Prediction of Underground Mine's Surface Subsidence using a Recursive Multi-Step Forecasting Model with an Artificial Neural Network

Tam Thanh Thi LE[1], Trong Gia NGUYEN[1], Chung Van PHAM[1], Canh Van LE[1], Huy Dinh NGUYEN[2]*

[1] Faculty of Geomatics and Land Administration, Hanoi University of Mining and Geology, Hanoi, Vietnam; ORCID https://orcid.org/0009-0001-5400-1776
[2] Faculty of Bridges and Roads, Hanoi University of Civil Engineering, Hanoi, Vietnam; ORCID https://orcid.org/0000-0002-2049-3338
* Corresponding author: phamvanchung@humg.edu.vn

http://doi.org/10.29227/IM-2024-01-116

Submission date: 26-05-2024 | Review date: 30-06-2024

Abstract

The subsidence of the surface due to mining activities is a significant issue in mining areas. Therefore, predicting surface subsidence is a necessary task to ensure safety and production efficiency. This article applied an Artificial Neural Network (ANN) model to predict surface subsidence resulting from underground mining operations in the Mong Dương mine. The ANN model proposed in this research uses a recursive multi-step forecasting model, where the predicted value at the previous step is added to the time series to forecast the next value. The experimental dataset consists of 12 monitoring cycles over 24 months, with a 2-month interval, divided into a training set containing the first 9 measurement cycles and a test set containing the last 3 cycles. First, the K-fold cross-validation method is applied to the training set to determine the best parameters for the model. Then, these parameters are used to predict surface subsidence for the values in the test set. The prediction error depends on the time gap between the last measurement cycle and the forecasting cycle. The relative errors in the tenth cycle for the four points are 0.9%, -1.7%, -1.7%, and 1.4%. These error values increase to 1.4%, -1.8%, -1.8%, and -1.7% in the eleventh cycle and further to 2.0%, -2.2%, -2.2%, and 2.5% in the twelfth cycle. The absolute errors are determined to be small, within the range of 20 mm. These results demonstrate that the proposed method and ANN model are suitable for the time-series monitoring data in mining areas.

Keywords: *surface subsidence, underground mine, artificial neural network, subsidence prediction*

1. Introduction

Vietnam is a country with diverse natural resources, including approximately 70 types of minerals (B. N. Nguyen, Boruff, & Tonts, 2017), among which coal is the primary mineral resource, mostly found in coal mines in Quang Ninh province. Among these, the ratio between underground and surface coal mines is approximately 60% and 40%, respectively, with the total extraction volume expected to increase annually (B.N. Nguyen, Boruff, & Tonts, 2021). Some surface coal mines are planned to be transformed into underground coal mines due to increasing extraction depths, resulting in a rise in the number of underground mines (Q.N. Nguyen, Nguyen, Pham, & Chu, 2021). The contribution of the coal industry in Vietnam is not only economic growth through mineral exports but also energy security through coal-based electricity generation (Dorband, Jakob, & Steckel, 2020).

Despite significant contributions to the economy, mining activities also bring about environmental challenges (Mohsin, Zhu, Naseem, Sarfraz, & Ivascu, 2021), among which land subsidence is a common consequence. Surface subsidence has posed significant risks to infrastructure, the environment, and the safety of workers in mining areas (Marschalko et al., 2012). Although surface subsidence due to mining activities can be measured after the occurrence of subsidence, the effective prediction of mining-induced surface subsidence in the future is also an important task for sustainable mining and resource utilization planning (Ma, Li, & Zhang, 2017). The prediction theories of surface displacement and deformation in mines are divided into three main groups, relying on geometric principles, the continuous mechanical environment, and the random theory. Scientists worldwide have developed many prediction methods based on these theories, which can be grouped into 5 method categories of experimental, intersection surface, influence function, analytical and physical modeling methods (Reddish & Whittaker, 2012).

With the development of computer science, artificial neural networks have been widely applied in various fields, including prediction. Artificial neural networks are capable of connecting and integrating different parameters in identification and forecasting applications. The strength of artificial neural networks is their ability to make good forecasts with complex data. For such data, artificial neural networks provide high generalization in forecasting; moreover, they can also forecast with non-linear variables.

