Mining
Mineração

Comparing blast-induced ground vibration models using ANN and empirical geomechanical relationships

http://dx.doi.org/10.1590/0370-44672017710097

Wilson Siguemasa Iramina
Universidade de São Paulo - USP
Escola Politécnica
Departamento de Engenharia de Minas e de Petróleo
São Paulo - São Paulo - Brasil
wilsiram@usp.br, wiramina@hotmail.com

Eduardo Cesar Sansone
Universidade de São Paulo - USP
Escola Politécnica
Departamento de Engenharia de Minas e de Petróleo
São Paulo - São Paulo - Brasil
esansone@usp.br

Michiel Wichers
Universidade de São Paulo - USP
Escola Politécnica
Departamento de Engenharia de Minas e de Petróleo
São Paulo - São Paulo - Brasil
michiel.wichers@usp.br

Sugeng Wahyudi
Kyushu University - Faculty of Engineering
Department of Earth Resources Engineering
Fukuoka – Fukuoka - Japan
wahyudi_sugeng@mine.kyushu-u.ac.jp

Sérgio Médici de Eston
Universidade de São Paulo - USP
Escola Politécnica
Departamento de Engenharia de Minas e de Petróleo
São Paulo - São Paulo - Brasil
smeston@usp.br

Hideki Shimada
Kyushu University - Faculty of Engineering
Department of Earth Resources Engineering
Fukuoka – Fukuoka - Japan
shimada@mine.kyushu-u.ac.jp

Takashi Sasaoka
Kyushu University - Faculty of Engineering
Department of Earth Resources Engineering
Fukuoka – Fukuoka - Japan
sasaoka@mine.kyushu-u.ac.jp

Abstract

Blasting remains as an economical and reliable excavation technique, but there are some environmental shortcomings such as the control of blast-induced vibration. The impacts of vibration over surrounding communities in a blast area have been investigated for decades and researchers have been using a myriad of empirical predictive attenuation equations. These models, however, may not have satisfactory accuracy, since parameters associated to geomechanical properties and geology affect the propagation of seismic waves, making vibration modeling a complex process. This study aims for application of an Artificial Neural Network (ANN) method and Geomechanical parameter relationships to simulate the blast-induced vibration for a Brazilian mining site and then compare them to the traditional approach. ANN had the best performance for this mine despite having demanded large datasets (as much as for the traditional approach), while geomechanical parameters like RQD and GSI may be used to deliver a fair approach even without seismic data. Also, ANN methods may be useful in dealing with a large amount of information to facilitate the simulation process when combined with other methods. Therefore, alternative prediction methods may be helpful for small budget mining operations in planning and controlling blast-induced vibration and helping mining in urban areas becoming a more sustainable activity.

Keywords: blast-induced vibration; attenuation equation; Artificial Neural Network; geomechanical relationships.

1. Introduction

Blasting is frequently the most cost effective technique for rock excavation. The use of explosives in mining and construction activities is almost unanimous and the development of new products and new blast design studies will keep blasting as the favorite technique in the coming decades. Although reliable and economical, the use of explosives must deal with some environmental shortcomings. Since many mining sites are surrounded by people, some of the effects of blasting like noise and ground vibration may be considered as annoying or even a threat. In fact, blasting in urban areas has become a challenge, since regulations concerning blast-induced vibration have become more rigid and this situation could severely affect the sustainability of the mining operations or construction activity. To avoid conflicts between communities and blasting areas, blast-induced vibration should be controlled and monitored. Enhancements in blast design and the use of new products will only prove sustainable if there is a precise and reliable way of knowing the impacts of the ground vibration. Therefore, in the last decades, predictive attenuation models have been proposed. However, due to their empirical nature, these models, known as predictive attenuation equations, had low accuracy when several directions needed to be studied. A general prediction equation is desired but with different parameters of the rock mass, such as geomechanical properties that affect the seismic wave propagation in different ways for different directions. Therefore, using a limited number of seismograph monitoring data may not be enough for a reliable characterization of the vibration behavior in one or more directions. The question is: is it possible to obtain a fair to good approach for predicting attenuation using a limited seismograph monitoring dataset? Is there any other approach?

