http://dx.doi.org/10.17159/2411-9717/2015/v115n7a10

Peak particle velocity prediction using support vector machines: a surface blasting case study

by S.R. Dindarloo*

Synopsis

Although blasting is one of the most widely used methods for rock fragmentation, it has a major disadvantage in that it causes adjacent ground vibrations. Excessive ground vibrations can cause a wide range of problems, from nearby residents complaining to ecological damage. Prediction of blast-induced ground vibration is essential for evaluating and controlling the many adverse consequences of surface blasting. Since there are several effective variables with highly nonlinear interactions, no comprehensive model of blast-induced vibrations is available. In this study, the support vector machine (SMV) algorithm was employed for prediction of the peak particle velocity (PPV) induced by blasting at a surface mine. Twelve input variables in three categories of rock mass, blast pattern, and explosives were used for prediction of the PPV at different distances from the blast face. The results of 100 experiments were used for model-building, and 20 for testing. A high coefficient of determination with low mean absolute percentage error (MAPE) was achieved, which demonstrates the suitability of the algorithm in this case. The very high accuracy of prediction and fast computation are the two major advantages of the method. Although the case study was for a large surface mining operation, the methodology is applicable to all other surface blasting projects that involve a similar procedure.

Keywords
blast-induced ground vibration, peak particle velocity, support vector machine, surface mining.

Introduction

Blasting is one of the most economical and energy-efficient methods of rock fragmentation, and is widely used in mining, civil, construction, and environmental projects around the world. However, there are several drawbacks, including (but not limited to) complaints from nearby residents (Kahriman, 2001), damage to residential structures (Singh *et al.*, 1997; Gad *et al.*, 2005; Nateghi *et al.*, 2009), damage to adjacent rock masses and slopes (Villaescusa *et al.*, 2004; Yi and Lu, 2006; Singh *et al.*, 2005), damage to existing groundwater conduits, and damage to the ecology of the nearby area (Khandelwal and Singh, 2007). The main cause of these undesirable effects is excessive blast-induced ground vibrations. Thus, predicting the adjacent ground vibrations is essential for safe, environmentally responsible, and sustainable blasting operations. Ground vibrations can be defined and measured in terms of peak particle displacement, velocity, acceleration, and frequency. The peak particle velocity (PPV) has been used by many researchers as a versatile metric for both predicting and controlling the blast-induced ground vibrations. There are three major methods cited in the literature for PPV prediction, including empirical, theoretical, and artificial intelligence techniques.

Conventionally, there are some widely used empirical predictors for estimation of the blast-induced ground vibrations. The US Bureau of Mines proposed the first ground vibration predictor (Duvall *et al.*, 1959). Subsequently, other empirical predictors were proposed (Langefors and Kihlstrom, 1963; Ambraseys and Hendron, 1968; Ghosh and Daemen; 1983; Pal Roy, 1993). These methods consider two main input parameters – maximum charge used per delay and distance between the blast face and the monitoring points. Despite the simplicity and fast application of these methods, several recent studies have shown their shortcomings in rendering acceptable predictions (Khandelwal and Singh, 2007). More recently, Chen and Huang (2001) conducted a seismic survey to predict blast-induced vibrations and PPV empirically. Ozer *et al.* (2008) examined the results of some 500 blasts in a limestone quarry in Turkey for an experimental analysis of PPV. Ak *et al.* (2009) performed a series of ground vibration tests in a surface mine in Turkey in order to measure PPV. Aldas (2010) proposed an empirical relationship between the explosive charge mass and PPV. Deb and Jha (2010) examined the effects of surface blasting on adjacent underground workings, using PPV measurements. Mesec *et al.* (2010) proposed an empirical relationship between PPV and distance for a series of vibration tests in some sedimentary rock deposits, comprising

* *Department of Mining and Nuclear Engineering, Missouri University of Science and Technology, Rolla, MO, USA.*

 Paper received Dec. 2014 and revised paper received March 2015.

mainly limestone and dolomite. Nateghi (2011) examined the effects of different rock formations, different detonators, and explosives on ground vibrations induced by blasting at a dam site.

