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PREDICTION OF PENETRATION RATE OF ROTARY-PERCUSSIVE DRILLING USING ARTIFICIAL NEURAL NETWORKS – A CASE STUDY

PROGNOZOWANIE POSTĘPU WIERCENIA PRZY UŻYCIU WIERTŁA UDAROWO-OBROTOWEGO PRZY WYKORZYSTANIU SZTUCZNYCH SIECI NEURONOWYCH – STUDIUM PRZYPADKU

Penetration rate in rocks is one of the most important parameters of determination of drilling economics. Total drilling costs can be determined by predicting the penetration rate and utilized for mine planning. The factors which affect penetration rate are exceedingly numerous and certainly are not completely understood. For the prediction of penetration rate in rotary-percussive drilling, four types of rocks in Sangan mine have been chosen. Sangan is situated in Khorasan-Razavi province in Northeastern Iran. The selected parameters affect penetration rate is divided in three categories: rock properties, drilling condition and drilling pattern. The rock properties are: density, rock quality designation (RQD), uni-axial compressive strength, Brazilian tensile strength, porosity, Mohs hardness, Young modulus, P-wave velocity. Drilling condition parameters are: percussion, rotation, feed (thrust load) and flushing pressure; and parameters for drilling pattern are: blasthole diameter and length. Rock properties were determined in the laboratory, and drilling condition and drilling pattern were determined in the field. For create a correlation between penetration rate and rock properties, drilling condition and drilling pattern, artificial neural networks (ANN) were used. For this purpose, 102 blastholes were observed and drilling condition, drilling pattern and time of drilling in each blasthole were recorded. To obtain a correlation between this data and prediction of penetration rate, MATLAB software was used. To train the pattern of ANN, 77 data has been used and 25 of them found for testing the pattern. Performance of ANN models was assessed through the root mean square error (RMSE) and correlation coefficient (R^2). For optimized model (14-14-10-1) RMSE and R^2 is 0.1865 and 86%, respectively, and its sensitivity analysis showed that there is a strong correlation between penetration rate and RQD, rotation and blasthole diameter. High correlation coefficient and low root mean square error of these models showed that the ANN is a suitable tool for penetration rate prediction.

Keywords: Penetration rate, Rotary-percussive drilling, Artificial neural networks, Top hammer drilling, Sangan iron mine

Postęp wiercenia przy wierceniach skał jest jednym z podstawowych parametrów decydujących o opłacalności przedsięwzięcia. Całkowite koszty prowadzenia prac wiertniczych określa się w oparciu

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o prognozowane tempo postępu wiercenia, parametr ten uwzględnia się następnie przy planowaniu prac wydobywczych. Niektóre spośród licznych czynników wpływających na postęp wiercenia przy użyciu wiertła obrotowo-udarowego nie zostały jeszcze w pełni rozpoznane. Przy prognozowaniu postępu wiercenia prowadzonego przy użyciu urządzeń udarowo-obrotowych uwzględniono cztery rodzaje skał obecnych w kopalni Sangan, leżącej w prowincji Khorasan-Razavi w północno -wschodniej części Iranu. Wybrane czynniki mające wpływ na postęp prac wiertniczych pogrupowano w trzy kategorie: właściwości skał, warunki prowadzenia prac wiertniczych oraz plan prowadzenia wiercenia. Parametry określające właściwości skał to gęstość, jakość skał (RQD) i wytrzymałość na ściskanie jednoosiowe, wytrzymałość skał otrzymywana w oparciu o test brazylijski, porowatość, twardość Mohra, moduł Younga, prędkość propagacji fali, Parametry określające warunki prowadzenia wierceń obejmują: udar, prędkość obrotowa, siła naporu, ciśnienie płukania, zaś parametry związane z planem prowadzenia wiercenia obejmują: wymiary otworu wiertniczego i długość. Właściwości skał określono laboratoryjnie, warunki i plan wierceń badano w terenie. Korelacji pomiędzy prędkością postępu wiercenia i właściwościami skał oraz warunkami i planem prac wiertniczych poszukiwano przy użyciu sztucznych sieci neuronowych (ANN). Zbadano 102 otwory wiertnicze, przeanalizowano warunki prowadzenia wierceń, plany prac i zarejestrowano czasy ich prowadzenia. W celu znalezienia korelacji pomiędzy tymi danymi a prognozowaną prędkością wiercenia wykorzystano oprogramowanie MATLAB. W treningu sieci neuronowej wykorzystano 77 danych, 25 z nich otrzymano w drodze testowania wzorca. Wyniki działania sieci neuronowych oceniono w oparciu o błąd średniokwadratowy (RMSE) oraz współczynnik korelacji (R2). Dla zoptymalizowanego modelu (14-14-10-1) błąd średniokwadratowy i współczynnik korelacji wynoszą odpowiednio 0.1865 i 86%. Analiza wrażliwości wykazała istnienie silnej korelacji pomiędzy prędkością wiercenia a jakością skały, prędkością obrotową wiertła i średnicą otworu wiertniczego. Wysoki współczynnik korelacji i niska wartość błędu średniokwadratowego otrzymana dla tych modeli wskazuje, że metody wykorzystujące sztuczne sieci neuronowe są odpowiednie do prognozowania prędkości wiercenia.

