Prediction of Road Subsidence Caused by Underground Mining Activities by Artificial Neural Networks

Hung Viet NGUYEN[1)], Duyen Quang LE[2)], Long Quoc NGUYEN[3,4)], Tomasz LIPECKI[5)]*

[1)] Faculty of Information Technology, University of Transport and Communications, Hanoi, Vietnam; ORCID https://orcid.org/0009-0005-1104-5161
[2)] Faculty of Petroleum and Energy, Hanoi University of Mining and Geology, Hanoi, Vietnam; ORCID https://orcid.org/0000-0001-6953-4762
[3)] Faculty of Geomatics and Land Administration, Hanoi University of Mining and Geology, Hanoi, Vietnam; ORCID https://orcid.org/0000-0002-4792-3684
[4)] Innovations for Sustainable and Responsible Mining (ISRM) Research Group, Hanoi University of Mining and Geology, Hanoi, Vietnam;
[5)] Faculty of Geo-data Science, Geodesy and Environmental Engineering, AGH University of Krakow, Kraków, Poland; ORCD https://orcid.org/0000-0002-3204-7343
* Corresponding author: lequangduyen@humg.edu.vn

http://doi.org/10.29227/IM-2023-02-49

Submission date: 30-08-2023 | Review date: 29-09-2023

Abstract

Mining-induced road subsidence is a significant concern in areas with extensive underground mining activities. Therefore, the prediction of road subsidence is crucial for effective land management and infrastructure planning. This paper applies an artificial neural network (ANN) to predict road subsidence caused by underground mining activities in Vietnam. The ANN model proposed in this study is adopted relying on the recursive multistep prediction process, in which the predicted value in the previous step is appended to the time series to predict the next value. The entire dataset of 12 measured epochs covering 12 months with a 1-month repeat time is divided into the training set by the first 9 measured epochs and the test set by the last 3 measured epochs. K-fold cross validation is first applied to the training set to determine the best model's hyperparameters, which are then adopted to predict land subsidence of the test set. Absolute errors of the predicted road subsidence depend on the separated time between the last measured epoch and the predicted epoch. Those errors at the 10th month of the three tested points are 3.0%, 0.1 %, and 0.1%, which increase to 4.8%, 3.3%, and 1.5% at the 11th month, and 7.2%, 2.5% and 1.3% at the 12th month. The absolute errors are found to be small, which were all ranged with 0.5 mm and demonstrates that the proposed method utilizing ANN in this study can produce good prediction for road subsidence time series at mining areas.

Keywords: *subsidence prediction, underground mine, machine learning, ANN*

1. Introduction

In many nations, including developing countries, mining activities have played an important role in economic development (Hilson, 2002), which includes resource provision with valuable minerals, metals, and other resources to various industrial sectors, e.g., manufacturing, construction, energy (Fan, Yan, & Sha, 2017). However, the relationship between mining activities and economic development has been proved to be complex (Knierzinger, 2014). Additionally, the mine industry provides jobs (Fleming & Measham, 2014) in various sectors, e.g., geology, surveying, electrics. The Vietnamese mining industry has a long history, which made contributions to the Vietnam's economy (B. N. Nguyen, Boruff, & Tonts, 2021). Vietnam has diversity in ore occurrence with around 70 types of minerals (B. N. Nguyen, Boruff, & Tonts, 2017), among which coal is the main mineral source – most of the Vietnam coal mines located in Quang Ninh province. Of those, the percentages of underground and open pit coal mines are about 60% and 40% respectively, with the exploration volume projected to increase yearly (B. N. Nguyen et al., 2021). With some open-pit coal mines being transmitted to underground mines due to their increasing depths, the proportion of underground mines is increasing (Q. N. Nguyen, Nguyen, Pham, & Chu, 2021). The roles of Vietnam coal are not only economic growth in terms of mineral export but also political energy security in terms of coal-fired electricity generation (Dorband, Jakob, & Steckel, 2020).

