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INVESTIGATION OF THE ACCURACY OF UNDERGROUND CONTROL SURVEYING NETWORKS THROUGH THE APPLICATION OF NEURAL NETWORK MODELING

Purpose. To evaluate the accuracy of an underground mine surveying control network (UMSCN) by applying neural network modeling and adaptive estimation of the position of the most distant traverse point. To conduct an analysis of methods for estimating the root mean square errors of point positions.

Methodology. Application of deep learning techniques, specifically Conditional Tabular Generative Adversarial Networks (CTGAN), to generate extended synthetic geodetic datasets for evaluating the accuracy of underground mine surveying control networks (UMSCNs). The study also includes an analysis of regulatory frameworks alongside both international and national scientific literature on assessing the accuracy and reliability of mine surveying and geodetic networks using artificial intelligence approaches, such as neural network modeling and adaptive estimation.

Findings. The use of neural network modeling and adaptive estimation enables a quantitative assessment of the accuracy of an underground mine surveying control network (UMSCN) by modeling the angular and linear root mean square errors (RMSE). This has a direct impact on the RMSE of the position of the farthest point within the UMSCN and reflects the convergence of the network's variance under the adaptive protocol. As the level of uncertainty nears the Safety Constraint Layer, the system indicates that additional gyroscopic measurements are required – data that cannot be derived through analytical approaches or handled using standard spreadsheet tools.

Originality. For the first time, it is proposed to assess the accuracy of a designed underground mine surveying control network (UMSCN) using modern artificial intelligence technologies. The assessment outcomes were examined in line with regulatory standards, applying both analytical techniques and modeling methods. The positional errors of the most distant point, No. 15, were calculated in accordance with the defined tolerance. Furthermore, the root mean square error (RMSE) of the measurements was determined, under which the required condition is met. The RMSE of the position of the most distant traverse point should not exceed 0.3 mm on the plan, which corresponds to 0.6 m for plans at a 1:2,000 scale in coal mines.

Practical value. The accuracy of the underground mine surveying control network (UMSCN) was evaluated using neural network modeling and adaptive estimation. As a result, a displacement of the farthest point in the network was detected, and the probability of failure-free operation of the UMSCN was estimated at 71 %. The proposed approach improves the reliability of accuracy predictions for surveying networks at both the design and operational stages. The use of neural network methods allows for optimization of field measurement volumes, timely identification of critical zones with increased uncertainty, and justification for additional observations (including gyroscopic measurements). The results can be used to automate quality control processes for mine surveying, reduce operational risks in mining conditions, and enhance the safety of operations in coal mines. The proposed methodology is also suitable for integration into modern geographic information and mine surveying decision-support systems.

Keywords: *mine surveying network, accuracy assessment, neural network modeling, adaptive estimation, polygon traverse*

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Introduction. Underground mine surveying control networks (UMSCNs) are used in many key areas of mining and engineering activities, in particular:

1. To support mining operations and ensure the precise setting-out of design solutions in the field, including the development of mine workings such as chambers, drifts, crosscuts, and shafts, as well as monitoring their spatial positions.

2. To properly orient underground workings in plan and elevation, and to accurately connect workings developed from different directions or horizons.

3. For monitoring rock mass movements, ground subsidence, and deformations of mine workings and underground structures.

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4. To serve as a basis for controlling hazardous zones, boundary contours of mining operations, protective pillars, and preventing inflows of water, gas, or adjacent workings.

5. To provide accurate determination of geometric parameters of deposits, and volumes of extracted and remaining mineral resources.

6. Intended for application during the construction and operation of underground facilities, including mines, tunnels, subways, underground storage systems, and utility networks.

7. To maintain the connection between surface and underground geodetic networks, which is critical for the consistency of all measurements.

8. For long-term monitoring of the condition of underground workings, engineering structures, and equipment during operation.

Thus, UMSCNs serve as the foundation for ensuring safe and efficient mining operations, accurate transfer of design solutions into the underground space, monitoring of deformations and rock mass movements, and compliance with regulatory requirements. Insufficient accuracy or instability of the network's positions can lead to the accumulation of measurement errors, operational mistakes, and a reduction in the safety level of underground activities.

The accuracy and reliability of an underground mine surveying control network (UMSCN) may be affected by a range of technical, geological, operational, and human factors, including:

1. Deformation of the rock mass: movements and subsidence occurring during mining operations lead to changes in the spatial positions of UMSCN points.

