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Comparison of a linear discrimination function and artificial neural networks approach to discriminate the seismic events in Ankara (Turkey)

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Abstract

In this study, natural and blast-induced ground vibrations (namely earthquakes and quarry blasts) in Ankara (Turkey) were analysed and distinguished from each other. A total of 156 digitized vertical component velocity seismograms of seismic events of 2009-2014 with Md≤3.5 were obtained from the Lodumlu broadband station (LOD) controlled by Boğaziçi University, Kandilli Observatory, and Earthquake Research Institute Regional Earthquake-Tsunami Monitoring Center (BU-KOERI-RETMC). We examined the following variables: the ratio of the highest amplitude value of the S-wave and the highest amplitude value of the P-wave (Amplitude ratio) of vertical component velocity seismograms, the power ratio (Complexity), the logarithmical value of the amplitude of the S-wave of the seismogram (Log S), and total signal duration of the seismogram. It is the first time that natural and blast-induced ground vibrations were separated from each other using the Fisher's Linear Discriminate Analysis (FLDA) technique and Artificial Neural Networks (ANNs) approach together in Ankara (The capital of Turkey). Ninety-two (59%) of the 156 seismic events studied were identified as earthquakes and sixty-four (41%) of them were described as blast-induced ground vibrations. Then the obtained accuracy percentage results of three pairs of some variables were compared. The amplitude ratio versus complexity and the amplitude ratio versus total signal duration had a high classification accuracy determination coefficient for the LOD dataset (94% for the FLDA technique and 100% for ANNs approach). ANNs approach is more successful than the FLDA technique.

Keywords: Ankara; Earthquake; Blast-induced Ground Vibrations; The Fisher's Linear Discriminate Analysis (FLDA) technique; Artificial Neural Networks (ANNs) approach

1. Introduction

All seismic events (natural and man-made) are recorded in seismicity catalogues together. For that reason, it can induce several probable mistakes in seismic hazard studies in academic investigations. Seismic catalogues should be purified from blast-induced ground vibrations as quarry blasts in the research region. Therefore, seismograms should be meticulously analysed [Horasan et al., 2006]. There are many different techniques which distinguish natural and blast-induced ground vibrations. For example, the FLDA technique is a commonly employed statistical method in the literature.

The FLDA technique is one of the main methods to discriminate the earthquakes and the explosions. Researchers have preferred to use this technique for this purpose. Horasan et al. [2006, 2009], Deniz [2010], Öğütçü et al. [2010], Kartal [2010], Kekovalı et al. [2010; 2012], Ceydilek and Horasan [2019], Badawy et al. [2019], Tan [2021] and Tan et al. [2021a-b] distinguished some seismic events by using the FLDA technique in some cities as Istanbul (Turkey), Bursa (Turkey), Konya (Turkey), Trabzon (Turkey), Kütahya (Turkey), Manisa (Turkey), Egypt, Edirne and Manisa (Turkey), respectively.

Some researchers have used the FLDA technique and another discrimination method together. Küyük et al. [2009, 2011] studied to discriminate the earthquakes and the explosions using the FLDA technique, the Quadratic Discriminate Function and Mahalabonis Discriminate Function in Istanbul (Turkey). Yılmaz et al. [2013] analysed the seismic catalogs using the FLDA technique and Short-Time Fourier Transform method in Eastern Black Sea Region (Turkey). Yavuz et al. [2018] classified to distinguish the natural and synthetical ground motion using the FLDA technique and the Quadratic Discriminate Function in Yalova (Turkey).

Furthermore, the synthetical seismic events were separated from the seismic catalogues by using some algorithms of the ANNs approach, too. The ANNs approach have been used for different purposes in the Earthsciences. Those purposes have been the management of seismic risk, forecasting of the magnitudes of the induced-seismicity, the determination of the natural seismic events with small magnitude and the correlation of the seismic parameters, the cumulation of the recent seismicity, and the hypocenters of the seismic events, respectively [Zonno et al., 2003; Samui and Kim, 2014; Wiszniowski et al., 2014; Ramdani et al., 2015; Mousavi et al., 2016].

The determination and the discrimination of the nuclear and seismic ground motions have been investigated by using the ANNs approach in the applied seismic and the seismology [Dowla et al., 1990; Ursino et al., 2001; Del Pezzo et al., 2003; Küyük et al., 2009, 2010, 2011a-b; Yıldırım et al., 2011; Farahani et al., 2012; Kundu et al., 2012; Hammer et al., 2013; Çaylak and Kaftan, 2014; Kortström et al., 2016].

Further the FLDA technique and the ANNs approach have been studied together for discrimination of the seismic events, too [Gitterman et al., 1998; Küyük et al., 2012; Tan, 2021 and Tan et al., 2021a-b].

In this study, seismic events which occurred from May 2009 to March 2014 in Ankara (the capital of Turkey) were analysed. This study is the first that uses the FLDA technique and the ANNs approach together to separate natural and blast-induced ground vibrations in Ankara.

The location of the seismic station and the dissociation of seismic activities are indicated in Figure 1. Blast-induced ground vibrations were deployed in the construction and mineral materials subtraction process regions.

The aims of this study were to individuate natural and blast-induced ground vibrations from each other, and to compare of the performances of a statistical method (The FLDA technique) and a machine learning approach (The ANNs approach). Therefore, the FLDA technique and the ANNs approach were performed on the vertical component velocity seismograms at the Lodumlu broadband station (LOD). Examined variables that belonged to the seismograms are the amplitude ratio, complexity, log S and total signal duration. The results of the accuracy percentage (%) were determined according to both of the FLDA technique and the ANNs approach separately. Acquired values of the accuracy percentage were controlled to define the real seismic activity. It shall increase the reliability of natural ground vibrations catalogues. Hence, seismic risks can be reduced in the main fault zones.

2. Data and Methods

In the study, 156 natural and man-made events with Md≤3.5 were recorded at the station LOD between May 2009 and March 2014. The study area was located on 39.70-40.70°N and 32.50-34.00°E (see Fig. 1). Data were obtained from BU, KOERI, RETMC.