The prediction of displacement resulting from underground mining activities using artificial neural networks has been conducted by many authors, such as the study by Ambrožič và Turk, 2003 to predict surface subsidence due to coal mining at the Velenje mine in Slovenia; Ki-Dong Kim et al, 2009 (Kim, Lee, & Oh, 2009) predicted mining-induced subsidence in the city of Samcheok, South Korea; Saro Lee et al. (2012) (Lee, Park, & Choi, 2012) employed artificial neural networks to forecast subsidence in the Jeong-am mining area, South Korea.

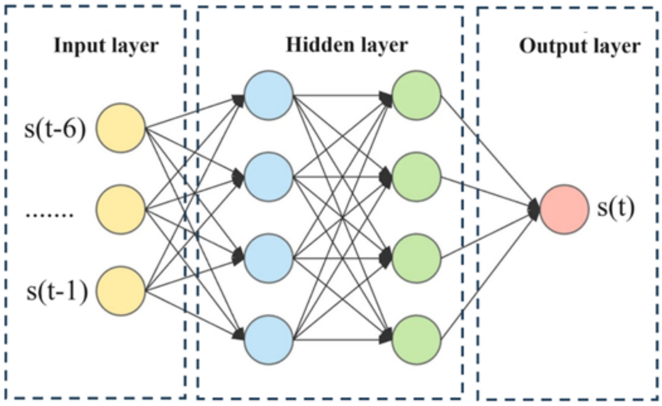

Fig. 1. Structure of an artificial neural network consisting of input layer, hidden layers, and output layer
Rys. 1. Struktura sztucznej sieci neuronowej składającej się z warstwy wejściowej, warstw ukrytych i warstwy wyjściowej

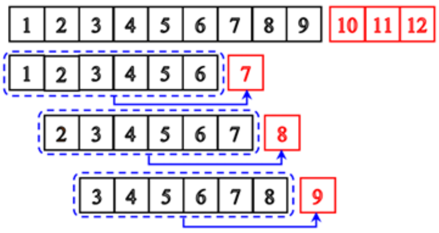

Fig. 2. Recursive multi-step prediction model. Black squares represent the input values of the model and red squares correspond to the output values
Rys. 2. Rekursywny wieloetapowy model predykcji. Czarne kwadraty reprezentują wartości wejściowe modelu, a czerwone kwadraty odpowiadają wartościom wyjściowym

Compared to traditional methods of subsidence prediction relying on a predefined function and its parameters, subsidence prediction using artificial neural networks is a parameter-free method with the ability to forecast for areas with specific geological and topographical characteristics. However, this method requires actual subsidence monitoring data as inputs for network training. This can be much easier to obtain than collecting the necessary influencing factors with high accuracy for the aforementioned traditional methods.

In Vietnam, several prediction studies have been conducted, including constructing forecasting models based on experimental monitoring data (Long et al., 2017; Long, My, & Luyen; L. Q. Nguyen, 2016), and determining parameters of models suitable for specific conditions of each mining area to enhance the accuracy of forecasting results (L. Q. Nguyen, 2016, 2020). Studies on the application of artificial neural networks in surface subsidence prediction in mines have confirmed the superiority of this method over traditional approaches when applied in Vietnam (L. Q. Nguyen, et al., 2023; Q. Nguyen, Nguyen, et al., 2021). Application of artificial neural network using recursive multistep prediction process to predict road subsidence caused by underground mining has been carried out in 2023 (Hung N.V, et al., 2023). A new ANN model with associated "optimal" hyperparameters to predict underground mining-induced land subsidence is proposed (Long Quoc Nguyen, et al., 2023).

In this paper, an artificial neural network (ANN) is applied to predict surface subsidence caused by underground mining in Vietnam. This research contributes methodologically by leveraging advancements in subsidence prediction techniques, thereby supporting sustainable mining operations.

