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A Re-Look Into Modified Scaled Distance Regression for Prediction of Blast-Induced Ground Vibration

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ABSTRACT

Underground blasts are conducted for deep excavations, tunneling, or mining activities. Scaled distance regression analysis is performed in industry to estimate peak particle velocity from charge weight and distance. For addressing the uncertainties in estimating safe charge weight for controlled blasting, 95% confidence expression is generally used. For addressing inaccuracies arising from superimposition of blast waves in multi-hole blasting when using attenuation equation developed from single-hole blast data, a modified approach was proposed in literature. This article presents comparisons to establish that industrial practice of scaled distance regression would be as satisfactory as the proposed modified approach, when various performance measures (including parsimony) are considered together. Furthermore, industrial practice of using 95% confidence expression generated from sufficient data (say, 40 numbers) would result in safe charge weight estimation, whereas modified scaled distance approach (mean expression) could still result in few non-conservative values.

KEYWORDS

Blast-Induced Ground Vibration, Controlled Blasting, Ground Vibration Attenuation Peak Particle Velocity, Safe Charge, Scaled-Distance Regression Analysis

INTRODUCTION

Background

Blasting becomes essential for various purposes such as excavations in rock, quarrying, tunnelling and mining. It is more efficient than mechanical excavation when larger volumes are involved, particularly for timely completion of the excavation activities. The safety of the surrounding rock strata or adjacent structures, as the case may be, during the process of blasting, need to be ensured by limiting the blast induced ground vibrations within the regulatory stipulations. For this purpose, empirical vibration attenuation relationship for underground blasts are developed from trial blast data and subsequently used for design of controlled blasting operation. This process involves multiple uncertainties including those arising the data collection, data analysis, variability of rock properties and blasting operation.

The damage potential of ground vibrations is generally quantified in terms of peak particle velocity (PPV) alone (Duvall & Fogelson, 1962) or PPV along with its associated frequency (Siskind et al., 1980; Khandelwal & Singh, 2006; Ozer, 2008). National codes stipulate the limiting PPV for different types of structures (BIS, 1973; BIS, 2001), along with suggested vibration attenuation relationship for underground blasts. However, these relationships are generalized for varieties of rock

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strata, and often result in over-conservative and uneconomical blasting design. Hence, development of site specific relationships from trial blast data is generally preferred to overcome this issue and efficient design of controlled blasting. Over the years, many researchers attempted application and / or improvements of the traditional method of development of empirical expression for blast induced ground vibration (Arora & Dey, 2010; Tripathy & Shirke, 2015; Tripathy et al., 2016; Monjezi et al., 2016; Ray et al., 2018; Dauji, 2018; Ray & Dauji, 2019; Matidza et al., 2020; Rana et al., 2020).

Development of empirical relationship from limited observed data invariably involves associated uncertainties. Uncertainty can be aleatory or due to natural randomness of the physical process, or it may be epistemic, which arises from the inaccuracy of data and models involved in the analysis (Coleman, 2009; Modarres et al., 2010). The aleatory uncertainty is always present and can be only estimated from observations. To a certain extent, more data would help to estimate the aleatory uncertainty better. The epistemic uncertainty can be reduced by better knowledge (more data, better model) about the process (Lombardi, 2017). The industrial approach to handle the uncertainty of the empirical expression of blast vibration attenuation is to adopt a relationship corresponding to the desired level of confidence (generally taken as 95%) and employ the equation thus derived for design of controlled blasting operation (Tripathy and Shirke, 2015; Tripathy et al., 2016). A recent study (Murmu et al., 2018) reported application of Monte Carlo simulation for probabilistic study of blast induced ground vibration using empirical relationship. A method for addressing the uncertainty of the empirical attenuation relationship was presented by Dauji (2019) adopting re-sampling approach.

Numerical analysis has been employed by many investigators to model the attenuation of ground vibration induced by blasting (Hao & Wu, 2005a, 2005b; Ma & An, 2008; Yilmaz & Unlu, 2013; Liu et al., 2017). However, numerical approach demanding large resources (data, computation), expertise and involving multiple parameterizations, it becomes difficult to adopt this for industrial application. Data driven tools have also found application in addressing this non-linear problem (Khandelwal & Singh, 2006; Khandelwal & Singh, 2009; Longjun et al., 2011; Faradonbeh et al., 2016; Kalayki & Ozer, 2016; Khandelwal & Mastorakis, 2016; Mottahedi et al., 2018; Ragam & Nimaje, 2018; Murmu et al., 2018, Nguyen et al., 2019; Dauji, 2020; Rana et al., 2020; Yu et al., 2020).

The phenomenon of superimposition of blast waves in case of multi-hole blasting would not be captured in data generated from single-hole trial blasts, and this would add to the aforementioned uncertainties. In an article by Agrawal & Mishra (2019), an approach was proposed to address this particular aspect of design of multi-hole controlled blasting from results of single-hole trial blasting. The traditional expression obtained from single-hole trial blast data was 'modified' using multi-hole blast data for subsequent use.

Whatever may be the tool (empirical, numerical, or soft-computing) used for development of the vibration attenuation relationship, evaluation of performance of the models is a critical step to identify the better approach or model for future applications. As indicated in literature (Dauji, 2018), development of empirical blast relationship and evaluation of the same need to be performed with different subsets of the data. This approach is not followed in the comparison of performances in certain cases, for example, in the study by Tripathy et al. (2016) and by Agrawal & Mishra (2019) in one case. Furthermore, using different performance indices for evaluation of the developed empirical expressions would help to appreciate the goodness-of-fit from various considerations. Coefficient of determination or correlation coefficient indicates the linear association of the observed and estimated values only. The range of errors does not indicate the association (if any) of the absolute value of the variable and the error in its estimation, which can be appreciated very easily in a scatter plot (plot of observed variable versus estimated variable). Comparison of the traditional scaled distance approach and modified scaled distance approach resulted in equations with different number of empirical constants. When comparison of performance of relationships with different number of empirical constants is performed, the metrics such as AIC and BIC become useful as they indicate the overall accuracy of the estimate considering parsimony of the expression as well (Dauji, 2018). In the evaluation empirical blast models in literature, some studies adopted similar approach (Ray &

Dauji, 2019) while in others, (Agarwal & Mishra, 2019), the parsimony factor was not considered thereby being a limitation.

