

A Comparison of Artificial Neural Networks and Exponential Function Methods for Predicting Surface Subsidence in Underground Mining Areas

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Abstract: *In mining activities, surface subsidence is an extremely important issue. Therefore, predicting surface subsidence is a necessary task to ensure the safety and efficiency of mining operations. This study aims to evaluate the prediction results obtained from the Artificial Neural Networks (ANN) and Exponential Function (EF) methods for predicting surface subsidence in underground mining areas. To achieve this objective, data from four observation points on the Quang Hanh mine surface were utilized for comparison with the prediction results. For both methods, data from the first 14 monitoring cycles were used as the training dataset to develop the prediction models, while the last 4 cycles were reserved for evaluating their accuracy. The results show the absolute errors of the ANN are determined to be small, within the range of 10 mm; while it is of 30 mm for EF method. Additionally, the ANN model demonstrated an accuracy improvement of approximately 10% over the EF method. These findings highlight the potential of the ANN model as a reliable and accurate tool for predicting surface subsidence in mining areas.*

Keywords: Subsidence prediction; underground mining; Artificial neural networks; Exponential function

1. Introduction

Underground mining has removed a substantial volume of soil and minerals from the earth, creating large space that disrupts the stress equilibrium within the ground. Under the influence of gravity, the overlying soil tends to shift to fill this space, establishing a new equilibrium state. This displacement propagates from the space through the soil layers to the surface, causing deformation of the rock mass and terrain surface (Knothe S., 2004; Mỹ, 2016; Popiolek. E & K, 1990), causing a dangerous threat to the natural and artificial structures on the surface. Globally, since the early 18th century, underground coal mining in several European countries such as Germany, Belgium, and France has had negative impacts on the natural environment and underground as well as surface structures, causing significant losses in terms of human lives and property (Reddish D.J & B.N, 2012). In Vietnam, damages due to surface deformation from mining activities have been quite common in both the past and present. Predicting the extent of surface subsidence due to mining is crucial for issuing early warnings to implement measures to mitigate economic and human losses caused by mining-induced subsidence.

To date, theories for predicting mine surface displacement and deformation are divided into three main approaches: based on geometric principles, continuous mechanical environments, and stochastic theory. Scientists worldwide have developed various prediction methods based on these theories, including mathematical functions describing the surface subsidence process (Reddish & Whittaker, 2012). One commonly used mathematical function is the exponential function. The subsidence prediction method based on the exponential function has been applied in many countries (Chen Lei, Ligu, Yixian, & Hong, 2018), including Vietnam (Long N.Q, V.C, & B.K, 2016). This method proves effective when monitored data is limited. Nowadays, with the advancement of geodetic equipment, the increasing amount of collected data necessitates the application of more modern prediction methods. With the development of computer science, artificial neural networks have been widely applied in many fields, including predictive science. Artificial neural networks can link and integrate different parameters to identify and predict various applications. The strength of artificial neural networks lies in their ability to make accurate predictions with complex data, even when the predictor lacks specific information and knowledge about the data's regularities. For such data, artificial neural networks offer high generalization capabilities in predictions and can predict nonlinear quantities. The prediction of subsidence due to underground mining using artificial neural networks has been conducted by many authors (Ambrožič Tomaž & Goran, 2003; Hejmanowski Ryszard & T., 2015; Ki-Dong Kim, Lee, & Oh, 2009; Kim Yangkyun, Min, Hyun-Koo, &

Seung-Ah, 2017; Lee Saro, Inhye, & Jong-Kuk, 2012; Long, 2016; Mahdevari Satar, Kourosh, Mostafa, & Dwayne, 2017; My V.C, Thanh, N.Q, & B.K, 2014; L. Q. Nguyen, Le, Nguyen, & Tran, 2023; Q. L. Nguyen, Nguyen, Tran, & Bui, 2021; Yao D.Y & J., 2002; Zhao Kang & Si-ni, 2011).