This study aims for the application of an Artificial Neural Network (ANN) and relationships based on geomechanical parameters to model the blast-induced vibration attenuation using blasting and rock mass parameters at a Brazilian mining operation. It is expected that the results may have better accuracy when compared to some empirical methods for feasibility purposes to help small budget mines and quarries in urban areas to become more sustainable.

2. Blast-induced ground vibration

Geology and geomechanical aspects of the rock mass affect the characteristics of ground vibration as waves move away from blasting area. This dissipation or "geometric spread" occurs when a finite amount of vibration energy needs to fill an increasing amount of the rock mass volume as it moves toward the farthest point of detonation. Thus, there is a decay in vibration amplitude with increasing distance from the source, similar to the inverse-square law. Other effects are the propagating energy losses by absorption and dispersion and the formation of surface waves. The great variation in geological conditions of rock masses presents difficulties in predicting vibration attenuation. Currently, most of the predictions were obtained by statistical-empirical relationships (Attenuation Equations or AE) where vibration can be correlated with structural damage. The most used parameter to represent the ground vibration is the peak particle velocity (PPV) and it basically depends on two main variables: the mass of the detonated explosive charge and the distance between the detonation point and the measuring point. This relationship can be mathematically established from the data obtained by seismographic monitoring. Among the many empirical relationships, the most used is the one that correlates the peak particle velocity with "scaled distance" used to predict the effects of ground vibration on structures and humans. Scaled distance (SD) is defined as the distance from blast divided by the n^{th} root of the weight (mass) of the explosive charge used in the blast.

The parameters that affect the characteristics of the vibrations are basically the same that influence the results of a blasting and they are generally classified into two groups: controllable and uncontrollable. Controllable parameters are those related to blast design and the uncontrollable parameters are features of the rock mass related to surrounding local geology and geomechanical characteristics that have a major influence on vibrations. In massive and homogenous rock vibration, the waves may propagate almost equally in all directions. However, in complex geological structures, the wave propagation may vary with the direction, therefore resulting in a different attenuation requiring representation by different propagation equations. In the last decades, several researchers established empirical equations to predict blast-induced vibrations. Some of the most important include those from USBM in 1959, Langefors–Kihlstrom in 1963, Ambraseys-Hendron in 1968, Nicholls *et al.* in 1971, Siskind *et al.* in 1980, Pal Roy in 1991 and CMRI in 1993. These and other equations were listed by authors such as Khandelwal and Singh (2009), Kamali and Ataei (2010), Wahyudi *et al.* (2011), Saadat *et al.* (2014) and Kumar *et al.* (2016).

3. Vibration attenuation modeling using the ANN method and relationships based on geomechanical parameters

3.1 Vibration attenuation and artificial neural network (ANN) simulation

According to Sansone *et al.* (2009), Artificial Neural Networks (ANN) constitute the mathematical expression of what is currently believed to be the way the human brain works. ANNs consist of processing units, called "neurons" connected to each other by synapses. The most common ANNs are formed by layers of neurons (input, hidden or intermediate and output ones) and the information flow crosses the direction from the input layer to the output layer. The synapses are characterized by weights that are used to make the output values compatible with the input values. The algorithms that define the weights of ANNs are called training algorithms. An ANN, properly constructed, can represent arbitrary relationships between variables from the data used in training and have proven generalization capability even when dealing with noisy input data. The operation of an already trained ANN is simple and can be easily incorporated into design methods.

Several algorithms can be used to train neural networks, but backpropagation-based algorithm (BP) has had preference among researchers to solve predicting problems (Wahyudi *et al.*, 2011; Monjezi *et al.*, 2013; Kamali and Ataei, 2010 and Saadat *et al.*, 2014). Saadat *et al.* (2014) have used, for function approximation, a feedforward ANN. These researchers recommend the use of a BP algorithm with sigmoid transfer functions in the hidden layers and a linear transfer function in the output layer. The BP training algorithm is applied to determine the set of weights of an ANN by using a corrective–repetitive process where the actual output is compared with the target output. The difference or error between both is processed back through the network, updating the individual weights of the synapses. These weights are adjusted by an error minimization technique so that a target output will be produced for a given input. The updating process is repeated until the network error converges to a threshold or reaches a desired number of iterations.