The various performance measures reported in literature include correlation coefficient / coefficient of determination (Nguyen et al., 2018; Dauji, 2018; Huang et al., 2019; Jayasinghe et al., 2019; Ray & Dauji, 2019; Rajabi & Vafaee, 2019; Agarwal & Mishra, 2019; Yu et al., 2020; Matidza et al., 2020; Rana et al., 2020; Dauji, 2020), root mean square error (Iramina et al., 2018; Nguyen et al., 2018; Yu et al., 2020; Matidza et al., 2020; Rana et al., 2020; Dauji, 2020), mean absolute error (Yu et al., 2020; Matidza et al., 2020; Dauji, 2020), mean absolute percentage error (Matidza et al., 2020), median absolute error (Matidza et al., 2020), error (Agarwal and Mishra, 2019), mean square error (Dauji, 2018; Ray & Dauji, 2019), overestimation (Dauji, 2020), underestimation (Dauji, 2020), mean absolute relative error (Dauji, 2020), and AIC (Dauji, 2018; Ray & Dauji, 2019). It can be observed that some of the studies relied on one or two performance measures (mostly correlation coefficient or the error) for evaluation of the developed models, and only a few employed multiple performance measures for comprehensive evaluation.

Furthermore, examination of the underestimation of the site specific attenuation would assume significance, as safety is of paramount importance in operations such as blasting. The national codes stipulate the limiting PPV values to be followed depending upon the adjacent structures (BIS, 1973; BIS, 2001) and these have been discussed in literature as well (Ray and Dauji, 2019). Underestimation of the PPV by the developed empirical expressions could thus result in unsafe design of controlled blasting operation. However, this issue has been rarely addressed in a specific manner in literature. As reported in literature (Tripathy & Shirke, 2015; Tripathy et al., 2016), the design of controlled blasting is generally carried out using the 95 percent confidence equation in industry. When critical structures / facilities are involved, more stringent (greater than 95 percent) equations might be used. But this traditional methodology generally adopted to account for the various uncertainties involved in the empirical vibration relationships of underground blasts was not considered in the article (Agrawal & Mishra, 2019). The main concern for the field blasting engineer would be underestimation of the PPV of actual blast and thereby probability of damage to the surrounding media / structures, as the case may be. It is therefore imperative to evaluate the underestimation aspect of the developed relationships. That this is an important consideration was indicated in the result presented by Agarwal and Mishra (2019) wherein they observed that the empirical equation developed from single-hole data yielded lower values of PPV for the production (multi-hole) blasting data. However, this important aspect of design of controlled blast was not addressed (Agrawal & Mishra, 2019) and only the best estimate (mean) expressions were discussed. It can thus be concluded that the comparison presented (Agrawal & Mishra, 2019) could be further improved upon for the purposes of evaluation of the performance of the proposed 'modified scaled distance' approach and its suitability of application for a practical scenario.

The underestimation aspect had been addressed in some blasting studies (Dauji 2020), whereas it had been missed by many studies till recent times (Khandelwal & Singh, 2009; Longjun et al., 2011; Singh et al., 2015; Tripathy et al. 2016; Kalayki & Ozer, 2016; Iramina et al., 2018; Ray & Dauji, 2019; Jayasinghe et al., 2019; Rajabi & Vafaee, 2019; Matidza et al., 2020; Rana et al., 2020; Yu et al., 2020). In this article, this aspect will be highlighted using the data from literature (Agarwal & Mishra, 2019). However, this might be equally pertinent for all other studies and should definitely be considered for design of controlled blasting operation.

In this article, therefore, the relative merits and limitations of the traditional industrial approach and the 'modified scaled distance' approach (Agrawal & Mishra, 2019) for design of safe controlled blasting operation are critically examined with special attention to the underestimation aspect. The 95 percent confidence expressions are presented and the underestimation aspect would be examined for the same and compared to that of the 'modified scaled distance regression analysis' approach (Agrawal & Mishra, 2019). While the research community may benefit by the 'modified scaled distance' approach (Agrawal & Mishra, 2019) in certain aspects, at the same time they should be sensitized of its limitations from certain other considerations. At this backdrop, the objective of this article is identified as the thorough performance evaluation strategy for empirical blast vibration relationship, which would be very useful for practising blasting engineers. For the purpose, the data and analysis from literature (Agrawal & Mishra, 2019) would be utilized and fresh insight would be offered on the traditional and the 'modified scaled distance' approach as well.

Research Significance

This article tries to highlight the following issues with a case study:

1. In literature, many researchers have endeavoured to improve performance of the regressions relationships, for estimation of vibration attenuation relationship in underground blasting. Performance evaluation, when conducted with the same data as used for the development of regression equation, often provides misleading conclusions. Despite being highlighted earlier in literature (Dauji, 2018), this aspect still appears to be generally neglected.
2. It has been indicated that for evaluation of performance of regression models, multiple metrics which examine various aspects of model performance should be employed in conjunction (Dawson & Wilby, 2001) and this had been highlighted for blasting studies as well (Dauji, 2018; Ray & Dauji, 2019). However, research community appears not fully sensitised regarding this aspect.
3. In safe design of controlled blasting, a very important aspect would be addressing uncertainties of the attenuation relationship and thereby reducing underestimation of PPV. Traditional approaches (Tripathy & Shirke, 2015; Tripathy et al., 2016) or re-sampling method (Dauji, 2019) can be used to address uncertainties. Examination of the underestimation aspect has not been performed specifically in most of the recent literature on safe controlled blast design.

