Blast Induced Vibration Estimation by Using Different Machine Learning Methods in a Tunnel Excavation

ABSTRACT

This study aimed to develop a new model in which rock characteristics, blasting design parameters and excavation planning were also considered by using various machine learning methods in a funicular line excavation where blast-induced vibrations could not estimate with a high correlation by using the commonly and successfully used PPV-SD (Peak Particle Velocity-Scaled Distance) estimation formula. In addition to developing a new model, another aim was to reveal the effect of rock characteristics, blasting and excavation planning parameters on PPV estimation numerically in the form of weights.

For this purpose, 225 events in 57 shots were recorded in the funicular line excavation. Each blasted cross-section's rock characteristics were obtained from on-site inspection and geological reports. At first, recorded blasting vibration data were evaluated using the well-known PPV–SD equation, and it was seen that the relationship between PPV and SD was not able to represent the site-specific vibration attenuation. Therefore, the obtained data were evaluated with Random Forest and other Machine Learning Methods. In these evaluations, RQD, UCS, unit of advance, the maximum charge per delay, the cross-sectional area of tunnel face, total charge, and distance between shot point and vibration measurement station were used as inputs, and peak particle velocity was used as output. The results showed that the random forest model's prediction accuracy was more acceptable than the well-known PPV–SD equation and other machine learning methods. Another significant finding of the study is that parameters not considered in PPV estimation, such as UCS, RQD, and cross-sectional area of tunnel face, may be more effective than the commonly used scaled distance.

Keywords: Tunnel blasting, blast-induced ground vibrations, rock characteristics, Random forest, machine learning.

INTRODUCTION

PPV is an important index to measure the blasting vibration intensity. When the PPV exceeds the limits specified in the regulations, it may cause damage to surroundings. Therefore, the study of blast-induced ground vibration propagation is still a current topic that many researchers have investigated. Among these studies, site-specific empirical relationships for calculating blast-induced vibrations are widely used. The commonly used PPV estimation formula in the literature is given in Equation 1, where, SD is scaled distance, R is distance between shot point and vibration measurement station point (m), W is maximum charge per delay (kg), k and β are statistical site-specific constants.

\[ PPV = k \left( SD \right)^{-\beta} \]  \hspace{0.5cm} (1)
\[ SD = \frac{R}{\sqrt{W}} \]  \hspace{0.5cm} (2)

Although this formula has been successfully applied in many previous studies, it is inadequate in predicting the vibration propagation in the field, in terms of both the lack of parameters used and the inability to represent the formation transitions sufficiently.

Researchers have proposed generalized empirical models to predict PPV by considering the effects of rock properties and various excavation parameters. DGMS (1982) presented that uniaxial compressive strength and destiny had no much change in the blast's small area. Khandelwal and Singh (2006, 2009) developed new PPV models based on rock parameters using artificial neural networks. Ak and Konuk (2008) found out that discontinuity frequency was an important parameter affecting ground vibration propagation, especially when the SD took low values. Kuzu (2008) revealed that vibration propagation differs even in two different geological environments located in different directions within the same site. Singh et al. (2008) presented that higher P-wave velocity and the Young's Modulus generated larger ground vibration. Ozer (2008) and Mesec et al. (2010) studied the effects of Hoek's geological strength index (GSI); both of these studies suggested that measurements should be carried out separately for different groups classified according to GSI. Nateghi (2011) found that PPV was less sensitive to change in geological conditions than acceleration or displacement. Gorgulu et al. (2015)
addressed the effects of rock units’ resistivity, P-wave and S-wave velocities and blasting design parameters on PPV and revealed that considering these parameters contributed positively to the PPV estimation. Kumar et al. (2016) proposed a new model to predict PPV by using RQD/GSI. Yuvka et al. (2017) studied the effect of the number of holes on PPV.

Many different techniques have been to predict blast-induced ground vibrations such as neuro-fuzzy inference system (Iphar et al., 2010; Koçaslan et al., 2017), random forest method (Longjun et al., 2011; Ohadi et al., 2019; Zhou et al., 2020), support vector machine (Hasanipanah et al., 2015), artificial neural networks (Dehghani & Atae-Pour, 2011; Monjezi et al., 2011; Armaghan et al., 2015; Hajihassani et al., 2015; Azimi et al., 2019; Ozer et al. 2019), Hilbert-Huang transform (Zhao et al., 2021) and dynamic finite-element method (Peng et al., 2021).