2. Damage or destruction of network points as a result of blasting, collapses, machinery movement, corrosion of supports, or flooding of workings.

3. Accumulation of measurement errors. Repeated network expansion and the execution of traverse surveys result in the accumulation of systematic and random errors.

4. Non-compliance with measurement procedures. Violations of surveying protocols, inaccurate instrument centering, improper orientation, and failure to follow regulations reduce network accuracy.

5. Adverse underground conditions. High humidity, dust, temperature fluctuations, limited visibility, and poor ventilation negatively affect measurement accuracy and the stability of network points.

6. Wear or obsolescence of instruments. Using equipment with insufficient metrological characteristics or without timely calibration reduces the reliability of results.

7. Human factor. Operator errors, insufficient personnel qualifications, or inattention during field and office work can distort results.

8. Insufficient network control and monitoring. Lack of regular inspections, repeat measurements, and analysis of point conditions leads to delayed detection of accuracy loss.

9. Failure to account for changes in mining-geological conditions. Changes in mine development plans, work depth, or mining stress without corresponding adjustments to the UMSCN reduce its reliability.

Together, these factors emphasize the necessity for continuous monitoring of UMSCN accuracy and reliability, as well as the use of advanced analytical methods, particularly neural network modeling and adaptive estimation.

Unsolved aspects of the problem. During the establishment of underground mine surveying control networks (UMSCNs), the requirements of current regulatory and technical documents are followed, which govern the procedures for their design, layout, measurements, and accuracy assessment, including:

1. Rules for conducting mine surveying works during the development of ore and non-ore mineral deposits [1].

2. Safety rules for mining operations in coal mines [2].

3. Mining Law of Ukraine [3].

4. State standards and industry norms in the field of geodesy and mine surveying [4, 5].

5. Methodical guidelines for the creation and development of geodetic and underground mine surveying networks.

6. Requirements for permissible measurement errors and the positional accuracy of network points depending on plan scale and working conditions.

Compliance with regulatory requirements ensures the necessary accuracy, reliability, and stability of the underground mine surveying control network (UMSCN), as well as the safe and efficient conduct of mining operations.

Underground mine surveying networks serve as the basis for surveying mine workings and are formed from theodolite traverses that rely on control network points. This highlights the need to assess the reliability of the points in the underground mine surveying control network.

Literature review. According to the research program, the authors H. S. Ishutina and S. V. Biehichev employed both traditional analytical methods for preliminary accuracy assessment of designed traverse surveys [6, 7] and innovative mine surveying methods – namely, the Monte Carlo method (MCM) – as well as modern scientific approaches using adaptive algorithms, which is the focus of this study.

The MCM for evaluating the accuracy and reliability of underground mine surveying control network (UMSCN) points demonstrated a novel, more reliable, and sensitive assessment approach compared to traditional methods. In the search for a method that could validate previously obtained MCM results and expand the research program toward developing a reliable way to assess UMSCN coordinate accuracy in comparison with classical and Monte Carlo methods, the authors analyzed the root mean square errors of point positions using artificial intelligence (AI) techniques.

Therefore, performing an accuracy assessment of UMSCN points using modern AI technologies is considered a highly relevant task. A comparison of these two methods across various criteria is provided in Table 1.

In recent years, AI has emerged as a key tool for addressing complex challenges in engineering geodesy and mine surveying. AI is a vast field that covers areas such as understanding the nature of intelligence, knowledge representation, and logical reasoning processes, ultimately enabling the creation of computer programs capable of exhibiting intelligent behavior, which in turn has significant practical applications.

Modern applications of AI methodologies in engineering geodesy encompass geodetic data analysis, de-

Table 1

Comparison of AI with the Monte Carlo method (MCM)