DATA AND METHODOLOGY

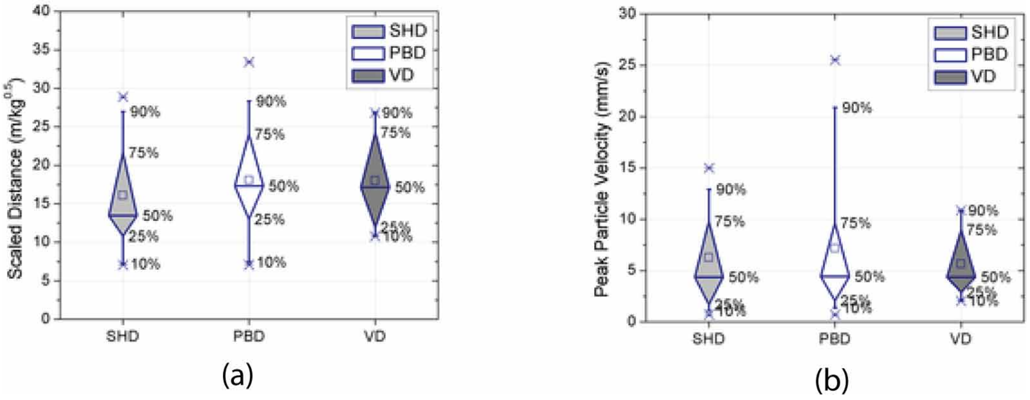
Data

In this article, the data listed by Agrawal & Mishra (2019) is used with the following nomenclatures for easy reference. For all other details regarding the experiments, blasting, measurements, site, etc., readers are referred to the article (Agrawal & Mishra, 2019). For brevity, the datasets are only referred and are not reproduced here. For distinguishing the tables, figures, or equations from Agarwal & Mishra (2019) and those developed in this analysis, in the remaining part of the article, a subscript: '$_{AM}$' would indicate that they are reproduced from Agarwal & Mishra (2019), and those generated in this analysis would be without any subscript. The following abbreviations are used in subsequent discussion:

SHD: single hole data – 14 datasets (Table 1 $_{AM}$)
PBD: production blasting data – 39 datasets (Table 2 $_{AM}$)
VD: validation data – 9 datasets (Table 4 $_{AM}$)

For visual appreciation of the variables used to develop the blast-induced ground vibration relationship, the box and whisker plots for the scaled distance and the PPV are depicted in Figure 1a and Figure 1b respectively. It may be mentioned that evaluation of expression developed with SHD and tested with PBD would involve higher errors as the ranges and statistical properties are different for the PPV in the two datasets. Similar evaluation with VD would incur less error, as the range of VD is within SHD. When the expression developed with PDB would be evaluated with SHD or VD, the errors involved would be comparatively less than the earlier cases, as the range of PBD covers both SHD and VD. Particularly for PPV, the total range and the 10% to 90% range observed in PBD are much larger than either SHD or VD. For scaled distance, the difference is there but of less magnitude.

Figure 1. Box and Whisker plots (a) Scaled Distance (b) Peak Particle Velocity



Methodology

The following discussion will be with reference to the article by Agrawal & Mishra (2019), unless otherwise stated. The authors adopted the traditional form of equation for scaled distance (Eq. (1)) and attenuation relationship (Eq. (2)) to develop Eq. (3) from single-hole blasting data (Table 1 $_{\mathrm{AM}}$), and thereafter refined it by using production blasting data (Table 2 $_{\mathrm{AM}}$) to finally arrive at Eq. (4). Thus, Eq. (4) was developed using 53 datasets and it involved evaluation of three empirical parameters in the model. The authors also developed Eq. (5) adopting the standard industrial practice using the production blasting data (Table 2 $_{\mathrm{AM}}$) and compared its performance with the Eq. (4). However, the fact that Eq. (5) was developed with less number of data (39 datasets) as compared to Eq. (4) (53 datasets) and further that Eq. (5) had less number of empirical parameters (2 nos.) as compared to the Eq. (4) (3 nos.) has not been considered in the comparison of performance of Eq. (4) and Eq. (5) using production blasting data (Table 3 $_{\mathrm{AM}}$ and Figure 7 $_{\mathrm{AM}}$). This issue can be addressed by use of performance measures such as Akaike Information Criteria and Bayesian Information Criteria (Dawson &Wilby, 2001) which considers parsimony factor, along with goodness of fit.

The performance evaluation should not generally be performed with the same data, which was used in model development (Dauji, 2018). Hence, the authors validated the developed Eq. (4) with fresh data from multi-hole blasting – presented in Table 4$_{\mathrm{AM}}$ and this definitely is a better approach of performance evaluation of Eq. (4), than compared to Table 3 $_{\mathrm{AM}}$ or Figure 7 $_{\mathrm{AM}}$. However, the performance of Eq. (5) with this fresh data was not presented, and this might uncover new information.

The expressions from the referred article (Agrawal & Mishra, 2019) used in this study are reproduced below.

For scaled distance (*SD*) (Eq. (1) $_{\mathrm{AM}}$):

$$SD = D \,/ \sqrt{W_d} \tag{1}$$

where, *D* is the distance between the blast and the observation point (m); W_d is the charge weight per delay (kg).

For traditional expression for peak particle velocity (PPV) of vibration attenuation relationship of underground blast (Eq. (2) $_{\mathrm{AM}}$):

$$PPV = K\left(SD\right)^{n} \tag{2}$$

where, K & n are empirical constants evaluated from the trial blast data.