Generally, empirical methods have two major limitations: lack of generalizability and limited number of input variables. Some researchers have proposed theoretical models based on the physics of blasting. For instance, Sambuelli (2009) proposed a theoretical model for prediction of PPV on the basis of some blast design and rock parameters. However, because of the complicated nature of the blasting process and its highly nonlinear interaction with the non-homogeneous and non-isotropic ground, a closed form mathematical model is almost impossible. Recently, following the rapid growth in soft computing methods, including artificial intelligence, several researchers have tried to benefit from these newly emerging techniques. In this category, artificial neural networks (ANNs) might be the most widely used method for prediction of the ground vibrations. ANNs are among the techniques that map input variables into the output(s). The technique is capable of handling extremely nonlinear interactions between different variables through assigning and adjusting proper weights. However, no functional relationship is proposed ('black-box' modelling). Khandelwal and Singh (2006) used ANNs for prediction of PPV in a large mine in India. Iphar *et al.* (2008) employed an adaptive neural-fuzzy inference system (ANFIS) for prediction of PPV in a mine in Turkey. Dehghani and Ataee-pour (2011) employed ANNs for prediction of PPV in a large open pit copper mine. Monjezi *et al.* (2011) used ANNS to predict blast-induced ground vibrations in an underground project. Bakhshandeh *et al.* (2012) used ANNs to adjust burden, spacing, and total weight of explosive used in order to minimize PPV.

The support vector machine (SVM) is a relatively new computational learning method for solving classification and nonlinear function estimation, which is based on statistical learning theory. The SVM has been adopted rapidly by many researchers in different fields of geology, geotechnical, and environmental engineering (Brenning 2005; Yu *et al.*, 2006; Samui 2008; Mountrakis *et al.*, 2011; Dindarloo, 2014). Experimental results have revealed the superior performance of SVMs with respect to other techniques. The reasons behind the successful performance of SVMs, compared to other powerful approaches like ANNs, are twofold. Firstly, rather than being based on empirical risk minimization (ERM) as ANNs, which only minimizes the training errors, a SVM makes use of structural risk minimization (SRM), which seeks to minimize an upper bound on the generalization error. Secondly, finding a SVM solution corresponds to dealing with a convex quadratic optimization problem. Thus, the Karush-Kuhn-Tucker (KKT) statements determine the necessary and sufficient conditions for a global optimum (Scholkoff and Smola 2002). For ANNs, however, it is not guaranteed that even a well-selected optimization algorithm will achieve the global minimum in finite computation time (Moura *et al.*, 2011).

In this study, the SVM was used for analysis of the blast-induced ground vibration by prediction of PPV. A large iron ore mine in Iran was selected as a case study. After obtaining different input variables, a SVM model was constructed and tested.

Methods

Developed by Boser, Guyon, and Vapnik (Boser, Guyon, and Vapnik, 1992; Vapnik, 1995, 1998), support vector machine (SVM) is a relatively new computational learning method for solving classification and nonlinear function estimation, which is based on statistical learning theory. SVM is based on Vapnik-Chervonenkis theory (VC theory), which recently emerged as a general mathematical framework for estimating (learning) dependencies from finite samples. This theory combines fundamental concepts and principles related to learning, well-defined formulation, and self-consistent mathematical theory. Moreover, the conceptual framework of VC theory can be used for improved understanding of various learning methods developed in statistics, neural networks, fuzzy systems, signal processing, *etc.* (Widodo and Yang, 2007).

LIBSVM is a library of SVM algorithms (Chang and Lin, 2011) that was used along with Rapidminer, a data mining (DM) software package (Hofmann and Klinkenberg, 2013). The theory of SVM regression, used in LIBSVM, is presented in the following section.

Support vector regression

Consider a set of training points, $\{(x_1, z_1), \ldots, (x_L, z_L)\}$, where $x_i \in R^n$ is a feature vector and $z_i \in R^L$ is the target output. Under given parameters $C > 0$ and $\in > 0$, the standard form of the support vector regression (SVR) (Equation [1]) with constraints (Equations [2]-[4]) are as follows (Chang and Lin, 2011):

$$\min_{w,b,\beta,\beta^*} \frac{1}{2} w^T w + C\sum_{i=1}^{L} \beta_i + C\sum_{i=1}^{L} \beta^* \quad [1]$$

subject to

$$w^T \varphi(x_i) + b - z_i \leq \epsilon + \beta_i \quad [2]$$

$$z_i - w^T\varphi(x_i) - b \leq \epsilon + \beta_i^* \quad [3]$$

$$\beta_i, \beta_i^* \geq 0, i = 1, \ldots, L \quad [4]$$

The dual problem (Equation [5]) is

$$\min_{\alpha,\alpha^*} \frac{1}{2} (\alpha - \alpha^*)^T Q(\alpha - \alpha^*) + \epsilon \sum_{i=1}^{L} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{L} z_i(\alpha_i - \alpha_i^*) \quad [5]$$