Although there are many studies investigating the effect of engineering rock characteristics on blast-induced ground vibration propagation, a study considering operational parameters and evaluating these variables together has not yet been revealed. Considering the state of the art literature, in this study, the important engineering properties affect the PPV magnitudes, such as RQD, UCS, unit of advance, the maximum charge per delay (W), the cross-sectional area of tunnel face, total charge, and distance between the shot point and vibration measurement station investigated by using the machine learning codes.

In the study's scope, 57 blast shots were monitored, and 225 events were recorded at 32 different measurement stations. Blasting and excavation operation parameters and rock properties of rock were recorded for each shot. Various machine learning methods were used to estimate PPV values. Neural Network (NN), Support Vector Machine (SVM), Linear Regression (LR), and Random Forest (RF) are commonly used methods among learning classifiers. The RF, which could evaluate all of these features together, was investigated, and the effect levels of the parameters on PPV were determined.

MATERIAL AND METHODS

Study Area

In this study, blasting operations within the Rumeli Hisarustu – Asiyan Funicular Line construction, which is a continuation of the Levent – Hisarustu/Bogazici University Metro Line, were investigated. The tunnel length is 956 meters, and the depth varies between 4.7 and 54.3 meters.

The funicular line is located on the European side of the Bosphorus in Istanbul, Turkey (Fig. 1). The area is a rich and touristic district adjacent to the Bosphorus and Rumeli Castle. There is a dense human circulation in the district, and social life is active at nearly all hours of the day. In addition to the density of human circulation and historical structure, many buildings are at very close distances on and around the tunnel route. For these reasons, minimizing the blast-induced environmental effects is very important to avoid causing damage to the surrounding structures and maintain the quality of social life.

Fig. 1. The Study Area and Its Sectional View

Geology

In the study area, Lower-Middle Devonian aged Kartal formation (DK) and Kozyataği member (Dkk), Lower Carboniferous Thracian Formation (Ct), and Holocene aged Filling (Yd) units are observed. Paleozoic units have been folded, faulted, and thrusts in places starting from the bottom. Stratified rocks have gained a wave-like structure due to the effect of tectonic forces. There is compatibility between fold axes and vertical fractures, and they are nearly parallel to each other. Therefore, it is believed that folds and fractures develop together. Due to overlapping folds and fractures, relatively thick dents zones have developed (Emay, 2014).

Random Forest (RF) Method

Boosting and Bagging (Quinlan, 1996) are two very successful methods for collective learning in trees' classification. Each tree is built by using training data in Bagging. Consecutive trees are independent of the previous one, and the biggest vote is taken for guessing. RF uses the bagging method (Breiman, 2001). Breiman aims to create each tree independently from each other using training data using the Bagging technique. Also, estimates are created by the random selection method.

Besides, each variable's significance is measured from the data generated during the collective learning method to estimate new data. This model can be beneficial for reduction when there are many predictors. RF is a collective learning method that uses repeated segmentation and shredding to produce multiple trees.
Random vectors are created to develop each tree in collective learning. The Bagging method is based on tree development by a random selection of samples obtained from the training data. Breiman created new training data by randomizing the original training data. In this approach, random vectors are created for each tree. The vectors are independent of each other. A tree is developed using and training data. The number of samples in the training data is S. Random vectors are randomly placed in S boxes. Then random split selection is made. Random split selection θ is an independent random number between 1 and n. The size and structure of θ depend on the structure and use of the tree to be created. Once a large number of trees are created, they are voted for the most popular class. Each tree is assigned one vote for the most popular class. These process steps are called random forest.

RF develops many classified trees and places the input data into each tree to classify a new object. Each tree gives a classification, and tree votes are determined for that class. The forest chooses the classification that has the highest vote.

- S random training data is obtained by replacing S's original data.
- R variables are selected from the total input variables to be random r ≤ R. This r value is constant during forest development for each node.
- Each tree is developed to the widest extent possible. During classification, pruning or rule stop operations are not performed (Archer, 2008). This is the most critical advantage that distinguishes RF from other decision trees methods (Pal, 2005).

