Prediction accuracy of underground blast variables: decision tree and artificial neural network

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Abstract: Accurate prediction of blast induced ground vibration variables such as particle velocity and frequency are of interest for safe design of controlled blasting operations for mining, tunnelling or excavation projects. There are certain limitations in the widely used empirical and numerical approaches especially when number of variables is large. Various data driven approaches have been employed for producing correct estimates for such cases. Decision tree (DT), earlier successfully employed for solving variety of civil engineering problems, is employed for prediction of blast variables for the first time in this article. The performance of DT models was found to be equally good (for particle velocity variable) or better than (for frequency variables) ANN models developed in this study, and unequivocally superior to the SVM or RF models reported in literature. Additionally, the clarity in decision rule-based estimation foster easy comprehension and future implementation.

Keywords: underground blast; decision tree; artificial neural network; ANN; ground vibration.

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1 Introduction

Execution of deep excavation work for large construction projects, as well as tunnelling and mining works necessitate underground blasting operations. The energy released by the explosive charge is partially (20%–30%) expended in fracturing the rock and the remaining energy is dissipated in the form of shock waves emanating in radial directions from the blast source (Monjezi et al., 2011). These shock waves generated due to underground blast affect the structures near the blasting site. The regulatory and safety guidelines stipulate that the blasting activity should be designed so that its adverse effects on the adjacent structures are minimal. Evaluating the effects of underground blasts at a certain distance from the source thus forms a very important consideration for design of controlled blasting for deep excavation, tunnelling or mining. The various factors affecting the blast response at a certain distance from the source would include the following:

a Properties of the rock media: rock properties; integrity coefficient; orientation of fracture planes.

b Blast parameters: charging amount at one time; total charging amount; explosive type; detonation velocity.

c Separation variables: horizontal distance; elevation difference; angle of minimum resistance line to measured point (°).

The various approaches for estimation of the effects of the underground blast at desired distances from the blast source can be broadly categorised as: empirical modelling, numerical methods and soft computing approaches. The empirical methods are generally advocated by national standards (IS 6922: 1973) for the ease of application and are favoured for their simplicity by the industry as well (Tripathy and Shirke, 2015; Tripathy et al., 2016; Ray et al., 2018; Ray and Dauji, 2019). Analytical hierarchy process had been suggested for the selection of the best-suited empirical expression for site-specific blast vibration prediction (Kalayki and Ozer, 2016). Dauji (2018) discussed a novel and efficient approach for improving the accuracy of the empirical models for prediction of vibration attenuation variables for underground blast. However, empirical models involve assumptions of the equation form, and evaluation of certain constants of the empirical formulation. The input variables generally considered are two in number, namely, maximum charge per delay and separation distance (Monjezi et al., 2011). At best, the empirical approaches can handle a limited number of input variables (four in Monjezi et al., 2011) for achieving efficient model development. The variations of the site-specific constants limit the prediction accuracy of generalised empirical vibration attenuation relationships (Mohamadnejad et al., 2012). Factors affecting the vibration attenuation in underground blasts being multiple in numbers and the interrelationship between them having various degrees of nonlinearity, the empirical approaches are at distinct disadvantage for accurate prediction of the vibration parameters such as peak particle velocity (PPV) and frequency (Monjezi et al., 2011). The preceding discussion explained the assumptions and the limitations of the generalised or site-specific empirical vibration attenuation relationships for underground blasts.

If properly implemented, the numerical prediction generally offer the better results – for they are based on the physics of the blast wave propagation and the rock properties are represented with the constitutive models as well (Hao and Wu, 2005a, 2005b; Ma and An, 2008; Yilmaz and Unlu, 2013; Liu et al., 2017). However, a large amount of input data is generally required for setting up of the numerical model for a particular site, and these are difficult to ascertain with good accuracy in the initial stages of excavation or mining. Additionally, they require expertise in setting up of the model domain, application of the blast load, validation with field observations and finally, interpretation of the results. The assumptions of the constitutive model for rock as well as the simulation of the blast load form the other limitations for numerical model based prediction. Furthermore, extensive studies are required for fixing up of optimum model domain, suitable constitutive model for the rock, proper blast load definition, insensitivity of mesh size, and other parameters for fine-tuning the model to the site observations. All these activities necessitate a huge computational demand, which oftentimes is not readily available for the studies conducted for design of controlled blasting.

At this backdrop, data driven approaches appear extremely attractive owing to their flexibility in the representation of the relationship (linear/nonlinear) of the different input variables with the output variable of interest. Additionally, their capability of handling more number of variables at a given time is especially useful. Furthermore, data driven models are tolerant to noise in data and the developed models can be continuously refined with fresh incoming data. Application of a variety of soft computing tools had been reported for blast related studies in literature. These included universally popular artificial neural network (ANN) (Khandelwal and Singh, 2009; Monjezi et al., 2010, 2011; Mohamadnejad et al., 2012; Jang and Topal, 2013; Saadat et al., 2014), support vector machine (SVM((Longjun et al., 2011; Mohamadnejad et al., 2012), random forest (RF) (Longjun et al., 2011), genetic program and gene expression program (GP/GEP) (Faradonbeh et al., 2016), adaptive neuro-fuzzy inference system (ANFIS) (Mottahedi et al., 2018), particle swarm optimisation (PSO) Mottahedi et al., 2018), and other AI or hybrid options (Sivandi-pour et al., 2015; Sivandi-pour and Farsangi, 2019) among others.