subject to constraints (Equations [6]-[7])

$$e^T(\alpha_i - \alpha_i^*) = 0 \quad [6]$$

$$0 \leq \alpha_i, \alpha_i^* \leq C, i = 1, \ldots, L \quad [7]$$

where

$$Q_{i,j} = K(x_i, x_j) \equiv \varphi(x_i)^T \varphi(x_j) \quad [8]$$

After solving Equation [5], the approximate function is:

$$\sum_{i=1}^{L}(-\alpha_i + \alpha_i^*)K(x_i, x) + b \quad [9]$$

The nomenclature is presented in Table I. For more detailed information about the theory and applications of SVR, see Burges (1998), Müller *et al.* (2001), Hsu and Lin (2002), Chapelle *et al.* (2002), and Smola and Scholkoff (2004).

Case study

Golegohar iron ore mine is located in southern Iran, 50 km from Sirjan, in the southwest of Kerman Province. This iron ore complex includes six known orebodies and is one of the largest producers and exporters of iron concentrate in the country. Mining is by open pit methods, and the measured and indicated reserves of over 1.1 billion tons of ore. The Golegohar deposits are situated in a metamorphic complex of probable Paleozoic age with a northwest-southeast trend, known as the Sanandaj-Sirjan zone, which is parallel to the Zagros thrust belt on the southwest and is bounded on the northeast by the Urmieh-Dukhtar volcanic belt (Moxham and McKee, 1990). The deposits are considered to be of sedimentary or volcano-sedimentary origin, laid down in deltaic or near-shore environments that resulted in abrupt lateral and vertical changes in the sedimentary facies. Subsequent deep burial, folding, metamorphism, and erosion left a group of folded or down-faulted magnetite-rich deposits as elongated remnants of an iron formation that originally had a broader, perhaps more continuous extent. The mine's metamorphic rocks consist mostly of gneiss, mica schist, amphibolite, quartz schist, marble, dolomite, and calcite (Karimi Nasab *et al.*, 2011). Figure 1 illustrates one of the operating pits. The geometry and slope stability factors of the mine are summarized in Table II.

Table I

SVR notations

b	Intercept
C	A parameter representing the compromise between machine capacity and training error
w	Weight vector
φ	Mapping function
α	Function parameter
Q	Regression function
β, β^*	Slack variables
K	Kernel function
l	Number of observations

Table II

Geometric parameters of pit No.1, Golegohar.

Final wall slopes in ore and waste	45 degrees
Slopes in overburden	38 degrees
Safety bench height	30 m
Safety bench width	10 m
Safety bench slope	65 degrees
Working bench height	15 m

Parameter selection

Rock mass, blast pattern and explosives, and distance from the face are the three major parameters in blast-induced ground vibrations, and hence the measured PPV. The dominant rock types at Golegohar include amphibolite schist, quartz schist, chlorite schist, haematite, and magnetite. Density (t/m^3), Young's modulus (Gpa), uniaxial compression strength (Mpa), and tensile strength (Mpa) of representative samples of all the rock types were measured in the rock and soil mechanics laboratory at the mine site (Table IIIa). The major discontinuities have a significant influence on blast wave propagation in the rock mass. The

Figure 1 – Open pit mining at Golegohar (CNES/Astrium image on Google Earth, 29°05'15.21" N and 55° 19' 03.24" E. Retrieved 3 April 2015)

Table III

Mechanica l and physical properties. (a) Intact rock, (b) discontinuities

Item		Petrology: (a) Intact rocks				
		Amphibolite schist	**Quartz schist**	**Chlorite schist**	**Haematite**	**Magnetite**
Density (t/m3)	Mean	2.81	2.69	2.84	4.02	4.41
	Range	2.76-3.02	2.63-2.84	2.76-2.95	3.65-4.35	4.15-4.62
Young's modulus (Gpa)	Mean	34.8	52.7	37.6	29.7	42.6
	Range	19.6-47.1	18.6-77.3	15.7-40.3	14.9-41.2	33-55.9
Uniaxial compressive strength (Mpa)	Mean	42.8	112.5	105.9	66.8	121.4
	Range	18.6-77.3	35.2-176.2	33.7-155.1	30.8-114.8	35.2-176.2
Tensile strength (Mpa)	Mean	15.4	7.54	13.47	6.95	9.24
	Range	12.1-17.8	6.99-9.42	8.24-18.42	4.63-10.52	5.5-14.62