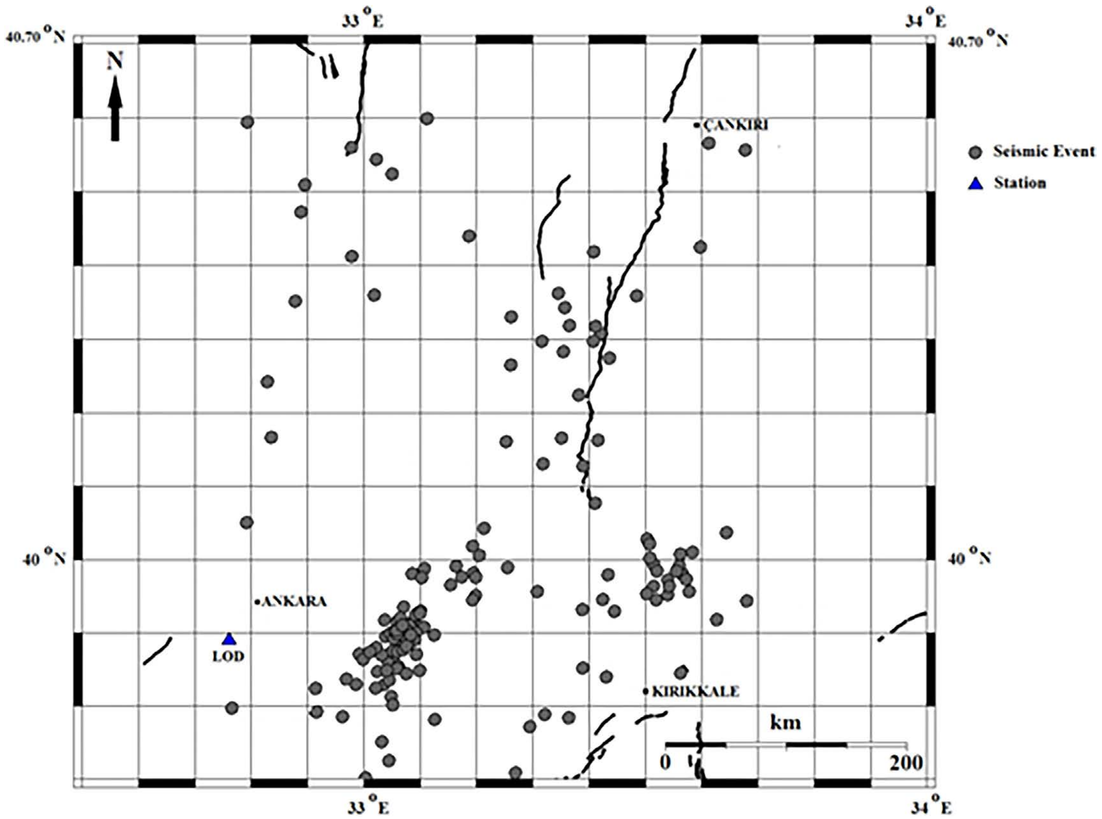


Figure 1. Location of the station LOD and seismic events with magnitudes of Md ≤3.5 in the study area between May 2009 and March 2014 (RETMC). Faults were taken from [Şaroğlu et al., 1992], [Emre et al., 2013], and [Yaltırak et al., 2012]. [Drawn by Wessel and Smith, 1995].

The histograms of the seismic activity versus daytime hours (in Greenwich Mean Time-GMT) are shown in Figures 2 and 3. After the removal of the man-made events from the seismic catalogue, the remaining natural events are shown as a histogram in Figure 3.

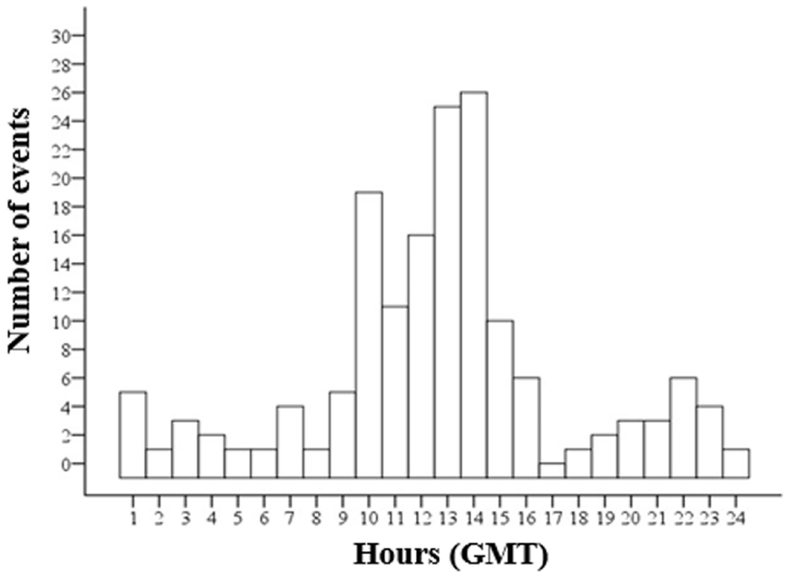


Figure 2. Histogram of the seismic activities (the number of events) that occurred between May 2009 and March 2014 vs hours (in GMT) in the research region (39.70-40.70°N and 32.50-34.00°E). The highest activity was observed at 14:00, and the increments at the seismic events were observed at 13:00 and 14.00 in GMT throughout the day.

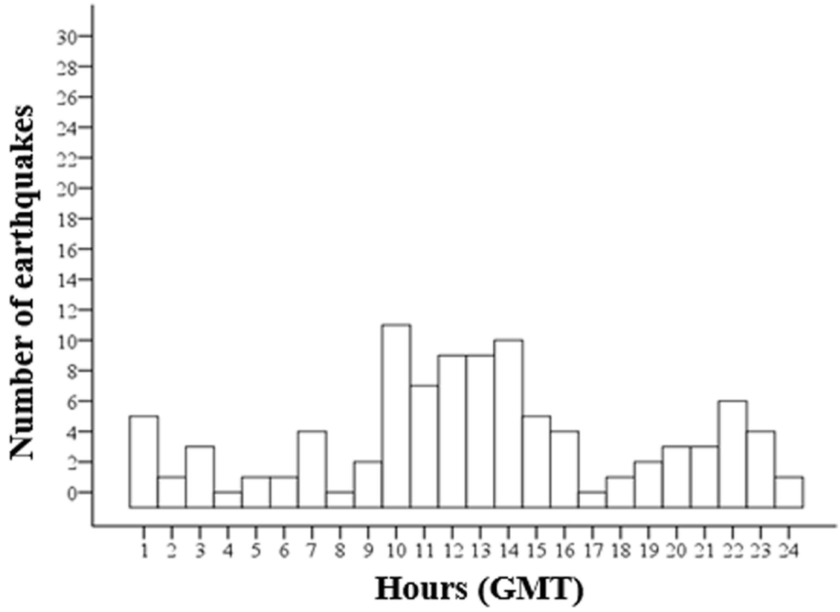


Figure 3. Distribution of seismic activities after the removal of the blast-induced ground vibrations.

Unfortunately, this process is not sufficient for discriminating seismic events. Furthermore, the vertical component velocity seismogram and spectrum will be analysed.

The seismogram and the spectrum of natural and blast-induced ground vibrations are demonstrated in Figures 4 and 5. The amplitude value of the P-wave belonging to the synthetic seismic event was more dominant than that of the earthquake as seen in Figure 4.

