Review of blast movement measurements for grade control[1]

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Abstract

Blasting is carried out in mining operations to break down rocks and to maximize material movement. In open pit mines, this invariably involves huge amount of explosive energy which causes rock materials to be displaced from their original position. This movement is detrimental to the accurate delineation of the predefined ore and waste zones and could lead to ore loss and dilution if not accounted for. Direct measurements such as the use of visual markers have been widely patronized in most campaigns. Sandbags retrieved after blasting show that pre-blast grades could be displaced up to 10-15 meters after blasting. Blast movement monitors (BMM) developed by a group of researchers from the University of Queensland currently provide the most accurate method of blast-induced rock movement despite the cost of data acquisition. In recent years, indirect determination of blast movement has been advocated using software and complicated simulation algorithms. In this paper, the limitations of direct blast movement techniques as well as the feasibility of indirect measurement models are discussed. Considering that there is no easy-way and cheap method to determine post-blast ore boundary, a machine-learning (ML) approach and a corresponding evaluation system have also been proposed in the literature.

1. Introduction

After tremendous work has been done to define and model the distribution of minerals in a rock mass, the rock undergoes a comminution process before the mineral is extracted. For most scenarios, the first stage of the comminution process is blasting, and this allows efficient excavation and haulage after the rock has been fragmented. Blasting is done using explosives inserted into holes drilled in the rock. Upon detonation, the chemical energy in the explosive is released, and the solid explosive becomes transformed into a pressurized gleaming gas that shatters and move rocks in the path of least resistance resulting in a muck pile (Hustrulid, 2011). Lawrence (1944), Thornton (2009) and Zhang (2016) provide more information on the detonation theory and the mechanics of rocks breakage.

Considerable amount of research has been done on blast optimization, but this has often been in the area of ground vibration, rock damage, fragmentation, blast design, strain energy, and in regard to environmental safety (Blair & Minchinton, 1997; Persson, 1997; Sołtys et al., 2017; Zou, 2017). The impact of blast-induced rock movement on predetermined grade distribution of the rock has not been extensively explored and leaves much to be desired (Thornton, 2009). Grade control is a compendium of procedures and practices aimed at sending the mined material to the right destination and that involves considering the post blast movement of rocks. Disregarding this situation will lead to misclassification, that is,

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mistaking ore for waste or waste for ore; a mixing of low grade and high grade materials; sulfides to oxides identification issues; or other contaminants – collectively referred to as ore loss and dilution (Rosa & Thornton, 2011). Figure 1 is an illustration of how ore loss and dilution occur due to ore block movement.

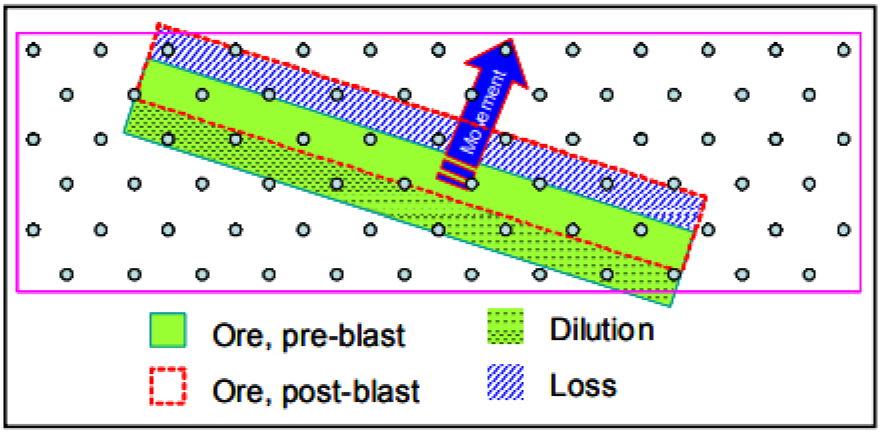


Figure 1 Ore loss and dilution during blast. Source: (Thornton et al., 2005)

