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Research Article

Application of artificial neural network with fine–tuning parameters for forecasting PM2.5 in deep open–pit mines: A case study

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Abstract: In this paper, an artificial neural network (ANN) model was applied to forecast PM2.5 at the Coc Sau open–pit coal mine (Northern Vietnam) with fine–tuning parameters. It aims to provide the feasibility and insights into controlling air quality in open–pit mines using artificial intelligence techniques. Accordingly, an air quality monitoring system was established to monitor hourly PM2.5 datasets for more than three months. Subsequently, 80% of the whole data was used to design and tune the ANN model, and the remaining 20% was used for testing the PM2.5 predictions. An ANN model with a single hidden layer and ten nodes was developed for this aim. The stochastic gradient descent algorithm was applied to train the ANN model under the learning rate of 0.001 to avoid the overfitting of the model. In addition, 10 time steps (multi–step forecasting model) were applied to forecast the next time step. The results indicated that ANN is a potential model for forecasting PM2.5 in open–pit mines with high accuracy (RMSE = 2.000), and it can be used to control real–time air quality in open–pit mines.

Keywords: Open–pit mine; Air quality controlling system; PM2.5; Artificial neural network; Multi–variate multi–step time series forecasting.

1. Introduction

Surface mining is one of the most popular methods for mineral exploitation; however, its side effects on the surrounding environment are significant. Of the side effects, dust is considered one of the significant concerns in open–pit mines, and it can spread from the surface of open–pit mines to the surrounding areas [1–2]. From the environmental point of view, particular matter (PM) of dust in the atmosphere is an important factor in evaluating the size of dust, as well as its dangerous levels for human health, particularly in the workers in mine sites [3–4]. Of those, PM2.5 is considered more dangerous than PM10 due to its size and the ability to enter the human body, primarily through inhalation [5]. Therefore, this study considered PM2.5 in open–pit mines as the main objective, and the feasibility of artificial neural network (ANN) will be discovered to forecast PM2.5 in open pit mine.

Review of related works shows that artificial intelligence (AI) techniques have been widely applied to forecast air quality and different PM, especially PM2.5. However, studies with the applications of AI for forecasting PM2.5 in door and out door are popular, but in open–pit mines is very rare. For instance, [6] applied a machine learning model, namely gradient boosting machine (GBM) associated with particle swarm optimization (PSO) to forecast PM2.5 in an open–pit mine with different scenarios. Average accuracy of 0.954 was indicated in their study with the proposed PSO–GBM model. [7] also applied a deep learning algorithm, namely long short–term memory (LSTM) neural network–attention for forecasting PM2.5, and it was then compared to the autoregressive integrated moving average (ARIMA) model. Their results showed that the LSTM–attention model could forecast PM2.5 with better accuracy (from 3–5.6%).

In this study, we tried to discover the feasibility of ANN in forecasting PM2.5 at an open–pit coal mine in Vietnam. The structure of the ANN, as well as its performance, will be diagnosed in this study to interpret whether it is suitable for forecasting and controlling air quality in open–pit mines in Vietnam. It is worth mentioning that the ANN model is developed as the second phase based on the dataset monitored by an air quality monitoring system that was developed by our research group (Innovations for Sustainable and Responsible Mining – ISRM), and they are considered a completed air quality controlling system in open–pit mine.

2. Background of ANN

In this study, ANN is considered and fine–tuned to forecast PM2.5 in deep open–pit mines. The applications of AI in general and ANN have been introduced and developed over the last decade [8–10]. ANN simulates the relationship between input and output variables and recognizes a biological brain function to solve complicated problems in nature [11]. Accordingly, complex non–linear problems can be recognized by the human brain through the input–output mapping in a short time. For simplicity, the computation speed of ANN can be divided into three simplified layers. The first layer is on a mission to gather information, either through observation or other components. They are then transferred to the neurons in the network (the second layer), and herein, they are analyzed and computed. Activation functions may be applied to transfer the information, and finally, in the last layer, the output is computed/ forecasted.