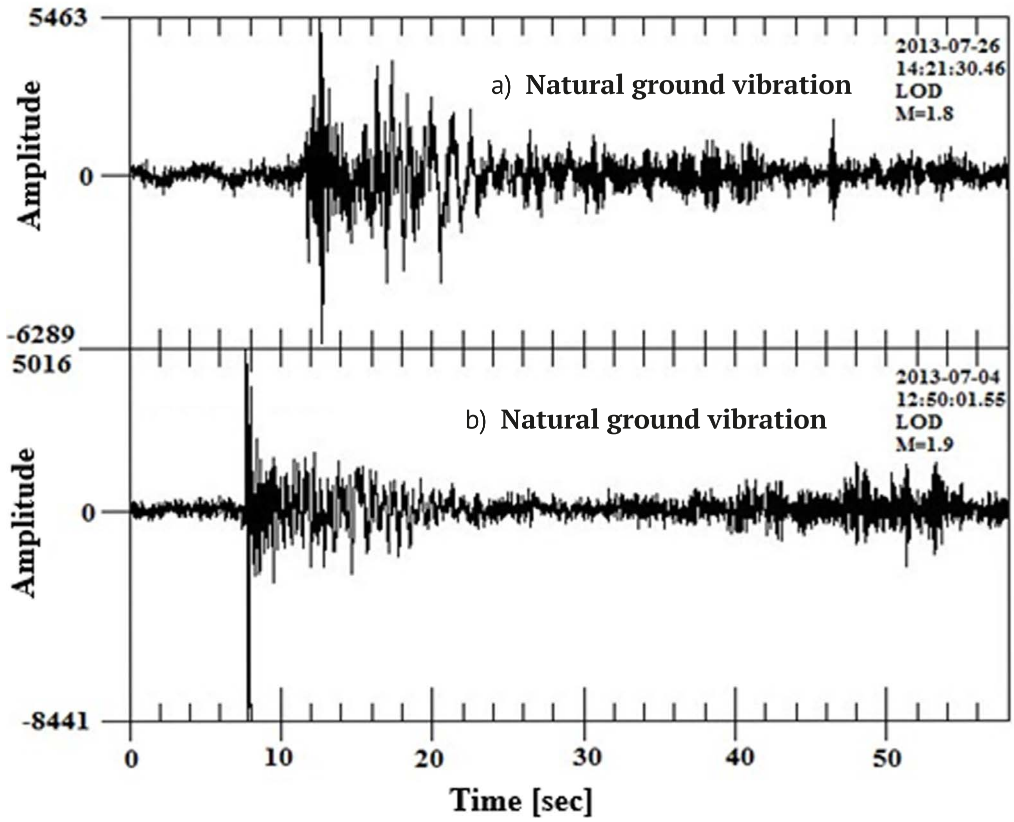
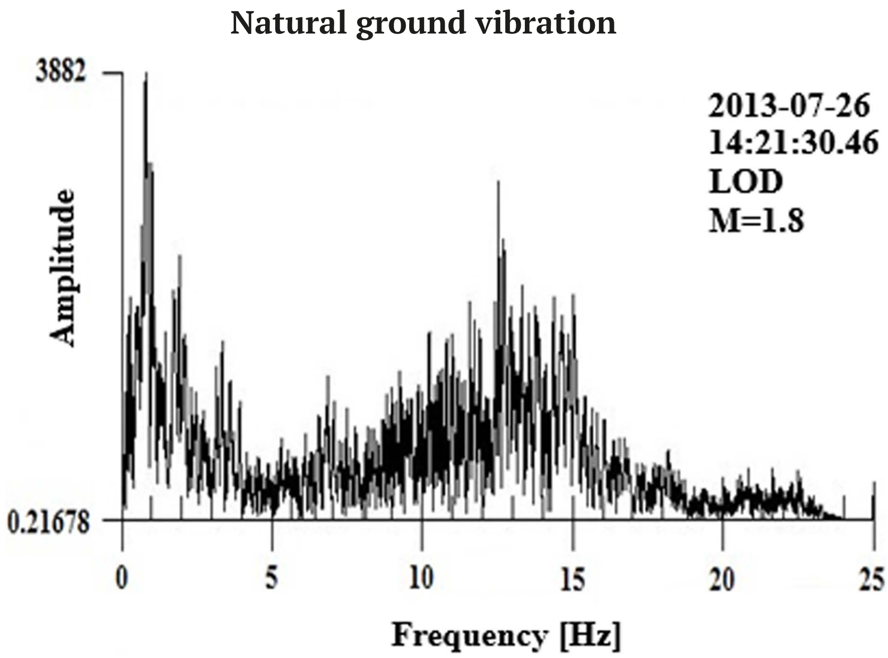


Figure 4. The vertical component of velocity seismogram recorded at station LOD (a) Natural ground vibration and (b) Blast-induced ground vibration.

a)



b)

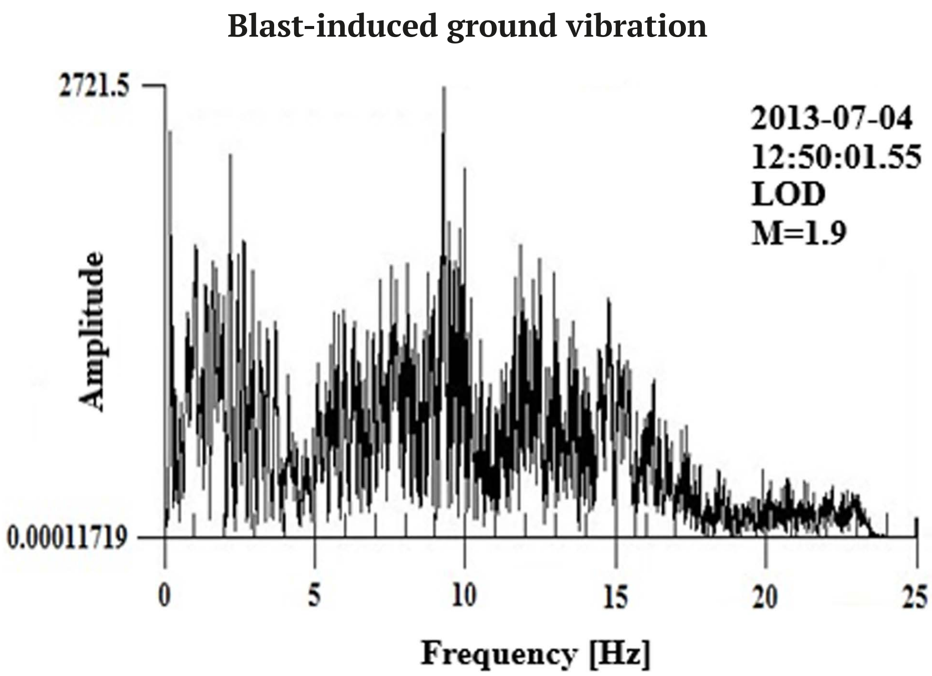


Figure 5. The amplitude spectrum that belonged to the signal recorded at station LOD (a) Natural ground vibration and (b) Blast-induced ground vibration.

We used the variables as the amplitude ratio, complexity, Log S, and the total signal duration in this study. Furthermore, some pairs of variables were decided, too. They are the pairs of amplitude ratio and complexity, the pairs of amplitude ratio and Log S, and the pairs of amplitude ratio and total signal duration.

We preferred to apply the Statistical Package for the Social Sciences (SPSS) Analysis Program software for the discrimination of seismic events [Spss, 2005].

In this study, before applying the FLDA technique to the LOD dataset, we must recognize the following variables.

The complexity was the ratio of the integrated powers of the vertical seismogram S^2 (t) in the chosen time windows. According to Arai and Yosida [2004], C may be clarified as next in Equation (1),

$$C = \int_{t1}^{t2} S^2(t)dt \bigg/ \int_{t0}^{t1} S^2(t)dt \tag{1}$$

Here, t_0 is the inception time of the signal, t_1 and t_2 are intervals of time window. In this study, values of t_1 and t_2 were taken as 1 s and 13 s for the LOD dataset.

