Академик Ю. И. Шокинді еске алуға арналған
"Computational and Information Technologies in Science, Engineering and Education" (CITech-2026)
атты Халықаралық конференциясының

ТЕЗИСТЕР ЖИНАҒЫ

СБОРНИК ТЕЗИСОВ

Международной конференции,
посвященная памяти
академика Ю.И. Шокина
"Computational and Information Technologies in Science, Engineering and Education"
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ABSTRACTS BOOK

of the International Conference dedicated to the memory of Academician Yu. I. Shokin
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8-9 қаңтар, 2026 жыл,Алматы, Қазақстан
8-9 января, 2026 года, Алматы, Казахстан
January 8-9, 2026, Almaty, Kazakhstan

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Есептеу ғылымдары және жоғары өнімді есептеулер

Секция 1
Вычислительные науки и высокопроизводительные вычисления

Section 1
Computational sciences and high-performance computing

HIGHER ORDER NUMERICAL SOLUTION OF THE INCOMPRESSIBLE NAVIER-STOKES EQUATIONS IN MOVING DOMAINS AND HEMODYNAMIC APPLICATIONS

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This work is concerned with the computational analysis of two strategies for the numerical solution of the Navier-Stokes equations in moving domains. Computational meshes in these domains preserve topological structure and admit movement of their nodes. Both strategies exploit Oseen linearization of the Navier-Stokes equations resulting in a linear system to be solved at every time step. The first strategy is based on a collocated finite volume method exploiting the Ostrogradsky-Gauss theorem for the time-space divergence operator. The second strategy is based on a finite element scheme for the Navier-Stokes equations written in a reference domain. We compare the accuracy of the methods on the same sequence of meshes for a problem with a known analytical solution. Also, we provide a comparative analysis of two approximate solutions for hemodynamics in the right ventricle of a patient given by a time series of computer tomography scans. We conslude the talk with applications of the first strategy to two blood coagulation problems: clot-in-transit and clot formation due to tissue inflammation after infarction.

Keywords: moving domain, finite volume method, finite element method, semi-implicit scheme

AMS Subject Classification: 65M08, 65M60

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MATHEMATICAL MODELING OF A CATALYTIC CONVERTER IN CURVILINEAR COORDINATES USING THE NAVIER-STOKES EQUATIONS

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Abstract:This article discusses the problem of numerically solving the Navier–Stokes equations, the heat conduction equation, and the transport equation in the orthogonal coordinates of a free curve. Since the numerical solution domain is complex, the curvilinear mesh method was used. To do so, first, a boundary value problem was posed for the elliptic equation to automate the creation of orthogonal curved meshes. By numerically solving this problem, the program code for the curvilinear mesh generator was created. The motion of a liquid or gas through a porous medium was described by numerically solving the Navier–Stokes equations in freely curvilinear orthogonal coordinates. The transformation of the Navier–Stokes equation system, written in the stream function, vorticity variables, and cylindrical coordinates, into arbitrary curvilinear coordinates, was considered in detail by introducing metric coefficients.

To describe the unsteady flow in the smooth, curved regions of the catalytic converter boundary, the system of Navier–Stokes equations in cylindrical coordinates can be written in the following form[1]. Since the system of equations is a stream function and the speed of the winding are variables, the continuity equation is automatically satisfied.

$$\frac{\partial\omega}{\partial t}+\frac{\partial(u\omega)}{\partial x}+\frac{\partial(v\omega)}{\partial r}=\frac{1}{\mathrm{Re}}\left(\Delta\omega+\frac{\partial}{\partial r}\left(\frac{\omega}{r}\right)\right)-\nabla\cdot\left(\frac{k_P}{r}\nabla\psi\right)-\frac{\mathrm{Gr}}{\mathrm{Re}^2}\frac{\partial\theta}{\partial x}. \tag{1}$$

$$\nabla\cdot\left(\frac{1}{r}\nabla\psi\right)=\omega. \tag{2}$$

$$u=\frac{1}{r}\frac{\partial\psi}{\partial r},\quad v=-\frac{1}{r}\frac{\partial\psi}{\partial x},\quad \omega=\frac{\partial u}{\partial r}-\frac{\partial v}{\partial x}. \tag{3}$$

Keywords: Navier–Stokes equations; incompressible fluid; catalytic converter; curvilinear coordinates; finite difference scheme.

MSC: 76Dxx; 76D05; 76D55

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INVESTIGATION OF COMPUTATIONAL ALGORITHMS DESCRIBING TRANSITIONAL REGIMES FOR THE UNSTEADY NAVIER–STOKES EQUATIONS

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The unsteady Navier–Stokes equations describe viscous incompressible fluid flows and are widely used in aerodynamics, hydrodynamics, and engineering applications. Transitional regimes arising during flow start-up, changes in boundary conditions, and external forcing are of particular interest, which motivates the development of efficient computational algorithms.

We consider the unsteady Navier–Stokes equations for an incompressible viscous fluid in a bounded domain $\Omega \subset \mathbb{R}^2$:

$$\frac{\partial \vec{V}}{\partial t} + (\vec{V} \cdot \nabla)\vec{V} + \nabla p = \frac{1}{\mathrm{Re}} \Delta \vec{V}, \tag{1}$$

$$\operatorname{div} \vec{V} = 0, \qquad x \in \Omega, \tag{2}$$

where $\vec{V} = (u, v)$ is the velocity vector, p is the pressure, and Re is the Reynolds number. The initial condition is prescribed as

$$\vec{V}(x, 0) = \vec{V}_0(x), \qquad x \in \Omega. \tag{3}$$

For the numerical investigation of transitional regimes, this work employs a time-splitting method based on the successive computation of an intermediate velocity field, solution of the pressure equation, and correction of the velocity field with enforcement of the incompressibility condition [1]. The influence of the time step, spatial grid parameters, and the Reynolds number on the dynamics of transitional flow formation is investigated. Similar numerical approaches and bifurcation phenomena for large Reynolds numbers are discussed in [3, 2].

Keywords: unsteady Navier–Stokes equations, transitional regimes, incompressible viscous flow, time-splitting method, numerical simulation, Reynolds number.

AMS Subject Classification: 65M06, 76D05, 76M20.

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CONTINUATION PROBLEM FOR THE ELECTRODYNAMIC EQUATION

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Electrodynamic Continuation Problem.

We consider the continuation of the horizontal component of the electric field intensity from the boundary $z = 0$ into the domain Ω. The electromagnetic field $u(z, y, t)$ satisfies the equation

$$\mu\varepsilon(z, y)u_{tt} + \mu\sigma(z, y)u_t = \Delta u, \tag{1}$$

$$u|_{t=0} = 0, \quad u_t|_{t=0} = 0, \tag{2}$$

$$u_z|_{z=0} = g(y, t), \tag{3}$$

$$u|_{y=0} = u|_{y=L_y} = 0, \tag{4}$$

$$u|_{z=0} = f(y, t). \tag{5}$$

The problem consists in continuing the solution from the boundary $z = 0$ into the interior of Ω.

Direct Problem. For given $\varepsilon(z, y)$, $\sigma(z, y)$, $g(y, t)$, and boundary data $u|_{z=0} = q(y, t)$, determine $u(z, y, t)$ in the domain Ω:

$$\mu\varepsilon(z, y)u_{tt} + \mu\sigma(z, y)u_t = \Delta u, \tag{6}$$

$$u|_{t=0} = 0, \quad u_t|_{t=0} = 0, \tag{7}$$

$$u_z|_{z=0} = g(y, t), \tag{8}$$

$$u|_{y=0} = u|_{y=L_y} = 0, \tag{9}$$

$$u|_{z=0} = q(y, t), \tag{10}$$

Inverse Problem. Determine the unknown boundary function $q(y, t)$ from additional measurements on the boundary:

$$u(0, y, t) = f(y, t). \tag{11}$$

Keywords: Electrodynamic continuation problem, inverse problem, direct problem, boundary measurements, electromagnetic field. keywords which can be used for indexing purposes.

AMS Subject Classification: 35R30, 78A25, 78M10, 65M32.

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Секция 2
Математикалық және компьютерлік модельдеу

Секция 2
Математическое и компьютерное моделирование

Section 2
Mathematical and computer modeling

INVERSE PROBLEM OF DETERMINING THE HEAT TRANSFER COEFFICIENT IN HYPERTHERMIA OF A CANCER TUMOR

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In this work, an inverse problem of determining the effective heat transfer coefficient between a cooling system and biological tissue during hyperthermia treatment of a cancer tumor is investigated through a boundary condition. The Pennes bioheat equation is employed as the mathematical model, describing the transient temperature distribution within biological tissue while accounting for thermal conduction, blood perfusion, and internal heat sources. The temperature distribution is governed by the Pennes equation supplemented with boundary conditions representing thermal contact with the cooling system, as well as appropriate initial conditions.

The overall heat transfer coefficient U, which characterizes the intensity of heat exchange at the tissue boundary, is treated as an unknown control parameter [1].