In spite of the economic contributions, mining activities also result in environmental challenges (Mohsin, Zhu, Naseem, Sarfraz, & Ivascu, 2021), of which surface subsidence is a popular outcome. This environmental problem in turn poses significant risks to infrastructure, environmental stability, and human safety in mining areas (Marschalko et al., 2012). Mining-induced land subsidence can be measured by different methods, such as leveling (e.g., Todorović, 1993), Global Navigation Satellite System (GNSS) (e.g., Bian, Zhang, Zhang, & Zheng, 2014; Jing-xiang & Hong, 2009), and Interferometric Synthetic Aperture Radar (InSAR) (e.g., Bui et al., 2021; Kim, Tran, Bui, & Lipecki, 2021; Q. L. Nguyen, Tran, & Bui, 2021). Land subsidence caused by mining activities can be measured after the Earth's surface has subsided, efficient management and prediction of mining-induced land subsidence in the future are also crucial for sustainable mining practices and land use planning (Ma, Li, & Zhang, 2017). The traditional empirical approach based on a combination of experience and analysis of a large set of observations (Aston, Tammemagi, & Poon, 1987), and the analytical approach relying on computerized mathematical models (Bahuguna,

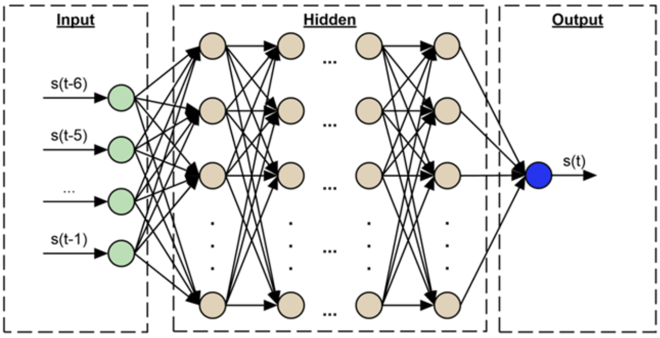

Fig. 1. Structure of artificial neural network with input, hidden, and output layers used in this study

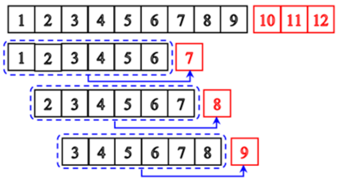

Fig. 2. Recursive multistep prediction process in this study. Black squares indicate inputs of the model and red squares correspond to outputs

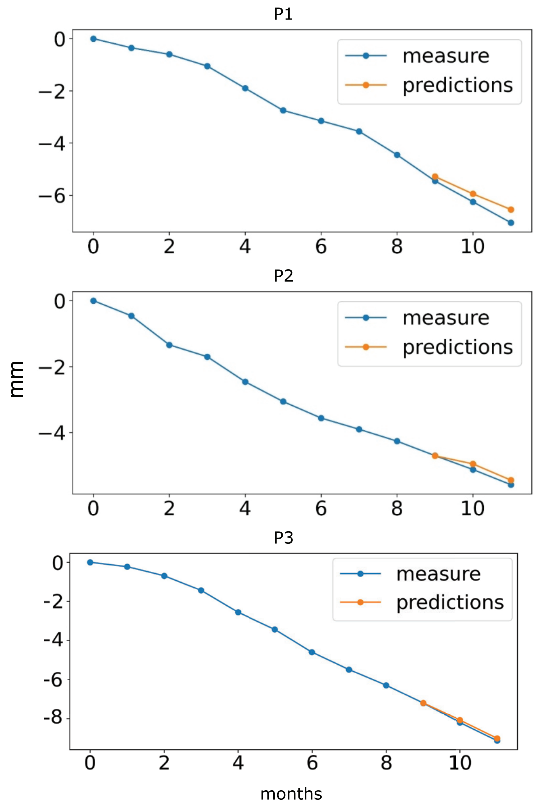

Fig. 3. Comparison between measured and predicted subsidence [mm] of point P1, P2 and P3

