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Artificial neural networks models for rate of penetration prediction in rock drilling

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Summary. Prediction of the rate of penetration (ROP) is an important task in drilling economical assessments of mining and construction projects. In this paper, the predictability of the ROP for percussive drills was investigated using the artificial neural networks (ANNs) and the linear multivariate regression analysis. The “power pack” frequency, the revolution per minute (RPM), the feed pressure, the hammer frequency, and the impact energy were considered as input parameters. The results indicate that the ANN with the regression model predicts the ROP under different conditions with high accuracy. It also demonstrates that the ANN approach is a beneficial tool that can reduce cost, time and enhance structure reliability.

Key words: artificial neural networks, rate of penetration, percussive drilling

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Introduction

The rate of penetration (ROP) in rock drilling is one of the most important parameters in drilling economics analyses. New modelling tools like the artificial neural networks (ANNs) are able to estimate non-linear and complex relations due to trial and error process. The ability of the ANN to learn complex relationships between the input and output parameters, and to allow the user to examine the effect of each parameter on the outcome make it a potential tool for the ROP prediction.

Very few works have addressed the application of the neural networks in percussive drilling modeling. Aalizad and Rashidinejad [1] studied the predictability of the ROP of rotary-percussive drilling based on intact rock properties, rock mass characteristics, the operational drilling parameters and some blast-hole parameters. Another recent work by Kahraman [2] investigated the ROP of percussive drills based on indirect tests. In the present paper, an attempt is made to understand the influence of operational parameters on the ROP of a percussive drilling system using the ANN approach. More specifically,

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the standard perceptron type of ANN with the backpropagation learning algorithm is used.

Artificial neural networks applied in prediction of the ROP in percussive drilling

Artificial neural networks (ANNs) are a computational model, consisting of interconnected groups of input, hidden and output nodes, used in machine learning, computer science and many other disciplines. ANN systems can be trained from examples to classify and discover new trends or patterns in a data. In the present case, the ANN model with the back propagation learning are applied in predicting the rate of penetration in percussive drilling based on laboratory data. The data generated in the laboratory drilling experiments provided by Sintef (Norway) was utilized for the development of ANNs model for the ROP prediction. Selected examples of the laboratory data are given in Table 1. Of the 20 laboratory tests available, 70 % (14 data points) was used to train the models while the remaining 15 % (3 data points) was employed in validation and testing of their performance.

Table 1. Selected test data.

Test	f_p	RPM	F_p	f	E_{imp}	ROP
n°	[Hz]	[rs/min]	[bar]	[Hz]	[J]	[mm/min]
3	12.5	62	0.3	14.5	21.0	85
13	12	60	0.29	13.8	8.6	32
20	18	85	0.35	19.5	40.8	208
21	18	125	0.55	19.6	42.4	240
22	18	45	0.55	19.7	41.0	193

The frequency of the “power pack”, f_p , provides the hydraulic power to the hammer and is a controlled parameter. It determines the frequency of the hammer, f , and the impact energy, E_{imp} , which are consequently not directly controlled. The RPM and the feed force, F_p are fully controlled parameters. Thereby, two simulation models were constructed. For model I, power pack frequency, RPM, the feed pressure were considered as input parameters and for model II, the RPM, the feed pressure, the hammer frequency, and the impact energy were considered as the input parameters. The ROP was the output parameter for both model.

The Mean Square Error (MSE) was used as the performance function to evaluate the robustness of the constructed model in every iteration. Figure 1 represents the training, validating, and testing errors for the finally selected ANNs system throughout the training process.

As the Figure 1 shows, when the neural network with the training data is trained, the error decreases. Considering the trend of the following curve, it is observed that the validation error decreased to 11 and 12 epochs for model I and II and then it increases. According to Figure 1, the appropriate epoch number are 11 and 12 for model I and II, respectively. Figure 2 shows the results of training, validating, and the total result of the ANNs for model I and II. The network after training has sufficient information about

characteristics of the model and can provide acceptable solutions for similar data. The results indicate that the ANNs models were satisfyingly successful in making the estimations of the ROP.

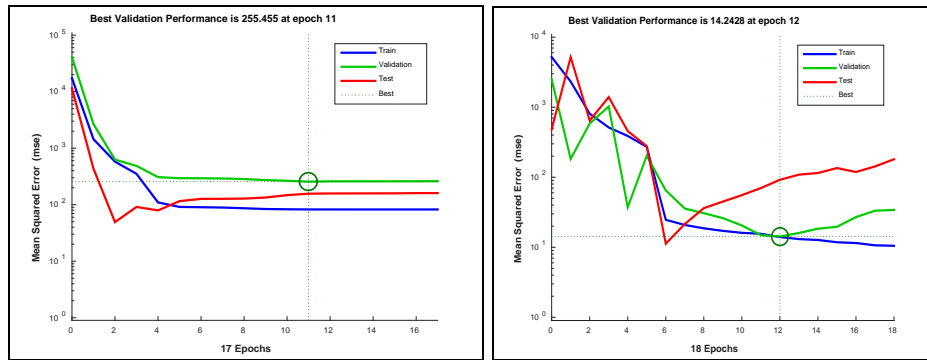


Figure 1. Training and validating and testing errors of the ANNs model model I (left) and model II (right).