The inverse problem is formulated as an optimal control problem, in which the objective is to determine the heat transfer coefficient U that ensures a prescribed temperature profile in both tumor tissue and surrounding healthy tissue. A quadratic misfit functional is constructed to measure the discrepancy between the computed and target temperature values at a finite number of control points over the entire treatment time. To solve the inverse problem, a gradient-based optimization method relying on the construction of an adjoint equation is applied. The direct and adjoint problems are solved numerically using the finite element method in the time domain [2].

An analysis of the convergence of the iterative process is performed, and the root mean square error of the temperature reconstruction is evaluated. The obtained results demonstrate the stability of the proposed approach and its effectiveness for controlling the thermal regime during hyperthermia treatment of a cancer tumor.

Keywords: inverse problem, Pennes equation, finite element method, optimization, heat transfer coefficient.

AMS Subject Classification: 35R30, 49J20, 65N30

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STRESS STRAIN CONSTITUTIVE MODELING OF 6061 ALUMINUM ALLOY DURING HOT DEFORMATION

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In this study, isothermal compression tests of cast 6061 aluminum alloy were conducted at temperatures of $350 - 500$ °C and strain rates ranging from 0.001 to 1 s^{-1} using a Gleeble-3500 thermal simulator. Based on the experimental data, a traditional Arrhenius-type constitutive model was established to describe the flow stress behavior during hot deformation. To further improve prediction accuracy, a back-propagation (BP) neural network constitutive model was developed with strain, strain rate, and temperature as input variables. The prediction results of the traditional model and the neural network model were systematically compared. The results indicate that although the Arrhenius-type model can capture the general trend of flow stress evolution, the BP neural network demonstrates higher prediction accuracy and stronger capability in handling complex nonlinear relationships. The proposed neural network-based constitutive model provides an effective and accurate approach for predicting hot deformation flow stress and offers reliable support for numerical simulation and process optimization of aluminum alloys.

Keywords: 6061 aluminum alloy, constitutive modeling, machine learning, flow stress

ANALYSIS OF LOTKA-VOLTERRA MODEL DYNAMICS VIA LYAPUNOV FUNCTIONS

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This report provides a qualitative analysis of the fixed points of a discrete Lotka–Volterra operator on the 4-dimensional simplex, using Lyapunov functions to characterize the global trajectory behavior. The operator corresponds to a tournament with five cyclic triples and is defined by

$$x'_k = x_k\left(1 + \sum_{i=1}^{m} a_{ki}x_i\right), \qquad k = 1, \ldots, 5,$$

where $x = (x_1, \ldots, x_5) \in S^4$, and the interaction matrix $A = (a_{ki})$ is skew-symmetric with bounded coefficients $|a_{ki}| \leq 1$ ([1]). The first Lyapunov function considered is the multiplicative functional $\varphi_p(x) = x_1^{p_1} \cdots x_5^{p_5}$, which becomes non-increasing under the dynamics when the exponent vector p is chosen in accordance with the interaction structure. This function allows us to determine the direction of trajectories and to reveal attraction to fixed points located on the cyclic triples of the simplex.

To strengthen the analysis, we additionally introduce an entropy-type Lyapunov function

$$H(x) = -\sum_{k=1}^{5} x_k \log x_k,$$

which is known to be non-increasing for discrete Lotka–Volterra operators with skew-symmetric interaction matrices. The function $H(x)$ strictly decreases on the boundary of the simplex, thereby reinforcing the conclusion that trajectories tend to cyclic triples. At the same time, $H(x)$ remains constant at the interior fixed point, confirming its neutral stability and clarifying the global geometric structure of the dynamics.

Together, the two Lyapunov functions give a coherent characterization of the global dynamics: the multiplicative function $\varphi_p(x)$ detects the attracting faces corresponding to cyclic triples, while the entropy function $H(x)$ confirms the neutral stability of the interior fixed point and clarifies the invariance of simplex subsets. Combined, they provide a clear and unified picture of the system's dynamics.

Keywords: Lotka Volterra operator, Lyapunov function, fixed point,interior point, neutral stability

AMS Subject Classification: 37B25, 37C25, 37C35

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Stability and Trajectory Analysis of the SEIR Model in the Discrete Lotka–Volterra Framework

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Nonlinear dynamical systems play a central role in the analysis of epidemiological, ecological, and socioeconomic processes [1]. The present work [2] develops this direction by studying the stability and geometric properties of a discrete analogue of the classical $SEIR$ epidemic model, formulated as a discrete Lotka-Volterra (LV) dynamical system on a four-dimensional simplex generated by a skew-symmetric interaction matrix.

Consider the 3-dimensional simplex

$$S^3 = \{x = (S, E, I, R) \in \mathbb{R}^4 : \ S, E, I, R \geq 0, \ S + E + I + R = 1\}.$$

Its vertices $e_1 = (1, 0, 0, 0)$, $e_2 = (0, 1, 0, 0)$, $e_3 = (0, 0, 1, 0)$, $e_4 = (0, 0, 0, 1)$ correspond to the compartments of the $SEIR$ model. On this domain we consider the discrete LV operator $V(x)_i = x_i\Big(1 + \sum_{j=1}^{4} a_{ij}x_j\Big)$, $i = 1, \ldots, 4$, where $A = (a_{ij})$ is a skew-symmetric matrix, $a_{ij} = -a_{ji}$, $|a_{ij}| \leq 1$. Such operators preserve the simplex, possess non-isolated stationary sets, and generate rich invariant structures on its boundary.

Within this framework we determine invariant subsets P and Q, compute the Jacobian matrix of V at stationary points, and obtain a full spectral characterization of the dynamics. This allows us to classify all equilibria (attracting, repelling, saddle) and to describe the geometry of convex polytopes F_i associated with signatures of the skew-symmetric matrix. The corresponding trajectory configurations and admissible dynamical routes along boundary strata of the simplex are analyzed in detail.

The discrete $SEIR$ model embedded into this structure is given by

$$\begin{cases} S^{(n+1)} = S^{(n)}(1 - aE^{(n)} - bI^{(n)}), \\ E^{(n+1)} = E^{(n)}(1 + aS^{(n)} - dI^{(n)}), \\ I^{(n+1)} = I^{(n)}(1 + bS^{(n)} + dE^{(n)} - fR^{(n)}), \\ R^{(n+1)} = R^{(n)}(1 + fI^{(n)}), \end{cases} \tag{1}$$

where a, b, d, f describe the transmission, progression, and recovery interactions. Representing (1) as a special case of a discrete LV system provides access to general geometric and spectral tools for studying its invariant sets, stability structure, and global qualitative behaviour.

The results offer new insight into the dynamics of discrete epidemic models, showing how skew-symmetric interactions naturally generate invariant manifolds and govern transitions between epidemiological states.

Keywords: Discrete Lotka–Volterra operator, invariant set, stability, trajectory, $SEIR$ model.
MSC2020: 37B25, 37C25, 37C35.

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NUMERICAL MODELING OF THE DYNAMICS OF SATURATED WATER UNDER LOCAL CHANNEL RUPTURE

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The instantaneous rupture of channels containing saturated water at high pressure produces complex compressible two-phase flow phenomena that are important for safety analyses in thermohydraulic and high-pressure engineering systems. In this work, we develop a mathematical model and numerical algorithm for the dynamics of saturated liquid water interacting with a gaseous environment after a local rupture. The flow is described by the compressible Euler equations in conservative form, coupled with a stiffened-gas equation of state for water and an ideal-gas law for the surrounding gas [1, 2]. A two-dimensional channel with a localized rupture window is considered, through which saturated water at 5 MPa is discharged into an atmospheric-pressure region.

The numerical method is based on a first-order explicit finite-volume scheme with the Rusanov (Lax–Friedrichs) flux, which provides robust shock capturing for strongly nonlinear wave interactions in multiphase mixtures. The analysis focuses on the expansion and rarefaction dynamics of saturated water, the hydrodynamic interaction with the gas phase, and the resulting thermodynamic changes during rapid depressurization. The obtained results reveal characteristic nonlinear wave structures and interface dynamics consistent with recent studies on depressurization of high-pressure liquids [3], demonstrating the suitability of stiffened-gas formulations for modeling saturated-water blowdown processes.

The proposed approach can be used for accident scenario simulation, analysis of mass and energy transport in high-pressure channels, and for studying fundamental mechanisms of liquid–gas interaction arising during fast rupture events.

Keywords: saturated water, channel rupture, two-phase compressible flow, stiffened-gas equation of state, Euler equations, finite-volume method, Rusanov flux, shock waves, depressurization, blowdown dynamics.

AMS Subject Classification: 35Q35, 76N15, 65M08.