In the early 21st century, numerous researchers tried to use ANNs to predict blast-induced ground vibration as an alternative method, since the Empirical Attenuation Equation (AE) may not work well due to noise (Wahyudi *et al.*, 2011). According to Kamali and Ataei (2010), ANN has been used in mining since 1990 and more specifically for blast-induced ground vibration studies since 2004. The prediction of PPV using up to four variables can be done effectively by a backpropagation algorithm with good performance.

3.2 Vibration attenuation prediction using geomechanical parameters

A rock mass may be rated using characteristics, such as the parameters of intact rock; characteristics of the discontinuities; in situ stress; presence of water; type of excavation (tunnel, slope, mining bench, etc.) and geometric characteristics of the excavation. The purpose of this rating is to frame the rock mass according to predefined classes and to deliver safety and support guidelines for carrying out the mining or construction project (Wyllie *et al,* 2009).

RQD classification was proposed by Deere (Wyllie *et al.,* 2009) to estimate the quality of rocks from the analysis of core samples. The rating is based on a single index (RQD - Rock Quality Designation), which is defined as the percentage of the total length of the fragments larger than 10 cm (4 inches) in relation to the total length of the core with a diameter at least equal to NW (54.7 mm). It is a parameter that depends on the direction of the drilling (Wyllie *et al.,* 2009).

The Geological Strength Index (GSI) provides a system to estimate the reduction in rock mass strength for different geological conditions. Values of GSI are related to both the degree of fracturing and the condition of fracture surfaces, as the strength of a jointed rock mass depends on the properties of the intact rock pieces. Such strength also depends on the freedom of the rock pieces to slide and rotate under different stress conditions. This freedom is controlled by the geometrical shape of the intact rock pieces and the condition of the surfaces separating the pieces. Angular rock pieces with clean, rough surfaces will result in a much stronger rock mass than one that contains rounded particles surrounded by weathered and altered material (Wyllie *et al,* 2009). GSI improves geological logic and reduces engineering uncertainty throughout the quantification of the many characteristics of a rock mass (Mesec *et al.,* 2017).

Kumar *at al.* (2016) proposed an interesting approach by using two empirical relationships: one between PPV and GSI (Geological Strength Index) and the other between PPV and RQD (Rock Quality Designation). Equation 1 shows the relationship for GSI.

$$PPV = \frac{(0.3396x1.02^{GSI}GSI^{1.13})^{0.642}SD^{-1.463}}{\gamma} \quad (1)$$

where: PPV= Peak particle velocity in (m/s)
GSI = Geological Strength Index
SD = Scaled Distance in (m/kg $^{0.5}$)
γ = Unit weight in (KN/m^3)

And the second approach, using the RQD relationship, is quoted by Equations 2 and 3.

For RQD ≤ 75

$$PPV = \frac{(0.5947RQD + 0.00893RQD^2)^{0.642}SD^{-1.463}}{\gamma} \quad (2)$$

For RQD > 75

$$PPV = \frac{(-7.91562RQD + 0.12152RQD^2)^{0.642}SD^{-1.463}}{\gamma} \quad (3)$$

where: PPV= Peak particle velocity in (m/s)
RQD = Rock Quality Designation
SD = Scaled Distance in (m/kg $^{0.5}$)
γ = Unit weight in (KN/m^3)

4. Applying ANN and GSI/RQD relationships to a Brazilian mine site vibration attenuation study

A granite quarry, surrounded by communities located in São Paulo State (Brazil), was previously studied by the Laboratory of Environmental Control, Industrial Hygiene and Safety in Mining at the University of São Paulo, Brazil. A seismographic monitoring was performed in this quarry and four blasts were recorded. All blasts had similar features and they were performed in the same bench. Several scaled-distance attenuation equations were estimated for different directions. Published field blast data (Ramirez Canedo 2013 and Ramirez Canedo *et al.*, 2015) were used in this study. Figure 1 shows a satellite view of the mine and the distribution of the sensors in Ramirez Canedo's study.

