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Comparing Empirical Models with ANN in Estimation of Vibrations Resulted from Blasting, Dareh-Baq Dam

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Abstract

Blast hole drilling and blasting are from among cost effective and economic methods of crushing the rock in civil projects, tunneling, as well as surface and underground mining. Ground vibration is the most important undesirable effect of blasting and if not controlled, it can lead to many damages. The paper is aimed at studying and prediction of effects of vibrations resulted from blasting on structure of dam on Dareh-Baq River. For this purpose, four empirical equations along with Artificial Neural Network (ANN) have been used to the aim of achieving a highly accurate model to predict vibrations of ground. Also, level of vibrations created would be compared through existing standards. According to the above goals, 73 blasting cases in Dareh-Baq River Dam area have been studied and required parameters as for prediction have been measured. From 73% of information related to blasting has been used to obtain empirical equation and also provide appropriate model in ANN; and, the remaining 27% of information have been used to specify performance and evaluate accuracy level of various models, in comparison to real values. After evaluation of the results, it became clear that ANN is of highest accuracy for prediction of vibrations resulted from blast. Also, in consideration of recorded vibrations and their comparison to existing standards, as well as distance of dam on Dareh-Baq River from location of blasting, energy from vibrations created will be dissipated and no undesirable effect would be imposed on dam structure.

Keywords: Dareh-Baq River Dam, Blasting, Ground vibration, Artificial Neural Network (ANN), Empirical models.
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1. Introduction

Cycle of mining includes crushing rocks, loading, and transportation. Nowadays, one of economic methods widely used to crush rocks is blast hole drilling and blasting [1]. Only about 20% of energy released from explosives would be used for crushing rocks; and, the remaining would produce undesirable effects such as ground vibrations, noise, and throwing rocks [2-4]. From among these effects, ground vibration is the most important undesirable effect of blasting; because, about 40% of energy released from explosives produces vibration. If ground vibration would not be controlled and minimized, it would be resulted in many damages in surrounding structures. So it is important to evaluate, predict, and control ground vibration [5, 6]. In this respect, many standards have been formulated by different countries so that authorized level of ground vibration would be specified. Considering vibrations created in structure of dam on Dareh-Baq River in present paper and also previous studies, vibrations created would be studied and evaluated based on two standards (Tables 1 & 2) [7, 8]. Research background in the field of predicting vibrations resulted from blasting has been extensive which is indicative of importance of the issue. These researches are divided into two groupss, in general. First group is related to those researches in which ground vibration prediction would be performed through methods and formulas. For example Ozer et al. and Kahriman, have predicted and control these vibrations with consideration of importance of control and minimization of destructive environmental effects of blasting. In their researches, prediction of ground vibration has been done through usage of empirical formulas; and, finally a relationship has been formulated to estimate vibration in the region [9, 10]. In second group, artificial intelligence methods including ANN have been applied. The related results show that they are closer to reality and this is why; they are more used. For example, Kazim et al. have predicted ground vibration in a mine located in Turkey. Accordingly, the results from prediction made by ANN have been closer to real values and indicative of high ability of the model [11]. Applying ANN method in prediction of vibrations created in Sar-cheshmeh Copper Mine has been studied by Bakhshandeh et al. Their results showed high accuracy of the model with least number of errors [12]. Vibrations produced from blasting in Golgohar Sirjan Mine have been predicted by Saadat et al. They concluded that ANN is of better performance, compared to other methods [13]. Other similar researches also in relation to prediction of vibrations resulted from blasting in Sar-cheshmeh Copper Mine have been done by Dehghani and Ataee-pour [14]; and, the results have been indicative of high accuracy of ANN. In a research performed by Vasovic et al. regarding control of vibrations produced from mine blasting in Serbia, and through comparison made between estimated vibrations and values obtained from various standards; better performance of ANN method has been suggested, compared to other methods [15]. Vibrations created from Bor Mine blasting have been predicted by Radojica et al. The mine is one of the biggest copper mines in Europe with about 5.6 million ton reserve. The results have shown high performance of ANN method, compared to empirical equations [16]. Also, comparing empirical methods and ANN by Monjezi et al. showed better performance of ANN in prediction of ground vibrations [17]. In present paper, ground vibration caused by blasting in Dam area of Dareh-Baq River would be predicted through empirical and also ANN methods. In continuation and based on the results obtained, best model as the one with minimum error level would be specified.

