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A NEW APPROACH ON AI APPLICATION FOR GROUNDING RESISTOR PREDICTION IN UNDERGROUND MINES OF VIETNAM

Purpose. To apply artificial intelligence (AI) technology for predicting the earthing resistor of underground mines with consideration of climate change parameters.

Methodology. In underground coal mines of Vietnam, the earthing system are everywhere equipped with individual rods combined with centralized grounding bed; this system significantly influences electrical safety and explosion safety. In daily operation, the resistor of the earthing system must be measured and tested regularly to ensure their value lower than the allowance limit (2Ω). However, because of being affected by climate parameters (humidity and temperature in mines) this value varies frequently. By applying a new Neural Network with 3 hidden layers including variable parameters, the paper presents a new approach on predicting the earthing resistor. An algorithm is formed with visible and easily usable software for assisting the operator to predict the resistor. The prediction could be used for onsite management of a mine operator in the field of observing and testifying the earthing system in underground mines.

Findings. Software is developed based on AI technology for assisting the operator to predict the value of the earthing resistor corresponding to climate change.

Originality. Neural network with AI technology application is utilized relying on onsite measurements.

Practical value. Prediction results could be used in case of difficulty in measurement. It will also help to correct or eliminate the measurement error from a mining technician.

Keywords: 660 V grid, Ai technology, earthing system, neuron network, underground mines

Introduction about earthing system in Vietnam underground mines. In recent years, in Vietnam underground mines, the rated voltage in underground mines has been increased from 380 to 660 and 1,140 V [1]. Besides the advantages of reducing power losses, increasing the productivity, this rise in nominal voltage will bring the threat of unsafety conditions to electricians who normally operate with electric equipment. To ensure the safety of mining technician in underground mines, earthing systems including earthing electrodes, conductors and earthing beds are installed in all mining areas. This system brings in intimate contact with the soil to obtain a reliable electrical connection to the earth. For lowering the value of the system, its electrodes and conductors should normally be installed in damp locations, for example, along drainage ditches, sumps. Generally, a low overall earth resistance is attained by providing a general underground earthing circuit, for which the steel armor and lead sheaths of all the armored cables are electrically connected to each other and also to main earthing electrodes and conductors installed in a sump or water-drainage basin.

In underground mining, operators of transportable and self-propelled machinery are in constant contact with their frames and enclosures. Hence, close attention must be paid to their earthing, because the danger of electric shock is especially high when the earthing is defective. For earthing motors and transformers, the following guidance must be followed: motors are earthed by connecting the lead from the earthing circuit to the bolt specially provided on the frame for this purpose. Transformers are earthed with an earth lead clamped to

the armor of the high-voltage supply cable at one end, and to the earthing bolt on the transformer enclosure at the other. This bolt also receives the second earth lead connected to the armor of the outgoing cable in the same way as on the supply cable [2–4].

Safety regulations require that the total earth resistance of the underground earthing circuit should not exceed 2 ohms as measured at the furthestmost point. The higher the earth resistance is, the poorer its protective action appears when a breakdown occurs in the insulation of a machine or apparatus. As the earth resistance depends on many factors, especially the moisture content of the soil, it must be measured regularly and at intervals not greater than one month [5]. The measurement device which is most extensively utilized is MS07 earth tester presented in Fig. 1.

This instrument (tester) has a voltage coil connected across the supply terminals and a current coil connected in series with the resistance to be measured. Therefore, it could measure resistance by the fall-of-potential (voltmeter-ammeter) method. With the coils connected like that, the pointer deflection is proportional to the resistance being measured. The tester voltage is provided by the hand-operated d.c. generator built into the instrument. To take the measurement, terminals E_1 and I_1 are made common and connected to the earth connection under test. Terminal E_2 is connected to the probe rod and terminal I_2 to an auxiliary earth rod. The probe and auxiliary rods may be steel bars or pipes driven into moistened ground to a depth more than 0.5 m.