Characteristics	AI	MCM
Principle	Data-driven learning	Repeated random modeling
Basis	Data + algorithms	Probability + statistics
Type of approach	Data-driven	Model-driven
Source of accuracy	Quality and quantity of training data	Number of simulations
Advantages	- ability to detect hidden nonlinear relationships; - high accuracy with large amounts of data; - automation of complex processes; - effective for prediction and classification; - adaptability (can "learn" over time)	- transparent mathematical interpretation of results; - does not require large experimental data sets; - performs well with random errors; - easily incorporates regulatory tolerances; - results have probabilistic interpretation (confidence intervals, probabilities)
Disadvantages	- requires large and high-quality datasets; - difficulty in explaining results (black box); - risk of overfitting; - dependence on data structure; - difficult to directly link to regulatory requirements	- high computational complexity with a large number of iterations; - accuracy depends on the correctness of specified error distributions; - does not "learn" from new data; - cannot detect hidden patterns
Consideration of random errors	Indirectly	Directly
consideration of systematic errors	Partially	Explicitly
Probabilistic assessment	Limited	Fully
Interpretability	Low	High
Regulatory compliance	Limited	High
Working with small datasets	Poor	Good

formation monitoring, navigation, comparison of deformation networks, optimization of complex measurement procedures, and various other areas. The close connection is explained by the fact that both geodesy in general and AI largely rely on methods of mathematical stochastic modeling. Furthermore, modeling the relationships between variables and parameters is fundamental for both disciplines.

Among the existing AI methods, the following can be highlighted:

1. Symbolic (classical) methods, which include:

- *expert systems* (operate based on a knowledge base and "if–then" rules);
- *logical inference* (propositional and predicate logic; theorem proving, automated planning).

2. Probabilistic and statistical methods, which deal with uncertainty and data noise. Among these methods, the following can be highlighted:

- *Bayesian methods* (Bayesian networks; Naive Bayes classifier);
- *Markov models* (Markov chains; Hidden Markov models).

3. Machine Learning, which in turn can be divided into:

- *Supervised learning* (Linear and Logistic Regression; Support Vector Machines (SVM); k-Nearest Neighbors (k-NN); Decision Trees, Random Forest);
- *Unsupervised learning* (Clustering (k-means, DBSCAN); Principal Component Analysis (PCA));
- *Reinforcement learning* (Q-learning; Deep Reinforcement Learning).

4. Neural network methods (Deep Learning):

- *Artificial Neural Networks* (ANN) (Convolutional Neural Networks (CNN) and Computer Vision, satellite imagery);
- *Recurrent Neural Networks* (RNN, LSTM) (time series, language);
- *Transformers* (GPT, BERT, Vision Transformer).

5. Evolutionary and bio-inspired methods:

- *Genetic algorithms* (optimization of complex systems);
- *Swarm algorithms* (Particle Swarm Optimization (PSO); Ant Colony Optimization).

6. Fuzzy Logic, which operates with concepts like "partially true" and is used in controlling technical systems.

7. Hybrid AI methods, which combine multiple approaches:

- *Neural networks + fuzzy logic*;
- *Machine Learning + statistics*;
- *AI + Monte Carlo method*.

8. Modern directions:

- Explainable AI (XAI);
- AutoML;
- Federated Learning;
- Generative AI (text, images, 3D).

The use of artificial intelligence methods in the Earth sciences has been explored by both domestic and international researchers, including Mrówczyńska M. [8], Horb O. I. [9], Reiterer A. [10], Neuner H. [11, 12], among others.

Professor Benedikt Soja (Switzerland) develops AI/ML applications to improve the quality of geodetic observations and products, such as automatic analysis of GNSS data and processing of gravimetry [13, 14].

In publication [13], Benedikt Soja emphasizes that classical statistical methods in geodesy remain important but have limitations due to strict assumptions regarding distributions and models. Machine learning methods offer greater flexibility and can efficiently handle large and complex datasets. AI is particularly suitable for tasks where it is difficult to construct an analytical model or account for all influencing factors.

The best results are achieved by combining classical approaches with machine learning rather than fully re-

placing them. Key considerations remain the interpretability of models, the quality of input data, and the training of specialists proficient in modern technologies.

Maria Kaselimi (Greece) co-organizes AI research in geodesy together with Soja, particularly in the context of machine learning and spatial data analysis [15, 16].

Wenwen Li, Chia-Yu Hsu, and Maosheng Hu [17] are the authors of a study on deep learning for spatial object detection within geospatial AI, serving as an example of current AI methods in geography, cartography, and geodesy. Roberto Pierdicca and Marina Paolanti have worked on AI approaches for processing complex geodata [18, 19].

A comparative characterization of AI methods is presented in Table 2.