2. Case study

The Dareh-Baq dam is a 42.5m high rockfill dam which is located approximately 20km southeast of Kuhdasht in Lorestan Province, Iran. It has been constructed on the Haleh River. Figs1 and 2 show location and typical cross-sections of the dam body, respectively. To construct dam structure, materials required have to become crushed in different sizes. So, these material have to be sent from

Table 1: Safety criterion based on distance and velocity of particles [7]

Distance from location of blasting (m)	Maximum authorized velocity of particles (mm/s)
Up to 92	31.75
93 to 1525	25.4
More than 1525	19.05

Table 2: Authorized velocity limit according to Australian standard [8]

Type of structure	Authorized particle velocity (mm/s)
Hospitals, structure with weak ceiling, dams, and other important structures	5
Usual trade buildings and residential areas	10
Important trade buildings and structures with reinforced concrete or steel skeleton	20

closest locations to dam. Through study and evaluation of surrounding areas and based on technical requirements related to specification of rocks required, two mines have been selected around the dam area. These mines have been called main and secondary mines, based on volume of materials extracted from them; and, their distances from dam structure have been 1000 and 500 meters, respectively. Crushing rocks in these mines takes place through blast hole drilling and blasting. One of the most important undesirable effects of blasting in the area is ground vibration. Vibrations created may have undesirable effect on dam structure. So, vibrations have to be predicted and evaluated. For this purpose, 73 blasting events have been monitored and maximum amounts of explosive charge used per delay (kg), distance between location of blast and installation place of geophone (m), and created vibration level based on maximum particle velocity (mm/s) have been measured. Ranges of values measured are shown in Table 3. To measure ground vibration level, geophone MR2002 manufactured by SYSCOM Co[1] has been used. These geophones are capable of recording created ground vibrations in three X, Y, and Z directiones [18]. A sample of vibration recorded by the tool and its output is observable in Figs 3 and 4.

Table 3: Values of measured parameters in present paper

Parameter	Range of changes
Maximum explosive charge in each delay (kg)	700-8250
Distance of blasting location to where the vibration is recorded	306-1408
Ground vibration parameter (mm/s)	1.9-8

3. Artificial Neural Network Model

ANN has been created and inspired by biological neural network and its function is similar to that of human brain, with capability of learning, as one of its notable features [19]. A network includes units