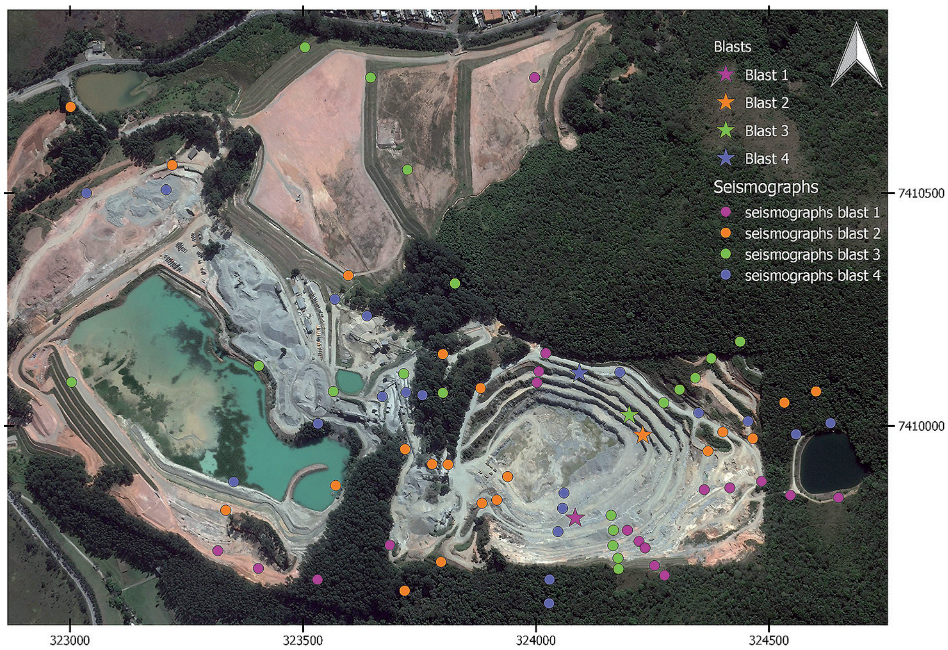

Figure 1
Blasting sites and distribution of sensors (modified from Ramirez Canedo *et al*, 2015).

4.1. Empirical Attenuation Equation (AE)

The square root scaled distance formula, proposed by the United States Bureau of Mines (USBM), is most commonly used and considers that the charge is distributed in a long cylinder (blasthole). The collection of data from several blasts and the use of an ordinary statistical analysis allow to determine the site constant k and site exponent b and replace them in the general equation shown by Equation 4. The result for the studied quarry, after processing 76 values, is the predictive formula quoted by Equation 5.

$$PPV = k[D/Q^{0.5}]^{-b} \tag{4}$$

$$PPV = 782.5[D/Q^{0.5}]^{-1.52} \tag{5}$$

4.2. Applying ANN simulation

Setting the ANN architecture is a crucial aspect and since there is no general rule for selecting the proper architecture, many researchers have concluded that finding the best-fit network type is a trial and error (and also time consuming) process because each network has particular properties (Kamali and Ataei, 2010). This study applied the same method used by Monjezi *et al.* (2013) with 3 input parameters: Maximum charge per delay (Q), Distance (D) and Total charge of explosives (Q_{tot}).

A measurement database, also used to construct the AE, was used for training the network. As performed by Wahyudi *et al.* (2011) and other authors, the network was designed using the trial and error method to determine the optimum number of hidden layers as well as the number of neurons. The best training parameters such as learning rate and momentum coefficient were also discovered using the trial and error method. While the learning rate is required to control the speed of training, the momentum coefficient is used to prevent the learning process from getting stuck in a local minima. To achieve the best network architecture, the network was validated and tested by using a new monitoring dataset, which was also used to validate the AE. As suggested by Monjezi *et al* (2013), the ANN testing and validation data should be considered separately, i.e., data employed for training should not be used for testing.