2. Methodology

2.1 Artificial Neural Networks

The artificial neural network (ANN) is one of the artificial intelligence (AI) tools used in surface subsidence prediction due to its ability to learn complex models with a large dataset, thus enabling accurate predictions (Ambrožič & Turk, 2003; Yang & Xia, 2013). ANN models are computational models developed based on the study of the human brain's structure, hence the name ANN (Zou, Han, & So, 2009). They consist of several layers of artificial interconnected neurons, which are divided into input, hidden, and output layers (see Figure 1). The input layer involves input parameters, which are then passed through the hidden layers with computations performed based on weights, resulting in predicted variables estimated in the output layer. The weights are initially assigned random values in the input layer, then propagated through the hidden and output layers. These weights are then recalculated using optimization algorithms such as gradient descent and backpropagation (Amari, 1993). Thus, the ANN model can accurately predict output variables by recalculating weight values.

In an ANN, each layer consists of one or more neurons depending on the specific problem under investigation. In this study, the input layer consists of six neurons corresponding to six previous subsidence measurement cycles from s(t-6) to s(t-1), used to forecast subsidence at time t (denoted as s(t)). The hidden layer(s) comprise one or more layers, each containing a number of hidden nodes. In this research, the optimal number of hidden layers, hidden nodes, and the number of iterations in the backpropagation process are experimentally determined through cross-validation using the k-fold method (Fushiki, 2011).

Tab. 1. Training set consisting of subsidence values for the first nine months (unit: mm)

Tab. 1. Zestaw treningowy składający się z wartości osiadania dla pierwszych dziewięciu miesięcy (jednostka: mm)

Month	Point P1	Point P2	Point P3	Point P4
1	0	0	0	0
2	-22	-25	-24	-15
3	-62	-67	-77	-54
4	-129	-115	-102	-109
5	-198	-192	-183	-165
6	-278	-342	-317	-303
7	-369	-429	-416	-441
8	-452	-558	-547	-569
9	-516	-638	-617	-639

Tab. 2. Comparison between the measured and predicted values at Point P1

Tab. 2. Porównanie zmierzonych i przewidywanych wartości w punkcie P1

Month	Measured (mm)	Predicted (mm)	Abs. Error (mm)	Rel. Error (%)
10	-589	-584	-5	0.9
11	-637	-628	-9	1.4
12	-664	-651	-13	2.0

Tab. 3. Comparison between the measured and predicted values at Point P2

Tab. 3. Porównanie zmierzonych i przewidywanych wartości w punkcie P2

Month	Measured (mm)	Predicted (mm)	Abs. Error (mm)	Rel. Error (%)
10	-725	-737	12	-1.7
11	-761	-775	14	-1.8
12	-797	-815	18	-2.2

Tab. 4. Comparison between the measured and predicted values at Point P3

Tab. 4. Porównanie zmierzonych i przewidywanych wartości w punkcie P3.

Month	Measured (mm)	Predicted (mm)	Abs. Error (mm)	Rel. Error (%)
10	-694	-706	12	-1.7
11	-740	-795	14	-1.8
12	-783	-827	18	-2.2

Tab. 5. Comparison between the measured and predicted values at Point P4

Tab. 5. Porównanie zmierzonych i przewidywanych wartości w punkcie P4

Month	Measured (mm)	Predicted (mm)	Abs. Error (mm)	Rel. Error (%)
10	-711	-701	-10	1.4
11	-762	-775	13	-1.7
12	-814	-834	20	-2.5

2.2 Recursive multi-step forecasting model

A total of 12 subsidence measurements are taken once per month, corresponding to a one-year period. With this number of measurements, we divide the dataset into a training set consisting of the first 9 measurements, and the remaining three measurements are chosen as the test set. To train the model based on the training set, we use the six previous measurements as input and the subsequent measurements as output, as illustrated in Figure 2. This process is called recursive multi-step prediction. Specifically, the first six months are used as input and the seventh month as output. Then, the time series is shifted forward by one step with months two through seven used as input and the eighth month as output. Similarly, month three to month eight are used as input to predict the ninth month. Through this process, the back-propagation algorithm is applied based on the difference between predicted and measured values in months 7, 8, and 9 (see Figure 2). The parameters of the model after the training process are then used to forecast subsidence in months 10, 11, and 12. To do this, values from the fourth to the ninth months are used to predict the subsidence of the tenth month. Then, the predicted value in the tenth month is added to the time series to predict the eleventh month. Finally, a similar process is applied to predict the subsidence of the twelfth month.

