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Article

A Solution Surface in a Nine-Dimensional Space to Optimise the Effects of Ground Vibration Through Artificial Intelligence During Blasting in an Open-Pit Mine

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Abstract: In this study, we model a solution surface with each point having nine components using artificial intelligence (AI) in optimising the effects of ground vibration during blasting operations in an open-pit diamond mine. This model has eight input parameters that can be adjusted by blasting engineers to arrive at a desired output value of ground vibration. It is built using the best performing artificial neural network architecture that best fits the blasting data from 100 blasting events provided by the Debswana diamond mine. Other AI algorithms used to compare the model performance were k-nearest neighbour, support vector machine, and random forest – together with more traditional statistical approach, i.e., multivariate and regression analysis. The inputs parameters were burden, spacing, stemming length, hole depth, hole diameter, distance from the blast face to the monitoring point, maximum charge per delay, and powder factor. The optimised model allows variations in the inputs values, given constraints, such that the output ground vibration will be within the minimum acceptable value. Through unconstrained optimisation, the minimum value of ground vibration is around 0.1 mm/s that is within the range caused by a passing vehicle.

Keywords: optimisation; prediction; ground vibration; artificial neural network; blast-induced

1. Introduction

Blasting is commonly used in mining, quarrying, and construction to break apart hard rocks and enable easier excavation and removal. Only 20 to 30 percent of the explosive energy during a blast is used for rock breaking, with the remainder contributing to negative environmental impacts, such as ground vibration, airblast, and flyrock [1,2]. The vibrations induced by blasting affect neighbouring residents and may damage structures [3]. Consequently, predicting blast-induced ground vibrations becomes imperative to manage and mitigate the undesirable effects of blasting. Ground vibrations originating from a blast are quantified in terms of peak particle velocity (PPV), measured in mm/s, at a designated ground position. Influencing factors for ground vibrations are categorised into controllable and uncontrollable parameters. The former pertains to man-made elements, such as explosive properties and blast design parameters, while the latter involves natural occurrences, such as geological conditions and rock-mass properties [4,5].

We present a method to establish the relationship of ground vibration versus input parameters as shown below

$$GV = f(S, B, T, L, D, MC, Pf, Di) \quad (1)$$

where GV = ground vibration, S = spacing, B = burden, T = stemming, L = hole depth, D = hole diameter, MC = maximum charge per delay, Pf = powder factor, and Di = distance from the blast point to the monitoring point.

Equation 1 above has been the subject of many studies to define the function $f()$, that is, to establish the effects of input parameters versus the output parameter in a blasting event in the mines. Most mining companies in the world use different software in estimating the function $f()$, namely, Blast Logic, Mining Excellence, O-Pit Blast, Surpac, etc. These will help them in the blast design efforts, that is, provide values of the input parameters and be able to estimate the outputs of blasting, e.g., rock fragmentation, ground vibration, airblast, and flyrock. Most of these software use empirical methods in defining the function $f()$.

Our solution is to use machine learning to model the function $f()$ and we are not the only ones who attempted to use this approach. What is unique about our approach is that we provide a solution surface, which is the problem's solution space, to further define the function $f()$. In previous studies, they only define the function $f()$ as a black box that is capable of predicting the output parameter given the input parameters, without providing a solution space. Our solution space enables us to do prediction as well as two other things:

1. Perform optimisation computations to find the minimum ground vibration using random initial points
2. Perform blast design by setting the desired value of ground vibration and searching in the solution space for the values of the corresponding input parameters. Or we can assign the value of ground vibration and some input parameters as constraints, and search in the solution space for the values of the remaining input parameters.

To the best of our knowledge, no other previous studies were able to do this.

1.1. Empirical Methods

Numerous empirical methodologies for predicting ground vibration due to blasting have been developed by researchers [6–8]. These techniques use data obtained from different blasting operations, in certain ground conditions which cannot be generalised for different rock types. There are two major shortfalls of empirical methods. First, it has a limited number of inputs, normally only two: maximum charge per delay and distance from the blast point to the monitoring point. Second, it has very low accuracy. Artificial intelligence methods provide generalisability, especially in terms of the number of inputs to the model. However, in terms of accuracy, the results may vary depending on the algorithm used. But in general machine learning methods provide much higher accuracy compared to empirical methods. From our study, accuracy comparisons are stated as follows. The empirical model United States Bureau of Mines (USBM) has an accuracy of 12.6% our artificial intelligence model accuracy ranges from 54.6% to 93.6%, and the statistical method has an accuracy of 66%.

Adding more input parameters in modelling ground vibration using empirical methods can be very difficult to achieve with high accuracy because of the complex, non-linear relationship between the input and output parameters. This could be the reason why empirical methods typically account for only two parameters and fail to incorporate the full range of factors affecting ground vibration. New approaches to estimating ground vibrations from blasting include artificial intelligence systems that consider many parameters influencing the outcomes of blasting [9–12].

1.2. Machine Learning Methods

Lawal et al. [13] utilised an ordinary artificial neural network (ANN), particle swarm optimisation (PSO), and dragonfly-optimised ANN to forecast how tunnel blasting may affect the environment. The PSO-ANN model, with an architecture of 4-15-15-1, yielded the best performance, exhibiting a coefficient of determination (R^2) of one, a mean square error (MSE) of 0.125, and a variance accounted for (VAF) of 98.29. In another study, Lawal et al. [14] used blast data from five granite quarries to predict ground vibration by employing gene expression programming (GEP), sine cosine algorithm-optimised

artificial neural network (SCA-ANN), and adaptive neuro-fuzzy inference system (ANFIS) models, using a total of 100 datasets for model development. The obtained R^2 values for the SCA-ANN, GEP, and ANFIS models were 0.999, 0.989, and 0.997, respectively.

