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Multilayer Perceptron Artificial Neural Network (MLPANN) Model to Predict Temperature During Rotary Drilling

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Abstract

In this paper, a multilayer perceptron neural network has been used to represent temperature measurement during rotary drilling of five types of rock samples. To forecast the temperature at various thermocouple depths, the experimentally collected data was standardized. Indicators of model performance was also obtained in order to assess the correctness of the model. One hidden layer and one output layer were employed with MLPANN, which has ten input parameters (bit diameter (DD), Spindle Speed (SS), Penetration Rate (PR), thrust, and torque) and rock properties. Levenberg Marquardt learning algorithm with transfer function of logsig is the most optimal neuron number of 10-16-1 was successfully forecasting the temperature with a correlation of 0.9936 and 0.9941 for training and testing algorithm during drilling after analysis based on the trial-and-error approach to identify the optimum algorithm. Ten input parameters, a logsig sigmoid transfer function, and the trainlm algorithm in this study provide good prediction ability with tolerable accuracy.

Keywords: *Interface Temperature, MLPANN, Transfer Function*

1.0 Introduction

In the mining industry, rotary drilling, rotary-percussive drilling, and percussion drilling are the three primary drilling techniques. In both big open-pit and underground mines, the production method known as rotary drilling is widely used. The temperature of the drill bit and the rock can increase by a few degrees centigrade throughout the drilling operation, depending on operating circumstances, drilling time, and friction between the drill bit and rock.

Numerous researchers have tested methods to gauge temperature when drilling rocks[3,5,7,13]. The bit bearing temperature was also influenced by the rotational speed and bit weight. At the bearing surface under investigation, the highest temperature increase measured was 196.1°C[9]. When evaluating the transient temperature in solids, the thermocouple's time response is typically a limiting issue.

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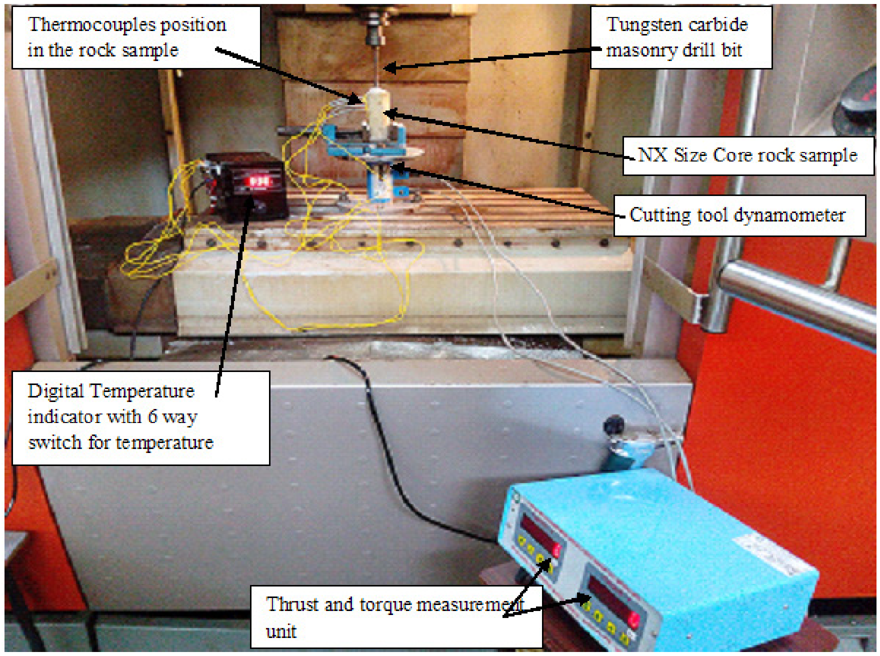

Figure 1. Rotary drilling temperature measurement setup in detail at bit-rock interaction.

For thermocouples with response periods of approximately 10 microseconds, the embedded thermocouple method is used[10]. Because welded thermocouples have a high thermal inertia and thermocouple procedures are difficult to use to monitor temperature, a thin, insulated wire thermal junction is put into the work piece[1]. The use of several operating variables, including spindle speed and feed rate, as well as touch and non-contact measurement methods, including K-type thermocouples and FLIR E60 infrared thermal imaging cameras, was made. It was found that the temperature essentially increased as operational parameters increased[11]. The temperature of the workpiece was determined using a variety of techniques. The accuracy of the output signals is strongly influenced by the thermocouple's junction type, size, and shape. With the predictive model, the single-pole thermocouple technique was found to be effective[2,4].