To account for this movement, various methods have been used to measure or model the pre and post blast rock locations. Two main approaches used to measure or model blast movement are the direct measurements based on the use of physical markers, and indirect measurements such as numerical modelling. Direct measurement method involves the use of objects inserted into the pre blast rock and their post blast location are retrieved after excavation and measured (Rosa & Thornton, 2011). The use of simple visual markers such as sandbags and poly-pipes have been employed in several open pit mines to track rock movement because it is simple and inexpensive. However, its limitations include a low turnout of recovered markers and its inability to provide a three dimensional movement pattern (Thornton, 2009). Another direct method used in blast movement measurement is the application of remote sensing devices (Vasylchuk, 2019). Developed by a group of researchers from the University of Queensland, Australia, the electronic blast movement monitor (BMM) quickly became a grade control to measure rock movement. The BMM device relies on transmitters that are installed in the blast prior to blasting, which are recovered after the blast by a special detector and the data is processed with a software.

Modelling the entire blasting process as an alternative for direct measurements have received a mixture of feedback even though it is a good prospect to monitoring blast movement. Lack of complete knowledge about the geological domain, location of rock breakage and mechanical properties of the rock, together with uncertainty in blast parameters undermines the accuracy of the model (Vasylchuk & Deutsch, 2019). Considering that the BMM method is expensive, and most companies cannot afford it, calibrating a numerical model that could measure rock movement is worthy of research (Vasylchuk & Deutsch, 2018).

In the next sections of this paper, we review the blast movement methods in operation in most mines according to case study, highlighting their limitations and the feasibility of indirect measurement approaches. Subsequently, a novel machine learning approach is discussed as an indirect method considering that there is no easy-way and cheap method to determine post-blast ore boundary.

2. Blast Movement Measurement

Understanding material movement during a blast has always been an intriguing area to mine operators especially where there is no clear visual distinction between ore and waste. Various methods used have demonstrated a mixture of success and some limitations. Traditional methods of understanding the movement of the rock was to compare and contrast pre and post blast topographic surfaces (Vasylchuk & Deutsch, 2018). In context, blast movement measurement has been categorized into i) direct measurements and ii) indirect measurements.

2.1 Direct Measurement of Blast-induced Rock Movement

This type of measurement involves the use of physical markers to track material movement. Two major direct approaches have been used: i) the use of visual markers, and ii) using remote sensing devices.

2.1.1 Visual Markers

The use of visual markers encompasses objects such as sandbags, chains or pipes inserted into the rock before blasting and their post blast location identified and measured (Rosa & Thornton, 2011). In their research, Taylor (1995) and Zhang (1994) appraised the use of sandbags and wooden stakes as markers for rock displacement during blasting. Results indicate that even though these visual markers are simple, cheaper, and relatively accurate, only about forty percent (40%) of the markers were recovered and it took several days for all the bags to be found. A more common industrial approach is the use of plastic pipes inserted into additional holes drilled within the blast area. And as the pipes are exposed during excavation, their locations are surveyed. For bench-by-bench excavation, the process is repeated for each level. Figure 2 shows an example of a recovered pipe after blasting.

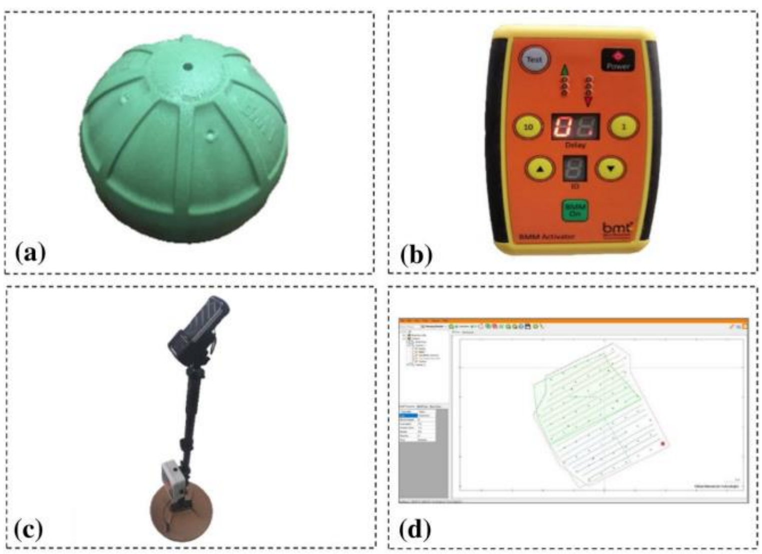
However, the disadvantage of this method is that the data for processing is not available until the markers are found and the ore has been excavated (Fitzgerald et al., 2011). This does not allow the proper design and adjustment of dig polygons prior to excavation. The use of the poly pipes also presents several limitations including the generation of only two-dimensional vector measurements, poor recovery of pipes for lower-level benches and it being labor-intensive. It must however be noted that the use of markers is an ad-hoc approach, and not many of such are published in literature.