Khandelwal and Singh (2009) employed ANN as well as multivariate regression for prediction of blast induced ground vibration and frequency. From their study, they concluded that ANN was superior in flexibility and accuracy. Monjezi et al. (2010) compared different types of ANN for predicting blast induced ground vibration and concluded that multilayered perceptron neural network was best suited for the application. Longjun et al. (2011) reported prediction accuracy of SVM and RF for blast variables and this study would be discussed in more detail subsequently. Mohamadnejad et al. (2012) compared empirical methods, ANN and SVM for accuracy in prediction of blast-induced ground vibration and reported SVM as the superior technique for that application. Jang and Topal (2013) explored over-break prediction based on geological parameters with ANN and multiple regression (linear as well as nonlinear) and concluded that the ANN would be the better suited tool for over-break warning. Saadat et al. (2014) reported that the ANN models performed better than the empirical models for blast vibration prediction in Gol-E-Gohar mines in Iran. Faradonbeh et al. (2016) compared prediction accuracy of GP and GEP for fly-rock assessment and concluded that GEP was better suited for the case examined. Mottahedi et al. (2018) employed ANFIS and ANFIS-PSO models for over-break prediction and reported that ANFIS-PSO resulted in estimates that were more accurate. As in other civil engineering problems, ANN had found the widest and most successful application in blast related studies as well.

Decision tree (DT), alternatively known as model tree or regression tree, is another promising data-driven tool that had not yet been utilised up to its potential in this area, to the best knowledge of the author. DT had found successful application in various other civil engineering problems including hydrology (Solomatine and Xue, 2004; Kim and Pachepsky, 2010; Gharaei-Manesh et al., 2016), oceanography (Garg et al., 2008), capacity estimation of structural steel members (Dauji, 2019), and concrete technology (Ayaz et al., 2015; Behnood et al., 2015; Dauji, 2016). In the geological and geotechnical domain, a study (Tiryaki, 2008) was reported wherein intact rock strength (uniaxial compressive strength, static modulus of elasticity) was estimated from rock index tests and intact rock properties with ANN, regression trees (or DT) and statistical models. The author concluded that the DT offered the best predictive model for the variables. Another study by Dindarloo and Siami-Irdemoosa (2015) examined the ground rippability (ease of excavation) with DT along with conventional diggability index rating and DT was found to be comparatively promising. However, application of DT for prediction of vibration variables for underground blast is sparse in literature.

Most of the blast related studies (empirical or soft computing) employ few input variables (charge weight, distances) for prediction of PPV either due to the limitation of the tool in handling larger number of variables efficiently, or due to limitation of the recorded trial blast data on which the models are developed. In this context, the study by Longjun et al. (2011) was rich in data wherein nine input variables were recorded along with three output variables. The output variables recorded included PPV, the first dominant frequency (FDF) as well as its duration. This formed one of the most comprehensive database reported in literature, which encapsulated the variables of interest in design of controlled blasting operations: PPV, FDF and its duration (DurFDF). The authors had concluded that the SVM was better in terms of average predicted error ratio whereas the RF had the advantage of definite weight parameters for all factors involved, thereby had ease of future estimation. Careful evaluation of the results from SVM and RF models as reported in literature (Longjun et al., 2011) strongly indicated that application of other data mining tools could be explored to achieve better accuracy in prediction.

The application of data driven techniques has eased out development of empirical models to a large extent. However, often it is observed that the researcher applies one or two tools to infer the prediction accuracy for a particular problem. It is generally accepted fact that the success of soft computing tools is problem specific: same tools may perform differently for different problems (datasets); and for a single problem (datasets), various tools could result in substantial variation in resulting accuracy. In the circumstances, the correct approach would be to explore many different available tools and choose the one yielding the best results for the given problem. In applications such as the ANN or SVM, the practical application requires the engineer to be conversant and knowledgeable about the tool. In contrast, tools such as DT or RF result in clear-cut decision rules and this simplifies the understanding and future implementation of the tools even by the engineers uninitiated in the specific tool. This is an important feature which should be carefully considered for choice of the soft computing tool for a particular application.

Therefore, in this article, the database reported by Longjun et al. (2011) has been utilised to develop data driven prediction models for PPV, FDF, and DurFDF separately with the objective of attaining better accuracy in prediction. For this purpose, this author selected the promising but relatively unexploited tool of DT along with the universally popular and successful model-free tool ANN for comparison. The advantage in case of the tool DT would be the domain splitting and definition of the decision rules for each domain, which would foster comprehension and make possible for practicing engineers to implement the rules in actual site without having detailed technical background of the model development. Thus, DT had special feature extraction option from the data, which could be very useful in practical application. This motivated the author to examine the accuracy of modelling of the blast parameters with DT, in addition to ANN. By adopting a similar data division for modelling and evaluation purposes as that reported in literature for SVM and RF (Longjun et al., 2011), the performance of four soft computing tools, namely, DT, ANN, SVM, and RF, could be compared in this study and relative merits would be discussed.

The article is organised as follows: the problem has been introduced along with the literature review in the present section. The data utilised for the study has been taken from the literature and this has been explained in the second section along with the brief description of the tools employed in the study (ANN and DT) and the performance metrics used for evaluation of relative performance of the explored tools. The results have been presented in pictorial form along with discussion on the relative performance and merits of the various tools in the third section. The salient conclusions drawn from the study are presented in the last section along with the suggested approach for soft computing solutions for addressing similar problems.

2 Data and methodology

2.1 Data

The underground blasts conducted for excavation or tunnelling result in release of explosive energy, which propagates through the surrounding media in the form of stress waves. The present study evaluates the estimation accuracy of DT and ANN for the ground vibration variables in case of underground blasts. The particle velocity and the frequency of vibration at certain distance from the source would describe the ground vibration quite well. The variables of interest would be the PPV and the dominant frequency and these would form the target variables.

In most of the studies (empirical as well as soft computing tools) reported in literature, the charge weight and the distance (horizontal) between the detonation point and the measurement point had been adopted as the input variables. As mentioned earlier, a more comprehensive measurement was reported (Longjun et al., 2011), which comprised of nine input variables and three output variables – recorded for a total of 108 sets and this data set was selected for this study. The blast data pertained to blasting vibration study conducted in a copper mine in China. The PPV, FDF and the duration of first dominant frequency (DurFDF) were the three target variables reported in the literature (Longjun et al., 2011) and these characterise the effects of underground blast on existing structures quite well. Therefore, these three had been selected as target variables in this study. For the estimation of the predicted variables, the authors (Longjun et al., 2011) recorded nine input variables, which were: charging amount at one time (kg); total charging amount (kg); horizontal distance (m); elevation difference (m); front row resistance line (m); presplit penetration ratio (%); integrity coefficient; angle of minimum resistance line to measured point (°); detonation velocity (m/s). These variables would be considered as input variables for prediction of the target variables, namely, PPV, FDF, and DurFDF with the tools of DT and ANN, with the aim of best possible prediction accuracy.