A maximum amount of time is needed to evaluate the outcomes of the experimental investigation and the analytical study. In order to predict the already available experimental data, the ANN technique provides a thorough comprehension of the modelling for any type of problem[8]. To determine the drilling temperature based on the 1D transient thermal conductivity, an unique projected thermal model was created. This shows that the maximum drilling temperature of the lunar regolith can be determined accurately from the experimental data and the anticipated model[15].

According to the pyrolysis process, the maximum center surface temperature difference constantly rises as the sample's diameter does[16]. Space engineering was very concerned about the temperature and other elements that could affect drilling, especially in a vacuum[6]. Sandstone was subjected to laboratory micro bit drilling procedures to determine the effects of pressure and temperature. Engineers regard the linked effect as being more significant than the separate effects[14]. The prediction model was created to investigate the impact of the surrounding rock's radius of drilling activity. Last but not least, the difference in error between the measured temperatures and the model that was developed is less than 10%, showing that the predicted model has a good ability to forecast the geothermal gradient[12].

In mining operations, measuring temperature during drilling is a difficult problem since predicting temperature is the main concern for energy conservation and raises the cost of production. So, in this article, multilayer perceptron neural network has been used to develop model for interface temperature measurement during rotary drilling of five types of rocks.

2.0 Experimental Investigations

Throughout the investigation, a 54mm-diameter core sample and 135mm-long core rock samples (NX size) were employed, both in accordance with ISRM standards. The rock sample's two ends were aligned parallel to one another (Figure 1). Using a CNC vertical machining machine with six operational parameters, including the DD, SS, PR, depth, thrust, and torque, as well as four rock properties, including UTS, BTS, Density, and Los Angle abrasion[18,19], the trials were carried out in a lab setting. Temperature is the output reaction that is seen while using a masonry drill bit in rotary drilling (tungsten carbide)[17].

For the five various types of rock samples used in the current investigation, models were built utilizing a total of 2500 data sets. The suggested Multi-Layer Perceptron Neural Network (MLPNN) model, as shown in Figure 2, predicts the temperature at the bit-rock interface for all bit-rock combinations taken into account. Ten input parameters were employed in the input layer. The output layer was chosen to be temperature.

3.0 Results and Analysis

With the aid of the rock's properties and the operational parameters DD, SS, PR, thrust, torque, and rock properties a performance analysis of the ANN model was developed. A total of 2500 test cases were used to train the network using a feed-forward back propagation learning technique (1750 training) and (750 testing). The training and testing phases of this study used the Levenberg-Marquardt (LM) back propagation approach (Figure 2). Before taking into account the weight functions of the input, a trial-and-error approach was used to identify the number of neurons in the hidden layer. This method has been applied using 10–19 neurons and a single hidden layer. It was believed that the logsig transfer function was sigmoid.

3.1 Temperature Prediction Model for Bit-Rock Interface Performance

ANN as shown in Table 1, the model's predicted R2 value for all varieties of rock sample using the trainlm algorithm with the logsig sigmoid transfer function is 99.36% during training and 99.41% during testing. The mean square error over a number of repetitions is shown in Figure 3 and the error graph, which depicts the overall level of uncertainty between the samples, is shown in Figure 4 respectively. The MLPNN model with the trainlm

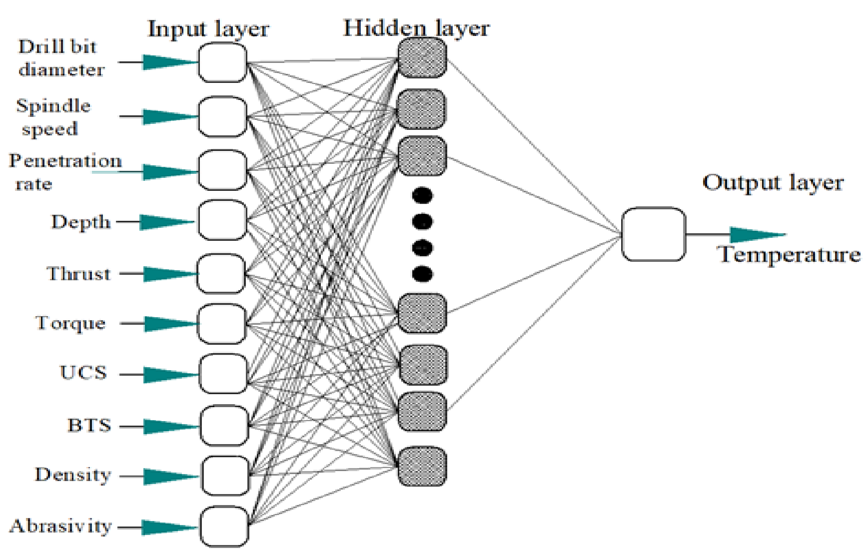

Figure 2. Rotary drilling process ANN architecture employing rock characteristics and operating parameters.