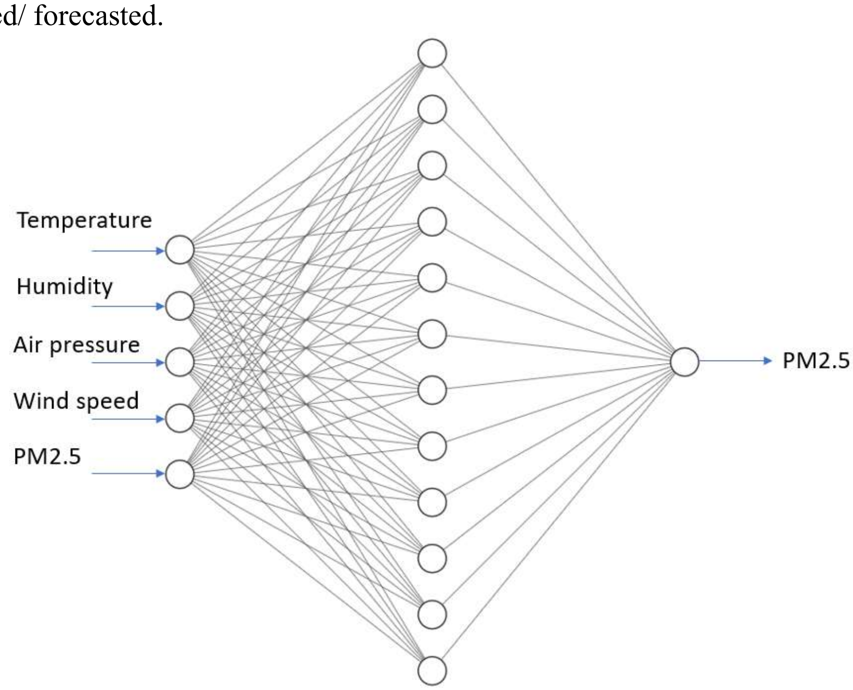

Figure 1. Architecture of the ANN model for forecasting PM2.5.

ANN applies the same logic to these layers. The first layer of the human brain is called the input layer in ANN with the same functions. They can be entered by human from the gathered information. Depending on each problem, the number of dimensions of the dataset may be different. It also depends on the difficulties of the data collection. Once the inputs are entered, they are transferred to the hidden layer (the second layer) to simulate the relationships between inputs and output. Similar to the human brain, ANN can consist of multiple hidden layers. In each hidden layer, a number of neurons (nodes) are designed for the computational functions. Finally, the desired variable based on the analyzed relationships will be predicted. Herein, ANN is used to forecast PM2.5 at an open–pit mine, and its structure is shown in Figure 1.

3. Application

As introduced above, this study intends to apply the ANN model to forecast PM2.5 and evaluate the air quality in open–pit mines. In the application field, a case study will be performed for this aim and the details are presented in the three sub–sections: data collection, design the topology network, and training the model.

3.1. Data collection

For forecasting PM2.5 in deep open–pit mines, the Coc Sau open–pit coal mine (Vietnam) was selected as a case study with a depth of –300 m (below sea level). It is worth noting that the air quality of the bottom is pretty bad at such depth. To collect the dataset, an air quality monitoring system based on the internet of things was designed and developed by the Innovations for Sustainable and Responsible Mining (ISRM) Research Group of the Hanoi University of Mining and Geology (HUMG). This system can monitor nineteen parameters using intelligent sensors and a wind measuring system, including air quality parameters and meteorological conditions. Many researchers indicated that meteorological conditions have significant effects on air quality index [12–14]. They are therefore used to forecast PM2.5 in this study. However, in this study, only five parameters were used for forecasting PM2.5, including temperature (T), humidity (H), air pressure (P), wind speed (WS) and PM2.5, and it is a multivariate dataset. This data represents a multivariate time series of PM2.5–related variables, that in turn could be used to model and even forecast future PM2.5 in open–pit mines. For this aim, the parameters were measured hourly from September 16 to October 28, 2020. Finally, a total of 1011 samples were recorded and compiled as the multi–variate dataset for forecasting hourly PM2.5. It is worth noting that the dataset measured using this monitoring system is the time series dataset and they are hourly observations. The dataset is visualized in Figure 2.