Longjun et al. (2011) reported the prediction performance of two soft computing techniques: RF and SVM. In the present study, two other machine learning tools were employed: DT and ANN. For this purpose, three separate models were developed with nine inputs and a single output: PPV, or FDF, or DurFDF. Thus, for each target variable (PPV, FDF or DurFDF), there was a separate model. This was deviation from the study (Longjun et al., 2011) with which the performance accuracy would be compared, wherein the authors had developed a single combined model with nine inputs and three outputs. Models with single target variable were adopted in this study with the objective of getting the best generalisation capability from the respective tool for each target variable.

The data for the study was adopted from literature (Longjun et al., 2011) and it comprised of a total 108 sets of records. As the performance of models developed in the present study would be compared with those from literature, similar division of the records for model development and performance evaluation was adopted. Out of the total data, 93 sets (~ 86%) had been employed for development of the models (modelling or training data) and the remaining 15 sets (~ 14%) were used for performance evaluation (evaluation or testing data). All the performance metrics reported throughout the present study pertain to those achieved with the evaluation or testing set, i.e., the data that was not used in development of the respective model. For further details regarding the blast activities and the recorded data, readers may refer literature (Longjun et al., 2011).

2.2 Methodology

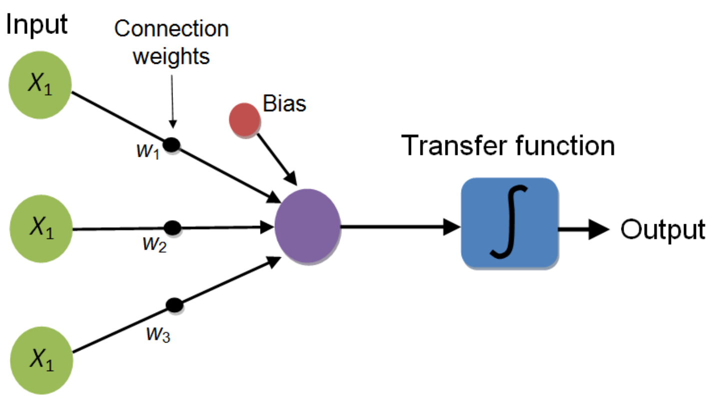
As mentioned earlier, the soft computing tools employed in this study were DT and ANN. ANNs had been quite popular in the blast studies (Khandelwal and Singh, 2009; Monjezi et al., 2011; Mohamadnejad et al., 2012; Jang and Topal, 2013; Saadat et al., 2014) and need little introduction. DT (also known as regression tree or model tree) was a relatively less exploited data mining tool (Tiryaki, 2008; Dindarloo and Siami-Irdemoosa, 2015) in the geotechnical domain, though it boasted of the additional attraction of the clearly defined decision rules for prediction of the variables. These tools are discussed briefly in the following subsections.

2.3 Artificial neural network

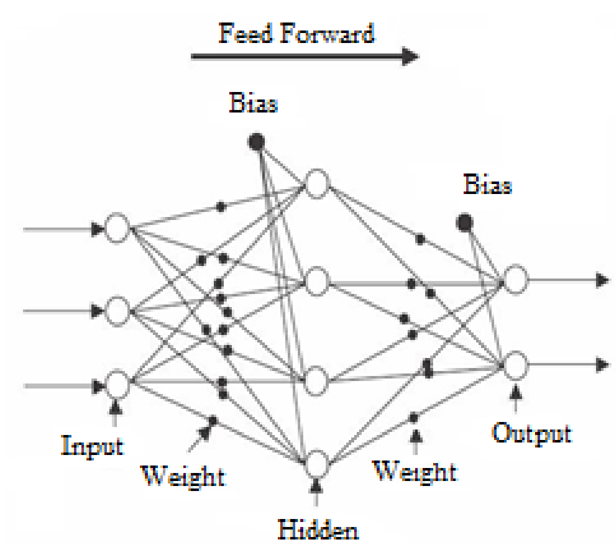
ANN is a soft computing tool that endeavours to map a set of input vector to the corresponding set of output vector with a non-linear relationship. It does not require any a-priori assumption on the dependency structure between the input and output. Structurally, ANN is an interconnection of neurons arranged in three or more layers

(Figure 1), with the input and output layers easily understood. In between input and output layers, there are one or more hidden layers of neurons in order to ensure the desired non-linearity in the prediction model. The neuron functions [Figure 1(a)] by getting a weighted sum of inputs, adding a bias term, and passing this sum through a transfer function to get the output of the neuron, which is then passed to subsequent neurons. In general, a layered structure (multi-layered perceptron, MLP) is preferred for ANN, comprising of the input layer, one or more hidden layers and the output layer [Figure 1(b)]. Training of ANN refers to the optimisation of the various weights and the biases of the selected network architecture.

Figure 1 ANN (a) basic structure (b) feed forward network (see online version for colours)



(a)



(b)

The architecture of the ANN is a very important decision, in which a balance between the sufficient degrees of freedom for representing (nonlinear) relationship between the various inputs, sufficiency of the available data length for achieving adequate training, and avoiding the problem of over-fitting. In many other studies (Monjezi et al., 2011), relatively higher number of model variables were trained with given dataset (111 variables with 162 training sets). However, the general consensus remains that for extracting the best results from data-driven tools, the number of training sets should be four to five times the number of independent variables in the ANN model. In this study dealing with nine inputs, the number of neurons in the hidden layer was limited to two to retain the generalisation capability of the ANN models trained with 93 sets of data (12 or 23 variables with 93 training sets). Thus, the possible architecture of ANN explored were 9-1-1 and 9-2-1.