Słowa kluczowe: prędkość wiercenia, wiertło obrotowo-udarowe, sztuczne sieci neuronowe, urządzenia udarowe, kopalnia rud żelaza Sangan

1. Introduction

Drilling is very common and prerequisite for any earthwork starting from exploration to exploitation of earth resources. Proper drill utilization is always associated with the cost of excavation as well as overall cost of the project (Singh et al., 2009). Today applications of drilling require proper identification of operations where a cost reduction is possible (Bilgesu et al., 1997). It is well known that penetration rate is the most important performance parameter for drilling performance optimization. However, other drilling parameters such as power consumption and bit wear should also be considered (Sazidy et al., 2010). Total drilling costs could be estimated by using prediction equations. Also, one could use prediction equation to select the drilling rig type, which is best suited for given conditions (Kahraman, 1999). Penetration rate or rate of drilling is the depth of penetration achieved per unit of time with a given type of rock, drill, bit diameter and air or water pressure (m/min). There should be noted that drilling rate, penetration rate and drilling speed have same meanings and their unit is velocity (Rustan, 1998). The drillability of the rocks mainly depends on operational variables and rock characteristics. Operational variables known as the controllable parameters are rotational speed, thrust, blow frequency and flushing. Rock properties and geological conditions are the uncontrollable parameters (Kahraman et al., 2003).

In the past, many researchers have tried to establish relationship between penetration rate and different rock properties. Protodyakonov (1962) has used the coefficient of rock strength test to measure resistance of rock. Teal has evolved significance of energy input to the rock drilling. The energy input directly influences the type of fracture and breakage developed in rock (Teal, 1965). Coefficient of rock strength test was then modified. Experiment conducted on percussive drilling studies in the field and developed quite fair relationships between penetration rate and rock properties like UCS, tensile strength, hardness and Young's modulus (Paone et al., 1969). Lundberg (1973) carried out detailed investigations on stress wave mechanics of percussive drilling. Oddsson (1979) evaluated the correlation between drilling rate and RQD (Rock quality designation) and degree of alteration and lithology in volcanic rocks. He believed that comparison of RQD with drilling rate was not suggested and high drilling rates can be caused by low RQD only in very fissile or incoherent rocks. From rock properties such as USC, tensile strength, specific energy (SE), shore hardness and Mohs hardness had been gathered that thiese parameters do not individually give good correlation with the penetration rate (Paithankar & Mishra, 1980).

Howarth et al. (1986) performed percussion drilling tests on ten sedimentary and crystalline rocks. They correlated penetration rate with rock properties and found that bulk density, compressive strength, apparent porosity, *P*-wave velocity and Schmidt hammer value exhibit strong relationships with the penetration rate. Muro (1988) had done a study on drilling rate as a function of the revolving energy, the impact energy, bit diameter, coefficient of crack of rock mass and shore hardness. Also he mentioned that the rock properties could be determined by measuring the drilling rate of a standard rotary-percussive drill machine. Pandey carried out drilling tests in the laboratory with microbit drilling machine, full scale dragbit rotary drilling and percussive drilling. They investigated the performance of different types of drilling using coal measure rock and developed a relationship between penetration rate and percussive drilling (Pandey et al., 1991). A detailed study had been done and established relationship between the rate of penetration and various rock properties for different drilling parameter to evaluate economics and its efficiency (Giri et al., 1997). The relationships between three different methods of brittleness and both drillability and borability statistically investigated using data obtained from the experimental works of different researchers (Kahraman, 2002). Singh and Monjezi (2003) have done work on Indian rocks to find out the contribution of abrasivity in the determination of penetration rate. Kahraman et al. (2003) reported correlation with different confidence level between penetration rate and rock properties like UCS, Brazilian tensile strength, point load strength, Schmidt hammer value, natural density, elastic modulus and *P*-wave velocity. Singh worked on Petrophysical parameters affecting drillability of rock (Singh et al., 2010).

This paper is organized as follows: In section 2 and 3, basic concepts of rotary-percussive drilling and ANN are explained. Section 4 and 5 describes the input and output parameters of the networks. In the next section application of ANN for prediction the penetration rate in Sangan iron mine of Iran is presented. In section 7 sensitivity analysis is performed by cosine amplitude method (CAM) on ANN model and the most effective parameters on the penetration rate are listed. Finally, section 8 concludes the paper.