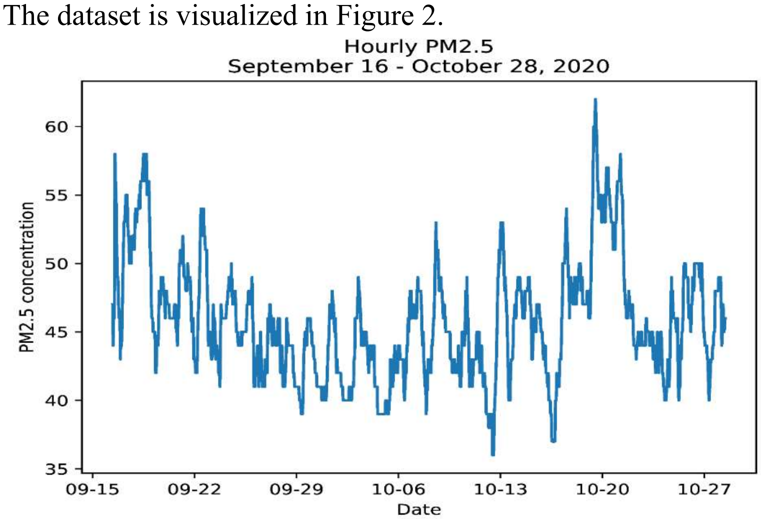

Figure 2. Timeseries dataset of the PM2.5 at the Coc Sau open–pit coal mine.

3.2. Design topology network

Prior to training the ANN model for forecasting PM2.5, a topology network was designed, including the number of hidden layers and the number of hidden nodes. Accordingly, a trial and error procedure was deployed with a different number of hidden layers and nodes through the MSE, which was used as the objective function. The dataset was normalized using the MinMax scaling method and the stochastic gradient descent (SGD) algorithm was used to train the ANN model with different topology networks, as shown in Figures 3 and 4. Please be noted that, due to the stochastic mechanism of the SGD algorithm, the results may be different with different runs.

Analyzing the performance of the ANN model with a different number of hidden layers, we can see that the best number of hidden layers is five hidden layers. However, the performances between different numbers of hidden layers are not too dissimilar. Furthermore, many researchers recommended that the ANN model with a single hidden layer can solve and model most problems [15–16]. Therefore, for simplicity, we selected the topology network with one hidden layer to improve the computational cost.

For the selection of the number of hidden nodes (Figure 4), it is clear that the ANN model with 15 hidden nodes provided the lowest MSE, and therefore, it was selected as the best unit of the ANN model. In other words, the ANN model with the structure of a single hidden layer and 15 nodes was selected for forecasting PM2.5 in this study.

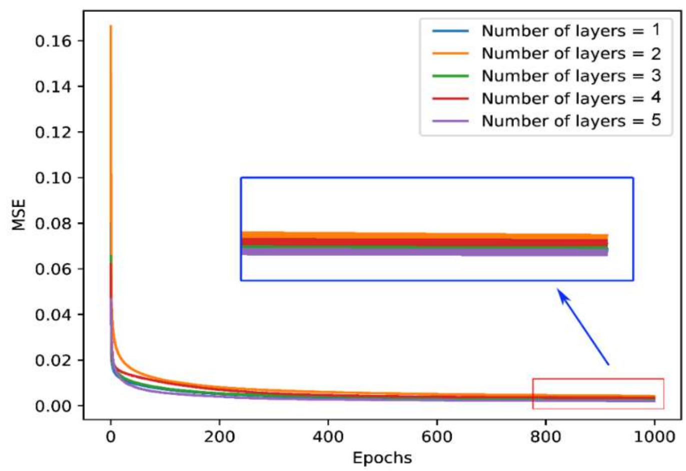

Figure 3. Selection of the optimal number of hidden layers for the ANN model.