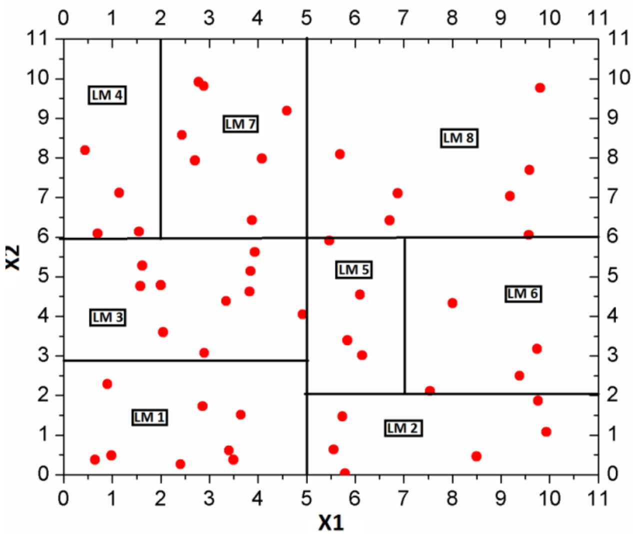
Of the various training options for feed-forward back propagation (FFBP) network, resilient propagation algorithm was adopted in this study. In this algorithm, the sign of the derivatives directs the weight update and the actual value of weight update is determined separately. In this way, the convergence issues associated with small derivative values (for large inputs) were avoided, thereby providing adequate and efficient training. For further details, readers may refer literature (Bose and Liang, 1993; Wasserman, 1993; Haykin, 2008).

2.4 Decision tree

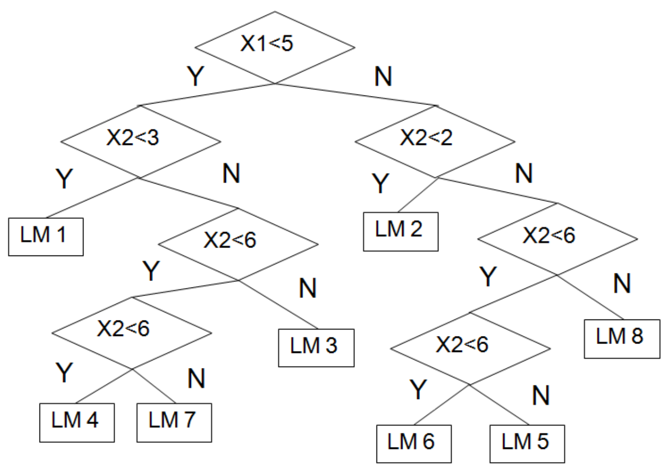
DT, sometimes known as model tree or regression tree, employs a computation process resembling a tree structure. The DT originates from a root node (decision box) to other nodes (decision boxes) or leaves (models) based on decision output: 'yes' or 'no'. As a result, the model space is subdivided into subspaces, within each of which a particular decision rule prevails. The subdivision or domain splitting is conducted by some algorithm, such as, minimum entropy in subdomain, or collecting as many samples as possible in the class, or any other. In popular M5 algorithm of DT, the domain splitting is performed by minimising the standard deviation of the class value reaching a node (Quinlan, 1992; Rokach and Maimon, 2015) and this approach has been adopted in this study. Figure 2(a) depicts the subdivision of the domain for two variables and Figure 2(b) pictures the corresponding DT, where the diamond correspond to a decision node and the rectangles represent the decision rule.

The attribute for the root node is selected according to its ability to maximise the standard deviation reduction. During model development, many possible options of input divisions are explored and the particular option that yields the maximum value of the standard deviation reduction is selected to build linear models in each subdomain. Methods for avoiding too many domain splits or large discontinuities between neighbouring models were reported in literature (Witten and Frank, 2000; Rokach and Maimon, 2015; Jekabsons, 2016). The development of DT for a particular data essentially means the subdivisions of the data hyper-space to achieve the desired objective (say, maximum reduction of standard deviation in M5 algorithm), and define the decision rules for each of the subdomains. Further details for DT development may be obtained from literature (Witten and Frank, 2000; Rokach and Maimon, 2015).

Figure 2 DT (a) domain subdivision (b) tree structure (see online version for colours)



(a)



(b)

2.5 Performance metrics

As mentioned earlier, the ‘performance’ detailed in this article referred to the performance corresponding to the evaluation or testing data set. In literature (Longjun et al., 2011), the performance of the developed models (with SVM and RF) were compared with the individual relative error values. In this study, however, the performance comparison were presented for the two tools (DT and ANN) used in this study along with the two tools (SVM and RF) reported in literature with the overall error metrics. These were correlation coefficient (R), the root mean squared error (RMSE), and mean absolute error (MAE) along with the limits of relative errors in maximum of overestimation and underestimation. With the concern of the vibration effects on the existing installations around the blast site in perspective, the maximum underestimation would be deemed particularly important. The median value of the absolute relative error was also reported. These performance metrics are self-explanatory. Individual relative errors would be compared for the two tools exercised in this study, namely, DT and ANN.

3 Results and discussions

Separate models were generated for the three output variables of interest, namely, PPV, FDF, and the DurFDF. As explained earlier, option of separate models were selected to achieve best generalisation ability of the models from the limited datasets. The results for each output variable are presented in separate subsections.

3.1 Prediction of PPV

The DT as well as the ANN models developed in this study was with nine inputs and single output (PPV) as detailed in the methodology section. The model development was performed with 93 sets and model evaluation was done with 15 sets, similar to that reported in literature (Longjun et al., 2011) for comparison. A sample training progression for 1,000 epoch is presented in Figure 3(a). The comparative performance of the training and testing data for ANN and DT are presented in Figure 3(b) and Figure 3(c) respectively. The performance obtained in this study with DT and ANN were compared with those reported in literature (Longjun et al., 2011) with other tools (SVM and RF), in Figure 4(a) to Figure 4(f) with the R, RMSE, MAE, maximum relative over prediction and maximum relative under prediction in pictorial form. ANN model yielded the highest R, lowest of RMSE and MAE; and DT was close second. The relative over prediction was minimum for DT with the relative under prediction being minimum for SVM (Longjun et al., 2011).The median of the absolute relative error, another indication of the accuracy of the developed model, was lowest for the SVM and followed by RF (Longjun et al., 2011). Out of the two tools employed in this study, the DT fared better in terms of the median of absolute relative error. However, the overall performance of the ANN was best for the variable PPV in this study.