Figure 2 Pipe recovered after blasting. Source: (Rosa & Thornton, 2011)

2.1.2 Remote Sensing Devices

A modern approach to directly measure blast movement is the remote detecting equipment. This is an electronic method that aims at alleviating some of the limitations of the visual methods such as reducing the arduity. In remote sensing methods, metallic or magnetic targets are used instead of marker bags or pipes, and their post blast locations identified using remote sensing or electronic devices. Various methods have been tested including *Ground Penetrating Radar*, *Magnetometry*, *Metal detection and recently, the Radio frequency (RFID) tags* (Thornton, 2009). However, most suffer limitations such as damage of targets by excavators, use of only one target in each hole and targets must be placed close to the surface or on the surface, which is detrimental to accurately measure movement dynamics.

By far, a remote sensing approach that has proven very effective and is almost the most accurate method of blast-induced rock movement monitoring is the blast movement monitoring (BMM) device. This method is used in mines such as the Husab Uranium mining project in Namibia, the second largest world producer of uranium (Yu, Shi, Zhou, Rao, et al., 2019). Developed by a team of researchers from the University of Queensland and later commercialized under the Blast Movement Technologies (BMT), the BMM system comprises of transmitters that are installed in separate holes drilled between blastholes and are held in place by drill cuttings or stemming (Fitzgerald et al., 2011). After the blast, the transmitters are located with a special detector and the data is processed with a purpose-designed software. The structure of a modern BMM device is shown in figure 3.



(a) ***BMM ball:*** *contains transmitters that emit electromagnetic signals which is detected by the BMM detector.*

(b) ***BMM activator:*** *activates the BMM ball prior to the blast.*

(c) ***BMM detector:*** *locates the BMM ball after the blast.*

(d) ***BMM explorer:*** *computer software that does the post blast ore boundary calculations.*

Figure 3 The blast movement monitoring system. Source: (Yu, Shi, Zhou, Rao, et al., 2019).

The BMM ball can be detected to a depth of around 25 m after blasting. Once the horizontal location of the ball is pinpointed, the signal is recorded to determine the depth below the surface, and then the three-dimensional (3D) movement vectors is calculated. The 3D movement vectors obtained is then applied to the ore block boundaries determination by the system software with results usually ready within an hour or two after the blast (Adam & Thornton, 2004). With a battery life of 12 hours and more, and excellent detection rates of about ninety per cent (90%), the BMM system has proven to be very effective and practical for grade control.

2.2 Indirect Measurement of Blast-induced Rock Movement

Indirect blast movement measurement methods became necessary to complement the direct measurement method in saving time and money. Visual markers are labor intensive and BMMs are not cheap. So an indirect measurement is suggested which involves the use of algorithms and software to infer the movement of rocks based on data and other field parameters collected (Vasylchuk & Deutsch, 2018). In most cases, the post blast topographic surface is traced and compared to the pre-blast topography and an approximate blast movement model is developed. In this section, we will look at numerical simulated models and machine learning (ML) models.

2.2.1 Numerical modeling of blast movement

Early attempts to numerically model blast movement was hindered by computational capability. Early blast movement models developed included the Universal Distinct Element Code (UDEC) by Cundall (1980) which attempts to model by simulating behavior of jointed rock masses subjected to high and transient loadings; the Block and Bump model by Schamaun (1986) where blast movement is represented by blocks and circles and where the dynamic movement of rock particles is controlled by parameters such as the geological characteristics of mine benches, shapes and sizes of the particles, and cohesive forces between rock particles. The advanced Distinct Motion Code (DMC) model presented by Preece et al. (1997) allowed the incorporation of the properties of explosives for modeling the motion of rocks.