Compared to previously used subsidence prediction methods based on defined formulas and parameters, the subsidence prediction method using artificial neural networks is considered a parameter-free prediction method capable of predicting areas with special geological and topographical characteristics. This is a crucial issue to address in predicting displacement quantities due to mining activities. Predicting subsidence levels using artificial neural networks is a modern method that requires actual subsidence observation data from mining areas as input data for network training. This paper compares the subsidence prediction results due to underground coal mining using the exponential function and artificial neural networks, and proposes a neural network model suitable for underground mining conditions in Vietnam.

2. Methodology and Data

2.1. Exponential function

The exponential function can be used to describe the process of subsidence such that the subsidence value of points is defined by the equation (1) (Edward Popiolek & Gren, 1990):

$$\eta(t_i) = \eta_k(1 - e^{-ct_i}) \quad (1)$$

Where, η_k is total value of subsidence at t time, c is time parameter, it is time of i^{th} stage monitoring from the first stage. It can be seen that when $t = \infty$ then $\eta_{\infty} = \eta_k = \eta_{\text{max}}$.

If the number of observation stages is greater than or equal to 3, the parameters η_k and c can be determined by the least square principle. The error equation of observations can be written as follows:

$$V_i = \eta_k(1 - e^{-ct_i}) - \eta_{t_i} \quad (2)$$

If the subsidence values are observed with the same accuracy, the parameters, η_k and c are solved with the condition of least square $[VV] = \min$. The approximate value of $\eta_k(\eta_0)$ is assigned by subsidence value of the last monitoring stage, and the approximate value of $c(c_0)$ is assigned by 0.1.

The equation of error (2) expanded by linear transformation is expressed as (Chinh, 1997):

$$V_i = A_i.d\eta + B_i.dc - L_i \quad (3)$$

where,

$$\begin{aligned} A_i &= (1 - e^{-c_0 t_i}) \\ B_i &= \eta_0.t_i e^{-c_0 t_i} \\ L_i &= \eta_{t_i} - \eta_0(1 - e^{-c_0 t_i}) \end{aligned} \quad (4)$$

The error equation (3) can be expressed in matrix form as below:

$$V = A.X - L \quad (5)$$

where,

$$V = \begin{bmatrix} V_1 \\ V_2 \\ \dots \\ V_n \end{bmatrix} \quad A = \begin{bmatrix} A_1 & B_1 \\ A_2 & B_2 \\ \dots & \dots \\ A_n & B_n \end{bmatrix} \quad X = \begin{bmatrix} d\eta \\ dc \end{bmatrix} \quad L = \begin{bmatrix} L_1 \\ L_2 \\ \dots \\ L_n \end{bmatrix} \quad (6)$$

The system of normal equations is as follows:

$$A^T A X = A^T L \quad (7)$$

Solving the system of normal equations obtained vector X , the best probability values of η and c are calculated as below:

$$\begin{aligned} \eta &= \eta_0 + d\eta \\ c &= c_0 + dc \end{aligned} \quad (8)$$

The parameters η_k and c show the rule of subsidence process, the subsidence of points at the time $t_k = t_n + \Delta t$ can be predicted (t_n is the time at the last monitoring stage). Subsidence value at t_k is computed as follows:

$$\eta_{t_k} = \eta_k (1 - e^{-ct_k}) \quad (9)$$

2.2. Artificial Neural Networks

Artificial neural networks (ANNs) are one of the artificial intelligence tools used in surface subsidence prediction due to their ability to learn complex models with a large dataset, which can then make accurate predictions. In an ANN neural network, each layer consists of one or more neurons depending on the specific problem being studied as shown in Figure 1. The input layer consists of six neurons corresponding to the previous six settlement measurement cycles from $s(t-10)$ to $s(t-1)$, which are used to predict the settlement at time t (i.e. $s(t)$). The hidden layer consists of one or more layers, each layer has a number of hidden nodes. In this study, the optimal number of hidden layers, hidden nodes, and the number of iterations in the backpropagation process are determined experimentally through the k-fold cross-validation method.