(b) Discontinuities			
Major joints	**Spacing (m)**	**Dip (degree)**	**Direction**
Set 1	1.1	45	Northeast-southwest
Set 2	0.8	75	North-south

spacing, dip, and direction of the two major joint sets are presented in Table IIIb (Dindarloo *et al.*, 2015). The second group of important parameters is related to the drilling pattern and explosives used. A typical production, buffer, and pre-split pattern are illustrated in Figure 2. The main explosive is ANFO, and a blast delay of 15–75 ms between rows is used. The descriptive statistics of the pattern geometry, including burden, spacing, hole depth to burden ratio, specific charge, and stemming are presented in Table IV. Thus, the 12 input variables include: density, Young's modulus, uniaxial compression strength, tensile strength, joint spacing, burden, spacing, hole depth to burden ratio, specific charge, stemming, delay per row, and distance between the measurement point and the blasting face. Since the main charge for all holes was ANFO, the parameter for type of explosive was omitted, as it was the same for all tests.

Results and discussions

One hundred and twenty experiments were conducted at different distances, 15 m to 7500 m, from the blasting faces. The PPV was measured using the procedures described by Dowding (1992). One hundred data-sets, including the 12 input variables and one output (PPV), were used in the SVR model. The results of 20 randomly selected experiments were

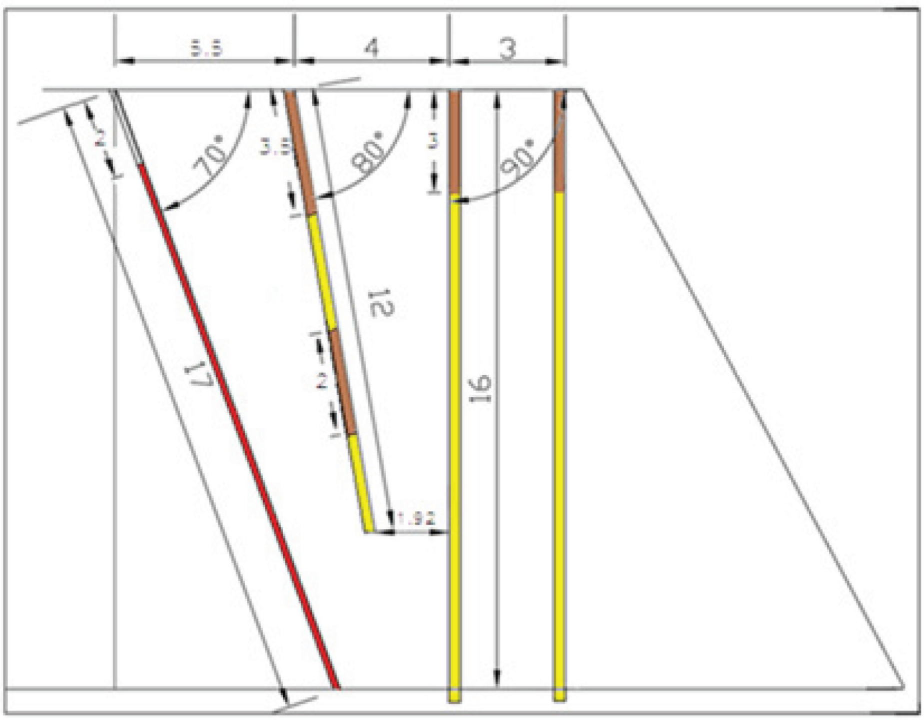

Figure 2 – Blast pattern (red: pre-splitting hole, yellow: ANFO, brown: stemming/crushed rock, white: no stemming/charging). Distances are in metres, and angles in degrees

Table IV

Descriptive statistics of the collected data.