Having mentioned that, in recent years, simple and efficient models have been developed such as the simple blast movement model by Furtney et al. This model illustrates among other things, how the chemical energy of the explosive is distributed during blasting and how it impacts the displacement of rocks. The model seems able to predict the face velocities using generic rock properties as inputs within a certain degree of accuracy. Detail of this work can be found in Furtney et al. (2013). In 2018, Vasylchuk and Deutsch described a blast movement model using pre and post blast topographic features. In the model, the algorithm proposed translated the the pre-blast grid locations to post-blast locations, and a 3D model of the post blast muck pile was created. Post-blast locations were inferred from discretized pre-blast locations. Figure 4 shows the pre and post blast models generated by their algorithm.

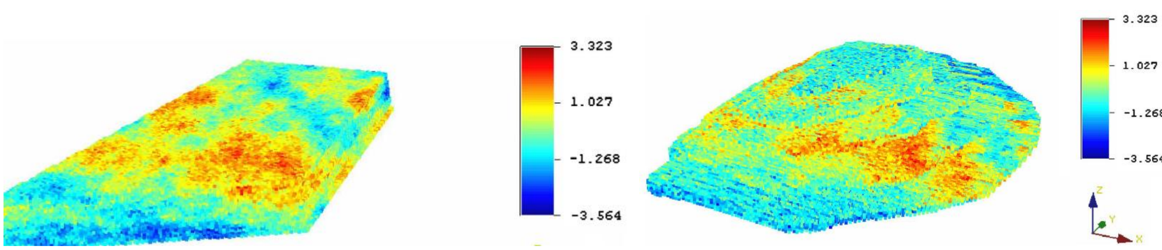


Figure 4 Pre (left) and post (right) blast 3D models with assigned grades Source: (Vasylchuk & Deutsch, 2018)

Vasylchuk and Deutsch (2019) advanced their research by developing an empirical optimization algorithm that incorporates the use of direct measurements to topographic monitoring. Results from a fabricated scenario demonstrated the model's ability to map pre-blast grade onto post-blast muck pile within a reasonable time and still honored real information about blast movement. Figure 5 shows the grade distributions prior to and after blasting by the model and their ultimate destinations.

Despite the interesting approach of numerically modelling blast movement, it also draws legitimate concerns. Some of which are the uncertainties in the blast parameters, lack of absolute knowledge of the geological features, fracture locations and mechanical properties of the rock (Vasylchuk & Deutsch, 2019). According to Yu et al. (2019), theoretical calculations and numerical simulations do not provide accurate blast-induced rock movement measurements. The discrepancy between a modelled and a measured blast movement was tested by Rosa and Thornton (2011) and the error margin was from 1 to 7 meters which is estimated to be equivalent to a loss of about 2.2 to 4.8 million dollars. They further suggested that blast models should be validated with actual pre and post blast bench configurations.

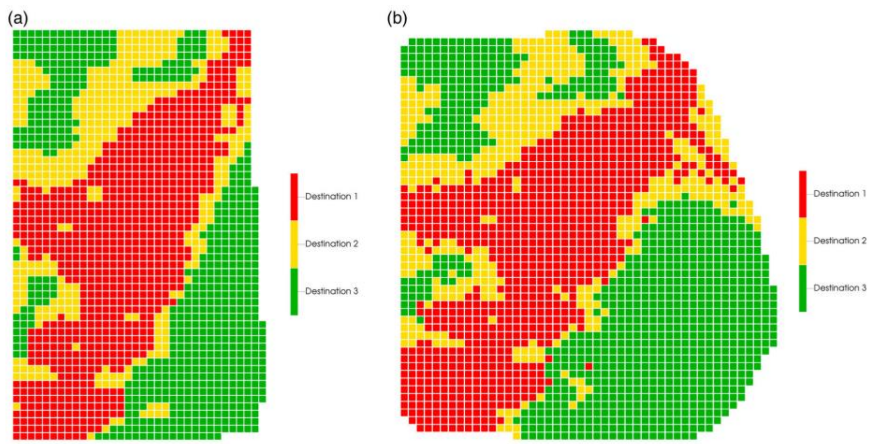


Figure 5 Pre (a) and post (b) blast classification of materials Source: (Vasylchuk & Deutsch, 2019).