Classical methods for accuracy assessment consider a geodetic or mine-survey network as a static system, ignoring the dynamics of changing external conditions in real time. Modern scientific approaches to managing complex systems increasingly rely on adaptive algorithms [20]. Although the study object in the cited work is traffic, the mathematical framework of dynamic resource redistribution (in our case – measurement weights) and the safety constraint layer proposed by the authors, in accordance with regulatory requirements, is critically important for implementation in underground mine surveying. Integrating such adaptive protocols allows transforming passive monitoring (error recording) into an active risk management system (error prevention).

In [21], the LF-GNSS framework is proposed, which combines learning and filtering based on deep neural networks. It is designed to enhance the reliability of satellite positioning in challenging urban environments. The approach leverages deep learning capabilities to analyze satellite signals in real time and adaptively form the observation noise covariance matrix. Innovative vectors for the Kalman filter were also adjusted, effectively reducing the impact of multipath effects and non-line-of-sight (NLOS) signals.

Additionally, a new feature representation method – DPC – was introduced, providing more accurate assessment of the quality of individual satellite signals and improving the measurement weighting procedure. The use of a dynamic Hard Example Mining strategy allows the model training to be more efficient by focusing on the most challenging signals.

The results of ablation studies confirm the significant contribution of both the DPC features and the HEM method to the overall improvement of system performance. The authors conducted experiments on both public and proprietary datasets, which demonstrated that the LF-GNSS approach provides higher positioning accuracy compared to both traditional methods and contemporary deep learning–based solutions.

Table 2

AI methods

Methods	Key idea	Example
Symbolic (classical)	Logic	Expert systems
Probabilistic and statistical	Probability	Bayesian networks
Machine learning	Data-driven learning	Classification
Deep Learning	Deep networks	Computer vision
Evolutionary and bio-inspired methods	Optimization search	Optimization
Fuzzy logic	Partial truth	Control

The aim of the study [22] was to evaluate the performance of machine learning algorithms (GBM, LightGBM, RF, XGBoost) in determining horizontal velocity based on GNSS velocity fields in Turkey. Seventy percent of the data were used for training and 30 % for testing. Special attention was given to accounting for tectonic structures: clustering was performed according to tectonic plates, and the algorithms were trained on the corresponding subsets of data. The results showed that considering tectonics improved prediction accuracy: GBM demonstrated a reduction in root mean square error, while RF exhibited the lowest error among all algorithms (with a maximum deviation from the reference field of 0.4 mm/year).

In the study [23], machine learning methods (XGBoost, LSTM) were applied for the analysis of GNSS time series, enabling the automatic detection of discontinuities and geodynamic changes, thereby improving the accuracy of GNSS data monitoring and interpretation.

This study focuses on the use of machine learning algorithms to improve the analysis of GNSS time series in geophysics and geodesy. Machine learning methods were applied, utilizing XGBoost and LSTM models on data from the tectonically active Anatolia region to detect discontinuities associated with earthquakes.

The authors of publication [22] demonstrated how machine learning algorithms (Gradient Boosting, Random Forest, XGBoost) can accurately estimate horizontal velocities of GNSS networks, optimizing predictions based on the tectonic structure of the region. This significantly impacts the precision of motion assessment in geodetic networks.

In publication [24], the author concluded that the use of artificial intelligence in geodesy significantly improves measurement accuracy and accelerates the data collection process. Intelligent technologies can automatically process large volumes of geospatial information, reduce errors, and adapt to changing conditions during operations.

The integration of unmanned aerial vehicles and geographic information systems with AI enables automation not only of data collection but also of data analysis. This significantly reduces the time required for geodetic tasks and enhances the efficiency of monitoring territories.

The use of intelligent solutions reduces the impact of the human factor, contributing to greater reliability of the obtained results. Machine learning algorithms, leveraging accumulated data, continuously improve, increasing accuracy and decreasing the likelihood of errors.

Despite numerous advantages, the implementation of artificial intelligence in geodetic measurements is accompanied by certain challenges. Primarily, these include significant costs for equipment and software. Full operation of AI-based systems requires powerful computational resources and specialized programs, which may be financially inaccessible for small companies or individual specialists.

Another challenge is the insufficient level of personnel training. Working with AI technologies re-

quires not only knowledge in geodesy but also skills in programming and handling large datasets. Training such specialists demands significant time and additional resources.

The classical approach to geodetic data analysis is usually aimed at determining distribution parameters, in particular the mean and variance, based on measurements that contain uncertainty due to environmental influences and instrument noise. Traditional methods, focused on analytical solutions, often require strict initial assumptions regarding the problem setup and the type of probability distributions, which limits their effectiveness in practical situations where regression under Gaussian noise conditions does not apply.