Because of importance of earthing system [6–8] many research works stated that “a properly designed grounding system capable of dissipating large currents safety into earth is

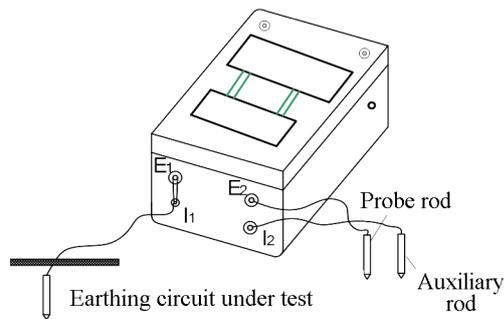


Fig. 1. Connections of earth tester MS 07 for verifying earthing resistor

required, regardless of earth fault types”. In order to be effective, the grounding system itself must be maintained with a low or very low value of resistance in all its long-life time [9, 10]. Moreover, in 660 V mining grid this system consisting of horizontal bar conductors interconnected with 4th wire (or rod) of transmission cables is aimed to minimize ground potential rise as small/low as possible [11]. If the value of system is small enough, the personnel could not be exposed to the death of electrical shock. In underground coal mines, the allowance limit of touching voltage is 36 V, the allowance current is 18 A, hence the allowance resistance of the whole earthing/grounding system is 36 V/18 A or 2Ω. Designing a proper earthing system in underground mines, electric system bases must rely on how to get a number of thresholds: mesh voltage, stepping voltage, touching voltage, ground potential rise.

In estimating the resistance of grounding system, many variable factors are taken into account such as:

1. Group of factors that impact earth resistivity: soil resistivity, soil condition, moisture, dissolved salts, climate conditions, physical composition.
2. Group of factors that influence structure and type of electrical earthing, for instance: plate earthing, pipe earthing, rod earthing, strip or wire earthing of combination of types of above earthing.
3. Group of enhancement materials used for improving the conductivity of ground that the earthing system is buried.

Because of containing many unpredicted factors, many new and model technologies have been applied to analyze and model the grounding resistance of system with considerations of seasonal inputs. One of very effective methods is artificial neural network (ANN) which is based on deep learning. At present a method is developed utilizing ANN methodology to estimate and predict ground resistance independently from soil resistivity measurement [12].

Amaral, et al. [13] attempted to correlate soil resistivity, injection current frequency and peak current with ground resistance value. While Gouda, et al. [14] developed an ANN for grounding system design which consisted of vertical rods. Other studies implemented by He, et al. [15], Asimakopoulou, et al. [16, 17], Anbazhagan [18] have estimated the varying of grounding rods installed in different kinds of natural soil at variety of locations. Those research works proved the effectiveness as well as the advantages of the ANN technology on predicting the value of grounding resistance despite unpredictable characteristics of input calculation data.

The paper introduces a new approach to applying AI technology with a new algorithm based on “Adam optimizer” for predicting earthing resistance in underground coal mines. The training data come from Vietnam with consideration of climate change and local geology characteristics in underground mines. The output results are recommended for operators in underground coal mines for improving the efficiency of the earthing system.

Lab measurements and onsite measurements for getting data to be trained in ANN. Lab measurements. To input the

training procedure of neural network, the following data are injected as input data: the humidity in the mines; the temperature in the mines; the length of local earthing rods (that the metal frame of each motor is wired to). The system installed in mines is very different from ones equipped for building and domestic devices. Each motor normally has an individual rod for earthing, and all of these rods are not buried 0.5 to 0.8 m under the ground. They usually have a 20 cm spare length above the ground for being easily connected to the motor frame. All of them are interconnected to the central earthing system, which has electrical interlocking with leakage relay setup at the main transformer substation of the mining area. Lab devices for measurement of these individual earthing rods are shown in Figs. 2, 3.

Some typical results of implementing the measurement with the variable parameters: humidity, the length of rod, temperature, are shown in Table 1.

The data in Table 1 is simulated according to the real conditions in underground coal mines of Vietnam. It can be seen in the table that the variation of humidity is only from 89 to 93 % and temperature is in the range of 24 to 28 °C (very similar to the environment of long-wall coal mines where the mining activities occurred). The measured value of the whole earthing system is implemented with 3 different lengths of earthing rod (1, 1.2 and 1.5 m). The output measurements showed that all the results are in the range of allowance limits required by the Vietnamese law [2–4].