Zhang et al. [15] applied five machine learning classifiers for predicting ground vibration, namely, chi-squared automatic interaction detection (CHAID), ANN, support vector machine (SVM), random forest (RF), and classification regression tree (CART), finding RF to offer substantially superior performance over the other regression models investigated. Qiu et al. [16] applied an extreme gradient boosting (XGBoost) model to predict blast-induced ground vibration using 150 data sets with thirteen input parameters. The grey wolf optimisation (GWO), whale optimisation algorithm (WOA), and bayesian optimisation algorithm (BO) were used to fine-tune the hyperparameters of the XGBoost model. Their investigation revealed that, the suggested WOA-XGBoost model performed better in comparison to other machine learning (ML) models.

Nguyen et al. [17] utilised a novel hybrid model combining the hierarchical k-means clustering algorithm with ANN (HKM-ANN). The model was compared to the fuzzy c-means clustering support vector regression (FCM-SVR), finding that the HKM-ANN model performed better than the FCM-SVR model in forecasting ground vibration. Yang et al. [18] employed ANFIS optimised by PSO and genetic algorithm (GA) to forecast ground vibration resulting from blasting, utilising data from two Iranian quarry mines. Their model demonstrated an accuracy of 0.979, a root mean square error (RMSE) of 0.240, and a mean absolute (MAE) of 0.199 in predicting ground vibration. Other researchers have employed hybrid artificial intelligence methodologies, predominantly ANNs, to model blast-induced ground vibrations, other blast-induced impacts and rock engineering problems [19–28].

This study uses an ANN model as a solution surface in a nine-dimensional space to minimise the effects of ground vibration during blasting operations in an open-pit diamond mine. This solution surface becomes the solution space such that each point on the surface is defined by nine components, i.e., eight input parameters and one output parameter ground vibration. An ANN model is designed for predicting ground vibrations during open-pit mine blasting, using data derived from the Debswana Orapa Diamond Mine in Botswana. The ANN model was chosen as the best-performing model among three other machine learning methods. The model has eight input parameters, which include both blast design parameters and explosive properties. The model's performance is compared against other machine learning algorithms and multivariate regression analysis. Sensitivity analysis is also conducted to determine the relative influence of input parameters on the output.

We explicitly list down our claim of contributions in this paper as follows:

- We present data from Debswana Diamond Company recorded from 100 blast events.
- We develop machine learning models, each with five different architectures, with eight input parameters and one output of ground vibration. The four models are compared against a statistical method.
- We optimise the architecture of the best performing machine learning model using Monte Carlo method.
- A solution space is created from the optimised machine learning model. Other machine learning models did not come out with a solution space, their results include only predicting the output parameter ground vibration. Our solution space is capable of inverse solution, i.e., we can search the solution space, given input parameters and the expected output to help the blast design engineers in adjusting the input parameters to arrive at an expected output of ground vibration.
- We optimise ground vibration using gradient descent method from the created solution space.
- Sensitivity analysis is performed using a statistical method and the results are confirmed from the created solution space.

The machine learning model allows us to predict the output ground vibration from the given eight input parameters by locating a unique point in the solution space. Because of this model, one can also predict not just the output parameter, but also an input parameter when seven other input parameters are given together with their corresponding output ground vibration. In this way, this

model can be very useful to blast design engineers by setting a target output ground vibration and searching for the corresponding input parameters in the solution space. This is a kind of inverse solution approach and can be very useful to blast design engineers.

1.3. Mine Case Study

The Orapa Diamond Mine in Botswana was discovered in 1967 by De Beers. The kimberlite igneous rocks span an area of 1.18 square kilometres, with two merging diatremes, each with preserved crater sedimentary facies known as the southern and northern lobes. These lobes overlay Archaean granite and belong to the Karoo Supergroup, incorporating Stormberg-aged basalt lava and tracing back approximately 93 million years. The anticipated yield of the Orapa mine is around 153 million carats from a total of 205 million tonnes of mineral reserves. Figure 1 depicts the current layout of the Orapa Diamond Mine.

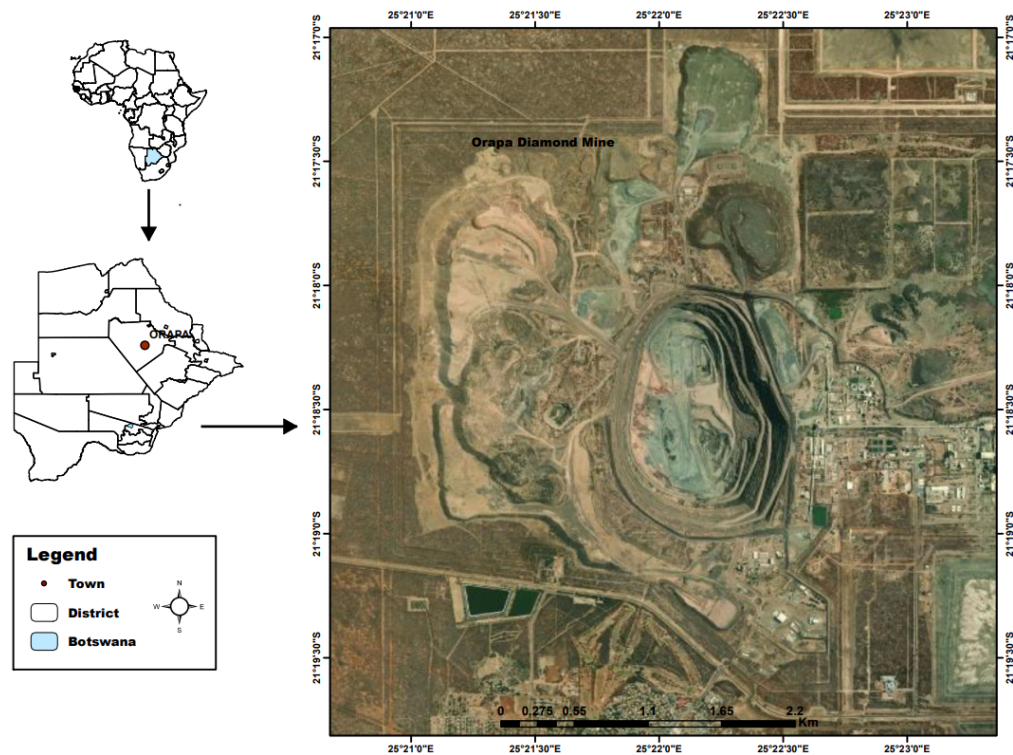


Figure 1. Layout of Orapa Diamond Mine.