In contrast, machine learning methods are characterized by greater flexibility regarding the structure of input data and the form of outputs, and they allow the use of non-parametric stochastic models. At the same time, this requires employing numerical approaches instead of analytical solutions. In [25], the common features of geodetic data analysis and machine learning are explored, and examples are provided of applying both supervised and unsupervised learning algorithms to tasks such as optimal estimation, signal separation, risk assessment, and the development of measurement strategies, which are typical in geodetic practice.

Mining geomechanics has a number of characteristics that complicate the application of artificial intelligence methods, big data analysis, predictive analytics, and machine learning. The main reason is that effective use of these technologies in geotechnical engineering requires the integration of four-dimensional data (x, y, z, t), which in itself is a complex task.

In article [26], an approach and software environment are presented that address the problem of 4D integration, providing a foundation for the systematic application of AI and machine learning algorithms. The proposed system combines heterogeneous data – both structured and unstructured – including information from boreholes, geological and geophysical data, rock properties, geotechnical parameters, production indicators, equipment data, and mine geometry. This ensures effective integration of information for solving mining engineering tasks using machine learning.

The system operates based on the use of a three-dimensional Earth model and a four-dimensional mine model, to which various data sets are linked. Depending on the type of information, it undergoes interpolation, scaling, or other processing to ensure consistency of parameters in space and time – a key requirement for the operation of analytical algorithms. In addition, the system allows storing and linking documents with data and the results of their interpretation, creating the necessary information environment for implementing AI-based solutions. The work also outlines the principles of system design, taking into account the specific tasks of the mining industry.

In the study [27], the authors developed an automated system (Geoscience INTEGRATOR) for real-time assessment of geological hazards in underground mines. This system is based on 4D analysis (space + time) and integrates heterogeneous data: geological, geophysical, seismic, geotechnical, and operational. The main outcomes of the work [27] include:

- development of a system that automatically collects, processes, and analyzes data;
- implementation of integration of 3D/4D mine models;
- enabling prediction of geological hazards, including rock bursts;
- implementation of visualization and automatic report generation;
- the fact that the system is already being applied in real mining conditions.

The authors concluded that the combination of big data, 4D modeling, and AI elements enables a shift from reacting to accidents to predicting and preventing them:

- the use of 4D data integration is key for accurate risk forecasting;
- automation significantly increases the speed and reliability of hazard assessment;
- AI and analytical methods help reduce the influence of the human factor;
- the system has the potential to become a standard for safety monitoring in mines.

In article [28], the use of machine learning methods in a complex system for assessing the content of valuable components is examined. In open-pit mining, sample analysis data obtained during operational drilling often allow refinement of geological surfaces that were initially constructed based on limited exploration information. Previously, a Bayesian approach to surface deformation had been proposed, which takes into account geochemical and spatial constraints derived from new blast-hole data.

In this work, this approach is enhanced by integrating machine learning, which allows for a generalized assessment of probabilities. The essence of the method lies in adjusting the positions of surface nodes to achieve the best possible alignment between the modeled geological boundaries and the available geochemical data. Theoretically, it is based on a Bayesian model, where the probability of belonging to a geological domain given a known chemical composition is used to automate a process that previously required manual calibration, as these probabilities can now be determined using machine learning algorithms applied to the data.

In this study, this approach is complemented by the integration of machine learning, enabling a generalized process for probability assessment. The essence of the method lies in adjusting the positions of surface nodes to achieve the closest possible alignment between the modeled geological boundaries and the available geochemical data. Theoretically, it is based on a Bayesian model, where the probability of belonging to a geological domain, given a known chemical composition, is used to automate a process that previously required manual calibration, as these probabilities can now be determined using data-driven machine learning algorithms.

To assess the effectiveness, various methods were applied, including gradient boosting, neural networks, and random forests, in both binary and multiclass classification tasks using accuracy and recall metrics. After incorporating machine learning models into the surface deformation process, the quality of the surface is evaluated on new data by analyzing the distribution of samples relative to the adjusted surface.

Purpose. The aim of this work is to evaluate the accuracy of the underground survey control network through the application of neural network modeling and adaptive assessment. A comparative analysis of methods for evaluating the root mean square errors of point positions is also to be conducted.

