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A Comparative Study of Machine Learning Methods for Prediction of Blast-Induced Ground Vibration

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Abstract

Blast-induced ground vibration (PPV) evaluation for a safe blasting is a long-established criterion used mainly by the empirical equations. However, the empirical equations are again considering a limited information. Therefore, using Machine Learning (ML) tools [Support Vector Machine (SVM) and Random Forest (RF)] can help in this context, and the same is applied in this work. A total of 73 blasts are monitored and recorded in this work. For the ML tools, the dataset is divided into the 80-20 ratio for the training and testing purposes in order to evaluate the performance capacity of the models. The prediction accuracies by the SVM and RF models in predicting the PPV values are satisfactory (up to 9% accuracy). The results obtained show that the coefficient of determination (R2) for RF and SVM is 0.81 and 0.75, respectively. Compared to the existing linear regressions, this work recommends using a machine learning regression model for the PPV prediction.

1. Introduction

Blasting is a damaging and irreversible operation by its very nature. However, due to its economics and adaptability, it is used in the open cast mines. Working professional's primary concern during blasting for excavation is a disruption to the excavation's boundary, which results in noticeable changes to the rock's appearance in the form of cracking, fragmentation, slabbing, back-break, and over-break [1-4]. If the magnitude of the damage and its impact on the surrounding rock can be anticipated, the blast design can be adjusted to minimize the ore and waste dilution and instability problems by adjusting the reverent parameters.

Ground vibrations, air blast, and fly-rock generation are the three main disruptions caused by blasting in the surface mines. Almost all of these issues cause severe damages to the buildings near the blasting zone, and, aside from that, they can lead to ongoing tension with the residents living near the activity site. As a result, a vibration control study in mines is required to predict the blast-induced ground vibration components, which is critical for mitigating the negative consequences.

Many researchers' use of empirical equations is one of the most recognized and highly used methods and procedures for the vibration prediction.

The engineers have been using the scaled distance regression analysis in order to predict PPV for decades because it is the simplest and least complicated tool. The scaled distance is a term based on the amount of energy released by explosives in air shock generation and seismic waves and the impact of distance on ground wave attenuation [5], [6]. The scaled distance is determined by multiplying the distance between the energy source and the measured points on the field by the maximum charge weight per delay. [7] stated that the effect of charge weight per delay on PPV was much more pronounced than a far distance (> 50 m).

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Although the approach is well-accepted due to its ease of use, it is merely an empirical approach that does not consider the inevitable phenomenon of blast wave superimposition. Many attempts have been made to obtain the actual charge weight per delay, contributing to the superimposed waveforms resulting from production blasting.

Table 1. Empirical equations for ground vibration prediction [1].

Sl. No.	Researchers	Year	Predictor equation
1	Langefors and kihlstrom	1958	$V_{max} = k(Q/D^{2/3})^{b/2}$
2	Duvall and Petkof	1959	$V_{max} = k(D/Q^{1/2})^{-b}$
3	Devine *et al.*	1963	$V_{max} = k(D/Q^{1/2})^{-b}$
4	Ambraseys and Hendron	1968	$V_{max} = k(D/Q^{1/3})^{-b}$
5	Nicholls *et al.*	1971	$V_{max} = k\ (Q^{a} D^{b)}$
6	Is 6922	1973	$V_{max} = k(D/Q^{2/3})^{b}$
7	Just-Free	1980	$V_{max} = k(D/Q^{1/3})^{-b} e^{-\alpha D/Q^{1/3}}$
8	Ghose and Daemen	1983	$V_{max} = k(D/Q^{1/2})^{-b} e^{-\alpha D}$
9	Ghose and Daemen	1983	$V_{max} = k(D/Q^{1/3})^{-b} e^{-\alpha D}$
10	Gupta *et al.*	1987	$V_{max} = k(D/Q^{1/2})^{n} e^{(\alpha XD/Q)}$
11	Pal Roy	1993	$V_{max} = n + k(D/Q^{1/3})^{-1}$
12	CMRI	1993	$V_{max} = n + k(D/Q^{1/2})^{-1}$
13	Rai and Singh	2004	$V_{max} = k\ R^{-b}\ Q_{max}\ e^{-\alpha}$
14	Ramulu	2004	$V_{max} = V(2(Bd/Bo)^{1/2}\ -1)$
15	Rai *et al.*	2005	$V_{max} = 0.438D^{-1.52}$
16	Nicholson	2005	$Q_{\ max} = k(vD^{2})^{\ b}$
17	Kahriman *et al.*	2006	$V_{max} = 0.561D^{-1.432}$
18	Ozer (sandstone)	2008	$V_{max} = 0.257D^{-1.03}$
19	Ozer (shale)	2008	$V_{max} = 6.31D^{-1.9}$
20	Ozer (limestone)	2008	$V_{max} = 3.02D^{-1.69}$
21	Kumar *et al.*	2016	$V_{max} = ((0.3396\ X\ 1.02^{GSI}\ GSI^{1.13})^{0.642} D^{1.463})/r$