After various architectures trials and based on the best-obtained simulation results, the characteristics of the ANN architecture are as follows:

- Number of input neurons: 1
- Number of output neurons: 1
- Number of hidden layers:2
- Number of nodes in the first hidden layer: 3
- Number of nodes in the second hidden layer: 3

4.3 Applying GSI/RQD simulation

A Geomechanical survey report indicated an average value of 45 for GSI ("*very blocky, interlocked, partially disturbed mass with multi-faceted angular blocks formed by four or more joint sets*"). The quarry's rock mass is considered as homogenous and fairly to highly fractured (Bureau de Projetos e Consultoria, 2015).

Eighteen core samples were analyzed to obtain the RQD, with values ranging from 65.5 to 100 with an average of 91 (Bureau de Projetos e Consultoria, 2015).

5. Results and discussion

Empirical attenuation equation (AE), Artificial Neural Network method (ANN), GSI based relationship and RQD based relationship approaches were performed in this study. The use of recorded field data allowed to rank the best estimation. Figure 2 shows the performance for each method compared to real data.

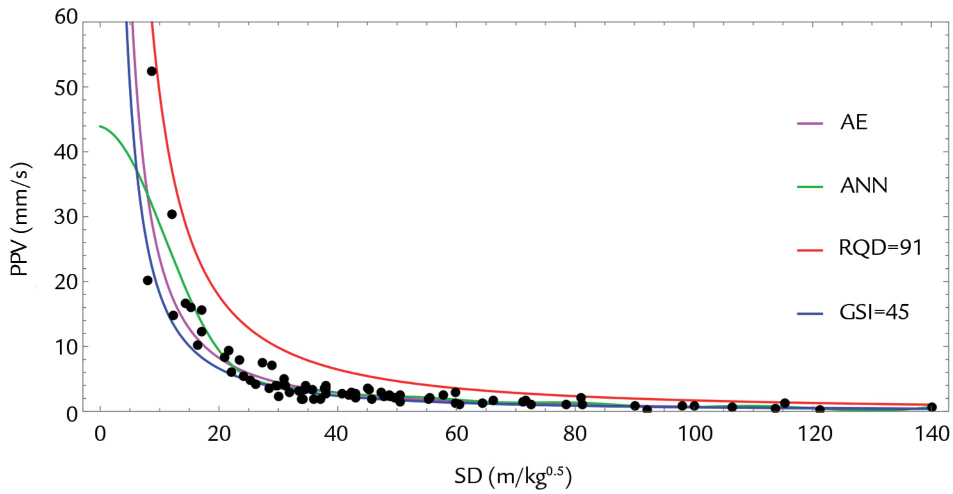

Figure 2
Comparing AE, ANN, GSI and RQD performances for PPV prediction.

RMS errors for AE, ANN, RQD and GSI methods were computed and presented the respective values of 3.63, 3.25, 7.81 and 4.36. These values indicate that ANN has the best estimation, followed by AE. This was expected considering that both methods use field data to deliver the vibration attenuation while GSI and RQD only used mean values of rock mass to estimate vibration. Since there is a range of variation in both GSI and RQD values, it would be interesting to know the influence of their variation along with the rock mass, as it may reflect differences in the direction of propagation.

Figure 3 shows the performances of GSI (left) and RQD (right) relationships for lowest and highest values obtained in field tests.