Results. Artificial neural networks (ANNs) are highly flexible tools for modeling, particularly when dealing with nonlinear relationships between input and output variables. The universal approximation theorem guarantees that any continuous function can be approximated using this approach. However, certain structural aspects of ANN-based models, such as the number of hidden neurons or the amount of data required to achieve good generalization capability, are not specified by the theorem. Therefore, the problem of model selection remains relevant.

Establishing an underground mine surveying control network in mining workings is accompanied by a number of challenges. This is due to operations being conducted under conditions of limited visibility, high dust load, strong air flows, and confined space caused by the presence of active equipment and personnel. These factors complicate precise measurements and monitoring the stability of network points. Additional challenges include the limited amount of initial geodetic data and possible displacement of fixed network points due to rock deformations and continuous movement of the mining front. To ensure the accuracy and reliability of the network, additional control measures are necessary.

Taken together, these factors, combined with the challenging conditions for performing additional checks and the limited opportunities to improve point coordinate accuracy, result in significant errors in both angular and linear measurements. This underscores the need for specialized methods for monitoring and correcting results to ensure the reliability of geodetic data.

As an example, consider the underground surveying reference network (USRN), which, due to the advancement of mining operations at the 818 m horizon of PJSC "Pokrovske Mine," requires further development. This network was used to test the neural network modeling method and the adaptive preliminary assessment of the accuracy of the designed polygonometric traverse.

The underground surveying reference network includes 15 points, with distances between them ranging from 107 to 147 m. Points 1, 2, and 3 serve as base points situated in the shaft-adjacent workings of the "VPS-2" shaft. According to the regulations [1], the primary requirement when designing an underground surveying reference network is to ensure that the positional error of the farthest point, No. 15, does not exceed 0.6 m on the ground for 1:2,000 scale plans, which are standard for use in coal mines.

During the establishment of the USRN, measurements are subject to both systematic and random errors, affecting angles, side lengths, and the determination of the directional angle of the initial traverse side.

Table 3 presents the characteristics of the designed underground surveying reference network.

According to the results of the preliminary accuracy assessment using the classical analytical method, the coordinate error of point 15 of the polygon traverse amounted to the overall root mean square error (RMSE)

Table 3

Coordinates of USRN points in a local (conditional) coordinate system

Point numbers of the traverse	Coordinates of the points	
	X_i, m	Y_i, m
15	1,790	299
14	1,704	192
13	1,659	95
12	1,518	130
11	1,377	167
10	1,238	202
9	1,096	237
8	958	209
7	821	179
6	685	150
5	549	121
4	412	91
3	274	61
2	137	31
1	0	0

of the designed underground mine control network (USRN), m.

$$M = \pm\sqrt{0.19^2 + 0.31^2} = \pm 0.36,$$

which does not exceed the permissible value of ±0.6 m.

Since the resulting error of ±0.36 m is below the ±0.6 m threshold, it can be concluded that the designed network complies with the requirements of the Rules [1] and is suitable for practical implementation.

The accuracy of the underground mine surveying control network was further evaluated using numerical statistical modeling based on the Monte Carlo method. Within the MS Excel environment, 3,000 random values were generated to simulate the possible states of the network's farthest point.

Further statistical analysis using 1,000 and 3,000 iterations to calculate the RMSE of point No. 15 demonstrated that repeated modeling of random measurement errors allows for determining the probabilistic characteristics of the network's accuracy and confirming its compliance with regulatory requirements.

Intelligent data augmentation and neural network modeling. In underground polygonometric traverses, the number of measurements is often limited, which complicates statistical analysis. Classical methods, for example, assuming a normal distribution in Excel, are often insufficient to accurately capture the complex relationships between measurement errors.

To enhance the reliability of assessments under limited sample conditions, which are typical in underground polygonometric traverses, a hybrid architecture based on Conditional Tabular GAN (CTGAN) is proposed. This approach enables the generation of synthetic data while preserving the statistical properties of the dataset and allows for obtaining more reliable analysis results.

CTGAN is a neural network capable of generating synthetic data that resemble real data. It does not simply sample random values from a normal distribution; instead, it learns to reproduce multidimensional relationships between parameters (for example, between angular and linear misclosures).

The optimization of the generator's and discriminator's loss functions is carried out using the Wasserstein distance with a gradient penalty, which ensures stable generation of synthetic error vectors and prevents mode collapse.