The mine utilises a staggered blasting pattern. The predominant explosives used are S135B emulsion and pentolite boosters. The mine has a bench height of 15 metres and makes use of blast holes with diametres of (127, 165, and 250) millimetres. Each blast comprises between 15 and 25 rows, with each row containing between 40 and 60 holes. The loading of the fragmented materials is done using shovels and hydraulic excavators, while the dump trucks are used for hauling.

2. Materials and Methods

This section explores the materials and methodologies employed in this study, focusing on the datasets collected from the mining operation, the machine learning techniques applied, and the optimisation processes implemented.

2.1. Materials

A dataset with 100 blasting events was collected from the blasting operations of the Debswana Orapa Diamond Mine. The dataset consists of eight inputs which include blast design parameters and explosive properties, and ground vibration as the output as shown in Table 1.

Table 1. Description of the input and output parameters for the models.

Parameter	Type	Unit	Symbol	Min	Max
Burden	input	m	B	4	6
Spacing	input	m	S	5	8
Stemming length	input	m	T	4	6
Hole depth	input	m	L	12	15
Hole diameter	input	mm	D	165	250
Distance from blast to monitoring point	input	m	DI	438	1500
Maximum charge per delay	input	kg	MC	216	552.6
Powder Factor	input	kg/m ³	Pf	0.3	1.17
Ground vibration	output	mm/s	GV	0.163	6.5

Ground vibration data in this study was recorded using seismographs placed at varying distances from the blast sources. These devices measured vibrations in three orthogonal components: radial, transverse, and vertical. The radial component corresponds to the direction of propagation of the vibration wave from the blast source, while the transverse and vertical components provide a complete three-dimensional representation of the vibration effects. This approach ensures that the dataset captures the full spectrum of vibrational impacts resulting from blasting activities. Starting from 1984 to the present, with around two blasts per month. However, Orapa mine is only willing to share blasting data starting from 2018, and they perform two blasts per month. One of the major problems in processing the data provided by Orapa is the integrity of information. Many entries in the blasting reports were incomplete and therefore not suitable to be included in our database. Thus, many entries were discarded resulting in only 100 complete blasting events.

2.2. Methods

Data preprocessing involved cleaning and normalising the data to prepare it for analysis; the data was divided into training (80%), validation (10%), and testing (10%) sets. The machine learning models employed are random forest, support vector machine, k-nearest neighbour (*k*-NN), and artificial neural network. Additionally, the statistical model multivariate regression analysis (MVRA) was utilised. These models were built using Python. The gradient descent method, coupled with the Monte Carlo method, was used for the optimisation of ground vibration based on the best-performing ANN model. The cosine amplitude approach was applied for sensitivity analysis to determine the relative impact of input parameters on the output. The metrics used for evaluating the performance of all predictive models are, RMSE and *R*². The RMSE is calculated using the formula:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y - y')^2} \tag{2}$$

The (*R*²) is determined by:

$$R^2 = \left[\frac{\sum_{i=1}^N (y - \bar{y})(y' - \bar{y}')}{\sqrt{\sum_{i=1}^N (y - \bar{y})^2 \sum_{i=1}^N (y' - \bar{y}')^2}} \right]^2 \tag{3}$$

In these equations, *y* and *y'* represent the measured and forecasted values, respectively, while $\bar{y}$ and $\bar{y}'$ denote the mean values.

For composite score calculation *R*² is normalised. We note that higher values of *R*² indicate better performance. For RMSE, lower values indicate better performance. To normalise RMSE values, we used:

$$\text{Normalized RMSE} = 1 - \frac{RMSE}{\text{Max RMSE}} \tag{4}$$

Once both metrics are normalised, we compute a composite score by adding the normalised R^2 and normalised RMSE.

The Monte Carlo technique was employed to randomly navigate the solution space and find the best ANN configuration. This optimal ANN structure comprises 34 neurons in the first hidden layer, 15 in the second layer and 50 in the third hidden layer. Upon establishing the optimal ANN model, we then use the gradient descent approach to find the minimum ground vibration and its corresponding input parameters. Gradient descent is a commonly employed iterative optimisation technique with applications spanning various computational fields [29]. The mathematical equation of the gradient descent method is shown by (5).

$$p_i^{\text{new}} = p_i - \eta \left(\frac{\text{nnet}(p_1, \dots, p_i, \dots, p_N) - \text{nnet}(p_1, \dots, p_i^{\text{old}}, \dots, p_N)}{p_i - p_i^{\text{old}}} \right) \tag{5}$$

In this equation, p_i^{new} represents the updated parameter, while p_i is the current parameter value being updated. The term p_i^{old} denotes the parameter value from the previous iteration. The learning rate is represented as η . The function $\text{nnet}(\cdot)$ represents the neural network model.

3. Results and Discussion

Table 2 shows the performance indices of the models. The ANN model with an 8-10-1 architecture showed the best performance, with the lowest RMSE (0.286), the highest accuracy R^2 (0.941), and the highest composite score (1.864), establishing it as the best model. The order of performance of the models according to their composite score is ANN (1.864), RF (1.768), k -NN (1.454), SVM (1.445), and MVRA, having the lowest composite score of 0.664.

Table 2. The calculated performance indices for all the algorithms.