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GENERATIVE MODELING OF CREDIT RISK FOR SECOND-TIER BANKS IN THE REPUBLIC OF KAZAKHSTAN

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Estimating the probability of default (PD) is a central task in credit risk management and banking analytics. For second-tier banks in the Republic of Kazakhstan, PD modeling based on borrowers' financial statements is often challenged by scarce default observations in individual segments, strong class imbalance, and heterogeneous tabular structures that combine continuous financial ratios and categorical attributes. In this paper, we propose a compact mathematical framework for *generative modeling* in PD estimation, where deep generative models augment tabular credit datasets with high-fidelity synthetic observations while preserving dependence structures essential for default prediction.

As an interpretable baseline, let $x \in \mathbb{R}^n$ denote the vector of financial-statement features and related attributes, and let $Y \in \{0,1\}$ indicate default. The logistic regression model is

$$\mathbb{P}(Y = 1 \mid X = x) = \sigma(\beta_0 + \beta^\top x) = \frac{1}{1 + \exp\big(-(\beta_0 + \beta^\top x)\big)}. \tag{1}$$

In low-default regimes, estimation and calibration can become unstable; therefore, we enrich the training distribution via controlled synthetic sampling.

GAN formulation. A generative adversarial network (GAN)[1] consists of a generator G_θ and a discriminator D_ψ. With $z \sim p_z$ and $\tilde{x} = G_\theta(z)$, the standard minimax objective is

$$\min_\theta \max_\psi \; \mathbb{E}_{x\sim p_{\text{data}}}[\log D_\psi(x)] + \mathbb{E}_{z\sim p_z}[\log(1 - D_\psi(G_\theta(z)))] \,. \tag{2}$$

For portfolio-aware PD modeling, conditional generation[2] is used to control segment and default status. Let c be a conditioning vector (e.g., industry, product type, size group, and/or target class). The conditional GAN objective is

$$\min_\theta \max_\psi \; \mathbb{E}_{(x,c)\sim p_{\text{data}}}[\log D_\psi(x,c)] + \mathbb{E}_{z\sim p_z,\, c\sim p(c)}[\log(1 - D_\psi(G_\theta(z,c),c))] \,. \tag{3}$$

We outline an end-to-end workflow: preprocessing of financial-statement variables with accounting constraints and treatment of missingness, conditional sampling to mitigate class imbalance and enrich rare default patterns, and multi-criteria validation of synthetic data. Validation combines distributional fidelity (key marginals and moments), dependence preservation (correlations and conditional relations), and downstream utility via out-of-sample PD tests using transparent baseline models (logit) and competitive machine-learning benchmarks. Overall, generative augmentation (GAN) is positioned as a practical tool for improving PD model development in data-scarce, imbalanced credit datasets.

Keywords: probability of default; credit risk; machine learning; synthetic data; GAN; class imbalance.

AMS Subject Classification: 91G40, 62P05, 68T07, 62J12.

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NUMERICAL SOLUTION OF AN INVERSE PROBLEM FOR IDENTIFYING THE SOURCE OF THROMBOSIS IN HEMODYNAMIC MODELS

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Mathematical models of blood flow and thrombus formation in vessels are widely used to study cardiovascular processes and to support clinical decision making [1]. In many situations, only indirect and noisy measurements of hemodynamic fields are available at a few locations, while the region where a thrombus originates cannot be observed directly. Recovering this region from limited data leads to an ill-posed inverse problem that requires appropriate regularization techniques [2, 3].

We consider a simplified hemodynamic model in a rectangular domain $\Omega \subset \mathbb{R}^2$. The concentration of fibrin $\psi(x, y, t)$ is governed by a linear kinetic equation of the form $\partial\psi/\partial t = k\,\theta(x, y, t)$ in $\Omega \times (0, T]$ with zero initial condition $\psi(x, y, 0) = 0$, where $k > 0$ is a known constant and $\theta(x, y, t)$ is the activation function of blood coagulation representing the thrombosis source. It is assumed that the final-time distribution of fibrin $\psi_T(x, y) = \psi(x, y, T)$ is known from measurements, possibly corrupted by noise.

The inverse problem consists in reconstructing the activation function $\theta(x, y, t)$ (or its spatial profile) from the noisy final-time data. To stabilize this reconstruction, we introduce a Tikhonov-type functional that combines the mismatch between the model prediction at $t = T$ and the measured ψ_T with a quadratic penalty term on θ. The gradient of this functional with respect to θ is derived using the associated adjoint kinetic problem, which is solved backward in time with a final condition at $t = T$. On this basis, a Landweber-type iterative scheme (a simple gradient method with a fixed step size) is used to approximate a minimizer of the regularized functional.

The direct and adjoint initial-/final-value problems are discretized by finite differences on a uniform grid in space and time. Numerical experiments are performed on synthetic test cases, where the "true" activation function θ^* is a localized Gaussian-type distribution and artificial noise (up to 5%) is added to the corresponding final-time fibrin concentration. The results show that the proposed regularized inverse method can recover both the location and approximate intensity of the thrombosis source with acceptable accuracy. The influence of the regularization parameter and the measurement configuration on the reconstruction quality is briefly illustrated.

Keywords: hemodynamics, thrombosis, inverse problems, Tikhonov regularization, Landweber iteration.

AMS Subject Classification: 35R30, 65M32, 92C35.

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DETERMINATION OF THE INTENSITY OF DISTRIBUTED GRAVITATIONAL AND INERTIAL FORCES ALONG THE JOINTS OF A SPATIAL RRRRRR MANIPULATOR CAUSED BY THE WEIGHT OF ITS LINKS

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In the present scientific work, algorithms and program codes were developed in the **Maple 2023** software environment to construct an interactive three-dimensional computer model of a spatial **RRRRRR-type manipulator** controlled by generalized coordinates. As a result of implementing the developed algorithms and program codes, three-dimensional computer models were obtained that clearly represent the manipulator's links, their cross-sections, kinematic pairs, as well as end-effectors and loads, differing in structure and degrees of freedom. The proposed models provide full visualization from all spatial directions and allow for a comprehensive analysis of the manipulator's kinematic and geometric characteristics.

The spatial position parameters of the manipulator's joints were determined based on the **Denavit–Hartenberg methodology**. The kinematic parameters required for dynamic analysis were calculated using the recursive **Newton–Euler equations**. In the course of the study, the intensity of **gravitational forces distributed along the joints** due to the self-weight of the manipulator's links, as well as the intensity of **inertial forces distributed along the joints**, was determined. The obtained dynamic characteristics make it possible to determine, over the entire operating cycle of the manipulator, the intensity of gravitational and inertial forces distributed along the joints of the interactive RRRRRR manipulator in motion.

Keywords: Manipulator, distributed inertial forces, intensity, cycle, distributed gravitational forces

AMS Subject Classification: UDC 621.865.8

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NUMERICAL MODELING OF SOME PROBLEM OF FINANCIAL MATHEMATICS

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This article examines the calculation of the option price $V(t, x)$, the stock price $x(t)$, and the optimal stopping (execution) time τ; $(\equiv t)$ over both finite and infinite time horizons. It then delves into determining a fair value for American-style options, leveraging the optimal stopping time within the framework of diffusion processes in stock markets, represented by (B, S). Additionally, the article explores the pricing of European-style options, starting with the buyer's perspective and then transitioning to the seller's viewpoint. The problems are solved either analytically, when the optimal stopping time is pre-determined, or numerically using methods like the sweep method and finite element techniques.These methods are applied by reducing the problem to Stefan's problem, where $Y^*(t, x)$ represents the rational option value, τ_T^* indicates the rational execution time, and $x^*(t)$ corresponds to the rational stock price.

Keywords: option prices, stock prices, equity diffusion markets, options of American and European types, Stefan's problem, numerical modeling.

AMS Subject Classification: 35R60, 39A50, 60G40, 65M06, 65M08.

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RELIABLE FBCSP BASELINE WITH NESTED CROSS-VALIDATION FOR ROBUST BCI DESIGN

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Motor-imagery brain–computer interfaces (BCIs) depend on interpreting electroencephalography (EEG) signals, and in rehabilitation tasks this interpretation must be stable and trustworthy [1]. One of the classical techniques that researchers still rely on is the Filter Bank Common Spatial Patterns method (Filter Bank CSP). Although it is widely used, its real-world implementations vary quite a lot. In some cases, Independent Component Analysis (ICA) is used only partially. In other cases, feature selection is organized in a way that unintentionally exposes information from the test set [2]. Besides that, the validation process sometimes produces folds where the classes are not evenly represented. When several of these issues appear together, the final accuracy does not show the actual performance of the method [3].

To minimize the influence of these factors, an adjusted version of the Filter Bank CSP pipeline is introduced. The updated workflow uses nested stratified cross-validation, which helps maintain class balance and improves the fairness of the evaluation. ICA components linked to artifacts are removed automatically by paying attention to their spatial activity in frontal regions and to sudden changes in amplitude. Performance is expressed through accuracy and the Cohen's Kappa coefficient (Kappa). When the method was tested on the BCI Competition IV-2a dataset, the average accuracy reached 81.8%, and the Kappa value was 0.757 [4]. Compared to the original Filter Bank CSP implementation by Ang and colleagues, who provided the winning solution for BCI Competition IV-2a, this represents an improvement of 7.5 percentage points. The results generally indicate that the way the evaluation is organized often has more influence on the final outcome than adding extra complexity to the algorithm itself [5].