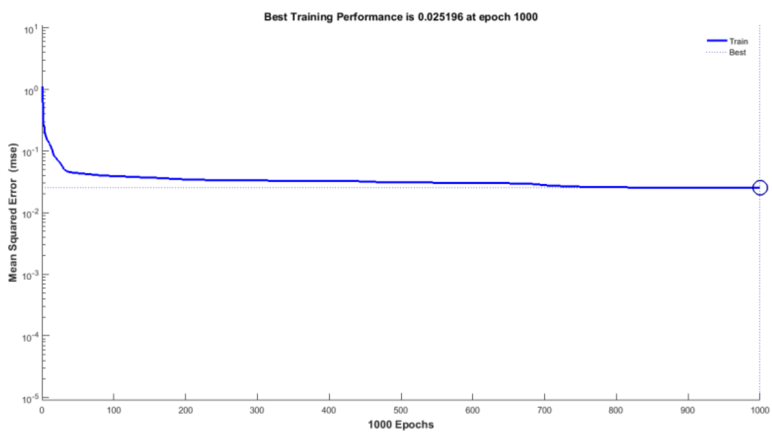
3.2 Prediction of FDF

Similar to those for PPV, Figure 5(a) to Figure 5(f) represent pictorially the R, RMSE, MAE, maximum relative over prediction and maximum relative under prediction obtained for the FDF. The results were for the models developed in this study (with DT and ANN) along with those from literature (SVM and RF) (Longjun et al., 2011) for comparison. DT model yielded the highest R, lowest of RMSE and MAE, and the relative over prediction was smallest for DT with the relative under prediction being smallest for SVM (Longjun et al., 2011). In case of the FDF, the median of the absolute relative error came to be almost same lowest value for the SVM (Longjun et al., 2011) and DT (this study), followed by ANN.

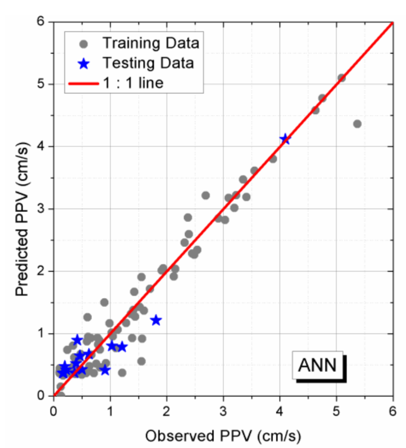
3.3 Prediction of DurFDF

For the DurFDF, as before, the R, RMSE, MAE, maximum relative over prediction and maximum relative under prediction were depicted in Figure 6(a) to Figure 6(f) respectively for DT and ANN (this study) as well as the SVM and RF (Longjun et al., 2011). DT model yielded the highest R, lowest of RMSE and MAE, and the relative over prediction was lowest for DT with the relative under prediction being smallest for ANN. The median of the absolute relative error was lowest for the ANN, followed by DT.

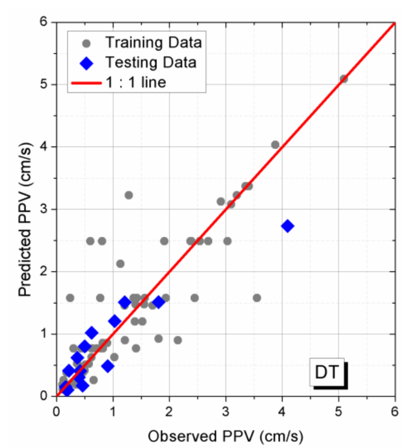
Figure 3 Sample performance for PPV (a) training performance of ANN in 1,000 epoch (b) comparison of training and testing performances for ANN (c) comparison of training and testing performances for DT (see online version for colours)



(a)



(b)



(c)

Figure 4 Performance metrics for PPV (a) correlation coefficient (b) RMSE (c) MAE (d) relative over estimation (e) relative under estimation (f) median absolute relative error [from L to R: SVM, RF, DT, ANN] (see online version for colours)