Method	R^2	RMSE	Composite Score
K nearest neighbor			
n-neighbors = 10	0.728	1.030	1.454
n-neighbors = 20	0.643	1.180	1.329
n-neighbors = 30	0.528	1.670	1.084
n-neighbors = 40	0.550	1.884	1.049
n-neighbors = 50	0.582	2.002	1.050
Support vector machine			
sigma = 1	0.675	1.130	1.374
sigma = 3	0.696	1.145	1.391
sigma = 5	0.720	1.035	1.445
sigma = 7	0.596	1.215	1.275
sigma = 9	0.590	1.245	1.260
Random forest			
n-estimators=5	0.904	0.510	1.768
n-estimators=15	0.892	0.545	1.748
n-estimators=25	0.865	0.605	1.705
n-estimators=35	0.856	0.680	1.676
n-estimators=45	0.848	0.760	1.646
Artificial neural network			
model 1 (10 neurons)	0.941	0.286	1.864
model 2 (20 neurons)	0.912	0.315	1.829
model 3 (30 neurons)	0.898	0.456	1.778
model 4 (40 neurons)	0.890	0.410	1.800
model 5 (50 neurons)	0.862	0.472	1.737
Multivariate regression analysis	0.664	3.760	0.664

Figure 2 shows the variation in RMSE for different models with their hyper-parameters. Figure 2a illustrates the variation in RMSE with the number of neighbours for the k -NN model. As the number of neighbours decreases, the RMSE also decreases, with the optimum performance found at $k = 10$ (lowest RMSE). For the RF model, increasing the number of trees results in a higher RMSE. The optimum model was found at 10 trees (lowest RMSE), as shown in Figure 2b. In Figure 2c, the RMSE decreases as the number of neurons decreases, leading to an optimum ANN model with 10 neurons (lowest RMSE). For the SVM model, smaller sigma values lead to an increased RMSE, and larger sigma values do as well. Medium sigma values result in a lower RMSE, with the optimum model being the SVM polynomial kernel, with $\sigma = 5$.

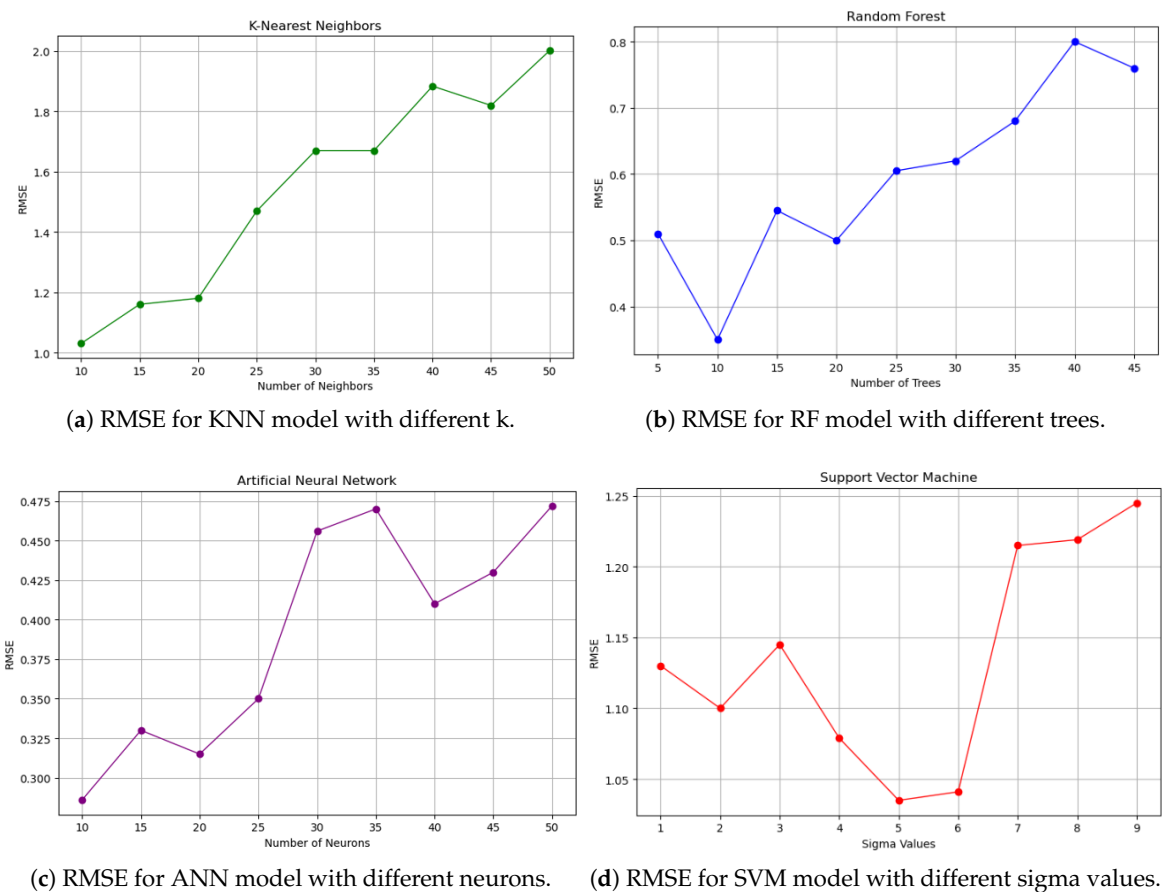
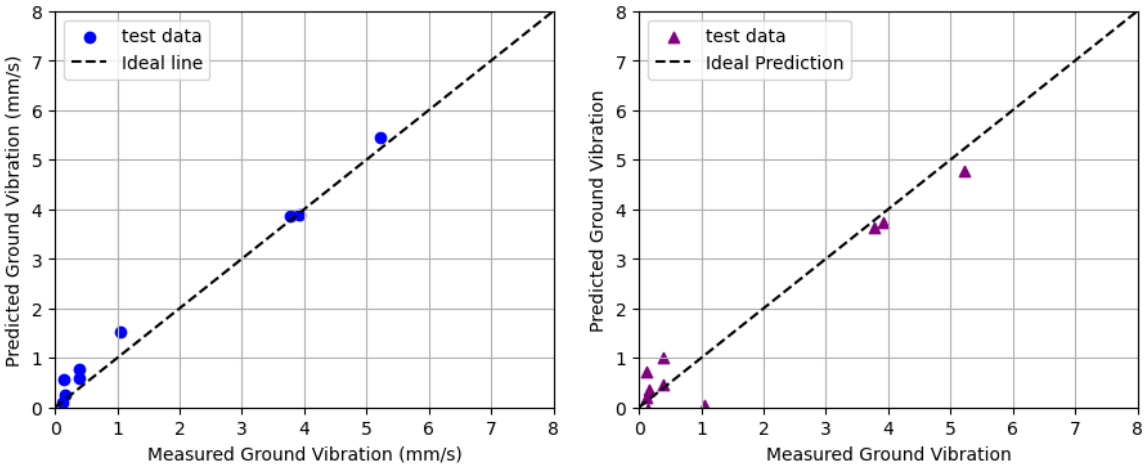
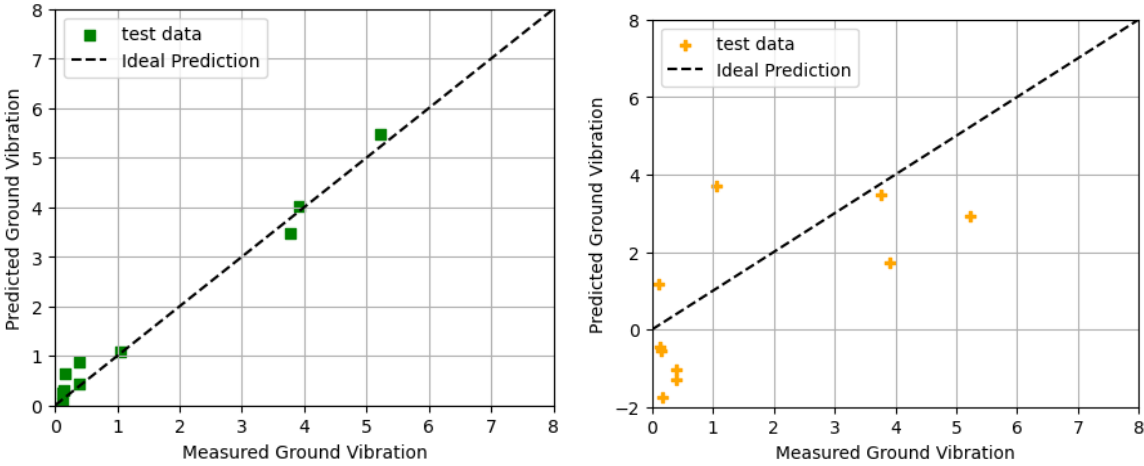