Srivastava, & Saxena, 1991) have been widely adopted. However, these methods often lack accuracy and predictive capability. In recent years, Artificial Neural Networks (ANNs) have emerged as a promising tool for subsidence prediction due to their ability to capture complex nonlinear relationships within datasets (e.g., Ambrožič & Turk, 2003; Lee, Park, & Choi, 2012; Rafie & Samimi Namin, 2015). This is because of the advantages of ANN that is an advanced computing system stimulating human neural networks. It is therefore a kind of data-driven self-learning, self-organizing system capable of solving a nonlinear dynamic system (Ambrožič & Turk, 2003).

In this article, ANN is adopted to predict underground mining-induced road subsidence, leveraging their strengths in pattern recognition, adaptive learning, and generalization, so as to introduce an alternative method of land subsidence in mining areas. By exploring the capabilities of the ANN models applied to underground mining-induced road subsidence, this study aims to contribute to the advancement of subsidence prediction techniques and support sustainable mining practices.

2. Neural Networks and Model Evaluation

2.1 Artificial Neural Networks

Tab. 1. Subsidence corresponding to the training set incorporating values from the first nine months. (Units: mm)

Month	Point P1	Point P2	Point P3
1	0	0	0
2	-0.4	-0.5	-0.2
3	-0.6	-1.3	-0.7
4	-1.1	-1.7	-1.4
5	-1.9	-2.5	-2.6
6	-2.8	-3.1	-3.4
7	-3.2	-3.6	-4.6
8	-3.6	-3.9	-5.5
9	-4.5	-4.2	-6.3

Tab. 2. Comparison of measured and predicted subsidence at Point 1

Month	Measured (mm)	Predicted (mm)	Abs. Error (mm)	Rel. Error (%)
10	-5.5	-5.3	-0.2	3.0
11	-6.3	-5.9	-0.4	4.8
12	-7.1	-6.5	-0.6	7.2

Tab. 3. Comparison of measured and predicted subsidence at Point 2

Month	Measured (mm)	Predicted (mm)	Abs. Error (mm)	Rel. Error (%)
10	-4.7	-4.7	0	0.1
11	-5.1	-4.9	-0.2	3.3
12	-5.6	-5.4	-0.2	2.5

Tab. 4. Comparison of measured and predicted subsidence at Point 3

Month	Measured (mm)	Predicted (mm)	Abs. Error (mm)	Rel. Error (%)
10	-7.2	-7.2	0.0	0.1
11	-8.2	-8.1	-0.1	1.5
12	-9.1	-9.0	-0.1	1.3

ANNs are among the artificial intelligence powerful tools used in land subsidence prediction owing to their ability to learn complex patterns with a large dataset by which accurate predictions can be conducted (e.g., Ambrožič & Turk, 2003; Yang & Xia, 2013). ANNs are computational models inspired by the structure of the human brain, and thus neural networks (Zou, Han, & So, 2009). They compose of a number of interconnected artificial neuron layers, which is divided into input, hidden, and output layers (see Figure 1). The input layer imports the input features then passes them through the hidden layers, in which computations are conducted with a series of weighted connections by which the predicted variables are estimated in the output layer. The weights are initially assigned with random values in the input layer, which are then propagated through the hidden and output layers. The weights are subsequently adjusted by optimization algorithms, e.g., gradient descent and backpropagation (Amari, 1993). In this way, ANN can accurately predict the output variables via adjusting the weights.

In an ANN, each layer involves one or more neurons depending on the specific problem under investigation. In this study, the input layer includes six neurons corresponding to six previous subsidence measurements from s(t-6) to s(t-1) used to predict the subsidence at the time t (i.e., s(t)). The hidden layer section includes one or more layers with each incorporating a number of nodes. In this study, the 'optimal' number of hidden layers, hidden nodes, and iterated backpropagation epochs are experimentally determined by the so-called k-fold cross validation (Fushiki, 2011).