[1]Switzerland

Figure 1: Location of Dareh-Baq Dam

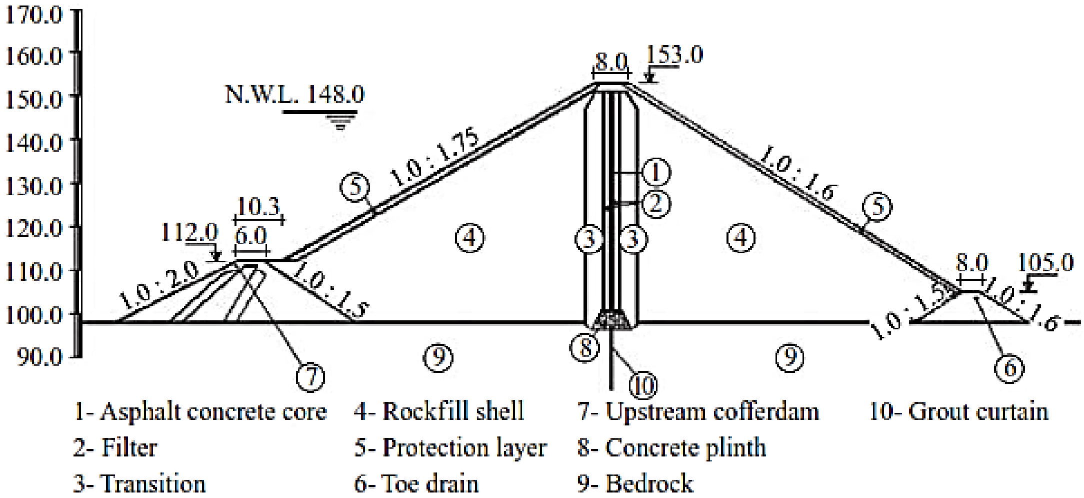

Figure 2: A typical cross-section of the dam body

called neural cells or neurons; and, using a group of input data, it can produce a group of arbitrary output [20]. Each neural network has at least three layers including: input layer, middle layer known as hidden layer, and output layer. Input layer is entrance point of data concerned by the network. Selecting type and number of network inputs has high impact on quality of network performance. Using high and unnecessary number of inputs and ineffective parameters as inputs causes much complexity in network, and also its inappropriate performance [21]. Hidden layers play performance arrangement role in an ANN. Numbers of hidden layers and neural cells existing in these layers are highly effective on network performance. This number would be determined based on trial and error. Final layer in each network is the output layer which presents result of ANN and performance of concerned parameters. Modeling in ANN has three stages including training, validation, and test. In fact, data would be used in three parts for training, validation, and test purposes. There are certain patterns for ANN training, from among which back propagation algorithm is very strong; and, it is widely functional in terms of learning method for multiple layers of neural network [22]. The network includes an input layer, one or more hidden layer(s), and one output layer. To train this network, usually back propagation algorithm is used. In Fig 5, a sample of multi-layer perceptron network is

Figure 3: MR2002 geophone for ground vibration recording

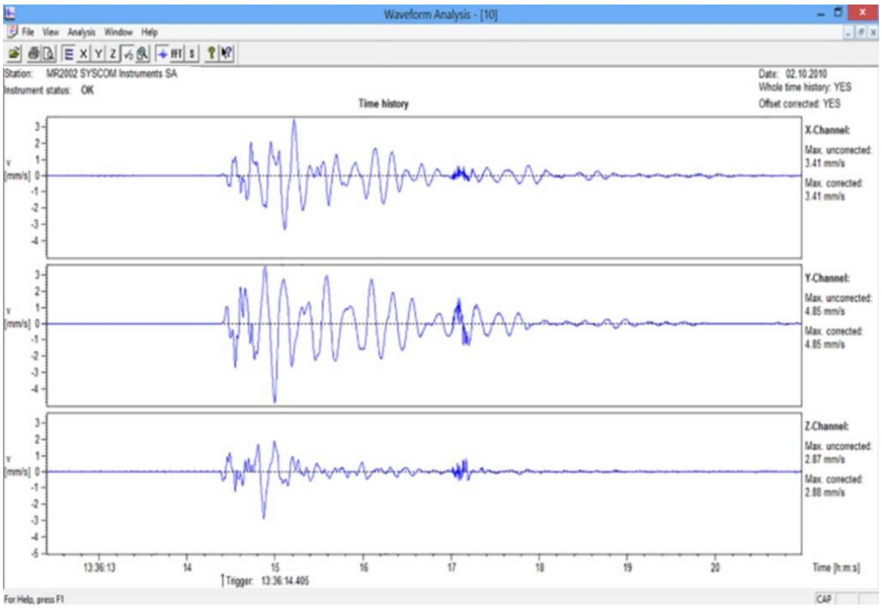

Figure 4: MR2002 output

shown [23].

Each back propagation network includes one or more transfer function(s) and also training function. Number of transfer functions depends on number of hidden layers. These transfer functions include Tansig and Logsig. For example, Tansig function produces between -1 and 1 output against $(-\infty, +\infty)$ input. This function and Purelin training function are specified in Fig 6 [24].

3.1. Predicting ground vibration through empirical equations

In this section, ground vibration component would be predicted through different empirical formulas. These empirical relationships are presented in Table 4 [25-29]. In these equations, PPV is Peak Particle Velocity (mm/s), D is distance of blasting location to place of ground vibration recording (m), W is maximum explosive charge used in each delay (kg), and K, B, A, α, and n are constant coefficients