(Levenberg-Marquardt) algorithm shows that 16 neurons offer a 1.0947 with 0.9936 of RMSE and R^2 was achieved using logsig transfer function (Table 2).

$$\mathrm{VAF} = 1 - \frac{var(x - x')}{var(x)} \times 100 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} (\mathrm{x} - \mathrm{x}')^2} \tag{2}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{N} \left| \frac{Fi - Ri}{Fi} \right| \times 100 \tag{3}$$

Table 1. Using the logsig transfer function of the trainlm method, distinct neurons' training performance for each of the five types of rock was examined.

Number of neurons	RMSE	R^2
10	3.2145	0.9910
11	3.0681	0.9917
12	2.7860	0.9931
13	2.9973	0.9936
14	2.6971	0.9935
15	2.1941	0.9957
16	1.0841	0.9941
17	2.4406	0.9948
18	2.4734	0.9946
19	2.4734	0.9946

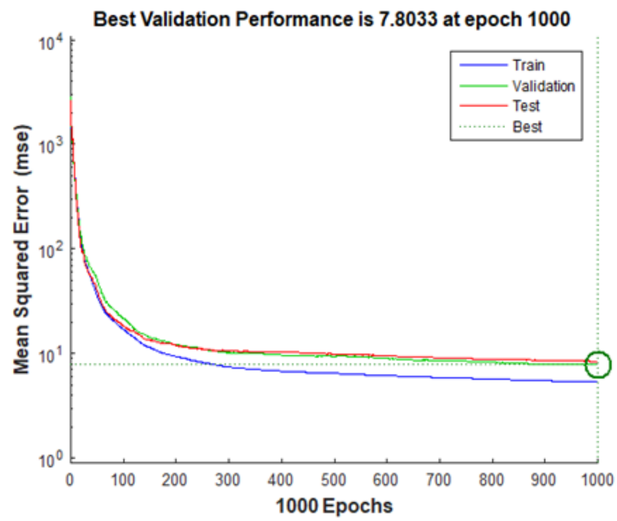

Figure 3. Training of each of the five types of rock samples using ANN analysis.

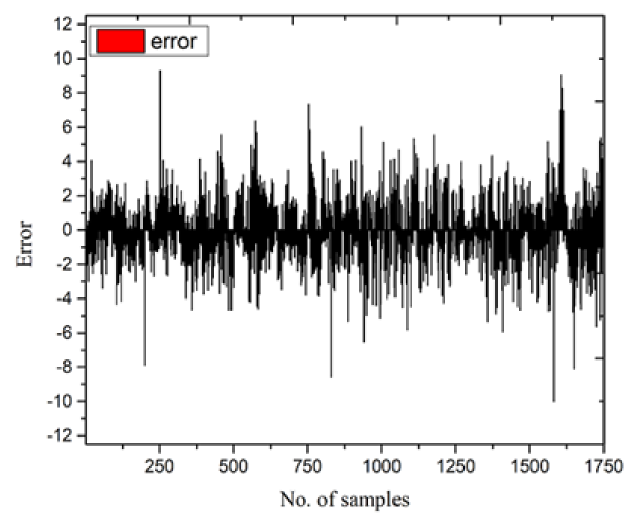

Figure 4. For 1750 data samples representing all five types of rock, the overall error graph.

Table 2. Training results of various training methods for all types of rocks

Algorithm	Training			Testing		
	RMSE	MAPE	R^2	RMSE	MAPE	R^2
Trainrp	3.5641	0.00321	98.965	2.9657	0.00654	98.124
Trainlm	1.0841	0.00198	99.412	1.6874	0.00295	99.532
Trainscg	3.1154	0.00295	98.954	3.0321	0.00651	98.933

4.0 Conclusions

Based on the experimentation of 2500 data sets was extracted for all the types of samples considered. Around 10 input parameters was considered to developed the model using operational parameters and rock properties. MLPNN model of LM algorithm with logarithmic function of 16 neurons yields best results with a performance prediction model of MAPE, RMSE and VAF for all the combinations were determined. For all the combinations 1.0841, 0.00198, and 0.9941 for the training data set and 1.6874, 0.00295 and 0.9953 for the testing data set. Hence the proposed model clearly shows that to predict the temperature during drilling.

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