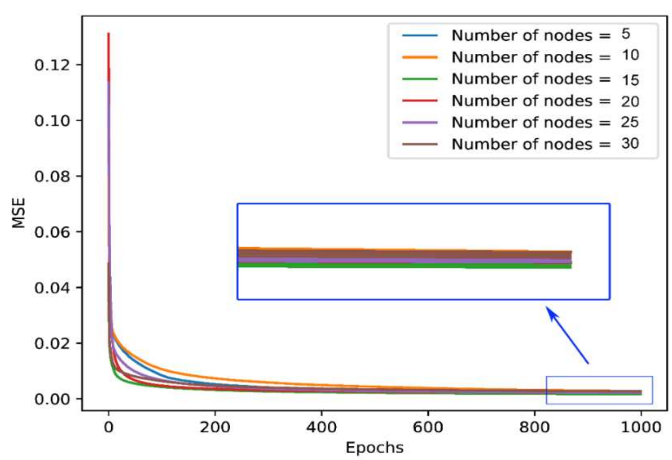

Figure 4. Selection of the optimal number of hidden nodes for the ANN model.

3.3. Training the model

Once the structure of the ANN model was defined, the SGD algorithm with the learning rate of 0.001 was applied to train the ANN model for forecasting PM2.5. The Minmax scaling method was applied to normalize the attributes in the range of 0 to 1. Besides, the selection of the learning rate of 0.001 is to avoid overfitting of the ANN model, and it was determined using the trial and error procedure, as well. It should be noted that 80% of the whole dataset was selected for this task, as shown in Figure 5.

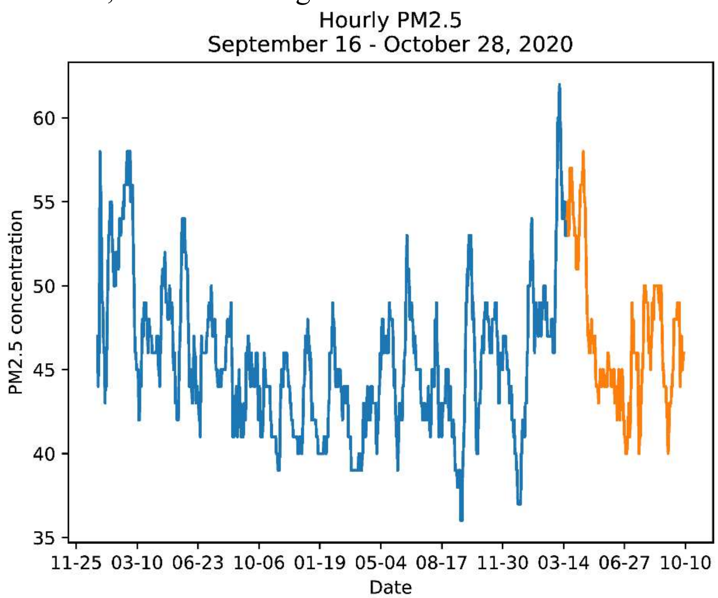

Fig. 5. Splitting dataset for training and testing the model (training dataset – blue line; testing dataset – orange line).

During training the model, to ensure the model's convergence, the training process was implemented with 1000 epochs through the loss function (i.e., MSE). In this study, multi–step time series forecasting model was used to forecast PM2.5 in the future. To do so, the number of time steps were selected as 10 to forcast the next time step. In other words, t–1, t–2, t–3, t–4, t–5, t–6, t–7, t–8, t–9, t–10 values were used to forecast the t value. The training results of the ANN model for forecasting PM2.5 are shown in Figure 6.