Traditional expression of PPV from SHD (Eq. (3) $_{\mathrm{AM}}$):

$$PPV = 682.4\left(SD\right)^{-1.896} \tag{3}$$

Expression for PPV from 'Modified scaled distance regression analysis approach' (Eq. (5 $_{\mathrm{AM}}$):

$$PPV = 954.46\left(SD\right)^{-1.896} + 0.5173 \tag{4}$$

Traditional expression of PPV from PBD (Eq. (7) $_{\mathrm{AM}}$):

$$PPV = 1018\left(SD\right)^{-1.909} \tag{5}$$

Performance Measures

The performance of developed empirical models needs to be evaluated before practical application. As highlighted in literature (Dauji, 2018), the evaluation of the model should happen with a fresh dataset, which had not been used in development of the model, and this was adopted by Agarwal and Mishra (2019) (Table 2 $_{\mathrm{AM}}$, Table 4 $_{\mathrm{AM}}$). The evaluation should include quantitative tools as well as qualitative tools, which would examine the developed model from various aspects. The examination should be performed for the errors over the entire range of values of the dependent variable, the extremes of errors, and the errors at the extremes, as well as for the parsimony of the model (number of parameters in the model, number of data used for developing the model). The various available quantitative measures include coefficient of determination / coefficient of correlation, root mean square error, mean absolute error, root mean square relative error, mean absolute relative error, maximum overestimation, maximum underestimation, mean overestimation, mean underestimation, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC), among others. The application of the various performance measures reported in literature for blasting studies, was discussed in the section: Introduction of this article.

The performance metrics for evaluation of models with different number of parameters should penalise models using more parameters, while considering the better model fit and this is performed by parsimony measures such as AIC and BIC. The qualitative tools would include scatter plot, variable plot, error plot, relative error plot, etc. and these help in visual appreciation of the goodness-of-fit of the developed model. In addition to evaluation of the overall fit, selection of the performance measures should also include performance metrics according to the application of the developed expressions. For example in case of Modified Scaled Distance Approach being compared to traditional Scaled Distance Approach, as the models have different number of parameters, the parsimony measures (AIC / BIC) must be included to check the models from the parsimony aspect. In case of the blast vibration attenuation relationship developed for design of controlled blasting operation, the underestimation of PPV assumes importance, whereas if this was estimation of some strength parameter such as compressive strength of rock, then the overestimation would have to be critically examined. Thus the choice of performance measures should be performed judiciously according to the target application of the empirical model.

In order to have a comprehensive evaluation of the developed models from different aspects, in this analysis, multiple performance measures are used in conjunction, as listed below:

1. R: correlation coefficient (self-explanatory);
2. MAE: mean absolute error (self-explanatory);
3. RMSE: root mean square error (self-explanatory);
4. AIC: Akaike Information Criteria (see Eq. (6)) (Dawson & Wilby, 2001);
5. BIC: Bayesian Information Criteria (see Eq. (7)) (Dawson & Wilby, 2001).

The following formulations for AIC and BIC were suggested by Dawson & Wilby (2001) for such cases:

$$AIC = m * \ln\left(RMSE\right) + 2 * p \tag{6}$$

$$BIC = m * \ln\left(RMSE\right) + p * \ln\left(m\right) \tag{7}$$

m: number of data points
p: number of free parameters

As can be discerned from the Eq. (6) and Eq. (7), both AIC and BIC would yield higher values for models with higher number of parameters, and / or models developed with higher number of data – even when the two models yield the same RMSE. Even if two models have same RMSE, models built with less number of parameters and / or less number of data should be selected and selection based on lower value of AIC / BIC would facilitate just that. Hence, model with lower AIC / BIC would be better in terms of parsimony and overall error. Readers may appreciate the significance of AIC and BIC in performance evaluation in this case, where comparison is discussed for Modified Scaled Distance Approach (three parameters, 53 data) with the traditional Scaled Distance Approach (two parameters, 14 data or 39 data). In this article, complete performance evaluation of Eq. (4) and Eq. (5) are presented with various error measures, including parsimony aspect. Variable and scatter plots are included to present graphical interpretations and qualitative evaluations.

Evaluation of Underestimation

The traditional approach of accounting for the various uncertainties of the empirical relationship (Eq. (2)) is to use the 95 percent expression for design of controlled blasting operations (Tripathy & Shirke, 2015; Tripathy et al., 2016; Ray & Dauji, 2019). This is performed by plotting the scaled distance (*SD*) and the PPV on a log-log scale and shifting the best fit straight line (to the data points) in parallel manner to capture 95% points below it. In other words, the slope (in log scale) is kept same and the intercept is modified to arrive at the 95 percent expression. Essentially, this amounts to modification of the parameter '*K*' of Eq. (2) while keeping '*n*' unchanged, to capture 95% points on the lower side of the straight line fit. This indicates that in practical application, the probability of the actual PPV being less than the PPV estimated from the empirical expression would be 95%. Following this procedure, the 95 percent confidence expressions are obtained from the traditional expressions: Eq. (3) and Eq. (5), as Eq. (8) and Eq. (9), for SHD and PBD respectively.

The 93 percent confidence expression (traditional) developed from SHD (using Eq. (3)) has the following expression:

$$PPV = 1341\left(SD\right)^{-1.896} \tag{8}$$

As the number of available data was 14 only, 93 percent confidence expression was chosen, the next higher confidence being 100 percent.

The 95 percent confidence expression (traditional) developed from the PBD (using Eq. (5)) has the following expression:

$$PPV = 1785\left(SD\right)^{-1.909} \tag{9}$$

As mentioned earlier, the underestimation aspect is extremely important for the safe blast design by practising engineers. Subsequently, the underestimation aspect of the 95 percent expressions (Eq. (8) and Eq. (9)), and the Eq. (4) obtained by 'Modified scaled distance' approach (Agrawal & Mishra, 2019) is examined in detail to appreciate their relative merits.