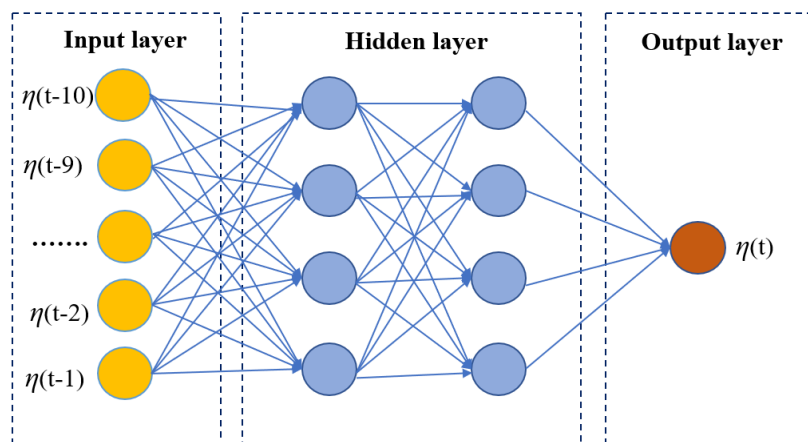


Fig. 1. The structure of an artificial neural network include an input layer, hidden layers, and an output layer.

Rys 1. Struktura sztucznej sieci neuronowej obejmuje warstwę wejściową, warstwy ukryte i warstwę wyjściową.

2.3. Artificial Neural Networks

A total of 18 settlement measurements were taken once per month, corresponding to a period of 1.5 years. With this number of measurements, the study divided the data set into a training set consisting of the first 14 measurements, and the remaining 4 measurements were selected as a test set (evaluation set). To train the model based on the training set, the previous 10 measurements were used as input and the following measurements were used as output as shown in Figure 2. This process is called recursive multi-step forecasting. Specifically, the first 10 months were used as input and the 11th month was used as output. Then, the time series was shifted forward by one step with months 2 to 11 used as input and month 12 as output. Similarly, months 3 to 12 are used as input to forecast month 13. Finally, months 4 to 13 are used as input to forecast month 14. Through this process, the backpropagation algorithm is applied based on the difference between the forecasted values and the measured values in months 11, 12, 13, and 14 (Figure 2). Blue are the periods used for training, orange are the forecast periods. The parameters of the trained model are then used to predict the subsidence in months 15, 16, 17, and 18. To do this, the values from months 5 to 14 are used to predict the subsidence of month 15. Then, the predicted value of month 15 is added to the time series to predict month 16. The same process is followed and finally, the subsidence of month 18 is predicted.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	2	3	4	5	6	7	8	9	10	11							
1	2	3	4	5	6	7	8	9	10	11	12						
1	2	3	4	5	6	7	8	9	10	11	12	13					
1	2	3	4	5	6	7	8	9	10	11	12	13	14				

Figure 2. Recursive multi-step prediction model

Rys 2. Rekurencyjny wieloetapowy model predykcji

2.4. Model Accuracy Evaluation

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

$$\text{Abs.Err}_i = \eta_i - \hat{\eta}_i \quad (10)$$

$$\text{Rel.Err}_i = \frac{\eta_i - \hat{\eta}_i}{\eta_i} \times 100\% \quad (11)$$

3. Results and Discussion

In this study, a total of four monitoring points (P1, P2, P3, P4) located in the Quang Hanh underground mine area were used to evaluate the proposed prediction model. As mentioned earlier, each point was measured with 18 cycles at a frequency of one cycle per month. Of which, the first 14 monitoring cycles were selected as the training data set to train the model, and the last 4 monitoring cycles were used as the test set to compare the actual data and the predicted subsidence data using the EF and ANN model. Table 1 shows the settlement measurements of the four monitoring points corresponding to the training set of the first 14 cycles.

Tab. 1. Training set consisting of subsidence values for the 14 months. (Unit: mm).