The revised pipeline may serve as a practical reference for later studies on motor-imagery signal classification.

Keywords: Brain–Computer Interface, Motor Imagery, Electroencephalography, Filter Bank Common Spatial Patterns, Nested Stratified Cross-Validation

AMS Subject Classification: 92C55

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OPTIMIZATION OF INVERSE PROBLEMS IN BREAST CANCER TUMOR GROWTH MODELING

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Breast cancer remains one of the leading causes of morbidity and mortality among women in Kazakhstan. According to official statistics, 5,507 new cases and more than 1,000 deaths were recorded in 2023 [1]. Mathematical modeling plays a crucial role in the analysis of tumor growth dynamics and the evaluation of treatment efficacy. However, identifying model parameters from clinical data leads to ill-posed and inverse problems that require robust numerical approaches.

The growth dynamics of breast cancer are described using a logistic growth model [2]:

$$\frac{dV(t)}{dt} = \alpha V(t)\left(1 - \frac{V(t)}{K}\right), \tag{1}$$

where $V(t)$ denotes the tumor volume (mm^3), α is the intrinsic tumor growth rate (day^{-1}), and K represents the carrying capacity corresponding to the maximum tumor volume (mm^3). The analytical solution is given by

$$V(t) = \frac{K}{1 + \left(\frac{K - V_0}{V_0}\right) e^{-\alpha t}}, \tag{2}$$

where $V_0 = V(0)$ denotes the initial tumor volume.

The reconstruction of the parameter vector $\delta = (\alpha, K, V_0)$ from clinical observations constitutes an inverse problem. Due to the inherent instability of inverse problems, optimization-based approaches will be employed for parameter estimation. Both deterministic and stochastic tumor growth models will be considered to estimate and compare model parameters and to assess their impact on tumor growth dynamics.

This approach aims to provide more accurate individualized prognostic models for oncological patients.

Keywords: inverse problem, optimization, breast cancer, tumor growth model.

AMS Subject Classification: 92C50, 35R30, 65M32

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THE EQUATION OF MOTION FOR THE VARIABLE MASS TRAPPIST-1 EXOPLANET SYSTEM IN THE JACOBI COORDINATE SYSTEM

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Abstract. In this work, the equation of motion for the seven-planet TRAPPIST-1 exoplanetary system, which has variable, non-isotropic masses and reactive forces, is derived in the absolute, relative, and, specifically, the Jacobi coordinate systems.

1. Introduction

A dynamic description of the variable mass N-body problem is a pressing issue for investigating phenomena such as stellar mass loss in astrophysical systems or the motion of space vehicles [1]. While most traditional approaches to studying N-body dynamics utilize relative coordinates, this method becomes increasingly complex as the number of bodies increases. The equations of motion in Jacobi coordinates for the N-body problem with masses changing isotopically have been previously obtained [2].

The main feature of this work is the first-time derivation of the generalized equations of motion in Jacobi coordinates for the seven-body problem with masses changing in a non-isotropic way. The practical significance of this research lies in the application of these derived equations to a specific astrophysical system. Specifically, the study is centered on the TRAPPIST-1 exoplanetary system [3]. By utilizing Jacobi coordinates, the dynamical stability and evolution of this seven-planet system are investigated in detail. The results enhance computational efficiency in theoretical N-body calculations and allow for the construction of more precise dynamical models for complex exoplanetary systems like TRAPPIST-1.

2. Equation of motion in Jacobi coordinates

The bodies attract one another in accordance with Newton's law of universal gravitation. Due to the variable nature of the masses, reactive forces arise, significantly complicating the problem. Based on the equation of relative motion and employing geometric methods for defining material points and their properties, the formula for transitioning to Jacobi coordinates is expressed as follows.

$$\vec{r}_i = \vec{R}_i - \sum_{j=0}^{i-1} \nu_j \vec{r}_j, \quad i = 1, 2, \dots, 7 \tag{1}$$

where $\nu_j = \nu_j(t) = \frac{m_j}{\sigma_j}$, $\sigma_j = m_0 + \sum\limits_{k=1}^{j} m_k$;

$\vec{r}_i$ – radius vector in Jacobi coordinates and $\vec{r}_0 = 0$.

Thus, for a specific seven-planet system, we obtain the equations of motion in Jacobi coordinates based on formula (1):

$$\mu_i \ddot{\vec{r}}_i = grad_{\vec{r}_i} U - \mu_i \dot{\Phi}_i + \mu_i \vec{F}_i; \tag{2}$$

This work was partially supported by ...

Where U – force function:

$$U = f\sum_{i,j}\frac{m_i m_j}{r_{ij}}, \quad i \neq j \tag{3}$$

μ – reduced masses:

$$\mu_i = \mu_i(t) = m_i\frac{\sigma_{i-1}}{\sigma_i} = \nu_i\sigma_{i-1}, \quad i = 1, 2, \dots, 7 \tag{4}$$

$$\dot{\Phi}_i = \sum_{i=1}^{7}(2\dot{\nu}_i\dot{\vec{r}}_i + \ddot{\nu}_i\vec{r}_i); \quad i = 1, 2, \dots, 7 \tag{5}$$

$\vec{F}$ – Reactive forces for the first, second, and respectively, seventh body:

$$\vec{F}_1 = \frac{\dot{m}_1}{m_1}\vec{V}_1 - \frac{\dot{m}_0}{m_0}\vec{V}_0 \neq 0, \tag{6}$$

$$\vec{F}_2 = \left(\frac{\dot{m}_2}{m_2}\vec{V}_2 - \frac{\dot{m}_0}{m_0}\vec{V}_0\right) - \nu_1\left(\frac{\dot{m}_1}{m_1}\vec{V}_1 - \frac{\dot{m}_0}{m_0}\vec{V}_0\right) \neq 0 \tag{7}$$

. . . .

$$\vec{F}_7 = \left(\frac{\dot{m}_7}{m_7}\vec{V}_7 - \frac{\dot{m}_0}{m_0}\vec{V}_0\right) - \nu_6\left(\frac{\dot{m}_6}{m_6}\vec{V}_6 - \frac{\dot{m}_0}{m_0}\vec{V}_0\right) - \dots - \nu_1\left(\frac{\dot{m}_1}{m_1}\vec{V}_1 - \frac{\dot{m}_0}{m_0}\vec{V}_0\right) \neq 0 \tag{8}$$

New equations of motion in Jacobi coordinates were developed for the seven-body TRAPPIST-1 system. These are applicable for investigating non-stationary gravitating systems.

Keywords: Astrophysical systems, non-isotropic mass variation, Jacobi coordinates, reactive forces, barycentric coordinates, perturbation theory, TRAPPIST-1, quasi-elliptical orbit.

AMS Subject Classification: The author(s) should provide AMS Subject Classification numbers using the link https://mathscinet.ams.org/msnhtml/msc2020.pdf.

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Секция 3

Геология мен экология мәселелерінде кеңістіктік деректерді өңдеу

Секция 3

Обработка пространственных данных в задачах геологии и экологии

Section 3

Spatial data processing in geology and environmental studies

COMPREHENSIVE ENVIRONMENTAL ASSESSMENT AS A BASIS FOR GOVERNMENTAL DECISION-MAKING (KENTAU AND ULYTAU REGION)

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Post-industrial cities in Kazakhstan are characterized by accumulated environmental impacts caused by long-term mining and processing activities. For many years, the lack of integrated and scientifically grounded assessments of environmental conditions and public health constrained the adoption of effective management and social policy measures, highlighting the importance of research supporting governmental decision-making.

In 2019–2020, Ecoservice-S LLP conducted a comprehensive assessment of environmental conditions and public health in the city of Kentau and adjacent settlements, commissioned by the local administration. The study aimed to substantiate the potential classification of the territory as a zone of ecological emergency in accordance with national environmental assessment criteria. The interdisciplinary methodology combined field and laboratory studies of air, soils, and water resources, assessments of radiological, geochemical, and hydrogeological conditions, medical-statistical analysis, and GIS-based spatial analysis.

The results identified persistent environmental degradation, including widespread heavy-metal soil contamination, dust transport of polluted particles, and combined environmental and geological risks consistent with the criteria of an ecological emergency zone. The findings were submitted to authorized governmental bodies and used in decision-making processes. In 2024, the industrial zone of Kentau was officially designated as a zone of ecological emergency until 2075, resulting in a special environmental management regime and social support measures for the population. In 2025, the results of the scientific assessment conducted by Ecoservice-S LLP were reflected in amendments to the legislation of the Republic of Kazakhstan, formally establishing the legal status of the population residing within this zone.

In 2023–2024, a similar methodology was applied to the cities of Zhezkazgan and Satpayev and settlements of the Ulytau district, including the development of an environmental geoinformation system and a monitoring framework. The results indicate complex environmental conditions in several areas and are currently undergoing staged governmental review.