2.2.2 Machine Learning (ML) approach

The advancement of computers and technology has aided the processing and manipulation of high volumes of data within the shortest possible time. Machine learning algorithms (MLA) are a collection of advanced statistical tools to provide a faster and better way of processing data using high-level processors. The application MLA has received a lot of successes such as the application of Artificial Neural Networks for grade estimation in mineral resource estimation (Abuntori et al., 2021). New methods such as deep networks performed excellently in its predictive ability with both structured and unstructured data (Shen et al., 2018). Random Forest have also been successively explored to perform classification of geological domains based on sample geochemical information (Cevik et al., 2019). However, not many applications of ML have been employed in measuring blast movement. The ML algorithms being discussed in the following paragraphs are novel and sets the tone for further research.

In the first scenario, three new hybrid models of Support Vector Machines (SVR); a genetic algorithm (GA), an artificial bee colony algorithm (ABC), a cuckoo search algorithm (CS), abbreviated as the GA-SVR, ABC-SVR and CS-SVR respectively, were proposed for the prediction of rock movement in the Husab Uranium Mine in Namibia, the Coeur Rochester Mine, USA and the Phoenix Mine, USA. Eight blasting parameters were used as input variables to develop the model: rock type, number of free faces, first centerline distance, hole diameter, power factor, spacing, subdrill and initial depth of monitoring, and horizontal blast-induced rock movement was the output variable. The use of the hybrid algorithms aided in finding optimal hyperparameters for the final model: i.e *gamma (γ)* and the *penalty factor (C)*. The best performing model was selected by examining the three models. Data collected for all algorithms were divided into training and testing for validation and comparison. The GA-SVR model was designed by simulating the biological process of evolution where the adaptive abilities of organisms were employed to generate a group of well adapted individuals after continued evolution. The behavior of scout honeybees in finding food sources close to the hive, inspired the development of ABC-SVR model. Finally, the CS-SVR was inspired by how the cuckoo bird searches, lays and hatches its eggs in the nest of another bird considered as the host bird. During calculation, a Levy flight method is used in the search for new nests in the CS algorithm. Figure 6 shows the framework of the proposed models. Details of this work can be found in (Yu, Shi, Zhou, Rao, et al., 2019).

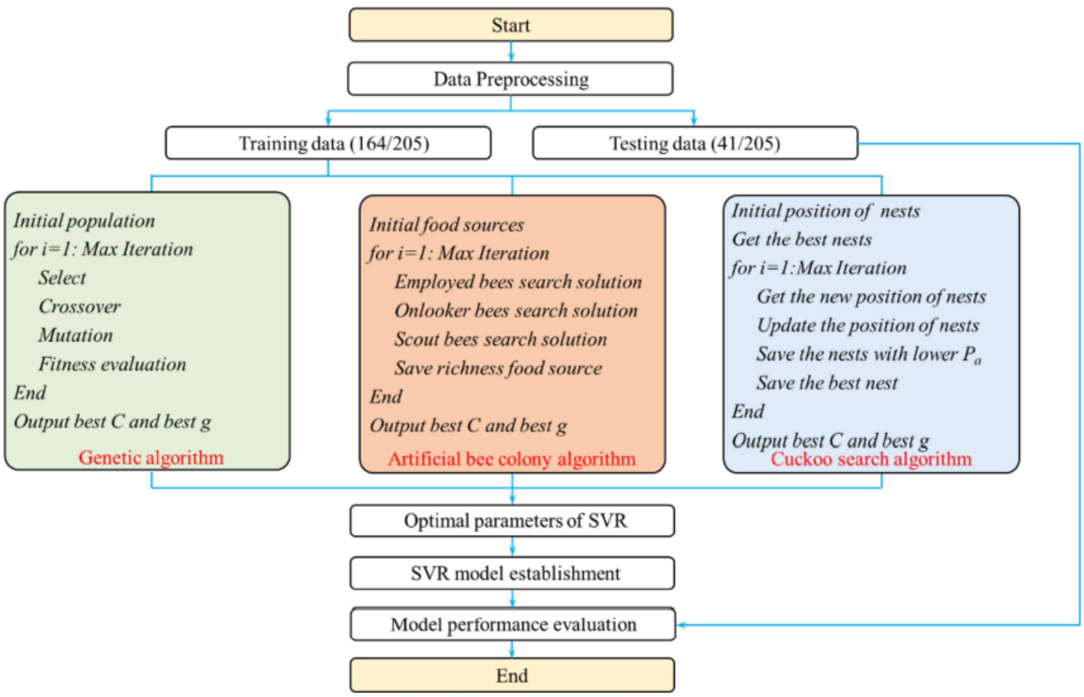


Figure 6 Model framework of GA-SVR, ABC-SVR and CS-SVR *Source: (Yu, Shi, Zhou, Rao, et al., 2019)*