2. Rottary-percussive drilling

Drilling by rotary percussion is the most classic system for drilling blastholes, and its chronological appearance coincides with the industrial development of the nineteenth century. The drilling principle of these rigs is based upon the impact of a steel piece (piston) that hits a utensil which transmits at the same time that energy to the bottom of the blasthole by means of the final element called the bit (Hustrulid, 1999). The rotary percussive rigs are classified in two large groups, depending upon where the hammer is located:

2.1. Types of rotary-percussive drills

2.1.1. Top hammer

In these drills, two of the basic actions, rotation and percussion, are produced outside the blasthole, and are transmitted by the shank adaptor and the drill steel to the drill bit. The hammers can be driven hydraulically or pneumatically.

2.1.2. Down the hole hammer

The percussion is delivered directly to the drill bit, whereas the rotation is performed outside the hole. The piston is driven pneumatically, while the rotation can be hydraulic or pneumatic. A typical top hammer drill is shown in Fig. 1

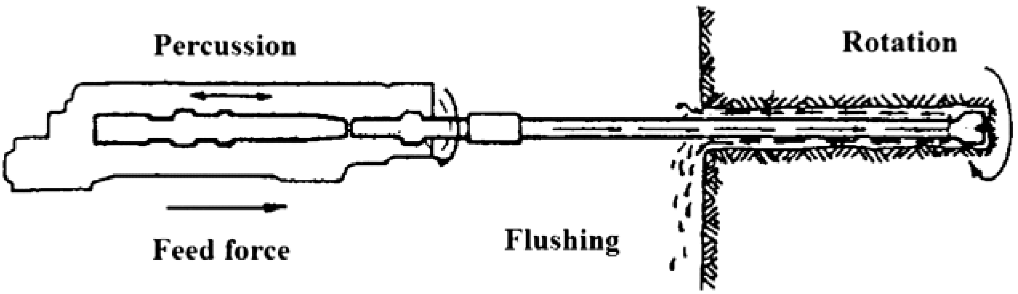

Fig. 1. A typical Top Hammer drill (Jimeno, 1995)

The main advantages of rotary-percussive drilling are:
- It can be applied to any type of rock, from soft to hard.
- Wide range of diameters;
- Versatile equipment, it adapts well to different operations and is very mobile;
- Only requires one operator;
- Easy, quick maintenance, and
- The capital cost is not high.

In view of these advantages and characteristics, the type of operations where it is used is:
- Underground civil engineering; tunnels, underground hydraulic plants, residual deposits, etc., and in surface operations; roads, highways, industrial excavations, etc.
- In underground mines and in small to medium sizes surface operations.

2.2. Fundamentals of rotary-percussive drilling

Rotary percussion drilling is based upon the combination of the following:

2.2.1. Percussion

The impacts produced by repeated blows of the piston generate shock waves that are transmitted to the bit through the drill steel (in top hammer) or directly upon it (down the hole).

2.2.2. Rotation

With this movement, the bit is turned so that the impacts are produced on the rock in different positions.

2.2.3. Feed, or thrust load

In order to maintain the contact of the drill bit with the rock, a thrust load or feed force is applied to the drill string.

2.2.4. Flushing

Flushing removes the drill cuttings from the blasthole.

The indentation forming process with which penetration is achieved in this drilling system is divided into five times, as indicated in Fig. 2

a) Crushing of the rough edges of the rock upon bit contact.
b) Radial cracks appear from the points of stress concentration and a V shaped wedge is formed.
c) The rock of the wedge is pulverized
d) The larger fragments are chipped in the zones next to the wedge
e) The drill cuttings are flushed away (Jimeno, 1995).

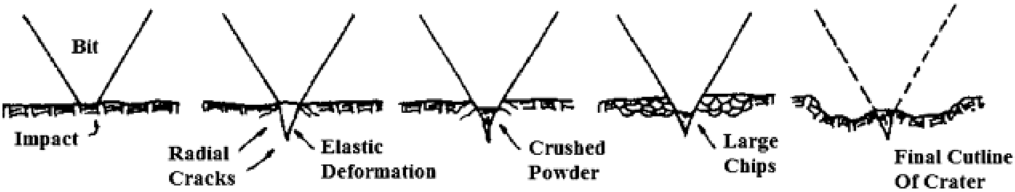

Fig. 2. Sequence of rock failure during center formation (Hartman, 1959)

3. Artificial neural networks

Neural network is a dynamic and non-linear system that formed of many process units (neural cell or neuron) and connections between these process units (Haykin, 1999). Neural networks have been successfully used in different fields due to their capability to identify complex relationships when sufficient data exist (Bilgesu et al., 1997). These networks have ability to learn and identify relations between input patterns and output(s). After proper training, we can give new inputs to neural network and predict the output (Haykin, 1999). The neurons are interconnected in predefined topology called layers. Usually the neurons operate in parallel layers (Menhrotra, 1997). A typical network topology consists of the input layer, one or more hidden layers and the output layers shown in Fig. 3.