Figure 2. The RMSE values for different models, where (a) is for KNN, (b) is for RF, (c) is for ANN, and (d) is for SVM.

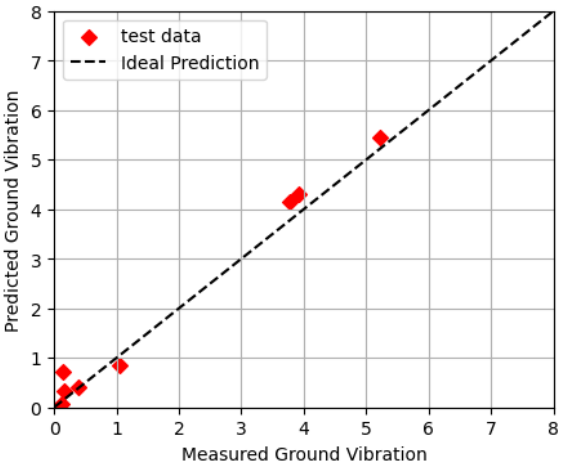
Figures 3a–e depict the correlation between the predicted and measured ground vibrations. The solid line represents a 1:1 slope, and it can be observed that the data points for the ANN model cluster closely around this line, indicating superior prediction capability compared to other models. Furthermore, a comparison of the predicted and measured ground vibration for each algorithm is shown in Figure 4. The graph illustrates that the predictions generated by the ANN closely align with the measured values, indicating the ANN’s proficiency in predicting these parameters compared to other models.



(a) Comparison between measured and predicted GV for ANN model 1. (b) Comparison between measured and predicted GV for SVM.



(c) Comparison between measured and predicted GV for k-NN. (d) Comparison between measured and predicted GV for MVRA.



(e) Comparison between measured and predicted GV for RF.

Figure 3. Scatter plots for all the models.

The ANN performs the best due to its ability to capture non-linear relationships among multiple input parameters through its flexible architecture and adaptive learning capabilities. The RF, while also capable of handling non-linearities through ensemble learning, is slightly less effective than ANN in capturing very complex interactions. The *k*-NN, which relies on the proximity of data points, performs adequately but struggles with high-dimensional data. The SVM, though powerful in high-dimensional spaces and capable of non-linear modelling using kernel functions, often requires meticulous tuning of hyper-parameters to perform optimally. Lastly, MVRA, being a traditional statistical approach, is limited by its linear assumption and cannot adequately capture the non-linear relationships present in the data, resulting in the poorest performance among the models.

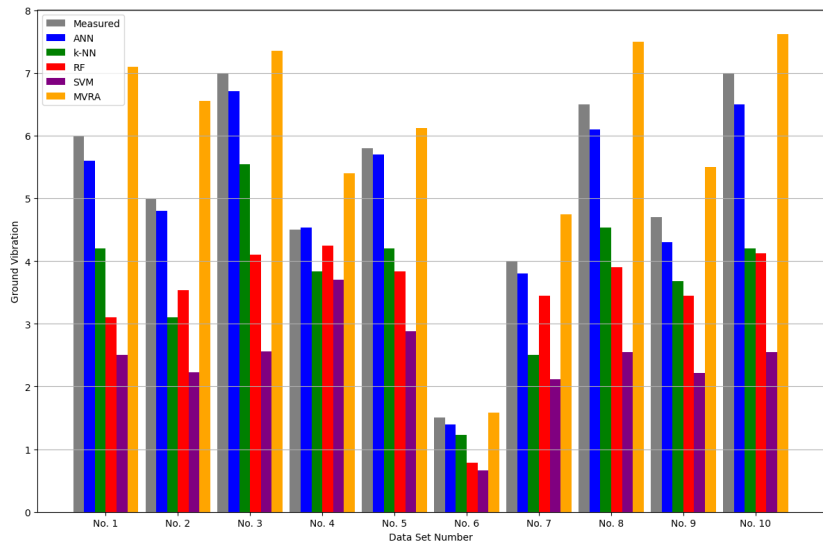


Figure 4. Comparison between measured and predicted GV by all algorithms.