Cycles	Point P1	Point P2	Point P3	Point P4
1	0	0	0	0
2	-13	-8	-12	-6
3	-37	-25	-34	-17
4	-47	-51	-72	-29
5	-61	-67	-89	-33
6	-68	-91	-110	-48
7	-77	-105	-133	-63
8	-85	-123	-167	-86
9	-99	-164	-205	-107
10	-108	-196	-251	-140
11	-112	-210	-268	-149
12	-118	-225	-287	-160
13	-125	-238	-306	-173
14	-131	-258	-327	-181

The surface subsidence values of the last four cycles were predicted based on the parameters derived from the training dataset. The results are presented in Table 2 (Point P1), Table 3 (Point P2), Table 4 (Point P3) and Table 5 (Point P4). In each of these tables, the predicted values from the EF and ANN model were compared with the actual observed values, from which the absolute errors (Abs.Err), Formula 10, were calculated in millimeters (mm). In addition, the relative errors (Rel.Err), Formula 11, were calculated by dividing the absolute errors by the observed subsidence values and expressing the results as percentages (%). To further assess the reliability and accuracy of the models, the aggregated mean absolute deviations and errors were calculated for each monitoring point (P1–P4) and summarized in Table 6. For example, the absolute deviations between observed and predicted subsidence values for point P1 during the last four cycles (15, 16, 17, and 18) are shown in Table 2 and illustrated in Figure 7. It can be seen that this absolute errors of the EF model were consistently larger than the ANN method, ranging from 10mm to 13mm; while

this value ranges from 13 - 23mm, 18 - 20mm, and 12 - 13mm for points P2, P3, and P4, respectively. Across all monitoring points in the underground mine area, the absolute errors are determined to be small, within the range of less than 25mm. In addition, as shown in Table 6 and Figure 11, the average of absolute values of points P1, P2, P3, and P4 were 13.9, 23.5, 24.3, and 16.7mm for EF and correspond to ANN of 2.7, 6.7 5.4 and 4.4mm. These results demonstrate the superior accuracy and reliability of the ANN model, highlighting its effectiveness in forecasting surface subsidence in underground mining areas.

Similar to the absolute errors, the relative errors for each monitoring point are presented in Tables 2 to 5 and illustrated in Figures 12 to 15. At all points and cycles, the relative error remained below 10% for both methods. However, the ANN method consistently provided more accurate predictions than the EF method, with an improvement margin of approximately 10%. Further, the study results show that the larger gap between the forecast time and the time corresponding to the final observed value of the training set leads to larger errors. For instance, the relative errors at the 15th period of the four experimental points using ANN were 1, 1, 1, and 1%, which increased to 2, 2, 2, and 2% in the 16th period and increased to the highest at the last period 18 were 3, 4, 3, and 3% . This shows that the further the forecast cycle, the greater the error, and the lower the accuracy.

The results indicate that the subsidence values predicted by the ANN model closely align with the observed values, with a small difference of less than 10mm compared to the measured value; while it is 30mm for the EF. Furthermore, the relative value of the ANN is approximately accurate 10% than the EF method. These findings confirm that the artificial neural network (ANN) model employed in this study demonstrates high reliability and accuracy, making it a robust tool for predicting subsidence time series in mining areas.

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

Cycles	Measured values (mm)	Exponential function			Artificial Neural Networks		
		Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)	Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)
15	-140	-128	12	9	-138	2	1
16	-144	-129	15	10	-142	2	1
17	-147	-133	14	10	-144	3	2
18	-151	-136	15	10	-147	4	3

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

Cycles	Measured values (mm)	Exponential function			Artificial Neural Networks		
		Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)	Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)
15	-272	-256	16	6	-269	3	1
16	-276	-257	19	7	-270	6	2
17	-285	-256	29	10	-279	6	2
18	-290	-261	29	10	-279	11	4

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

Cycles	Measured values (mm)	Exponential function			Artificial Neural Networks		
		Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)	Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)
15	-342	-320	22	6	-338	4	1
16	-348	-325	23	7	-342	6	2
17	-353	-328	25	7	-347	6	2
18	-356	-328	28	8	-348	8	3

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

Cycles	Measured values (mm)	Exponential function			Artificial Neural Networks		
		Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)	Predicted values (mm)	Abs.Err (mm)	Rel.Err (%)
15	-186	-171	15	8	-184	2	1
16	-188	-172	16	9	-184	4	2
17	-190	-173	17	9	-185	5	3
18	-192	-174	18	9	-348	6	3