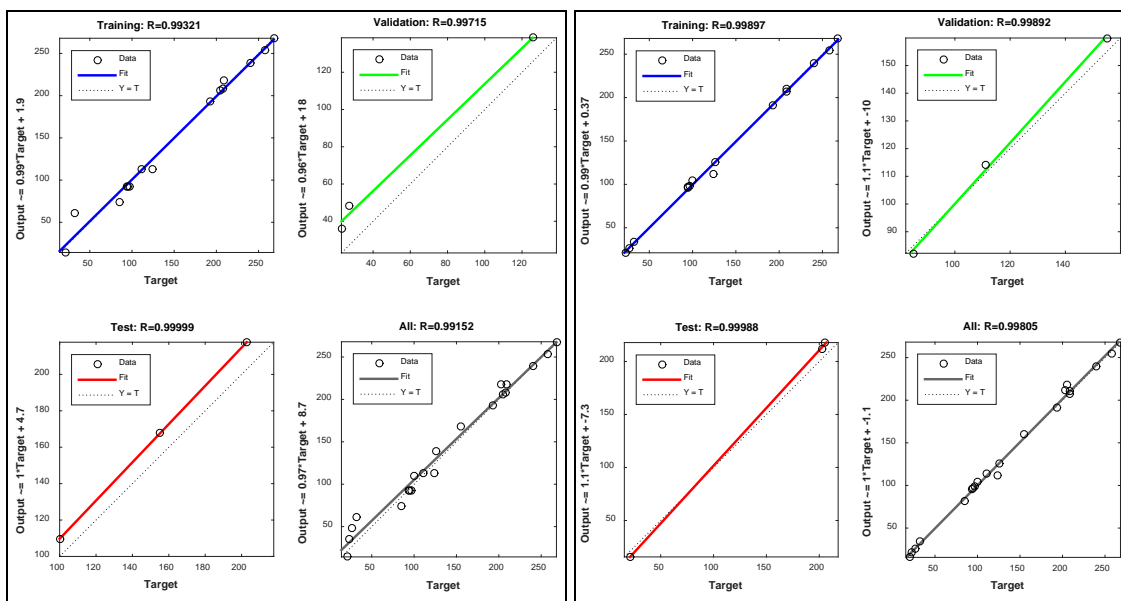


Figure 2. Predicted versus measured ROP for ANNs model I (left) and model II (right).

Linear multivariate regression (LMR) method

In order to assess the results of artificial neural networks, Linear Multivariate Regression (LMR) model was used. The same data as used in the ANNs was also considered in this approach. According to Figure 3, this model also shows good ability of estimating the ROP.

The relationships between the input parameters and the predicted ROP for model I and model II are as follows: $ROP = -0.858f_p + 0.182RPM + 325.324F_p$ (model I), $ROP = 0.352RPM - 7.266F_p - 3.513f + 5.713E_{imp}$ (model II).

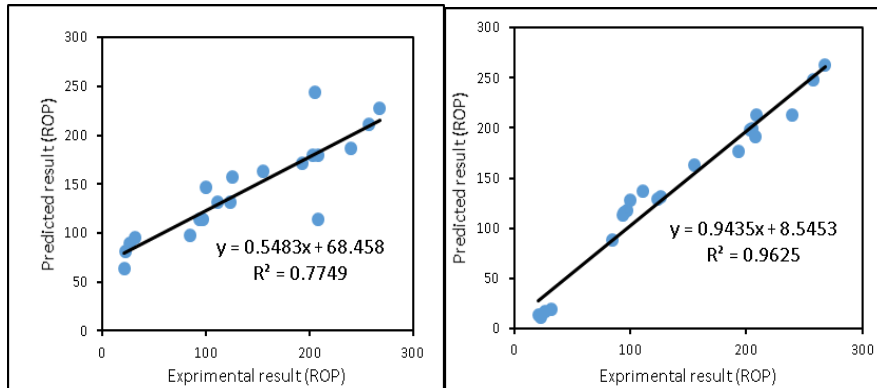


Figure 3. Relationship between predicted and measured ROP, model I (left), model II (right).

Conclusions

Artificial neural networks approach was applied in predicting the ROP in percussive drilling based on laboratory data. The results suggest that if the data is large enough, the ROP can be reliably predicted with this approach.

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