where Vmax is the magnitude of ground vibration; Q is the maximum charge weight in any delay interval; D is the distance from blasting; K, a,and b are constants whose values depend on the condition of the site; B is the slope of the best fit line of the Vmax versus scale distance; $e\text{-}\alpha^{D}$ is the inelastic attenuation factor; α is the inelastic attenuation coefficient; n is the parameter related to the rock properties and geometrical discontinuities; V is the Vibration due to optimum burden; Bd is the deviated burden; Bo is the optimum burden; and GSI is the geological strength index.

Due to the non-homogeneous nature of rocks, the geology of civil structures and the explosive blast design parameters are optimized by testing on the field. In addition, monitoring blast vibrations during the actual excavation helps to ensure a proper and safe operation and provide the necessary data to improve the blasting patterns if deemed necessary [8].

According to USBM [9], the empirical relationship between PPV and scaled distance (D) is as follows:

$$V = K(SD)^{-b} \tag{1}$$

where V is the PPV (m/s); SD is the scaled distance, which is defined as the ratio of the distance from charge point, R (m), to the square root of charge mass, Q (kg), expressed in TNT net equivalent charge weight, i.e. $SD = R/Q^{0.5}$; and k and b are site-specific constants.

In the recent years, the researchers have developed a variety of soft computing techniques and approaches in order to predict and provide solutions to reduce the adverse effects of blast-induced ground vibration in the surface mining methods including machine learning such as artificial neural networks [10]–[13], genetic algorithm, CART analysis, neural fuzzy technique [14]. The recent works on the prediction of blast-induced ground vibration by various AI techniques with their efficiency are as follows:

Table 2. Soft computing technique used by various research works for predicting ground vibration.

Researchers	Predictive model	Input parameters	R^2
(Kamali and Atai 2010)	ANN	MCPD, TCPR, D, ϕ, L, NH, D_t, N_d, SC	$R^2 = 0.99$
(Kamali and Ataei, 2011)	ANN	MCPD, TCPR, D, ϕ, L, NH, D_t, N_d, SC	$R^2 = 0.99$
(Mohamadnejad, Gholami, and Ataei 2012)	SVM, GRNN	D, MCPD	$R^2_{SVM} = 0.946$ $R^2_{GRNN} = 0.92$
(Mohamad Ataei and Kamali, 2013)	ANFIS	D, MCPD	$R^2 = 0.9897$
(Ghasemi, Ataei, and Hashemolhosseini 2013)	FIS	S, B, ST, D, MCPD, NH	$R^2 = 0.9459$
(M. Ataei and Sereshki, 2017)	GA	D, MCPD	$R^2 = 0.92$
(Armaghani et al. 2018)	ICA	MCPD, D	$R^2 = 0.9458$
(Zhang et al. 2020)	PSO-XGBoost	PF, B, S, D, MCPD	$R^2 = 0.968$
(Nguyen et al. 2020)	HKM-ANN	PF, B, S, D, MCPD	$R^2 = 0.983$
(Bayat et al. 2020)	ANN	B, S, D, CPD	$R^2 = 0.977$
(Chen et al. 2021)	MFA-SVR	MCPD, BS, E, V_p, ST, D	$R^2 = 0.984$