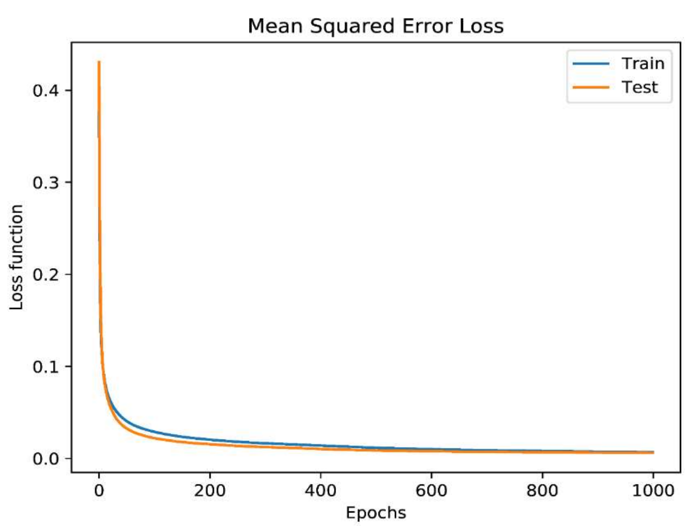

Figure 6. Training performance of the ANN model for forecasting PM2.5.

4. Results and discussion

As depicted in Figure 5, it is conspicuous that the performance curves are excellent, and the model has no overfitting. In other words, the training and testing performances are high convergence with very low lost function values, and the trained ANN model is feasible for forecasting PM2.5 at the Coc Sau open–pit mine.

Once the ANN was well–trained, it was applied to forecast PM2.5 in the testing dataset (out–of–samples) to check the model's goodness. It is worth mentioning that the out–of–samples have not been used before during training the model, as illustrated by the orange line in Figure 5. This step aims at providing the forecast results of PM2.5 in the future (e.g., next hours – hourly PM2.5) by the developed ANN model. The results are shown in Figure 7.

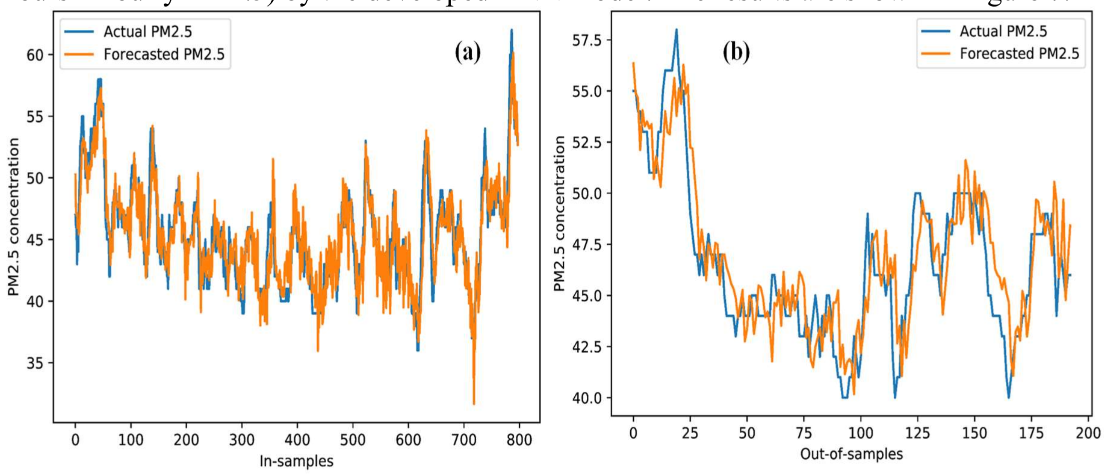

Figure 7. Comparison of the actual and forecasted PM2.5 by the trained ANN model (a) Training dataset; (b) Testing dataset.

As compared between the actual and forecasted PM2.5 values in Figure 7, we can see that the developed ANN model worked very well in both the in–samples and out–of–samples. The trends and forecasted values are pretty close to the actual values, even though at several peak points. On the other hand, it seems that the performance on the training dataset is slightly better than the performance on the testing dataset. Therefore, statistical metrics and regression analysis are necessary to evaluate whether the model is overfitted. Herein, the root mean squared error (RMSE) and mean absolute percentage error (MAPE) were used to consider the error of the model, as calculated using equations (1) and (2). In addition, the correlation analysis is performed in Figure 8 to show how the forecasted PM2.5 is far from the actual PM2.5.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)}{n}} \tag{1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{2}$$

where y_i is the actual PM2.5; $\hat{y}_i$ is the forecasted PM2.5, and n denotes the number of samples.