These projects demonstrate that comprehensive scientific assessment provides an effective basis for environmental policy and social protection decisions and can be applied in future projects focused on monitoring, territorial rehabilitation, and the integration of scientific evidence into governmental decision-making.

Keywords: Keywords: environmental assessment, ecological emergency, public health, Kazakhstan.

AMS Subject Classification: 86A10.

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INTEGRATED ASSESSMENT OF GEOLOGICAL AND REMOTE SENSING DATA FOR ORE-BEARING TERRITORIES

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In the context of increasing requirements for the efficiency of mineral exploration, the integration of heterogeneous geological, geophysical, and remote sensing data using modern analytical approaches has become increasingly important. This study develops and tests an approach to the integrated assessment of source data for ore-bearing territories within a unified digital information environment.

The methodology is based on a structural–hierarchical analysis framework, in which input data are considered as a system of indicators of different origin and significance, ranging from deep structural and tectonic factors to surface features identified from Earth remote sensing data. The initial dataset includes spatial and attribute geological, geophysical, and geochemical information, as well as satellite observations and derived spectral indices. All data are standardized and integrated into a specialized geological information system.

At the next stage, the informativeness of individual indicators and their relationships with known ore objects are evaluated using analytical and modeling approaches aimed at identifying spatial patterns and the relative significance of ore-controlling factors. The analysis is conducted without rigid *a priori* criteria, allowing both universal indicators applicable to different types of mineralization and specific factors reflecting individual ore-forming systems to be considered.

Special attention is given to structural control, geodynamic setting, and lithological–formational conditions as key factors influencing ore potential, as well as to the role of remote sensing data in spatial refinement and preliminary prospectivity assessment. The preliminary results demonstrate the feasibility of integrated use of heterogeneous datasets for evaluating ore potential and identifying areas with increased mineralization probability.

The proposed approach is universal in nature and can be adapted to a wide range of tasks related to mineral prospectivity assessment. The methodology may serve as a basis for the further development of intelligent geoinformation systems supporting decision-making in mineral exploration and subsurface resource management.

Keywords: Keywords: ore prospectivity, data integration, geological information systems, remote sensing, mineral exploration.

AMS Subject Classification: 86A05.

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ANALYSIS AND SYNTHESIS OF GEOLOGICAL DATA FOR RARE-METAL OBJECTS OF EASTERN KAZAKHSTAN

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Based on the analysis and systematization of data on rare-metal objects of Eastern Kazakhstan, a comprehensive integrated database is at the final stage of preparation within the project "Methods and technologies for prospecting and evaluation of mineral deposits using artificial intelligence." The database includes information on host and ore-generating rocks, geochemical, structural, mineralogical, and petrochemical indicators of rare-metal mineralization, as well as object parameters and prospecting criteria. More than 260 objects have been identified, ranging from medium-sized deposits to mineralization points.

Rare-metal mineralization of Eastern Kazakhstan is represented by ore-bearing formations of the Kalba–Narym belt, including rare-metal pegmatites (Ta, Be, Nb, Li, Sn, REE), greisen–quartz vein Sn–W formations, and albite–greisen Sn–Ta–Li metasomatites associated with concealed granite intrusions.

Prospecting criteria suitable for encoding as ore-potential indicators in AI-based correlation matrices have been identified. The main controlling factors are deep magmatic feeder faults of northwest and latitudinal strike and their intersections with northeast-trending strike-slip faults, which control the central parts of ore-bearing massifs. Under stable tectonic conditions, weakly mineralized or barren massifs formed despite compositional similarity to ore-bearing intrusions.

Pegmatite mineralization is genetically related to granitoids of the Kalba complex (P_1), while hydrothermal tin–tungsten mineralization is associated with the final stages of granitoid emplacement of the Kalba and Monastyrsky complexes (P_2). Lithological control is provided by chemically favorable host rocks, mainly shales of the Takyr Formation (D_3).

Geochemical indicators of mineralization include Cu, Zn, Ti, B, F, P, Be, Li, Sn, and W. The rare-metal potential of Eastern Kazakhstan is not limited to known deposits and includes albitite metasomatites, contact–metasomatic Sn–W mineralization, and Kalba granitoids overlain by Cenozoic sediments northwest of the Delbegetey massif.

Keywords: rare-metal mineralization, geological database, mineralogical indicators, ore prospecting, Eastern Kazakhstan.

AMS Subject Classification: 86A25.

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The research is funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. BR27100483 "Development of predictive exploration technologies for identifying ore-prospective areas based on data analysis from the unified subsurface user platform 'Minerals.gov.kz' using artificial intelligence and remote sensing methods").

NUMERICAL METHODS FOR SOLVING A GEOCHEMICAL INVERSE PROBLEM BASED ON A FREDHOLM INTEGRAL EQUATION

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This paper addresses a geochemical inverse problem aimed at reconstructing an unknown subsurface distribution from surface measurement data. The problem is formulated as a Fredholm integral equation of the first kind, which belongs to the class of ill-posed problems and is highly sensitive to measurement noise.

Three numerical approaches are employed to solve the problem: the classical Galerkin method, the Galerkin method combined with Lavrentiev regularization, and a method based on Singular Value Decomposition (SVD). The discretization of the integral equation leads to a poorly conditioned system of linear algebraic equations. To ensure stability, the influence of regularization techniques and singular value truncation is investigated. The performance of the proposed methods is evaluated through numerical experiments with artificially perturbed data, allowing a comparative analysis of their stability and reconstruction accuracy.

The results demonstrate that the classical Galerkin method is highly sensitive to noise, whereas the Lavrentiev-regularized Galerkin method and the SVD-based approach significantly improve the stability of the solution. The accuracy of the reconstructed solutions is assessed and their physical meaning is interpreted within a geochemical context. The proposed methodology proves to be an effective numerical tool for solving geochemical inverse problems governed by the Fredholm integral equations.

Keywords: Fredholm integral equation, inverse problems, Galerkin method, Lavrentiev regularization, singular value decomposition, geochemical modeling

AMS Subject Classification: 45B05, 65R30, 65F22, 86A32.

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METHODS OF FILTERING GEOPHYSICAL DATA IMAGES

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The Kalman filter is an optimal recursive estimation algorithm based on the combination of a dynamic process model and measurement data, taking into account the statistics of noise. Its key state correction operation is formalized by the expression

$$\hat{x}_k = \hat{x}_k^- + K_k \left(z_k - H\hat{x}_k^- \right), \tag{1}$$

where the innovation term ensures the minimization of the mean squared estimation error. Due to its adaptive nature and consideration of the covariance properties of the data, the Kalman filter preserves the structural features of signals and geophysical images, providing high accuracy while suppressing noise artifacts.

The Butterworth filter is a classical frequency-domain low-pass filter with a monotonic amplitude-frequency characteristic, ensuring maximally smooth behavior in the passband. Its transfer function is defined as

$$|H(\omega)|^2 = \frac{1}{1 + \left(\frac{\omega}{\omega_c}\right)^{2n}}, \tag{2}$$

which guarantees the absence of ripples and stable suppression of high-frequency components. The application of the Butterworth filter results in uniform smoothing of geophysical data and significant reduction of high-frequency fluctuations, making it an effective tool for preliminary data processing prior to subsequent automated analysis.

Keywords: Kalman filter, Butterworth filter, geophysical data, image filtering. keywords which can be used for indexing purposes.

AMS Subject Classification: 68U10, 86A32, 65T07, 68T50.

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DEVELOPMENT OF ALGORITHMS USING MACHINE LEARNING TO IDENTIFY ANOMALIES IN GEOLOGICAL OBJECTS

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In the geological study area, geochemical samples n were collected at the coordinates $\mathbf{x}_i = (x_i, y_i)$. For each sample, the measured concentration of the target component (of the elements n) $z(\mathbf{x}_i)$ was obtained. For each point of the given computational grid $\mathbf{x}_0^{(j,k)} = (x_0^j, y_0^k)$, the following quantities must be determined: the predicted value of the target component $\hat{z}(\mathbf{x}_0)$ and the kriging variance $\sigma_K^2(\mathbf{x}_0)$, which characterizes the uncertainty of the prediction. These quantities are computed using geostatistical methods.

The purpose of the study is to develop models and algorithms that identify spatial anomalies in geological objects, interpolate component concentrations, and precisely localize anomalies using geostatistical approaches and machine learning methods.

During the study, geochemical data were preprocessed and the coordinates normalized. Spherical and Gaussian variogram models were used to describe the spatial dependence between samples. Based on these variograms, Ordinary Kriging interpolation was performed and predicted values and kriging variances were obtained at the grid points [1]. The accuracy of the models was evaluated using the Leave-One-Out cross-value method. In addition, spatial associations of gold with other elements were identified using graphical and multivariate analysis techniques [2].