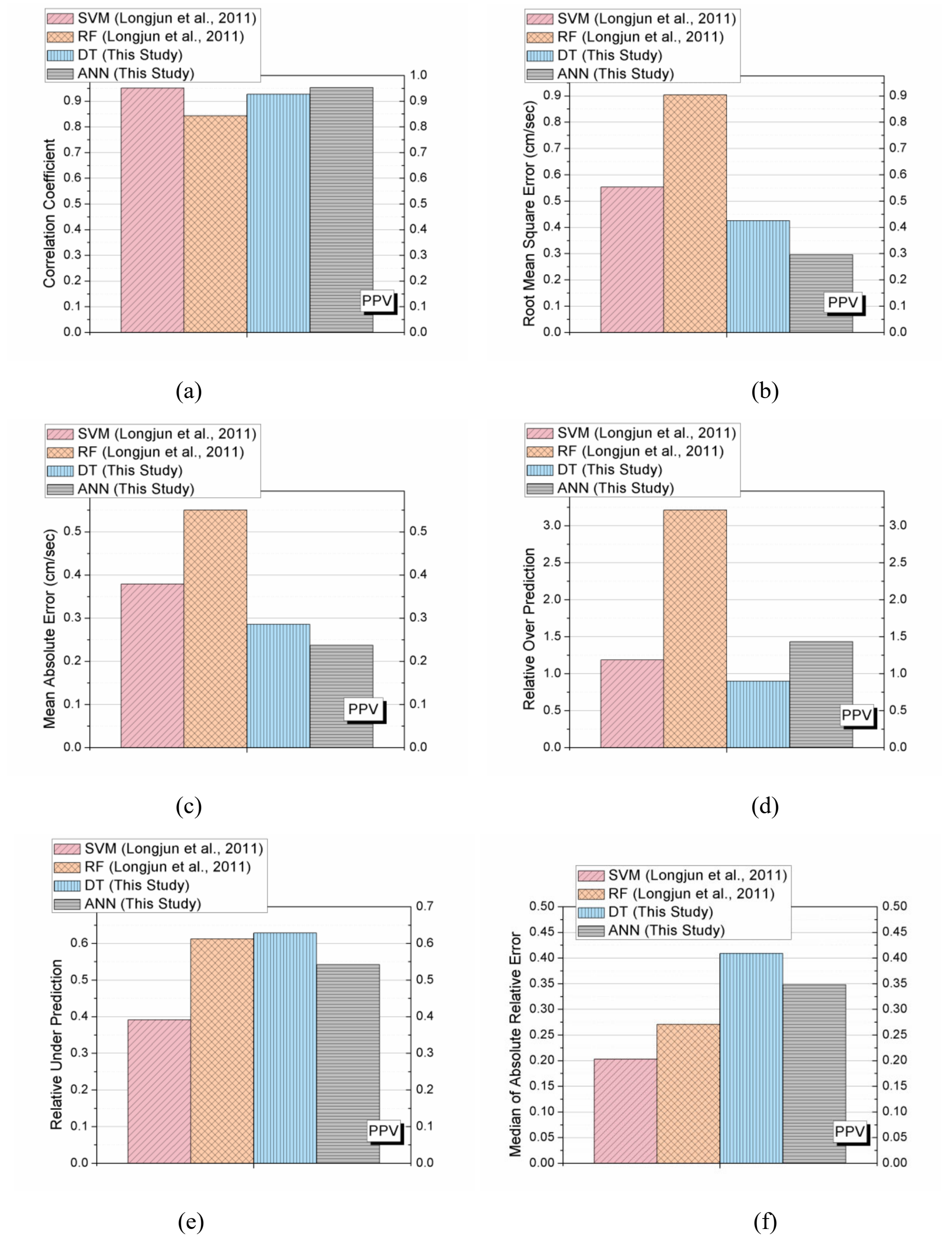


Figure 5 Performance metrics for FDF (a) correlation coefficient (b) RMSE(c) MAE (d) relative over estimation (e) relative under estimation (f) median absolute relative error [from L to R: SVM, RF, DT, ANN] (see online version for colours)