Based on the calculations using equations (1) and (2), the accuracy of the ANN model obtained an RMSE of 2.152 and MAPE of 0.037 on the training dataset. Meanwhile, they are 2.000 and 0.035 for the RMSE and MAPE on the testing dataset, respectively. With these statistical metrics, we can claim that the developed ANN model has not been overfitted. In contrast, its accuracy is very good, with a MAPE of 0.037 only on the training dataset and 0.035 on the testing dataset.

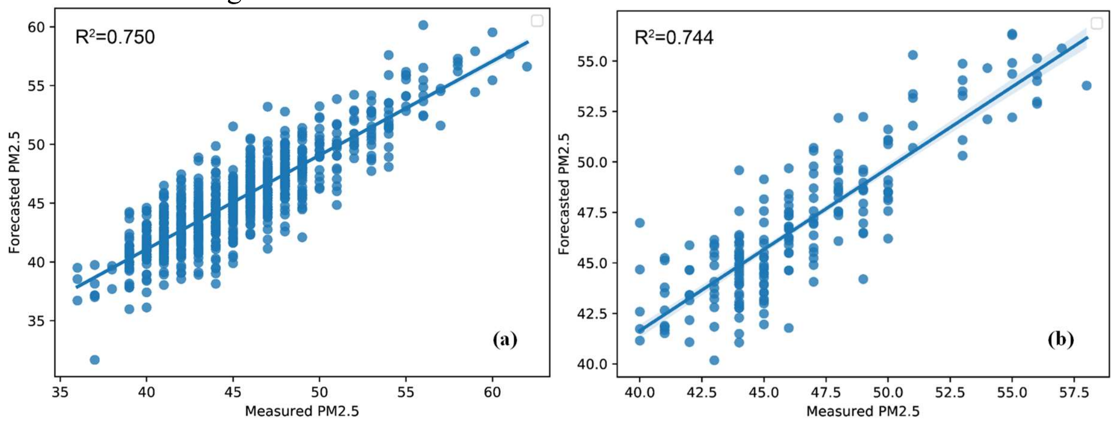

Figure 8. Regression analysis of the forecasted PM2.5 by the ANN model: (a) Training dataset; (b) Testing dataset.

Furthermore, the regression analysis in Figure 8 showed that the dataset used is equivalent suitable to the developed ANN model, although its determination coefficient (R^2) is only 0.75 and 0.744 on the training and testing datasets, respectively. Nonetheless, R^2 is rarely used to evaluate the accuracy of a time–series model [17]. Thus, RMSE, MAPE, and comparison in Figure 7, as well as the curves performance in Figure 6, are conspicuously enough to conclude that the developed ANN model is a good candidate for forecasting PM2.5 in open–pit mines, especially at the Coc Sau open–pit coal mine, as analyzed and discussed in this study.

5. Conclusion

This study discovered the feasibility of the ANN model for forecasting PM2.5 in deep open–pit mines under the consideration of meteorological conditions. The obtained results indicated that ANN is a good approach for forecasting PM2.5 in open–pit mines. By the use of the monitoring system combined with the ANN model, engineers can control the air quality in general, and especially PM2.5 in open–pit mines.

Despite this, further studies in the future are still needed to provide more detailed arguments for the application of AI models to forecast air quality in open–pit mines, as well as improve their accuracy.

Author contribution statement: X.N.B., H.N.: Conceptualization; Investigation; Resources; Writing - Original Draft, Writing - Review & Editing; Q.T.L., T.Q.H.: Formal analysis; Writing - Original Draft; Visualization.

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Competing interest statement: The authors declare no conflict of interest.

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