There are a total of 12 subsidence observations measured once a month, corresponding to a year of measurement. With this number of observations, we divide the dataset into the training set incorporating the first nine measurements and the remaining three months are selected as the test set. To train the model based on the training set, we use the previous six measurements as the inputs and the next measurement as the output as shown in. This process is called recursive multistep prediction. Specifically, the first six months are first used as the inputs and the seventh month as the output. Then, the time series is one-step moved forward with the second month to the seventh month as inputs and the eighth month as output. Likewise, the third month to the eighth month are used as the inputs to predict the ninth month. In this way, the back propagation process is utilized based on the differences between predicted and measured values at the months 7, 8, and 9 (see Figure 2). The model's parameters after training are then used to predict subsidence at the months 10, 11, and 12. To this end, the values from the fourth month to the ninth month are used to predict the subsidence of the tenth month. Then, the predicted at then tenth month is appended to the time series to predict the eleventh month. Finally, a similar process is adopted to predict subsidence of the twelfth month.

2.2 Model Performance Evaluation

To evaluate the performance of mining-induced road subsidence prediction by ANN in this study, two validation metrics are employed in this study, including absolute and relative errors, which are:

$$Abs.Err_i = \eta_i - \hat{\eta}_i \tag{1}$$

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

where η_i and $\hat{\eta}_i$ are the measured and predicted subsidence.

3. Numerical Examples

In this study, three points measured by the leveling method over an underground mine in Vietnam are tested as numerical examples. The three points are named P1, P2, and P3 located in a road where transportation for mining is active. As mentioned above, each point was measured with 12 epochs at a monthly interval. The first nine months are selected as the training set, i.e., to train the model, and the last three months as the test set, i.e., to forecast subsidence. Programming code is written in Python with the scikit-learn package (Pedregosa et al., 2011). Table 1 shows the measurements of the three tested points corresponding to the training set of the first nine months.

Road subsidence of the last three months are predicted relying on the parameters found from the training set with the results shown in Table 2 (Point 1), Table 3 (Point 2), and Table 4 (Point 3). In those tables, the predicted values are compared with the measured values by which the absolute (Abs.) errors in mm are computed. Additionally, the relative (Rel.) errors are computed by dividing the absolute errors by the measured subsidence in percent (%). The results indicate that longer separations between the predicted time and the last value of the training time results in higher relative errors. Relative errors at the 10th month of the three points are 3.0%, 0.1 %, and 0.1%, which increase to 4.8%, 3.3%, and 1.5% at the 11th month, and 7.2%, 2.5% and 1.3% at the 12th month. In all cases, the absolute errors are small, which are all less than 0.5 mm, which indicates that the proposed method utilizing ANN in this study can produce good prediction for road subsidence time series at mining areas. This is confirmed by the results shown in Figure 3, in which the measured and predicted subsidence are very close.

4. Conclusions

This study has applied ANN to predict road subsidence measured by leveling caused by underground mining in Vietnam. The recursive multistep prediction process is designed and adopted, in which the first nine months are used as inputs to train the model of which the parameters are then used to predict subsidence for the last three months. Three points located at the road of the mine were measured with 12 epochs. subsidence was measured by the leveling method for each epoch.

The hyperparameters of the ANN model, including the number of hidden layers, hidden nodes, and iterated epochs, were determined by k-fold cross validation before they were utilized to estimate the model's parameters by the training set and predict land subsidence for the test set. The proposed ANN model with 'optimal' hyperparameters found in this study was demonstrated to be a good tool for underground mining induced road subsidence. The absolute errors were found to be small, which were all ranged with 0.5 mm. The absolute errors depend on the separations between the month in which the prediction was made and the last value in the training set. Relative errors at the 10th month of the three tested points are 3.0%, 0.1%, and 0.1%, which increase to 4.8%, 3.3%, and 1.5% at the 11th month, and 7.2%, 2.5% and 1.3% at the 12th month.

Acknowledgements

This research is funded by the University of Transport and Communications (UTC) under grant number T2023-CN-003.