where E is the Young's modulus; B is the burden; S is the spacing; MCPD is the maximum charge per delay; TCPR is the total charge per round; L is the hole length; NH is the number of holes; SC is the specific charge; D_t is the total delay time; N_d is the number of delay interval; ST is the stemming; D is the distance form the blast site; PF is the powder factor; BS is the burden to spacing ratio; ϕ is the direction of firing; CPD is the charge per delay; V_p is the p-wave velocity; SVM is the support vector machine; GRNN is the general regression neural network; FIS is the fuzzy inference system; ANFIS is the adaptive neuro-fuzzy inference system; ICA is the imperialist competitive algorithm; PSO is the particle swarm optimization; XGBoost is the extreme gradient boosting; HKM is the K-means clustering algorithm; ANN is the artificial neural network; MFA is the modified firefly algorithm; and SVR is the support vector regression.

2. Objective of study

- Determine the values of site constants in the USBM equation in order to predict PPV, and accordingly, find the maximum charge per delay using the statistical regression analysis.
- Use the machine learning algorithm of 'random forest' and 'support vector regression' in order to predict the peak particle velocity.
- Make a comparative study statistical approach, random forest, and support vector regression in order to predict the peak particle velocity.

3. Machine learning techniques-a brief overview

Ensemble learning: An ensemble method is a technique that combines the predictions from several machine learning algorithms in order to make more accurate predictions than any individual model developed by a user. A model comprised of a number of models is called an ensemble learning method.

Decision tree in machine learning: A decision tree can be used to describe the decisions and decision-making in a decision tree analysis. It employs an inverted tree-like model of decision-making based on the statistical filters, as the name implies. Though it is most commonly used in data mining to develop a strategy to achieve a specific target, it is also widely used in machine learning, which will be the subject of this article.

The resulting tree is inverted, with the root at the top. The text in bold in black in the image below (Figure 1) represents a condition/internal node based on which the tree is divided into branches. The decision/leaf is the end of the branch that can no longer be split; in our example, whether the plane passenger died or survived is expressed as red and green text, respectively.

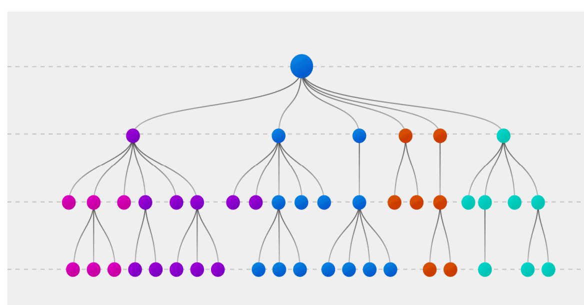

Figure 1. Decision tree (source: Internet).

Problems with decision trees: The dataset on which the decision trees are trained is significant. If the training data is updated, the decision tree results will be somewhat different, which will have an equivalent impact on the prediction.

Also since the algorithm cannot be moved back after the split is made, the decision trees are challenging to train, and have a high chance of overfitting the dataset. They also appear to find the local optima.

We use the random forest algorithm to fix these flaws in a decision tree model, which demonstrates the power of integrating several decision trees into a single model for a more accurate prediction.

3.1. Random forest

Random forest is a supervised machine learning algorithm that performs classification, and uses an ensemble learning model of predictions [26]. Random woods have trees that run parallel to each other. As a result, when constructing a model, there is no interaction between these trees. It works by training a large number of decision trees, and then calculating the class that is the mode of the classes (classification) or the mean prediction (regression) of the individual trees, as shown in Figure 2.