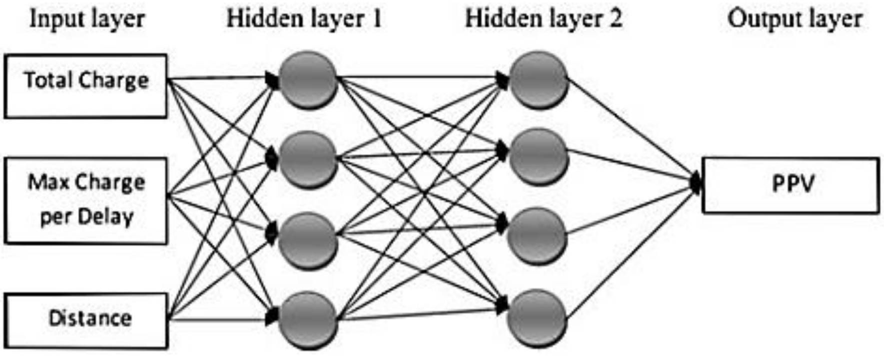

Figure 5: ANN Architecture

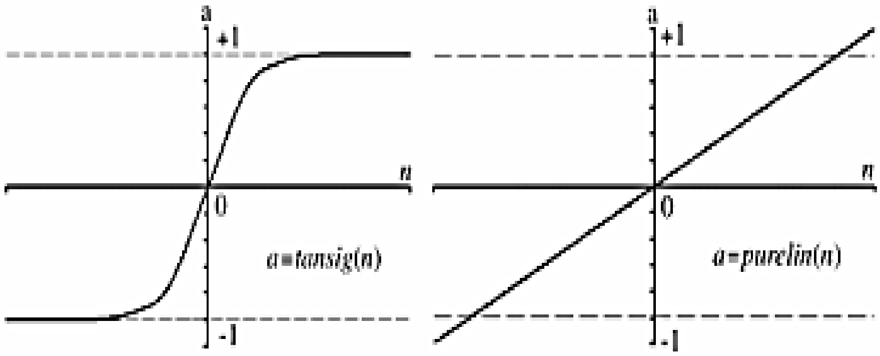

Figure 6: Tansig transfer function and Purelin training function

in relationships that would be specified through regression analysis. To determine relationships, 58 categories of data would be used and in next stage, 15 new categories would be used to compare measured values and predicted values, through different relationships. Those relationships referred to are shown in Table 4; and, their constant coefficients based on regression analysis performed are shown in Table 5. So, it goes without saying that these relationships have been specified based on 58 categories of data.

Table 4: Empirical relations to predict ground vibration

Empirical relations	Equation
Ambraseys & Hendron [25]	$PPV = K \times \left(D/W^{0.33}\right)^{B}$
USBM [26]	$PPV = K \times \left(D/\sqrt{W}\right)^{B}$
Indian Standard [27]	$PPV = K \times \left(W/D^{2/3}\right)^{B}$
Roy [28]	$PPV = n + K \times \left(D/\sqrt{W}\right)^{-1}$
Rai-Singh [29]	$PPV = K \times D^{A} \times W^{B} \times e^{-\alpha D}$

3.2. Predicting Peak particle Velocity through ANN model

To use ANN, 58 data from among about 73 data have been used for network training; and, 15 data have been used for network testing. Input parameters are maximum explosive charge per delay

Table 5: Constant coefficients related to empirical relationships

Empirical relations	K	B	A	α	n
Ambraseys-Hendron [25]	122.24	-0.858	-	-	-
USBM [26]	48.36	-0.92	-	-	-
Indian Standard [27]	1.21	0.37	-	-	-
Roy [28]	50.93	-	-	-	-0.64
Rai-Singh [29]	0.38	0.43	-6.21	-0.001	-

(kg), and distance of blasting location to installation place of seismograph device (m). Also, output parameters of PPV component have been measured (mm/s). After review and evaluation of various models and using trial and error method in relation to determination of number of hidden layers and number of neurons in each of them, appropriate architecture as for better performance of ANN is as provided in Table 6.

Table 6: Specifications of ANN for ground vibration prediction

Network used	Back propagation
Number of neurons in input layer	2
Number of neurons in output layer	1
Number of hidden layers	1
Number of neurons in hidden layer	3
Transfer function related to first hidden layer	Tansig
Transfer function of output layer	Purelin
Network training function	Trainlm
Number of data for network training	58
Number of data for network testing	15
Number of Epoch	1000

4. Comparing the results obtained from empirical relationships and ANN model

In the paper and to determine accuracy level of empirical models and ANN, various statistical variables have been used for accurate determination of performance level of different models. These variables are RMSE, VAF, and R^2. Relationship related to these variables is consistent with following formulas:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \times \sum_{\mathrm{i}=1}^{\mathrm{n}} \left[(\mathrm{x_i} - \mathrm{x_p})^2 \right]} \tag{4.1}$$

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{var}\,(\mathrm{x_i} - \mathrm{x_p})}{\mathrm{var}\,(\mathrm{x_i})} \right] \times 100 \tag{4.2}$$

$$\mathrm{R}^2 = \frac{\left[\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{x_i} - \mathrm{x_{mean}})^2 \right] - \left[\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{x_i} - \mathrm{x_p})^2 \right]}{\left[\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{x_i} - \mathrm{x_{mean}})^2 \right]} \tag{4.3}$$

where, x_i is real value, x_p is predicted value, x_{mean} is mean value, n is number, and var is data variance. Under ideal condition, of the value obtained from predictive models including empirical relationships and ANN would be completely consistent with real values, concerned statistical criteria would be such as those provided in Table 7.

