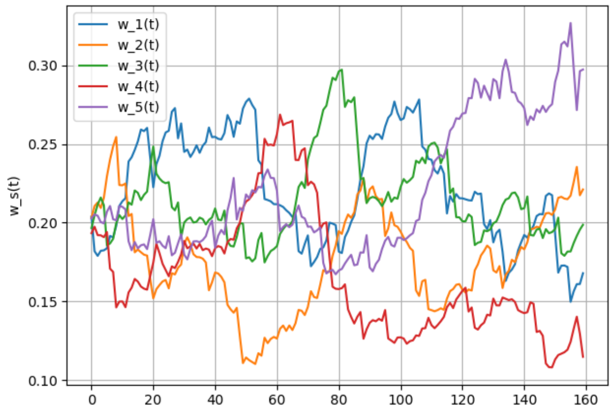

Fig. 3. Weight dynamics of sources $w_s(t)$

The resulting model can be used to study the functioning of complex information systems, analyse the relationships between different system parameters, and improve the efficiency of information processing in multi-level information structures.

VI. CONCLUSIONS

The paper presents a mathematical model for integrating heterogeneous data within multi-level information structures, which enables formalising the interaction of multiple information streams with different characteristics. The proposed approach takes into account temporal dynamics, variability of data arrival, noise influence, and differences in data reliability, which significantly affect the integration process.

The developed model introduces a multi-stage integration mechanism based on preprocessing, normalisation, alignment, and aggregation of data into a unified representation. The use of a weighting mechanism for data sources allows adaptive consideration of their reliability, which improves the robustness of the integration process under conditions of uncertainty and incomplete information.

During the research, the features of heterogeneous information flow formation in modern information systems were analysed, and the main problems arising during their integration were identified. It is shown that the key factors affecting the efficiency of data integration include differences in information structure, variations in data arrival frequency, and the presence of noise and uncertainty in measurements. In this regard, a multi-level approach to organising the data integration process is proposed, which enables stepwise processing and generalisation of data. The paper proposes a model for integrating heterogeneous data based on the formation of a consistent information representation through the analysis of multiple information flows. Within the proposed model, the data integration process is represented as a sequence of stages that include the formation of a set of input data, their preprocessing, parameter normalisation, alignment of information flows, and the formation of an integrated representation of the system state. This approach allows the characteristics of different data types to be considered and ensures the possibility of their coordinated analysis.

The proposed model takes into account the multi-level structure of the information system, in which data processing is performed at several hierarchical levels. At the lower levels, primary data processing and the formation of basic parameters are carried out, while at the higher levels the integration of information flows and the formation of generalised characteristics of the system state are performed. Such an organisation of the information processing process improves the efficiency of data integration and reduces the influence of noise and random disturbances.

The obtained results demonstrate that the use of the proposed approach makes it possible to formalise the process of integrating heterogeneous data in complex information systems and to ensure a consistent representation of information flows. This, in turn, creates the prerequisites for improving the efficiency of system state analysis and enhancing decision-making processes based on multidimensional information.

The practical significance of the results lies in the applicability of the model to complex information systems, decision support systems, and data processing platforms, where the integration of heterogeneous data is required. The proposed approach creates a basis for further development of adaptive and intelligent data integration methods in multi-level information structures.

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Kashkevych Svitlana. ORCID 0000-0001-5615-2474. Senior Lecturer.
Department of Intelligent Cybernetic Systems, State University Kyiv Aviation Institute, Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine, (2011).
Research area: data processing and analysis in unmanned aerial vehicle communication channels; modelling and optimisation of information network functioning; application of artificial intelligence for data analysis.
Publications: 110.
E-mail: svitlana.kashkevych@npp.kai.edu.ua

Lastivka Oleksandr. ORCID 0009-0005-4754-259X. Postgraduate Student.
Department of Intelligent Cybernetic Systems, State University "Kyiv Aviation Institute", Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine, (2012).
Research area: modelling and optimisation of information network functioning.
Publications: 15.
E-mail: 2450626@stud.kai.edu.ua

С. О. Кашкевич, О. І. Ластівка. Модель інтеграції різнотипних даних у багаторівневих інформаційних структурах

У статті розглянуто задачу інтеграції різнотипних даних у багаторівневих інформаційних структурах, що функціонують в умовах неоднорідності джерел та змінної динаміки інформаційних потоків. Актуальність дослідження зумовлена зростанням обсягів даних, різноманітністю форматів та необхідністю формування узгодженого інформаційного представлення для подальшого аналізу. Метою роботи є розроблення математичної моделі інтеграції різнотипних даних, яка забезпечує формалізацію процесів узгодження інформаційних потоків різної природи. У роботі проаналізовано особливості формування інформаційних потоків та визначено фактори, що впливають на ефективність інтеграції даних, зокрема різну частоту надходження, рівень шуму та достовірність джерел. Запропоновано багаторівневу модель інтеграції, яка включає етапи попередньої обробки, нормалізації, узгодження та формування інтегрованого представлення.

Отримані результати показали, що використання багаторівневого підходу дозволяє підвищити узгодженість інформаційних потоків та зменшити вплив шуму і невизначеності. Запропонована модель може бути використана в системах обробки даних та підтримки прийняття рішень у складних інформаційних середовищах.

Ключові слова: інформаційна система, математична модель, об'єднання даних, інтеграція даних з різних джерел, модель обробки інформації, гетерогенні потоки інформації.

Кашкевич Світлана Олександрівна. ORCID 0000-0001-5615-2474. Старший викладач.
Кафедра інтелектуальних кібернетичних систем, Державний університет Київський авіаційний інститут, Київ, Україна.
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Напрям наукової діяльності: обробка та аналіз даних у каналах зв'язку безпілотних літальних апаратів; моделювання та оптимізація функціонування інформаційних мереж; застосування штучного інтелекту для аналізу даних.
Кількість публікацій: 110.
E-mail: svitlana.kashkevych@npp.kai.edu.ua

Ластівка Олександр Іванович. ORCID 0009-0005-4754-259X. Аспірант.
Кафедра інтелектуальних кібернетичних систем, Державний університет «Київський авіаційний інститут», Київ, Україна.
Освіта: Національний авіаційний університет, Київ, Україна, (2012).
Напрямок наукової діяльності: моделювання та оптимізація функціонування інформаційних мереж.
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E-mail: 2450626@stud.kai.edu.ua