Onsite measurements for determining the earthing resistance of the grounding system. The precision of the proposed AI model (prediction model) significantly relies of the number of input data. The paper relies on the values of over 800 training



Fig. 2. Lab setup of devices for earthing resistance measurement with two motors which are wired to earth



Fig. 3. Individual earthing rod that is wired to the motor frame with 20 cm spare length for easy installation

Table 1

Lab measurement results of individual earthing rod

Length of rod, m	Humidity, %			Temperature, °C				
	93	90	89	24	25	26	27	28
1.0	1.9	1.9	1.89	1.87	1.87	1.86	1.86	1.85
1.2	1.81	1.8	1.8	1.84	1.78	1.78	1.76	1.74
1.5	1.76	1.77	1.78	1.83	1.76	1.75	1.73	1.73

data items, 24 testing values in table 1 utilized to test. The on-site measurements are implemented corresponding to various climate change factors in underground mines (humidifies, temperature and the length of grounding rods). Some of them are shown in Table 2.

In Table 2 R1 and R2 are the resistances of individual rods which are measured separately; R is the resistance value of the whole grounding system.

Proposed algorithm for artificial neural network (ANN) to predict the earthing system. *Proposed Algorithm.* The ANNs are vigorous implements for the presaging and simulation in sundry engineering application [18]. In this research, ANN model is developed with data from humidity, temperature for electrodes with length of 1, 1.2 and 1.5 m. The model of ANN is presented in Fig. 4. It is mainly based on the proposed algorithm shown in Fig. 5. An optimizer combined with programming in Python is implemented and expressed in Fig. 6.

Like other ANN techniques shown in previous research [19–21], the model, first, calculates the weight vector for each pair of in-out vectors from training set. Then it calculates the difference between input and predictive value (calculates loss and accuracy). A comparison is implemented to send the value to optimizer or not. The loop is repeated until it is over the maximum allowance setting. By utilizing 3 hidden layers, the ANN is considered significantly to predict the value of earthing resistance. The following parts will demonstrate the accuracy of the model.

Table 2

Sample data for AI model training

T, °C	Humidity, %	L pile, m	R _{measured} , Ω	R1, Ω	R2, Ω
27	89	1.5	1.60	47	41
27	89	1.5	1.55	50	35
28	89	1.5	1.58	47	40
26	90	1.5	1.55	49	38
28	90	1.5	1.51	48	37
27	90	1.5	1.43	45	35
27	90	1.5	1.58	47	36
27	90	1.5	1.59	56	39
27	90	1.5	1.58	46	40
28	90	1.5	1.50	45	40
28	90	1.5	1.55	49	39
28	90	1.5	1.44	47	40
27	90	1.5	1.56	48	39
27	91	1.5	1.37	44	41
27	91	1.5	1.58	48	44
26	91	1.5	1.48	50	41
28	91	1.5	1.42	48	40
28	91	1.5	1.51	47	41
28	91	1.5	1.57	47	39

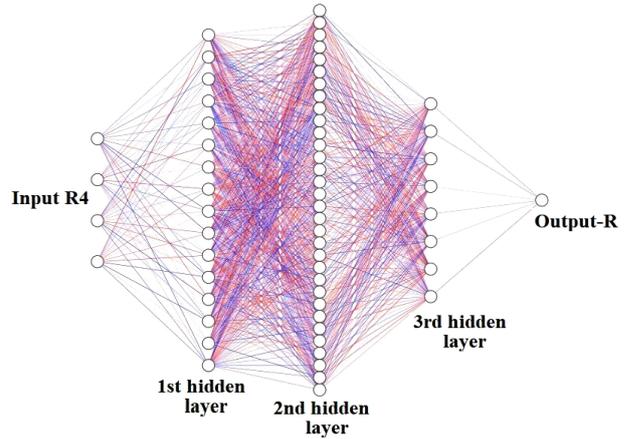


Fig. 4. Implementation of ANN for climate variation to predict the value of the earthing system