Tab. 6. The average absolute value of four points and their errors

Point	Exponential function		Artificial Neural Networks	
	Abs.Err (mm)	Rel.Err (%)	Abs.Err (mm)	Rel.Err (%)
P1	13.9	1.3	2.7	0.8
P2	23.5	6.6	6.7	3.4
P3	24.3	2.5	5.8	1.6
P4	16.7	1.3	4.4	1.7

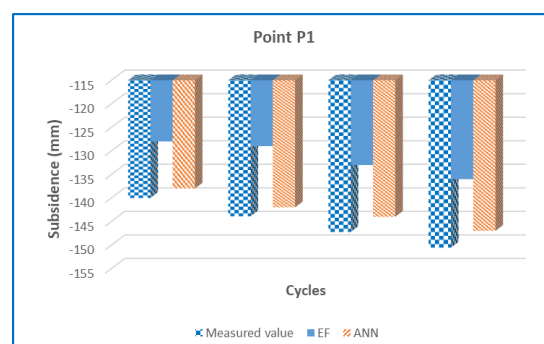
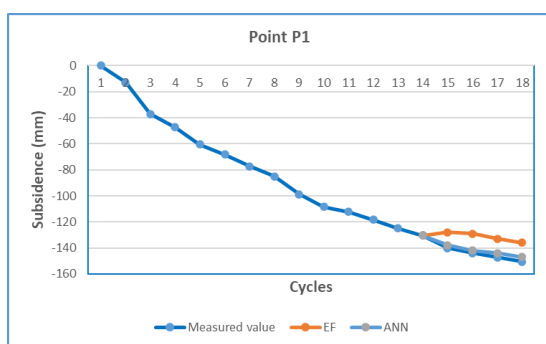


Fig. 3. Comparison results of observed settlement curve and predicted value at point P1

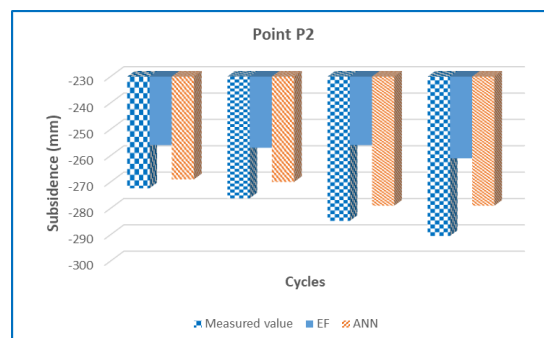
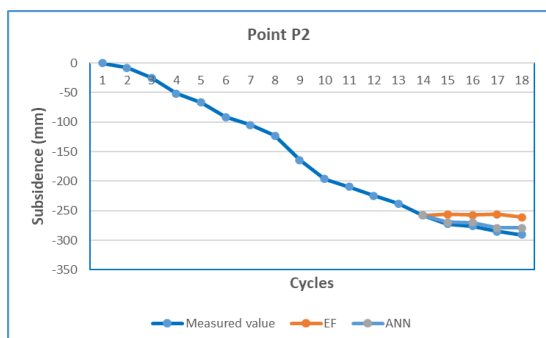


Fig. 4. Comparison results of observed settlement curve and predicted value at point P2

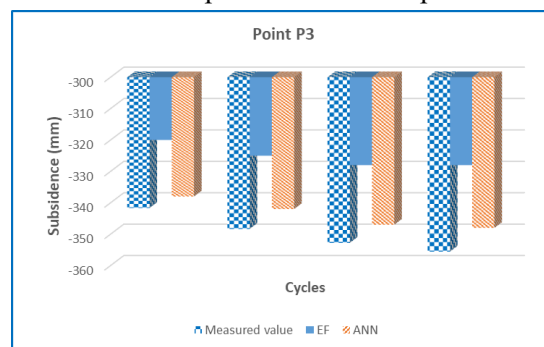
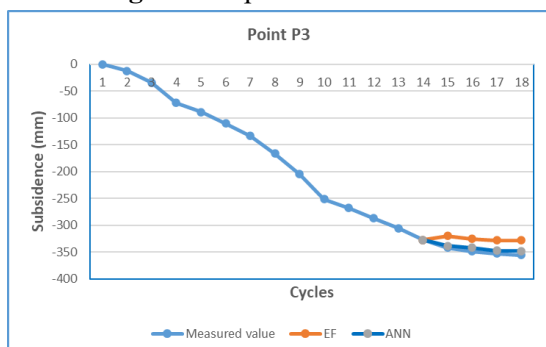