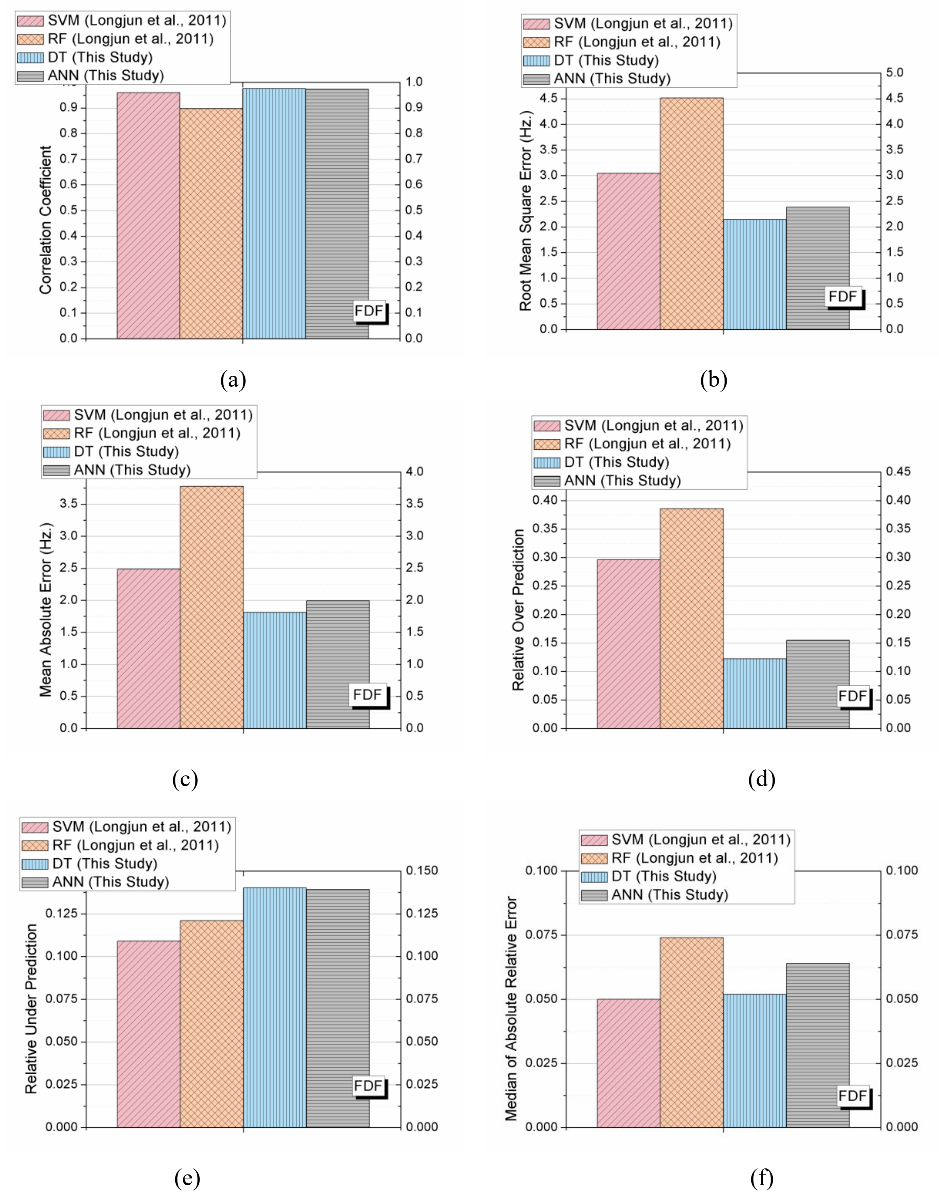
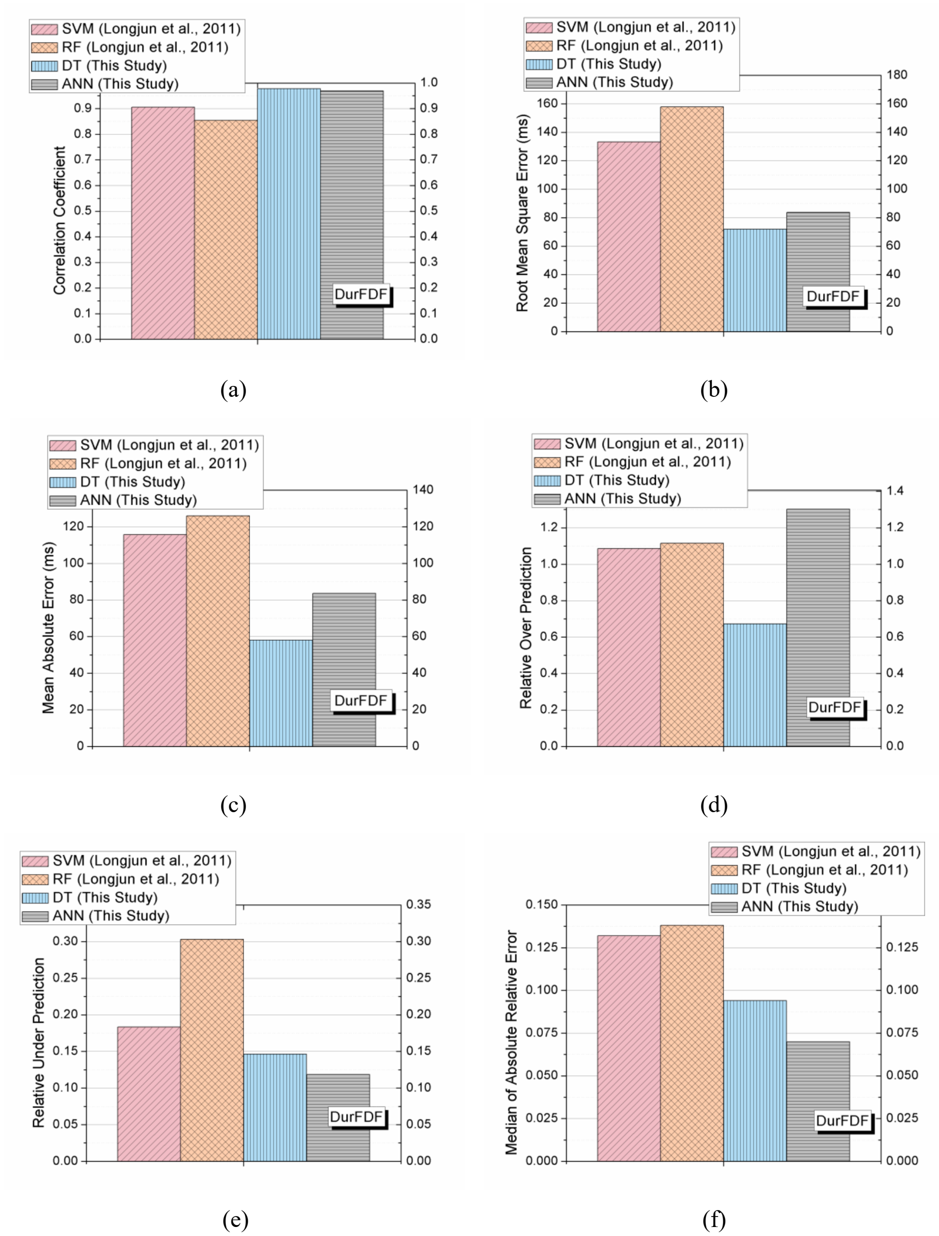


Figure 6 Performance metrics for DurFDF (a) correlation coefficient (b) RMSE (c) MAE (d) relative over estimation (e) relative under estimation (f) median absolute relative error [from L to R: SVM, RF, DT, ANN] (see online version for colours)



4 Discussions

The individual relative errors for testing data obtained with DT were compared to those obtained with ANN in Figure 7 for PPV, Figure 8 for FDF, and Figure 9 for DurFDF. It was noteworthy that the limits of relative errors in ANN models were higher than the DT models. This was true even for model for PPV, for which the overall performance of ANN models were better than the DT models. This could have been due to the limited number of training sets (93) and hidden neurons (two) used for ANN in this study, which could be sub-optimal for the number of inputs (nine) and one output.

Figure 7 Individual relative errors for PPV: DT and ANN [L to R] (see online version for colours)

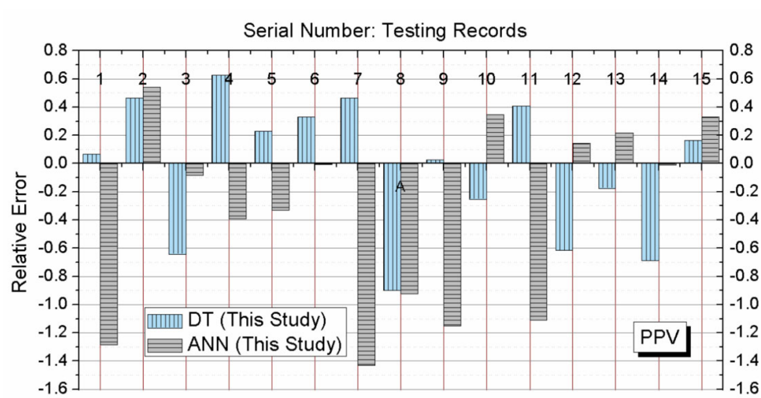


Figure 8 Individual relative errors for FDF: DT and ANN [L to R] (see online version for colours)