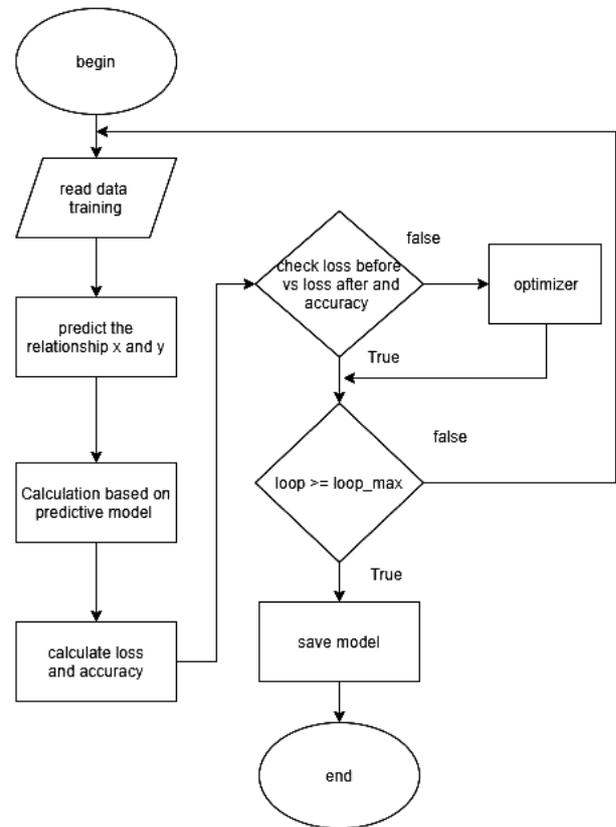


Fig. 5. Proposed algorithm for predicting the earthing value of the grounding system

Fig. 5 shows the block diagram of procedure to predict earthing value based on over 2 thousand training data. Optimizer used in this Algorithm is Adam – the one that has the following advantages [22]:

- it is sufficient computationally;
- a small amount of memory space is required;
- solving well both the problems with noisy or sparse gradients and big data sets with large parameters;
- easy to be implemented.

Moreover, the proposed algorithm could calculate loss and accuracy to measure the require accuracy according to the need of a user. With Adam optimizer the algorithm could “significantly optimize the models better than regular gradient descent or stochastic gradient descent”, the user can “reduce the cost function and produce useful models”.

```

1 from keras.models import load_model
2 from keras.layers import Dense
3 from numpy import loadtxt
4 from keras import Sequential
5 from sklearn.model_selection import train_test_split
6 import numpy
7 import csv
8 dataset = loadtxt('data2.csv', delimiter=',')
9 model = load_model('test1.h5')
10 val = 0.0
11 n = 0
12
13 while n<=959:
14     X_new = dataset[n]
15     print(X_new)
16     X_new = numpy.expand_dims(X_new, axis=0)
17     y_s = model.predict(X_new)
18     val = float(y_s)
19     print(val)
20     data = [val]
21     n = n+1
22
23 with open('data3.csv', 'a', encoding='UTF8', newline='') as f:
24     writer = csv.writer(f)
25
26     # write the data
27     writer.writerow(data)
28
29 while n<=959

```

Fig. 6. Coding figure showing the predictive procedure in Python

Relying on block diagram shown in Fig. 5, a coding procedure is implemented by Python; parts of codes are expressed in Fig. 6.

Simulation results. This part of the paper describes the testing procedure of underground mine earthing resistance corresponding to climate variation. In Figs. 7 and 8 there are result values deduced from the predictive model. The variations as input here are the humidity, temperature and the length of the electrodes. The outcome of the model (R_{guess} -orange curves) is compared with the onsite measurements ($R_{measure}$ -blue curves). In Fig. 9, all of input variations are utilized to get the value and testify the exact of the model.

It can be seen in Figs. 7, 8 that the predicted values (orange lines) are fallen within the lab measurements and on-sites

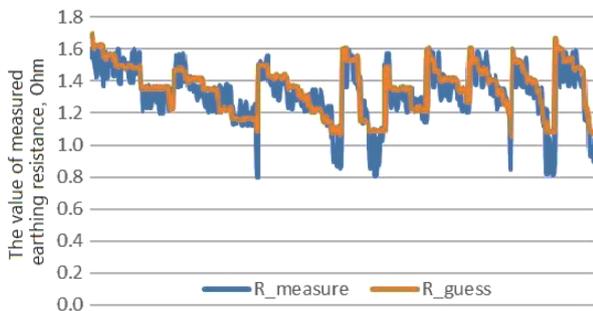


Fig. 7. Predicted values and measured ones corresponding to 1.5 m length of the earthing electrode