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USING ARTIFICIAL INTELLIGENCE TO FORECAST ORE-PROSPECTIVE TERRITORIES IN EASTERN KAZAKHSTAN

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Machine learning algorithms can be used to analyze and synthesize historical geological data in conjunction with mathematical geophysics and geochemistry, as well as Earth remote sensing (ERS) data [1]. The development of geographic information systems (GIS) for such Big Data, followed by processing using artificial intelligence methods, offers unique opportunities for more accurate mineragenic zoning and forecasting of ore-prospective territories in Eastern Kazakhstan, significantly increasing the efficiency of geological exploration. One area of such research is based on the construction of mineragenic models, which represent a mathematical or computer visualization of the geological space formed as a result of chemical interactions occurring in the Earth39;s crust. It is used to explain the spatial distribution of mineral deposits, ore processes in the Earth39;s interior, and the geochemical migration of chemical elements in rocks. Minerogenic models can incorporate various parameters, such as the geological structure of the studied areas, their geophysical and geochemical fields and anomalies, patterns of mineralization localization, and chemical element concentrations in ore and near-ore environments, as well as Earth remote sensing data. These models can serve as test objects that allow us to understand the origin and evolution of geological and ore formations, as well as predict the mineragenic characteristics of geological space. A series of experiments aimed at determining the presence of minerals within the test object allowed us to predict ore-promising areas. GIS technologies based on the ArcGIS platform were used to analyze the obtained data in spatial and temporal aspects. The result of these studies was the development of a distributed, integrated geoinformation technology that enables the processing and analysis of geological data for a more effective assessment of predicted resources.

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SPATIAL PREDICTION OF GEOCHEMICAL ANOMALIES BASED ON RBF INTERPOLATION FOR AU, AL, AG, SB AND HG ELEMENTS

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The reconstruction of the spatial distribution of geochemical data is a key task in mineral exploration, especially for the prediction of gold-related anomalies. This study aims to apply the Radial Basis Function (RBF) interpolation method to restore the spatial distribution of Au, Al, Ag, Sb and Hg elements, to predict their values at 50,000 new coordinate points, and to construct a combined geochemical anomaly index based on all elements.

The RBF interpolation is expressed as

$$f(x,y) = \sum_{i=1}^{N} \lambda_i \, \varphi\Big(\sqrt{(x-x_i)^2 + (y-y_i)^2}\Big), \tag{1}$$

where (x_i, y_i) are observation points, λ_i are weighting coefficients, $\varphi(r)$ is a radial basis function, and N is the number of measurements.

For each element, spatial fields were reconstructed on a dense grid of predicted points. The obtained results were normalized and integrated into a combined anomaly index:

$$A_{\text{total}} = w_1 A_{Au} + w_2 A_{Al} + w_3 A_{Ag} + w_4 A_{Sb} + w_5 A_{Hg}. \tag{2}$$

The results show that Ag, Sb and Hg exhibit strong spatial correlation with Au anomalies, forming distinct prospective mineralization zones. The proposed approach demonstrates that RBF interpolation is an effective tool for multi-element geochemical anomaly prediction and integrated spatial analysis in gold exploration.

Keywords: RBF interpolation, geochemical anomaly, gold (Au), silver (Ag), antimony (Sb), mercury (Hg), spatial prediction.

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EXPERIENCE IN CREATING A DATABASE FOR DEVELOPING AN INTEGRATED MAPPING METHODOLOGY OF MINERALOGICAL INDICATORS TO IDENTIFY PROMISING ORE DEPOSIT LOCATIONS

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Ecoservice-S LLP conducts research within the project "Methods and technologies for mineral deposit prospecting and evaluation using artificial intelligence," aimed at developing an integrated mapping methodology for identifying promising ore-bearing areas within a test region.

The test area includes the Aleisk–Ashalinskaya polymetallic subzone, the Priirtysh and Kalbinskaya rare-metal subzones, and the West Kalbinskaya gold-bearing subzone, covering approximately 49,000 km^2. The study focuses on gold, rare-metal, and polymetallic mineralization.

The main objective was the collection and systematization of archival geological materials and scientific publications, as well as the preparation of standardized memos and attribute tables for further analysis. Archival reports were examined at the Vostkaznedra Department archive, and additional data were obtained through open-access sources and formal requests to the Regional Center for Geological Information (Kazgeoinform LLP).

For each deposit or occurrence, a standardized memo was compiled using primarily textual materials from archival reports. These memos formed the basis for attribute tables processed in ArcGIS Pro and Excel.

The Alexandrovsky gold prospect was analyzed as an example of data systematization. Relevant reports related to the Kuludzhun ore field were identified, and key information was transferred into standardized memos with an assessment of data completeness.

As a result, structured information on gold deposits and ore occurrences was compiled, forming a unified data basis for subsequent analytical stages and further application of artificial intelligence methods.

Keywords: geological database, mineralogical indicators, integrated mapping, ore prospecting, East Kazakhstan.

AMS Subject Classification: 86A25, 86A05.

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EVALUATION OF RADIOACTIVITY FOR PROSPECTING AND EXPLORATION OF ORE DEPOSITS IN THE KALBA–NARYM RARE-METAL ZONE

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The Kalba–Narym rare-metal ore zone is included in a scientific research program of the Ministry of Science and Higher Education of the Republic of Kazakhstan aimed at developing predictive and prospecting technologies based on data from the unified subsoil-use platform *Minerals.gov.kz* using artificial intelligence and Earth remote sensing methods. According to the Technical Assignment, digital datasets for a test site, including information on geological radioactivity, are required for pilot system operation.

Analysis of archival geological reports showed that the most complete information is available mainly for geology (lithology, metasomatism, tectonics), geochemistry, and ore geophysics (magnetic and electrical surveys), while gravity surveys, aerospace data, and radiometric information are poorly represented. Radiometric surveys, although mandatory during large-scale prospecting, are often mentioned only in the context of uranium exploration, usually without analysis of their effectiveness.

According to studies by JSC *Volkovgeology*, within the Kalba–Narym zone (about 29.5 thousand km^2), 42 uranium and thorium deposits and occurrences have been identified, and approximately 4.6 thousand km^2 of areas with elevated radioactivity have been delineated. This paper presents an assessment of the radiological state of the subsurface and aquifers at the Sarymbet deposit, demonstrating the effectiveness of radiometric investigations.

The results indicate that geological and structural formations characterized by increased radioactivity can be considered indicators for prospecting, primarily for rare and rare-earth element deposits. At the same time, the extraction and processing of such ores require careful consideration of radiation safety issues during and after mining operations.

Keywords: radioactivity, ore prospecting, radiometric surveys, Kalba–Narym zone, rare-metal deposits.

AMS Subject Classification: 86A25, 86A05.

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PREDICTIVE MODELING OF SUBSURFACE MINERALIZATION BASED ON GEOSPATIAL DATA AND ARTIFICIAL INTELLIGENCE METHODS

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This study presents an integrated workflow for predictive subsurface modeling based on multicomponent geospatial data and artificial intelligence methods. USGS and NASA satellite datasets, combined with local geological sampling points, were processed in ArcGIS to generate spatially meaningful raster and vector features, including terrain derivatives, spectral indices, lithological attributes, and structural proximity metrics. During the feature engineering stage, a unified machine-learning-ready dataset was created, followed by systematic division into training and test subsets. Several machine learning models, such as Random Forest, Gradient Boosting, and neural networks, were examined to predict mineralization indicators at different depths (100 m, 200 m, and 500 m). A three-dimensional spatial grid was constructed to enable depth-oriented prediction, resulting in continuous predictive raster outputs. The generated predictive maps were exported in GIS-compatible formats, including GeoTIFF and shapefile. The results demonstrated that integrating multispectral remote sensing data, terrain derivatives, and geological features significantly improves the ability to predict subsurface anomalies. The proposed workflow provides a scalable methodology for identifying zones with increased mineralization potential and can be adapted to different study regions and target elements.

Keywords: Geospatial data, Subsurface modeling, Machine learning, ArcGIS, Remote sensing, Mineralization mapping.

AMS Subject Classification: 62M30, 68T01, 68T05, 86A60, 35R30.

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The research is funded by Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. BR27100483 "Development of predictive exploration technologies for identifying ore-prospective areas based on data analysis from the unified subsurface user platform "Minerals.gov.kz" using artificial intelligence and remote sensing methods").

INTERPOLATION METHODS FOR ESTIMATING GOLD CONCENTRATION AT UNKNOWN POINTS

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Interpolation is an important tool in geology and geochemistry for estimating the concentration of minerals, such as gold, in areas where direct measurements are not available. The use of interpolation methods allows for the construction of continuous models of concentration distribution based on point sample data. Among the most common methods are: IDW (Inverse Distance Weighting) — which applies inverse distance weighting; Kriging methods (Ordinary Kriging, Universal Kriging) — statistically based approaches that take into account the spatial correlation of data, which is evaluated using a variogram, allowing the dependence of value differences on the distance between points to be determined and the prediction accuracy to be assessed.