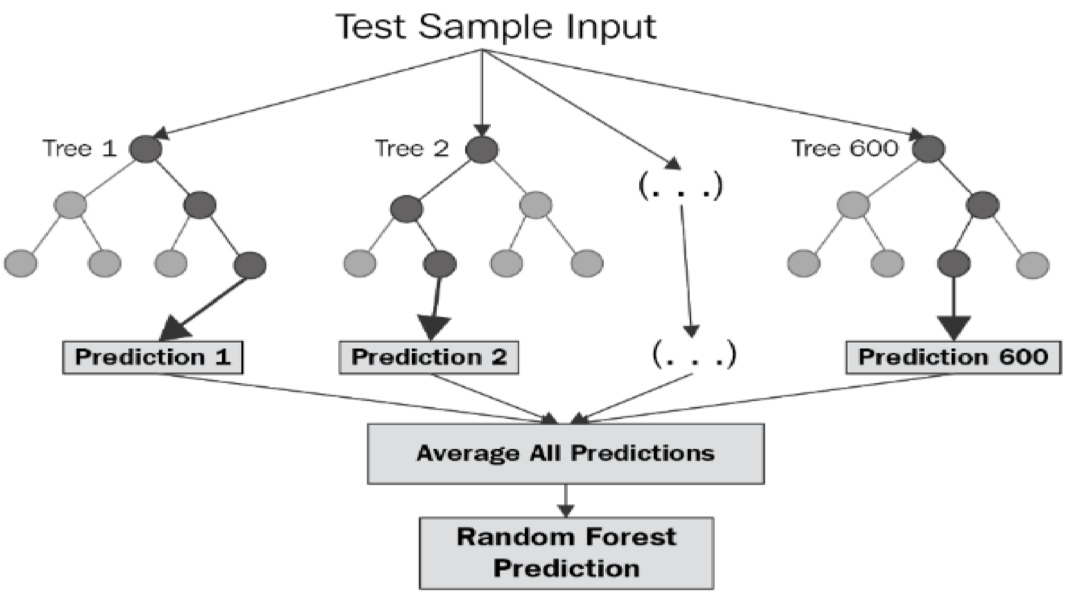

Figure 2. Ensemble learning model of prediction (source: Internet).

A random forest combines the result of multiple predictions, which aggregates many decision trees, with some helpful modifications:

- The number of features that can be split at each node is limited to some percentage of the total (that is known as the hyperparameter). This ensures that the ensemble model does not rely too heavily on any single individual feature given to the model, and makes use of all the potentially predictive features.
- When generating its splits, each tree draws a random sample from the original data set, adding a further element of randomness that prevents overfitting.

3.2. Support vector regression

Support Vector Regression (SVR) is a supervised machine learning technique that utilizes the idea of support vectors in a model [27]. SVR seeks to reduce the prediction error by determining the hyperplane and minimizing the range between the expected and the observed values, referred to as 'tolerance.'

Unlike ordinary least square, which aims to minimize error and find the best fit, the SVR's goal is to reduce the coefficients—specifically, the l2-norm of the coefficient vector. Instead, the model's error is treated in the constraints function, where we set the absolute error to be less than or equal to a given value/margin, referred to as the maximum error (epsilon). In order to achieve the desired accuracy of our model, we can adjust the margins or epsilon.

4. Research methodology and field study

4.1. Mine details and data collection

The mine is being worked by the mechanized drilling and blasting method with 6.0 to 9.0 m high benches and a bench angle close to 80^0 to 85^0.

Drilling: Crawler mounted DTH drills of 110 mm are being used to drill blast holes. The general dip of the formations is steep, dipping away from the face. Therefore, the holes are made close to vertical.

Blasting was carried out using explosives, namely, Raj blast Super Emulsion Explosive (Make: Raj. Explosive and Chemical Ltd.) and NONEL (Orica make).

A total of 73 blasting data was recorded using engineering seismographs, which provided us with peak particle velocity, frequency of the seismic waves, and air overpressure.

A database was prepared with burden, spacing, hole depth, maximum charge per delay, distance from the blast, total charge per hole, and delays of 17 ms between the holes in a row and 42 ms between the holes the rows with NONEL initiation system.