Table 7: Ideal mode for predicted values

Statistical Variables	Ideal Value
RMSE	0
VAF	100
R^2	1

In Figs 7 to 12, the results from predictions have been shown through various models and real values; and, their convergence coefficients have been specified. After evaluation of results obtained from prediction of peak particle velocity (PPV) through various statistical methods, it became clear that ANN model provides closest prediction to reality. The model also is of lowest number of errors among existing methods. Results related to statistical criteria for evaluation of predictive models are as shown in Table 8. Also, real and predicted values by aforementioned models are shown in Fig 13.

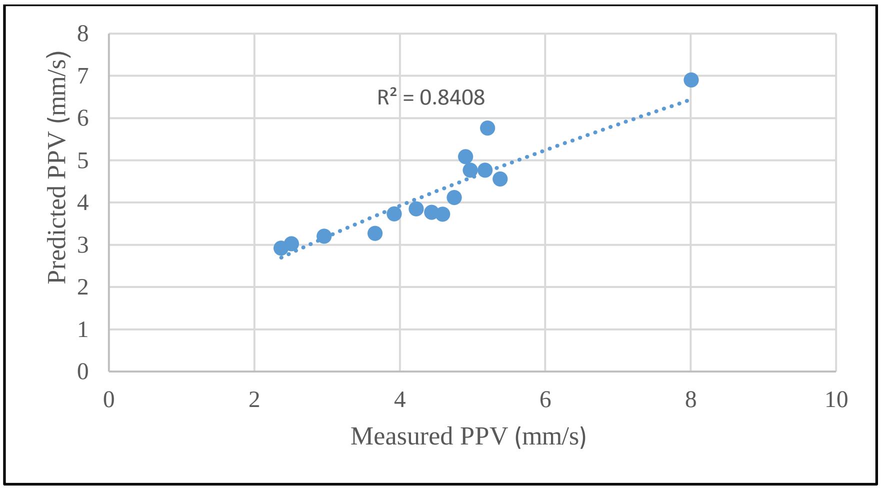

Figure 7: Real and predicted values by Abbraseys-Hendron relationship

Table 8: Comparing performance of predictive models

Model	R^2	VAF	RMSE
Ambraseys–Hendron	0.84	84.39	0.57
USBM	0.92	88.49	0.46
Indian Standard	0.63	52.53	0.91
Roy	0.89	86.78	0.5
Rai-Singh	0.86	87	0.47
ANN	0.98	97.61	0.2