In the second case, three original machine learning techniques: support vector regression (SVR), the Gaussian process (GP), and the extreme learning machine (ELM) were used to develop a predictive model for blast movement. The genetic algorithm (GA) and a whale optimization algorithm (WOA) was used in place of the trial-and-error method, to obtain the optimal hyperparameter search. The ELM, based on neural network theory, was used for its fast-learning ability and good generative performance. The only hyperparameter tuned was the number of neurons. Having extended support vector machine (SVM) from just solving classification but to also solve regression problems, SVR was used. Hyperparameters were γ and C as mentioned in section above. GP is a nonparametric model based on random parameters in a gaussian distribution. The mean and covariance functions make up the hyperparameter. The metaheuristic algorithms used were also inspired by natural phenomena just as the previous case. The GA algorithm used is like the one described in the above scenario, and WOA algorithm is designed from the predating nature of whales in the ocean. Like the other swarm-based algorithms, mathematical models inspired by these phenomena are utilized to reduce the error between the predicted values and real values, and the process is terminated when the set error level is reached. Details of this work can be found in (Yu, Shi, Zhou, Gou, et al., 2021).

4. Discussion

The results presented here are case studies from machine learning approaches as proposed by (Yu, Shi, Zhou, Rao, et al., 2019) and (Yu, Shi, Zhou, Gou, et al., 2021). According to literature, BMM methods, even though very costly, provide far better measurement results than the use of visual markers and numerical simulation. However, there is no performance metric in literature that compares their performances with real time or synthetic data.

For the first case study involving GA-SVR, ABC-SVR and CS-SVR, their results together with an artificial neural network (ANN) model were evaluated using correlation coefficient (R^2), mean square error (MSE), variance account for (VAF) and the computing time. Based on the results from these performance metrics, a ranking method was used to the model performance and results are summarized in table 1. From the results, GA-SVR was found to be the best predictive blast movement model and has a faster computing speed.

Table 1 Performance of models Source: (Yu, Shi, Zhou, Rao, et al., 2019)

Method	**Model**	**Results**				**Rank value**				**Total rank**
		R^2	MSE	VAF	Run time (s)	R^2	MSE	VAF	Run time (s)	
GA-SVR	Training	0.9489	0.0025	94.858	40.56	2	3	2	3	22
	Testing	0.9245	0.0031	91.405		4	4	4		
ABC-SVR	Training	0.9494	0.0024	94.903	48.67	3	2	3	2	20
	Testing	0.9240	0.0031	91.366		3	4	3		
CS-SVR	Training	0.9497	0.0024	94.936	97.28	4	2	4	1	19
	Testing	0.9233	0.0031	91.2842		2	4	2		
ANN	Training	0.8835	0.0237	88.167	2.36	1	4	1	4	15
	Testing	0.9002	0.0172	87.666		1	3	1		

Similarly, in the second case study, the three original ML methods (SVR, GP and ELM), together with two hybrid models each of their kind (GA-SVR, WOA-SVR, GA-GP, WOA-GP, GA-ELM, and WOA-ELM) were evaluated and the best predictive model was selected using a simple ranking method as in the first case study. Results show that WOA-GP obtained the best rank of 53 among the nine models as summarized in table 2. The actual and predicted values of the chosen model is also shown in figure 7.