Furthermore, we identified the highest amplitude value of the Primer wave and the highest amplitude value of the Seconder wave of the vertical component velocity waveforms of natural and blast-induced ground vibrations. Then the ratio of the highest amplitude value of the Seconder wave to the highest amplitude value of the Primer wave (Amplitude ratio) was calculated for the events. The duration variable was determined from the waveform of the LOD dataset. We applied the normalization process to the data after we calculated these variables. We used these variables to distinguish earthquakes and quarry blasts (namely natural and blast-induced ground vibrations) using the FLDA technique and ANNs approach, respectively.

2.1 FLDA technique

The FLDA technique was used to discriminate different data groups from each other [Fisher, 1936]. Generally, Linear Discriminate Functions were shown as again simplified in Equation (2):

$$F_{FLDA} = a + b_1X_1 + b_2X_2 + \dots + b_mX_m \tag{2}$$

Here, a is constant number, b_1, ..., b_m are regression coefficients and X_m is the numerical response of independent variable m.

X_1: Normalized value of X_m discriminate variables.

Here, X_1 is the X_m discrimination variable that has been normalized value using a normalization technique. K-fold cross validation method has been used in this study. X_1 is the k-fold cross validation value of each of discriminated in Eq. (2). Namely X_1 represents the X_m value which has been normalized between −1 and 1.

K-fold cross validation is applied for obtaining consistent results at the same scale for all dataset. It is a necessity for the FLDA technique.

And then data groups could be discriminated from each other using the regression coefficients in Eq. (2). Thus a linear function is drawn. So the discrimination process has been carried out.

The FLDA technique has been applied to LOD dataset in this study. So obtained Amplitude ratio, complexity, Log S and total signal duration variables have been used. These values have been normalized using k-fold cross validation. X_1 is the k-fold cross validation value of each of discriminated X variables in Eq. (2). Namely, It represents X_m value which has been normalized between −1 and 1 [Patro and Sahu, 2015].

And then, this technique has been applied to the pairs of Amplitude ratio vs complexity, Amplitude ratio vs Log S and Amplitude ratio vs total signal duration variables separately. The function of FLDA technique has been drawn for each of pairs of variables. So three graphics have been obtained (Fig. 6).

The amplitude ratio vs complexity for the LOD dataset was drawn, and we discriminated natural and blast-induced ground vibrations using the FLDA technique. The functions were drawn, and the accuracy percentages were calculated using SPSS software [Spss, 2005]. We firstly applied the FLDA technique to the LOD dataset (Table 1 and Fig. 6).

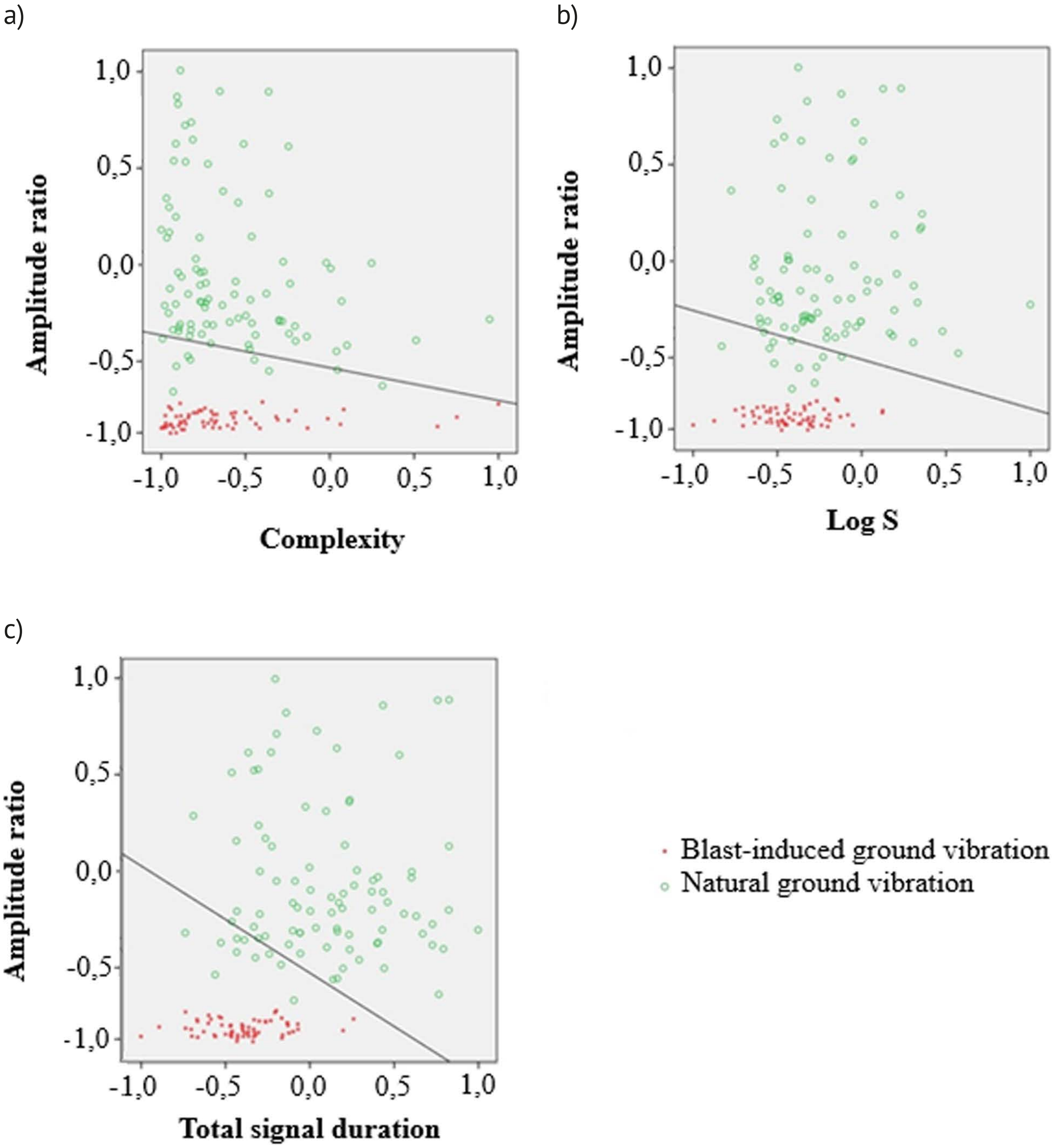


Figure 6. Plots show the distribution of a) Amplitude ratio vs complexity, b) Amplitude ratio vs LogS, and c) Amplitude ratio vs total signal duration for the LOD dataset using the FLDA technique. The accuracy percentages were 94% for pairs of amplitude ratio vs complexity variables, 92% for pairs of amplitude ratio vs Log S variables, and 94% for pairs of amplitude ratio vs total signal duration variables, respectively.