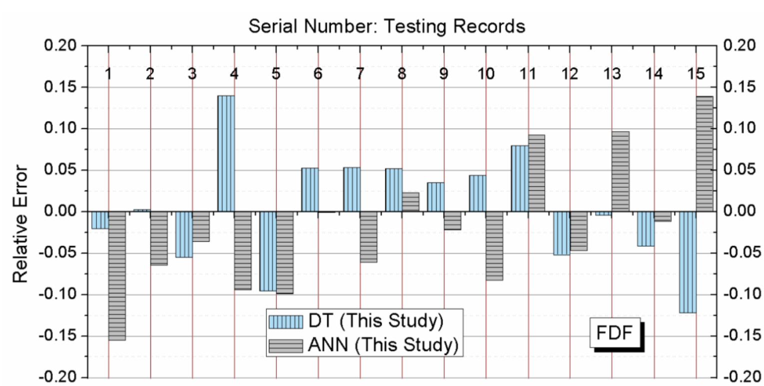
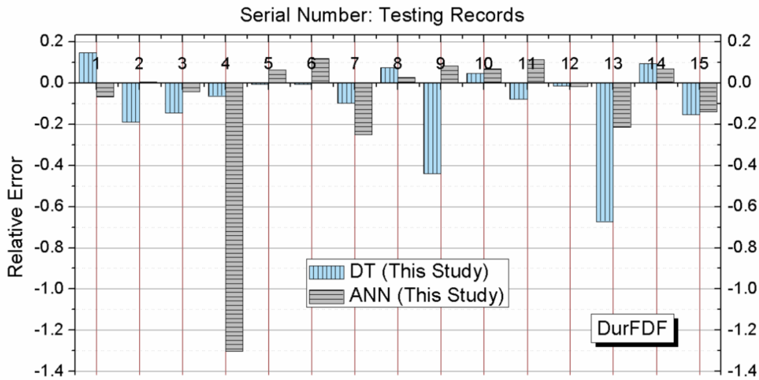


Figure 9 Individual relative errors for DurFDF: DT and ANN [L to R] (see online version for colours)



From the results, it was concluded that overall performance of both the tools explored in this study, namely, DT and ANN, was better than the tools reported in literature (SVM and RF) (Longjun et al., 2011) in case of all the three target variables, namely, PPV, FDF, and DurFDF. This study highlighted the fact that different data mining tools could be suited for different target variables, in the same data set. In general, the ANN model was better suited for PPV, whereas the DT models were superior in case of FDF and DurFDF. It must be mentioned here that even in case of PPV, the DT models yielded comparable correlation and lower errors than those reported in literature (Longjun et al., 2011) with SVM and RF.

The relatively better performance of the models developed in this study with ANN and DT, when compared to those reported in literature for the same data (SVM and RF) (Longjun et al., 2011) could be due to the simpler model structure adopted in this study, with individual model for each variable. This aspect would be particularly important when dealing with limited datasets for development of the models. A possible reason for the better performance of the DT could be the basic approach of domain subdivision implemented for DT. The approach of all other three tools (ANN, SVM, or RF) was to arrive at the generalised model for the entire model space. Particularly, the generalised models with ANN in this study could not possibly achieve the most optimal architecture and/or weight-bias values due to the limitation of the data. With larger data, the relative performance of DT and ANN might vary. However, as trial blast records are generally limited in number, DT would emerge as useful tool in prediction of ground vibration variables for underground blasts. Henceforth, DT can be gainfully employed in design of controlled blasting for large-scale excavation, tunnelling, or mining applications, due to its higher accuracy and ease of implementation.

5 Summary and conclusions

The development of vibration attenuation relationship for underground blasts is an important step for design of controlled blasting for large-scale excavation, tunnelling or mining activities. The safety and regulatory stipulations require limiting the PPV and/or the frequency experienced near the existing structures to a certain value and this could only be achieved with accurate prediction of the ground vibration variables for a given underground blast. The data driven approaches offer the advantage of flexibility in model development and noise tolerance when compared with the empirical or numerical approaches.

Prediction of ground vibration variables for underground blast was reported in literature (Longjun et al., 2011) with SVM and RF algorithm, wherein nine input variables were considered. The variables were charging amount at one time; total charging amount; horizontal distance; elevation difference; resistance line; presplit blasting effect; rock mass structure; comparative distance between measured point and explosive region; and explosive type. The target (or output) variables were PPV, FDF, and its duration. A single model was developed with nine inputs and three outputs with each of the tools.

In this study, same data was taken and prediction models were developed separately for each target variable with the objective of achieving better generalisation and accuracy in predictions. The prediction models were based on two different soft computing tools: erstwhile-unexploited DT and universally popular ANN. The overall error measures were reported for the models developed in this study (DT and ANN) as well as those reported in literature (SVM and RF) (Longjun et al., 2011). From the study, the following conclusions were drawn:

- Different soft computing tools could yield most accurate results for different target variables for a given location.
- When dealing with limited data, employment of simpler models (for example, separate models for each individual output variable) could result in better prediction accuracy.
- In this case, the particle velocity variable, namely, PPV was best predicted with ANN, closely followed by DT, as indicated by higher correlation and lower errors. The correlation of SVM model reported in literature (Longjun et al., 2011) was comparable, but was accompanied by much higher errors. The RF model (Longjun et al., 2011) was poor in performance from all respects.
- The frequency variables, namely FDF and DurFDF, were better predicted by DT, as indicated by higher correlation and lower errors. This performance was closely followed by ANN, and was much superior to the performance of SVM or RF models reported in literature (Longjun et al., 2011).
- The performance of ANN models may be improved in case of availability of larger data set, such that optimal network architecture and training could be achieved.
- For limited data, the approach of model domain subdivision and piecewise linear models in each subdomain of DT appeared to be very efficient for the variables under consideration. This was in contrast with the other tools (ANN: this study;

SVM and RF: literature) wherein a generalised model was sought for the entire domain. Additionally, DT model had the advantage of clear-cut decision rules for easy comprehension and implementation.

It is suggested that for any given problem, a variety of soft computing tools need to be examined in terms of different overall error metrics, and the model considered best in terms of accuracy and ease of practical application could thereafter be selected for implementation.

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