RESULTS AND DISCUSSION

Performance Comparison of Eq. (4) and Eq. (5)

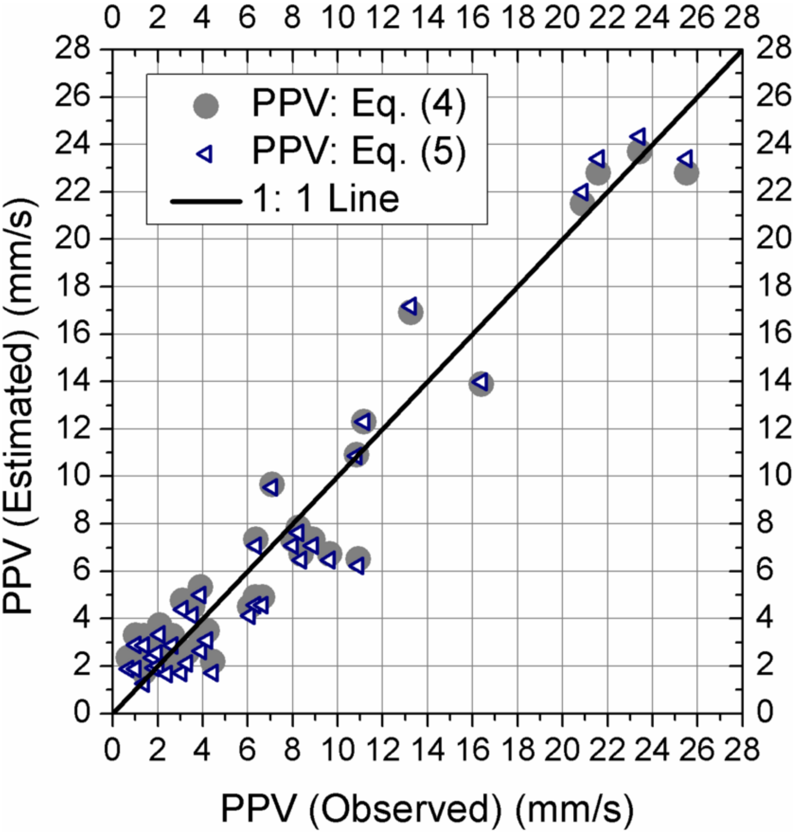
To start with, the scatter plot for the PBD is presented for the Eq. (4) and Eq. (5) in Figure 2, wherein it can be clearly observed that the accuracy of either of the expressions is quite comparable when evaluated with the PBD, over the entire range of PPV values. Subsequently, the percent error is presented in a slightly different format in Figure 3, than was depicted in Figure 7 $_{AM}$. Instead of the blast number as abscissa, which would change if the data is rearranged and would thus can often be misleading, the percent error is plotted against the absolute PPV values in Figure 3 here. It is instructive to note that the values of error are limited between -5% and +3% of the PPV for both the equations (Eq. (4): - 4.41% to + 2.58%; Eq. (5): - 4.69% to + 2.45%). In 17 out of 39 cases (44% cases), the percent errors arising from estimation using Eq. (4) are higher than those derived from Eq. (5). Thus, it can be easily discerned that the difference in the prediction accuracy of the two equations are nominal in most cases, and might even be incidental. It should be noted that this difference in error visible in the Figure 3 is in the percentage value and not the absolute value of error, which would in turn depend on the absolute value of PPV.

However, as indicated earlier, the performance evaluation of empirical equations should be performed with fresh data, i.e. data which was not used in development of the equation. Presently, the same is performed for the Eq. (4) and Eq. (5) with the VD and the results are presented in Table 1 and Figure 3. Out of the five error measures, Eq. (4) is better by one (RMSE) while the Eq. (5) is better by three (MAE, AIC, BIC). Considering the fact that the Eq. (4) was developed using higher number of data, it can be concluded that Eq. (5), which was developed by the traditional approach, is quite satisfactory. Similar inferences emerge from the variable and scatter plots of Figure 4. These aspects were missed by Agrawal & Mishra (2019) due to the fact that comprehensive performance evaluation was not performed.

Evaluation of Underestimation of 93 Percent Expression From SHD Eq. (8) vis-à-vis Eq. (4)

As indicated earlier, underestimation of PPV may result in non-conservative estimate of safe charge weight and might result in damage to the adjacent structures / strata. For safe design of controlled blasting therefore, the underestimation aspect is critically examined in this sub-section. Evaluation of the underestimation aspect is performed for the 93 percent expression developed from SHD (Eq. (8)) using fresh data (PBD and VD) and compared with the Eq. (4) in Table 2 and Table 3 respectively. It is reminded here, that the PBD had gone into development of Eq. (4) earlier and is totally fresh only for Eq. (8).

Figure 2. Scatter plot for PBD: Observed PPV and estimated PPV with Eq. (4) and Eq. (5)



The 93 percent confidence equation developed with 14 numbers of data (Eq. (8)) resulted in underestimation in 26% and 11% in respective test cases (PBD and VD), which are lower than the respective underestimations from Eq. (4): 44% and 22%. It is noteworthy in Table 2, that though the PBD (39 numbers) had been used in development of the Eq. (4), still use of the mean expression resulted in underestimation of PPV in many cases. As the higher percent (93) confidence expression was used for Eq. (8), the errors of estimation (MAE & RMSE) involved were higher in Eq. (8) compared to Eq. (4). However, more errors in PPV estimation were on higher side in case of Eq. (8) – which would be on the conservative side and would result in safer design of controlled blasting. It may be noted that the Eq. (8) was developed using only 14 data. Considering this fact, use of a higher percent confidence expression in place of the 93 percent expression might help to arrive at a safe design of controlled blasting. From the variable and scatter plots presented in the Figure 4, it is clear that the Eq. (4) definitely results in higher underestimation compared to Eq. (8), particularly for values of scaled distance less than 20 – 25 m/kg$^{0.5}$. As indicated earlier in the Section 'Data', the errors observed in Table 2 (evaluation with PBD) are higher than Table 3 (evaluation with VD).