Fig. 5. Comparison results of observed settlement curve and predicted value at point P3

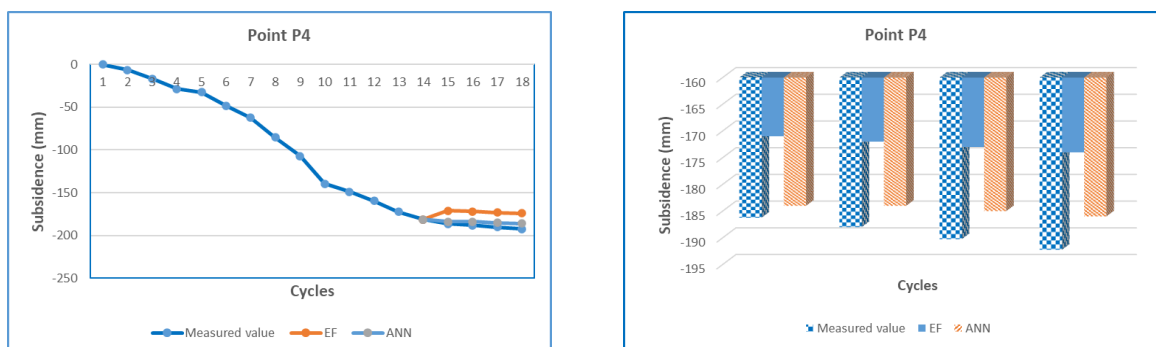


Fig. 6. Comparison results of observed settlement curve and predicted value at point P4

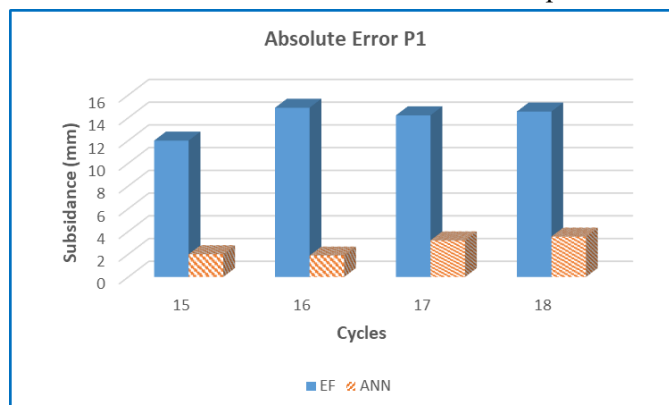


Fig.7. The absolute value results between observations and forecast values at point P1

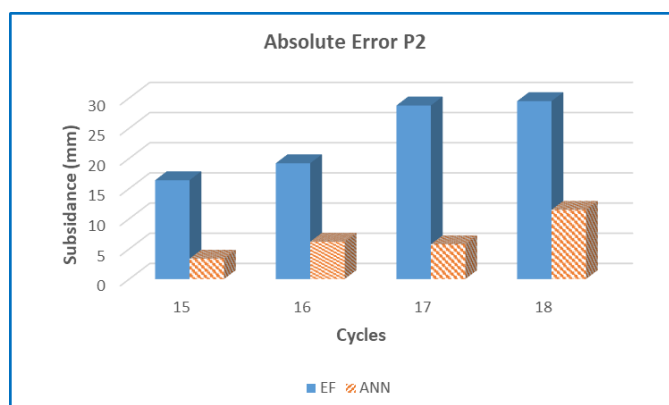


Fig. 8. The absolute value results between observations and forecast values at point P2