Applying interpolation methods provides the following results: a map of gold concentration distribution in unknown points; identification of zones with a high probability of gold occurrence (anomalous areas); quantitative assessment of prediction accuracy using the variogram and confidence intervals.

The application of these methods in mineral exploration allows for the optimization of drilling plans, reduction of costs, and increased efficiency in the search for gold deposits.

Keywords: Kriging, interpolation, variogram, IDW.

AMS Subject Classification: 62H11, 86A32 from https://mathscinet.ams.org/msnhtml/msc2020.pdf.

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PREPROCESSING OF DATA IN PREDICTING GEOCHEMICAL ANOMALIES USING NEURAL NETWORKS

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In the context of modern geological exploration, where the role of scientific forecasting is steadily increasing, effective prediction of geochemical anomalies, such as mineral concentrations, has become one of the key challenges.

To address the problem of predicting gold content at newly generated points within a given area, a geochemical analysis dataset is used. The data include the geographical coordinates (longitude and latitude) of geochemical sampling points and the corresponding gold concentration values c_i. These data were obtained through field investigations and are represented as discrete points on a geographical map.

The objective of this study is to predict gold concentrations at new locations where gold content data are unavailable, based on existing geochemical data. To solve this problem, a multilayer perceptron (MLP) is employed—a neural network trained on the available data and used to predict gold concentrations at new points.

One of the main challenges in applying neural networks is the low correlation between the input data (coordinates) and the target variable (gold concentration), which complicates the identification of hidden patterns and reduces prediction accuracy [2].

To improve prediction accuracy, data preprocessing is performed using feature transformation methods, in particular anisotropy-based transformations, which allow spatial dependencies and directional variability of geochemical indicators to be taken into account. This enhances the relationship between the input and output variables and improves the quality of predictions [2].

The aim of this work is to increase the accuracy of gold content prediction using multilayer perceptrons trained on preprocessed data. The results demonstrate that the application of anisotropic preprocessing significantly improves prediction accuracy at new locations lacking geochemical data and contributes to increasing the efficiency of geological exploration activities.

Keywords: geology; multilayer perceptron; feature transformation; geochemical anomaly predic-tion;

AMS Subject Classification: The author(s) should provide AMS Subject Classification numbers using the link https://mathscinet.ams.org/msnhtml/msc2020.pdf.

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PREPROCESSING OF GEOPHYSICAL RASTER DATA USING MACHINE LEARNING METHODS

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In this work, we implemented preprocessing of geophysical raster data, focusing on noise and artifact removal using a convolutional neural network (CNN). The main objective was to enhance the quality of magnetic survey images and extract a numerical magnetic field intensity map (nT) from raster formats such as JPG, PNG, and TIFF. At the initial stage, the average image dimensions were computed and used to standardize all inputs to a unified resolution, ensuring consistent processing across datasets with varying geometry. The images were normalized, artificially noised for training purposes, and then fed into a CNN consisting of two convolutional layers and a reconstruction output layer [1, 2].

The trained CNN successfully removed noise while preserving the structural features of magnetic anomalies, which was confirmed both visually and quantitatively. For each sample, PSNR and SSIM metrics demonstrated high-quality reconstruction and structural similarity to the original clean data. Comparative visualizations of the original, noisy, and denoised images were produced, allowing a clear assessment of the model's impact on the magnetic field structures. In addition, trained CNN filters and activation maps were extracted and visualized, showing that the network learned characteristic geophysical textures and boundary patterns associated with magnetic anomalies.

After the denoising stage, the processed images were resized to match a reference PNG template and converted from RGB format into numerical magnetic field values using a calibration function. To ensure correct integration with geospatial workflows, georeferencing information (GeoTransform) and the coordinate reference system (CRS) were inherited from the original GeoTIFF, enabling the generation of a spatially accurate magnetic field product. The final outputs included denoised magnetic images, a magnetic field intensity map, a CSV matrix of extracted values, the training history, PSNR/SSIM quality metrics, and visualizations of the CNN's internal layers.

Keywords: cnn, machine learning, geophysical data, magnetic data, data extraction, data preprocessing.

AMS Subject Classification: 68T01, 68T07, 86A04 from https://mathscinet.ams.org/msnhtml/msc2020.pdf.

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ARCGIS PRO–BASED MULTILAYER FEATURE ENGINEERING FOR MACHINE LEARNING PREDICTION OF GOLD MINERALIZATION

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This study presents a geospatial–machine learning framework for predicting gold mineralization using multilayer feature engineering developed in ArcGIS Pro. The study area was divided into four mineragenic subzones, and a unified database of verified mineral occurrences and background samples was constructed.

A high-resolution digital elevation model (DEM) was reprojected into WGS 84 / UTM Zone 45N, enabling extraction of key geomorphological attributes such as slope, curvature, and structural edge indicators [1]. Spatial predictors were integrated into a Python-based workflow using `pandas`, `numpy`, and `scikit-learn` [2].

Several supervised machine learning models were evaluated using cross-validation procedures. Future work planned for 2025–2026 includes the incorporation of regional geochemical datasets, interpolated geochemical surfaces, and advanced DEM-derived metrics such as topographic position index (TPI), terrain ruggedness index (TRI), and surface roughness.

Benchmarking of modern machine learning architectures [3] will support the development of a reproducible and scalable mineral prospectivity mapping pipeline suitable for regional gold exploration.

Keywords: gold mineralization, ArcGIS Pro, geospatial feature engineering, machine learning, DEM analysis.

AMS Subject Classification: 62H30, 68T09, 86A60.

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ALGORITHMS FOR PROCESSING AND ANALYSIS OF GEOCHEMICAL DATA

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The work is devoted to the development and testing of algorithms for processing and analysis of multivariate geochemical data arising in mineral exploration. The main goal is to construct predictive models for the contents of target elements and to quantify the influence of geochemical indicators. The data set consists of several hundred samples with geographic coordinates and concentrations of major, trace and rare-earth elements. Preprocessing includes format harmonisation, removal of non-informative variables, detection and treatment of missing values, transformation of strongly skewed distributions and scaling of numerical features.

A set of regression models is investigated, ranging from classical statistical approaches [2] to modern machine-learning algorithms, including linear and regularised regression models as well as tree-based ensemble and other nonlinear methods [1, 3, 4] . Model performance is evaluated using train–test splits and cross-validation with the coefficient of determination R^2 [2]

and complementary error metrics. Feature-importance measures are employed to identify the most informative geochemical indicators and to reveal geochemical associations related to elevated contents of target elements [1, 4].

Preliminary results indicate that purely linear models are not sufficient to capture the complex relationships present in the data, whereas nonlinear and ensemble approaches provide more stable, though still limited, predictive ability [1, 2, 3, 4] . The proposed methodology forms a flexible framework that can be further extended by incorporating spatial validation schemes and additional geological features and can be applied to different geochemical exploration datasets.

Keywords: geochemical data, predictive modelling, regression, ensemble methods, feature importance, mineral exploration.

AMS Subject Classification: 62J05, 86A60, 68T09.

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МЕТОДИКА ПРОГНОЗИРОВАНИЯ ГЕОХИМИЧЕСКИХ АНОМАЛИЙ С ИСПОЛЬЗОВАНИЕМ ПРЕДВАРИТЕЛЬНОЙ ОБРАБОТКИ ВХОДНЫХ ГЕОЛОГИЧЕСКИХ ДАННЫХ И ДВУКРАТНОГО ИСПОЛЬЗОВАНИЯ МНОГОСЛОЙНОГО ПЕРСЕПТРОНА

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Последние десятилетия характеризуются постоянным ростом потребления минерального сырья. Наряду с количественным ростом расширяется и номенклатура потребляемого сырья: в сферу промышленного потребления непрерывно вовлекаются всё новые виды полезных ископаемых, которые становятся основой технического и инновационного развития мировой экономики. В таких условиях резко возрастает роль научного прогнозирования для поиска новых месторождений, что требует постоянного совершенствования методологии и применения новых технологий для активизации возможностей современных прогнозно-поисковых методов.

Огромный объём информации и недоступность большинства геологических объектов и процессов для непосредственного наблюдения (как в пространстве, так и во времени) делают необходимым применение математических методов в геологии. Одной из перспективных технологий, уже показавших свои возможности при моделировании месторождений и построении цифровых моделей местности, являются методы и технологии искусственных нейронных сетей (ИНС).

В отличие от известных способов моделирования месторождений, математический аппарат искусственных нейронных сетей позволяет получить более объективную прогнозную оценку исследуемого геологического объекта, что способствует переходу на качественно новый уровень обработки результатов инженерно-геологических изысканий и минимизации объёма ручного труда при анализе и преобразовании больших массивов геологической информации.

Одними из наиболее быстро развивающихся нейросетевых технологий для решения задач выявления и прогнозирования геохимических аномалий являются многослойные персептроны, позволяющие прогнозировать геохимические показатели, моделировать пространственное распределение элементов и строить двумерные и трёхмерные геологические модели.