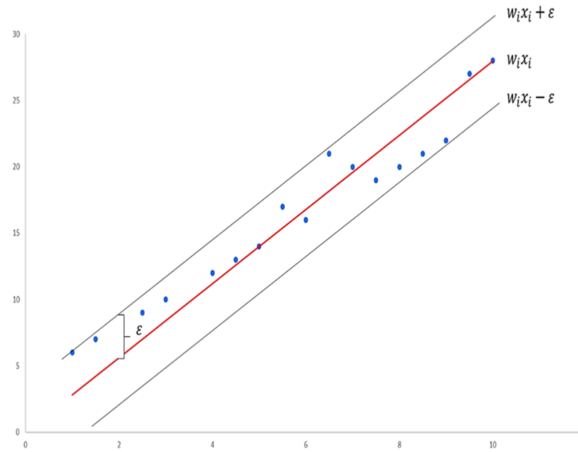

Figure 3. Solution of linear SVR (source: Intel, 2012).

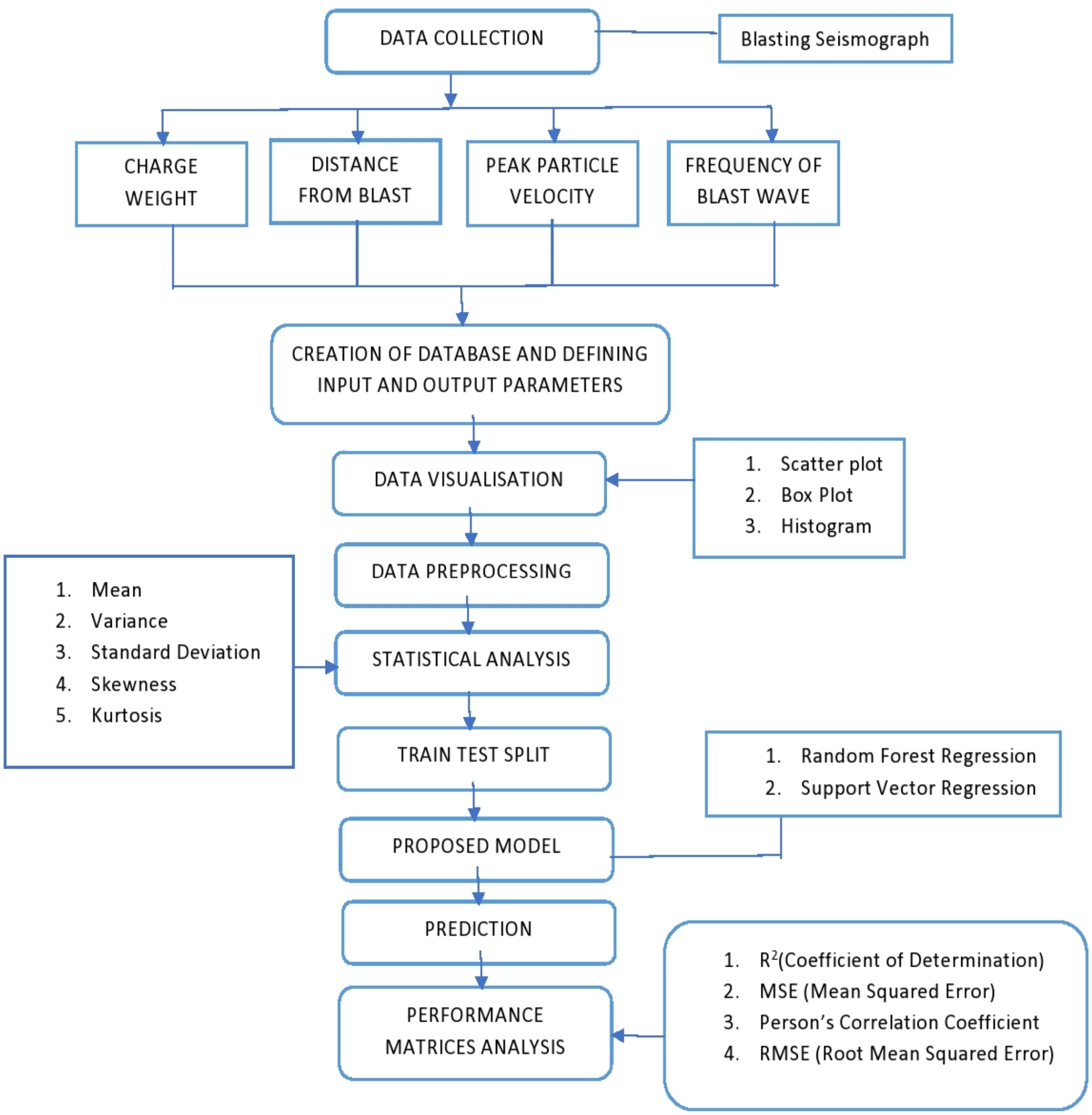

Figure 4. A flow chart of the study.