2.3 Model Accuracy Evaluation

To evaluate the effectiveness of the surface subsidence prediction using the ANN model, two evaluation metrics are utilized in this study, including absolute (Abs.Err) and relative errors (Rel.Err):

$$Abs.Err_i = \eta_i - \hat{\eta}_i \qquad (1)$$

$$Rel.Err_i = \frac{\eta_i - \hat{\eta}_i}{\eta_i} \times 100\% \qquad (2)$$

$$r = \frac{\sum_{i=1}^{n}(\eta_i - \overline{\eta_i})\left(\eta_i^p - \overline{\eta_i^p}\right)}{\sqrt{\sum_{i=1}^{n}(\eta_i - \overline{\eta_i})^2 * \sum_{i=1}^{n}\left(\eta_i^p - \overline{\eta_i^p}\right)^2}} \qquad (3)$$

where η_i and η^p are the measured and the predicted values at t_i; $\overline{\eta}$ and $\overline{\eta}^p$ are the corresponding medium values of measured and predicted values, respectively.

3. Results and Discussion

In this study, four Global Navigation Satellite System (GNSS) measurement points in the Mong Duong underground coal mine area were used to test the proposed model. These four points are named P1, P2, P3, and P4, located on the surface within the mining area. As mentioned earlier, each point is measured over 12 measurement cycles at two months apart. The first nine measurement cycles are selected as the training dataset to train the model, and the last three measurement cycles are used as the test dataset for subsidence prediction. The data processing and prediction modules are programmed in Python using the scikit-learn package (Pedregosa et al., 2011). Table 1 shows the subsidence measurements of the four points corresponding to the training dataset of the first nine cycles.

The surface subsidence values for the last three cycles are predicted based on the parameters found from the train-