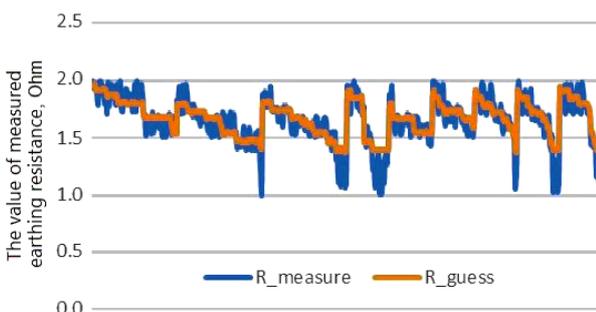


Fig. 8. Predicted values and measured ones corresponding to 1.2 m length of the earthing electrode

measurements. The training processes are carried out with variation of input data – the length of earthing rods (1.2 and 1.5 m – Figs. 7, 8). In Fig. 9, all climate parameters (including humidity, temperature) and the length of the rod are inputs in the predicting models. The curves presenting the value of $R_{measurements}$ versus R_{guess} are well overlapped. Obviously, the proposed model utilizing AI technology proved that the values of the earthing resistance in underground mines with many varying-input parameters could be predicted effectively.

Fig. 10 illustrates the series value of earthing resistance when all input data are considered. To estimate the accuracy of the model, another analysis is implemented with difference epochs. The results are presented in Table 3.

Following Python programming, a simple Interface is presented in Fig. 10. There are four kinds of input data needed to predict the value of earthing resistance: time (month), temperature, humidity, and the length of rod. With these kinds of data, the prediction is generalized for getting the required values of the earthing system in all underground mines. Some comparison is expressed in Fig. 11. The real values (R_{real}) closely match with the predicted values ($R_{forecast}$).

In Table 3, the accuracy of the model is proved. The accuracy of the proposed model is lower than 3 % (the last col-

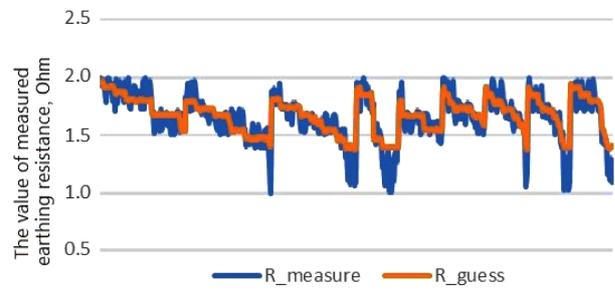


Fig. 9. Predicted values and measured ones corresponding to all variations of climate factors ($R_{measure}$ vs R_{guess})

Table 3

Accuracy analysis of the model with different epochs

Epochs	loss	acc	Val-loss	Val-acc
100	0.0529	0.0193	0.0425	0
200	0.0203	0.0167	0.0214	0.0115
300	0.0249	0.0129	0.0246	0.0260
400	0.0124	0.0180	0.0132	0.0115
500	0.0124	0.0154	0.0092	0.0230

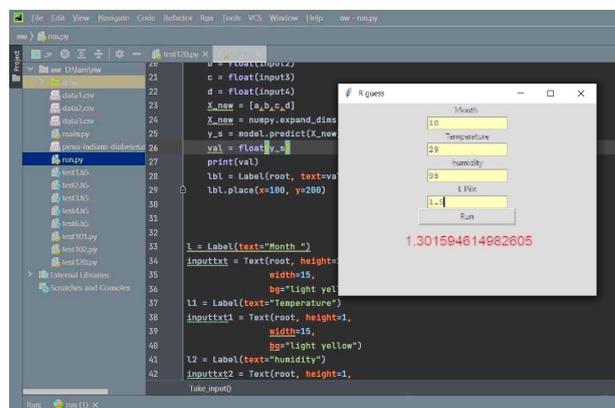


Fig. 10. Interface for predicting the value of the whole system with consideration of all input variations