Table 3. Statistical information of data collected.

Sl. No.	Variables	Minimum	Maximum
1.	Burden (m)	3.5	3.5
2.	Spacing (m)	4.0	4.5
3.	Hole depth (m)	7.0	8.5
4.	Charge per hole (kg)	26.0	48.3
5.	Charge per round (kg)	215	645
6.	Stemming length (m)	2.50	3.25
7.	Number of blast hole per round	9	20
8.	Powder Factor (Te/kg)	3.50	4.25
9.	Maximum charge per delay (kg)	28.4	200
10.	Distance (m)	50	450
11.	PPV (mm/s)	2	59.90

5. Results and discussion

5.1. Relationship between scale distance and PPV

The ground vibration data for 73 blasts were recorded during blasting, and used to plot a curve between the scale distance and PPV, and shown in Figure 5.

- From the above plot, the equation relating the peak particle velocity and the square root scaled distance using regression was obtained and given as:

$$V = K(SD)^n \tag{2}$$

where K = 370.09 and n = -1.149

- In order to design a safe blast, we are required to increase the value of site constant 'k' so that it covers every value lying above the previously obtained equation and gets a new equation at a 95% confidence level.

$$V = K(SD_{95})^n \tag{3}$$

where K = 723 and n = -1.149

5.2. Random forest regression results

73 blast data was collected during the study. 58 data was used to prepare the model, and 15 data was used to predict PPV. Table 4 shows the result obtained from applying the random forest regression algorithm to the blasting data.

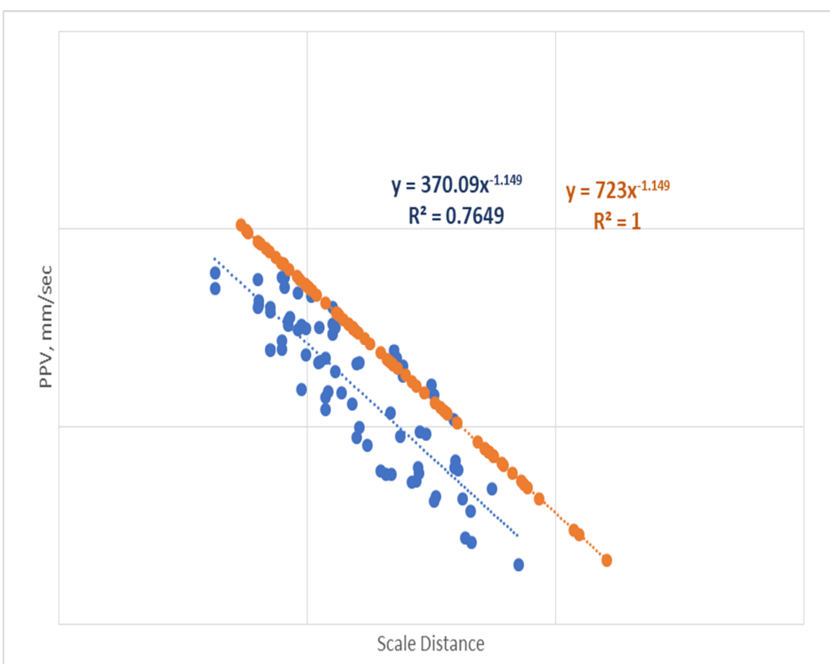

Figure 5. Relation between scale distance and PPV

Table 4. Predicted PPV using random forest regression.