No	Parameter	Symbol	Unit	Min.	Max.	Mean	DS
1	Burden	B	metre	3.83	5.88	4.81	0.68
2	Spacing	S	metre	4.37	7.11	6.14	0.91
3	Hole depth – burden ratio	H/B		2.04	4.44	3.40	0.62
4	Stemming	ST	metre	3.86	7.95	5.19	0.79
5	Powder factor	PF	kg/t	0.21	0.47	0.32	0.07

used for model testing. Figure 3 depicts a scattergram of the predicted SVR *versus* the measured PPVs for the 20 testing data-sets. The coefficient of determination (Equation [10]), root mean squared error (RMSE, Equation [11]), and mean absolute percentage error (MAPE, Equation [12]) were used as the statistical metrics for evaluation of the SVR model (Table V). The obtained R2 value of 0.99 shows a very good correlation between the predicted and measured PPVs. The obtained MAPE value of less than 10% demonstrates the high accuracy and applicability of the method in PPV estimation, using the 12 input variables.

$$R^2 = 100\left[\frac{\left(\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})(y_{pred}-\bar{y}_{pred})\right)^2}{\sqrt{\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})^2\sum_{i=1}^{N}(y_{pred}-\bar{y}_{pred})^2}}\right] \qquad [10]$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{meas}-y_{pred})^2} \qquad [11]$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{meas}-y_{pred}}{y_{meas}}\right|\times 100 \qquad [12]$$

where

y_{meas} and y_{pred} are the observed and predicted values, respectively

y_{meas} and y_{pred} and are mean observed and predicted values, respectively.

Sensitivity analysis

In order to analyse the effect of each individual variable on the SVM prediction accuracy, a sensitivity analysis was performed.

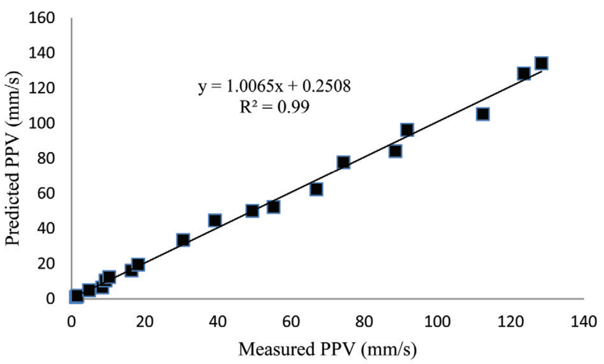

Figure 3 – SVM predicted vs. measured PPV (mm/s)

Table V

Statistics of SVM in PPV prediction

R2	MAPE (%)	RMSE (mm/s)
0.99	8.5	3.45

The optimized SVM parameters were kept the same for twelve sensitivity analysis runs. In each run, one of the input variables was omitted and its effect on prediction accuracy was examined. The results showed that omission of distance, specific charge, delay per row, and joints spacing had the highest negative effects on SVM predictions. Hence the method is more sensitive to these variables. The results of sensitivity analysis for other variables are shown in Figure 4.

Comparison with traditional methods

The partial least-square regression (PLSR) method is mainly used for modelling linear regression between multiple dependent variables and multiple independent variables. An advantage of this method over linear and nonlinear multiple regressions is that PLSR combines the basic functions of regressing models, principal component analysis, and canonical correlation analysis (Zhang *et al.*, 2009). In addition, PLSR avoids the harmful effect of multi-collinearity and regressing when the number of observations is less than the number of variables. In the context of linear MR, the least-squares solution for Equation [13] is given by Equation [14].

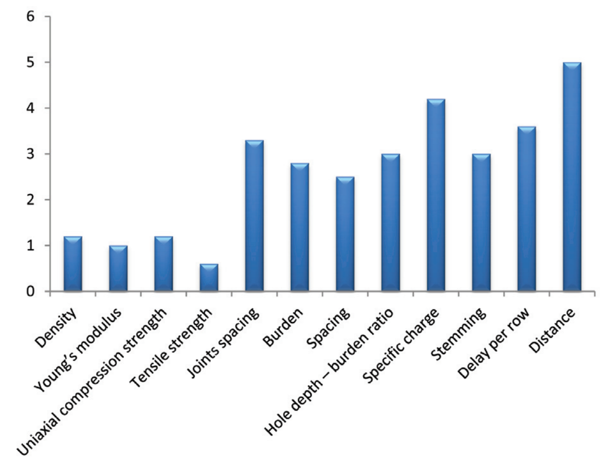

Figure 4 – Sensitivity analysis

$$Y = XB + \varepsilon \quad [13]$$

$$B = (X^TX)^{-1}X^TY \quad [14]$$

Often, the problem is that X^TX is singular, either because the number of variables (columns) in X exceeds the number of objects (rows), or because of collinearities. PLSR circumvents this by decomposing X into orthogonal scores (T) and loadings (P) (Mevik and Wehrens, 2007):

$$X = TP \quad [15]$$

Furthemore, PLSR regresses Y, not on X, but on the first α columns of the scores. The goal of PLSR is to incorporate information on both X and Y in the definition of the scores and loadings. The scores and loadings are chosen in such a way to describe as much as possible of the covariance between X and Y.