As a result, it is possible to generate ***synthetic error scenarios*** that account for hidden nonlinear correlations between different types of misclosures. This is something that simple spreadsheet tools (such as Excel) cannot achieve, as they operate only with basic statistical models.

Within the framework of the study, $N = 10^5$ synthetic scenarios were generated, accounting for hidden nonlinear correlations between angular and linear misclosures of the position of the farthest point, No. 15, in the UMSCN. The results of the modeling are presented in the figure.

As illustrated in the diagram (Figure, *a*), the error distribution obtained using AI exhibits heavy tails, indicating a higher likelihood of large deviations compared to the classical normal distribution. This observation indicates a more complex error structure in geodetic networks that standard statistical models fail to capture, and it supports the hypothesis that minimizing entropy in geodetic networks requires adaptive algorithms capable of responding to error variations and adjusting the measurement process accordingly.

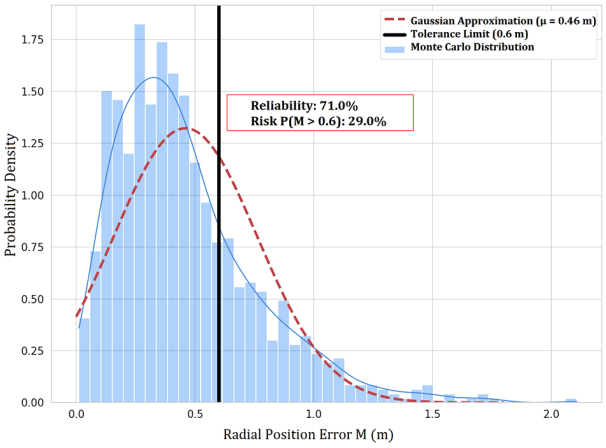
The graph (Figure, *b*) illustrates the convergence of the network's variance under the adaptive protocol: as the uncertainty approaches the Safety Constraint Layer, the system signals the need to incorporate additional gyroscopic measurements. The presented graph demonstrates how the system automatically responds to increasing uncertainty.

Conclusions. The traditionally recognized analytical method for the preliminary accuracy assessment of an underground surveying reference network allows, during the design of a USRN, ensuring that the positional error of the most remote points does not exceed the established regulatory tolerances [1]. At the same time, this approach relies on fixed parameters of the designed polygonal traverse in its calculations, without accounting for the variable values of potential angular and linear measurement errors, which reduces the reliability of the analytical method used.

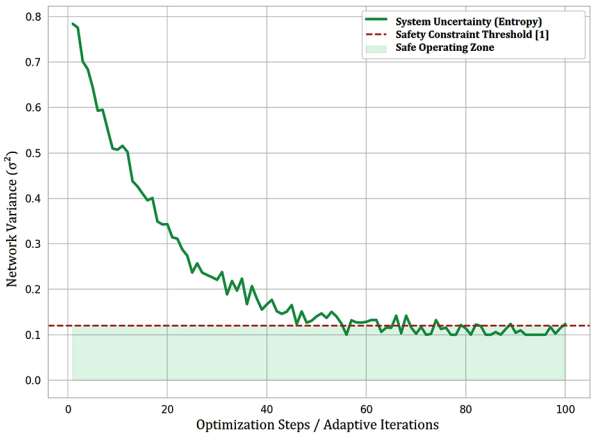
The calculated probability of complying with the allowable root-mean-square error for the most remote point of the traverse is 71 %, which confirms that the designed network meets the requirements of the regulatory documents and can be implemented at the enterprise.

Currently, artificial intelligence (AI) is a core technology in numerous modern innovative applications. It is used to incorporate knowledge and logic (cognitive analysis) into systems. The Monte Carlo method is a classical statistical tool for assessing accuracy and analyzing the impact of random and systematic errors, providing a transparent probabilistic interpretation of results. In contrast, AI methods are focused on processing large datasets and identifying complex nonlinear relationships; however, they exhibit reduced interpretability and limited compliance with regulatory standards. The Monte Carlo method is appropriate for use when:

- accuracy assessment is required;
- adherence to tolerances and standards is important;



a



b

Fig. Results of neural network modeling and adaptive estimation:

a – stochastic error distribution (point 15); b – dynamics of adaptive optimization

- measurement errors are being modeled;
- a probabilistic interpretation of results is needed.