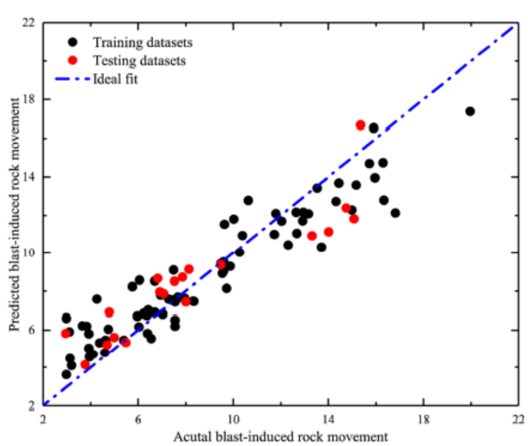


Figure 7 Actual rock movement measurement vrs predicted values by WOA-GP. Source: (Yu, Shi, Zhou, Gou, et al., 2021)

Table 2 Performance of models Source: (Yu, Shi, Zhou, Gou, et al., 2021)

Method	Model	Results			Rank value			Total rank
		R^2	MSE	VAF	R^2	MSE	VAF	
GP	Train	0.828	1.705	82.822	7	7	7	42
	Test	0.788	1.817	78.924	7	7	7	
WOA-GP	Train	0.858	1.475	85.833	9	9	9	53
	Test	0.819	1.679	82.007	9	9	8	
GA-GP	Train	0.858	1.550	85.792	9	8	8	52
	Test	0.819	1.679	82.010	9	9	9	
SVR	Train	0.692	2.284	69.154	1	1	1	6
	Test	0.640	2.367	64.266	1	1	1	
WOA-SVR	Train	0.795	1.862	79.523	4	4	4	18
	Test	0.713	2.116	72.078	2	2	2	
GA-SVR	Train	0.795	1.860	79.564	5	5	5	25
	Test	0.713	2.113	72.160	3	3	4	
ELM	Train	0.725	2.156	72.529	2	2	2	17
	Test	0.719	2.093	72.144	4	4	3	
WOA-ELM	Train	0.800	1.839	80.007	6	6	6	36
	Test	0.781	1.849	78.061	6	6	6	
GA-ELM	Train	0.786	1.904	78.560	3	3	3	24
	Test	0.775	1.871	77.514	5	5	5	

5. Conclusion

Measuring the blast-induced rock displacement is very crucial to reducing ore loss and dilution. Theoretical review has shown that the blast monitoring device (BMM) is very effective in providing a near accurate and reliable measurement of rock displacement than the use of visual markers and numerical modeling. Numerical simulation models have their own merits but the challenges to be addressed to provide a more accurate model persists. There has been considerable amount of research in this area, nonetheless. The machine learning approaches discussed have also proven been effectual in predicting material movement, reducing misclassification, and subsequently providing dig limits for shovels and reducing losses. The data collected from direct measurement was almost consistent with the predicted values of the ML model. Even though the approach is novel, it sets the tone for further exploration of its use for blast movement monitoring.

6. References

Abuntori, C. A., Al-Hassan, S., & Mireku-Gyimah, D. (2021). Assessment of Ore Grade Estimation Methods for Structurally Controlled Vein Deposits—A Review. Ghana Mining Journal, 21(1), 31–44. https://doi.org/10.4314/gm.v21i1.4

Adam, M., & Thornton, D. (2004). A New Technology for Measuring Blast Movement. 6.

Blair, D., & Minchinton, A. (1997). On the damage zone surrounding a single blasthole. Fragblast, 1(1), 59–72. https://doi.org/10.1080/13855149709408390

Cevik, S. I., Olivo, G., & Ortiz, J. M. (2019). Knowledge discovery from geochemical data with supervised and unsupervised methods (Annual Report 2019 No. 2019–02; Predictive Geometallurgy and Geostatistics Lab, pp. 17–29). Queen's University.

Cundall, P. A. (1980). UDEC - A Generalised Distinct Element Program for Modelling Jointed Rock. (PCAR-I-80). Peter Cundall Associates, European Research Office. https://apps.dtic.mil/sti/pdfs/ADA087610.pdf

Fitzgerald, M., York, S., Cooke, D., & Thornton, D. (2011). Blast Monitoring and Blast Translation – Case Study of a Grade Improvement Project at the Fimiston Pit, Kalgoorlie, Western Australia. NEW ZEALAND, 13.