Criterion		Diagnosis	Estimated Group Membership		Sum
			Blast-induced ground vibrations (QB)	Natural ground vibrations (EQ)	
1	Original Number	QB	64	0	64
		EQ	9	83	92
	%	QB	100	0	100
		EQ	9.8	90.2	100
2	Original Number	QB	64	0	64
		EQ	12	80	92
	%	QB	100	0	100
		EQ	13	87	100
3	Original Number	QB	64	0	64
		EQ	10	82	92
	%	QB	100	0	100
		EQ	10.9	89.1	100

Table 1. The results of the discriminate classifier applying the FLDA technique for pairs of Criterion 1: Amplitude ratio vs complexity, Criterion 2: Amplitude ratio vs Log S, and Criterion 3: Amplitude ratio vs total signal duration variables for the LOD datum set. The original grouped events were accurately categorized for three criteria as natural and blast-induced ground vibrations, 94%, 92%, and 94%, respectively.

2.2 ANNs approach

We used ANNs approach to compare the results of accuracy percentage of the FLDA technique. This technique was applied to the LOD dataset for the first time. In this study, we used Back Propagation Feed Forward Neural Networks (BPNNs) learning algorithm. [Çetin et al., 2006] stated that it has benefits such as decreasing error from output to input. It also has a simple neural network topology [Çayakan, 2012]. We then selected weights according to the quantity of error [Yıldırım, 2013]. Generally, the elements of the neural network architecture are shown in Figure 7 [Rumelhart, 1986; Gülbağ, 2006].

Pairs of variables were used in this study. This is because the input variable was for testing and the other variable was the output as the type. These pairs of variables were determined as the amplitude ratio vs the ratio of powers of two time-domain windows that was determined on the seismogram (Complexity), the amplitude ratio vs the logarithmic expression of the highest amplitude value of the Seconder wave (Log S), and the amplitude ratio vs the total signal duration of the waveform, respectively (see Fig. 7).

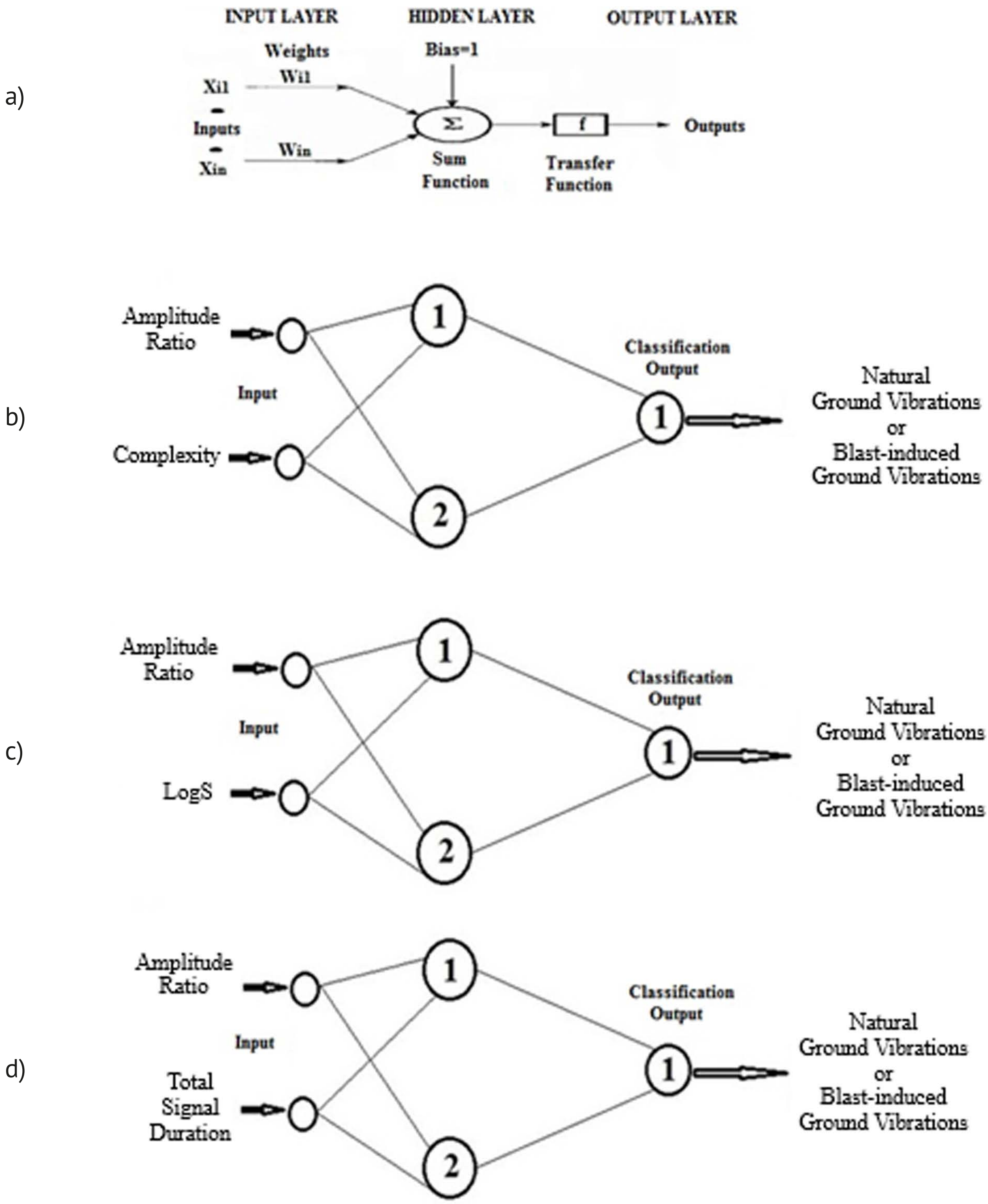


Figure 7. (a) Elements of the ANNs topology, a ANNs topology for seismic activities (b) Amplitude Ratio vs Complexity, (c) Amplitude Ratio vs Log S and (d) Amplitude Ratio vs Total Signal Duration. Modified from [Gülbağ, 2006].

After we chose the learning algorithm, we started to prepare the dataset as "the training data" and "the testing data" for ANNs approach.

Dissimilar researchers preferred their data using values of the accuracy percentage values for separation of training data and test data; namely, there is no special rule for separating the dataset [Ursino et al., 2001; Gülbağ, 2006; Yıldırım et al., 2011; Kundu et al., 2012; Yıldırım, 2013; Kaftan et al., 2017]. We randomly arranged the dataset using one station (LOD) in this study. We decided to use 70% of all data as training data and 30% as testing data. The

LOD dataset had 156 natural and blast-induced ground vibrations. We separated the LOD dataset into two parts: training data (109 data) and testing data (47 data). Namely, the number of training data was 109 (70%) using ANNs approach (see Table 2).

Criteria	The # of All Data Set	The # of Training Set	The # of Testing Set	The # of Misclassified Testing Set	The accuracy (%) (ANNs approach)
1	156	109	47	0	100
2	156	109	47	0	100
3	156	109	47	0	100

Table 2. The number of seismic events in the training set, testing set, error testing set, and error blast-induced ground vibrations for all datasets using ANNs approach (For pairs of Criterion 1: Amplitude ratio vs complexity, Criterion 2: Amplitude ratio vs Log S and Criterion 3: Amplitude ratio vs total signal duration variables for the LOD dataset).

All outcomes were acquired using ANNs approach in MATLAB Programming Language [Matlab, 2011]. We obtained the outcomes of accuracy percentage using this method and applied k-fold cross validation technique to all data, too [James et al., 2017]. We wanted to verify ANNs approach again.