Conflicts of Interest

The authors declare no conflict of interest.

Literatura – References

1. Amari, S.-i. (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. Aston, T. R. C., Tammemagi, H. Y., & Poon, A. W. (1987). A review and evaluation of empirical and analytical subsidence prediction techniques. Mining Science and Technology, 5(1), 59-69. doi:10.1016/S0167-9031(87)90924-8
4. Bahuguna, P. P., Srivastava, A. M. C., & Saxena, N. C. (1991). A critical review of mine subsidence prediction methods. Mining Science and Technology, 13(3), 369-382. doi:10.1016/0167-9031(91)90716-P
5. Bian, H.-f., Zhang, S.-b., Zhang, Q.-z., & Zheng, N.-s. (2014). Monitoring large-area mining subsidence by GNSS based on IGS stations. Transactions of Nonferrous Metals Society of China, 24(2), 514-519. doi:10.1016/S1003-6326(14)63090-9
6. Bui, X.-N., Tran, V. A., Bui, L. K., Nguyen, Q. L., Le, T. T. H., & Ropesh, G. (2021). Mining-Induced Land Subsidence Detection by Persistent Scatterer InSAR and Sentinel-1: Application to Phugiao Quarries, Vietnam, Cham.
7. 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
8. Fan, S., Yan, J., & Sha, J. (2017). Innovation and economic growth in the mining industry: Evidence from China's listed companies. Resources Policy, 54, 25-42. doi:10.1016/j.resourpol.2017.08.007
9. Fleming, D. A., & Measham, T. G. (2014). Local job multipliers of mining. Resources Policy, 41, 9-15. doi:10.1016/j.resourpol.2014.02.005
10. 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
11. Hilson, G. (2002). Small-scale mining and its socio-economic impact in developing countries. Paper presented at the Natural resources forum.
12. Jing-xiang, G., & Hong, H. (2009). Advanced GNSS technology of mining deformation monitoring. Procedia Earth and Planetary Science, 1(1), 1081-1088. doi:10.1016/j.proeps.2009.09.166
13. Kim, T. T. H., Tran, H. H., Bui, L. K., & Lipecki, T. (2021). Mining-induced Land Subsidence Detected by Sentinel-1 SAR Images: An Example from the Historical Tadeusz Kościuszko Salt Mine at Wapno, Greater Poland Voivodeship, Poland. Inżynieria Mineralna, 48(2), 41-52. doi:10.29227/IM-2021-02-04
14. Knierzinger, J. (2014). The socio-political implications of bauxite mining in Guinea: A commodity chain perspective. The extractive industries and society, 1(1), 20-27. doi:10.1016/j.exis.2014.01.005
15. Lee, S., Park, I., & Choi, J.-K. (2012). Spatial Prediction of Ground Subsidence Susceptibility Using an Artificial Neural Network. Environmental Management, 49(2), 347-358. doi:10.1007/s00267-011-9766-5
16. 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
17. 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
18. 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
19. 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
20. 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
21. Nguyen, Q. L., Tran, V. A., & Bui, L. K. (2021). Determination of Ground Subsidence by Sentinel-1 SAR Data (2018-2020) over Binh Duong Quarries, Vietnam. VNU Journal of Science: Earth and Environmental Sciences, 37(2), 69-83. doi:10.25073/2588-1094/vnuees.4605
22. 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

23. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., . . . Dubourg, V. (2011). Scikit-learn: Machine learning in Python. the Journal of machine Learning research, 12, 2825-2830.

24. Rafie, M., & Samimi Namin, F. (2015). Prediction of subsidence risk by FMEA using artificial neural network and fuzzy inference system. International Journal of Mining Science and Technology, 25(4), 655-663. doi:10.1016/j.ijmst.2015.05.021

25. Todorović, R. T. (1993). Precise Levelling Network Adjustment in Mining Subsidence Regions, Berlin, Heidelberg.

26. 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

27. 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.