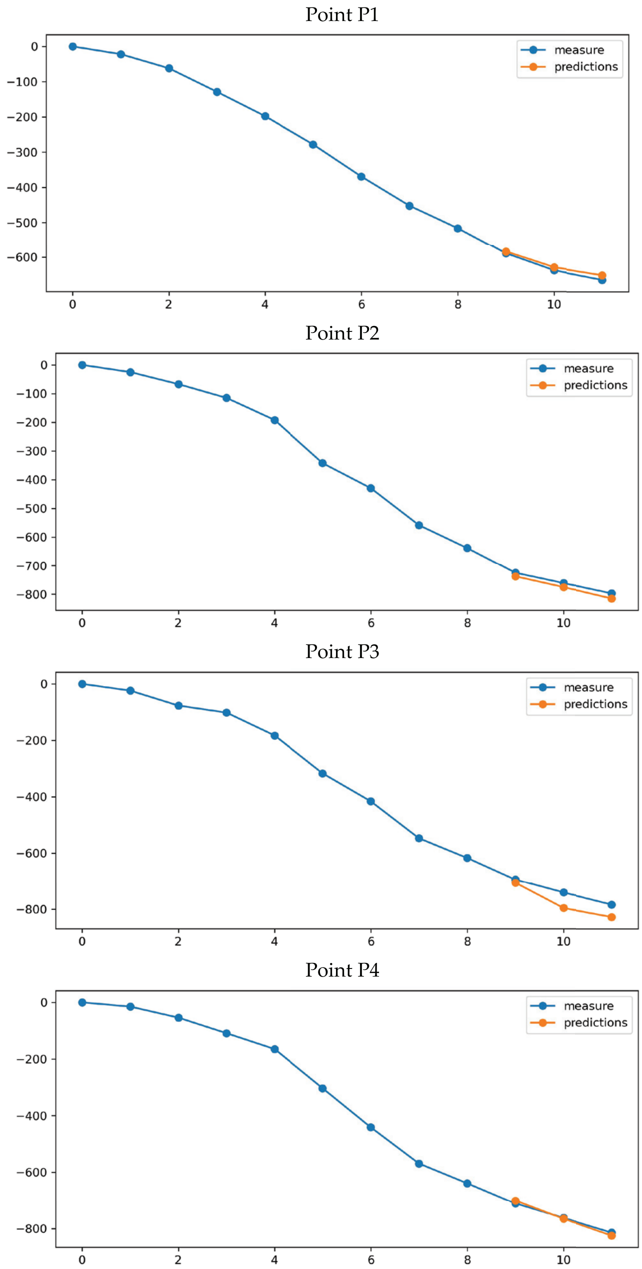

Fig. 3. Comparison between measured subsidence and predicted values
Rys. 3. Porównanie zmierzonego osiadania z wartościami przewidywanymi

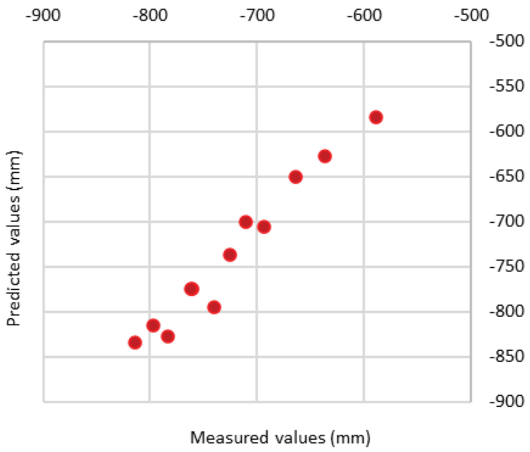

Fig. 4. Correlation between the measured and predicted values of 4 points
Rys. 4. Korelacja między zmierzonymi i przewidywanymi wartościami dla 4 punktów

ing dataset, with the results shown in Table 2 (Point P1), Table 3 (Point P2), Table 4 (Point P3), and Table 5 (Point P4). In these tables, the predicted values are compared with the measured values, from which absolute errors (Abs. errors) are calculated in millimeters 0(mm). Additionally, relative errors (Rel. errors) are computed by dividing the absolute errors by the measured subsidence values, calculated as a percentage (%). The results show a larger discrepancy between the forecasted time and the corresponding time of the last measured value in the training set leading to larger errors. The relative errors in the 10th month for the four experimental points are 0.9%, -1.7%, -1.7%, and 1.4%. These errors increase to 1.4%, -1.8%, -1.8%, and -1.7% in the 11th month, and 2.0%, -2.2%, -2.2%, and 2.5% in the 12th month. The absolute errors are found to be small, within the range of 20 mm. The correlation between the measured and predicted values of 4 points is high with r=0.980. This indicates that the ANN method used in this study can effectively forecast the time series of surface subsidence in mining areas. This is confirmed by the results displayed in Figure 3, where the measured and predicted subsidence values are very close. The correlation coefficients between predicted and measured values for 4 points are plotted in Fig. 4. With high values in the prediction results (r=0.980), it indicates that the predictive model is consistent with the measured data.

4. Conclusion

In this study, we utilized an ANN to forecast surface subsidence caused by underground coal mining at the Mong Duong coal mine, Vietnam. A recursive multi-step prediction process was designed and applied, where the first nine cycles were used as input to train the ANN model. Subsequently, the parameters of the model were used to predict subsidence for the last three cycles.

The parameters of the ANN model, including the number of hidden layers, hidden nodes, and iterations, were determined through the k-fold cross-validation method before being used to identify the model parameters with the training dataset and predict surface subsidence for the test dataset. The proposed ANN model with 'optimized' parameters found in this study has been demonstrated as an effective tool for predicting surface subsidence due to underground mining activities. The absolute errors were determined to be small, within the range of 20 mm. The absolute error depends on the time gap between the forecasted month and the month corresponding to the last measurement in the training dataset. The relative errors in the 10th month were 0.9%, -1.7%, -1.7%, and 1.4%. These errors increased to 1.4%, -1.8%, -1.8%, and -1.7% in the 11th month, and 2.0%, -2.2%, -2.2%, and 2.5% in the 12th month.