S. No.	Distance (m)	MCD (kg)	Scaled distance (m/kg^1/2)	Actual PPV (mm/s)	Predicted PPV (mm/s)
1	150	57.6	19.764	5.970	6.630
2	350	80	39.131	6.220	5.920
3	125	51.1	17.486	8.000	9.780
4	125	106	12.141	15.000	15.400
5	60	28.4	11.259	21.160	23.320
6	75	90	7.906	56.800	28.350
7	75	40	11.859	22.000	19.550
8	175	28.4	32.838	4.450	5.180
9	250	40	39.528	6.670	7.450
10	250	38	40.555	6.000	5.750
11	150	120	13.693	14.700	12.390
12	100	200	7.071	40.300	38.540
13	120	90	12.649	40.300	36.870
14	165	33.7	28.423	9.400	7.890
15	110	52.8	15.138	13.000	13.990

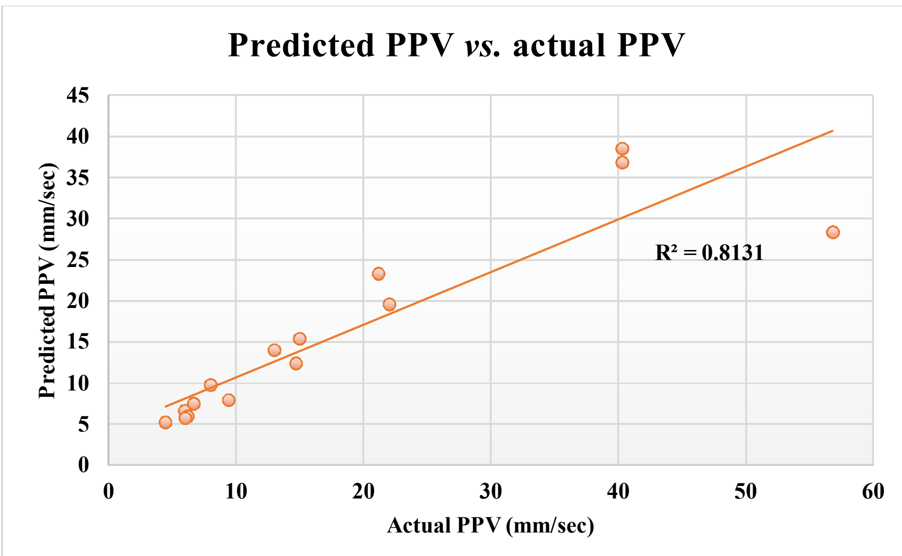

Figure 6. Predicted PPV *vs.* actual PPV using RF.

- The R^2 value for the predicted PPV and actual PPV is 0.81.
- The results obtained from the algorithm are highly correlated with a correlation coefficient of 0.901.

5.3. Support vector regression results

73 blast data was collected during the study. 58 data was used to prepare the model, and 15 data was used to predict PPV. Table 5 shows the results obtained by applying the support vector regression algorithm to the blasting data.

Table 5. Predicted PPV using support vector regression.

Sl. No.	Distance (m)	MCD (kg)	Scaled distance (m/kg^0.5)	Actual PPV (mm/s)	Predicted PPV (mm/s)
1	150	57.6	19.764	5.99	11.70
2	350	80	39.131	6.23	5.16
3	125	51.1	17.486	8.00	13.46
4	125	106	12.141	15.03	20.49
5	60	28.4	11.259	21.12	22.65
6	75	90	7.906	56.83	34.12
7	75	40	11.859	21.98	21.33
8	175	28.4	32.838	4.44	6.36
9	250	40	39.528	6.69	5.10
10	250	38	40.555	5.99	4.95
11	150	120	13.693	14.73	17.81
12	100	200	7.071	40.45	38.86
13	120	90	12.649	40.45	19.69
14	165	33.7	28.423	9.39	7.54
15	110	52.8	15.138	12.94	14.88