Therefore, the results with high accuracy percentage were suitable. They were observed between 91% and 100%. In other words, the results of ANNs approach were very successful.

To obtain the network architecture of the ANNs, the choice of the number of neurons (the number of N) was a considerable criterion in the ANNs approach [Kermani et al., 2005; Gülbağ, 2006]. That is because it is one of the important agents for discriminating between different data clusters [Çetin et al., 2006]. According to Yıldırım [2013] and Kaftan et al. [2017] the number of N was determined experimentally. Then, the number of N which had the maximum accuracy percentage was selected for the defined ANNs approach according to Gülbağ [2006]. There are dissimilar intervals used with different increments for the number of N by researchers in the literature [Gülbağ, 2006; Küyük et al., 2009; Yıldırım, 2013; Kaftan et al., 2017]. In this study, it was increased by 5 between 5 and 25, and then the results were compared with each other for every pair of variables separately (see Table 3).

Criterion	Accuracy (%) for # of N:5	Accuracy (%) for # of N:10	Accuracy (%) for # of N:15	Accuracy (%) for # of N:20	Accuracy (%) for # of N:25
1	100	100	100	91	98
2	100	100	100	100	100
3	100	100	100	100	100

Table 3. The number of N according to the accuracy percentage results of ANNs approach for pairs of Criteria 1: Amplitude ratio vs complexity, Criteria 2: Amplitude ratio vs Log S, and Criteria 3: Amplitude ratio vs total signal duration variables.

The training was continued until the determination coefficient (R^2) was approximated to be 1. When a suitable value was obtained, the network model was stopped, and the test was started (see Table 4).

Criterion	R^2 (# of N:5)	R^2 (# of N:10)	R^2 (# of N:15)	R^2 (# of N:20)	R^2 (# of N:25)
1	0.98	0.97	0.98	0.80	1
2	1	0.98	1	1	1
3	0.98	1	0.97	1	0.97

Table 4. The variation of R^2 according to the number of N that was obtained using ANNs approach for pairs of Criterion 1: Amplitude ratio vs complexity, Criterion 2: Amplitude ratio vs Log S, and Criterion 3: Amplitude ratio vs total signal duration variables.

We selected the number of N as 5 for each pair of variables since the number of N was the lowest and the accuracy percentage was the highest for a pair of variables. In other words, the architecture of the network was not complex and was close to 1 as R^2 (see Table 5).

Criterion	The Selected # of N	Accuracy (%) (ANNs) approach
1	5	100
2	5	100
3	5	100

Table 5. The selected the number of N according to the accuracy percentage results for pairs of Criterion 1: Amplitude ratio vs complexity, Criterion 2: Amplitude ratio vs Log S, and Criterion 3: Amplitude ratio vs total signal duration variables.

In addition, we used the Levenberg-Marquardt training algorithm and Hyperbolic Tangent-Sigmoid (tanh) transfer function [Kermani et al., 2005; Küyük et al., 2009]. They had a very effective implementation in MATLAB software [James et. al, 2017; Matlab, 2011; Charrier et al., 2007; Levenberg, 1944 and Marquardt, 1963]. The selected activation function, indicated by $\varphi(k)$, determined the output of a neuron according to the induced local field. We might use the Hyperbolic Tangent-Sigmoid transfer function, determined by applying Eq. (3)

$$\varphi(k) = \frac{2}{1 + e^{(-2k)}} - 1 \tag{3}$$

where, $\varphi(k)$: tanh transfer function [Gradshteyn and Ryzhik, 2007].

Later, the normalization process was applied to all data, and a substantial percentage of the data was randomly chosen as the training data. Hence, the remaining part was used as the testing data [Kermani et al., 2005]. The acquired outputs were then matched with tested outputs, and the accuracy percentage values were computed (see Fig. 8).

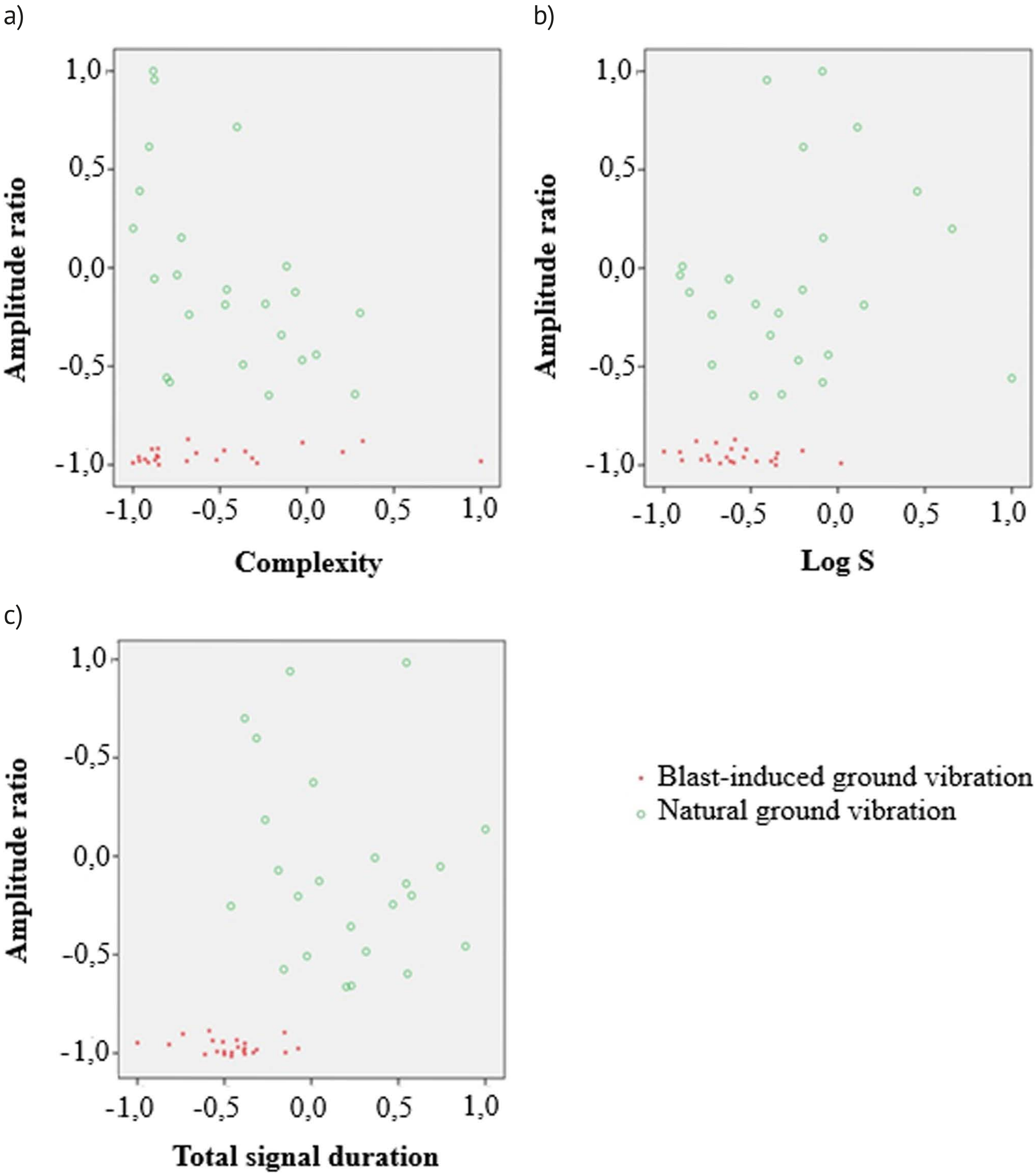


Figure 8. Plots show the distribution of a) Amplitude ratio vs complexity, amplitude ratio vs Log S, and amplitude ratio vs total signal duration for station LOD dataset using ANNs approach (Selected all Nn:5). The accuracy percentage was 100% for all pairs of variables.