The highest-performing model in Table ?? is the PSO-ANN by Lawal et al. [13], which achieved an R^2 of 1.00 using 56 datasets with four inputs, namely, charge per delay (Q), number of holes (N), DI and rock mass rating (RMR). This model’s superior performance can be attributed to the optimisation capabilities of the PSO technique combined with ANN, which likely captures non-linearities more effectively than other models. In contrast, the lowest-performing model is the ANN by Dindarloo [30] with an R^2 of 0.81 using only 15 datasets and five inputs (D, L, N, B, S). The limited dataset size and potentially less complex model architecture might have restricted the model’s ability to generalise and capture the variability in the data, leading to lower predictive accuracy. In the middle range, the HKM-ANN by Nguyen et al. [17] achieved an R^2 of 0.98 using 185 datasets with six inputs (S, PF, B, DI, maximum charge per delay (MC)). This model combines hierarchical k-means clustering with ANN, enabling it to handle larger and more diverse datasets effectively. Its performance is close to the highest-performing models, indicating that hybrid techniques can significantly enhance predictive capabilities.

Comparing these with our results, our ANN model achieved an R^2 of 0.941 with 100 datasets and eight inputs. It performs well and aligns closely with other high-performing models, such as the ANN by Armaghani et al. [31], which achieved an R^2 of 0.97 with 109 blasting events. This suggests that our model may attain comparable accuracy with minor adjustments, such as including more input parameters and increasing the dataset size. However, hybrid models that use advanced techniques and larger datasets, including PSO-ANN ($R^2 = 1.0$, Lawal et al. [13]) and HKM-ANN ($R^2 = 0.98$, Nguyen et al. [17]), perform slightly better than our model. These results imply that the accuracy and generalisability of our model can be improved by investigating hybrid models and adding more inputs, allowing it to capture more complex interactions and improve generalisability, as seen in the highest-performing models.

Table 3 highlights the significant impact of dataset size, the number of input parameters, and the type of model used on the performance of predictive models. Models using hybrid techniques and larger datasets tend to perform better, as they can capture complex patterns and interactions within the data more effectively.

Table 3. Performance indices from other studies.

Best Model	Other Models	Inputs	Dataset	R ²	Reference
ANFIS		L, B, S, T, Q, DI	25	0.89	[25]
RF	CART, CHAID, ANN, SVM, RF	BS, DI, T	102	0.94	[15]
HKM-ANN	ANN, SVR, FCM-ANN	MC, PF, L			
	HKM-SVR, FCM-SVR	S, Pf, B	185	0.98	[17]
ANFIS-GA	ANFIS, ANFIS-PSO	DI, MC			
	USBM, Indian Standard	B, S, T	86	0.98	[18]
GEP		Pf, MC, DI			
SVM	USBM, MLR, PSO power, PSO linear	BS, L, T, Pf, Q, DI	102	0.88	[22]
WOA-XGBoost	GWO-XGBoost, BO-XGBoost, CatBoost, RF, GBR	DI, MC	80	0.96	[32]
		D, L, B, S, MC	150	0.97	[16]
		CL, DI, BI			
ANFIS	ANN	E, PR, Pv, VOD, DOE			
PSO-ANN	ANN, DA-ANN	DI, MC	109	0.97	[31]
ANN		Q, Nh, DI, RMR	56	1.00	[13]
ANN		MC, DI, TC	20	0.93	[33]
	MVRA, Indian Standard	L, MC	174	0.99	[34]
	Langefors-Kihlstrom, USBM	B, S			
GRNN	General predictor, Ambraseys-Hendron	DI, BI, E, PR, Pv			
	USBM, CMRI, Indian Standard	MC, DI	14	0.99	[35]
	Langefors-Kihlstrom, Ambraseys-Hendron				
ANN	USBM, Indian Standard, MVRA	MC, DI, BS, L, T, D, Pf	180	0.99	[36]
	Langefors-Kihlstrom, Ambraseys-Hendron				
FIS	USBM, Indian Standard	B, S	120	0.94	[37]
	Langefors-Kihlstrom, Ambraseys-Hendron	T, N			
	CMRI, Ghosh-Daemen 1, Ghosh-Daemen 2	MC, DI			
ANN	MVRA, General predictor				
	GEP	D, L, N ,B, S	15	0.81	[30]
		RDI, HDI, T, Q			
SVM	USBM, Indian Standard, MVRA	DI, MC	174	0.96	[38]
	Langefors-Kihlstrom, Ambraseys-Hendron				
	Ghosh-Daemen, CMRI, General predictor				
FS-RF	FS-BN, Langefors-Kihlstrom	MC, DI, B, D, TC, S	102	0.90	[5]
	Ghosh-Daemen, Roy, Indian Standard	L, T, Sd, N, Pf, Q			
ANN-KNN	ANN, USBM	MC, DI	75	0.88	[23]
RVR-GWO	BA-GWO	MC, BS, D, T	95	0.84	[28]

USBM, United States Bureau of Mines; MLR, Multi-Linear Regression; GBR, Grad+i+ent Boosting Regression; GRNN, Generalised Regression Neural Network; GEP, Gene Expression Programming; CMRI, Central Mining Research Institute; FIS, Fuzzy Inference System; FS, Feature Selection; 'RVR, Relevance Vector Regression; GWO, Grey Wolf Optimisation; BA, bat-inspired algorithm; BN, Bayesian Network; BS, Burden to Spacing Ratio; Q, Charge per Delay; Sd, Subdrill; Total Charge, TC; DI, Distance; Number of holes, N; MC, Maximum Charge per Delay; BI, Blastability Index; E, Young's Modulus; PR, Poisson's Ratio; VOD, Velocity of Detonation; DOE, Density of Explosives; Pv, P-wave Velocity.