The result of the prediction of PPV by the PSLR technique is illustrated in Figure 5. Statistics of the predictions, for the same testing data-set as SVM, are summarized in Table VI. The R^2 value in PLSR decreased to 94% (*i.e.*, the PLSR can model 94% of the variability in PPV based on the 12 independent variables). Furthermore, both the obtained RMSE and MAPE values in PLSR (see Table VI) were poorer than the SVM (see Table V).

Conclusions

Blast-induced ground vibration control is a major challenge in construction projects that employ blasting. Peak particle velocity (PPV) is a widely used metric for evaluation of the magnitude and severity of the possible inconvenience to people and damage to adjacent structures and the environment. This study demonstrates that the support vector machine (SVM) approach is a versatile tool for prediction of PPV based on the 12 input variables used. The very high accuracy of prediction and fast computation are the two major advantages of the method. Results of the sensitivity analysis demonstrated the considerable effect of distance, specific charge, delay per row, and joint spacing on PPV. Thus, in specific instances where the level of PPV is higher than a pre-specified threshold, appropriate remedies can be applied. Modification of the specific charge and the amount of delay per row are expected to have direct effects on PPV reduction. Although the SVM was used in a large surface mining case study, it is applicable to all other surface blasting projects with a similar procedure.

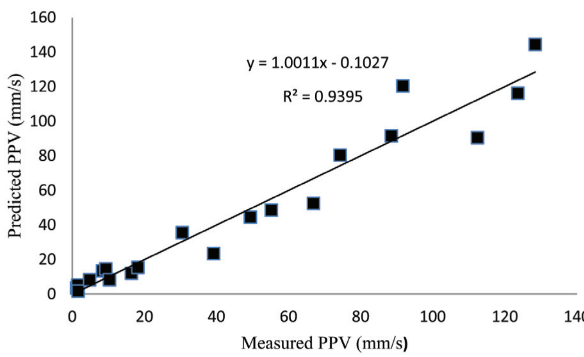

Figure 5 – PLSR predicted vs. measured PPV (mm/s)

Table VI

Statistics of PLSR in PPV prediction

R^2	MAPE (%)	RMSE (mm/s)
0.94	16.7	8.43

Acknowledgements

We would like to thank two anonymous reviewers for their critical reviews and constructive comments. Golegohar mine management and staff are acknowledged for their support.

References

Aldas, G.G.U. 2010. Explosive charge mass and peak particle velocity (PPV)-frequency relation in mining blast. *Journal of Geophysics and Engineering*, vol. 7, no. 3. pp. 223–231.

Ak, H., Iphar, M., Yavuz, M., and Konuk, A. 2009. Evaluation of ground vibration effect of blasting operations in a magnesite mine. *Soil Dynamics and Earthquake Engineering*, vol. 29, no. 4. pp. 669–676.

Ambraseys, N.R. and Hendron, A.J. 1968. Dynamic Behaviour of Rock Masses: Rock Mechanics in Engineering Practices. Wiley, London.

Bakhshandeh Amnieh, H., Siamaki, A., and Soltani, S. 2012. Design of blasting pattern in proportion to the peak particle velocity (PPV): artificial neural networks approach. *Safety Science*, vol. 50, no. 9. pp. 1913–1916.

Boser, B., Guyon, I., and Vapnik, V. 1992. A training algorithm for optimal margin classifiers. *Proceedings of the Fifth Annual Workshop on Computational Learning Theory*. ACM, Pittsburgh. pp. 144–152.

Brenning, A. 2005. Spatial prediction models for landslide hazards: review, comparison and evaluation. *Natural Hazards and Earth System Science*, vol. 5, no. 6. pp. 853–862.

Burges, C.J.C. 1998. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, vol. 2, no. 2. pp. 121–167.

Chang, C.-C. and Lin, C.-J. 2011. LIBSVM: a library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, vol. 2, no. 3. Article no. 27.

Chapelle, O., Vapnik, V., Bousquet, O., and Mukherjee, S. 2002. Choosing multiple parameters for support vector machines. *Machine Learning*, vol. 46, no. 1-3. pp. 131–159.