Однако возникают определённые трудности непосредственного использования геологических данных для их обработки многослойными персептронами. Проблемой обучения многослойных персептронов для решения задач прогнозирования на малом количестве данных типа (Xi, Yi, Ci), где (Xi, Yi) — геодезические координаты точки геохимического опробования, а Ci — результаты геохимического опробования, является получение сильно упрощённых решений задач прогнозирования.

Получение упрощённого решения связано с малой информативностью и низкой корреляцией между входными данными (Xi, Yi) и целевой переменной Ci обучающей выборки. Для увеличения корреляционной зависимости входных и выходных переменных

Исследование финансируется Комитета науки Министерства науки и высшего образования Республики Казахстан (ИРН BR27100483 Разработка прогнозно-поисковых технологий выделения рудоперспективных территории на основе анализа данных единой платформы недропользователей «Minerals.gov.kz» с применением искусственного интеллекта и методов дистанционного зондирования Земли").

необходимо предварительно выполнить предобработку обучающей выборки с использованием методов преобразования признаков (feature transformation).

Введение понятия «анизотропии, сходящейся к точке» позволяет сформировать обучающие выборки, повышающие корреляционную зависимость входных переменных и выходных прогнозных значений, и влечёт за собой необходимость двухкратного использования многослойного персептрона. Двухкратное использование многослойного персептрона позволяет получать адекватные результаты прогнозирования значений геологических аномалий.

Секция 4
Жасанды интеллектінің математикалық әдістері

Секция 4
Математические методы искусственного интеллекта

Section 4
Mathematical methods of artificial intelligence

TRAINING ALGORITHM OF A FULLY CONNECTED NEURAL NETWORK WITH BACKPROPAGATION

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The application of neural networks in geology helps accelerate research processes, improve the accuracy and reliability of results, and reduce the cost of geological investigations. Currently, advanced neural networks such as GigaChat, YaGPT, GPT–40, and Gemini 1.5 Flash represent top-tier technologies for modern geology. In all neural network systems, GIS technologies hold the leading position, followed by 3D modeling of geological structures, artificial intelligence, remote sensing of the Earth, and the analysis of large geological datasets (Big Data), including multiparametric geostatistics.

Artificial intelligence enables faster processing of geological data, more accurate identification of patterns, and reduced risks in decision-making. Therefore, this work considers a fully connected neural network with backpropagation. A general overview of the development of machine learning in geological sciences is presented in [1].

The algorithm under consideration consists of three stages: forward propagation (Forward), backward propagation (Backward), and parameter update (Update). As a result of the forward propagation, the error $E(\Omega^t)$ is computed. At the backward-propagation stage, using the error $E(\Omega^t)$, the gradient vector $\frac{\partial E}{\partial \Omega}(\Omega^t)$ must be determined. Afterwards, the learnable parameters are updated according to the rule:

$$\Omega^{t+1} = \Omega^t - \alpha \frac{\partial E}{\partial \Omega}(\Omega^t).$$

This work focuses on the transition from mathematical foundations and theoretical knowledge to the development of software for model validation. The presentation of results moves from textual explanations to code examples, which complement the theoretical framework and illustrate model verification and key machine-learning concepts.

Keywords: Neural Networks, Geological Modeling, Machine Learning, Backpropagation Algorithm.

AMS Subject Classification: 68T07

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TOWARDS THE PRACTICAL IMPLEMENTATION OF THE CONCEPT OF DIGITAL IMMORTALITY

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The concept of digital immortality, which involves the transfer of individuality to a non-biological information carrier, has been discussed in the literature for a long time. However, its practical implementation continues to face challenges, including those of a philosophical nature. We propose a concept of "partial" digital immortality, which allows us to clearly formulate the corresponding technical specifications for programmers. This concept, in particular, distinguishes between human consciousness and intellect [1]. It is also based on the proof of the dual nature of human intellect and consciousness [2]. This dualism implies that, alongside the collective unconscious, there is also a collective consciousness, and human intellect represents the structural component of individuality that is most closely related to the collective consciousness [3]. It is this component that can be transferred to a non-biological information carrier in the foreseeable future. The proposed interpretation of intelligence allows us to view it as a "black box" that transforms information according to certain algorithms (the term is interpreted as broadly as possible, i.e., it is taken into account that the operations performed by human intelligence cannot be reduced to binary/Aristotelian logic). The key to solving the problem of digital immortality, therefore, is the development of algorithms that can decipher the true algorithms of a neural network based on experimentally discovered input-output relationships. It should be noted that this problem has long been addressed in the current literature in connection with the problem of explainable neural networks. We propose a new approach to developing algorithms for such deciphering, based on the analogy between the functioning of neural networks and error-correcting codes [4], as well as on new approaches to the construction and use of irreducible polynomials over Galois fields, which are used in error-correcting coding [5]. It is precisely this that makes it possible, in the foreseeable future, to reveal the code of an individual's intelligence and ensure its recording on a non-biological information carrier.

Keywords: Digital immortality, Partial digital immortality, Collective consciousness, Explainable neural networks (XAI), Error-correcting codes, Galois fields (irreducible polynomials).

12-11, 12F99

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AI AS A GEOPOLITICAL FACTOR: THE GROWING IMPORTANCE OF IMPROVING THE ALGORITHMIC FRAMEWORK

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The rapid development of AI is becoming a geopolitical factor, a fact that no longer requires extensive proof. In addition to the potential for using AI for various types of informational influence (including at the level of sociocultural code [1]), the supply of energy to the service centers that support AI is becoming increasingly important. Energy demand is becoming so significant that the question of redistributing energy generation on a global scale is already being raised. In this regard, improving the algorithmic foundation of AI, closely linked to the use of quasi-biological components, in particular neuromorphic materials [2], is particularly relevant. The use of such materials, among other things, allows one to overcome one of the main drawbacks of the von Neumann architecture: the spatial separation of the memory unit and the computing processor necessitates the continuous movement of data between them [3], and consequently, increased energy consumption. The literature also discusses the possibility of creating neuromorphic materials (and, consequently, AI) based on biological information macromolecules—DNA and RNA, their modifications, and synthetic analogs [4]. The ultimate goal of research in this area is, obviously, gradually approaching the "information efficiency" of the human brain [5]. However, the advantages of neuromorphic materials remain unrealized due to a distinct contradiction [6]: existing approaches rely on the use of the same algorithms developed on known neural networks (which are, in fact, nothing more than computer simulations). Based on the fact that AI in the global context is closely linked to society, we propose a concept of sociomorphic materials [8], based, on the one hand, on the use of multi-valued logic and modular arithmetic, and, on the other, on the neural network theory of society. This concept is the next logical step in the development of AI as a factor of social significance.

Keywords: AI geopolitics, Neuromorphic materials, Post-Neumann architecture, sociomorphic materials.

12-11, 12F99

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МЕТОДОЛОГИЯ ИНТЕГРАЦИИ ИНТЕЛЛЕКТУАЛЬНЫХ ОБУЧАЮЩИХ СИСТЕМ В ПРЕПОДАВАНИЕ ВЫСШЕЙ МАТЕМАТИКИ В УСЛОВИЯХ МНОГОЯЗЫЧНОЙ АУДИТОРИИ: ПРЕОДОЛЕНИЕ АКАДЕМИЧЕСКОГО НЕДОБРОСОВЕСТНОСТИ (НА ПРИМЕРЕ LLM) И ОБЕСПЕЧЕНИЕ АДАПТИВНОГО ОБУЧЕНИЯ ИНОСТРАННЫХ СТУДЕНТОВ

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Современные вызовы цифровизации и интернационализации высшего образования требуют кардинального пересмотра дидактических подходов к преподаванию математических дисциплин. Целью данной работы является разработка и анализ эффективности методологии интеграции Интеллектуальных Обучающих Систем (ИТС) как ключевого инструмента, способного оптимизировать учебный процесс и облегчить работу преподавателя. В работе рассматриваются две критически важные проблемы. Во-первых, анализируется рост академической недобросовестности, вызванный доступностью больших языковых моделей (LLM, например, ChatGPT). Предлагается методология использования ИТС для создания адаптивного тестирования, которое фокусируется на пошаговом объяснении метода, а не на финальном ответе, что позволяет эффективно детектировать некорректно сгенерированные или не до конца понятые решения. Во-вторых, исследуется проблема адаптации иностранных студентов, прибывающих из-за рубежа (в частности, из Китая и Туркменистана), которые часто начинают обучение с опозданием и сталкиваются с языковым барьером. Предлагается модель многоязычной интеграции ИТС, которая обеспечивает возможность дистанционного начала обучения и предоставляет дополнительные ссылки на учебные материалы на родных языках, используя универсальность математической символики (постулат "Математика – язык един"). Делается вывод, что ИТС – это не "зло", а незаменимая помощь для преподавателя и студента, позволяющая персонализировать траекторию обучения, повысить усвоение материала в гетерогенных группах и трансформировать роль педагога в сторону менторства и проектирования образовательной среды.

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