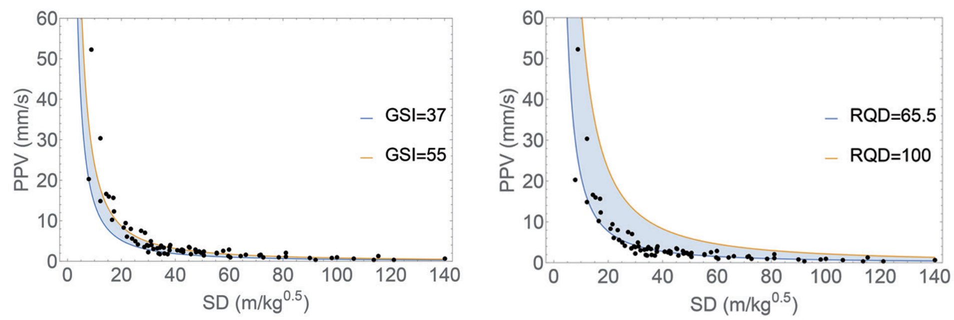

Figure 3
Comparing performances for lowest and highest field values of GSI (left) and RQD (right).

The analysis of the ranging values obtained for GSI and RQD show that there may be differences in the vibration propagation possibly related to rock mass properties of the quarry. However, comparing the prediction performance for the extremes in the scaled distance range suggests that there is a certain homogeneity in terms of vibration propagation. Therefore, in this case both GSI and RQD averages could be used to fit actual values when correlating vibration with rock mass properties.

If we could establish a relationship between geomechanical parameters (GSI and/or RQD) for each direction, it is believed that the results could be even more accurate, and in addition, applying ANN to study geomechanical parameters accurately could be a more effective solution. For the particular directions elected by Ramirez Canedo (Ramirez Canedo, 2013 and Ramirez Canedo *et al.*, 2015) to obtain the attenuation, the resulting equations might be preferable over other solutions (ANN, GSI, etc.), despite the relatively few number of sensors used in the interpolation. The way the surveys were carried out make them reliable for predicting the attenuation for those specific directions. PPV prediction by Kumar et al.´s model was limited to scaled distances up to 80 m/kg$^{0.5}$ but for the studied quarry, it seems to be acceptable for values up to 120 m/kg$^{0.5}$. Near-field attenuation may also affect the prediction for small scaled distance since interactions in this field are not well known.

Not always ANN itself may be the best solution for an attenuation study. Its processing capacity relies on a large number of previously obtained recorded data that are sometimes very difficult to get, not to mention time spent and costs for collecting them (years and tens of thousands of dollars). Additionally, a large variety of input parameters may not result in better simulation, as distance and charge per delay are the most prevailing parameters when applying ANN. However, for far field attenuation, ANN may be a good solution. As new data are collected, ANN methods may be very useful to deal with a large amount of information. This facilitates the process itself, either for simulation purposes or for validation of AE methods.

6. Conclusions

A Brazilian mine was studied using an empirical attenuation equation, Artificial Neural Network and geomechanical parameters-based relationships, to obtain a more accurate blast-induced vibration attenuation model. The availability of input parameters, the size of the dataset and the purpose of the seismograph monitoring may affect the resulting simulations.

Developing countries and small mines require the development of a suitable empirical model for PPV prediction since site-specific empirical models are available but they cannot be generalized for different sites. Mining is an important activity in many countries and mining in urban areas has become a challenge as complexities of rock sites demand accurate PPV models considering a number of effects. These effects are related to rock discontinuities, rock types, rock formation, rock joints and their orientation, groundwater presence and soil-rock interface. Seismograph monitoring in countries like Brazil is expensive and most of the time is performed by using few sensors (usually up to two sensors for each blast), which may affect the quality of the empirical attenuation equation and Artificial Neural Network approaches. On the other hand, using geomechanical based relationships could be a useful alternative for a satisfactory estimation of vibration, helping mining in urban areas to become a more sustainable activity.

Acknowledgment

The authors express their gratitude to CNPq - Conselho Nacional de Desenvolvimento Científico e Tecnológico, of the Ministry of Science, Technology and Innovation of Brazil, who has granted a scholarship for the corresponding author.

References

BUREAU DE PROJETOS E CONSULTORIA. ***Relatório de análise do projeto da cava de expansão.*** São Paulo: EMBU S.A. Engenharia e Comércio, 2015. Relatório RC-SP-059/15. (Documento acessível mediante autorização da Empresa/Restricted access).