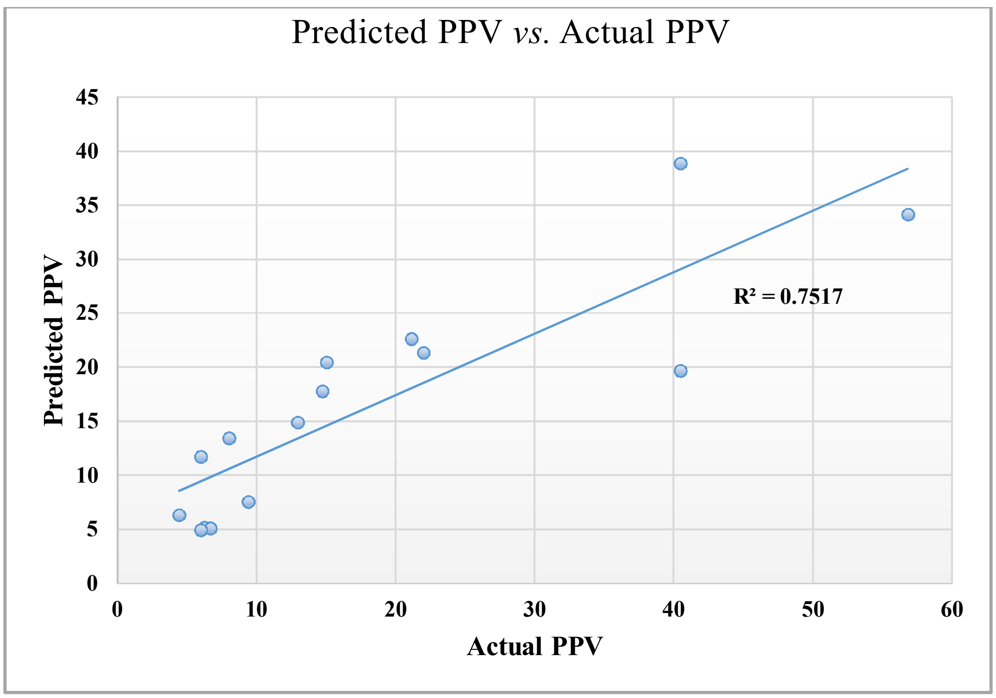

Figure 7. Predicted PPV *vs.* actual PPV using support vector regression.

- The R^2 value for the predicted PPV and actual PPV is 0.75.
- The results obtained from the algorithm are highly correlated with a correlation coefficient of 0.86.

6. Conclusions

From the results of this work, the following conclusions can be drawn:

- The statistical approach for predicting the peak particle velocity provides sufficient information to design a blast considering maximum charge per delay, reducing the ground vibration. However, in this method, it is not easy to include all the input parameters, and therefore, the accuracy in the prediction of PPV is very less.
- When the ML tools like random forest **regression model** and support vector machine regression were used, it was found that the

random forest regression model had a better prediction capability than the support vector machine regression.

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چکیده:

ارزیابی ارتعاش زمین ناشی از انفجار (PPV) برای یک انفجار ایمن، یک معیار قدیمی است که عمدتا توسط معادلات تجربی مورد استفاده قرار می‌گیرد. با این حال، معادلات تجربی اطلاعات محدودی را در نظر می‌گیرند. بنابراین، استفاده از ابزارهای یادگیری ماشین (ML) (بردار پشتیبان ماشین (SVM) و جنگل تصادفی (RF)) می‌تواند در این زمینه کمک کند، و همین امر در این کار اعمال شده است. در مجموع ۷۳ انفجار در این کار نظارت و ثبت شده است. برای ابزارهای ML، مجموعه داده‌ها به منظور ارزیابی ظرفیت عملکرد مدلها به نسبت ۲۰-۸۰ برای اهداف آموزش و آزمایش تقسیم شده است. دقت پیش بینی مدل های SVM و RF در پیش‌بینی مقادیر PPV رضایت بخش است (بیش از ۹ درصد دقت). نتایج بدست آمده نشان می‌دهد که ضریب تعیین (R2) برای RF و SVM به ترتیب ۰/۸۱ و ۰/۷۵ است. در مقایسه با سایر رگرسیون‌های خطی موجود، این پژوهش استفاده از مدل رگرسیون ML را برای پیش بینی PPV توصیه می‌کند.

کلمات کلیدی: معادله تجربی، ارتعاش زمین، حد نهایت سرعت ذرات، رگرسیون جنگل تصادفی، رگرسیون بردار پشتیبان.