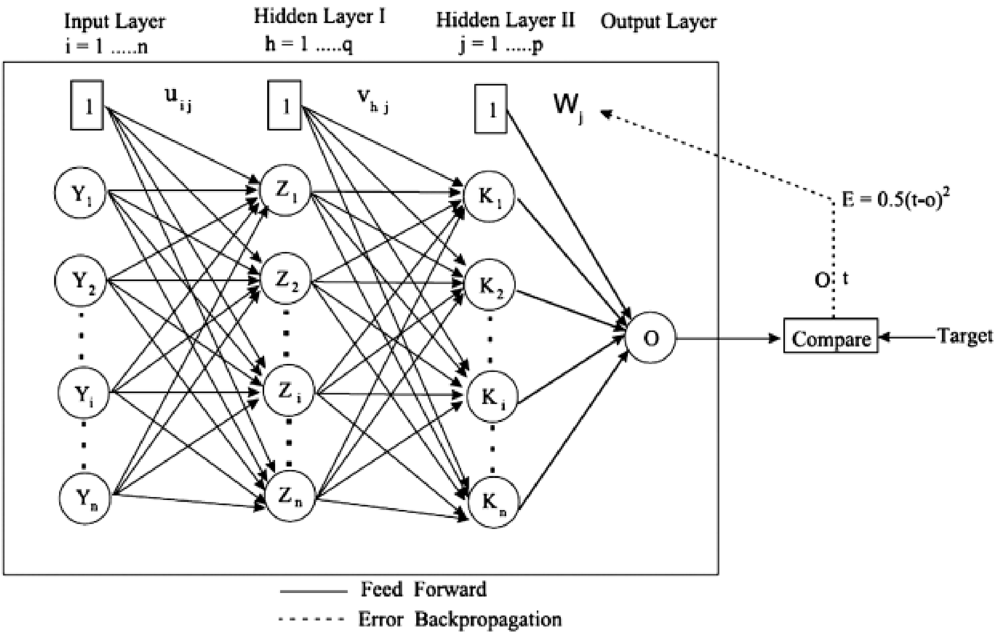

Fig. 3. A typical neural network with two hidden layers (BPNN) (Neaupane & Achet, 2004)

Learning from examples is the main operation of any ANN. Learning in this case means the ability of an ANN to improve its performance through an interactive process of adjusting it's free parameters. The adjustment of an ANN's free parameters is simulated by a set of examples presented to the network during the application of a set of well-defined rules for improving it's performance called a learning algorithm. There are many different learning algorithms for ANN's, such as BackPropagation, Levenberg-Marquardt, Conjugate Gradient, each with a different way of adjusting the synaptic weights of processing units and different way of formalizing the measurement off ANN's performance (Kapageridis, 2002).

Back-propagation networks have a very long history; they were originally introduced by Werbosin 1974. It is considered the most popular, effective and easy-to-learn model for complex, multi-layered networks of the supervised learning techniques. The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but typically one or two hidden layers are enough for complex problems. Each layer is fully connected to the succeeding layer. In the back Propagation training, the connection weights are adjusted to reduce the output error (Tawadrous, 2006).

4. Input parameters

The factors which affect penetration rate are exceedingly numerous and are not completely understood. Undoubtedly influential variables exist which are as yet unrecognized. A rigorous analysis of drilling rate is complicated by the difficulty of completely isolating the variables under study. For example interpretation of field data may involve uncertainties due to the possibility of undetected changes in rock properties.

As mentioned many factors are affect on penetration rate but because of some limitations just 14 parameters in 3 categories have been considered:

- Rock properties: Density, rock quality designation (RQD), uni-axial compressive strength (USC), Brazilian tensile strength, porosity, Mohs hardness, Young modulus, P-wave velocity.
- Drilling condition parameters: Percussion, rotation, thrust load and flushing pressure.
- Drilling pattern: Blasthole diameter and length.

4.1. Rock properties

This study has been done in Sangan iron mine. This mine is situated in Khorasan-Razavi province in northeastern Iran, about 300 km southeast of Mashhad and 16 km north of the city of Sangan, between 60°16' and 60°30' longitudes and 34°24' - 34°40' latitudes, at an altitude of 1,000 m above the sea level. Sangan deposit is part of volcanic-plutonic Khaf-Doruneh belt which contains several types of iron oxides. There are several anomalies in this area whit 1.2 billion tonnes geological resource and 172 million tones approximately indicated and measured reserve for the first phase development (Esmaeili, 2011). The drilling performance was measured on hydraulic top hammer drill rigs on four types of rocks. These 4 types of rocks are two iron ore (Hematite and Magnetite) and two waste rocks (Dolomite Limestone and Quartzite). Rock properties were determined in the laboratory (table 1), and drilling condition and drilling pattern were observed and recorded in the field. 102 blastholes randomly selected and their mentioned properties recorded (Aalizad, 2011).