Acknowledgment

The authors would like to sincerely thank Hanoi University of Mining and Geology for providing financial support to conduct this study under the project T23-39.

Literatura – References

1. Amari, S. (1993). Backpropagation and stochastic gradient descent method. Neurocomputing, 5(4), 185-196. doi:10.1016/0925-2312(93)90006-O
2. Ambrožič, T., & Turk, G. (2003). Prediction of subsidence due to underground mining by artificial neural networks. Computers & Geosciences, 29(5), 627-637. doi:10.1016/S0098-3004(03)00044-X
3. Dorband, I. I., Jakob, M., & Steckel, J. C. (2020). Unraveling the political economy of coal: Insights from Vietnam. Energy Policy, 147, 111860. doi:10.1016/j.enpol.2020.111860
4. Fushiki, T. (2011). Estimation of prediction error by using K-fold cross-validation. Statistics and Computing, 21(2), 137-146. doi:10.1007/s11222-009-9153-8
5. Kim, K.-D., Lee, S., & Oh, H.-J. (2009). Prediction of ground subsidence in Samcheok City, Korea using artificial neural networks and GIS. Environmental Geology, 61-70.
6. Lee, S., Park, I., & Choi, J.-K. (2012). Spatial Prediction of Ground Subsidence Susceptibility Using an Artificial Neural Network. Environmental Management, 49, 347-358.
7. Long, N. Q., Bui, X.-N., Bui, L. K., Huynh, K. D. V., Van Le, C., Buczek, M., & Nguyen, T. P. (2017). A Computational Tool for Time-Series Prediction of Mining-Induced Subsidence Based on Time-Effect Function and Geodetic Monitoring Data. Paper presented at the International Conference on Geo-Spatial Technologies and Earth Resources.
8. Long, N. Q., My, V. C., & Luyen, B. K. Divergency verification of predicted values and monitored deformation indicators in specific condition of Thong Nhat underground coal mine (Vietnam). Geoinformatica Polonica, 2016(2016)), 15-22.
9. Long Quoc Nguyen, T. T. T. L., Trong Gia Nguyen, Dinh Trong Tran. (2023). Prediction of underground mining-induced subsidence: Artificial neural network based approach. Mining of Mineral Deposits, 17(4).

10. Ma, C., Li, H., & Zhang, P. (2017). Subsidence prediction method of solid backfilling mining with different filling ratios under thick unconsolidated layers. Arabian Journal of Geosciences, 10(23), 511. doi:10.1007/s12517-017-3303-7

11. Marschalko, M., Yilmaz, I., Křístková, V., Fuka, M., Kubečka, K., Bouchal, T., & Bednarik, M. (2012). Optimization of building site category determination in an undermined area prior to and after exhausting coal seams. International Journal of Rock Mechanics and Mining Sciences, 54, 9-18. doi:10.1016/j.ijrmms.2012.05.021

12. Mohsin, M., Zhu, Q., Naseem, S., Sarfraz, M., & Ivascu, L. (2021). Mining Industry Impact on Environmental Sustainability, Economic Growth, Social Interaction, and Public Health: An Application of Semi-Quantitative Mathematical Approach. Processes, 9(6), 972. doi:10.3390/pr9060972

13. Nguyen, B. N., Boruff, B., & Tonts, M. (2017). Mining, development and well-being in Vietnam: A comparative analysis. The extractive industries and society, 4(3), 564-575. doi:10.1016/j.exis.2017.05.009

14. Nguyen, B. N., Boruff, B., & Tonts, M. (2021). Looking through a crystal ball: Understanding the future of Vietnam's minerals and mining industry. The extractive industries and society, 8(3), 100907. doi:10.1016/j.exis.2021.100907

15. NGUYEN, H. V., LE, D. Q., NGUYEN, L. Q., & LIPECKI, T. (2023). Prediction of Road Subsidence Caused by Underground Mining Activities by Artificial Neural Networks. Inżynieria Mineralna, 52(2).

16. Nguyen, L. Q. (2016). Sectional diagram of dynamic subsidence trough at the Mong Duong coal mine: Evaluation and prediction. Journal of Mining and Earth Sciences Vol, 56, 58-66.