Furtney, J., Sellers, E., & Onederra, I. (2013). Simple models for the complex process of rock blasting. 275–282. https://doi.org/10.1201/b13759-36

Hustrulid, W. A. (2011). Blasting. Encyclopedia Britannica. https://www.britannica.com/technology/blasting

Lawrence, R. W. (1944). Mechanism of Detonation iin Explosives. A Journal of General and Applied Geophysis, 9(1). https://pubs.geoscienceworld.org/geophysics/article/9/1/1/74049/Mechanism-of-detonation-in-explosives

Persson, P.-A. (1997). The relationship between strain energy, rock damage, fragmentation, and throw in rock blasting. Fragblast, 1(1), 99–110. https://doi.org/10.1080/13855149709408392

Preece, D. S., Tidman, J. P., & Chung, S. H. (1997). Expanded Rock Blast Modeling Capabilities of DMC-BLAST, Including Buffer Blasting (No. DEAC04-94AL8500). Sandia National Laboratories, IC1 Explosives Canada. https://digital.library.unt.edu/ark:/67531/metadc685897/m2/1/high_res_d/432902.pdf

Rosa, D. L., & Thornton, D. (2011). Blast Movement Modelling and Measurement. 13.

Schamaun, J. T. (1986). Methods for predicting rubble motion during blasting. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, 23(3), 100. https://doi.org/10.1016/0148-9062(86)91162-9

Shen, C., Laloy, E., Albert, A., Chang, F.-J., Elshorbagy, A., Ganguly, S., Hsu, K., Kifer, D., Fang, Z., Fang, K., Li, D., Li, X., & Tsai, W.-P. (2018). HESS Opinions: Deep learning as a promising avenue toward knowledge discovery in water sciences [Preprint]. Catchment hydrology/Modelling approaches. https://doi.org/10.5194/hess-2018-168

Sołtys, A., Twardosz, M., & Winzer, J. (2017). Control and documentation studies of the impact of blasting on buildings in the surroundings of open pit mines. Journal of Sustainable Mining, 16(4), 179–188. https://doi.org/10.1016/j.jsm.2017.12.004

Taylor, S. L. (1995). Blast induced movement and its effect on grade dilution at the Coeur Rochester Mine [Master's].

Thornton, D. M. (2009). The Application of Electronic Monitors to Understand Blast Movement Dynamics and Improve Blast Designs. 14.

Thornton, D., Sprott, D., & Brunton, I. (2005). Measuring Blast Movement to Reduce Ore Loss And Dilution. https://blastmovement.com/wp-content/uploads/2005/09/2005_ISEE.pdf

Vasylchuk, Y. V. (2019). Advanced Grade Control with Multivariate Geostatistics, Blast Movement Modeling, and Optimized Dig Limits. 236.

Vasylchuk, Y. V., & Deutsch, C. V. (2018). Improved grade control in open pit mines. Mining Technology, 127(2), 84–91. https://doi.org/10.1080/14749009.2017.1363991

Vasylchuk, Y. V., & Deutsch, C. V. (2019). Approximate blast movement modelling for improved grade control. Mining Technology, 128(3), 152–161. https://doi.org/10.1080/25726668.2019.1583843

Yu, Z., Shi, X., Zhou, J., Gou, Y., Rao, D., & Huo, X. (2021). Machine-Learning-Aided Determination of Post-blast Ore Boundary for Controlling Ore Loss and Dilution. Natural Resources Research, 30(6), 4063–4078. https://doi.org/10.1007/s11053-021-09914-5

Yu, Z., Shi, X., Zhou, J., Rao, D., Chen, X., Dong, W., Miao, X., & Ipangelwa, T. (2019). Feasibility of the indirect determination of blast-induced rock movement based on three new hybrid intelligent models. Engineering with Computers, 37(2), 991–1006. https://doi.org/10.1007/s00366-019-00868-0

Zhang, S. (1994). Rock movemnt due to blasting and its impact on ore grade control in Nevada open pit gold mines [Master's]. University of Nevada.

Zhang, Z.-X. (2016). Theory of Detonation. In Rock Fracture and Blasting (pp. 197–216). https://doi.org/10.1016/B978-0-12-802688-5.00009-9

Zou, D. (2017). Contour Blasting Technique for Surface Excavation. In D. Zou, Theory and Technology of Rock Excavation for Civil Engineering (pp. 325–342). Springer Singapore. https://doi.org/10.1007/978-981-10-1989-0_10