Evaluation of Underestimation of 95 Percent Expression From PBD Eq. (9) vis-à-vis Eq. (4)

In this sub-section, the underestimation aspect is investigated for the 95 percent confidence equation (Eq. (9)) obtained in traditional approach from PBD. Evaluation of the underestimation aspect is performed for Eq. (9) using fresh data (SHD and VD) and compared with the Eq. (4) in Table 4 and

Figure 3. Percent error for PBD of PPV estimated with Eq. (4) and Eq. (5)

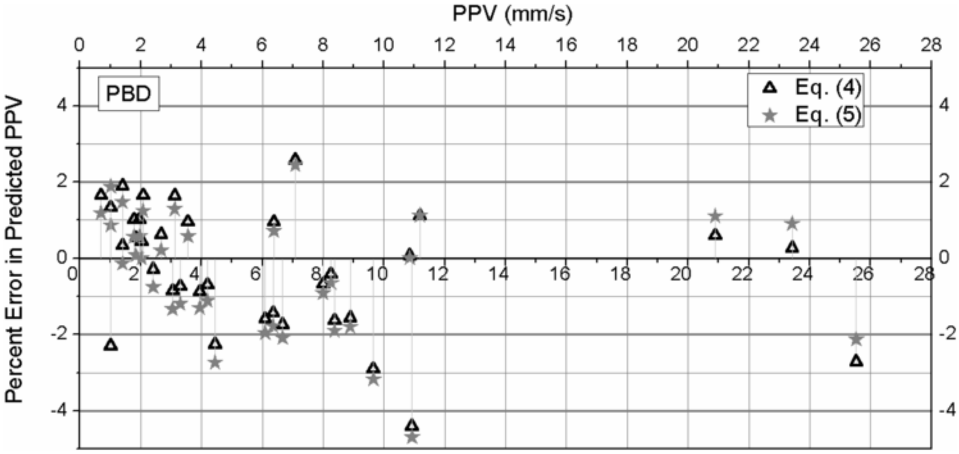
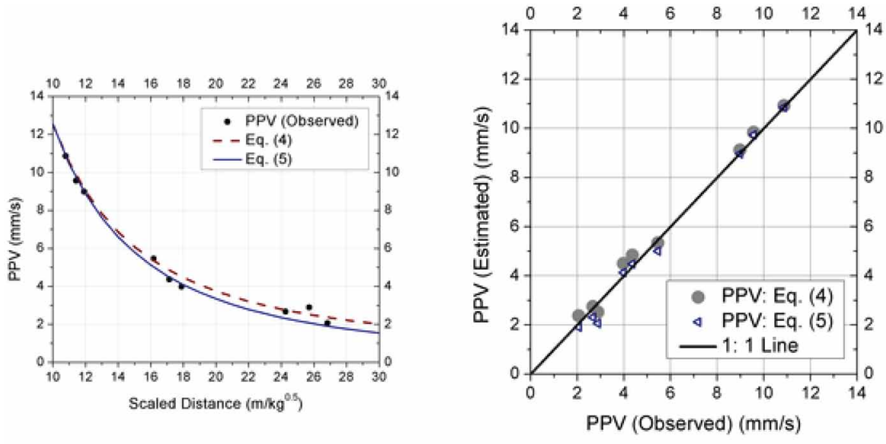


Table 1. Performance of Eq. (4) and Eq. (5) with Evaluation Data: VD (9 nos.)

Equation used	R	MAE (mm/s)	RMSE (mm/s)	AIC	BIC	Data Used for Development of Equation
Eq. (4)	0.996	0.261	0.307	-4.614	-4.022	SHD (14) and PBD (39)
Eq. (5)	0.996	0.250	0.349	-5.462	-5.068	PBD (39)

Figure 4. Performance evaluation for VD: PPV estimated with Eq. (4) and Eq. (5) (a) Variable plot (b) Scatter plot



(a)

(b)

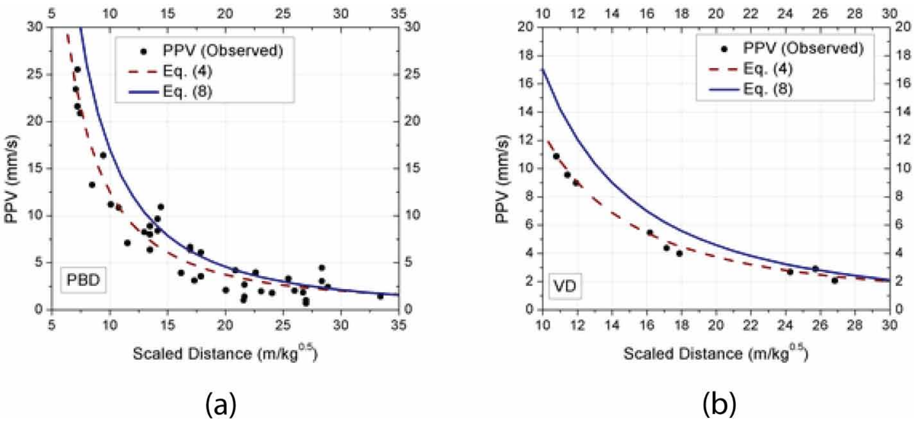
Table 2. Evaluation of Underestimation of PPV by Eq. (4) and Eq. (8) with Evaluation Data: PBD (39 nos.)

Equation used	R	MAE (mm/s)	RMSE (mm/s)	Number of Under Estimation (out of 39)	Maximum Percentage Under Estimation (PPV value –mm/s)	Data Used for Development of Equation
Eq. (4)	0.965	1.400	1.691	17 (44%)	50.88% (4.445)	SHD (14) and PBD (39)
Eq. (8)	0.965	2.666	3.855	10 (26%)	46.84% (4.445)	SHD (14)

Table 3. Evaluation of Underestimation of PPV by Eq. (4) and Eq. (8) with Evaluation Data: VD (9 nos.)

Equation used	R	MAE (mm/s)	RMSE (mm/s)	Number of Under Estimation (out of 9)	Maximum Percentage Under Estimation (PPV value –mm/s)	Data Used for Development of Equation
Eq. (4)	0.996	0.261	0.307	2 (22%)	12.75% (2.890)	SHD (14) and PBD (39)
Eq. (8)	0.996	1.857	2.295	1 (11%)	1.64% (2.890)	SHD (14)

Figure 5. Underestimation performance evaluation for PPV estimated with Eq. (4) and Eq. (8) (a) PBD (b) VD



(a) (b)

Table 5 respectively. Again it should be kept in mind that the SHD had been used to develop Eq. (4) and is totally fresh only for Eq. (9).