The comparison of the results of ANNs approach with the results of the FLDA technique can be seen in Table 6.

Criterion	Technique / Approach	Accuracy (%)
1	FLDA	94
	ANNs	100
2	FLDA	92
	ANNs	100
3	FLDA	94
	ANNs	100

Table 6. Comparison of the accuracy percentage values for the LOD dataset using the FLDA technique and ANNs approach. Criterion 1: Amplitude ratio vs complexity, Criterion 2: Amplitude ratio vs Log S, and Criterion 3: Amplitude ratio vs total duration.

3. Results and Discussion

Firstly, the identities of the earthquakes and the quarry blasts were determined from the seismic catalogues. As a result, 92 (59%) of the 156 seismic activities studied were defined as natural ground vibrations and 64 (41%) were specified as blast-induced ground vibrations (see Figure 9).

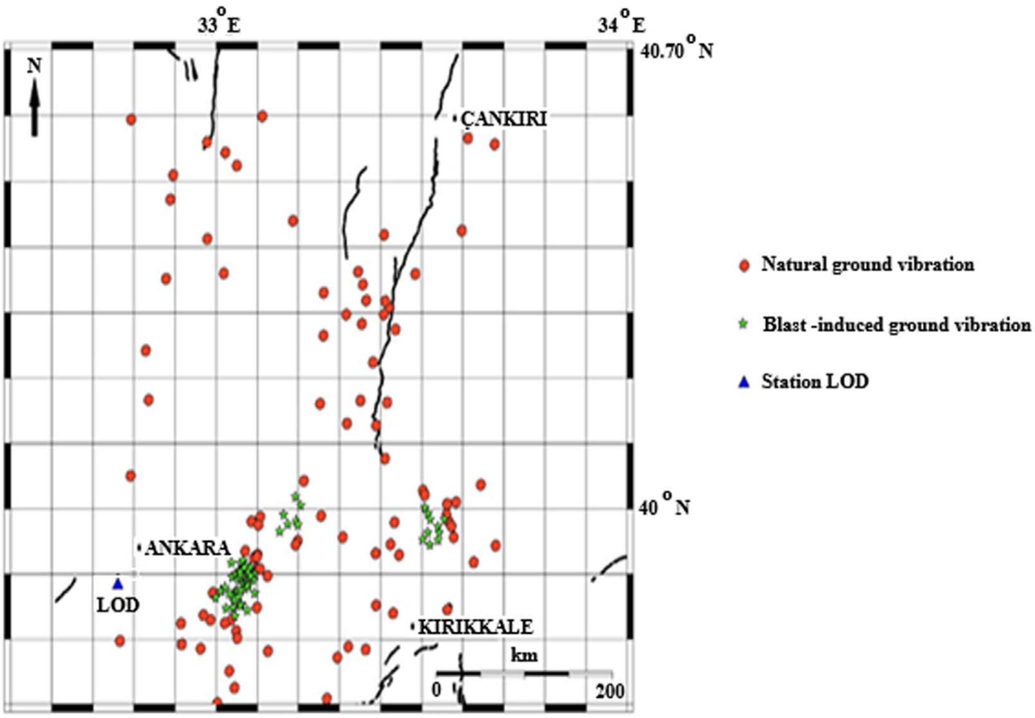


Figure 9. Location of the station LOD and discriminated earthquakes and quarry blasts with Md ≤3.5 in the research region between May 2009 and March 2014 (RETMC). Faults were taken from [Şaroğlu et al., 1992], [Emre et al., 2013], and [Yaltırak et al., 2012].

We compared the locations of the quarries with the mining or quarry areas in the Ankara province as a mining and quarry map modified from the General Directorate of Mineral Research and Exploration (GDMRE) in Figures 10a and 10b. We showed that the quarries (as shown in green stars) were clustering if there were mining or quarry areas (see Figures 10a and 10b).