Chen, G. and Huang, S.L. 2001. Analysis of ground vibrations caused by open pit production blasts - a case study. Fragblast, vol. 5, no. 1–2. pp. 91–107.

Dindarloo, S.R. 2014. Support vector machine regression analysis of LHD failures. *International Journal of Mining, Reclamation and Environment*. [doi: 10.1080/17480930.2014.973637].

Dindarloo, S.R., Askarnejad, N-A., and Ataei, M. 2015. Design of controlled blasting (pre-splitting) in Golegohar iron ore mine, Iran. *Transactions of the Institution of Mining and Metallurgy, Section A*: Mining Technology, vol. 124, no. 1. pp. 64–68.

Deb, D. and Jha, A.K. 2010. Estimation of blast induced peak particle velocity at underground mine structures originating from neighbouring surface mine. *Transactions of the Institution of Mining and Metallurgy, Section A: Mining Technology*, vol. 119, no. 1. pp. 14–21.

Dehghani, H. and Ataee-Pour, M. 2011. Development of a model to predict peak particle velocity in a blasting operation. *International Journal of Rock Mechanics and Mining Sciences and Geomechanics Abstracts*, vol. 48, no. 1. pp. 51–58.

Dowding, C.H. 1992. Suggested method for blast vibration monitoring. *International Journal of Rock Mechanics and Mining Sciences and Geomechanics Abstracts*, vol. 29, no. 2. pp. 145–156.

DUVALL, W.I. and PETKOF, B. 1959. Spherical propagation of explosion generated strain pulses in rock. *Report of Investigation* 5483. US Bureau of Mines. 21 pp.

GAD, E.F., WILSON, J.L., MOORE, A.J., and RICHARDS, A.B. 2005. Effects of mine blasting on residential structures. *Journal of Performance of Constructed Facilities*, vol. 19, no. 3. pp. 222–228.

GHOSH, A. and DAEMEN, J.K. 1983. A simple new blast vibration predictor. *Proceedings of the 24th US Symposium on Rock Mechanics*, College Station, Texas, USA, 20–23 June 1983. pp. 151–161.

HOFMANN, M. and KLINKENBERG, R. 2013. RapidMiner: Data Mining Use Cases and Business Analytics Applications. Chapman & Hall/CRC Data Mining and Knowledge Discovery Series. CRC Press, Boca Raton, FL.

HSU, C-W. and LIN, C-J. 2002. A comparison of methods for multiclass support vector machines. *IEEE Transactions on Neural Networks*, vol. 13, no. 2. pp. 415–425.

IPHAR, M., YAVUZ, M., and AK, H. 2008. Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system. *Environmental Geology*, vol. 56, no. 1. pp. 97–107.

KAHRIMAN, A. 2001. Prediction of particle velocity caused by blasting for an infrastructure excavation covering granite bedrock. *Mineral Resources Engineering*, vol. 10, no. 2. pp. 205–218.

KARIMI NASAB, S., HOJAT, A., KAMKAR-ROUHANI, A., AKBARI JAVAR, H., and MAKNOONI, S. 2011. Successful use of geoelectrical surveys in Area 3 of the Gol-e-Gohar iron ore mine, Iran. *Mine Water and the Environment*, vol. 30, no. 3. pp. 208–215.

KHANDELWAL, M. and SINGH, T.N. 2006. Prediction of blast induced ground vibrations and frequency in opencast mine: a neural network approach. *Journal of Sound and Vibration*, vol. 289, no. 4–5. pp. 711–725.

KHANDELWAL, M. and SINGH, T.N. 2007. Evaluation of blast-induced ground vibration predictors. *Soil Dynamics and Earthquake Engineering*, vol. 27, no. 2. pp. 116–125.

LANGEFORS, U. and KIHLSTROM, B. 1963. The Modern Technique of Rock Blasting. Wiley, New York.

MESEC, J., KOVAČ, I., and SOLDO, B. 2010. Estimation of particle velocity based on blast event measurements at different rock units. *Soil Dynamics and Earthquake Engineering*, vol. 30, no. 10. pp. 1004–1009.

MEVIK, B-H. and WEHRENS, R. 2007. The pls package: principal component and partial least squares regression in R. *Journal of Statistical Software*, vol. 18, no. 2. pp. 1–23.