KAMALI, M., ATAEI, M. Prediction of blast induced ground vibrations in Karoun III power plant and dam: a neural network. ***The Journal of the Southern African Institute of Mining and Metallurgy,*** Johannesburg, v. 10, p. 481-490, Aug. 2010.

KHANDELWAL, M., SINGH, T.N. Prediction of blast-induced ground vibration using artificial neural network. ***International Journal of Rock Mechanics Mining Science,*** Oxford, v. 46, n. 7, p. 1214–1222, Oct. 2009. [doi:10.1016/j.ijrmms.2009.03.004].

KUMAR, R., CHOUDHURY, D., BHARGAVA, K. Determination of blast-induced ground vibration equations for rocks using mechanical and geological properties. ***Journal of Rock Mechanics and Geotechnical Engineering,*** Beijing, v. 8, n. 3, p. 341–349, 2016. [http://dx.doi.org/10.1016/j.jrmge.2015.10.009].

MESEC, J., STRELEC, S., TEZAK, D. Ground vibrations level characterization through the geological strength index (GSI). ***The Mining-Geology-Petroleum Engineering Bulletin,*** Zagreb, p. 1-6, 2017. [DOI: 10.17794/rgn.2017.1.1].

MONJEZI, M. et al. Predicting blast-induced ground vibration using various types of neural networks. ***Soil Dynamics and Earthquake Engineering,*** Oxford, v. 30, n. 11, p. 1233-1236, Nov. 2010.

MONJEZI, M., HASANIPANAH, M., KHANDELWAL, M. Evaluation and prediction of blast-induced ground vibration at Shur River Dam, Iran, by artificial neural network. ***Neural Computing and Applications,*** London, v. 22, n. 7/8, p. 1637-1643, 2013. Disponível em: < https://link-springer-com.ez67.periodicos.capes.gov.br/content/pdf/10.1007%2Fs00521-012-0856-y.pdf>. Acesso em: 15 set. 2016. [DOI 10.1007/s00521-012-0856-y].

RAMIREZ CANEDO, G. ***Mapa de iso-velocidades: uma ferramenta para o controle das vibrações nas pedreiras.*** São Paulo: Escola Politécnica, Universidade de São Paulo, 2013. 161 p. (Tese de Doutorado).

RAMIREZ CANEDO, G. et al. Iso-velocity maps. A vibration control tool in quarries. ***REM : Revista Escola de Minas,*** Ouro Preto, v.68, n.3, p. 313-318, 2015. Disponível em: < http://www.scielo.br/pdf/rem/v68n3/0370-4467-rem-68-03-0313.pdf>. Acesso em: 25 ago. 2016. [https://dx.doi.org/10.1590/0370-44672014680163].

SAADAT, M., KHANDELWAL M., MONJEZI, M. An ANN-based approach to predict blast-induced ground vibration of Gol-E-Gohar iron ore mine, Iran. ***Journal of Rock Mechanics and Geotechnical Engineering, Beijing,*** v. 6, n.1, p. 67-76, Febr. 2014.

SANSONE, E. C., RUSILO, L. C., IRAMINA, W. S. Modeling the creep mechanical behavior of salt rocks in artificial neural networks. In: INTERNATIONAL SYMPOSIUM ON MINE PLANNING AND EQUIPMENT SELECTION, 18th, 2009, Banff, Canada. MPES 2009: proceedings. [Irvine, CA]: The Reading Matrix, 2009. v.1, p. 738-747. 1 CD-ROM.

WAHYUDI, S. et al. A review study of predictive model blast vibration attenuation equation by using neural network as an evaluator. ***International Journal of Mining, Reclamation and Environment,*** London, v. 25, n. 1, p. 69-85, 2011. [http://dx.doi.org/10.1080/17480930.2010.509482].

WYLLIE, D. C., HOEK, E., MAH, C. W. ***Rock slope engineering: civil and mining.*** New York, NY: Spon Press, 2009.

Received: 29 June 2017 - Accepted: 21 August 2017.