4.1.1. Density

Dry density for this 4 type of rocks has been evaluated in kilogram on cube meter.

4.1.2. Rock quality designation (RQD)

The percentage of RQD for these 4 types of rocks is between 50 to 90%.

4.1.3. Uni-axial compressive strength (UCS)

Uni-axial compressive test were accomplished in laboratory. The core samples had diameter of 5.35 cm and length of 11.00 cm. The stress rate was 0.5 MPa per second.

4.1.4. Brazilian tensile strength

Brazilian tensile strength tests were performed in laboratory. Core samples had a diameter of 5.35 cm and the height/diameter ratio for them was between 0.44 and 0.64.

4.1.5. Porosity

Porosity is resulted from the following equal at percentage:

$$\frac{(B-A)}{(B-C)}\times 100 \tag{1}$$

That B is saturated sample's weight with dry surface, A is dry sample's weight, and C is soak sample's weight in water.

4.1.6. Mohs hardness

In the laboratory, from Mohs hardness scale, the hardness of each type of rocks determined.

4.1.7. Young's modulus

Basis of last ISRM suggestion, the young modulus for selected rocks determined. The samples for this test had a diameter of 5.35 cm and 11.1 cm.

4.1.8. Ultrasonic test

For achieving P-wave velocity an ultrasonic test carried out. The length of samples was between 10.50 and 11.20 meter.

TABLE 1

Some mechanical and physical properties of studied rocks*

Rock Type	D	UCS	BTS	P	H	YM	PV
Hematite	4395	151	12.97	4.6	6	166	4773
Magnetite	4632	63	8.45	0.9	6	74.6	5889
Dolomite Limestone	2870	60	7.2	0.5	3.5	37.6	5600
Quartzite	2570	38	3	2.4	7	10.55	3500

* D: Density (kg/m^3), USC: Uni-axial compressive strength (MPa), BTS: Brazilian tensile strength (MPa), P: Porosity (%), H: Hardness (Mohs scale), YM: Young's modulus (GPa), PV: P-wave velocity (m/s).

4.2. Drilling pattern parameters

These parameters are absolutely controllable and depend on the drilling pattern design. There were three diameters for blastholes: 3.5", 4", 4.5". The length of blastholes varied between 2.5 up to 10.2 m.

4.3. Drilling Condition Parameters

These parameters had been recorded from the field and drilling machines. Four top hammer drilling machine were selected for this purpose: Two D7 Atlas Copco drilling machines, one F7 Atlas Copco drilling machine and one Tomrock 1000 drilling machine. The minimum and maximum of percussion, rotation, feed and flushing pressure is shown in table 2.

Despite these parameters are semi-automatic in this machines, i.e. the machine itself unitage rock condition (being soft or hard) controls these parameters but in some cases and machines these parameters have low or high gear that is in authority of operator's desire.

TABLE 2

Minimum and maximum values of drilling condition parameter

Parameter	Minimum	Maximum
Percussion pressure (Bar)	85	200
Rotation pressure (Bar)	40	55
Thrust (KN)	40	55
Flushing pressure (KPa)	3	8.5

5. Output parameter

The penetration rate is output parameter. As mentioned before, penetration rate obtains from this equal:

$$PR = \frac{L}{T} \tag{2}$$

That L is length of blasthole (meter) and T is time of blasthole drilling (minute). For each blasthole, length of it and time of drilling accurately recorded. Minimum and maximum values of penetration rate are shown in table 3.

TABLE 3

Minimum and maximum values of output

Output parameter	Minimum	Maximum
Penetration rate (m/min)	0.588	2.903

6. Structure of neural network

Feed-forward back-propagation neural network (FBPNN) is usually used for input-output mapping problems where closer mapping is required. Using this technique the network is able to precisely predict target pattern for a given input pattern. As such, maximum efforts should be made to consider all the pertinent parameters or inputs (Chandok et al., 2008).

To recognize the optimum network, different topologies were tried and compared by calculating root mean square of error (RMSE) (Eq. 3)

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n} \left(y_{pre,m} - t_{mea,m}\right)^2}{n}} \tag{3}$$

In addition, the correlation coefficient (R^2) is defined as followed:

$$R^2 = 1 - \frac{\sum_{m=1}^{n} (y_{pre,m} - t_{mea,m})^2}{\sum_{m=1}^{n} (t_{mea,m})^2} \tag{4}$$

where n is the number of data pattern in the independent data set, $y_{pre,m}$ indicates the predicted, $t_{pre,m}$ is the measured value of one data point m, and $t_{mea,m}$ is the mean value of all measured data points.