MONJEZI, M., GHAFURIKALAJAHI, M., and BAHRAMI, A. 2011. Prediction of blast-induced ground vibration using artificial neural network. *Tunnelling and Underground Space Technology*, vol. 26, no. 1. pp. 46–50.

MOUNTRAKIS, G., IM, J., and OGOLE, C. 2011. Support vector machines in remote sensing: a review. *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 66, no. 3. pp. 247–259.

MOURA, M.D.C., ZIO, E., LINS, I.D., and DROGUETT, E. 2011. Failure and reliability prediction by support vector machines regression of time series data. *Reliability Engineering and System Safety*, vol. 96, no. 11. pp. 1527–1534.

MÜLLER, K-R., MIKA, S., RÄTSCH, G., TSUDA, K., and SCHÖLKOPF, B. 001. An introduction to kernel-based learning algorithms. *IEEE Transactions on Neural Networks*, vol. 12, no. 2. pp. 181–201.

NATEGHI, R. 2011. Prediction of ground vibration level induced by blasting at different rock units. *International Journal of Rock Mechanics and Mining Sciences and Geomechanics Abstracts*, vol. 48, no. 6. pp. 899–908.

NATEGHI, R., KIANY, M., and GHOLIPOURI, O. 2009. Control negative effects of blasting waves on concrete of the structures by analyzing of parameters of ground vibration. *Tunnelling and Underground Space Technology*, vol. 24, no. 6. pp. 608–616.

OZER, U., KAHRIMAN, A., AKSOY, M., ADIGUZEL, D., and KARADOGAN, A. 2008. The analysis of ground vibrations induced by bench blasting at Akyol quarry and practical blasting charts. *Environmental Geology*, vol. 54, no. 4. pp. 737–743.

PAL ROY, P., 1993. Putting ground vibration predictors into practice. *Colliery Guardian*, vol. 241. pp. 63–67.

SAMBUELLI, L. 2009. Theoretical derivation of a peak particle velocity-distance law for the prediction of vibrations from blasting. *Rock Mechanics and Rock Engineering*, vol. 42, no. 3. pp. 547–556.

SAMUI, P. 2008. Slope stability analysis: a support vector machine approach. *Environmental Geology*, vol. 56, no 2. pp. 255–267.

SCHOLKOFF, B. and SMOLA, A.J. 2002. Learning with kernels—support vector machines, regularization, optimization, and beyond. MIT Press, Cambridge MA.

SINGH, P.K., VOGT, W., SINGH, R.B., SINGH, M.M., and SINGH, D.P. 1997. Response of surface structures to rock blasting. *Mineral Resources Engineering*, vol. 6, no. 4. pp. 185–194.

SINGH, P.K., ROY, M.P., and SINGH, R.K. 2005. Responses of roof and pillars of underground coal mines to vibration induced by adjacent open-pit blasting. *Environmental Geology*, vol. 47, no. 2. pp. 205–214.

SMOLA, A.J. and SCHOLKOFF, B. 2004. A tutorial on support vector regression. *Statistics and Computing*, vol. 14. pp. 199–222.

VAPNIK, V. 1995. The Nature of Statistical Learning Theory. Springer-Verlag, New York.

VAPNIK, V. 1998. The support vector method of function estimation. *Nonlinear Modeling: Advanced Black-box Techniques*. Suykens, J.A.K. and Vandewalle, J. (eds). Kluwer Academic Publishers, Boston. pp.55–85.

VILLAESCUSA, E., ONEDERRA, I., and SCOTT, C. 2004. Blast induced damage and dynamic behaviour of hangingwalls in bench stoping. *Fragblast*, vol. 8, no. 1. pp. 23–40.

WIDODO, A. and YANG, B-S. 2007. Support vector machine in machine condition monitoring and fault diagnosis. *Mechanical Systems and Signal Processing*, vol. 21, no. 6. pp. 2560–2574.

YI, C-P. and LU, W-B. 2006. Research on influence of blasting vibration on grouted rockbolt. *Yantu Lixue/Rock and Soil Mechanics*, vol. 27, no. 8. pp. 1312–1316.

YU, P-S., CHEN, S-T., and CHANG, I-F. 2006. Support vector regression for real-time flood stage forecasting. *Journal of Hydrology*, vol. 328, no. 3–4. pp. 704–716.

ZHANG, M., MU, H., LI, G., and NING, Y. 2009. Forecasting the transport energy demand based on PLSR method in China. *Energy*, vol. 34, no. 9. pp. 1396–1400. ◆