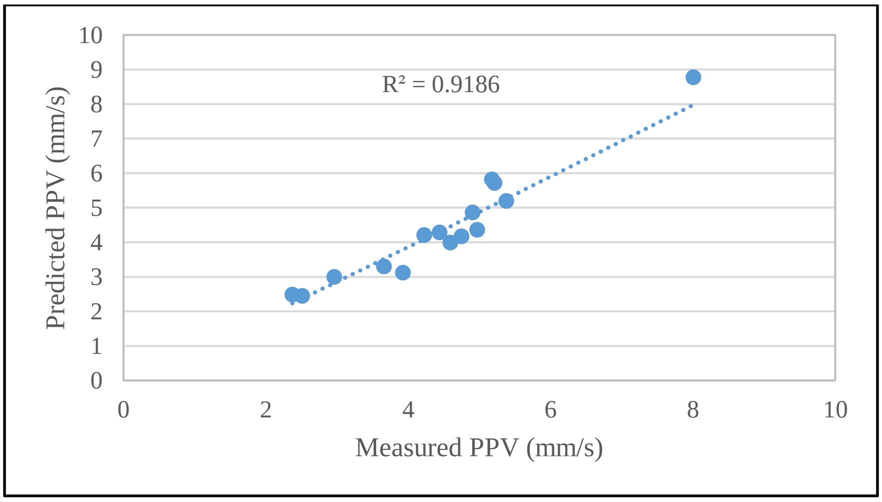

Figure 8: Real and predicted values by USBM relationship

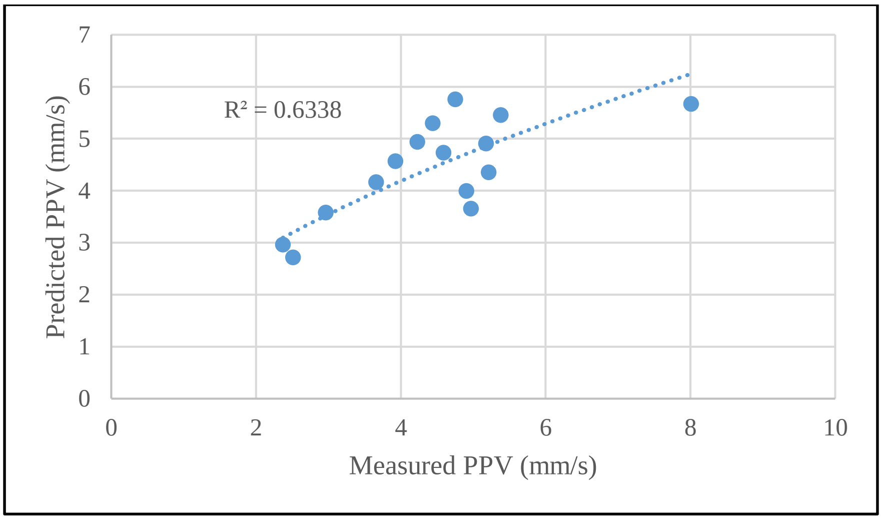

Figure 9: Real and predicted values by Indian Standard relationship

5. Conclusion

Evaluation results based on standards presented show that, vibrations created are within the safe range and no danger would be imposed on structure of dam on Dareh-Baq River. As far as Australian standard is concerned and as presented in Table 2, maximum authorized velocity for sensitive structures like dams is 5mm/s; whereas, according to Table 3, maximum ground vibration has been recorded as 8mm/s. In this respect, it has to be noted that the vibration has been recorded with 461m distance from blasting location. Since dam structure at lowest has 1000m distance from blasting location, 8mm/s vibration will never happen where dam is constructed. The reason is that, in distances over 1000m, maximum recorded velocity has been 4.95mm/s and within safe range, based on the dam structure's standard. Moreover, in the paper, various statistical criteria have been used to determine error of predictive models. After review of values of these criteria, it became clear that ANN bears lowest level of error and highest level of convergence among predictive and real values. For example, lowest RMSE and highest R^2 values have been related to ANN model; and, this is indicative of ANN being a strong tool for prediction of vibrations resulted from blasting.