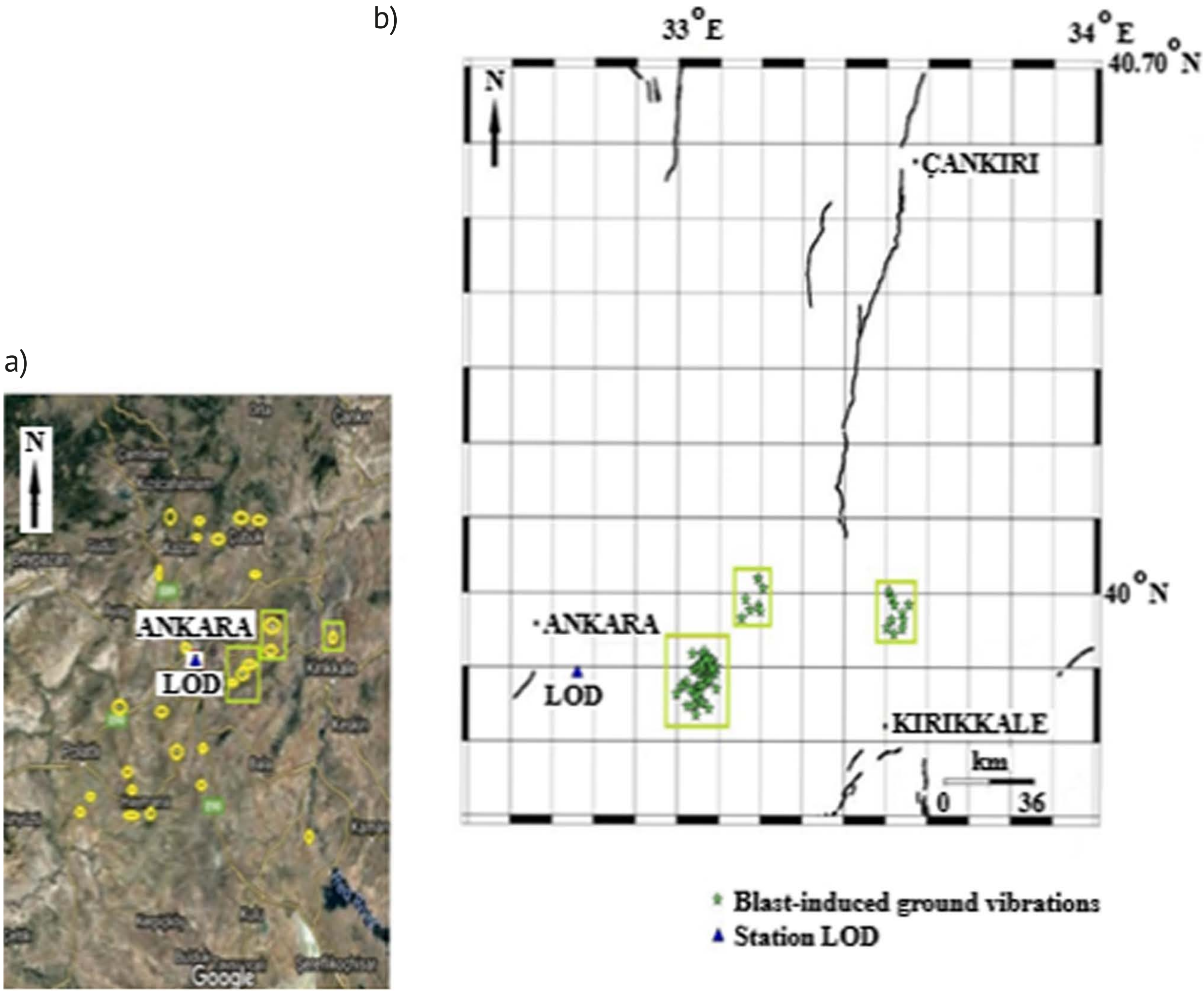


Figure 10. Comparison of the quarries that located in 39.70-40.70°N and 32.50-34.00°E coordinates according to the distribution of the mining and quarry operations in the research region. a) The location of the mining and blast-induced operations that were specified by GDMRE (the areas shown inside the red rectangular modified from Google Maps), b) The location of the Station LOD and the quarries in the study area in Ankara (Drawn by GMT program [Wessel and Smith, 1995]).

We determined that the quarry blast locations found in this study are consistent with the Ankara province mining and quarry map that was modified from the GDMRE, as shown in these figures, too.

According to the FLDA technique and ANNs approach, obtained all results are shown for the LOD dataset in Figures 6 and 8. The values of the accuracy percentage for the FLDA technique and ANNs approach are given in Table 6. When the accuracy percentage values were compared for the three criteria, the amplitude ratio vs complexity and the amplitude ratio vs the total signal duration had higher classification percentage values for the LOD dataset (94% for the FLDA technique and 100% for ANNs approach) than the other discriminant pair of variables (Amplitude ratio vs Log S) in Table 7. In the FLDA technique, the accuracy percentage values were as successful as the results using ANNs approach. However, ANNs approach was more successful than the FLDA technique in distinguishing between earthquakes and quarry blasts. In addition, we obtained 100% accuracy for all pairs of variables (for amplitude ratio vs complexity, amplitude ratio vs Log S, and amplitude ratio vs total signal duration) for station LOD datum set using ANNs approach. Since a value higher than 88% is achieved, it can be argued that these methods are successful. Moreover, the success rate of the ANNs approach is higher than the FLDA technique.

The FLDA technique is one of the most common and successful statistical methods for clustering natural and blast-induced ground vibrations in the earth sciences. Horasan et al. [2009] acquired the accuracy percentage results for pairs of variables (The amplitude ratio vs Log S) as 98.6%, 93.8%, 97.7%, and 95.8% for Gaziosmanpasa, Catalca, Gebze-Hereke, and Omerli, respectively, in Istanbul (Turkey). Yılmaz et al. [2013] defined the accuracy variables as 96.3%, 89.3%, 100%, 100%, 96.5%, and 100% for stations KTUT, ESPY, BAYT, PZAR, GUMT, and BCA, respectively. Badawy et al. [2019] acquired low accuracy percentage values (91.7%, 83.7% and 83.2%) using the ratio value of the highest amplitude of the Seconder wave to the value of the highest amplitude of the Primer wave and the complexity in Egypt compared with the other country values. The accuracy percentage of those variables depends on the number of data, tectonic properties, and location impacts.

Further, the blast-induced ground vibrations in the study were separated effectually, which may develop seismic risk examinations. Ceydilek and Horasan [2019] also used the FLDA technique at four stations (AKHS, BLN, CAM and KTT) to classify the natural and man-made seismic events in Manisa, Turkey. From the seismic events recorded by the same stations, the accuracy percentages of the pairs of the amplitude ratio vs Log S and amplitude ratio vs total signal duration variables for the discrimination were calculated as 94.4%, 95.8%, 90.0%, 93.2% and 91.2%, 89.6%, 91.4%, 88.6%, respectively. Tan et al. [2021a] studied the FLDA technique and ANNs approach together in Manisa, Turkey and found 94% (for the amplitude ratio vs complexity and amplitude ratio-Log S) for KULA dataset and 90% for amplitude ratio vs total signal duration for the FLDA technique, and 100% for all the pairs of variables for ANNs approach in their study, too. It can be concluded that these results were compatible with each other. Furthermore, Tan et al. [2021b] applied the FLDA technique and ANNs approach together in Edirne, Turkey and obtained the high results for their dataset (95% for amplitude ratio vs complexity and 94% amplitude ratio vs Log S) for the FLDA technique and (97% for amplitude ratio vs complexity and 99% amplitude ratio-Log S) for ANNs approach, too. Using FLDA technique, the values of the accuracy percentage were observed as 94% for pairs of amplitude ratio vs complexity variables, 92% for pairs of amplitude ratio vs Log S variables, and 94% for pairs of amplitude ratio vs total signal duration variables, respectively.

Further, the BPNNs learning algorithm is effective for the achievement of the ANNs approach in this study. The success of the models was determined as 99% for the BPNNs learning algorithm, 97% for probabilistic neural networks, and 96% for adaptive neural fuzzy inference systems in the literature. They were as successful as the LOD dataset outcomes. Three similar techniques were used to separate the natural and blast-induced ground vibrations in Istanbul (Turkey) and its surrounding areas by [Yıldırım et al., 2011].

4. Conclusions

The purpose of this study is to distinguish between natural and blast-induced ground vibrations (namely earthquakes and quarry blasts) by applying the FLDA technique and ANNs approach. According to obtained results, it is observed that the ANNs approach is more successful than the FLDA technique. In addition to being able to deal with nonlinear regression problems, the ANNs approach was observed to have a higher success rate than the FLDA technique. Further, the success of the ANNs approach depends on the artificial neural network architecture. For that reason, the selection of the elements of the neural network is very important.

Firstly, dataset was obtained as amplitude ratio, complexity, Log S, and total signal duration variables. For example, 4 different parameters can be given to the system as the inputs and then, the same outputs can be tested again. Used all four variables as the amplitude ratio, the complexity, Log S and the total duration can be examined using the FLDA technique and the ANNs approach in another study simultaneously. They can be determined as the input data. The successes of the FLDA technique and the ANNs approach can be compared to each other. Since the ANN approach proceeds with a logic of trial-and-error, the attention and patience of the researcher are very important during the process. In addition, the data set should be prepared with precision before the technique and approach are applied. For that reason, all data set has to be arranged carefully before the application of the technique and approach.

Ankara is located in Central Anatolia, which is an active tectonic region in Turkey. Since it is the capital of the country, this situation is of great importance. It has a high risk of seismic activity. Studies on seismology will make earthquake catalogues cleaner for earthquake hazard risk studies.

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