3.1. Sensitivity Analysis

Sensitivity analysis was used to determine the relative influence of input parameters on the output using the cosine amplitude method [39]. The strength of the relation between the dataset, x_i and x_j is given by:

$$r_{ij} = \frac{\sum_{k=1}^m X_{ik} X_{jk}}{\sqrt{\sum_{k=1}^m X_{ik}^2 \sum_{k=1}^m X_{jk}^2}} \tag{6}$$

where x_i and x_j are inputs and outputs, respectively; and m is the dataset number.

In Figure 5, it can be inferred that spacing is the most influential input parameter on ground vibration. It is noted that hole diameter is the least influential parameter on ground vibration. This observation is consistent with findings from other studies, which have also demonstrated that spacing exerts a greater influence on ground vibration than hole diameter [5,16,36]. The high sensitivity of spacing suggests that even minor adjustments can lead to significant changes in vibration levels,

providing a powerful lever for engineers to control blast outcomes. On the other hand, the relatively low sensitivity of hole diameter indicates that it can be considered a secondary factor, allowing engineers to focus their optimisation efforts on more influential parameters.

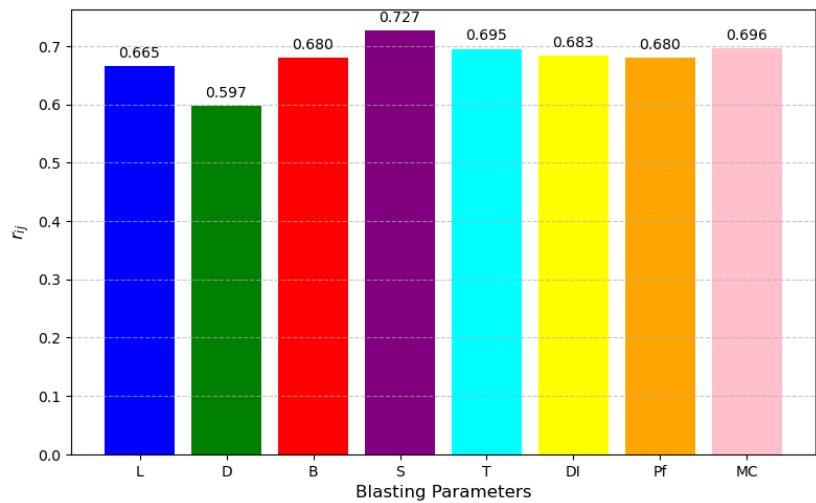


Figure 5. Sensitivity analysis for ground vibration.

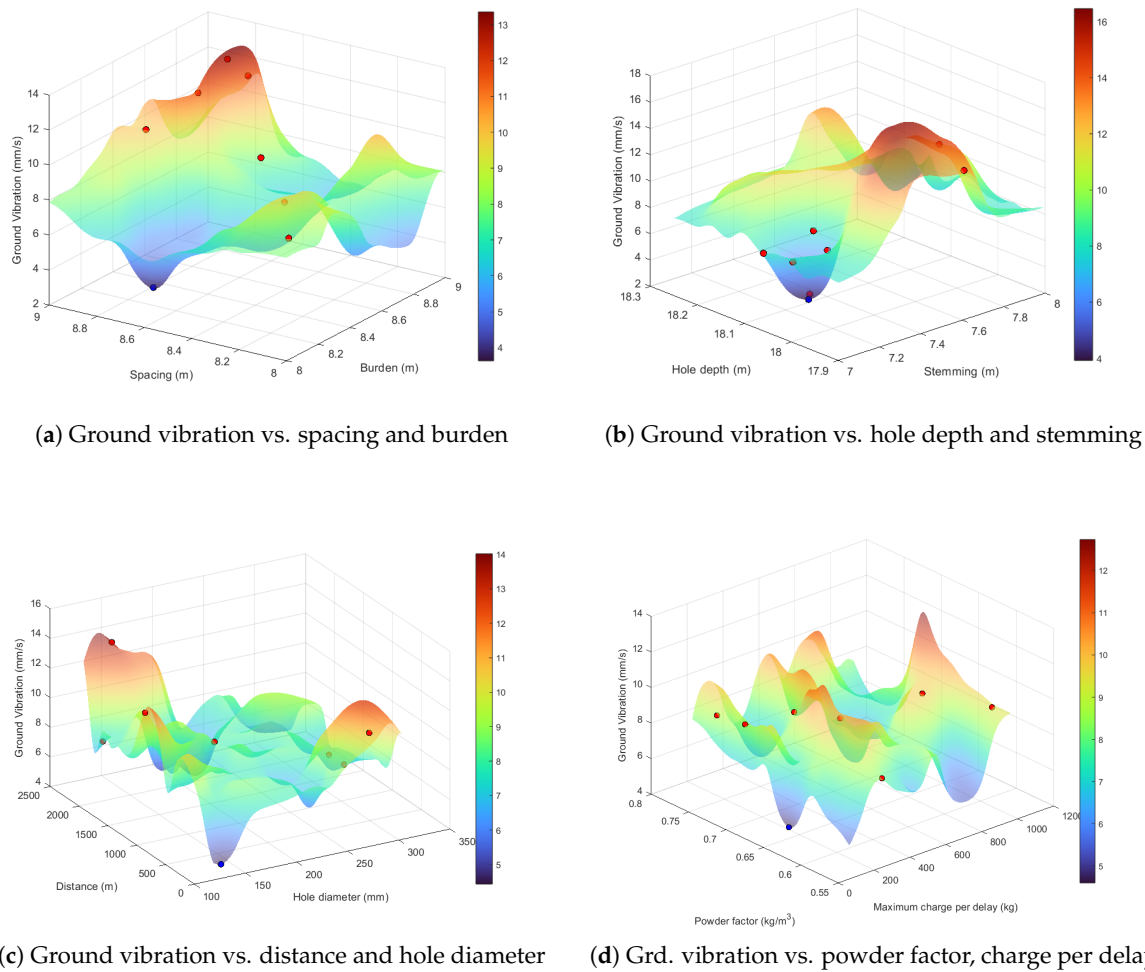


Figure 6. Solution space for ground vibration as the output parameter with eight input parameters, taken two at a time. The red dots are random initial values that always converge to the optimal point, the blue dot, for every minimisation computation.