RF uses the CART (Classification and Regression Tree) algorithm to develop maximum size trees without pruning (Breiman, 2001). In the CART algorithm, splitting is performed by applying a certain criterion in a node. Firstly, the values with all the qualities are taken into account, and after all matches, two divisions are obtained. The selection process is applied to these divisions. In splitting processes, nodes with homogeneous class distribution are preferred. The RF model uses the Gini (Pal, 2005) index to measure node homogeneity. Gini index for a given node t;

\[ Gini = 1 - \sum (p_i)^2 \]  

Equation 3

In Equation 3, \( p_i \) shows the relative probability of its class in node \( t \). The splitting position, which has the smallest Gini index, is determined. According to the division criteria determined using the training data created, the nodes are divided into splits as in Fig. 2, and tree structures are formed.

**Fig. 2. Example of tree structure created according to the optimal division positions determined in the RF classifier.**

**Statistical Performance Validation**

In this study, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Correlation Coefficient (R) values were calculated. These performance values can be formulated as follows.

\[ MAE = \frac{1}{n} \sum_{i=1}^{n} |d_i - p_i| \]  
Equation 4

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (d_i - p_i)^2} \]  
Equation 5

\[ R = \frac{\sum (d_i - \bar{d})(p_i - \bar{p})}{\sqrt{\sum (d_i - \bar{d})^2 \sum (p_i - \bar{p})^2}} \]  
Equation 6

where \( d_i \) and \( p_i \) are the desired and estimated output (PPV) respectively; \( \bar{d} \) and \( \bar{p} \) represent averages values, and \( n \) represents each sample in the data set.

**FIELD STUDY**

In this study, 57 shots were performed on two different tunnels, one with 110 m\(^2\) cross-sectional area and another with 33 m\(^2\) cross-sectional area. Each blasted tunnel faces’ RQD and UCS values were obtained from on-site inspection, laboratory tests and geological reports (Ozer et al., 2018). After each blasting, units of
advance were measured by topographic devices. At the end of the field study, a data with 225 events was recorded. A representative set of obtained data is shown in Table 1.

Table 1: A representative set of field data

The blasting vibration data were evaluated with the classical PPV-SD equation given in Eq.1, and the site-specific vibration equation was obtained (Eq. 7). By considering its mediocre correlation, it can be said that the equation could not make predictions in the field. It was thought that the main reason for this is the insufficient number of parameters evaluated on blasting vibration. Therefore, the need for analysis with advanced techniques has arisen.

\[
PPV = 42,314 \times SD^{-0.649} \quad (R = 0.59)
\]  

In the following sections of the study, PPV estimation via machine learning and comparison of the estimation abilities of different machine learning methods were studied. The RF method was found to be the method that achieved meaningful and acceptable estimation results. Also, the parameters affecting the blasting vibrations and the degree of their impact have been researched and presented.

Table 2 presents the input and output parameters; minimum, maximum, mean, and standard deviation parameters were defined. In Table 2, RQD, UCS, unit of advance, the maximum charge per delay, the cross-sectional area of tunnel face, total charge, and the distance data were used as inputs, and PPV was used as output.

Table 2: Statistical characteristics of data set that reveals Minimum (Min), Maximum (Max), Mean and Standard Deviation.

RESULTS AND DISCUSSION

PPV values were estimated from the RF method's data. Fig. 3 shows the block diagram of this study. Here, the 10-fold Cross-Validation (CV) method and holdout methods are used to avoid over-fitting the system during the learning process. The data set was divided into ten groups during learning. When nine groups were used for learning, the remaining 1 group was used in the testing process. This process was carried out ten times. In the holdout method, 66% of the data were used as the training process, and the rest were in testing. Fig. 4 presents how CV and Holdout methods are performed.

Fig. 3. Block diagram of the proposed model

Fig. 4. Representation of CV and Holdout methods

The prediction and the actual results are shown in the graphs in Fig. 5. When looking at the results obtained from different methods, it was possible to compare the models. The results were the values obtained after training. The blue line shows the actual PPV values, while the red shows the values obtained after the estimate.

Fig. 5. Results graphics after training process, respectively; Neural Network, Support Vector Machine, Linear Regression and recommended Random Forest

As can be seen from Fig. 5, the RF method has given very successful results. Correlation Coefficient (R) regression curves for these results are shown in Fig. 6.

Fig. 6. Regression graphics of Neural Network, Support Vector Machine, Linear Regression and recommended Random Forest, respectively.