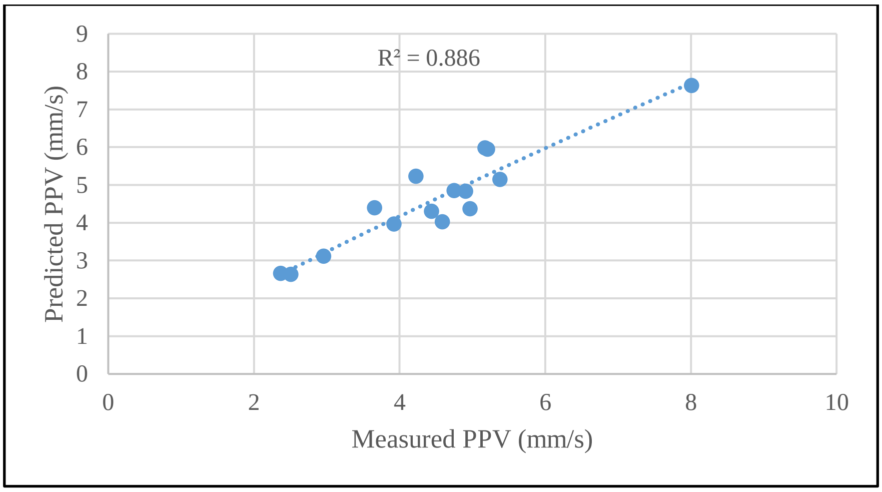

Figure 10: Real and predicted values by Roy relationship

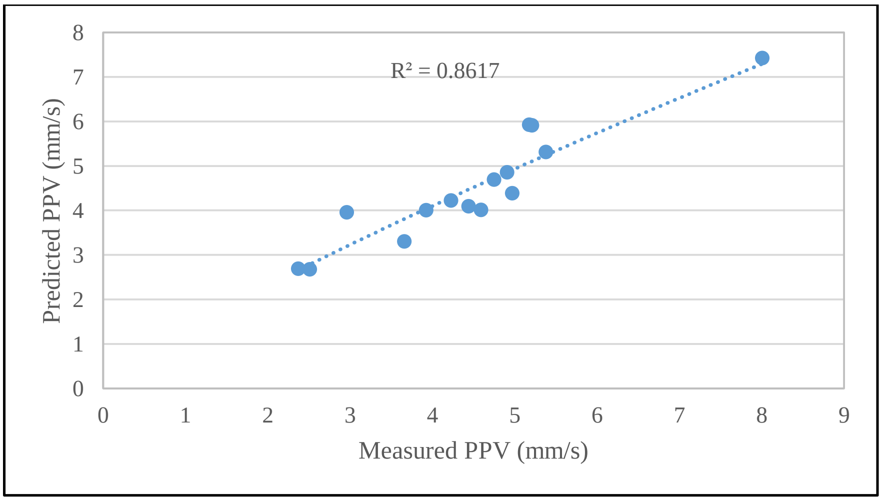

Figure 11: Real and predicted values by Rai-Singh relationship

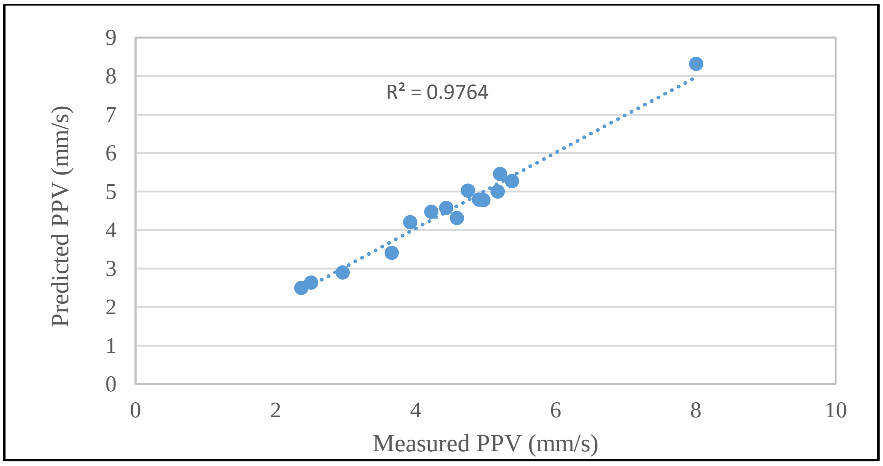

Figure 12: Real and predicted values by ANN relationship

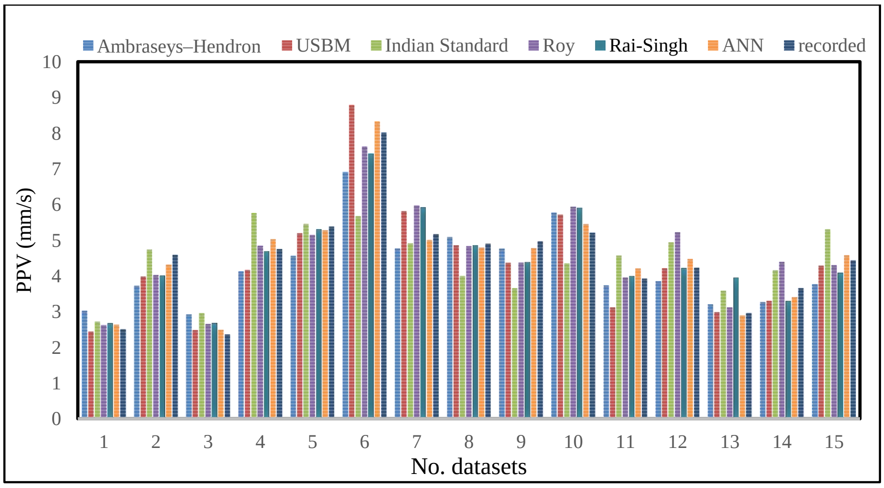

Figure 13: Comparing Predicted and real values

References

[1] Hasanipanah. M, Monjezi. M, Shahnazar. A, Jahed Armaghani D, Farazmand A, Feasibility of indirect determination of blast induced ground vibration based on support vector machine, Measurement. 75 (2015) 289–297.

[2] Mohammad. MT, Artificial neural network for prediction and control of blasting vibration in Assiut limestone quarry, Int. J. Rock Mech. Min. Sci. 46(2) (2009) 426–31.

[3] Khandelwal. M, Singh. TN, Evaluation of blast-induced ground vibration predictors, Soil Dynamic Earthq Eng. 27 (2007) 116-25.

[4] Shirani Faradonbeh. R, Monjezi. M, Jahed Armaghani. D, Genetic programing and non-linear multiple regression techniques to predict back-break in blasting operation, Eng Comput. 32(1) (2016) 122-133.