The 95 percent confidence equation developed with 39 numbers of data (Eq. (9)) resulted in no underestimation when tested with the fresh data (SHD and VD), in contrast to the Eq. (4), which resulted in 21% and 22% underestimations respectively for SHD and VD. It is noteworthy in Table 4, that though the SHD (14 numbers) had been used in development of the Eq. (4) along with the PBD (39 numbers), still use of the mean expression resulted in underestimation of PPV in few cases. As the higher percent (95) confidence expression was used for Eq. (9), the errors of estimation (MAE & RMSE) involved were higher in Eq. (9) compared to Eq. (4). However, all errors in PPV estimation were on higher side in case of Eq. (9) – which is conservative and would result in safe design of controlled blasting. Equation (9) developed from 39 datasets has resulted in safe blast design using

Table 4. Evaluation of Underestimation of PPV by Eq. (4) and Eq. (9) with Evaluation Data: SHD (14 nos.)

Equation used	R	MAE (mm/s)	RMSE (mm/s)	Number of Under Estimation (out of 39)	Maximum Percentage Under Estimation (PPV value –mm/s)	Data Used for Development of Equation
Eq. (4)	0.828	3.795	5.098	3 (21%)	33.13% (14.99)	SHD (14) and PBD (39)
Eq. (9)	0.827	9.463	13.592	0	-	PBD (39)

Table 5. Evaluation of Underestimation of PPV by Eq. (4) and Eq. (9) with Evaluation Data: VD (9 nos.)

Equation used	R	MAE (mm/s)	RMSE (mm/s)	Number of Under Estimation (out of 9)	Maximum Percentage Under Estimation (PPV value –mm/s)	Data Used for Development of Equation
Eq. (4)	0.996	0.261	0.307	2 (22%)	12.75% (2.890)	SHD (14) and PBD (39)
Eq. (9)	0.996	3.991	4.793	0	-	PBD (39)

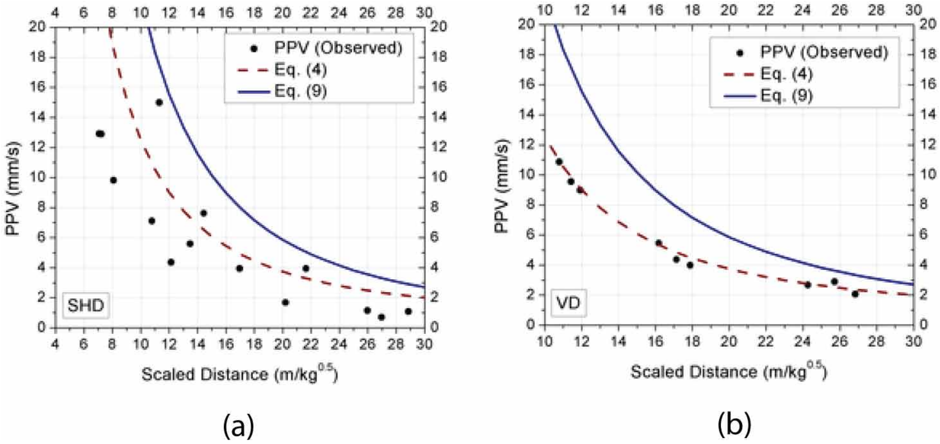
95 percent confidence expression, by adopting the standard industrial practice. The importance of sufficient sample size required for development of empirical relations and incorporation of the various uncertainties of parameter estimation is highlighted. Here as mentioned in Section ‘Data’, it can be noticed that the performance (underestimation) has improved over that observed in previous section for expression developed from SHD (Eq. (8)).

From the variable and scatter plots presented in the Figure 5, it is visible that whereas Eq. (9) never underestimates, Eq. (4) definitely results in several underestimations for both datasets. This highlights the fact that in addition to the better overall prediction, the underestimation of PPV is also an important consideration for practising blast engineers as the more accurate Eq. (4) had relatively more underestimation cases as compared to the Eq. (8) or Eq. (9). The various uncertainties in the process of empirical model development were considered in Eq. (8) and Eq. (9), which led to better performance when this underestimation (non-conservative) aspect was considered. Addressing the uncertainties of the developed models is essential for safe design of controlled blasting operation and this can be possible according to traditional industrial practice (Tripathy & Shirke, 2015; Tripathy et al., 2016) or re-sampling method (Dauji, 2019).

DISCUSSION

The first objective was to highlight the significance of evaluation of performance of the regression equation with fresh data set, as used for the development of the equation. Whereas Agarwal and Mishra (2019) had evaluated performance with fresh data in two cases (Table 2 $_{AM}$, Table 4 $_{AM}$), they used same data for one (Table 3 $_{AM}$). Evaluating the performance with fresh data (VD: Table 1) resulted in different inferences in this study. The second objective was to establish that the performance evaluation needs to be conducted using multiple error metrics which examine various aspects of accuracy of model and include parsimony factor, especially when the equations have different number of empirical constants. Otherwise, evaluation might remain incomplete. The authors (Agrawal & Mishra, 2019) had concluded that the expression derived by adopting the ‘Modified scaled distance regression

Figure 6. Underestimation performance evaluation for PPV estimated with Eq. (4) and Eq. (9) (a) SHD (b) VD



(a) (b)

analysis' approach was predicting the blast-induced ground vibration more accurately compared to the traditional approach. The comparison with various error metrics in this study established that the improvement in accuracy was marginal when both the equations were tested with fresh datasets (Table 1). The authors (Agrawal & Mishra, 2019) had concluded that the reduction in errors to the tune of 8.5% was possible by the 'Modified scaled distance regression analysis' approach (Agrawal & Mishra, 2019). The comparison of the individual errors in prediction of PPV was examined in this study and minor improvement could be observed in the 'Modified scaled distance regression analysis' approach (Agrawal & Mishra, 2019). But then, the Eq. (4) was developed with 53 datasets and contained 3 empirical constants, which could have led to the observed improvement. Furthermore, in 44% of the cases evaluated, the 'Modified scaled distance regression analysis' approach, developed with 53 datasets (Agrawal & Mishra, 2019) resulted in higher errors (Figure 2) compared to traditional approach developed with 39 datasets. The comprehensive performance evaluation brought out the fact that the traditional approach was better in terms of three out of the five error metrics (correlation, RMSE, MAE, AIC, BIC) while the 'modified' approach was better in terms of one error measure.