AI is appropriate when:

- there are large archives of measurement data;
- forecasting or anomaly detection is required;
- the problem is poorly formalized;
- complex spatial or temporal patterns are being analyzed.

The most promising strategy is to combine them into hybrid methods. The proposed hybrid architecture based on Conditional Tabular GAN (CTGAN) enables the generation of synthetic data while maintaining the statistical characteristics of the sample and ensures that the assessment results meet established regulatory requirements.

Optimization of the generator and discriminator loss functions using the Wasserstein distance with gradient penalty can be recommended for practical applications in surveying tasks. This approach ensures stable synthesis of error vectors, which enhances the reliability of accuracy assessment for underground reference networks and guarantees compliance of the results with regulatory requirements.

The use of a method for generating synthetic scenarios that accounts for hidden nonlinear correlations between angular and linear discrepancies enables more

realistic error modeling, enhances the reliability of accuracy assessments for underground polygonometric traverses, and exceeds the capabilities of conventional spreadsheet-based approaches. The proposed method allows for verifying compliance with regulatory requirements even in cases where real data are scarce.

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Дослідження точності підземних опорних маркшейдерських мереж шляхом застосування нейромережевого моделювання

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Мета. Оцінити точність підземної маркшейдерської опорної мережі (ПМОМ) шляхом застосування нейромережевого моделювання й адаптивної оцінки положення найвіддаленішого пункту ходу. Виконати аналіз методів оцінки середніх квадратичних похибок положення пунктів.

Методика. Застосування методів глибокого навчання, зокрема умовні табличні генеративно-змагальні мережі (CTGAN), для синтезування розширених наборів геодезичних даних із метою оцінки точності підземних опорних маркшейдерських мереж (ПМОМ). Аналіз нормативно-правових доку-

ментів, закордонних і вітчизняних літературних джерел щодо аналізу точності й надійності маркшейдерських і геодезичних мереж шляхом застосування штучного інтелекту (нейромережевого моделювання й адаптивної оцінки).

Результати. Застосування нейромережевого моделювання й адаптивної оцінки дозволяє кількісно оцінити точність підземної опорної маркшейдерської мережі шляхом моделювання величин кутових і лінійних середніх квадратичних помилок (СКП). Це безпосередньо впливає на СКП положення найвіддаленішого пункту ПМОМ і вказує на процес збіжності дисперсії мережі при використанні адаптивного протоколу. При цьому, як тільки невизначеність наближається до Safety Constraint Layer, то система сигналізує про необхідність введення додаткових гіроскопічних вимірювань, що неможливо отримати аналітичними методами та неможливо зробити засобами табличного процесора.

Наукова новизна. Уперше запропоновано виконувати оцінку точності запроєктованої ПМОМ із застосуванням сучасних технологій штучного інтелекту. Проаналізовані відповідно до вимог нормативних документів результати оцінки із використанням аналітичного метода й метода моделювання. Похибки положення найвіддаленішого пункту № 15 ПМОМ визначено відповідно до заданого допуску. Також встановлені значення СКП вимірювань, за яких виконується необхідна умова. Середньоквадратична похибка положення найбільш віддаленого пункту ходу не повинна перевищувати 0,3 мм на плані, що відповідає 0,6 м для планів масштабу 1:2 000 у вугільних шахтах.

Практична значимість. Виконана оцінка точності ПМОМ шляхом застосування нейромережевого моделювання й адаптивної оцінки. У результаті виявлене зміщення найвіддаленішого пункту мережі та визначена ймовірність безвідмовної роботи ПМОМ на рівні 71 %. Запропонований підхід дозволяє підвищити достовірність прогнозування точності маркшейдерських мереж на етапі їх проєктування й експлуатації. Використання нейромережевих методів дає змогу оптимізувати обсяги польових вимірювань, своєчасно виявляти критичні зони із підвищеною невизначеністю та обґрунтовувати необхідність додаткових спостережень (зокрема гіроскопічних). Результати можуть бути використані для автоматизації процесів контролю якості геодезичних робіт, зниження виробничих ризиків у гірничих умовах і підвищення безпеки ведення робіт у вугільних шахтах. Запропонована методика також придатна для інтеграції у сучасні геоінформаційні й маркшейдерські системи підтримки прийняття рішень.

Ключові слова: *маркшейдерська мережа, оцінка точності, нейромережеве моделювання, адаптивна оцінка, полігонометричний хід*