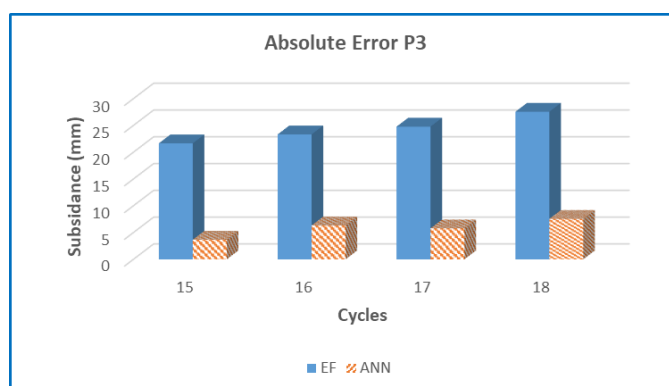


Fig. 9. The absolute value results between observations and forecast values at point P3

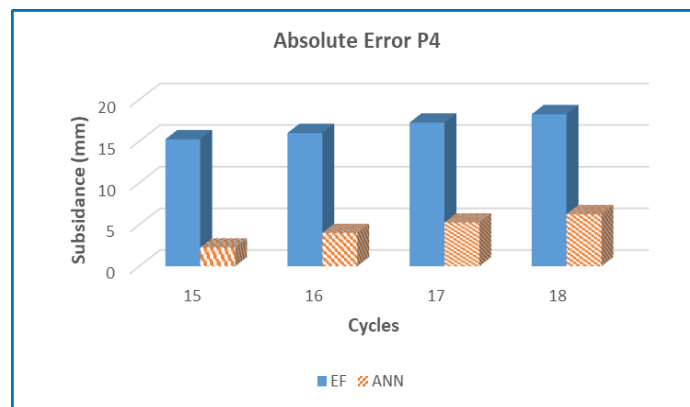


Fig. 10. The absolute value results between observations and forecast values at point P4

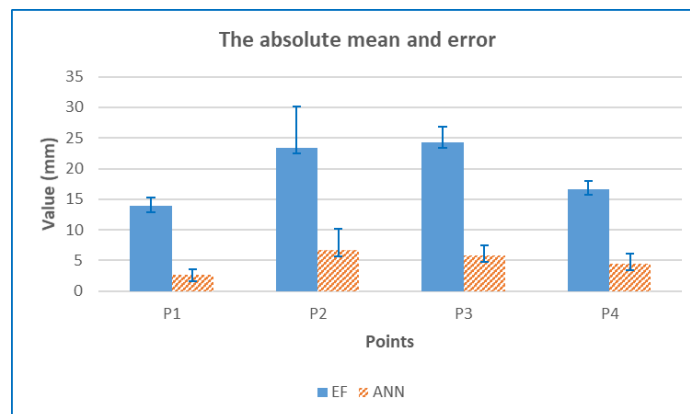


Fig. 11. The absolute mean of all monitoring points and their errors

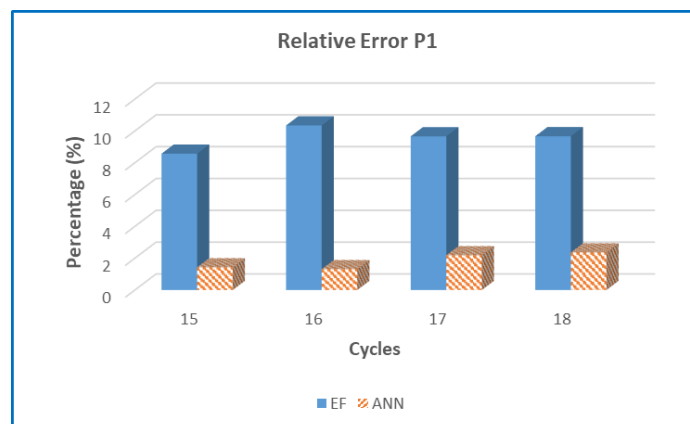


Fig. 12. The relative value is calculated as a percentage (%) of forecast points P1