For training the network 77 blasthole randomly selected and used, and other 25 blastholes used for testing the network. As it can be seen from table 4, a network with architecture 14-14-10-1, having the lowest RMSE and high correlation coefficient, is the optimum model. The network architecture and its correlation coefficient are shown in Fig. 4 and 5.

TABLE 4

Result of a comparison between some of models

Transfer function	Architecture	RMSE
LOG-LOG-LOG-POSLIN	14-9-14-1	0.5819
LOG-LOG-LOG-PURELIN	14-12-8-1	0.3410
TAN-TAN-TAN-POSLIN	14-14-10-1	0.1865
TAN-TAN-TAN-PURELIN	14-13-9-1	0.2327
TAN-TAN-PURELIN	14-24-1	0.3404
TAN-TAN-POSLIN	14-12-1	0.2281
LOG-LOG POSLIN	14-6-1	0.2395
LOG-LOG-PURELIN	14-17-1	0.2588

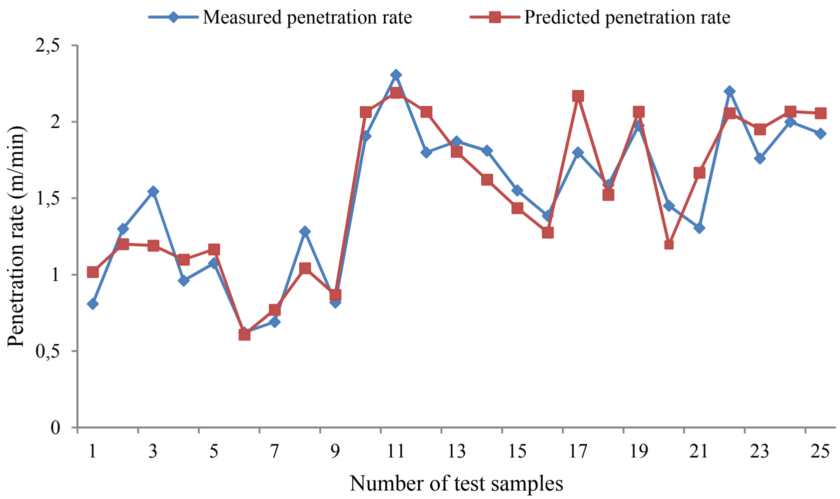

Fig. 4. Comparison between the measured and the predicted penetration rate for ANN model

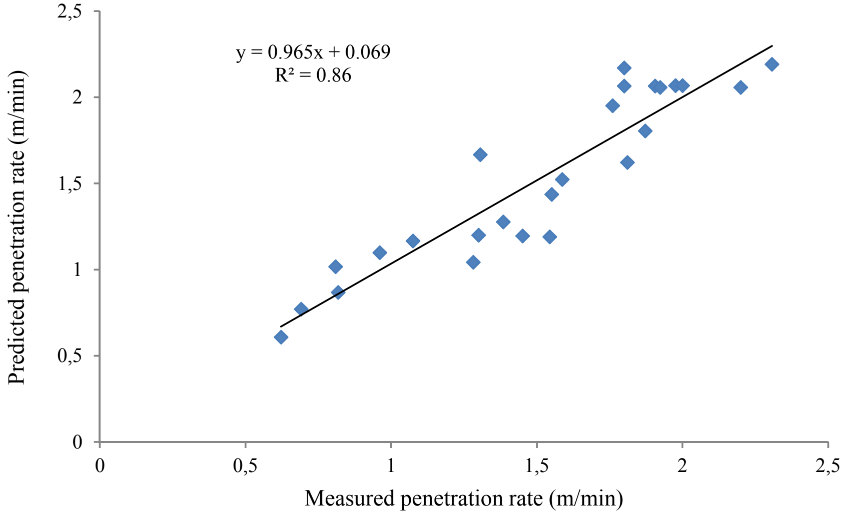

Fig. 5. Correlation between measured and predicted penetration rate for ANN model

7. Sensitivity analysis

The strength of the relationship between the penetration rate and the input parameters was analyzed by the Cosine Amplitude Method. The CAM was used to obtain the express similarity relations between the related parameters (Jong & Lee, 2004).