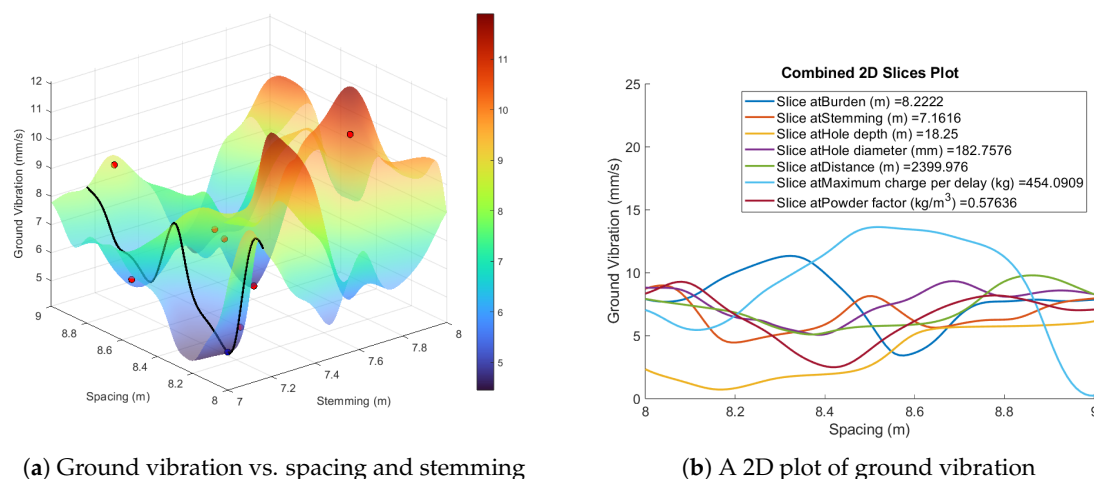


Figure 7. Ground vibration versus spacing, the most influential input parameter, presented in a 2D plot. The values of the other seven input parameters at the optimal point are kept constant, while spacing is plotted in its entire range. Each curve plotted in subfigure (b) is one of the seven input parameters. Subfigure (a) shows a 3D plot where stemming, the second most influential parameter, is kept constant in the traced curve that includes the blue dot which is the minimum point. The red dots are random initial points converging to the blue dot at every optimisation computation.

3.2. Analysis of the Optimisation Results

Figure 6a through 7a display the results of the optimisation procedure, starting with seven initial points (depicted as red dots) chosen at random and converging towards the optimised value (illustrated as a blue dot), which is the lowest point in the surface. The optimised blast design parameters are as follows: powder factor (0.58), maximum charge per delay (454.09), burden (8.22), spacing (8.30), stemming (7.16), distance from blast point to monitoring point (2399), hole depth (18.25), and diameter (183). Therefore, the lowest point on the solution surface corresponds to the minimum value of ground vibration predicted by the model (approximately 0.1 mm/s). Every point in the solution surface has nine components, i.e., eight components of the eight input parameters plus the output component of the ground vibration.

From the sensitivity analysis, spacing is the most influential parameter. Because of this, we compare spacing versus all the other seven input parameters kept constant, to observe the variations in the values of the output parameter in a two-dimensional plot. We assign spacing to be the x -axis, while ground vibration is assigned as the y -axis.

Figure 7a shows that as spacing decreases with stemming length fixed at 7.16, ground vibration initially fluctuates and finally decreases towards an optimal spacing value for minimal vibration, after which it increases again. The solution space also confirms the results of the sensitivity analysis. As can be seen in Figure 7b, generated by varying spacing and fixing all the other parameters, and taking a slice through the lowest, optimised point in the solution space. Maximum charge per delay, Stemming, burden, and powder factor are the most influential input parameter after spacing, and have the most fluctuations in Figure 7b. This indicates a high sensitivity, as changes in these parameters significantly impact ground vibration. Hole diameter is the least influential parameter, this parameter shows least variations suggesting lower sensitivity.

The significance of these results lies in their practical application for blasting engineers seeking to minimise the environmental and structural impacts of ground vibrations during blasting operations. By providing a set of optimised parameters, the model enables engineers to design blasts that adhere to safety regulations and reduce the risk of damage to nearby structures and communities. Reducing ground vibrations not only mitigates the risk of structural damage but also enhances the efficiency of the blasting process. Minimising ground vibration may lead to a greater part of the total energy in blasting to be concentrated more towards its main goal, that is, rock fragmentation.

4. Conclusions

This study successfully demonstrates the application of machine learning techniques to predict and optimise ground vibrations induced by blasting operations at the Debswana Orapa diamond open-pit mine. Among the evaluated models, ANN, k-NN, SVM, RF, and the MVRA, the ANN model emerged as the most effective, evidenced by its highest predictive accuracy, with an R^2 value of 0.941 and a minimal RMSE of 0.286. Using the ANN algorithm, we optimise the architecture of the ANN model using the Monte Carlo method resulting in an architecture, consisting of three hidden layers with 34, 15, and 50 neurons, respectively. We then optimise the resulting ANN model using the gradient descent method to find the minimum ground vibration which is 0.1 mm/s. The solution space, therefore, is capable of predicting ground vibration given input parameters, as well as setting the desired output value of ground vibration and looking for the corresponding values of the input parameters. Thus the solution space demonstrates its efficacy in minimising, predicting, and designing ground vibrations. Sensitivity analysis confirmed the results provided by the solution space. Although the findings of this study are specific to the Orapa Diamond Mine, the methodologies employed, are designed to be scalable and adaptable to other mining operations. By incorporating site-specific data and retraining the model, the approach can be extended to mines with different geological, topographical, and operational conditions.

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