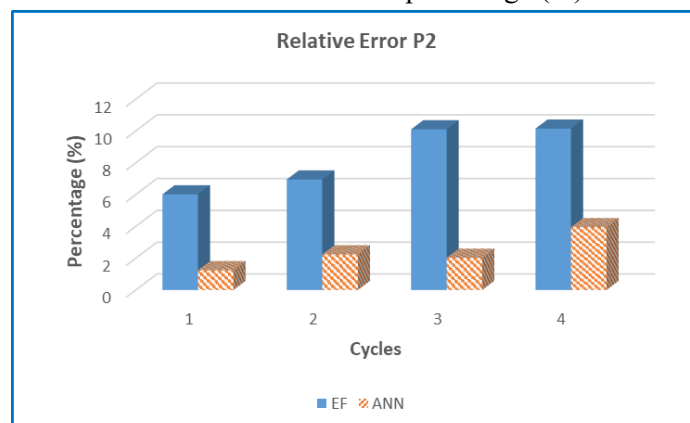


Fig. 13. The relative value is calculated as a percentage (%) of forecast points P2

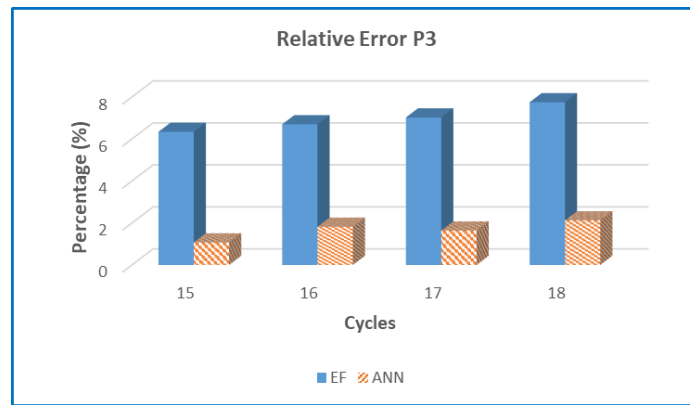


Fig. 14. The relative value is calculated as a percentage (%) of forecast points P3

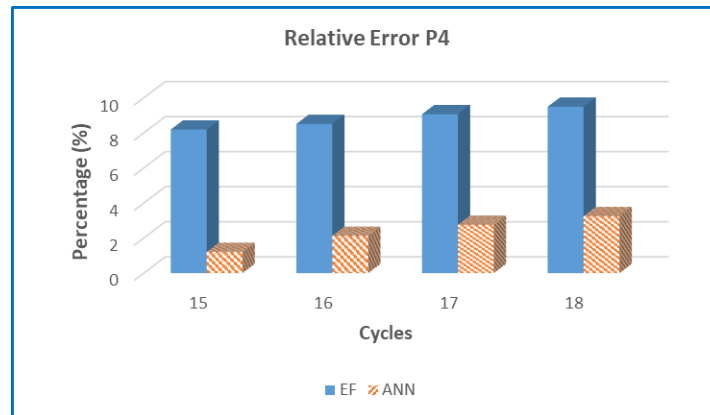


Fig. 15. The relative value is calculated as a percentage (%) of forecast points P4

5. Conclusion

In recent years, the global energy demand has increased rapidly, along with the exploitation of underground minerals such as coal, mines, oil and gas, etc., which playing an important role in the energy supply. However, the extraction of these natural resources always faces many challenges and risks; therefore, the forecasting of surface subsidence due to underground mining is a critical task. While traditional forecasting methods have been widely used, it is necessary to study new theories and methods applying modern scientific and technological products such as artificial intelligence (AI) to enhance forecasting accuracy and efficiency. This study employs the Artificial Neural Networks (ANN) and Exponential Function (EF) method to predict surface subsidence due to underground mining at Quang Hanh mine. A recursive multi-step forecasting process was implemented; in which the first 14 cycles were used as input data to train the network model and the last 4 cycles were used to assess the accuracy of the subsidence of points.

The results demonstrate that the ANN model proposed in this study is a more effective tool for predicting surface subsidence caused by underground mining compared to the EF method, as evidenced by both absolute and relative errors. The difference between the observed and predicted subsidence values using the ANN model is minimal, remaining under 10 mm, whereas the EF method exhibits a larger error of approximately 30 mm. Additionally, the ANN model achieves a relative accuracy improvement of about 10% over the EF method. It is also observed that the relative error is influenced by the time interval between the forecasted cycle and the final measurement in the training dataset. As the forecasted cycle extends further from the training data, prediction accuracy decreases.

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