To apply this method, all of the data pairs were expressed in common *X*-space. The data pairs used to construct a data array *X* defined as:

$$X = \{X_1, X_2, X_3, \ldots, X_n\} \tag{5}$$

Each of the elements, X_i, in the data array *X* is a vector of lengths of *m*, that is:

$$X_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}\}_1 \tag{6}$$

Thus, each of the data pairs can be thought of as a point in *m*-dimensional space, where each point requires *m*-coordinates for a full description. Each element of a relation, r_{ij}, results in a pair wise comparison of two data pairs. The strength of the relation between the data pairs, x_i and x_j, is given by the membership value expressing the strength:

$$r_{ij} = \sum_{k=1}^{m} x_{ik}\, x_{jk} \Bigg/ \sqrt{\sum_{k=1}^{m} x^2_{ik} \sum_{k=1}^{m} x^2_{jk}} \tag{7}$$

Inspection of equation (6) reveals that this method is related to the dot product for the cosine function. When two vectors are collinear (most similar), their dot product is unity; when two vectors are at right angles to one another (most dissimilar), their dot product is zero (Ross, 1995).

In Fig. 6, the parameters are: YM: Young's modulus, BL: blast hole length, BTS: Brazilian tensile strength, P: porosity, D: density, PV: P-wave velocity, H: Mohs hardness, UCS: uni-axial compressive strength, PR: percussion, FP: flushing pressure, Th: thrust, BD: blasthole diameter, R: rotation, RQD: rock quality designation.

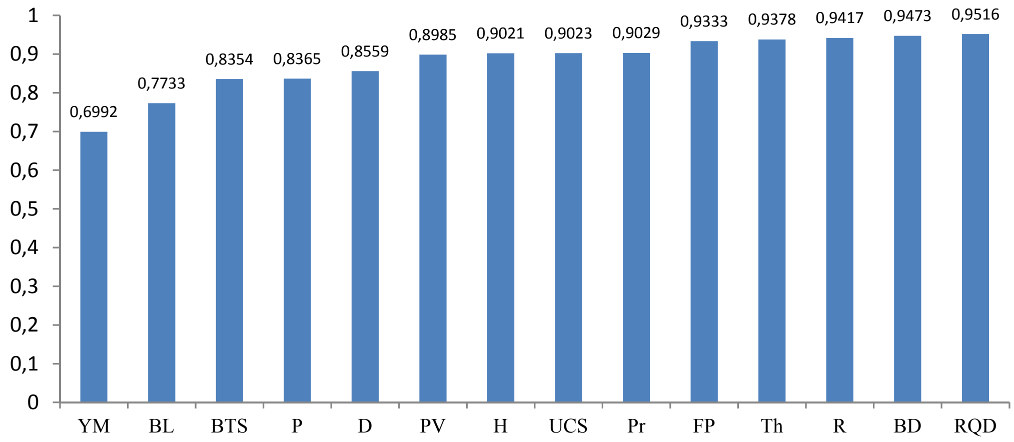

Fig. 6. Sensitivity analysis between the penetration rate and input parameters

8. Conclusion

Drilling is widely used in mining, civil and petroleum engineering. Penetration rate is very significant parameter in project planning and its cost estimation. It is clear that penetration rate is depending on many parameters such as rock properties, drilling condition and drilling pattern and predicting the penetration rate none of mentioned parameters can lead this point alone. In this study fourteen parameters and over one hundred blasthole selected for evaluating the rate of penetration. For this purpose, artificial neural networks had been used. For training the network, 77 blasthole data randomly selected and 25 blasthole data remained for testing the network architecture. The optimum ANN architecture has been found to be fourteen neurons in the input layer, two hidden layers with 14 and 10 neurons, respectively, and one neuron in the output layer.

A good root mean square error (RMSE=0.1865) and coefficient of correlation (R^2=86%) obtained. From the results of this study, there is a very significant correlation between penetration rate and RQD, rotation, diameters of blastholes and thrust. In next stage of importance, there is a good correlation between penetration rate and flushing pressure, percussion, uni-axial compressive strength, hardness, P-wave velocity. Porosity, density, blasthole's length have a fair to weak correlation with penetration rate and Young modulus has a very weak correlation with it. Of course there are other parameters effecting on penetration rate that could be evaluated. It seems that artificial neural network is a very good method for predicting the penetration rate in Sangan iron mine. At last it is suggested that for future studies more blastholes and more parameters simultaneously evaluated.

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References

Aalizad S.A., 2011. *Prediction penetration of rotary-percussive drilling using artificial neural networks- A case study Sangan Iron mine Project (SIMP)*. MSc. Thesis, Islamic Azad University, Science and Research Branch, Tehran, Iran.

Bilgesu H.I., Tetrick L.T., Altmis U., Mohaghegh S., Ameri S., 1997. *A new approach for the prediction of rate of penetration (ROP) values*. Proceeding of SPE Eastern Reginal Meeting, Lexington, USA, 175-179.

Chandok J.S., Kar I.N., Tuli S., 2008. *Estimation of furnace exit gas temperature (FEGT) using optimized radial basis and backpropagation neural networks*. J. Rock Energy Convers Manag., 49, 1989-1998.