17. Nguyen, L. Q. (2020). A novel approach of determining the parameters of Asadi profiling function for predictiong ground subsidence due to inclied coal seam mining at Quang Ninh coal basin.

18. Nguyen, L. Q., Le, T.T.T., Nguyen, T.G., & Tran, D.T. . (2023). Prediction of underground mining-induced subsidence: Artificial neural network based approach. Mining of Mineral Deposits, 4(17), 45-52. doi: https://doi.org/10.33271/mining17.04.045

19. Nguyen, Q., Nguyen, Q., Tran, D., & Bui, X. Prediction of ground subsidence due to underground mining through time using multilayer feed-forward artificial neural networks and back-propagation algorithm–case study at Mong Duong underground coal mine (Vietnam). MINING SCIENCE ANDTECHNOLOGY (Russia), 241.

20. Nguyen, Q. N., Nguyen, V. H., Pham, T. P., & Chu, T. K. L. (2021). Current Status of Coal Mining and Some Highlights in the 2030 Development Plan of Coal Industry in Vietnam. Inżynieria Mineralna. doi:10.29227/IM-2021-02-34

21. Reddish, D. J., & Whittaker, B. N. (2012). Subsidence: occurrence, prediction and control. England: Elsevier.

22. Yang, W., & Xia, X. (2013). Prediction of mining subsidence under thin bedrocks and thick unconsolidated layers based on field measurement and artificial neural networks. Computers & Geosciences, 52, 199-203. doi:10.1016/j.cageo.2012.10.017

23. Zou, J., Han, Y., & So, S.-S. (2009). Overview of Artificial Neural Networks. In D. J. Livingstone (Ed.), Artificial Neural Networks: Methods and Applications (pp. 14-22). Totowa, NJ: Humana Press.

Prognozowanie osiadania powierzchni kopalni podziemnej przy użyciu rekurencyjnego modelu prognozowania wieloetapowego z wykorzystaniem sztucznej sieci neuronowej

Osuwanie się powierzchni z powodu działalności górniczej jest istotnym problemem w obszarach górniczych. Dlatego przewidywanie osiadania powierzchni jest niezbędnym zadaniem, aby zapewnić bezpieczeństwo i efektywność produkcji. W tym artykule zastosowano model sztucznej sieci neuronowej (ANN) do przewidywania osiadania powierzchni wynikającego z podziemnych operacji górniczych w kopalni Mong Dương. Proponowany w tym badaniu model ANN wykorzystuje rekurencyjny model prognozowania wieloetapowego, w którym przewidywana wartość z poprzedniego kroku jest dodawana do szeregu czasowego, aby prognozować następną wartość. Zbiór danych eksperymentalnych składa się z 12 cykli monitorowania w ciągu 24 miesięcy, z dwumiesięcznym odstępem, podzielonych na zestaw treningowy zawierający pierwsze 9 cykli pomiarowych i zestaw testowy zawierający ostatnie 3 cykle. Najpierw metoda walidacji krzyżowej K-fold jest stosowana do zestawu treningowego, aby określić najlepsze parametry dla modelu. Następnie te parametry są używane do przewidywania osiadania powierzchni dla wartości w zestawie testowym. Błąd prognozy zależy od przerwy czasowej między ostatnim cyklem pomiarowym a cyklem prognozowania. Błędy względne w dziesiątym cyklu dla czterech punktów wynoszą 0,9%, -1,7%, -1,7% i 1,4%. Te wartości błędów wzrastają do 1,4%, -1,8%, -1,8% i -1,7% w jedenastym cyklu i dalej do 2,0%, -2,2%, -2,2% i 2,5% w dwunastym cyklu. Błędy bezwzględne są określane jako małe, w zakresie 20 mm. Wyniki te pokazują, że proponowana metoda i model ANN są odpowiednie dla danych monitorowania szeregów czasowych w obszarach górniczych.

Słowa kluczowe: *osiadanie powierzchni, kopalnia podziemna, sztuczna sieć neuronowa, prognozowanie osiadania*