The third objective was to highlight that for safe design of controlled blasting, the uncertainties should be addressed either by traditional methods (Tripathy & Shirke, 2015; Tripathy et al., 2016) or re-sampling method (Dauji, 2019). This would help in limiting the underestimation to the desired level (generally a value of 5% is deemed suitable in most cases). The authors (Agrawal & Mishra, 2019) had concluded that the 'Modified scaled distance regression analysis' would be handy for the practising blasting engineers and would enable them to have better control over the blasting operation. In this study, the comparison (Table 1) established that the traditional approach is equally good. As regards to the control over the blasting activity at site, the 'Modified scaled distance regression analysis' (Agrawal & Mishra, 2019) could result in non-conservative estimation of PPV (underestimation) and might lead to unsafe blasting operation. This occurs because the uncertainty aspect was not considered in development of the 'Modified scaled distance regression analysis' and thus resulted in more underestimation cases when tested with fresh data leading to non-conservative (may even be unsafe) design of controlled blasting operation. The traditional practice of using the 95 percent confidence relationship from the trial blast data accounts for the various uncertainties in the process of generation of the empirical expression in an ad-hoc fashion. When executed from a dataset of sufficient numbers (in this case: 39), it resulted in conservative estimates of PPV when evaluated with fresh data. Thus the traditional approach is quite efficient and handy for safety of the underground blasting operations.

As can be discerned from Tables 1 and 3, the traditional approach resulted in better performance when developed with more data (39 PBD over 14 SHD), which is intuitive in nature. More number of data in development of equation implies that more information about the process goes into the analysis, thus enabling more accurate determination of empirical constants for the correlation expression. For this very reason it is prudent to update the empirical constants of the vibration attenuation relationship as and when the data from the controlled blasting operation becomes available. Invariably, for the 'Modified scaled distance regression analysis' also, similar results would be obtained when developed with more number of data. The inferences drawn from this case study using the data from Agarwal and Mishra (2019), regarding the performance evaluation could be significant for the other studies in literature (discussed earlier) as well, wherein the model evaluation was limited to one or two performance measures, or was conducted with the same data set (as used for model development).

Therefore, this article attempts to highlight the importance of the performance evaluation of empirical models for application in practical engineering problems. The salient guidelines for empirical model evaluation would be as follows:

- The data employed for model development should not be used for evaluation of its performance. Goodness-of-fit of the developed models should always be examined by a fresh set of data. For this purpose, data splitting should be done beforehand, prior to development of the empirical model.
- The examination should include qualitative as well as quantitative tools for comprehensive evaluation. The numerical comparison of performance by quantitative tools is complemented by the visual appreciation of the model performance using qualitative tools.
- When comparing models with different numbers of empirical parameters, and / or models developed from different numbers of data, performance measures should include those which include a parsimony check on model performance.
- The model performance measures to be employed should be chosen judiciously depending on the target application of the empirical model. In addition to the overall goodness-of-fit, for the strength parameters overestimation should be critically checked, whereas for the demand parameters, underestimation aspect would be more critical.
- Wherever possible, the empirical model should be presented along with an estimate of uncertainty associated with it, following procedures in literature (Tripathy & Shirke, 2015; Tripathy et al., 2016; Dauji, 2019).

CONCLUSION

From the comparison of performances of different equations presented in this article, the following conclusions can be highlighted:

- Sample size for development of empirical relationship should be preferably large for capturing all the peculiarities of the relationship, say, more than 40 numbers.
- Performance evaluation of empirical expression should always be conducted with a fresh subset of the data.
- Uncertainties of the derived empirical expression should be addressed in some way to arrive at the safe design of controlled blasting operation. For that purpose, the traditional industrial practice is to use the 95 percent confidence expression for design of controlled blasting, and this has been found to be adequate in the present case study.
- The traditional expression Eq. (5) appears slightly better than the Eq. (4) obtained by adopting the 'Modified scaled distance regression analysis' approach (Agrawal& Mishra, 2019), when various error measures are considered together, and the parsimony aspect is included. Particularly

since trial blast data are limited in number, the additional parameter in the Eq. (4) could be a concern in certain cases.

- The underestimation aspect of the PPV estimation should be given consideration while designing safe controlled blasting operations. For this purpose, the uncertainties need to be adequately addressed either by traditional approach (Tripathy & Shirke, 2015; Tripathy et al., 2016) or other methods such as re-sampling approach (Dauji, 2019). The proposed Eq. (4) derived by 'Modified scaled distance regression analysis' (Agrawal & Mishra, 2019) could result in non-conservative design of controlled blasting in certain cases. The standard industrial practice of using 95 percent confidence expression would result in safe design of blast when sample size is sufficient (say, more than 40 in the present case).

Agarwal and Mishra (2019) had identified and attempted to address a very important aspect for design of controlled blasting from single-hole trial blasts, namely, the effect of superimposition of the blast waves in case of multi-hole production blasting on the empirical ground vibration attenuation relationship. This short analysis examined the accuracy of incorporation of blast wave superimposition phenomena in the empirical expression for prediction of PPV as proposed by Agarwal & Mishra (2019). When evaluated with fresh data, the improvement in accuracy of prediction happened in terms of one performance metric, whereas in terms of three others, the accuracy diminished. Therefore, this remains an important aspect which definitely presents scope of further studies and improvements. The traditional approach for blast vibration prediction was implemented for one set of expression for scaled distance as well as for the PPV. As reported in literature (Dauji, 2018; Ray & Dauji, 2019), other expression forms for the same might yield better results and can be explored in future empirical blast models.

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Conflict of Interest

The author declares that there was no known competing interest pertaining to the study presented in this article.

Data Availability Statement

The data reported by Agrawal and Mishra (2019) in their study have only been used in this study. All data are available in the published article.

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