Esmaeili M., Aghajani Bazazi A., Borna S., 2011. *Reliability analysis of a fleet of loaders in Sangan iron mine*. Arch. Min. Sci., 56, 4, 629-640.

Giri A.K., Swamliama C., Singh T.N., Singh D.P., 1997. *Strength properties and their relations with abrasiveness of some Indian Rocks*. 1st Asian Rock Mech. Symp., Korea, 537-541

Hartman H.L., 1959. *Basic studies of percussion drilling*. Min. Eng., 11, 68-75.

Haykin S., 1999. *Neural network: A comprehensive foundation*. Prentice hall.

Howarth D.F., Adamson W.R., Berndt J.R., 1986. *Correlation of model tunnel boring and drilling machine performances with rock properties*. Int. J. Rock Mech. Min. Sci., 23, 171-175.

Hustrulid W., 1999. *Blasting principles for open pit mining*, Vol. 1, General design concept. A. A. Balkema, Rotterdam, Brookfield.

Jimeno C.L., 1995. *Rock drilling and blasting*. A.A. Balkema, Rotterdam, Brookfield, pp. 8-35.

Jong Y.H., Lee C.I., 2004. *Influence of geological conditions on the powder factor for tunnel blasting*. Int. J. Rock Mech. Min. Sci., 41, 533-538.

Lundberg B., 1973. *Energy transfer in percussive rock destruction-I*. Int. J. Rock Mech. Min. Sci., 10, 381-399.

Menhrotra K., Mohan C.K., Ranka S., 1997. *Elements of Artificial Neural Networks*. Cambridge: MIT Press.

Muro T., Fukugava R., Watanabe M., 1988. *Rotary percussion forces affecting a drilling rate of bit for rock mass*. Proceeding of Japan Society Civil Engineering, 391, 206-213.

Neaupane K.M., Achet S.H., 2004. *Use of back propagation neural network for landslide monitoring: a case study in the higher Himalaya*. Engineering Geology, 74, 213-226

Oddsson B., 1982. *Rock quality designation and drilling rate correlated with lithology and degree of alteration in volcanic rocks from the 1979 Surtsey drill hole*. Surtsey Research Progress Report IX, 94-97.

Paithankar A.G., Mishra G.B., 1980. *Drillability of rocks in percussive drilling from energy per volume as determined with microbit*. Min. Engineering, 21, 1407-1410.

Pandey A.K., Jain A.K., Singh D.P., 1991. *An investigation into rock drilling*. Int. J. Surf. Min. Recl., 5, 114-139.

Paone J., Madson D., Bruce W.E., 1969. *Drillability studies–laboratory percussive drilling*. USBM RI 7300, 537-541.

Protodyakonov M.M., 1962. *Mechanical Properties and Drillability of Rocks*. Proceedings of the Fifth Symposium on Rock Mechanics, University of Minnesota, Minneapolis, MN, 103-118.

Kahraman S., 1999. *Rotary and percussive drilling prediction using regression analysis*. Int. J. Rock Mech. Min. Sci., 36, 981-989.

Kahraman S., 2002. *Correlation of TBM and drilling machine performances with rock Brittleness*. Eng. Geol., 65, 269-283.

Kahraman S., Bilgin, N. and Feridunoglu, C., 2003. *Dominant rock properties affecting the penetration rate of percussive drills*. Int. J. Rock Mech. Min. Sci., 40, 711-723.

Kapageridis I.K., 2002. *Artificial neural network technology in mining and environmental applications*. Mine Planning and Equipment Selection, 172-179.

Ross T.J., 1995. *Fuzzy logic with engineering applications*. New York: McGraw-Hill.

Rustan A., 1998. *Rock Blasting terms and Symbols*. A.A. Balkema, Rotterdam, Brookfield.

Sazidy M.S., Rideout D.G., Butt S.D., Arvani F., 2010. *Modeling percussive drilling performance using simulated visco-elastic-plastic rock medium*. 44th US Rock mechanics Symposium and 5th U.S.-Canada Rock mechanics Symposium, USA, 434-443.

Singh T.N., Jain A., Sarkar K., 2009. *Petrophysical parameters affecting the microbit drillability of rock*. Int. J. Mining and Mineral Engineering, 1(3), 261-277.

Singh T.N., Monjezi M., 2003. *Abrasivity of some Indian rocks-an experimental approach*. Int. Conf. on Drilling, Iran, 39-46.

Tawadrous A.S., 2006. *Evaluation of artificial neural networks as a reliable tool in blast design*. Int. Soc. Explos. Eng., 1, 1-12.

Teal R., 1965. *The concept of specific energy in rock drilling*. Int. J. Rock Mech. Min. Sci., 2, 57-73.

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