As seen in Fig. 6, the regression graph of the RF model has the most successful result.

The comparison of the RF and other Classical Machine Learning Methods results

The results of machine learning methods such as Neural Network (NN) (Schmidhuber, 1992), Support Vector Machine (SVM) (Vapnik, 1995) and Linear regression (LR) (Seber and Lee 2012) which are very successful in
the literature, were compared with the proposed RF method. The training results are shown in Table 3, the results after the CV method are shown in Table 4, and the results obtained after the Holdout method are shown in Table 5, respectively. As shown in the tables, the RF model has the lowest error and the highest R values.

Table 3: Comparisons of prediction performances by using various approaches (Training results).

Table 4: Comparisons of prediction performances by using various approaches (CV results).

Table 5: Comparisons of prediction performances by using various approaches (Holdout results).

Parameter Analysis

In this study, estimation accuracy increased due to creating an RF model by considering RQD, UCS, unit of advance, and cross-sectional area with scaled distance variables as inputs. Based on this result, input parameter importance level on PPV estimation was calculated according to the average impurity decrease for selected RF parameters (Louppe et al., 2013, Chen et al., 2019), given in Table 6 and illustrated in Fig. 7.

Table 6: Input’s importance level on PPV Estimation and number of nodes in RF

Fig. 7. The input parameter importance based on the average impurity decrease for the RF model.

According to the created RF model, UCS was the most critical parameter on PPV attenuation in the study area. In other words, the strength of the geological units in the field, the cross-sectional area of the tunnel face, and the RQD values are the most critical factors on PPV attenuation. Also, the cross-sectional area and advance rate are other parameters that affect PPV.

The results have revealed more critical parameters on blasting vibration than SD, and for a proper analysis, these parameters should be evaluated.

CONCLUSION

Considering the absence of a study that takes excavation planning parameters and rock characteristics into account and evaluates these variables together, this study aims to use RQD, UCS, unit of advance, distance, maximum charge per delay and cross-sectional area of tunnel face as inputs of blast-induced ground vibration prediction process. The research stages and the significant results of the study are listed below.

In conditions where test shots cannot be made or the commonly used PPV-SD equation (Eq. 1) cannot make acceptable predictions as in this study, it is important to evaluate different parameters other than scaled distance and to develop new models by using various methods. Therefore, in this study, PPV estimation via machine learning and comparison of the estimation abilities of different machine learning methods were studied. The results of machine learning methods which are very successful in the literature, were compared with each other. The RF method was found to be the method that achieved the most meaningful and acceptable estimation results. Therefore, it could be said that RF method was a useful tool to estimate PPV where commonly used formula could not make acceptable predictions.

As a result of using the RF method and considering new parameters that are not considered in commonly used formula, a new model was developed that could make more accurate predictions. In this model, parameter analysis was made in order to reveal how important that the added new parameters were in PPV estimation. It was concluded that, UCS was the most effective parameter on PPV attenuation; the cross-sectional area and RQD followed it. Also, the advance rate was another parameter that affects PPV. The results showed that parameters not considered in PPV estimation, such as UCS, RQD, and cross-sectional area of tunnel face, may be more effective than the commonly used SD. Therefore, these parameters should be evaluated for a more accurate PPV estimation.

While designing blasting parameters based on risk analysis, it was revealed that the evaluation of only PPV and SD data pairs might be inadequate; in such conditions, many other parameters, such as the tunnel face's cross-sectional area, operational blasting parameters, and rock characteristics should be considered as well. By considering all of these parameters, it will be possible to make more precise applications and estimations; therefore, increasing blasting efficiency will occur.

Based on these findings, it can be said that the proposed model will help to estimated rock type-based blast-induced ground vibrations. While this methodology sheds light on the basic problems of blasting engineering, the parameter analysis also contributes significantly to the subject's infrastructure. Following the
proposed methodology in solving the problems encountered in different sites will significantly contribute to the solution.

Acknowledgment
This work was financially supported by the Executive Secretariat of Scientific Research Projects of Istanbul University-Cerrahpasa (project code: 21628) and Engineering Faculty Revolving Fund (project code: 10.07.2018-24898). The authors would like to thank Istanbul University-Cerrahpasa Engineering Faculty, Executive Secretariat of Scientific Research Projects of Istanbul University-Cerrahpasa and Ankara Construction Company.

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