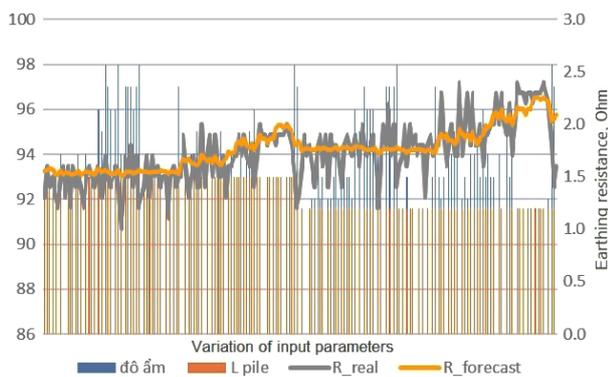


Fig. 11. Predicting the earthing value of the whole system with consideration of all input variations (include humidity, the length of piles)

um). The effectiveness of the research is shown again because this accuracy is very strong in comparisons with other models shown in the research of [19–21].

The above proposed algorithm and the AI model presented in this paper proved its effectiveness on predicting the value of the earthing resistance. By applying this technique, a future scope should be fulfilled with a software which is compatible by remote supervising/measuring meters. The operator could significantly reduce the errors resulted by manual measurement or very fast recognize the violation of the earthing system (earthing resistance) which is very important to the human-being safety.

Conclusions. The paper presented an effective ANN model with a suitable optimizer in order to predict the variation values of grounding resistance in underground mines of Vietnam. The input data used for the training model include not only the climate/weather conditions (temperature, humidity) but also the internal factor of earthing electrodes. By applying this technique, the following advantages could be obtained:

- the onsite measurement results could be compared with the prediction of the model in order to reduce the errors caused by a technician;

- the model is also applied for a new designing mine for predicting/verifying the earthing value of grounding electrode, it will save time and enhance the calculation accuracy of electric designing.

The proposed interface software-based Python programming is easy and friendly to use for not only a technician but also for all operators (who have little understanding about grounding knowledge). People can pre-estimate the safety condition of mining without onsite measurement.

This model also opens the ability to modernize the electrical-safety supervising system in underground mines of Vietnam. By analyzing the possibility of equipping the remote-sensor/measurement meters with the assistance of this computer-aid software, an online system could be utilized for 24/7 supervising the grounding system in the mines.

The proposed model is tested with thousand onsite measurements. It is proved that the model is applicable for all Vietnam underground mines to predict earthing value with an error lower than 3%. The model is also extendable improved by considering other impact parameters such as the manners of rods, the resistivity of the soil in underground mines. These ones are not of so significant influence on the grounding resistance, but they are worth of further research.

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Новий підхід до застосування штучного інтелекту для прогнозування заземлюючих резисторів у підземних шахтах В'єтнаму

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Мета. Застосувати технологію штучного інтелекту (ШІ) для прогнозування опору заземлення в підземних шахтах з урахуванням параметрів зміни клімату.

Методика. У підземних вугільних шахтах В'єтнаму системи заземлення повсюдно обладнані окремими стрижнями, з'єднаними із централізованим заземлювачем; дана система істотно впливає на електробезпеку та вибухобезпеку. За щоденної експлуатації опір системи заземлення необхідно регулярно вимірювати й перевіря-

ти для забезпечення значення нижче допустимої межі (2Ω). Однак через вплив кліматичних параметрів (вологість і температура в шахтах) ця величина часто змінюється. Грунтуючись на застосуванні нової нейронної мережі із 3 прихованими шарами, включаючи змінні параметри, у роботі представлено новий підхід до прогнозування опору заземлення. За допомогою наочного й легкого у використанні програмного забезпечення формується алгоритм, що допомагає оператору прогнозувати опір. Прогноз може бути використаний під час оперативного управління гірничим оператором, коли проводиться спостереження й перевірка системи заземлення в підземних шахтах.

Результати. Розроблено програмне забезпечення на основі технології ШІ, що допомагає оператору прогнозувати значення заземлюючого резистора в залежності від зміни клімату.

Наукова новизна. Нейронна мережа із застосуванням технології ШІ використовується з урахуванням вимірювань на місці.

Практична значимість. Результати прогнозування можуть бути використані у разі виникнення складнощів при вимірюванні. Вони також допоможуть виправити або усунути помилки вимірювання, допущені гірничим техніком.

Ключові слова: мережа 660 В, технологія штучного інтелекту, система заземлення, нейронна мережа, підземні шахти

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