[5] Khandelwal. M, Singh. TN, Prediction of blast-induced ground vibration using artificial neural network, Int. J. Rock Mech Min. Sci. 46 (2009) 1214-22.

[6] Khandelwal. M, Kankar. PK, Prediction of blast-induced air overpressure using support vector machine, Arabian J Geosci. 4 (2011) 427–33.

[7] Dowding. CH, Construction vibrations, Intl Society of Explosives, (2000).

[8] Gupta. R, The Recent Global Developments on Blasting & Rock Fragmentation. Dissertation, Tarbiat Modarres University, (2005).

[9] Ozer. O, Kahriman. A, Aksoy. M, Adiguzel. D, Karadogan. A, The analysis of ground vibrations induced by bench blasting at Akyol quarry and practical blasting charts, Environ Geol. 54 (2008) 737–743.

[10] Kahriman. A, Analysis of parameters of ground vibration produced from bench blasting at a limestone quarry, Soil Dynamic Earthq Eng. 24 (2004) 887–892.

[11] Kazim. G, Ercan. A, Ahmet. D, Arzu. K, Investigation of blast-induced ground vibrations in the Tulu boron open pit mine, Bull Eng Geol Environ. 72 (2013) 555–564.

[12] Bakhshandeh Amnieh. M, Mozdianfard. M.R, Siamaki. A, Predicting of blasting vibrations in Sar-cheshmeh copper mine by neural network, Safety Science. 48 (2010) 319–325.

[13] Saadat. M, Khandelwal. M, Monjezi. M, An ANN-based approach to predict blast-induced ground vibration of Gol-E-Gohar iron ore mine Iran, J. Rock Mech. Geotech. Eng. 6 (2014) 67-76.

[14] Dehghani. H, Ataee-pour. M Development of a model to predict peak particle velocity in a

blasting operation, Int. J. Rock Mech. Min. Sci. 48 (2011) 51–58.
[15] Vasovic. D, Kostic. S, Ravilic. M, Trajkovic. S, Environmental impact of blasting at Drenovac limestone quarry (Serbia), Environ Earth Sci. (2014). DOI 10.1007/s12665-014-3280.
[16] Radojica. L, Srdjan. K, Radoje. P, Nebojsa. V, Prediction of blast-induced ground motion in a copper mine, Int. J. Rock Mech. Min. Sci. 69 (2014) 19–25.
[17] Monjezi. M, Ghafurikalajahi. M, Bahrami. A, Prediction of blast-induced ground vibration using arti?cial neural networks, Tunn Undergr Sp Tech. 26 (2011) 46-50.
[18] SYSCOM, User Manual, Instruments SA, Kornhausstr Zurich, Switzerland.
[19] Menhaj. M.B, Fundamentals of Neural Networks, AUT university of technology, (2002).
[20] Mohamed. MT, Performance of fuzzy logic and artificial neural network in prediction of ground and air vibrations, Int J Rock Mech Min Sci. 48 (2011) 45–51.
[21] Alvarez-Vigil. AE, Gonzales-Nicieza. C, Lopez Gayarre. F, Alvarez-Fernandez. MI, Predicting blasting propagation velocity and vibration frequency using artificial neural network, Int. J. Rock Mech. Min. Sci. 55 (2012) 108–16.
[22] Shahin. MA, Maier. HR, Jaksa. MB, Predicting settlement of shallow foundations using neural networks, J Geotech Geoenviron Eng. 128 (2002) 785–93.
[23] Fausett. LV, Fundamentals of Neural Networks: Architecture, Algorithms and Applications, Prentice-Hall, Englewood Cliffs, (1994).
[24] Nelson. M, Illingworth. WT, A Practical Guide to Neural Nets, Addison-Wesley, Reading MA, (1990).
[25] Ambraseys. NR and Hendron. AJ, Dynamic behavior of rock masses. In: Stagg KG and Zienkiewicz OC (Eds) Rock Mechanics in Engineering Practices New York, (1968).
[26] Duvall. WI and Petkof. B, Spherical propagation of explosion generated strain pulses in rock. US Bureau of Mines Report of Investigation 5483, (1959).
[27] Indian Standard Institute, Criteria for safety and design of structures subjected to underground blast. ISI Bull IS: 6922, (1973).
[28] Pal. Roy P, Vibration control in an opencast mine based on improved blast vibration predictors, Min Sci Tech. 25 (1991) 157–165.
[29] Rai. R and Singh. TN, A new predictor for ground vibration prediction and its comparison with other predictors, Indian J Eng Mater S. 11 (2004) 178–184.